Come Out and Play: How Music Streaming is Affecting the Supply of New Music

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Abstract

In the business model of music streaming, artists earn revenues over extended consumption histories instead of direct record sales shortly after the release of a record. In this paper we study how the introduction of online streaming changes artists' releasing strategies. Using an extensive data set of artists' historical music releases collected from MusicBrainz.org, we systematically compare the release strategies of artists before and after the introduction of music streaming. To that extent, we employ a difference-in-differences methodology, relying on comparing the US market (where music streaming became a dominant way of music consumption by 2011), with the Japanese (where music streaming only became a dominant way of music consumption in 2017). First, we document an increase in the number of collaborations between artists over time. However, we cannot conclude that this is caused by music streaming. Contradictory to our expectations, we find that after the treatment of music streaming the increase in collaborations does not significantly differ from our control group. Second, we find that artists' focus shifts from releasing albums to releasing singles. Third, we find that albums and singles contain fewer songs. Fourth, and contrary to our expectations, we discover that artists leave more time between subsequent releases. We discuss the implications for artists and record labels.

Keywords: online music streaming, music supply, music industry, digitization, entertainment industry

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1 Introduction

Over the last two decades, digitization transformed the structure of the music industry. In 1999 global recorded music industry revenues completely consisted of physical sales; by 2016 this had declined to 34% (IFPI, 2017). In the years in-between, the consumption of music shifted from physical to digital products. First the distribution of digital products mainly took place via illegal online file sharing, which caused steep revenue decreases (Liebowitz, 2013). Later, with the introduction of digital music marketplaces such as Apples iTunes revenues from digital sales grew, but could never offset the overall decline (Waldfogel, 2010). A turning point was 2015, when after years of decline, the downward trend stopped (IFPI, 2017). This change was caused by online music streaming services like Spotify, which form a substitute for illegal consumption (Aguiar & Waldfogel, 2015). In 2008 Spotify officially launched in Sweden (Spotify, 2008). Subsequently the consumption of music via online streaming services gained enormous popularity.

The most important characteristic of music streaming is that it is changing the way music is consumed. Consumers get access to a nearly unlimited music library, without owning the products (Aguiar & Waldfogel, 2015). Instead of paying for each individual product consumers pay a fixed subscription fee to get unlimited access, or can even use the free advertising supported version (Aguiar, 2015). This brought about two major implications for the music industry: First, it affected the consumption of music and how consumers listen to music (Datta, Knox, & Bronnenberg, 2018). Second, it changed the business model of artists, who no longer generates revenues from physical sales but over extended plays (Wikström, 2012). For artists, record companies and others involved it is crucial to have insights in how to stay relevant and how to generate plays in this new business model. Because there is insufficient research focusing on the supply side we cannot draw any firm conclusions about the response of artists, and how it changed their release strategies. Therefore, it is crucial to study how music streaming is affects the supply of music.

Over the last decade academic research on the music industry has focused on the effects of digitization. Three main streams of literature can be distinguished, starting with how file sharing affected the aggregated demand of music sales. It is widely believed and demonstrated that piracy (using online file-sharing software) harmed the industry revenues (Liebowitz, 2013).

This was followed by examining the effect of digitization on the supply of music. Digitization not only made an impact on the sales of music but also on the production and distribution costs (Waldfogel, 2017). The supply of new music has not suffered, because technological developments resulted in significantly lower costs of bringing music to the market, hence the two traditional barriers of costs and skills fell. These developments allowed a much higher number of musicians to enter the industry and function as independent producers (Benner & Waldfogel, 2016; Graham, Burnes, Lewis , & Langer, 2004; Hracs, 2012). The number of new songs released and made available to consumers increased. Moreover, the quality of the products and thus consumer welfare was also enhanced (Aguiar, 2015; Bockstedt, Kauffman, & Riggins, 2006; Handke, 2012; Waldfogel, 2012; Waldfogel, 2017).

A third stream of literature focuses on the effects of music streaming on the music industry. Studies on music streaming mainly focused on the demand side of the industry. An important discussion was whether music streaming caused the increase in revenues after 2015. Wlömert & Papies (2016) and Aguiar & Waldfogel (2015) found evidence that after years of decline the increase in revenue is indeed caused by music streaming. Next, Datta et al. (2018) shed light on how music streaming affects consumption behavior. The study reveals that adoption of streaming services leads to a large increase in the quantity and variety of music consumption of individual consumers. It also found a decrease in the staying power of songs and artists in consumers' consumption sets. Less is known about the effect of music streaming on the supply of music. The new business model of music streaming is replacing the traditional ownership model of (physical) sales (Wikström, 2012). Streaming services are providing consumers access to an unlimited music catalog for free, or in return for a fixed subscription fee (Aguiar, 2015; Aguiar & Waldfogel, 2015; Datta et al., 2018; Richardson, 2014; Swanson, 2013). Studies on the supply side by Aguiar and Waldfogel (2016) and Waldfogel (2017) focus on the effects of digitization on the total number of new artists and products. Thus, there is still a knowledge gap regarding the effects of music streaming on the supply of music.

Our research extends extant research by providing information on how music streaming affects the release strategies of artists. Previous research on the supply side provided a more aggregated view by focusing on the quantity of products brought to the market. However, it remains unclear how the individual artist responds to music streaming. What we do know is that first, the shift in business model moves the incentives of artists from generating one-time sales to generating extended streams, which could have implications on their release strategies. Second, we do know that music streaming and digitization decreases production and distribution costs. The process of producing music and bringing it to the market became less time consuming and more dynamic, which provides artists with the opportunity to release music where, when and with whomever they want. Third, we know that music streaming is making it harder for artists to stay top-of-mind (Datta et al., 2018). And fourth, we know that consumption habits are shifting to individual songs rather than albums (Aguiar & Martens, 2016). What we do not know is how these factors affect the release strategies of individual artists. Therefore, in this study we will provide insights into how music streaming affects the time that artists leave between subsequent releases, the collaborations between artists, the choice of release type (album, EP, single), and the number of songs on a release. We are not only interested in the direction of the effects, but also in their volume. More broadly this thesis contributes to knowledge about on-demand services (e.g. movies, books) in comparable industries, where a comparable transition from ownership to an access-based model is taking place.

To investigate the effect, we make use of data stored in the MusicBrainz database. MusicBrainz is an open source online music encyclopedia that contains meta data of music (Swartz, 2002). The database contains artists' historical music releases, with detailed information on artist, release and track level. MusicBrainz started collecting data in 2000 (MusicBrainz, 2017). Therefore, data can be compared between the pre and post streaming era. The data will be replicated in a virtual locally Linux machine. Next the data will be selected using SQL client software. We systematically compare the release strategies of artists before and after the introduction of music streaming. To that extent, we employ a difference-in-differences methodology, relying on comparing the US market (where music streaming became a dominant way of music consumption by 2011), with the Japanese market (where the same phenomenon only occurred in 2017).

This thesis is structured as follows. First, in Chapter two we present an overview of existing literature related to music streaming and the effect of digitization on the supply of music. Next, in Chapter three we elaborate on our expectations. Followed by an overview of our data set in Chapter four. Next, the methodology used in Chapter five is discussed, after which the results of the analysis are presented in Chapter six. Finally, Chapter seven presents the conclusion and discussion.

2 Literature Review

In this chapter we provide an overview of relevant literature on the subjects in this study. First previous research on the effects of file sharing on the music industry is discussed. Second we elaborate on studies that focus on the effects of digitization on the supply side of music. Third, studies on the effect of music streaming on the music industry are outlined.

2.1 File Sharing

Research on digitization first mainly focused on the effects of file sharing on the revenue stream of the industry. Illegal file sharing services started in the late 90s and gained enormous popularity at the beginning of this century (Zentner, 2006). Illegal music downloads formed a substitute to legal (physical) sales (Zentner, 2009), and caused heavy decreases in revenues (Hong, 2007; Liebowitz, 2013; Rob & Waldfogel, 2006; Waldfogel, 2010; Zentner, 2009). It took a long time for the music industry to react in an effective way. The first reaction of the major record labels, which suffered from the steep decreases in revenue, was to take legal action. This led to the disappearance of some file sharing platforms, but others kept coming back, which resulted in an ongoing decline in revenues (Jaisingh, 2007). The first successful legal alternative was the Apples iTunes store (Waldfogel, 2010). The success of iTunes led to an increase in legal digital music consumption. However, it could not offset the decreasing effect of illegal file sharing services on the music industry's revenue (Waldfogel, 2010).

2.2 Digitization and the Supply of Music

Studies on the supply side of the music industry focused on the debate whether digital copying would reduce the number and quality of original works supplied.

A study by Handke (2012) found empirical evidence that illegal copying did not reduce the supply of new music in Germany. The annual number of titles released continued to expand

and showed no significant difference from a long-term upward trend. Moreover, Handke (2012) provides evidence that the amount of time spent listening to sound recordings has not decreased over this period, suggesting no strong decline in the quality of new work. The reason that the supply of music has not decreased is that digitization not only affected sales but also production and distribution costs (Waldfogel, 2017). With a computer and relatively cheap software, music can be produced at a much lower price than previously (Waldfogel, 2012). Furthermore, music can be distributed globally at low cost by using digital online platforms. The developments allowed a much higher number of musicians to enter the industry and function as independent producers (Benner & Waldfogel, 2016; Bockstedt et al., 2006; Graham et al., 2004; Hracs, 2012). Moreover, digitization affected the distribution between major and independent labels (Waldfogel, 2012). Benner and Waldfogel (2016) found that after digitization the number of releases made by major record labels declined, while the number of releases by independent record labels increased. Not only the total number of independent record labels increased, but they also found that major labels are focusing more on specific groups of artists that are already successful (Benner & Waldfogel, 2016). Aguiar and Waldfogel (2016) found that the share of products produced by independent and "young" artists among commercially successful products is growing. These findings point to a changing, more powerful role of the artist within the industry.

2.3 Music Streaming

2.3.1 Music Streaming is Increasing the Revenues of the Music Industry

Research on music streaming is gaining in popularity. Because of the newness of the phenomenon, there are only few studies to date that focus on this topic. Studies conducted by Wlömert & Papies (2016) and Aguiar & Waldfogel (2015) reveal that the growth in revenue since 2015 is caused by music streaming services.

2.3.2 The New Business Model of Music Streaming

The new way of distributing music has several applications for the music industry, with a huge potential impact. One of the most important aspects is that the business model of music streaming significantly differs from the traditional business model (Marshall, 2015). Wikström (2012) describes the differences between the new and traditional distribution model to explore the impact of the new model. The core difference is the change from ownership of the product to access. The traditional business model is the ownership model, which dominated most of the last century (Vaccaro & Cohn, 2004). It refers to the mass production and distribution of physical products that are distributed via brick-and-mortar stores (Hughes & Lang, 2003). With the rise of online subscription music services the ownership model is rapidly being replaced at the expense of the fast-growing access model (IFPI, 2017).

The access model is based on unlimited access for consumers to a music catalog in return for a fixed subscription fee (Aguiar, 2015; Aguiar & Waldfogel, 2015; Waldfogel, 2017; Wikström, 2012). In the access model it is not relevant whether music listeners actually are the owners of a song or not, it is more important that they can find and access the music, everywhere and at any time (Wikström, 2012). A fundamental difference between the two is that in the ownership model, rights holders primarily earn their revenues as a fixed royalty based on how many copies of a song or an album the music retailer is able to sell (Wikström, 2012). In the access model, rights holders are paid on the basis of how many times their songs are streamed (Marshall, 2015). As a third distribution model Wikström (2012) mentions the context model. It is an evolution of the access model where service providers deliver extra context to increase the consumers' listening experience to distinguish themselves from competitors.

2.3.3 Effects of Music Streaming on the Demand Side

On the demand side, Datta et al. (2018) found that streaming services are changing the way consumers listen to music. Streaming services lead to a large increase in the quantity and variety of music consumption. However, a decrease was found in the staying power of songs and artists in the consumption set of consumers. Music streaming makes it easier to enter the consumption set, but it is harder for artists to stay there. Hence, artists may exert more effort than before to stay top-of-mind (Datta et al., 2018).

2.4 Contribution to the Literature

Less is known about how music streaming affects the supply side of music. Previous research used a general approach by looking at the effect of digitization on the number of new songs or albums in a given year. This provides an aggregated view, but the response of the individual artists remains unclear. This is underlined by Waldfogel (2012), who states that there is a variety of supply responses that are not yet covered by academic research. He also mentions that the effect of music distribution via streaming services (e.g. Spotify) on the supply of new products is a fertile area for further research (Waldfogel, 2017). In this study we contribute to the literature stream on the supply of music in two ways. First, we go further by focusing on music streaming, which is the latest step in the digitization process. Second, we provide deeper knowledge on the response of individual artists instead of the general approach of looking at the quantity of supplied work.

To conclude, it can be said that literature on the supply of music has focused on the aggregated effects of digitization and that studies on the effect of music streaming have focused on the demand side of the industry, while the role of the artist is subject to change. Hence, a gap remains in our knowledge regarding the effects of music streaming on the supply of music. In the next chapter we substantiate our expectations.

3 Expectations

Here we discuss why and how we expect music streaming to affect the variables in our study. We start discussing whether artists tend to leave more or less time between subsequent releases. Moreover, we discuss the collaborations between artists, and we finish by discussing the shift from albums toward shorter release types (e.g. singles and EPs).

3.1 Effect of Streaming on Release Schedule

There is an ongoing discussion about whether artists are heading toward an accelerated or decelerated release pattern. On the one hand, an argument for an accelerated pattern is that artists can distribute music directly to consumers, which cuts out delays in the distribution process. Besides rapid distribution, technological developments have made the creative and technical process of producing music less time consuming. Artists can also release an individual song immediately, in contradiction to the pre-digital era where one would bundle songs in order to spread distribution costs. Furthermore, according to Datta et al. (2018) it is harder to stay on top-of-mind for artists, and thus they need to exert more effort than before. In order to engage with audiences there can be a tendency to the continuous release of material (Hughes, Evans, Morrow, & Keith, 2016).

On the other hand, artists may start to decelerate the pace of releasing music as a result of the new access-based business model of music streaming. The incentive to release music for direct income of physical sales is diminished, artists can now lean back and rely on revenues from extended plays of previously released work. Mortimer, Nosko, and Sorensen (2012) found that as a result of the decline in album sales artists are leaving more time between album releases. This could also be the case in the music streaming business model, where earnings from record sales are replaced by earnings over extended consumption histories.

Overall, we can say that both effects exist, and are likely to affect artists' release schedule. The question remains as to which effect will dominate. On the whole we expect that the flexible distribution process and the willingness to stay top-of-mind will predominate, and push artists to an accelerated release pattern. This means we except music streaming to decrease the mean time between subsequent releases.

3.2 Effect of Streaming on Collaborations

We expect artists to join forces and collaborate more with each other. This will lead to more tracks with two or more performing artists. An example is the developments in the rap and hip-hop genres where many collaborative projects featuring additional appearances of different artists are released, in order to gain attention and boost sales (Coley, 2018). According to Graham et al. (2004) the dominance of the major record labels is decreasing, which is an opportunity for a greater variety of potential partners to work together. This helps the traditional, static music industry supply chain to become increasingly dynamic. More directly related to music streaming, we expect the collaborations to increase because they provide artists with an opportunity to be discovered by a new audience via a collaboration with an established artist (Hughes et al., 2016). A collaboration can function as a strategy to boost streams, income and fame. Overall, we expect that online music streaming leads to more intensified collaborations between artists, therefore we expect that the share of released tracks with more than one performing artists will increase.

3.3 Effect of Streaming on Release Types and Length

We are expecting that artists will focus less on releasing full-length albums in favor of individual singles and EPs. This is fueled by the separability of digital music, which provides artists with new incentives to unbundle full-length albums and focus on producing singles (Bockstedt et al., 2006). As the production and distribution costs also decreased, there are fewer incentives to bundle songs from a cost-saving perspective, even more so as consumption habits of music listeners are increasingly oriented toward individual songs rather than albums (Hughes et al., 2016). Music streaming is increasing the ease of consuming individual songs; this is promoted by interactive playlists, which are an important part of music streaming platforms. Consumers are becoming more focused on those (self)-customized playlists that contain a collection of individual songs of different artists that can be created and shared with friends (Shukla & Stewart, 2017). Taken together we expect that artists' focus is shifting from releasing albums to releasing singles, and we expect a tendency toward releases that contain fewer songs.

4 Data

We now describe the data that we collect in order to analyze how the introduction of online streaming changes artists' releasing strategies.

4.1 Institutional Background

Over the last seven years, the consumption of music via music streaming services grew steeply (Datta et al., 2018). The market leader in the industry is Spotify. In January 2018 the service reached 70 million subscribers worldwide, a number that is growing continuously. The closest competitor Apple Music currently has 36 million subscribers (Richter, 2018). Spotify was first launched in October 2008 in Europe, and the company entered the US market in July 2011 (Spotify, 2011). The launching date in the US marks an important point because we use this date to measure a causal effect in a difference-in-differences setting. The date was chosen because Spotify was the first widely used streaming platform; after the launch year the revenues generated by music streaming in the US grew steeply from 0.7 billion dollars in 2011 to approximately 5.7 billion dollars in 2017 (IFPI, 2017; Statista, 2017). Globally there was no simultaneous shift to music streaming. We use this to estimate the treatment effect of music streaming. We choose the US market as our treatment group, and a market where music streaming became a dominant way of music consumption at a later point in time as our control group. A suitable control group would be a country with a comparable music market to the US, with the difference that the switch to music streaming took place on a later point in time. This applies to the Japanese music industry. Japan is the second largest music industry in the world after the United States (IFPI, 2016). In Japan the use of music streaming services did not gain popularity for a long time. In 2016, 73% of the revenues of the Japanese music industry still consisted of physical sales, while these declined to 18% over the years in the US (IFPI, 2017). Spotify waited with a launch in Japan until

September 2016 (Spotify, 2016). Up to that point in time no other streaming service could really make a mark on the Japanese market. Over the years several companies tried to launch a paid subscription music streaming service in Japan, but none of them were very successful, e.g. the on-demand service KKBox in 2013 and Apple music in 2015 (Manabe, 2016). Manabe (2016) mentions that streaming services caught on later in Japan because there was a lack of statutory licenses, and record companies were reluctant to supply streaming companies with Japanese content. Because the Japanese market is mainly focused on Japanese music, an often-heard complaint about failed streaming services was the lack of a broad Japanese music catalog. Spotify waited so long because it was signing deals with several record labels with the aim of being able to deliver more Japanese music. That streaming music was slower to catch on in Japan makes it a suitable control group for our study. However, we would like to point out that this approach is not free of limitations, which we discuss in chapter seven.

4.2 Meta data on Releases from MusicBrainz

To collect the data for our analysis we use the open source database MusicBrainz. The database contains artists' historical music releases, and started collecting data in 2000. The MusicBrainz database is built on the PostgreSQL relational database engine. We want a final data set that lists monthly number of releases, number of tracks per release, type of release and number of performing artists per track. However, the data in MusicBrainz are stored at a much more detailed level. There are multiple tables: artist, release groups, medium and track that contain information. Hence, we need to combine these tables, we do this by using SQL queries. The full schema of MusicBrainz database can be found in Appendix A. To explain the abstract MusicBrainz table names we provide some practical examples. A release group is a collection of separate music releases that belong together. For example, if Ed Sheeran is releasing a new album he could release his album on a CD, a vinyl record and in digital format. In the MusicBrainz database this would be registered as three separate releases, but in the release group the three releases that belong together are bundled in one release group. Furthermore, in the release group entity the type of a release, e.g. album, EP or single is registered for each release group. In the MusicBrainz database mediums are always included in a release. A medium contains information about the format of the release, e.g. vinyl, CD or digital. The number of songs on each medium are also stored in the medium section. In the track section information is stored about each individual song that is represented on a release. You can find the track title, and every track is credited to one or more artists who performed on that track.

4.3 Sample

Because the data of our interest are spread across different locations in the MusicBrainz database we compile different datasets to analyze our variables. Below we discuss the datasets for each variable, starting with the steps that we take in order to clean our data. All datasets cover a period from 01-01-2005 to 31-12-2016.

4.3.1 Cleaning Process

The first step is to remove all releases that have missing values in the date column. Then we only retain data of Japanese artists who released in Japan and American artists who released in the US. This is a necessary step because artists release globally, which could lead to confusing the releases of the treatment and the control group. Next, we take out releases that are stored under the artists' ID #1which is a collective term for various artists. For the US we were able to clean out all non-music releases such as audio books, which are distinguished by the phrase "read by" in the title. Furthermore, we clean out the remaining outliers in our sample, e.g. albums with an unrealistically high number of tracks (above a hundred).

4.3.2 Release Schedule

For our sample to measure whether artists accelerated or decelerated the release of music we make use of the MusicBrainz table release group. The sample contains 47,451 numbers of distinct release groups for the US and 36,561 for Japan. In the US 10,909, and in Japan 5,179 distinct artists are responsible for these releases. In the US the mean number of months between subsequent releases was 19, with a standard deviation of 3.5, and for Japan 9.6, with a standard deviation of 1.7. We exclude artists who only released music once in our observation period.

The unit of analysis is the time between subsequent releases in months for individual artists. We look at the overall effect and at the effect for three groups of artists, which we divide based on their total number of releases. We opted for this approach to see if our results are affected by a phenomenon called "the long tail." The long tail is driven by the lowered distribution and production costs of music, and can be described by the growing number of releases that are created by artists who release very few products over their careers (Aguiar & Waldfogel, 2016). The first group had fewer than five total releases, the next between five and twenty, and the last group of artists had over twenty releases. We distinguish between the three groups to acquire deeper knowledge, and to see if the growing number of artists who release fewer songs have an effect on our results.

4.3.3 Collaborations

To measure the collaborations between artists we examine the tracks on releases. The sample contains 794,430 distinct tracks for the US and 567,851 unique tracks for Japan. We define a collaboration as a track with more than one performing artists. We compute our variable by dividing the number of collaborations in a given period by the number of total tracks in the same period. The mean share of monthly collaborations was 11.8 for the US and 8 for Japan. To gain insight into the changing collaborations between artists we analyze the share of collaboration tracks among total tracks on a monthly level. We choose an analysis on track level because typically a collaboration is registered for an individual track, but for an album or EP typically only the main performing artist is registered.

4.3.4 Release Types

To measure the distribution between release types we also use the release group table. This sample contains 50,418 release groups for the US and 34,337 for Japan. To analyze the distribution between release types we measure the distribution between the three most common release types (album, EP, single) over time. The unit of analysis is the number of release groups of a specific type divided by the total number of release groups.

4.3.5 Release Length

To measure the length of a release we use data from the medium table in the MusicBrainz database. The sample includes 66,945 observations for the US and 58,372 for Japan. The unit of analysis in this dataset is the number of tracks on each medium. We do this for albums, EPs and singles in order to acquire knowledge on how music streaming affects the average number of tracks on each of the release types.

The next step we take is aggregating the data to a monthly level. In order to analyse the data we merge the individual datasets. In our final dataset that we use for our analysis the columns are the dependent variables, with one row for each month in our observation period for both the US and Japan.

Table 1. Variable Operationalization

Dimensions	Operationalization
(1) Mean months between release	• Mean number of months artists leave between subsequent releases
(2) Share of collaboration	• Total number of released tracks in a given period with more than one performing artist divided by the total number of released tracks in that period
(3) Distribution of release types	
• Share of albums	• Number of album release groups in a given period divided by the total number of release groups in the same period
• Share of EPs	• Number of EP release groups in a given period divided by the total number of release groups in the same period
• Share of singles	• Number of single release groups in a given period divided by the total number of release groups in the same period
(4) Release length	
• Album length	• Average number of distinct songs on an album
• EP length	• Average number of distinct songs on an EP
• Single length	• Average number of distinct songs on a single

Table 2: Summary Statistics

Statistic	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max
(1) Mean months between release			**The US**					**Japan**		
• Overall	144	19	3.5	11.9	31.1	144	9.6	1.7	6.4	15.6
• Total releases <5	144	28.1	6.2	13.8	48.4	144	19.7	6.4	7.5	36.4
• Total releases >5<=20	144	21.9	3.6	14	33.6	144	12.7	2.3	7.1	18.4
• Total releases >20	144	13.5	2.8	8	23.1	144	6.5	1.4	4	10.8
(2) Share of collaboration	144	11.8	3.6	5.5	22	144	8	2.9	0.7	16.6
(3) Distribution of release types										
• Share of albums	144	71.9	9.2	49.5	88.9	144	52.4	7.7	32.3	69.3
• Share of EPs	144	11.7	3.1	5.8	20.8	144	4	1.6	0.8	11.1
• Share of singles	144	16.4	7.7	4.1	37.8	144	43.5	7.2	27.5	61.8
(4) Release length										
• Album length	144	12.8	0.7	10.9	14.5	144	13.2	0.9	11.2	15.4
• Ep length	144	5.2	0.3	4.4	6.5	144	5.5	0.6	4.3	7.8
• Single length	144	1.9	0.6	1	3.6	144	3.4	0.2	2.9	3.9

5 Methodology

5.1 Difference-in-Differences

We use a difference-in-differences (DiD) approach to measure the effect of streaming services on the supply of music. DiD is a quasi-experimental design that makes use of longitudinal data from treatment and control groups to obtain an appropriate counterfactual to estimate a causal effect (Athey & Imbens, 2006). DiD is a useful approach to estimate the effect of a specific event or treatment, in this case the introduction of music streaming services. The changes in outcomes over time are compared between a group where the event did happen (the intervention group) and a group where the event did not happen (the control group). This removes bias for comparing two groups: from differences between the groups that already existed before the specific event happened, and from comparisons over time in the treatment group that could be the effect of other changes in the environment or society (Angrist & Krueger, 1999). We compare the outcome measures of the US before and after the introduction of music streaming with the outcome measures of Japan where streaming services had not (yet) taken off. A DiD approach was also used by Waldfogel (2012) and Datta et al. (2018) in studies regarding this topic.

We estimate models of the following type:

$$\text{Log } Y_{it} = \gamma_t + \beta_1 D^{treated}{}_i + \beta_2 D^{time}{}_t + \delta D^{treated}{}_i \times D^{time}{}_t + \varepsilon_{it}$$

where Y_{it} is the dependent variable of interest. γ_t is a month-level fixed effect, and ε_{it} is the error. $D^{treated}{}_i$ takes value 1 if an observation is part of the treatment group. $D^{time}{}_t$ takes value 1 if it is in the post-treatment period and is zero otherwise, in our case after the introduction of Spotify in the US in July 2011. The fixed effects control for common time trends and month-to-month fluctuations.

5.2 Placebo Tests

The DiD approach relies on the assumption of parallel pretreatment trends. To test whether the assumption holds, we carry out “placebo” treatment tests that are also used by Datta et al. (2018). We use pretreatment data where we define the placebo “treatment” at the midpoint of the period before the introduction of Spotify. Next, we estimate a DiD model for all dependent variables listed in Table 1. The results are shown in Appendix B. For seven of our eleven variables, we failed to reject the null hypothesis of no treatment effect for placebo treatments. This means that pretreatment trends in seven cases are statistically different across both countries and in the other four cases show parallel trends.

6 Results

6.1 Growing Intervals Between Subsequent Releases

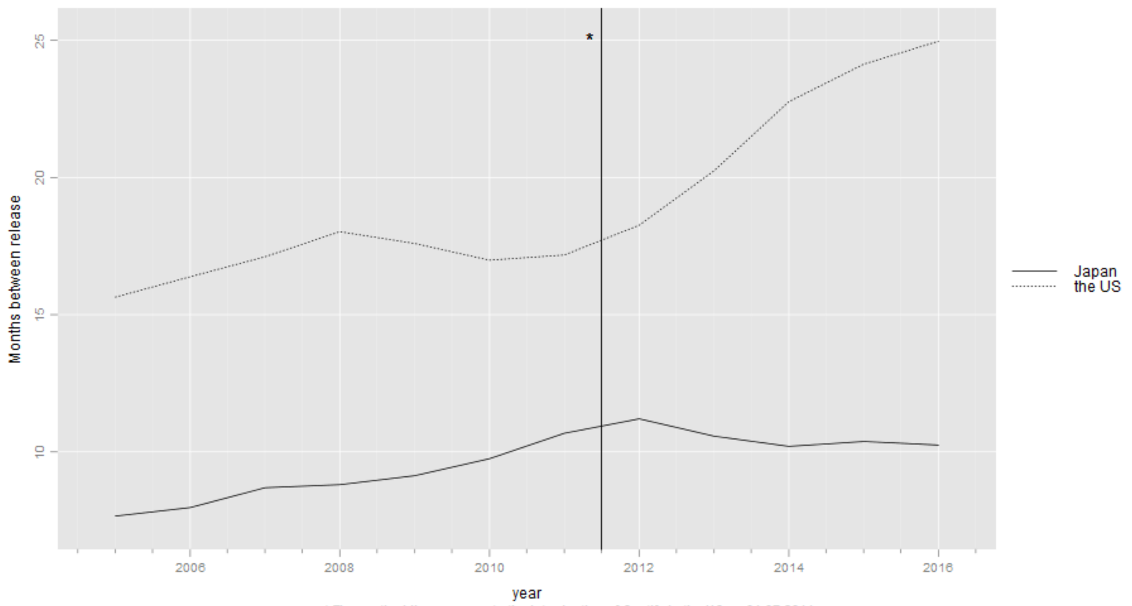
The first question we address is whether music streaming leads to artists leaving more or less time between subsequent releases. Figure 1 shows the mean months artists leave between subsequent releases, overall, for both our treatment group (US) and our control group (Japan). The vertical line in July 2011 is the point in time when Spotify was launched in the US. We distinguish between three groups of artists based on their total releases; the first group released five products or fewer, the next group released between six and twenty products, and the last group released over twenty products.

The results are shown in Table 3, column (1), (2), (3) and (4); our dependent variables are the log time between subsequent releases in months. For column (1), (3) and (4) holds that the pretreatment trends are not parallel. In column (1) we see the overall effect, which is significant at the level of $p < 0.1$. We observe that music streaming is increasing the time that artists leave between releases overall by 6.61% (=exp(0.064)-1). For artists with five or fewer releases the time between subsequent releases grows by 33.51% (=exp(0.289)-1). For artists with between five and twenty releases the time between subsequent releases grows by 14.68 % (=exp(0.137)-1). Both are significant at the level of $p < 0.001$. We observe no significant effect for artists who released more than twenty times. Graphical representations for all three groups are shown in Appendix C and D.

They visualize that the effect of music streaming decreases along with the increased number of releases of an artist. This is explained by a phenomenon called the long tail. The long tail can be defined as the growing number of products with low ex ante appeal, including independent-label releases and releases by “young” artists (Aguiar & Waldfogel, 2016). Typically they release very few products over time, but together these artists are responsible for the growing total number of products. The driving forces behind this are the decreased production and distribution costs (Anderson, 2004). Every enthusiast artist (professional or not) with an internet connection, a computer and some basic hardware is able to release music online, e.g. via Spotify. This can be done at a very low-cost level without the backing of a record label. Because of the low costs, business considerations of artists are often secondary. Instead, people create for a variety of other reasons, e.g. expression, fun, and experimentation (Anderson, 2004). Because these artists are often not full-time professional musicians they typically only release a few products. In our analysis we see that the time between subsequent releases increases for artists with only a few releases; this implies that music streaming facilitates the long tail, which explains why we see a smaller effect for artists with more total releases.

To sum up, the introduction of Spotify leads to an overall increase in time that artists leave between subsequent releases. The overall effect is driven by artists who released just a few products over their careers; for artists with over twenty releases there are no significant visible effects.

Figure 1. Mean Months Between Subsequent Releases, overall



* The vertical line represents the introduction of Spotify in the US on 01-07-2011

Table 3. Model Results Release Schedule

	Dependent variable:			
	Release Schedule			
	Log Mean Months Between Release	Log Mean Months Between Release	Log Mean Months Between Release	Log Mean Months Between Release
Artist's total releases :	overall	<=5	>5<=20	>20
	(1)	(2)	(3)	(4)
Treated	0.652^{***}	0.252^{***}	0.490^{***}	0.748^{***}
	(0.022)	(0.045)	(0.027)	(0.026)
Time	0.316^{**}	0.153	0.246	0.096
	(0.140)	(0.283)	(0.167)	(0.165)
DiD effect	0.064^{*}	0.289^{***}	0.137^{***}	-0.014
	(0.033)	(0.066)	(0.039)	(0.039)
Constant	2.024^{***}	2.653^{***}	2.310^{***}	1.759^{***}
	(0.099)	(0.200)	(0.118)	(0.117)
Observations	288	288	288	288
R^2	0.935	0.665	0.872	0.925
Residual Std. Error (df = 142)	0.139	0.281	0.166	0.164
F Statistic (df = 145; 142)	14.085^{***}	1.941^{***}	6.660^{***}	12.165^{***}
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$			

The table shows a regression model with robust standard errors in parentheses. Estimates are calculated over a period started at 01-01-2005 until 31-12-2016. For every dependent variable applies that we take the logarithm. The dependent variables are time between subsequent releases in months: (1) overall (2) for artists with 5 or less total releases (3) for artists with between releases between 5 and 20 total releases (4) for artists with over 20 releases. The independent variable Time is an indicator for whether Spotify was introduced or not. The independent variable Treated is an indicator for whether the observed country was the (1) US or (0) Japan. The DiD variable is an interaction term between Time and Treated. The fixed effect to control for the influence of monthly differences is omitted from this table.

6.2 Increasing Collaborations not caused by Music Streaming

The second question we address is whether music streaming is changing the way artists are collaborating with each other. In Table 4, column (1) our dependent variable is the log share of collaborations, which has no parallel pretreatment trend. We compute the variable by dividing the total number of monthly collaborations by the total number of released monthly tracks. A track is marked as a collaboration when two or more performing artists are registered. Figure 2 shows an increase, we can see that after the introduction of Spotify the share of collaborations for both countries is showing an upward line. In Table 4, column (1) we can see that our interaction term is not significant. Our dummy time is significant at the level of p<0.01, which means that over time the collaborations are increasing. However, because our interaction term is not significant, this means that in the US, which is exposed to music streaming, the increase does not differ significantly from the unexposed country Japan. Therefore we find, contradictory to our expectations, that music streaming does not lead to more collaborations.

An explanation can be that the increase in collaborations is driven by the effects of digitization and social media, which makes it easier for artists to collect themselves, to share ideas, and to work on music projects together. Hughes et al. (2016) state that technology has affected creative practices related to songwriting. Artists are able to discover new music (and be discovered themselves) through websites and streaming services such as iTunes and Apple Music, Spotify, Facebook, YouTube. This facility, as well as the ability to communicate easily and quickly online, has led to new possibilities for collaboration between artists. For Japan holds that the streaming services did not catch on, but social media platforms such as Facebook, Twitter and YouTube did. These platforms, which facilitate easy and quick communication for artists, can therefore be the reason that we see an increase in collaboration in both countries. Another reason can be that in Japan other variables outside the reach of our study are causing an increase in collaboration. More research is needed to explain the relation between collaborations and music streaming.

Figure 2. Share of Collaborations for the US and Japan

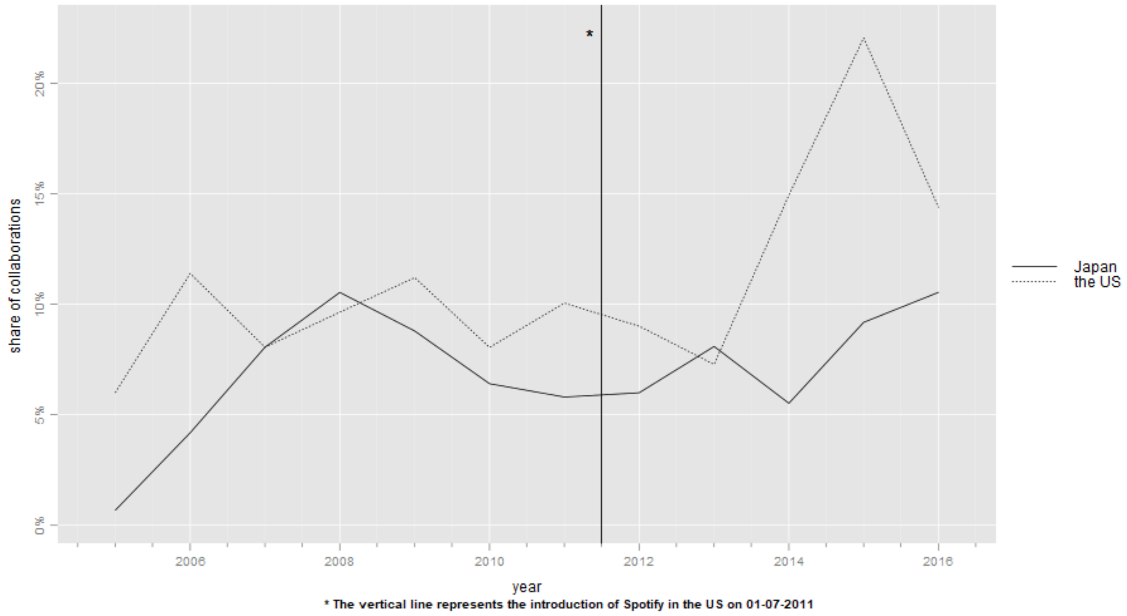


Table 4. Model Results Collaborations

	Dependent variable:
	Collaborations
	Log Share of Collaborations
	(1)
Treated	0.400***
	(0.042)
Time	1.808***
	(0.266)
DiD effect	0.039
	(0.062)
Constant	0.506***
	(0.188)
Observations	288
R^2	0.807
Residual Std. Error	0.264 (df = 142)
F Statistic	4.082*** (df = 145; 142)
Note:	*p<0.1; **p<0.05; ***p<0.01

The table shows a regression model with robust standard errors in parentheses. Estimates are calculated over a period started at 01-01-2005 until 31-12-2016. For every dependent variable applies that we take the logarithm. The dependent variable (1) is the number of tracks with two or more performing artists divided by the total number of tracks. The independent variable Time is an indicator for whether Spotify was introduced or not. The independent variable Treated is an indicator for whether the observed country was the (1) US or (0) Japan. The DiD variable is an interaction term between Time and Treated. The fixed effect to control for the influence of monthly differences is omitted from this table.

6.3 Increasing Share of Singles

The third question we address is whether the focus of artists is shifting toward the release of shorter types (singles, EPs) over longer types (albums). For EPs we report a parallel pretreatment trend, for albums and singles there is no parallel pretreatment trend. In Table 5 column (3) we can see that music streaming leads to an increase in the share of singles by 99.97% (=exp(0.693)-1). And in column (2) we see that the share of EPs is decreasing by 32.5% (=exp(-0.393)-1), both significant at $p<0.01$. The change in the share of albums is not significant. We expected to see a significant decrease in albums and an increase in EPs and singles. Figure 3 shows a graphical representation of the share of singles among total release groups; Figures 4 and 5 show the trend for EPs and albums.

A visual inspection of all three figures reveal that the patterns we expected to see for the US after the introduction of Spotify mostly occurred prior to the introduction, after which the trends stabilized somewhat. The patterns seen in the US before the introduction of Spotify are seen in Japan after 2011. An explanation can be that the digitization of the music industry in Japan started later. The Japanese market was for a long time focused on physical sales, but is slowly heading toward digital music formats (IFPI, 2017). Because the Japanese market was focused on physical sales for so long, it was not very appealing for artists to switch from albums to shorter formats, because the production and distribution costs of physical music formats are high. Now the production of physical products is slowly decreasing at the expense of digital music, and consumers tend to listen to music more on digital sources, e.g. YouTube (Music Ally, 2017). At the same time there is a release pattern, heading from albums to EPs and singles. we can see a comparable pattern at an earlier point of time in the US, which saw an earlier switch from physical to digital music. This would imply that the shift from albums to shorter release types is more driven by digitization than by music streaming; more research is needed to test this assumption.

Figure 3. Share of Albums Among Total Release Groups for the US and Japan

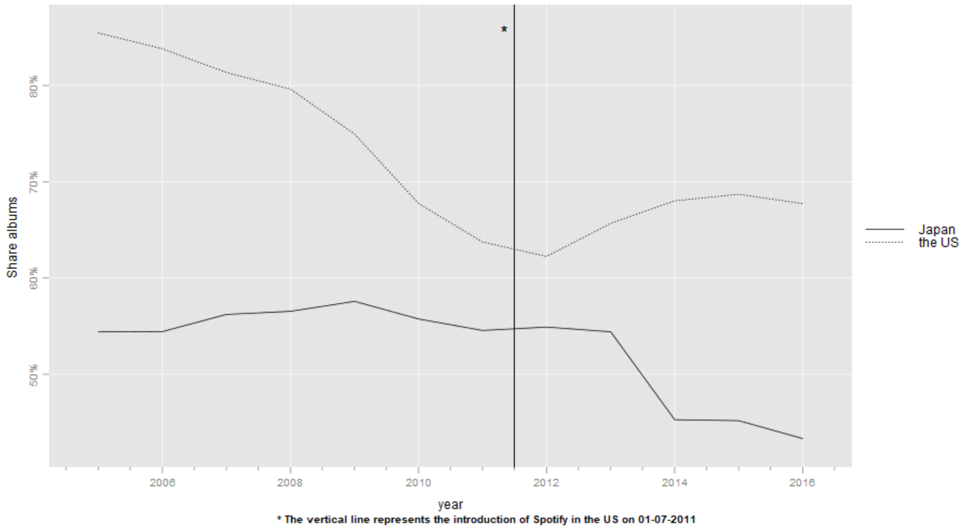


Figure 4. Share of EPs Among Total Release Groups for the US and Japan

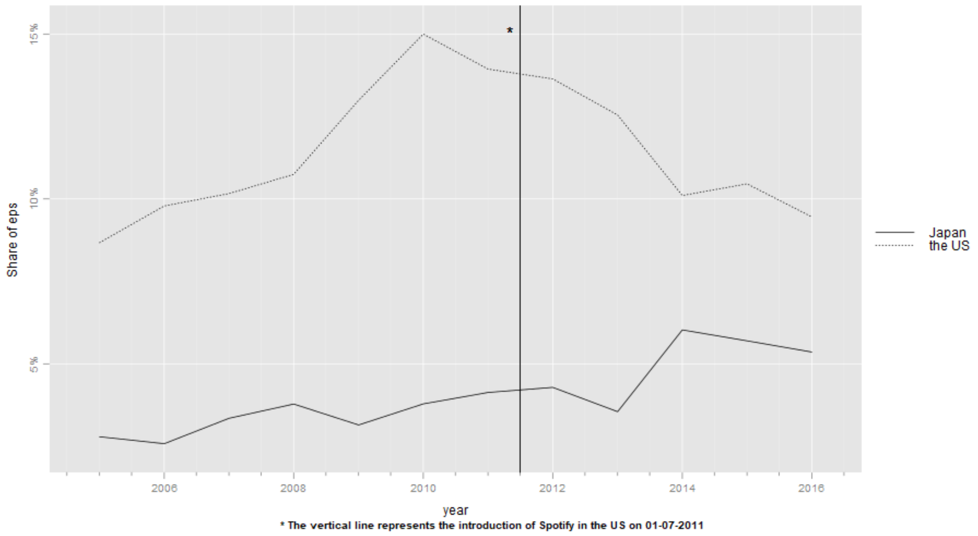


Figure 5. Share of singles Among Total Release Groups for the US and Japan

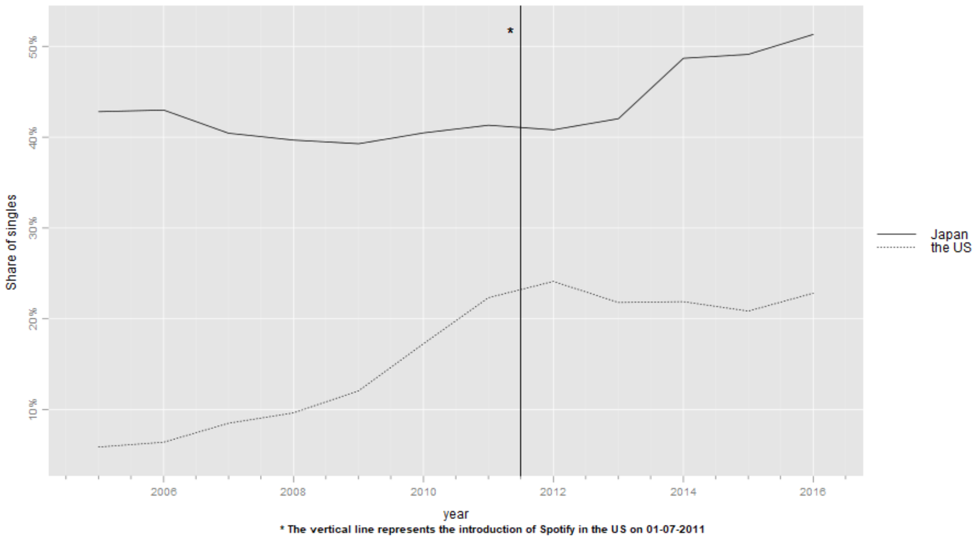


Table 5. Model Results Release Type

	Dependent variable:		
	Release Type		
	Log Album Share	Log EP Share	Log Single Share
	(1)	(2)	(3)
Treated	0.332***	1.285***	-1.414***
	(0.022)	(0.049)	(0.049)
Time	-0.177	0.781**	0.372
	(0.137)	(0.309)	(0.308)
DiD effect	-0.028	-0.393***	0.693***
	(0.032)	(0.073)	(0.072)
Constant	4.046***	0.848***	3.536***
	(0.097)	(0.219)	(0.218)
Observations	288	288	288
R^2	0.800	0.889	0.901
Residual Std. Error (df = 142)	0.136	0.307	0.306
F Statistic (df = 145; 142)	3.925***	7.880***	8.863***
Note:	*p<0.1; **p<0.05; ***p<0.01		

The table shows a regression model with robust standard errors in parentheses. Estimates are calculated over a period started at 01-01-2005 until 31-12-2016. For every dependent variable applies that we take the logarithm. The dependent variables are (1) number of release groups labelled as album divided by total number of release groups (2) number of release groups labelled as EP divided by total number of release groups (3) number of release groups labelled as single divided by total number of release groups The independent variable Time is an indicator for whether Spotify was introduced or not. The independent variable Treated is an indicator for whether the observed country was the (1) US or (0) Japan. The DiD variable is an interaction term between Time and Treated. The fixed effect to control for the influence of monthly differences is omitted from this table.

6.4 Decreasing Length of Albums and Singles

The fourth question we address is whether the length of releases is changing in terms of number of tracks per release, we compare across the major release types (album, EP, single). Our dependent variables are the log average number of songs on released albums, EPs and singles. Albums and EPs have parallel pretreatment trends; this assumption does not hold for singles. In Table 6 we can see that there is no significant evidence for the change in the number of songs on EPs. For albums and singles however, there are. We see significant effects at $p<0.05$ for albums and at $p<0.001$ for singles. A small decrease of 2.96% (=exp(-0.03)-1) is visible in the length of an album. The length of a single is decreasing by 38.43% (=exp(-0.485)-1). In Japan singles are still released in a physical format, where it is customary to have more songs on one single. In the US there is mostly only one track on a single, because digital single releases mostly contain one song. In line with our expectations the impact of music streaming is not significant for EPs. Music streaming does cause a decrease in the number of songs on albums and singles. This is in line with the trend toward the unbundling of music releases that we expected to see.

Figure 6. Average Number of Tracks on Albums for the US and Japan

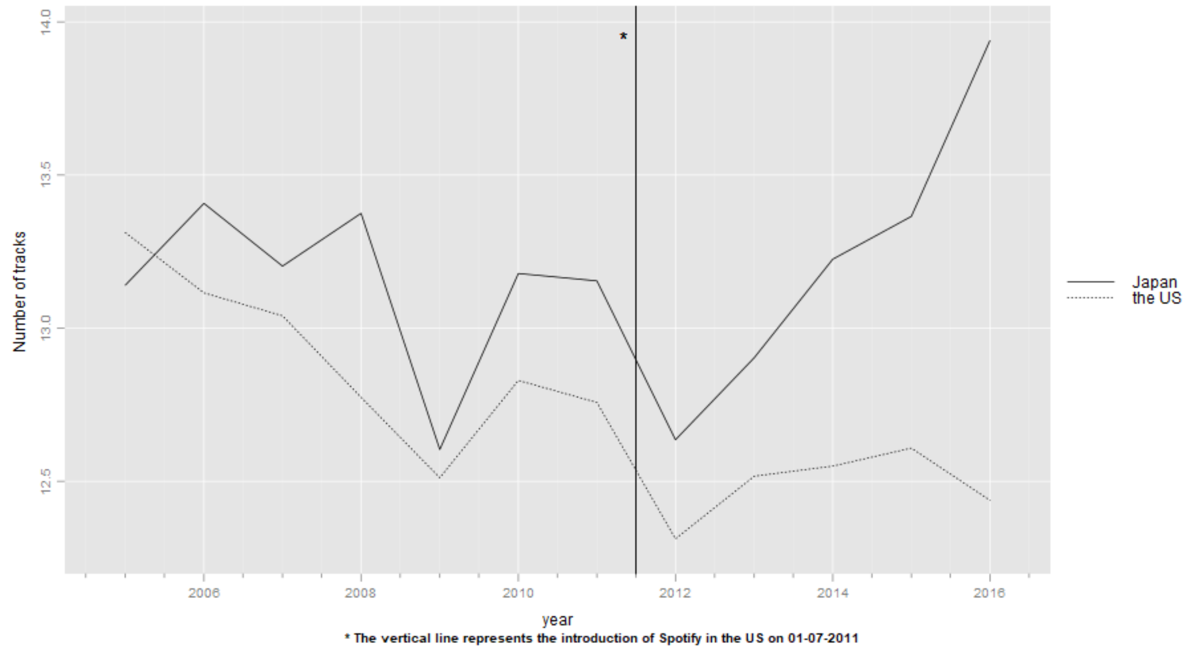


Figure 7. Average Number of Tracks on EPs for the US and Japan

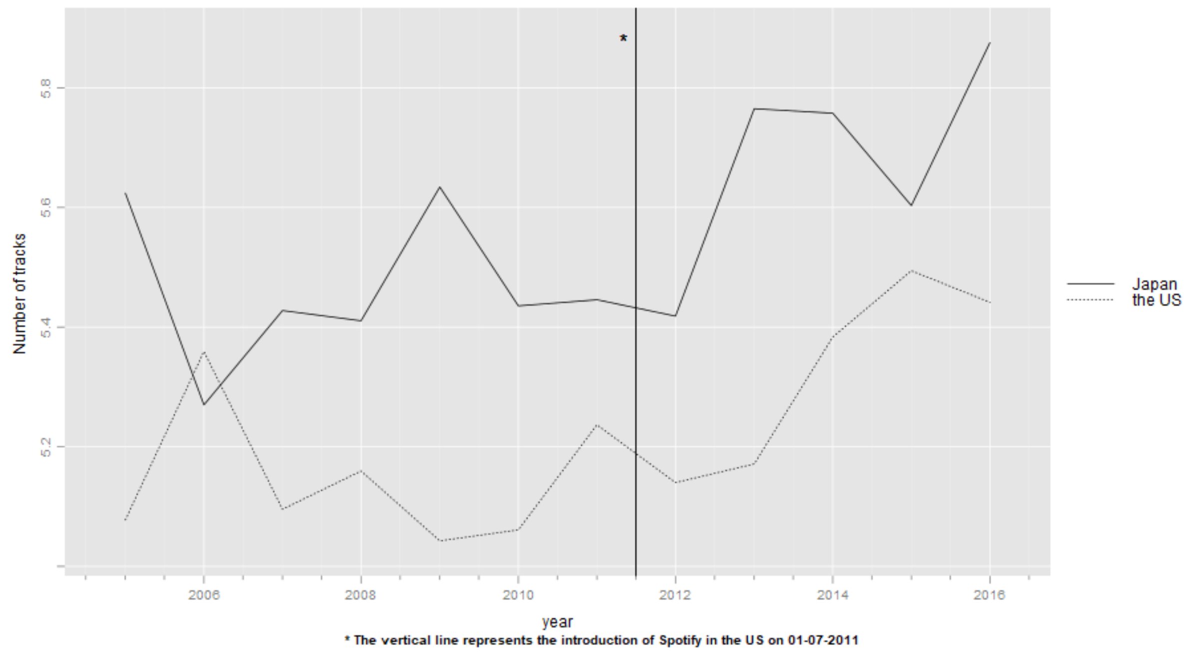


Figure 8. Average Number of Tracks on Singles for the US and Japan

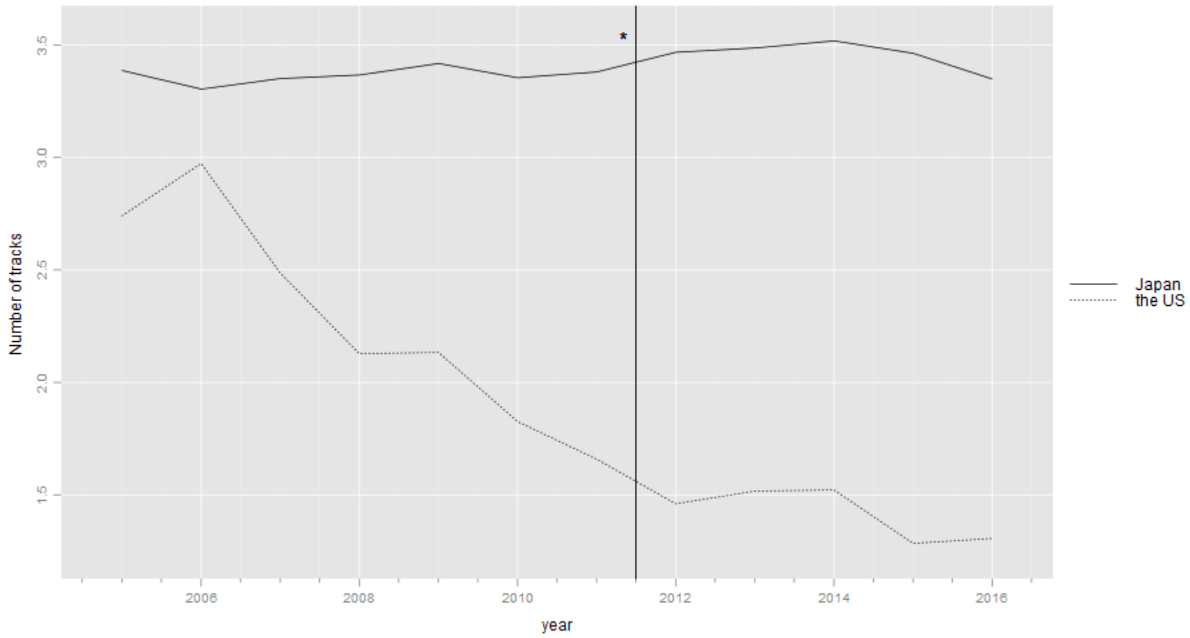


Table 6. Model Results Release Length

	Dependent variable:		
		Release Length	
	Log Album Length	Log EP Length	Log single Length
	(1)	(2)	(3)
Treated	-0.017*	-0.059***	-0.390***
	(0.009)	(0.013)	(0.021)
Time	-0.061	0.031	-0.287**
	(0.054)	(0.083)	(0.134)
DiD effect	-0.030**	0.004	-0.485***
	(0.013)	(0.019)	(0.032)
Constant	2.662***	1.757***	1.407***
	(0.038)	(0.058)	(0.095)
Observations	288	288	288
R^2	0.604	0.592	0.936
Residual Std. Error (df = 142)	0.054	0.082	0.133
F Statistic (df = 145; 142)	1.493***	1.420**	14.419***
Note:	*p<0.1; **p<0.05; ***p<0.01		

The table shows a regression model with robust standard errors in parentheses. Estimates are calculated over a period started at 01-01-2005 until 31-12-2016. For every dependent variable applies that we take the logarithm. The dependent variables are (1) the average number of songs on an album (2) the average number of songs on a EP (3) the average number of songs on a single The independent variable Time is an indicator for whether Spotify was introduced or not. The independent variable Treated is an indicator for whether the observed country was the (1) US or (0) Japan. The DiD variable is an interaction term between Time and Treated. The fixed effect to control for the influence of monthly differences is omitted from this table.

7 Discussion

7.1 Summary

In this paper we study how the introduction of online streaming changes artists' release strategies. Using an extensive data set of artists' historical music releases collected from MusicBrainz.org, we systematically compare the release strategies of artists before, with the release strategies after the introduction of music streaming. To that extent, we employ a difference-in-differences methodology, relying on comparing the US market (where music streaming became a dominant way of music consumption by 2011), with the Japanese market (where this only happened in 2017). First we document an increase in the number of collaborations between artists over time. We cannot conclude that this is caused by music streaming, because the increase in the US, our treatment group, after the introduction of music streaming did not significantly differ from the control group Japan. Second, we find that artists' focus is shifting from releasing albums to releasing singles. Third, we find that albums and singles list fewer tracks. Fourth, and contrary to our expectations, we discover that artists leave more time between subsequent releases.

7.2 Managerial Takeaways

The results of our study show several interesting managerial implications. Artists in countries where music streaming has not yet replaced the traditional business model can use the results of our study in order to apply the right release strategies at an early stage after the market entry of music streaming. Artists in general can use our results to (re)define their release strategies, moreover they can encourage them to start switching their focus to producing singles in order to be successful in the streaming business model.

We do not focus on the demand side in this study, hence we do not know if the observed changing release strategies are actually rewarding. Therefore, royalty holders, e.g.

artists and record labels, can use our results to test whether the trends in release strategies are rewarding in the streaming business model.

Record labels can learn from our results that artists' behavior is changing. Being closely connected to artists, this means for record labels that they have to adapt their business strategies. Contracts between artists and record labels are often based on a number of future albums that the artist will release via that specific record label. Because the focus of artists is shifting more to singles, record labels have to reconsider these strategies. Record labels can use the increase found to boost the reach and fame of new artists by facilitating collaborations between their major artists and new undiscovered artists. They can also respond to the needs of artists by becoming more dynamic, for example by allowing collaborations between artists from different record labels.

Our findings point to a pattern where singles are becoming increasingly important. Music streaming services can use this information to improve and adapt their digital environment so that individual songs are placed more in the center, where we currently still see albums.

In addition, our findings can be used by parties concerned in other media industries, where a comparable shift from ownership to access-based business models is taking place.

7.3 Theoretical Takeaways

The outcomes of this study have several theoretical implications. To start with, the results contribute to the knowledge on effects of online music streaming on the supply of the music industry. Previous research looked at the effects of digitization (Aguiar & Waldfogel, 2016; Waldfogel, 2017); we contribute to this stream by taking the latest developments of music streaming into account. Previous research speculates about the effect of new business models on artists, based on theoretical expectations (Bockstedt et al., 2006; Bourreau, Moreau, & Gensollen, 2008; Graham et al., 2004; Wikström, 2012). We contribute to that stream of literature by testing how the access business model of music streaming is affecting artists' release strategies. Our finding are in line with the Hughes et al. (2016) and Bockstedt et al. (2006) who expected a trend toward the unbundling of music, and a shift from albums to singles. In contrast to the expectations of Hughes et al. (2016), but in line with the findings of Mortimer et al. (2012), we find that artists are leaving more time between subsequent releases. Although suggestive, we contribute to Aguiar and Waldfogel (2016) by reporting an effect of the growing long tail in the music industry.

Future research can build upon our findings to further investigate the relationship between music streaming and the supply of music. We used a DiD model to investigate the effects of music streaming. This approach can be repeated and fine-tuned to be applied in different settings in order to gain deeper knowledge and identify the underlying mechanisms that caused our variables to change.

7.4 Limitations and Future Research

The limitations of this study are clear. This study is primarily concerned with the comparison of the US, our treatment group, and Japan, our control group. However, more research is needed to test whether our results are generalizable for other music industries. Not only do other industries have to be tested, but further work is also called for on the differences between Japan and the US, preferably based on a variety of data sources to test whether our results hold or not.

In addition, a DiD estimation relies on the assumption of parallel pretreatment trends. We tested for this assumption and have to acknowledge that for seven of our eleven variables the pretreatment trends are not parallel. Complete test result are shown in Appendix B. Future research can overcome this problem by first matching artists who are exposed to music streaming with comparable artists who are not.

Moreover, we use data from the user-generated MusicBrainz database. Aguiar and Waldfogel (2016) report that after 2006 the number of new songs in the MusicBrainz database is decreasing, in contrast to other databases such as Discogs. Using Google trends data they found that the decline reflects a decrease in reporting at MusicBrainz. For future research we highly recommend to test whether our results hold using (combinations) of other data sources.

Furthermore, as mentioned we expected that artists would leave less time between subsequent releases. However, the results of our analysis point in the opposite direction. An explanation can be the purpose of MusicBrainz. The main purpose of MusicBrainz is to provide information for software tools that helps with automatically tagging mp3 file collections correctly (MusicBrainz, 2017). When consumers switch from consuming mp3 files to music streaming it would be logical that there is less demand for such “mp3-file taggers”, and therefore, that the incentives to contribute to the MusicBrainz database would decrease. Fewer subscriptions are a logical explanation for our results that reveal more time between subsequent releases. More importantly, it provides an explanation why the time between subsequent releases in Japan remains stable over time. As Japan is not treated with music streaming the demand for mp3 tagging products did not decrease, hence the motivation to contribute to the MusicBrainz database remains. This implies that our findings could not be caused by the treatment of music streaming but by the decreased contribution to MusicBrainz in the US.

In addition, our analysis on the effects of the introduction of music streaming does not allow us to address, in satisfactory detail, the underlying mechanisms that lead to the changing release strategies. We believe that examining how collaborations, the duration of individual songs and the popularity of genres are affected by music streaming are fruitful areas for future research. Finally, it would have high managerial value to test which release strategies are leading to more plays, and hence to income in the music streaming business model.

Future investigation is necessary to validate the kinds of conclusions that can be drawn from this study. However, our study provides meaningful insights into the effect of music streaming on artists' release strategies, we offer a foundation for future research to build upon in order to explore all the opportunities that music streaming offers in more depth.

References

Aguiar, L. (2015). Let the Music Play? Free Streaming,Product Discovery, and Digital Music. *Institute for Prospective Technological Studies Digital Economy Working Paper 2015/16*. doi:10.1016/j.infoecopol.2017.06.002

Aguiar, L., & Martens, B. (2016). Digital music consumption on the Internet: Evidence from clickstream data. *Information Economics and Policy*(34), 27-43. doi:10.1016/j.infoecopol.2016.01.003

Aguiar, L., & Waldfogel, J. (2015). Streaming reaches flood stage: Does Spotify stimulate or depress music sales? *National Bureau of Economic Research*. doi:10.3386/w21653

Aguiar, L., & Waldfogel, J. (2016). Even the losers get lucky sometimes:New products and the evolution of music quality since Napster. *Information Economics and Policy, 34*, 1-15. doi:10.1016/j.infoecopol.2015.12.003

Anderson, C. (2004). The long tail. *Wired magazine, 12*(10), 170-177.

Angrist, J. D., & Krueger, A. B. (1999). *Handbook of Labor Economics* (Vol. Chapter 23 - Empirical Strategies in Labor Economics).

Athey, S., & Imbens, G. W. (2006). Identification and Inference in Nonlinear Difference-in-Differences Models. *Econometric, 74*(2), 431-497. doi:10.1111/j.1468-0262.2006.00668.x

Benner, M. J., & Waldfogel, J. (2016). The Song Remains the Same? Technological Change and Positioning in the Recorded Music Industry. *Strategy Science, 1*(3), 129-147. doi:10.1287/stsc.2016.0012

Bockstedt, J. C., Kauffman, R. J., & Riggins, F. J. (2006). The Move to Artist-Led On-Line Music Distribution: A Theory-Based Assessment and Prospects for Structural Changes in the Digital Music Market. *International Journal of Electronic Commerce, 10*(3), 7-38. doi:10.2753/JEC1086-4415100301

Bourreau, M., Moreau, F., & Gensollen, M. (2008). The Digitization of the Recorded Music Industry: Impact on Business Models and Scenarios of Evolution. *Telecom ParisTech Working Paper No. ESS-08-01*. doi:10.2139/ssrn.1092138

Coley, J. (2018). Why 2017 Was the Year of the Rap Collab Album. Retrieved from https://www.theringer.com/2017/12/18/16788868/year-of-the-rap-collab

Datta, H., Knox, G., & Bronnenberg, B. J. (2018). Changing Their Tune: How Consumers' Adoption of Online Streaming Affects Music Consumption and Discovery. *Marketin science*. doi:10.1287/mksc.2017.1051

Graham, G., Burnes, B., Lewis , G. J., & Langer, J. (2004). The transformation of the music industry supply chain: A major label perspective. *International Journal of Operations & Production Management, 24*(11), 1087-1103. doi:10.1108/01443570410563241

Handke, C. (2012). Digital copying and the supply of sound recordings. *Information Economics and Policy*, 15–29. doi:10.1016/j.infoecopol.2012.01.009

Hong, S. H. (2007). The recent growth of the internet and changes in household-level demand for. *Information Economics and Policy, 19*(3), 304–318. doi:10.1016/j.infoecopol.2007.06.004

Hracs, B. J. (2012). A Creative Industry in Transition: The Rise of Digitally Driven Independent Music Production. *Growth and Change, 43*(3), 442-461. doi:10.1111/j.1468-2257.2012.00593.x

Hughes, D., Evans, M., Morrow, G., & Keith, S. (2016). *The new music industry, Disruption and Discovery*: Springer International Publishing AG.

Hughes, J., & Lang, K. R. (2003). If I had a song: The culture of digital community networks and its impact on the music industry. *International Journal on Media Management, 5*(3), 180-189. doi:10.1080/14241270309390033

IFPI. (2016). *Global Music Report* Retrieved from http://www.ifpi.org/news/IFPI-GLOBAL-MUSIC-REPORT-2016

IFPI. (2017). *Global music report* Retrieved from http://www.ifpi.org/downloads/GMR2017.pdf

Jaisingh, J. (2007). Piracy on File-sharing Networks: Strategies for Recording companies. *Journal of Organizational Computing and Electronic Commerce, 17*(4), 329-348. doi:10.1080/10919390701636239

Liebowitz, S. J. (2013). How much of the decline in sound recording sales is due to file-sharing? *Journal of Cultural Economics, 40*(13), pp 13–28. doi:10.1007/s10824-014-9233-2

Manabe, N. (2016). Streaming Music in Japan: Corporate Cultures as Determinants of Listening Practice. In R. Nowak & A. Whelan (Eds.), *Networked Music Cultures: Contemporary Approaches, Emerging Issues* (pp. 67-76). London: Palgrave Macmillan UK.

Marshall, L. (2015). Let's keep music special. F—Spotify': on-demand streaming and the controversy over artist royalties. *creative industries Journal, 8*(2), 177-189. doi:10.1080/17510694.2015.1096618

Mortimer, J. H., Nosko, C., & Sorensen, A. (2012). Supply responses to digital distribution: Recorded music and live performances. *Information Economics and Policy, 24*(1), 3-14. doi:10.1016/j.infoecopol.2012.01.007

Music Ally. (2017). RIAJ research gives new insights into streaming challenge in Japan. Retrieved from http://musically.com/2017/09/25/riaj-research-streaming-japan/

MusicBrainz. (2017). MusicBrainz is a community-maintained open source encyclopedia of music information. Retrieved from https://musicbrainz.org/doc/About

Richardson, J. H. (2014). The Spotify Paradox: How the Creation of a Compulsory License Scheme for Streaming On-Demand Music Platforms Can Save the Music Industry. *UCLA Entertainment Law Review, 22*(1).

Richter, F. (2018). *Apple Music Struggles to Keep Pace With Spotify's Growth*. Retrieved from https://www.statista.com/chart/8399/spotify-apple-music-paid-subscribers/

Rob, R., & Waldfogel, J. (2006). Piracy on the high C’s: Music downloading, sales displacement, and social welfare in a sample of college students. *Journal of Law and Economics, 49*(1), 26-62. doi:10.1086/430809

Shukla, R., & Stewart, R. (2017). Metronome Music Time Capsule: rematerialising music consumption and exchange. *In Proceedings of AM ’17*. doi:10.1145/3123514.3123548

Spotify. (2008). We’ve only just begun! Retrieved from https://news.spotify.com/us/2008/10/07/weve-only-just-begun/

Spotify (Producer). (2011, 7 14). Hello Amarica spotify here. Retrieved from https://news.spotify.com/us/2011/07/14/hello-america-spotify-here/

Spotify (Producer). (2016, 9 29). Spotify arrives in Japan. Retrieved from https://press.spotify.com/is/2016/09/29/spotify-arrives-in-japan/

Statista. (2017). *Music streaming revenue in the U.S. 2010-2017*. Retrieved from https://www.statista.com/statistics/437717/music-streaming-revenue-usa/

Swanson, K. (2013). A case study on Spotify: exploring perceptions of the music streaming service. *MEIEA Journal*, *13*(1), 207.

Swartz, A. (2002). MusicBrainz: a semantic Web service. *IEEE Intelligent Systems, 17*(1), 76 - 77. doi:10.1109/5254.988466

Vaccaro, V. L., & Cohn, D. Y. (2004). The Evolution of Business Models and Marketing Strategies. *International Journal on Media, 6*(1-2), 46-58. doi:10.1080/14241277.2004.9669381

Waldfogel, J. (2010). Music file sharing and sales displacement in the iTunes era. *Information Economics and Policy, 22*(4), 306-314. doi:10.1016/j.infoecopol.2010.02.002

Waldfogel, J. (2012). Music piracy and its effects on demand, supply, and welfare. *Innovation Policy and the Economy*, *12*(1), 91-110

Waldfogel, J. (2017). How Digitization Has Created a Golden Age of Music, Movies, Books, and Television. *The Journal of Economic Perspectives, 31*(3), 195-214. doi:10.1257/jep.31.3.195

Wikström, P. (2012). A Typology of Music Distribution Models. *International Journal of Music Business Research*, 7-21.

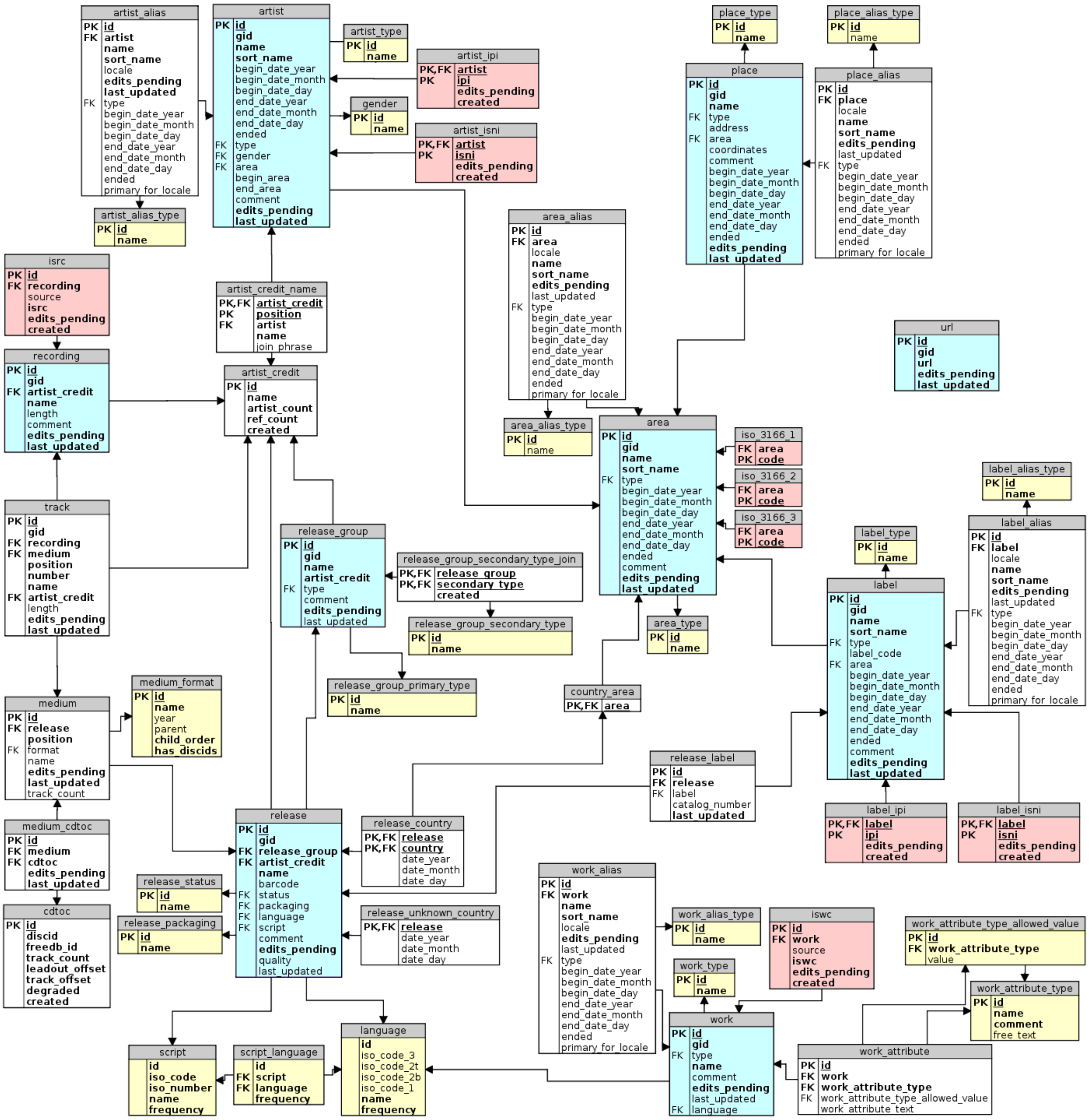
Wlömert , N., & Papies, D. (2016). On-demand streaming services and music industry revenues—Insights from Spotify’s market entry. *Int. J. Res. Mark*, 314–327. doi:10.1016/j.ijresmar.2015.11.002

Zentner, A. (2006). measuring the effect of file sharing on music purchases. *Journal of Law and Economics, 49*(1), 63-90. doi:10.1086/501082

Zentner, A. (2009). Ten Years of File Sharing and Its Effect on International Physical and Digital Music Sales. *SSRN*. doi:10.2139/ssrn.1724444

Appendices

Appendix A: Schema Diagram MusicBrainz Database



source:MusicBrainz.org

Appendix B: Regression Output Placebo Tests

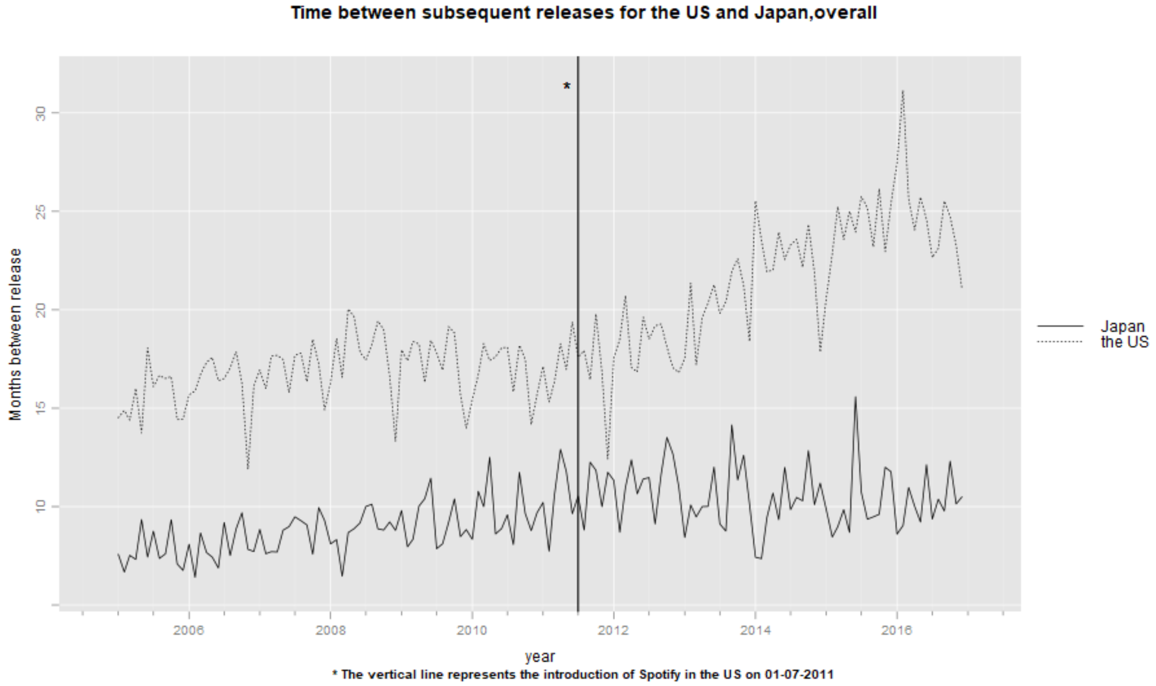
Regression Output Placebo Tests

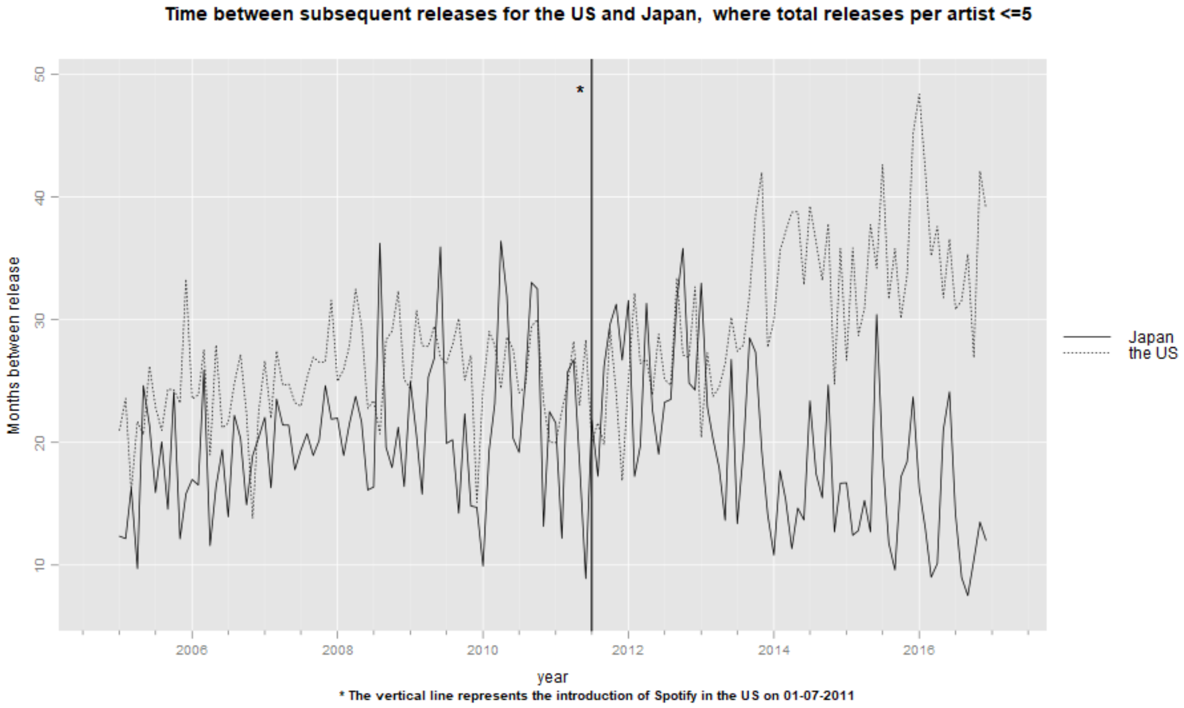
	Dependent variables:										
	Log mean months between release	Log mean months between release	Log mean months between release	Log mean months between release	Log album length	Log EP length	Log single length	Log share of albums	Log share of EPs	Log share of singles	Log share of collaborat ions
Artist's total releases	<=5	>5<=20	>20	Overall							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Treated	0.281***	0.544***	0.814***	0.709***	-0.007	-0.058**	-0.187***	0.440***	1.263***	-1.885***	0.565***
	(0.054)	(0.034)	(0.036)	(0.026)	(0.013)	(0.022)	(0.028)	(0.025)	(0.074)	(0.067)	(0.076)
Time	0.010	0.491***	0.087	0.310***	-0.105**	-0.021	-0.189*	-0.040	0.481*	0.174	1.772***
	(0.212)	(0.132)	(0.142)	(0.102)	(0.052)	(0.087)	(0.111)	(0.097)	(0.289)	(0.265)	(0.300)
DiD effect	-0.047	-0.088**	-0.107**	-0.091***	-0.015	-0.002	-0.329***	-0.176***	0.035	0.766***	-0.268***
	(0.069)	(0.043)	(0.046)	(0.033)	(0.017)	(0.028)	(0.036)	(0.032)	(0.094)	(0.086)	(0.097)
Constant	2.639***	2.283***	1.726***	1.996***	2.658***	1.757***	1.306***	3.992***	0.859***	3.771***	0.424**
	(0.150)	(0.094)	(0.101)	(0.072)	(0.037)	(0.061)	(0.079)	(0.069)	(0.205)	(0.188)	(0.212)
Observations	156	156	156	156	156	156	156	156	156	156	156
R^2	0.702	0.898	0.940	0.960	0.550	0.538	0.907	0.885	0.924	0.947	0.723
Adjusted R^2	0.392	0.793	0.878	0.918	0.082	0.057	0.809	0.765	0.844	0.891	0.436
Residual Std. Error (df = 76)	0.209	0.130	0.140	0.100	0.052	0.085	0.109	0.096	0.285	0.261	0.296
F Statistic (df = 79; 76)	2.265***	8.495***	15.075***	22.920***	1.176	1.119	9.337***	7.383***	11.625***	17.100***	2.517***

Note: *p<0.1; **p<0.05; ***p<0.01

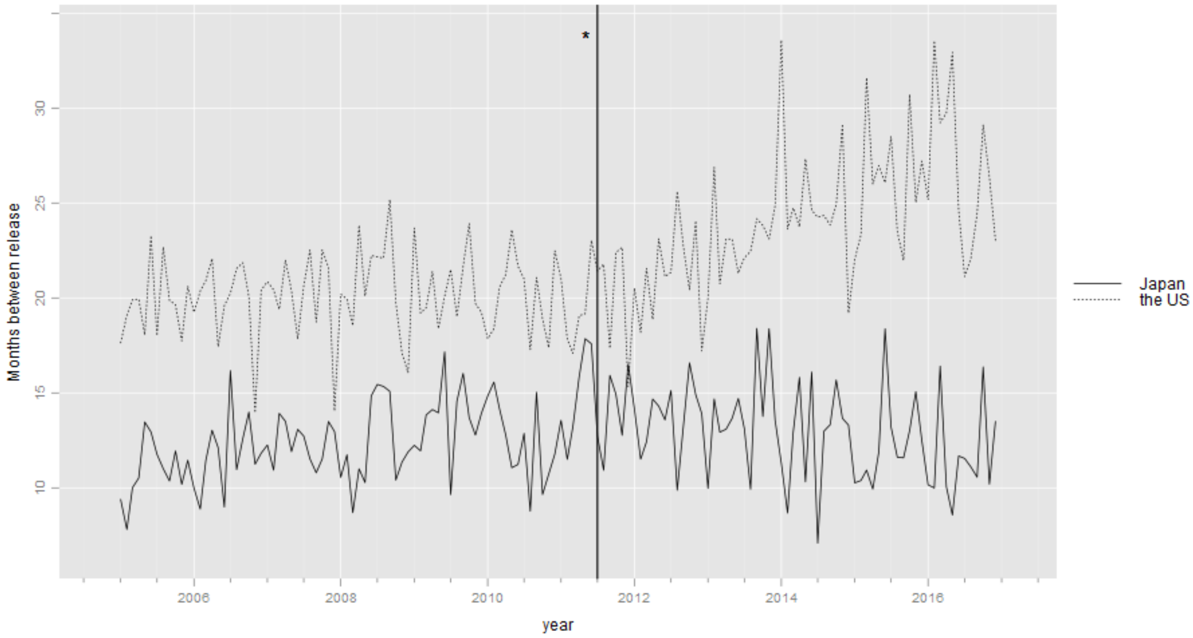
We used a data set with all the observations before the introduction of Spotify in the US. Next we define a placebo "treatment" at the midpoint of the pretreatment data, which is July 2011.

Appendix C: Visualizations of Dependent Variables on Monthly level



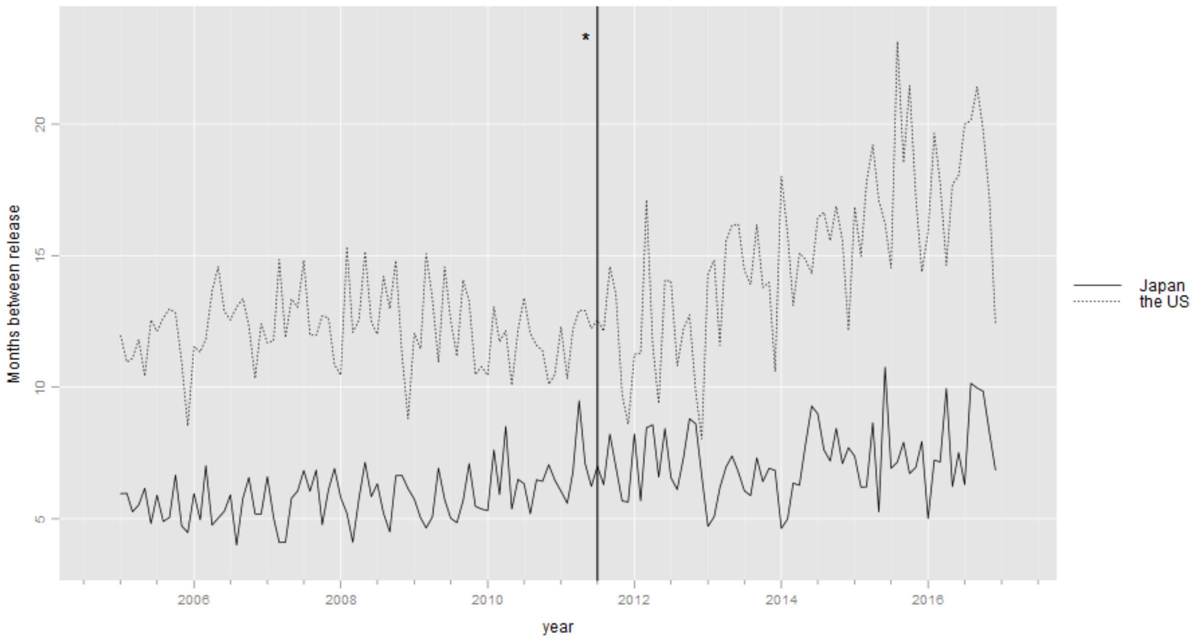


Time between subsequent releases for the US. and Japan, where total releases per artist >5 <=20



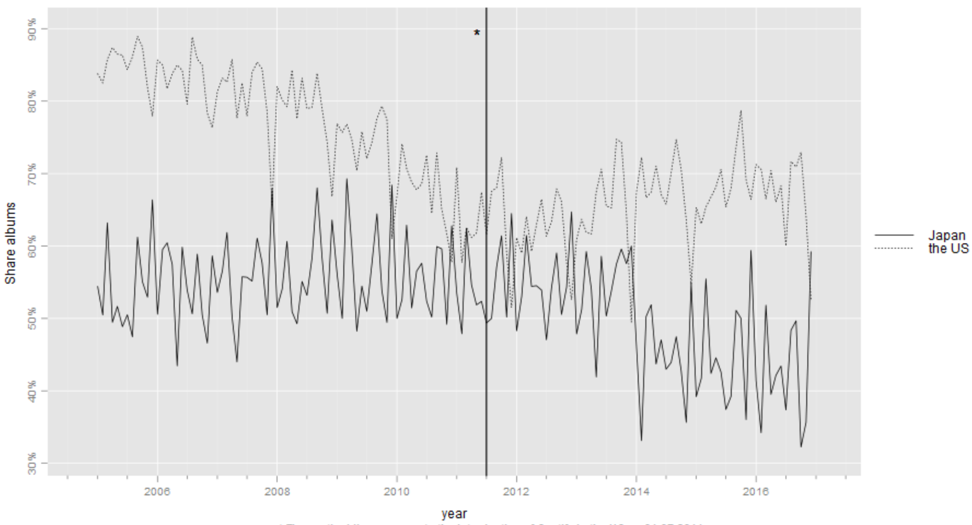
* The vertical line represents the introduction of Spotify in the US on 01-07-2011

Time between subsequent releases for the US and Japan, where total releases per artist >20



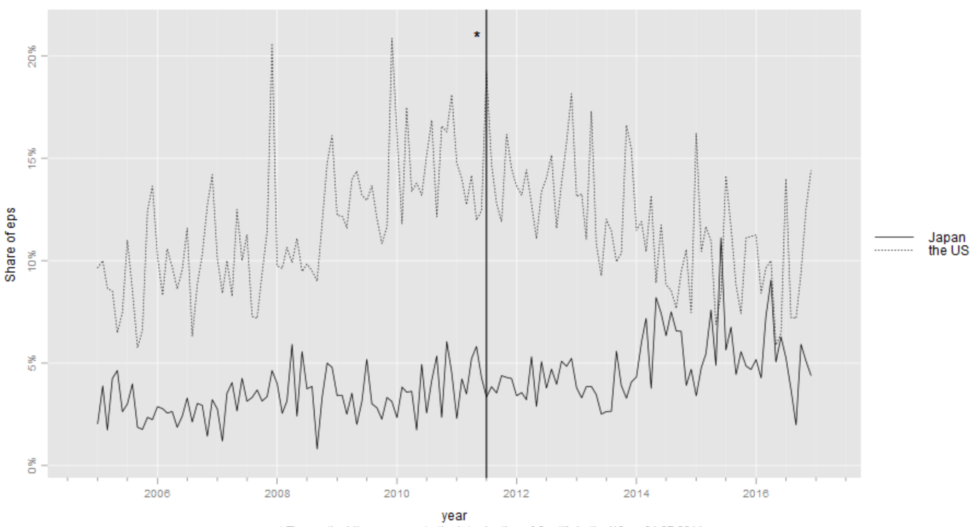
* The vertical line represents the introduction of Spotify in the US on 01-07-2011

Share of albums among total releases for Japan and the US



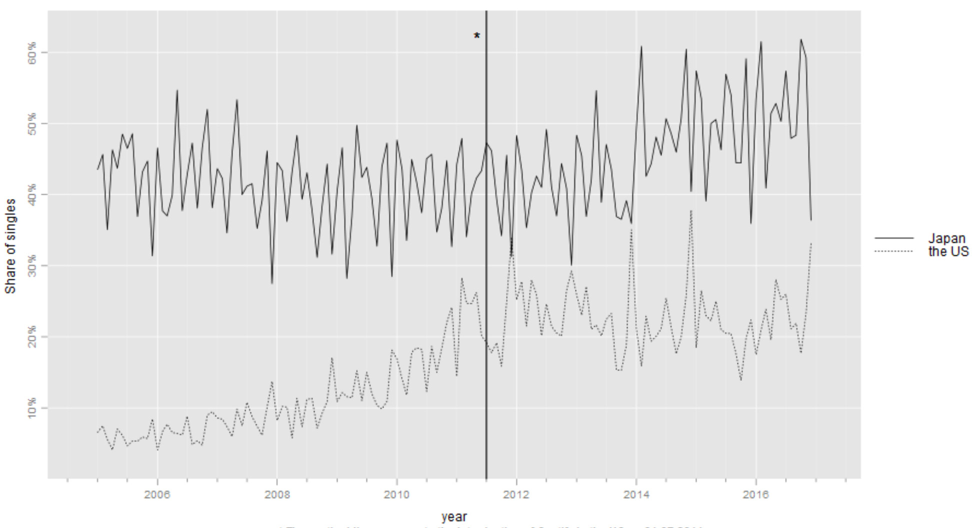
* The vertical line represents the introduction of Spotify in the US on 01-07-2011

Share of EPs among total releases for Japan and the US



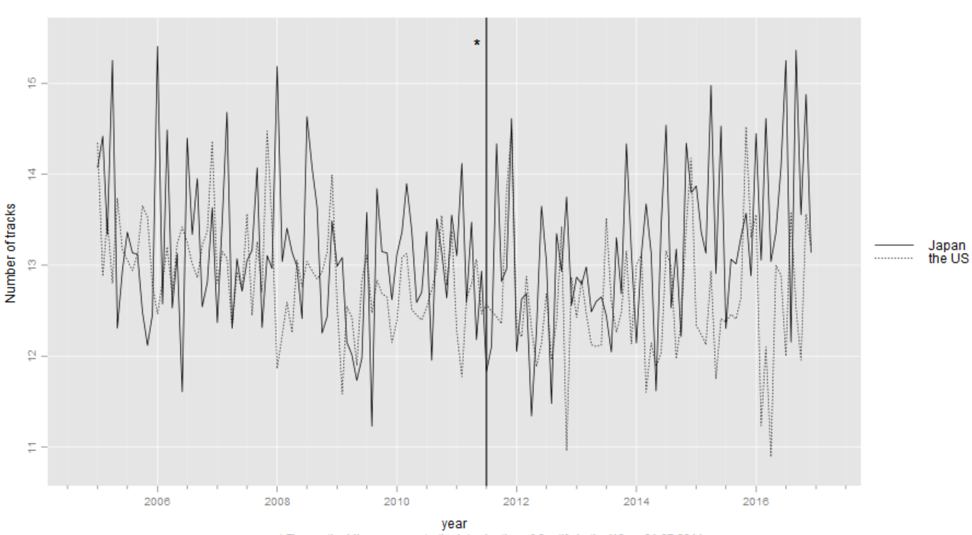
* The vertical line represents the introduction of Spotify in the US on 01-07-2011

Share of singles among total releases for Japan and the US



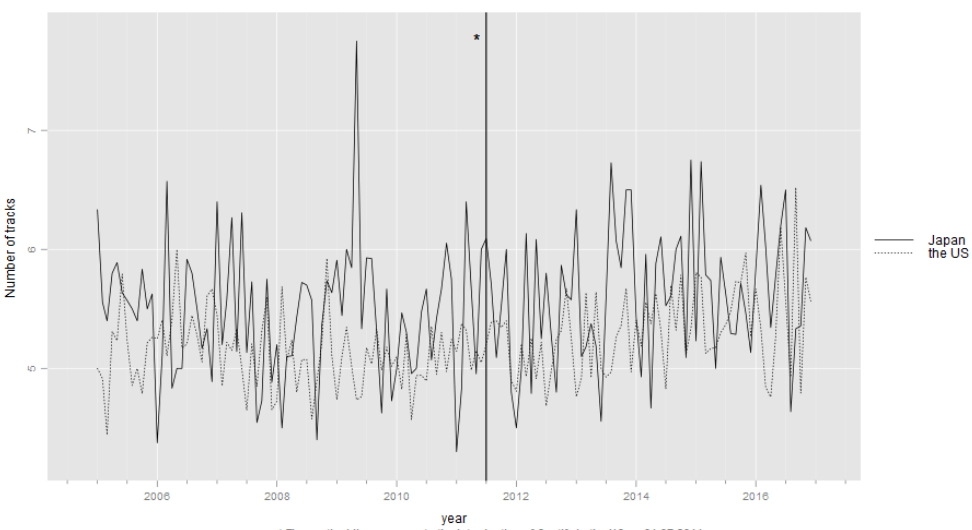
* The vertical line represents the introduction of Spotify in the US on 01-07-2011

Album length for the US and Japan



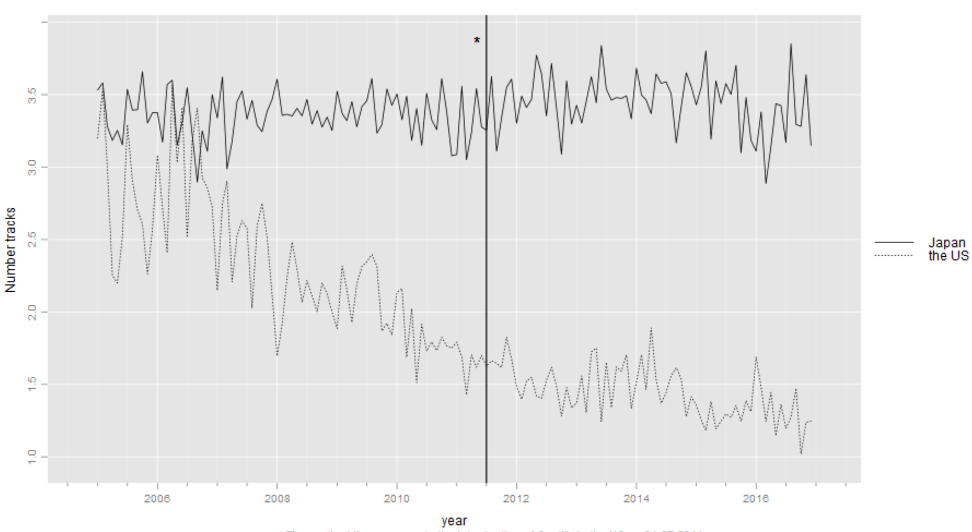
* The vertical line represents the introduction of Spotify in the US on 01-07-2011

EP length for the US and Japan

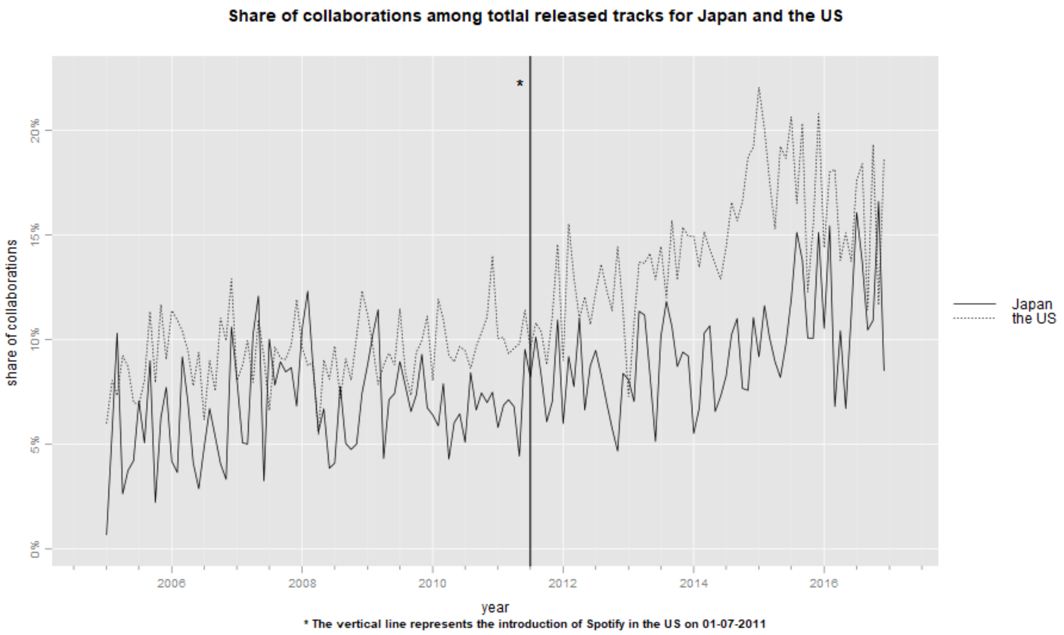


* The vertical line represents the introduction of Spotify in the US on 01-07-2011

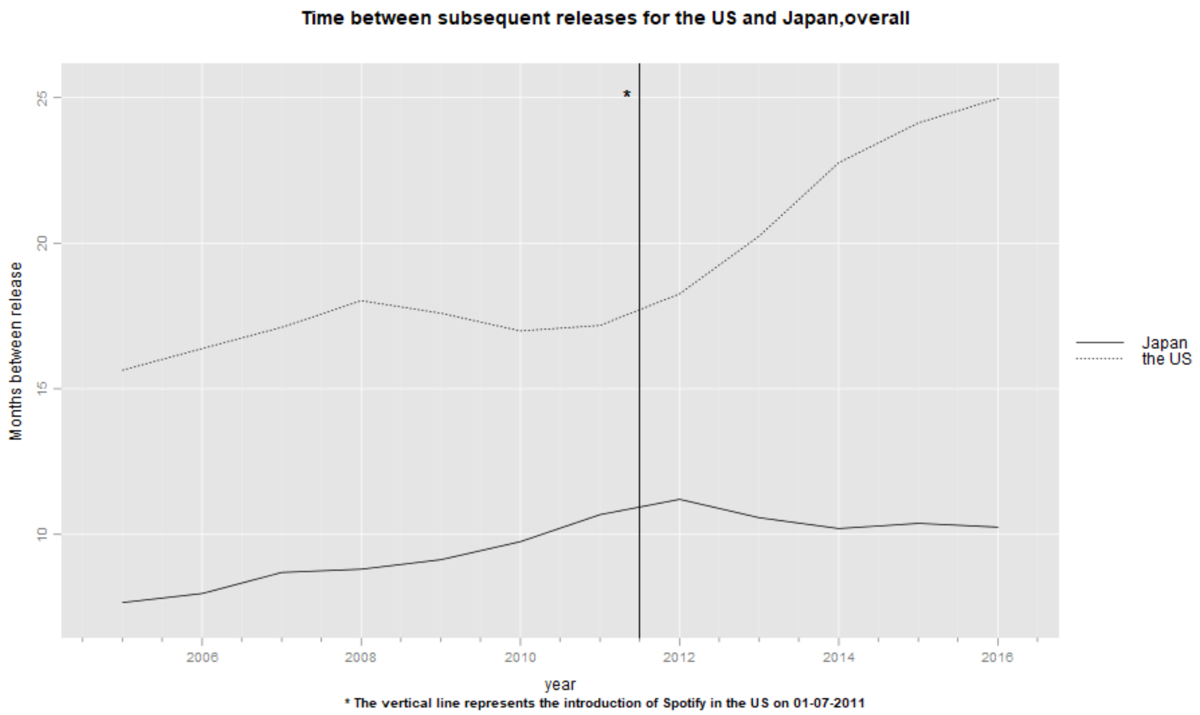
Single length for the US and Japan

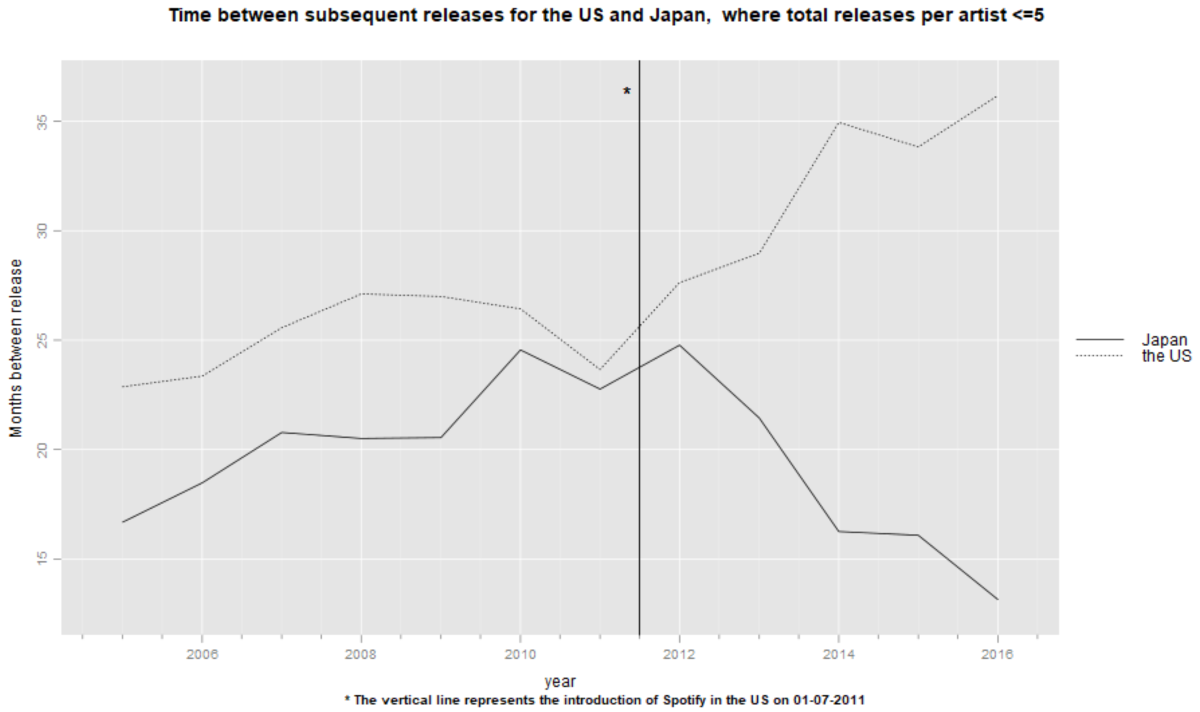


* The vertical line represents the introduction of Spotify in the US on 01-07-2011

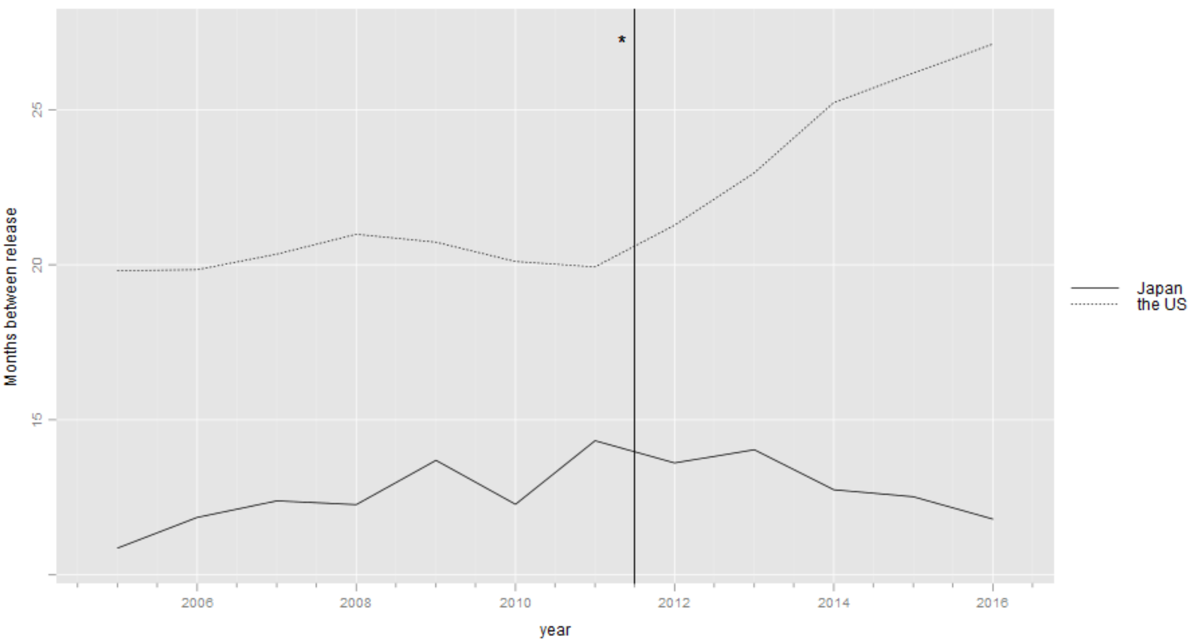

Share of collaborations among totlal released tracks for Japan and the US
share of collaborations
0%
5%
10%
15%
20%
2006
2008
2010
2012
2014
2016
year
*
Japan
the US
* The vertical line represents the introduction of Spotify in the US on 01-07-2011

Appendix D: Visualizations of Dependent Variables on Year Level



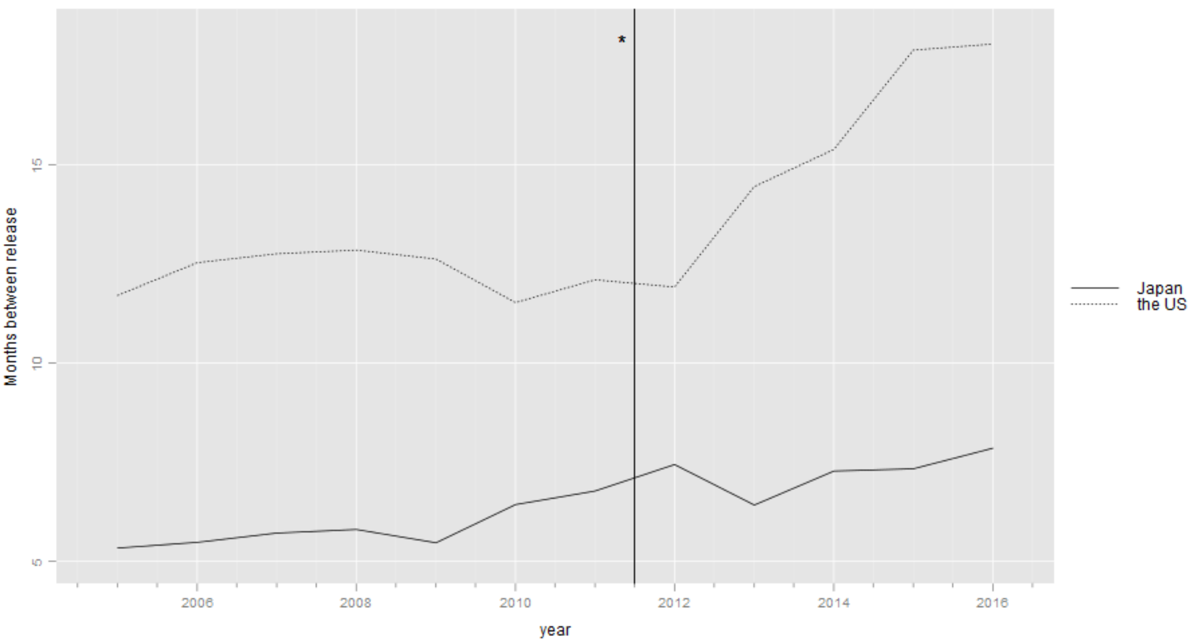


Time between subsequent releases for the US and Japan, where total releases per artist >5 <=20



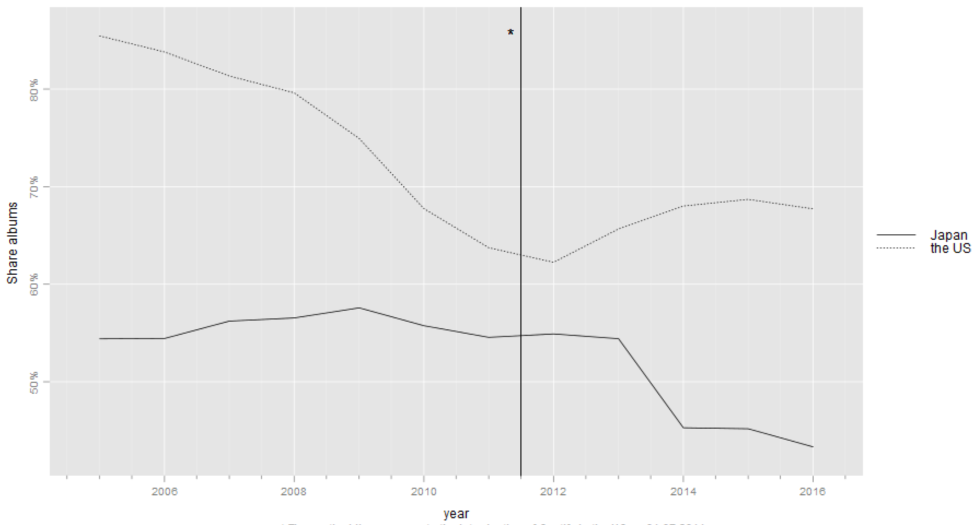
* The vertical line represents the introduction of Spotify in the US on 01-07-2011

Time between subsequent releases for the US and Japan, where total releases per artist >20



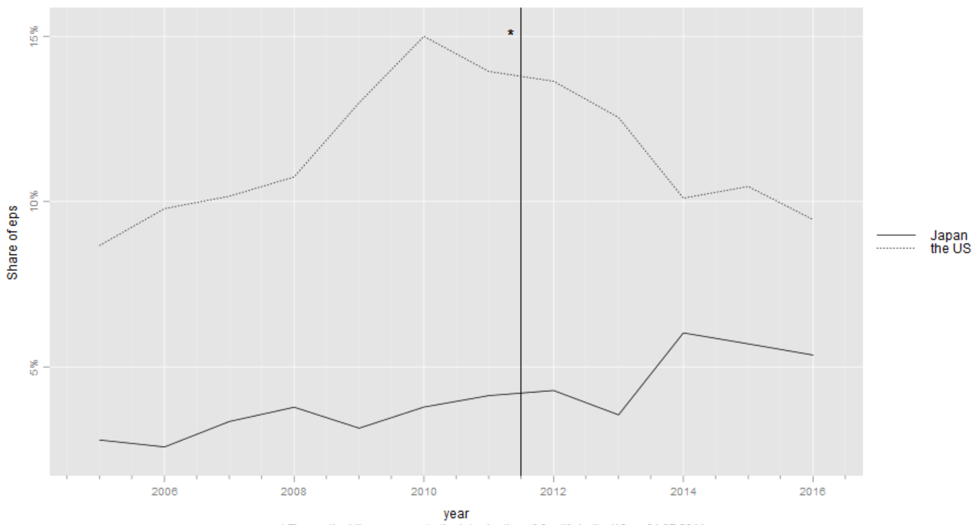
* The vertical line represents the introduction of Spotify in the US on 01-07-2011

Share of albums among total releases for Japan and the US



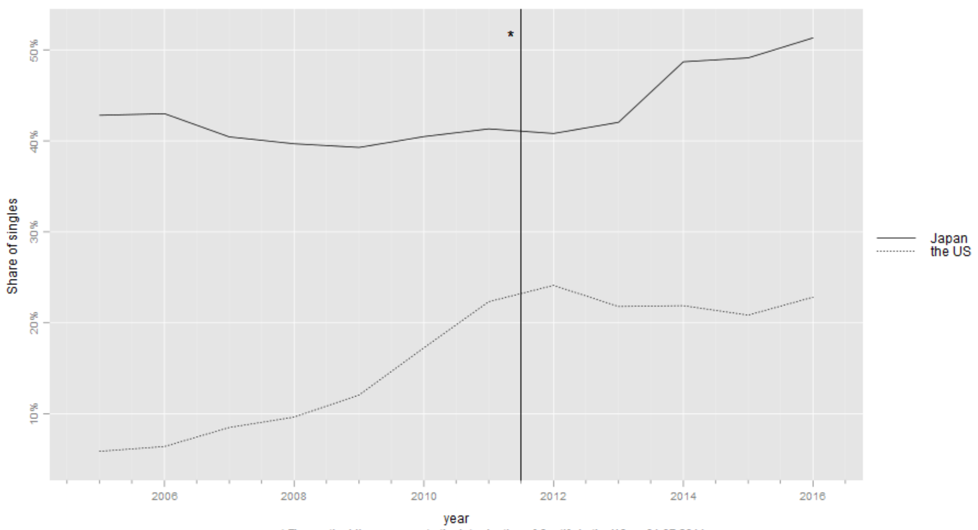
* The vertical line represents the introduction of Spotify in the US on 01-07-2011

Share of EPs among total releases for Japan and the US



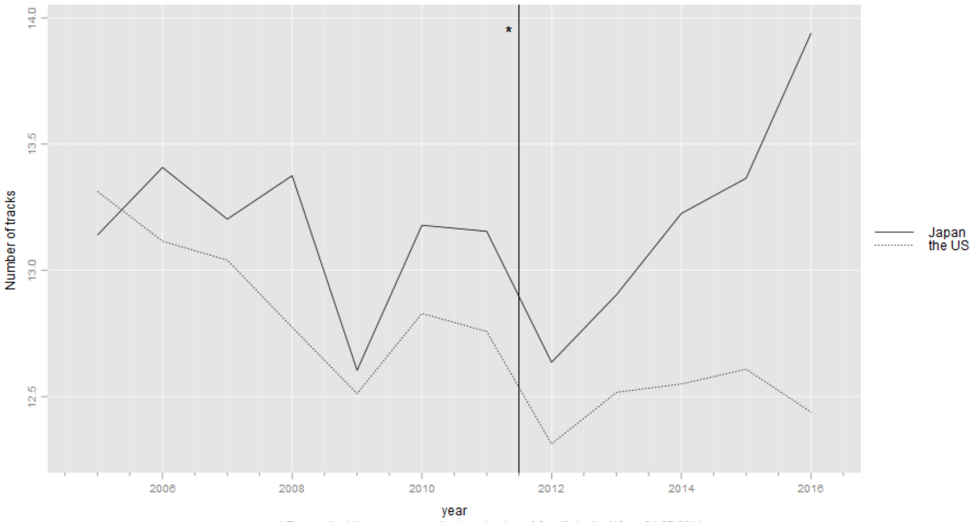
* The vertical line represents the introduction of Spotify in the US on 01-07-2011

Share of singles among total releases for Japan and the US



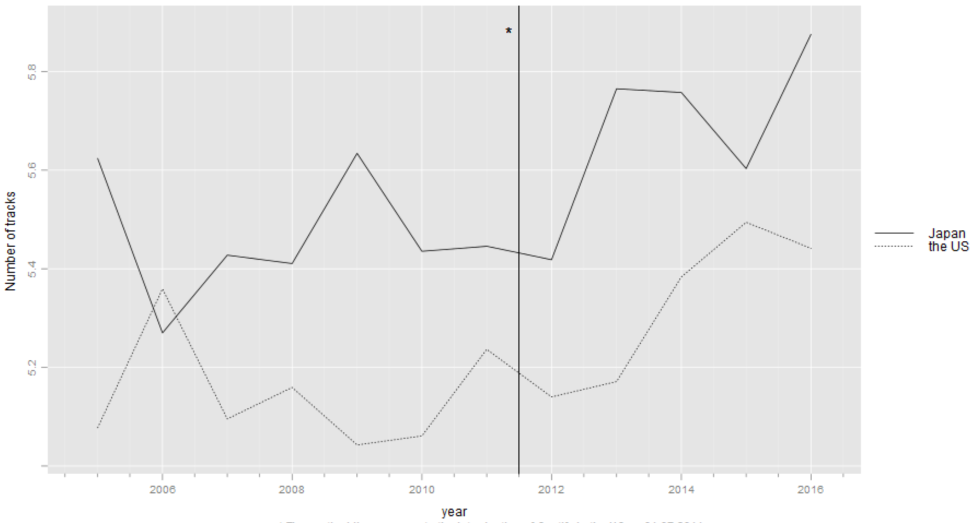
* The vertical line represents the introduction of Spotify in the US on 01-07-2011

Album length



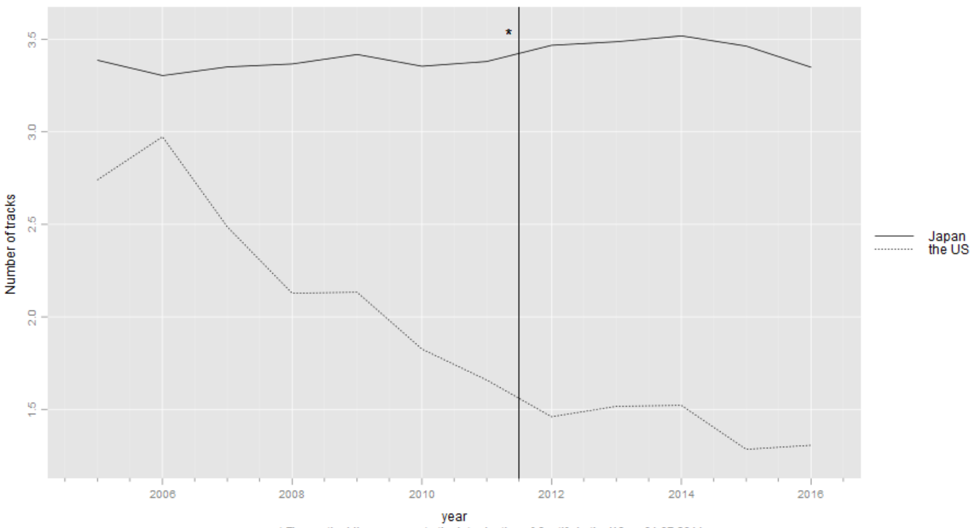
*** The vertical line represents the introduction of Spotify in the US on 01-07-2011**

EP length



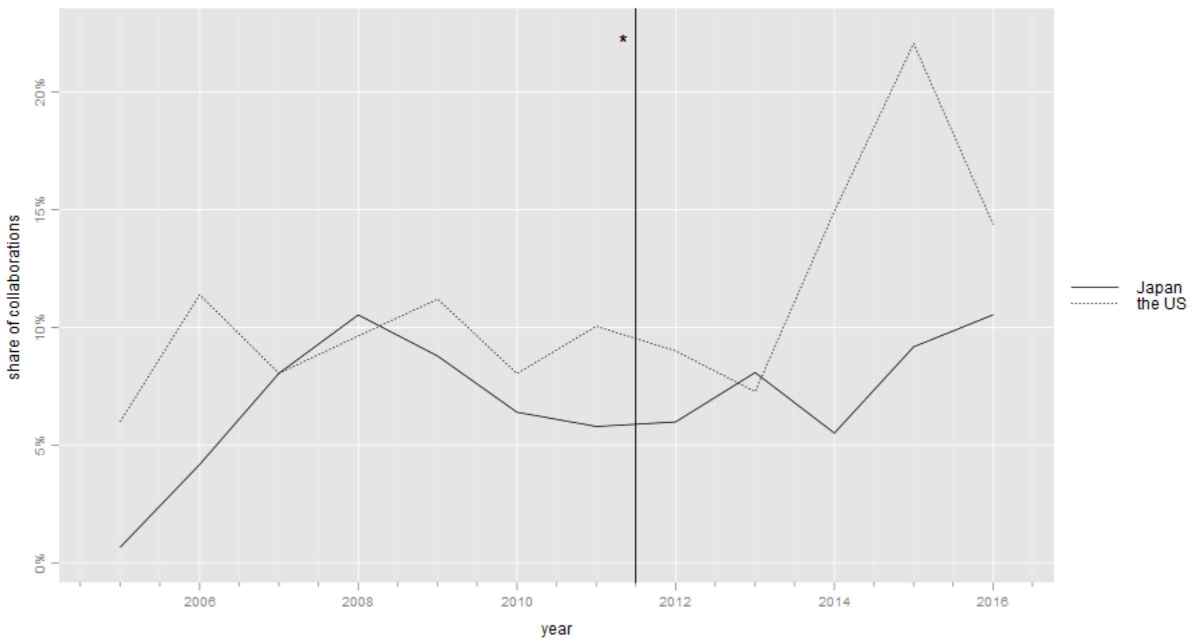
*** The vertical line represents the introduction of Spotify in the US on 01-07-2011**

Single length



*** The vertical line represents the introduction of Spotify in the US on 01-07-2011**

Share of collaborations among totlal released tracks for Japan and the US



*** The vertical line represents the introduction of Spotify in the US on 01-07-2011**

Appendix D: Overview of Used Code

Here we provide a short overview of the R code that we used to compute and analyze our variables. Our working depository contains three folders: Sql_code, preclean and analysis. Per folder we describe the purpose of its containing files.

1. sql_code

This folder contains three SQL queries. We use these queries to select the data from the MusicBrainz database. We use the file collaborations.sql to create a csv file that we will use for our dependent variable collaborations. We use release_groups_release_type.sql for our dependent variables release schedule and release type. We use Track_count.sql for our dependent variable release length. The output of these three SQL files will be the input of the preclean folder.

2. Preclean

The preclean folder contains three subfolders: code, input and output.

Input contains the raw data we selected with the SQL Queries. Output contains the aggregated and cleaned data that we use for our analysis. The folder code contains R scripts that we use to clean our data, aggregate our data and compute our dependent variables. For all four files holds that we aggregate by month and country for our analysis, and aggregate by year and country to create clear graphs.

load_release_schedule.R

The first step is cleaning the raw data. The next step is computing the time that artists leave between subsequent releases. Next, we aggregate the data by months and country, we make subsets for three groups of artists and one for the overall effect. Thereafter, we merge the subsets and write our csv file to the output folder.

load_collabs.R

We use this script for our dependent variable collaborations. We first clean our data. Next, we computer the total number of tracks and total number of collaborations aggregated by month and country. We compute the share of collaborations per month by dividing the number of collaborations by the total number of tracks. Thereafter, we write the csv file to the output folder.

load_release_types.R

We make use of this script to clean our data and compute our dependent variable release type. The first step is cleaning the data. The second step is to count the number of monthly releases for Albums, EPs and Singles. Thereafter, we measure the share of each type by dividing the number of releases of that type by the total number of release.

load_release_length.R

We make use of this script to clean our data and compute our dependent variable release length. The first step is to clean the data, the next step is to compute the average length of releases for Albums, EPs and Singles.

merge.R

Here we merge the output files that we generated with the scripts described above, The output of this file we use for our analysis.

3. **Analysis folder**

The subfolder code contains four R scripts. In the Analysis.R file we run our regression models, placebo tests and create our summary statistics table**.** In the Graphs_year.R file we create our graphs based on data aggregated by year, and in the Graphs _month.R file we create graphs based on data aggregated by month. We use the proc_rename.R file to automatically label the variables in our regression models. The output folder contains our regression models, summary statistics and graphs.