Another Loudness War: How Record Labels Release Singles to Compete for Consumer Attention in the Digital Age*

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Abstract

In markets with thousands of products, firms cannot take it for granted that consumers are even aware of their articles' existence. Advertising and actions to attract consumer attention are therefore integral components of a firm's competitive toolbox. We study firms' behavior in a perfect example for such a market: The music industry, in which consumers can choose from a plethora of albums and songs. We study a specific strategic instrument of firms, single releases, applying unique micro-level data. Arguing that the digitization of the industry via MP3, filesharing, and iTunes amounts to forced unbundling, the role of singles has changed from individual revenue generators (pre-digital era) to pure attention gatherers. In accordance with this driving hypothesis, we observe an inverse U-shaped relationship between competition intensity and the number of singles released in the digital era, while previously competition had a purely negative effect.

Keywords: Consumer Attention, Digitization, Music Industry, Single Releases, Advertising and Competition

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1 Introduction

Firms compete along multiple dimensions, in particular, price, quality, and consumer attention. In markets with a multitude of products, the costs of information acquisition for consumers are substantial; therefore, capturing and retaining consumer interest is of particular importance. This is of special relevance in entertainment markets due to the large variety of offerings in film and television programmes, video games, smartphone applications, books and music. In such settings, consumers cannot possibly be aware of every offering that exists, so that producers must muscle for their attention. In that vein, *Loudness War* generally refers to the practise of ramping up the audio levels on music recordings in the belief that it will make tracks more appealing (or at least noticeable) to listeners. The idea is that, especially on the radio, louder songs stand out, and attract consumers' notice more easily.

As we argue in this paper, a loudness war is also at work in a further sense, since the music industry has become digitized. Music singles are potential individual sources of revenue. Prior to the rise of phenomena such as MP3, filesharing, and iTunes, single releases were at the same time spinoffs of these products from the underlying album and thereby equivalent to partial unbundling. Now, changes to the industry, in particular the digital revolution, have inverted the standard: Immediately upon an album being released, consumers can purchase each individual track – a (forced) unbundling of albums has taken place. In this paper, we argue that this has fundamentally changed the role of single releases in the strategic arsenal of record labels. In the digital era, they have mainly become discrete, observable advertising events to garner attention for the underlying album – a further battlefield in the loudness war. They are effective via the channel of radio airplay, which is one of the central determinants for music purchase decisions, which, in turn, is strongly contingent on a song being released as a single (see, e.g. Peitz and Waelbroeck, 2004).[1]

Competition along the dimensions of price and quality has been extensively studied, both theoretically and empirically. How firms compete for attention, on the other hand, is still less well understood. Also using the music industry as an application, Hendricks and Sorensen (2009a) show how consumer awareness and information affect purchasing

[1] Accordingly, record labels (and artists) have close ties to radio stations (Vogel, 1986; Caves, 2000).

behavior and the success of products; this may depend on gathering external information (Cai et al., 2009; Tucker and Zhang, 2011; Hendricks et al., 2012). Firms can influence the information available to consumers by their activities including advertising. Intriguingly, singles can mostly be assigned to a certain album, which therefore allows us to derive insights into product-specific advertising decisions at the micro-level. The idea that firms use advertising to transmit information is well accepted (Telser, 1964; Nelson, 1970).[2] Through informative advertising firms can, either directly or through signalling, communicate their existence (Haan and Moraga-Gonzalez, 2011). Various studies have shown that the primary effect of advertisements is that of informing consumers (Ackerberg, 2001, 2003).[3] Single releases, through the increased airplay that they entail and (at least originally) by giving consumers the opportunity to sample the work of a band (Halbheer et al., forthcoming), can be solidly placed in the realm of informational advertising.

To inform our empirical exercise, we propose a simple mechanism to elucidate the tradeoff that firms face and from which we derive testable hypotheses. After the initial release of a product, it is noticed by consumers at a rate that decays over time, which we define as attention. Through discrete activities, the firm can "refresh" attention for its product. In the digital era, single releases are guided mainly by this attention gathering calculus. Previously, in the era of the "Maxi CD", single releases were associated with the partial unbundling of products – firms therefore had to take additional effects of unbundling individual songs from the album into account. Since the time-dimension of our data engulfs both eras, we can use the increasing importance of the digital distribution and sales channel to try to disentangle the effects of unbundling and attention gathering: In the current era, for the vast majority of digitally released albums, customers can purchase any given song separately, whether or not it was released as a single, which is equivalent to forced unbundling ex ante. Clearly, other factors change over time that affect the single-release calculus of firms, such as cost structures, music consumption behavior, etc. Therefore we consider the release behavior through the lens of competition: Firms should react to stronger competition differently when only competing for attention through single

[2] See Vakratsas and Ambler (1999) for an overview of research on how advertising influences customers.

[3] The alternative (or complementary) view of advertising emphasizes its persuasive effect, see, e.g., Dixit and Norman (1978); Bloch and Manceau (1999).

releases than if unbundling directly affects revenues, for any given cost structure. We derive these systematic differences and take them to the data.

As a result, we demonstrate how a changing market environment and new sales channels affect the strategic (advertising) behavior of firms. Our empirical analysis is based on a rich dataset from the large online music platform MusicBrainz.org. The data offer ample sources of variation, with monthly releases varying substantially across countries, genres and time.

In the setting in which single releases are mostly informative instead of independent sources of revenues, we find that competition has an inverted U-shaped effect on the number of released singles. This corresponds to our theoretical framework in which competition is associated with a faster decay of consumer attention, leading returns to advertising to decrease beyond a certain optimal point. Our results further show that the time-intervals between releases are strictly decreasing in competition; competition leads record labels to fight harder for attention and to use their instruments more frequently. During the earlier period, the business model of singles as an independent revenue source was still (mostly) intact and single releases must be understood as partial unbundling of songs from an album. Corresponding to our theoretical framework, for the earlier time period, we do not observe an inverted U-shaped effect of competition on single releases; the number is strictly decreasing in competition. This lends empirical support to the idea that the digitization of music distribution changed the nature of the single, and thereby the nature of competition in the music industry.

2 Industry Background and Hypotheses

In the following, we develop a simple framework to derive and motivate the central hypotheses that will inform the subsequent empirical analysis. In the music industry, firms generate two (very similar) products simultaneously: singles and albums. In principle, both of these are sources of revenues for the firm, although the role of singles in this regard is dwindling.[4] The music industry is a good representative of the digital economy:

[4]According to 2012 data from the Recording Industry Association of America (RIAA), US album sales (digital, CD, vinyl) accounted for 3.85 billion USD, which is 70% of the total market, compared to 1.63 billion USD from single sales (digital, CD, vinyl). However, measured in units, singles accounted for 81% of all sales, with 1.39 billion units, compared to 0.32 billion album units.

There is an ongoing flood of new products and releases[5] raining down on consumers, who have to sift through the information overflow to find what they like. Correspondingly, product life-cycles tend mostly to be short, which allows us, the researchers, to observe them entirely. Firms compete for consumer awareness and try to make optimal use of the tools at their disposal.

2.1 Awareness for a product over time

A firm tries to sell its product to a group of consumers with mass M, who are originally not aware of the product's existence. The product is a music album, which is composed of N tracks that can potentially be individually released and marketed as singles. Assume that if the firm simply releases its product at $t = 0$ and then remains passive, a consumer is aware of the product at a given point in time with probability $0 \leq f(t, .) < 1$, which depends on the time since release t and other factors. An aware consumer then decides whether or not to purchase the album, depending on her type, as discussed in the following section. The rate at which consumers take note of the product is decreasing in time: The original buzz surrounding the album release dissipates and on average interest in the product (e.g., manifested in radio airplay, TV features and newspaper or magazine articles) tends to decay. By time t, in expectation a total of $M \int_0^t f(t)dt$ consumers have noticed the album. However, the firm can generate additional buzz for its product by releasing a new single. Radio-stations in practice predominantly feature the album's latest single in their program.[6] For simplicity, imagine that a single release "resets" the rate at which consumers become aware of the product to $f(0, .)$, as illustrated in the left-hand panel of figure 1.

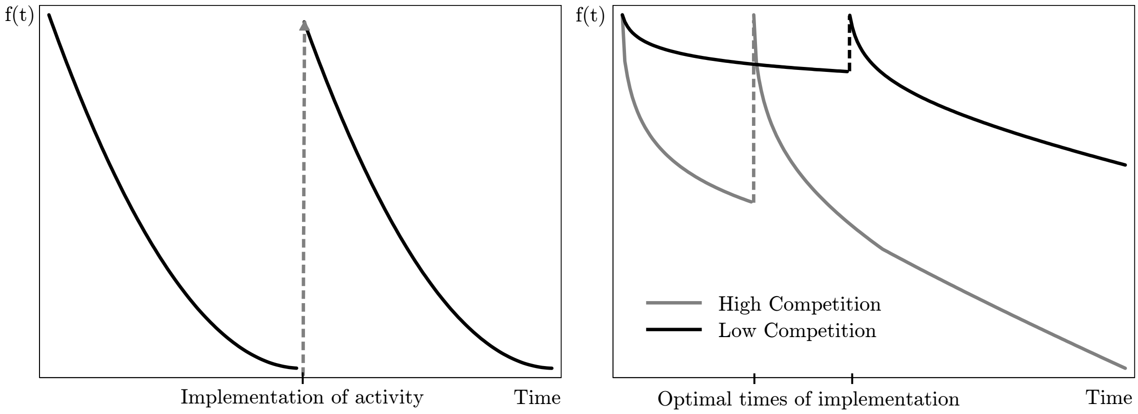
The release of a single is costly, with the firm incurring marketing outlays vis-a-vis news media, radio and TV stations (Caves, 2000), the time and effort of the artist in promoting the song, in addition to the costs of physical production. The firm will release an additional single only as long as the benefits outweigh these costs.

Now consider the benefits of such a measure from the perspective of attention gathering. In choosing whether and when to release a single, the firm considers the rate at which

[5]In the US alone, 75.000 albums were released in the year 2010, according to market research firm Nielsen, see `http://tinyurl.com/nd2hsfg`.

[6]Using song-level data from 2,000 radio stations from 2004 to 2008, Waldfogel (2012) shows that airplay is largely skewed towards new releases. 29% of all played songs are not older than two years.

Figure 1: Attention decay, activity implementation, and competition



Attention decay and activity implementation *Decay of attention under competition*

attention decays as well as the market size M of potential customers. In our setup, the most effective use of an attention gathering measure — i.e., the most consumers will be reached by the original album plus the single — is to release it once $f(t)$ has fallen to 0. A release before this point means that the previous release is still generating attention on its own. Note however, that this behavior is only optimal, if the firm does not discount profits; if firms are impatient, there is an incentive to reach consumers sooner rather than later, and the optimal release date of singles will be earlier. The basic mechanism remains, i.e. to wait until the *additionally* generated attention from the single is large enough. M also affects the behavior of the firm — the larger the market, the more potential customers can be reached and the more likely it is that the expenditures for an additional single release will be recuperated. By the same logic, once most consumers in the market were aware of the album and had an opportunity to purchase it, new releases attract only few additional customers. In the extreme, if a firm would immediately reach all M consumers with its album release, there is no (attention gathering) incentive to release a further single.

2.2 Albums as bundles of songs and forced unbundling in the iTunes-era

An album can be considered as a bundle of products: The songs it is composed of. A single release therefore resembles (partial) unbundling by the firm, so that additional effects on revenues must be taken into the firm's calculations, in particular cannibalization and direct revenue generation, which we outline below in an extension of our toy model of awareness. Consider a situation in which both the album and a subset of its songs are available for purchase in the market in parallel. A consumer, upon becoming aware of the products,[7] may then purchase *either* one unit of the album *or* a subset of the independently released singles *or* nothing, depending on which decision grants her the highest utility.[8] For simplicity and in line with empirical observations in the recorded music industry, in the following discussion we assume that both prices of the album and of singles are fixed and exogenous (Shiller and Waldfogel, 2011).[9]

Let the utility from purchasing nothing be 0 for all consumers. A consumer prefers the album over nothing if $u_a(N) - P > 0$, where $u_a(N)$ is the monetary equivalent of the consumer's utility derived from owning all songs on the album and P is the album price. Therefore, consumers for whom this holds will buy the album when they become aware of it. Cannibalization of album sales by a subset of songs S_N (each priced at p) occurs, if consumers of type i exist for whom S_n yields utility

$$u_i(S_n) - p > u_i(N) - P > 0. \tag{1}$$

In this case, the consumer would prefer purchasing her favorite subset of singles *at a discount* $P - p$ to buying the entire album.[10] The firm loses revenue from customer i due to the fact that the singles were released.

On the other hand, consider a different type of consumer j who would never purchase the entire album, since $u_j(N) - P < 0$, but who would purchase a subset of singles, since $u_j(S_n) - p > 0$. Through unbundling, the firm can reach this type of customer for additional sales; we refer to this second effect as direct revenue generation through singles. For the first type of consumer, i, the firm suffers revenue losses from releasing, or unbundling, singles from the album, for the second type, j, it generates additional

[7] According to the process set out in the previous section.

[8] Since the album includes the single, she will not buy both — we exclude behavioral aspects such as wanting to own all releases of a given band. We further abstract from the fact that singles often constitute mini-albums themselves, i.e. contain remixes and bonus songs ("B-sides", referring to vinyl records that had two sides to play on a turntable) that are not part of the original album, but may grant additional utility to the consumer. For simplicity, we therefore assume in the remainder of the paper that a *single* always comprises one *song* that is part of an album.

[9] A firm setting prices optimally would attempt to minimize cannibalization and maximize overall sales, since variable costs are almost negligible in the industry. Optimal prices therefore depend on the shares of consumers with different preferences. Further, with each single release, the optimal price of the album would be (at least weakly) decreasing in optimum to offset cannibalization.

[10] Denoting the share of consumers of type-i as q_i, we can write the expected losses via cannibalization for a single release at $\hat{t}$ as $M \int_{\hat{t}}^{\infty} f(t, .)q_i(P - p)dt$.

revenues. Finally, a third type of consumer, h, might always prefer to buy the entire album, since

$$u_h(N) - P > max\{u_h(S_n) - p, 0\} \tag{2}$$

Assume that consumers do not anticipate unbundling by the firm in their purchase decisions.[11] As long as only the album has been released, upon becoming aware of it, consumers of type j decide not to purchase, while consumers of types i and h buy the album. By releasing the single, the firm generates additional awareness, as discussed in the previous section; it also starts selling singles to consumers of type j who would otherwise not have purchased anything. But consumers of type i, *who have not yet purchased the album*, now prefer buying the single over the whole album. The direct revenue effect gives the firm an additional monetary incentive for releasing the single; but, internalizing cannibalization there is an incentive to postpone the single release – by doing this, the firm can skim the cream off the top first (i.e., sell the album to all interested consumers who become aware of it prior to single release), without originally offering the opportunity to only pay for the single.

This brings us to the central motivation for this paper: Due to the technological and social development of the music industry, there are real-world ramifications to the theoretical exercise of differentiating between a case in which singles only serve to generate attention and the case in which bundling/unbundling considerations play a role for music firms. The technological revolution that is responsible for this and that has changed listening and purchasing behavior of music consumers for ever, is the forced unbundling of songs from albums through the advent of the MP3-technology, which was made commercially feasible through digital music stores, for which Apple's iTunes is the dominant example. Due to this revolution to the music market, firms by default make every individual song available for purchase immediately upon releasing the original album. As a result, additional single releases no longer generate additional revenues; cannibalization of album-sales through

[11]This is very much in the spirit of the model: In a market with thousands of products, if the consumer fleetingly becomes aware of an album, for which no singles are currently released, she only decides whether she is better off owning the album for the given price or not, but does not make the mental calculations regarding the likelihood of her favorite songs being released in the future as singles.

singles takes place ex initio, and therefore also no longer affects the release behavior of firms. Therefore, in the iTunes-era, singles can be considered purely an attention gathering device.

2.3 Competition and awareness with and without unbundling

An immediate implication of forced unbundling is that firms should release singles in closer proximity to the album after digitization, all else equal, because they no longer take cannibalization into account. In fact, as we lay out in more detail below, that the average time between releases did decrease substantially, by more than 40 days, controlling for a number of other factors. This number, by itself, is suggestive, but should not be over-interpreted. Clearly, there are other forces at work (shifters to costs, consumer outside options, different channels through which music has become available), which affect the timing and optimal number of single releases, in addition to the forced unbundling outlined above. In our empirical application, we will therefore study the effects of the digital revolution in the music industry through the lens of competition. Albums that are released at approximately the same time compete both for the attention and the budget of potential customers, in their fight for space on screens and in shelves, top lists, and journalistic media.

We consider two central channels through which the level of competition that an album faces, denoted by C, affects the incentives of a firm to release attention and revenue generating singles: First, competition is related to the rate at which attention decays. To account for this, we expand f to $f(t, C)$, such that $\frac{\partial f(t,C)}{\partial t}$ is decreasing in C. The rate at which consumers become aware of the product decreases faster in more competitive markets, as illustrated in the right-hand panel of figure 1. In the framework outlined above, this has two partially countervailing implications for the firm. On the one hand, faster decay implies that the optimal frequency of releases should increase: With attention reaching rock-bottom faster, the firm has an incentive to release its singles sooner. Parallel to this, each single in expectation reaches fewer consumers. On the one hand, this implies that there are more remaining potential buyers after any given release, which paves the way for more singles to be released. On the other hand, and this is the countervailing effect, the expected reach of a single is related to its potential profitability – if the expected generated revenues fall below the costs, it will not be released. Even from these simple considerations, we are able to derive insights with regard to the shape of the problem. Assume that at very low competition, the first single's revenues are strictly above costs. Since the profitability constraint is not binding, the countervailing affect will not immediately apply as competition increases and we should first observe an increase in releases and frequency. When competition reaches the level at which the profitability constraint becomes binding, it starts to negatively affect the number of singles to be released in optimum (but not the optimal frequency, i.e. time between releases, given that singles are released). In our stylized model, for the setting in which there is forced unbundling, this immediately allows us to derive predictions to be tested empirically:

Hypothesis 1 *In the case with forced unbundling (the iTunes-era), the following should hold: a) The optimal number of singles per album is first increasing in competition (while the profitability constraint is not binding); at higher levels of competition (profitability constraint becomes binding), the effect of competition on the optimal number may become more negative. b) The frequency of releases is increasing in competition, i.e., the time between releases is decreasing.*

It should be noted that these predictions are not intuitively obvious: Notice that hypothesis 1a indicates that when singles are purely awareness-raising, then the optimal number of released singles should assume an inverse U-shape in competition. This result is nice, because purely awareness-raising singles can be understood as a form of advertising – a consistent finding in the advertising literature is that the intensity of advertising is inverse U-shaped in competition.[12] Further, tougher competition at the time of album release could conceivably also lead firms to spread out single-releases to avoid bunching, which would lead to a prediction opposing hypothesis 1b.

The second channel is related to the profitability of individual releases: Competition is a determinant of the potential market size M for a given album, with M decreasing in the level of competition. Consumers facing budget restrictions may be less likely to buy an

[12]This relationship has been established in the past using industry-level data (Greer, 1971; Cable, 1972; Sutton, 1974; Brush, 1976; Strickland and Weiss, 1976; Martin, 1979; Buxton et al., 1984; Willis and Rogers, 1998), though not at the level of individual products.

album, the more comparable albums are on offer at the same time; or equivalently, competition could force the price that can be optimally charged for the album (and released singles) downwards.[13] Competition thereby immediately **decreases the direct revenue effect** of singles. This allows us an immediate prediction concerning the comparison of the pre- and post-digitization regimes: The effect of competition on the optimal number of single releases should be more negative prior to digitization, since the direct revenue effect no longer affects calculations in the forced-unbundling setting. Finally, we are able to compare the timing decisions under the (strong) assumptions that relative prices of singles and albums and the shares of consumers of different types are not affected by competition. Denoting the share of cannibalized consumers as q_i, the losses from cannibalization $M \int_{\hat{t}}^{\infty} f(t;C) q_i (P-p) dt$ are decreasing in C. The incentive to increase the duration between releases due to cannibalization is therefore decreasing in the level of competition, an effect that only holds pre-digitization. Again, we combine these observations into the following empirical predictions:

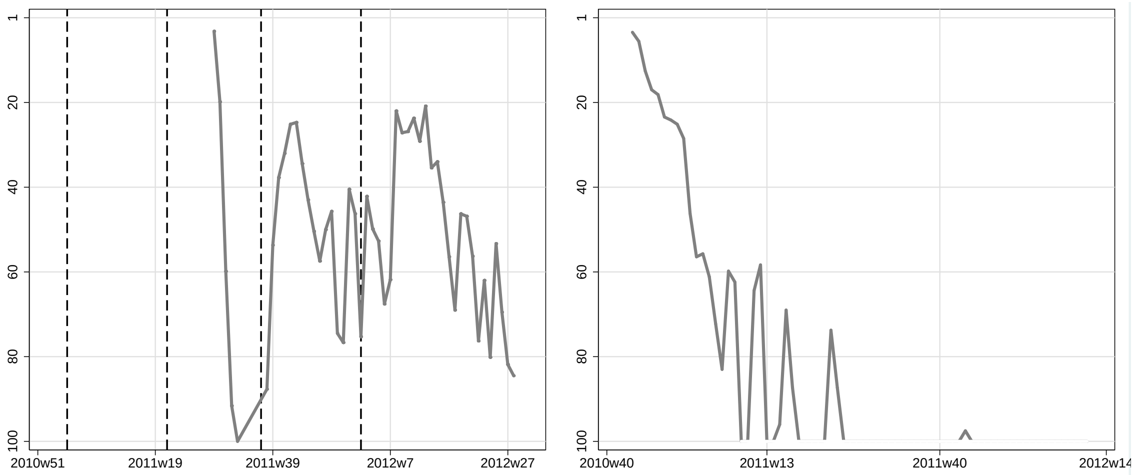
Hypothesis 2 *a) The effect of competition on the optimal number of singles should be more negative for the pre-digitization era than the post-digitization era (direct revenue effect). b) The effect of competition on the optimal frequency of releases should be stronger for the pre-digitization era (cannibalization).*

Note that hypthesis 2b depends on the strong assumptions stated above.

In the next step, we take this structure of hypotheses to the data. Clearly, there was no clean switch from a purely physical to a purely digital distribution system in the music industry, therefore we have to use an imperfect proxy. To delineate the two eras, we take the introduction of Apple's iTunes music store in 2003; from then on, consumers are easily able to purchase any individual song from albums for the majority of albums at relatively uniform prices. Previous, the dominant business model was the sale of full albums, with unbundled singles as physical objects. As representative for the digitized era of music, we therefore use the period since 2003, while for the "unbundling" era, we use data from the period 1990-2002, in which the digital distribution channel played a very minor or no role

[13] Alternatively, consumers may on average buy the album at a later point in time due to competition, which for impatient firms is equivalent to a decrease in M.

Figure 2: Chart ranking and single releases



Sorry for Party Rocking *(LMFAO)*

BBC Radio 1's Live Lounge, Vol. 5 *(Various Artists)*

***Note**: Average weekly iTunes top 100 album ranking in the United Kingdom.*
Vertical lines in the left-hand panel indicate release dates of singles.
***Data source**: itunescharts.net and musicbrainz.org.*

with regard to labels' direct revenues.

3 Empirical Analysis

3.1 Illustrative example

The main focus of our empirical analysis is to investigate the effect of competition on the number and frequency of actions firms take to make consumers aware of a product. It is beyond the scope of this paper to show the effectiveness of those measures in terms of firm performance. For illustrative purposes it is nevertheless useful to consider the examples of sales dynamics of two different albums, measured as the average weekly chart rankings in the UK iTunes store in figure 2. The first of these is a "typical" album in the sense that it contains new songs by an artist, each of which might be released as a single: "Sorry for Party Rocking" by US electronic-dance duo LMFAO in the left-hand panel. The second, on the other hand, is a compilation – a collection of successful songs by different artists, from which no singles are typically released: "BBC Radio 1's Live Lounge, Vol. 5" in the panel on the right. Both albums were released at roughly the same point in time and entered the top 100 charts at similar positions. Single releases by LMFAO are depicted by the vertical dashed lines — two singles in advance and two after the release of the album. As expected, no singles were released from the compilation. The left graph suggests that chart positions of an album noticeably improve after the release of a single. This is both in line with our theory as well as the findings of Hendricks and Sorensen (2009b) regarding the effects of the releases of additional albums. On the other hand, the chart positions for the compilation almost strictly decay after its release. Also, the charts retention time is significantly shorter for the album without single releases.

3.2 Data

3.2.1 Main datasource

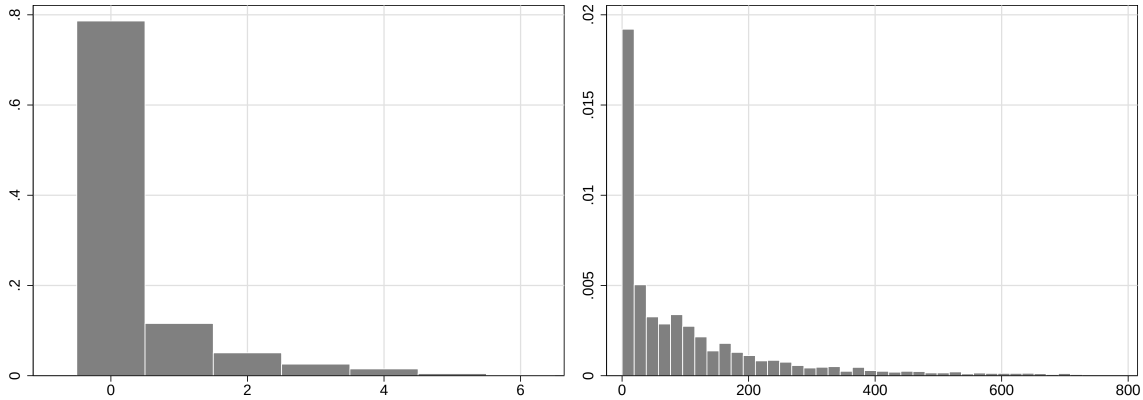
Our main source of data is MusicBrainz, an online platform for music enthusiasts, which contains user-generated information on roughly 15 million tracks from more than 1.3 million releases in over 60 countries from the 1950s until recently. The dataset provides general facts regarding the artist, such as genre and label affiliation (from which we infer whether the artist is signed with one of the major labels), but also detailed information regarding individual releases. We match track titles of singles with track titles of albums to identify single-album combinations. Based on these matches, we calculate the number of singles that were released from an album and the time difference between the releases.[14] The final dataset includes 17,752 albums, in 8 genres, from 55 countries,[15] released between 1990 and 2010. We choose 1990 as the start of our observed period for two reasons. First, we want to abstract from the changes to the music market induced by the introduction of the Compact Disc.[16] Second, we want to avoid sample selection that may arise because older releases tend to be less represented in the MusicBrainz data as a result of its user-generated nature (see the discussion in section 4.3.1). For similar reasons, we do not extend our data beyond 2010. During the last years, the market for recorded music has seen a transition towards more and more digital services that automatically carry meta-information about releases (iTunes, Amazon, etc.), such that incentives for users to contribute to MusicBrainz have dramatically decreased (see the Google search volume for

[14] We do not observe all entries in the database with the same level of detail. Unfortunately, for a significant amount of albums, information is lacking (in most cases label, genre or release dates), so that observations have to be dropped.

[15] Although we observe a large number of different countries, over 80% of the observations in our sample are from the US (34%), UK (21%), Japan (14%), and Germany (12%).

[16] For example, the CD version of Michael Jackson's 1987 album "Bad" featured a bonus track that was not part of the Vinyl and Tape version. Rumor has it this was done to encourage consumers to switch to the new technology, see `http://tinyurl.com/njl8fza` (in German).

Figure 3: Number of singles per album, and average time between single releases



Total number of singles from the same album | *Average number of days between releases of singles from the same album*

***Data source**: musicbrainz.org.*

"musicbrainz" in the right-hand-panel in figure 4 as an illustration). Subscription and streaming services have recently gained momentum (IFPI Digital Music Report, 2013), introducing changes to the advertising rationale of record labels that are beyond the scope of this paper. To test the different parts of Hypothesis 1 (the forced unbundling case), we use data from 2003 to 2010, the period during which digitization of the music market took off. For Hypothesis 2, the comparison of the two cases, we juxtapose these results with data from 1990 to (and including) 2002, the pre-digitized era.

The descriptive statistics in table A.1 show that we observe 8,543 albums and 3,927 singles in the "CD-era", and 9,209 albums and 4,489 singles in the "iTunes-era". The average album contains around 13 songs. The average number of countries in which an album in our sample is released is 1.3.

3.2.2 Variables and descriptive statistics

To obtain the **total number of singles** released from an album, we match the track titles of singles with track titles of albums of the same artist. Note that our algorithm requires that single and album have to be released in the same country; albums released in different countries can have varying counts of released singles. Matches indicate that the same song was both included in an album and released as a single. This allows to attribute singles to a particular album. We then count the number of corresponding singles for each album.[17] On average, we observe 0.35 and 0.42 singles per album, between 1990–2003,

[17] This method might produce some incorrect attributions of singles that were re-released on Best-of-albums. Tracks on singles that were released more than once, are attributed to the earliest observed album. In

and 2003–2010, respectively. For 15,781 albums (78%) in our full sample (1990–2010) we do not observe corresponding singles.[18] Among albums with at least one single release, the average number of singles is 1.8. The distribution of this variable across 1990–2010 in figure 3 shows that most albums only have one corresponding single. On the other hand, a small number of albums generate five or more singles; the mean is around 2.[19]

We measure the **time difference between releases** as the number of days between releases associated with an album. Note that this measure is only defined for albums with at least one single release. More precisely, we count the days between subsequent releases (including the album itself, in absolute terms) and take the average across the "release group" defined by the album. We include the album itself, because, as argued in the theoretical section, we also interpret the release of an album as a source of consumer awareness, which then decays over time. Figure 3 illustrates the distribution of time differences in the sample 1990–2010. Note that a large share of releases are less than 20 days apart from each other, which indicates that record labels try to further trigger album sales by releasing a single shortly before or after the album (compare the illustrative example in figure 2).

We consider the music album as the main product of interest. One of the contributions of this paper is that we can measure competition at the product-, i.e., album-level. We assume that albums compete for the attention of consumers with other albums of the same genre that are released at a similar point in time.[20] The variable **competition** is measured as the number of albums released within the same genre, in the same country and the same month. On average this amounts to 5.5 new albums (there is no significant difference between eras, see table A.1). One month is a relatively short time-window for

some cases, however, the initial album might be missing in our data which would result in upward biased time-differences between the single and the corresponding album. We therefore disregard singles released more than two years after the corresponding album. Our results do not depend on this two year-cutoff.

[18] Although we are confident that these are "true zeros", because we applied manual checks and employed high thresholds of data quality such as the exact release date and a parent label, we cannot rule out that we miss some singles. However, this measurement error should not be systematic. Nevertheless note that albums without singles are less likely to be issued by major labels, are older, feature more songs and stem from artists that have already released albums in the past. Most importantly, however, there is no significant difference regarding our competition measure.

[19] A famous example for an album that has released a large number of singles is Michael Jackson's 1987 "Bad". Seven out of eleven songs were released as a single in the US; the UK and Germany even saw nine single releases.

[20] For example, most radio stations specialize according to music genres, so these albums are most likely to compete for airplay.

competing releases; as an important robustness check, we therefore propose two further measures which broaden the window for competition by plus-minus one and two months, respectively. The corresponding results are discussed in section 4.3.4.

To account for genres, we make use of user-generated "tags" for each release which describe the style of music in the MusicBrainz data. We manually cluster these tags to derive a unified notation of **genres**. We categorize albums along the eight genres *Alternative*, *Classical*, *Electronic*, *Hip Hop*, *Metal*, *Other*, *Pop*, and *Rock*. Some albums, however, might have tags which would qualify the release to be categorized into multiple genres[21]. We eventually listed the album in the genre for which we counted the most corresponding tags. For example, tags that we associated with the genre *Electronic* include house, techno, electro, ambient, dub, dance, disco, and minimal. Besides using the genre information to calculate the level of competition, we further use genre fixed effects to control for unobserved heterogeneity in our regressions.

We further control for the **track count** of the album. The number of songs on an album mechanically defines an upper bound of singles that can be released.

We observe both newcomers as well as artists who have released previous albums in our sample. After the first release, an artist already has an established fan base and therefore might have to release less singles to promote an album. To capture effects associated with different stages of artists' careers, we introduce the variable **album history**, which counts the number of previous albums by the same artist in a country. To allow for non-linearity (decreasing returns to popularity or a distinctive "debut album"-effect), we include this information as categorical dummy variables in our regression models (we call this Album History fixed effect in the results tables).

In a similar vein, one could expect advantages to larger firms in promoting their artists; either through economies of scale and scope, more established connections to networks, or recognizable brand names. The data provides information on the label under which the single/album is released. A specific feature of the recorded music industry is that firms usually have many subsidiaries (or at least brand names), which makes it challenging to distinguish "independent" labels from entities that are under legal or economic control

[21] For example, tags for "Sorry for Party Rocking" by LMFAO are *electronic*, *pop rap*, *club/dance*, *comedy rap*, *dance-pop*, *electro*, *party rap*, *pop*, *pop/rock*, *dance*, *hip hop*, and *rap*.

of one of the big four major labels, i.e., EMI, Sony BMG, Universal Music Group and Warner Music Group. MusicBrainz provides a tree-structure that enables us (after a few iterations) to determine the ultimate parent firm. Accordingly, we code each release by a dummy variable indicating a **major** label affiliation. Measured this way, table A.1 shows that the big four do control the majority of the market. Over time, though, the percentage of major label albums decreases from almost 69% between 1990 and 2003 to around 61% between 2003 and 2010.

We further control for seasonality by introducing **calender month** and **year** fixed effects. This is important since particular events during the year drive sales, especially holidays and the festival (open air concert) season, which in turn might affect marketing strategies of albums and therefore single release behavior. Controlling for year fixed effects at least partially addresses issues such as changes in costs and technology, e.g., due to developments in the digital distribution of music (and corresponding growth in demand for digital music), including changes in the importance of music piracy and filesharing (Waldfogel, 2010).

Table A.2 shows that most genres are relatively similar in terms of average number of singles, time difference between releases and number of tracks. However, there is substantial heterogeneity along multiple other dimensions. *Classical* albums release much less singles; also the time difference between releases is lower. Still, competition in this genre is intense. Competition is also particularly fierce in *Pop*, however, in this genre there are more singles on average. *Metal* albums are less often issued by major record labels, the highest share of major releases is in the *Hip Hop* category.

Pairwise correlations are reported in Table A.3. The unconditional overall correlation between competition and the number of singles is positive. Further, competition and the time between releases are negatively correlated, which suggests that with more competition labels release singles faster. Major labels and albums with more tracks on average release less singles. In the following section, we address our central questions in a regression framework.

3.3 Model specification

3.3.1 Regression models

We estimate two sets of OLS regressions to test our hypotheses. The baseline specifications are as follows:

$$N_{i,j,c,g} = \beta_0 + \beta_1 C_{c,g} + \beta_2 C_{c,g}^2 + \mathbf{X}'_{i,j,c,g}\theta + \varepsilon, \tag{3}$$

$$\Delta T_{i,j,c,g} = \beta_0 + \beta_1 C_{c,g} + \mathbf{X}'_{i,j,c,g}\theta + \varepsilon, \tag{4}$$

where N is the number of singles, ΔT is the time difference between releases, C denotes our measure of competition, and the indices i,j,c and g denote artist, album, country and genre, respectively. β_k and θ are parameter (vectors) and the error term ε is assumed to have the standard properties. The vector $\mathbf{X}'$ comprises all control variables and fixed effects introduced above. We run these regressions on a sample ranging from 2003 to 2010 to test hypothesis 1, and for the time-period 1990–2003 to test hypothesis 2, by comparing the results for the two periods.

The strategic player in this setting is the record label, which coordinates release dates of its artists. Decisions regarding albums from the same label might be correlated. We therefore cluster standard errors at the level of the parent label.

3.3.2 Alternative estimation approaches

The OLS estimator may be problematic in our setting: Our dependent variables are truncated (can never be negative), by definition, and are not continuous. One may alternatively interpret the number of singles, or the number of days between releases as count data, or as ordered choice variables. To address and control for these issues, we additionally apply Tobit, Poisson and Ordered Logit models of the specifications (3) and (4). The corresponding results are reported in section 4.3.5.

The results discussed in the main text of this paper are based on the OLS specification. In the spirit of the theoretical arguments presented in section 2, we are mainly interested in interpreting the results in qualitative (coefficient signs) rather than quantitative (coefficient size and forecasting) terms.

Table 1: Results: Number of singles 2003-2010

	DV: Total Number of Singles				
	(1)	(2)	(3)	(4)	(5)
Competition	0.0315***	0.0290***	0.0312***	0.0130***	0.0315***
	(0.00471)	(0.0108)	(0.0109)	(0.00432)	(0.00896)
Competition^2	-0.00101***	-0.00134***	-0.00144***		-0.00101***
	(0.000212)	(0.000428)	(0.000425)		(0.000363)
Major Label	0.102***	0.144*	0.146*	0.106	0.102
	(0.0189)	(0.0799)	(0.0781)	(0.0720)	(0.0721)
Track Count	-0.00761***	-0.00640***	-0.00727***	-0.00709***	-0.00761***
	(0.00129)	(0.00238)	(0.00246)	(0.00256)	(0.00257)
Constant	0.516***	0.326***	0.433***	0.524***	0.516***
	(0.0777)	(0.0697)	(0.114)	(0.132)	(0.130)
Fixed Effects					
Month	Yes	No	Yes	Yes	Yes
Year	Yes	No	Yes	Yes	Yes
Genre	Yes	No	No	Yes	Yes
Album History	Yes	No	No	Yes	Yes
Observations	10,630	10,630	10,630	10,630	10,630
R^2	0.0795	0.0103	0.0162	0.0781	0.0795
Standard errors	White	Clustered	Clustered	Clustered	Clustered

Note: Reported coefficients are OLS point estimates. Standard errors (in parentheses) in columns (2)–(5) are clustered on the parent label level. * p<0.1, ** p<0.05, *** p<0.01

4 Results and Discussion

4.1 Single releases with forced unbundling, "digitized era", 2003–2010

The results of the OLS estimation for the effect of competition on number of singles under forced unbundling are reported in Table 1. The first two columns show the results for the regression with White-robust standard errors. Columns (3), (4), and (5) report the results with gradually more fixed effects using clustered standard errors. Looking at the coefficients of the month and year fixed effects (not reported), we find a slight trend towards more singles over time but no significant pattern within each year. Furthermore, artists that have released more previous albums do not systematically release more or less singles than newcomers. *Metal* and *Hip Hop* are the only genres that show significant differences with regard to the single release behavior. In those genres, on average, half a single less is released compared to the base category *Alternative*.

With regard to Hypothesis 1a, we find the following: The intensity of album competition at release has a positive and significant effect on the number of released singles. Labels do prefer to release more singles when they are confronted with more rival albums in their market. We expected a non-linear component, since very strong competition may reduce the potential market size for an album, and thereby the profitability of marginal singles down below costs. Indeed, the squared term of competition is significant and negative. Taken together, this suggests that firms release more singles as competition increases; however, when competition exceeds a critical level, the effect of competition on single releases becomes negative under forced unbundling.[22] The critical level of competition, depending on the specification, is around 12 simultaneous releases per month, which is well above the average observed in our data. A formal test of an inverted U-shape against the alternative of a linear relationship or U-shape (Lind and Mehlum, 2010), supports the inverted U-shaped relationship within the observed range of competition ($p < 0.001$). This result supports hypothesis 1a.

The coefficient for major label affiliation is positive but not significant in our preferred specification shown in column (5) of table 1. Interestingly, the coefficient of track count is negative, i.e. more songs on an album translate into fewer singles.

Next, we turn to Hypothesis 1b. Table 2 reports the results for the regression on release timing. Again, fixed effects are gradually introduced throughout the columns. In accordance with our prediction, stronger competition at album release has a negative and significant effect on the time between releases in all specifications. This suggests that labels release their singles at a faster pace when confronted with more competition.[23] This lends support to our hypothesis 1b. Again, major labels do not differ in their release-timing compared to independent labels. The coefficient of track count is positive and significant. We additionally test for a non-linear relationship between competition and time between releases. Column (5) in table 2 shows that the linear term of competition is still negative, but no longer significant, due to higher standard errors, and the squared term is positive and not significant. We therefore estimate an additional specification that leaves more

[22] A one standard deviation increase in competition results in a 0.122 increase in released singles. Given that the mean count of released singles is roughly 0.42, this is a reaction of 29%.

[23] A one standard deviation increase in competition leads a label to release the single 6.4 days earlier. With a mean time difference of 73 days, this is almost a reaction of 9%.

Table 2: Results: Time between releases 2003-2010

	DV: Average Time between Releases					
	(1)	(2)	(3)	(4)	(5)	(6)
Competition	-1.407*	-1.346**	-1.461**	-1.407***	-2.863	-3.541**
	(0.768)	(0.522)	(0.556)	(0.456)	(1.912)	(1.781)
Competition sq.					0.0914	0.128
					(0.115)	(0.109)
Major Label	-7.539	-7.588	-9.761	-7.539	-7.596	-10.38
	(6.448)	(7.455)	(7.276)	(7.031)	(6.979)	(7.494)
Track Count	3.275**	2.991**	2.895**	3.275**	3.276**	2.708**
	(1.308)	(1.282)	(1.219)	(1.269)	(1.270)	(1.157)
Genre: Classical						-34.13*
						(19.40)
Constant	46.03	47.92***	35.68*	46.03*	47.81*	47.62*
	(35.28)	(16.53)	(20.03)	(27.33)	(27.93)	(26.32)
Fixed Effects						
Month	Yes	No	Yes	Yes	Yes	Yes
Year	Yes	No	Yes	Yes	Yes	Yes
Genre	Yes	No	No	Yes	Yes	No
Album History	Yes	No	No	Yes	Yes	Yes
Observations	2,415	2,415	2,415	2,415	2,415	2,415
R^2	0.0370	0.00657	0.0156	0.0370	0.0372	0.0305
Standard errors	White	Clustered	Clustered	Clustered	Clustered	Clustered

Note: Reported coefficients are OLS point estimates. Standard errors (in parentheses) in columns (2)–(5) are clustered on the parent label level. * p<0.1, ** p<0.05, *** p<0.01

variation in the data, by not including fixed effects for all genres, but only a dummy indicating whether an observation is within the genre *Classical* or not. We chose this definition, because descriptive statistics in table A.2 suggest that *Classical* is the most likely outlier in terms of competition and release timing compared to all other genres. The corresponding results reported in column (6) show a negative and significant coefficient of competition, the squared term remains positive and not significant. This lends further support to hypothesis 1b: the relationship between competition and the frequency of releases is monotonically negative.

Table 3: Number of Singles: Pre and Post Digitization

	DV: Total Number of Singles			
	1990–2003		2003–2010	
	(1)	(2)	(3)	(4)
Competition	-0.00353***	-0.00780**	0.0130***	0.0315***
	(0.00118)	(0.00347)	(0.00432)	(0.00896)
Competition^2		0.000185		-0.00101***
		(0.000125)		(0.000363)
Major Label	0.0704	0.0704	0.106	0.102
	(0.0657)	(0.0658)	(0.0720)	(0.0721)
Track Count	-0.00256*	-0.00255*	-0.00709***	-0.00761***
	(0.00139)	(0.00139)	(0.00256)	(0.00257)
Constant	0.418***	0.420***	0.524***	0.516***
	(0.148)	(0.148)	(0.132)	(0.130)
Observations	9,440	9,440	10,630	10,630
R^2	0.111	0.111	0.0781	0.0795
Standard errors	Clustered	Clustered	Clustered	Clustered

Note: Reported coefficients are OLS point estimates. All specifications control for month, year, genre and album history fixed effects. Standard errors (in parentheses) are clustered on the level of parent labels. * p<0.1, ** p<0.05, *** p<0.01

4.2 The effects of forced unbundling - contrasting results to the "CD-era", 1990–2003

To test hypotheses 2a and 2b, we run the same regressions on the sample ranging from 1990 until 2003 and then compare coefficients. We begin with discussing the results concerning the number of single releases in columns (1) and (2) of table 3. We include the results obtained from an estimation on the sample between 2003 and 2010 in columns (3) and (4) (same as columns 4 and 5 in table 1) to facilitate the comparison.

Regarding the main control variables, we find that the effect of major label affiliation and the number of tracks on the album remains stable when moving back in time; both in terms of significance and the direction of the effect.

What we are mainly interested in is how single release behavior of firms is associated with competition, when the single is still an independent revenue generating product to be unbundled from the album. It turns out that prior to digitization, the behavior of firms was fundamentally different than after: Pre-2003, effect of competition on the optimal number of singles released is negative and significant in column (1). Testing

Table 4: Time between releases: Pre and Post Digitization

	DV: Time between releases	
	1990–2003	2003–2010
	(1)	(2)
Competition	-1.613	-1.407***
	(1.660)	(0.456)
Major Label	0.518	-7.539
	(12.26)	(7.031)
Track Count	2.795***	3.275**
	(0.970)	(1.269)
Constant	85.63***	45.17
	(23.74)	(27.36)
Observations	1,874	2,415
R^2	0.0523	0.0370
Standard errors	Clustered	Clustered

Note: Reported coefficients are OLS point estimates. All specifications control for month, year, genre and album history fixed effects. Standard errors (in parentheses) are clustered on the level of parent labels. * p<0.1, ** p<0.05, *** p<0.01

for a non-linear relationship in column (2), the results suggest a purely linear, negative, and significant effect of competition. Clearly, the coefficients in the two eras are highly significantly different. This result strongly supports our predictions derived in hypothesis 2a. When the singles were still independent products, the direct revenue effect implied that more competition made single releases much less attractive for the firm.

We compare the effects of competition on the time between releases for the two eras in table 4. We find that the coefficients are similar, both in terms of magnitude and direction and slightly larger in the pre-iTunes era. For the time before 2003, though, the standard error is substantially higher, so that the coefficient is no longer significant. We interpret this as implying that the strong ceteris-paribus conditions regarding the shares of consumers and the relative prices of album and singles required to derive Hypothesis 2b do not hold, and therefore the regression is noisier for the earlier era. Interestingly, the constant is almost twice as large in the CD era as in the iTunes era, i.e., labels waited twice as long to release a new single, which is in line with an incentive to avoid cannibalization of sales.

4.3 Robustness checks

In the following sections, we address a number of potential issues in terms of data, alternative explanations and methods.

4.3.1 Data quality and completeness

The data, on which our study is based is user-generated. MusicBrainz relies on anonymous users supplying inputs into an online database without remuneration; nevertheless, it had managed to become the industry quasi-standard for online music-databases in the first decade of the 21st century, cooperating with, e.g., the BBC to supply meta-data on songs in their program.[24] Towards the end of the decade and in the subsequent years, factors such as the rising popularity of streaming services – each equipped with databases of their own – resulted in a decreasing popularity of the MusicBrainz project, as can bee seen in the righthand panel of figure 4. Due to this, we limit our sample to observations prior to and including 2010.

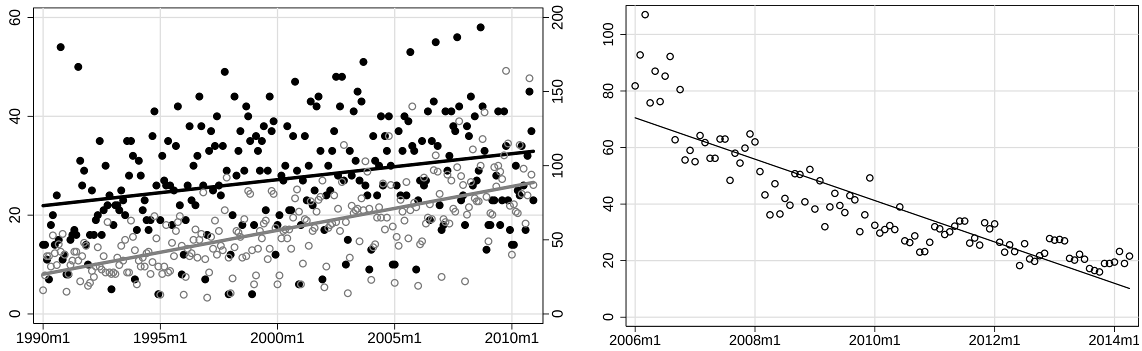
An important issue to address is the selection of observations into the database. We observe all data required for our analysis for about 20,000 albums; including the extremely long tail in the music business, the full figure of publications in the period we consider easily exceeds one million. As such, we are dealing with a truncated version of the distribution. This cannot be avoided.[25] In fact, since the hypotheses that we derive depend on the observed albums actually competing for customer attention, the (low) popularity threshold of entry into a user-generated database may contribute to ensuring that the competition measured by our approach is actually relevant.

What we further want to ensure is that our competition measure varies in accordance with the actually occurring competition in the market. To check if the number of album releases observed by us is related to the true number of releases, we use data from the Billboard 200 list, the most influential album charts in the United States. We count the number of new chart entrants each month and correlate this with the number of monthly new releases in the United States using the MusicBrainz database. The left-hand-panel of

[24] See http://blog.musicbrainz.org/2007/06/28/the-bbc-partners-with-musicbrainz-for-music-metadata/

[25] To compare: **?**, using sales-data and searching for artists for whom one debut-album is observed using the Billboards charts between 1993 and 2002 are able to include 888 albums from three genres in their study to derive their results.

Figure 4: Sample representativeness: Musicbrainz, Billboard 200, Google Trends



Note left-hand-panel: *Gray dots and fitted line correspond to the weekly number of new US releases in our estimation sample (left axis). Black dots and fitted line correspond to the weekly number of new entrants in Billboard 200 album charts (right axis).*
Note right-hand-panel: *Relative weekly search volume on Google in the US. Search term: "musicbrainz".*
Data source: *billboard.com, musicbrainz.org, Google Trends.*

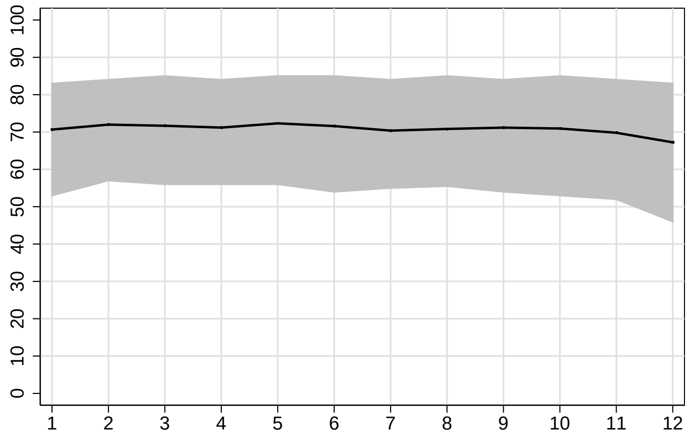
figure 4 shows both variables in a scatterplot with the corresponding linear fits. The figure shows that while we do not observe the entire population of new releases, the correlation is high and the trends match each other well.

4.3.2 Endogenous release timing and album quality

Other studies, such as Hendricks and Sorensen (2009a) consider the album release date to be exogenous. On the other hand, if there are focal points for album publication during the year (e.g., prior to the holiday season), then this could enter the calculus of firms, which might give rise to an alternative explanation for parts of the pattern that we observe. Assume that higher-quality albums have more potential singles and are likely to fare better against tougher competition. Then firms may publish these at the focal points during the year, while placing their weaker albums at times when they face less competition. If it is quality that is driving the number of singles, then this would also explain parts of the relationship between competition and number of singles released observed by us.

To explore the relevance of this effect, we turn to an independent website which aggregates the quality assessments of released albums to calculate the metascores for albums (Metacritic.com). This metascore is used as an indicator of quality for the releases, and ranges from 0 to 100. It provides quality information on more than 5100 albums between 1999 and 2010. The data provided information on the artist, genre, album title, and release date.

Figure 5: Metacritic scores of albums released during different seasons



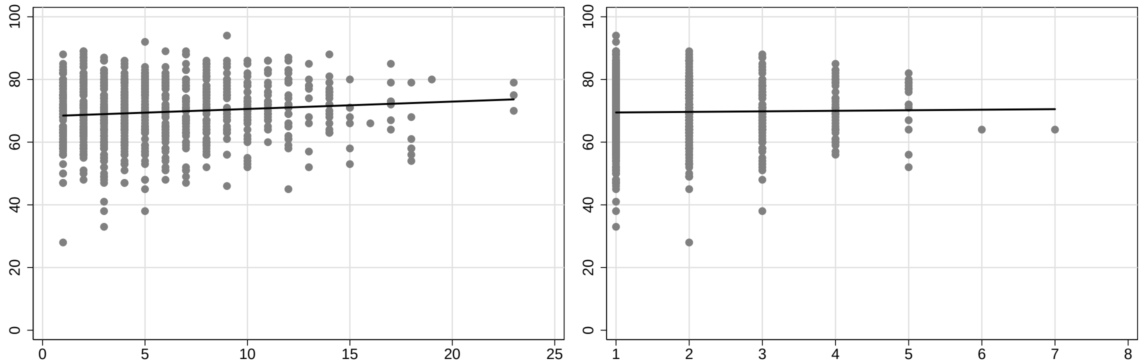
***Note**: The solid line gives the average Metacritic score for 5100 music albums, released during the years 1999–2010. The gray area indicates the corresponding 5th to 95th percentile range. The horizontal axis is the release month independent of release year. **Data source**: metacritic.com*

If the alternative explanation were to hold, then we would expect better quality albums to be released in months with higher competition and worse quality albums to be released in lulls. Figure 5 shows the distribution of Metascores dependent on the release month. The mean of scores stays remarkably constant at 70 while the interval between the 5^{th} and the 95^{th} percentile lies roughly 15 points above/below the mean. The only support for the alternative hypothesis is only that during December (i.e., too late for the holiday season) the lower bound slides downwards; the mean, however, is unaffected.

The graph suggests that the concern of lower quality albums selecting into particular months does not find much support in the data. However, one might still argue that labels, while not selecting particular months, wait until competition is lower. We would then expect to find a positive correlation of our measure of competition and Metascores, as lower quality albums should select into phases of low competition.

To investigate this, we match Metacritic to Musicbrainz, using the criteria artist name and release date (month-year). We are able to find 812 albums in both datasets. Because the majority of albums we observe in the combined sample are recent releases not older than three years, we do not run regressions on this data, but stick to a descriptive analysis. The left-hand-panel of figure 6 shows how Metascores are distributed given the level of competition, along with a linear fit line. Although some patterns are visible, we only find a very small correlation between Metascores and competition. This suggests no convincing

Figure 6: Metacritic scores, competition, and number of singles



Metacritic scores and level of competition *Metacritic scores and number of singles*
Solid line indicates fitted values of a simple OLS regression.
***Data source**: musicbrainz.org and metacritic.com, based on 812 album matches.*

evidence in favor of the concern of strategic release timing conditional on album quality. Any remaining effect is likely to be minor and should be captured by season fixed-effects in our approach.

4.3.3 Endogenous popularity of genres and artists

There is a subtle effect to consider when using the number of rival albums as a driver of single releases which is related to the (potentially faddish) popularity of entire genres. If genres are, temporarily, en vogue then it would be reasonable to observe more albums being released as music firms jump onto the "band waggon". If albums from popular genres release more singles ipso facto, then genre popularity might drive both competition and single releases.

We use data from Google Trends to take this into account at least to some extent. This yields a time-series with the weekly search volume of the terms "alternative music", "classical music", "electronic music", "hip hop music", "metal music", "pop music", and "rock music", relative to the search term with the highest volume. By simultaneously querying search volumes for different genres, the results are indexed according to the most frequently searched term. That is, if "hip hop music" was the most popular, querying for "rock music" gives us the search volume relative to the volume of "hip hop music", etc. We use this as a measure for the relative popularity of genres.

Google Trends data is only available starting from 2004, therefore a direct match comes at the cost of losing many observations and we can only perform this exercise for the forced unbundling era – which is the relevant case, because only here the positive relationship between competition and single releases could be found. Columns (1) and (3) of table A.4 show the results of regressions similar to those above. The popularity of the genre has no significant effect on the number of singles; the effect of competition remains positive and significant; the effect is even larger than in our preferred regression. Also, in column (3) we find a remaining negative and significant effect of competition on the time between releases.

Building on an analogous argument, single release behavior could be driven by an artist's popularity. To control for this alternative explanation, we use data from Wikipedia. We proxy for artist popularity with the logarithmized cumulative clicks on the artist's Wikipedia page in the month of album release. This approach, however, comes with two major limitations. First, we only observe clicks on Wikipedia pages starting in January 2008. Consequently, we lose all album releases up until December 2007. Second, several of the artists in our sample are not popular enough to have their own Wikipedia page. Therefore we do not have Wikipedia clicks for a substantial number of artists. We set their popularity to the minimum level as we interpret the lack of a Wikipedia page as an indication of low popularity of an artist.

The results are reported in model (2) for the number of singles and (4) for the time between releases in Table A.4. The findings suggests that artist popularity has a positive and significant effect on the number of singles released. However, the main and squared effect of competition remain as in the preferred regression which lends further support to our hypothesis.

4.3.4 A wider perspective on competition

As discussed in the definition of variables, it could be considered too restrictive to argue that the label only responds to competition in the month of the release. We consider two additional definitions for the variable competition; one with the number of albums from the same genre released in the same month plus the month before and after and one with competition measured in the release month plus the two months before and after. The results in table A.5 remain qualitatively unchanged. The estimation results therefore do not depend on our definition of the time horizon for competition.

4.3.5 Alternative estimation approaches

As detailed in section 3.3.2, one may have concerns regarding the estimation method. Violations of OLS assumptions may produce results that are qualitatively different to those obtained using other estimators, which may fit our set-up better. We therefore estimated Tobit and Poisson regressions for both dependent variables as well as an ordered Logit model to explain the number of singles released (Table A.6). The results are comparable in terms of coefficient sign and significance.

5 Conclusions and Implications

The music industry is a poster-child for a sector that has been fundamentally affected by the digitization of the economy. In this paper, we focus on one important aspect that helps us better understand this process: The different motives for music firms to unbundle individual songs from their albums, i.e., to release singles. As Hendricks and Sorensen (2009b) have shown, customer information and the lack thereof play an important role in determining albums. This makes awareness for albums a crucial commodity in the industry. Single releases, which, for example, affect the airtime dedicated to artists, are one of the central ways to manage awareness for albums. In a simple framework, we show how competition should affect the incentives to release singles if this is the sole motive of firms – with the optimal number of singles following a U-shape in competition. Moreover, we allow for other motives for single releases, in particular the unbundling-result which makes singles independent generators of revenues. The "experiment" that we empirically focus on is the forced unbundling through digitization – both completely involuntarily through the introduction of the mp3-format and the rise of (at the time illegal) filesharing platforms, such as Napster, as well as through new business models such as Apple's iTunes-service. In the digital era, approximated by the time after 2002, unbundling motives should therefore no longer play a role (at least to the same extent) and therefore, the effects of album competition on the single release behavior of firms should differ across the two eras. What we find empirically strongly supports this interpretation: Prior to 2003, competition has a purely negative effect on the number of singles released by firms – a single is an independent, revenue generating product. In the digital era, this is inverted and we observe the inverse U-shape in competition that is generally associated with advertising efforts. Also, singles are released in closer succession to each other: In the information era, singles have become a measure to raise and maintain attention. In this way, they have managed to escape becoming obsolete: In fact, the average number of single releases per album that we observe is not remarkably different across the two eras.

We use a rich, unique dataset covering the music industry which has not been previously utilized in this fashion: With data from the online platform MusicBrainz, we are able to observe exogenous variation in the level of competition at album release within a genre to estimate its effect on the number of and intervals between single releases. In this way, we can study the interactions between competition at the level of individual products (albums) and measures to increase their commercial success.

Clearly, the nature of our data is associated with certain limitations. Using user-generated data, there are always some doubts concerning the data quality of individual entries. We carry out some robustness checks utilizing other, independent sources of data to rule out certain competing explanations. Further, while it allows us to observe variation at the product level, our measure of competition (number of releases in the same genre in the same month/surrounding months) is by necessity a crude one. One could argue that this is not the relevant set of competing products that labels take into account. It would be interesting future research to more closely study which products are the truly relevant competition in settings like the music industry, in which such a plethora of products compete for consumer attention. Again, we try to address alternative explanations using external data and by using different time-windows to define the competition set.

Beyond demonstrating the effects of forced unbundling through digitization on the release behavior of music firms, our paper contributes to the strand of literature concerned with how firms market their products and compete for attention. First, our finding of the non-linear effect of competition on amount of advertising adds product-level evidence to the classic literature (Sutton, 1974; Reekie, 1975; Rees, 1975; Brush, 1976; Ehrlich and Fisher, 1982) which studied competition only at the industry level. Our findings provide further evidence that consumer awareness of products affects sales in certain industries (Cai et al., 2009; Hendricks and Sorensen, 2009a; Tucker and Zhang, 2011; Hendricks et al.,

2012) and shows that firms do take this into account in their strategy. Moreover, it adds to the literature on competition and product introduction (Bayus et al., 1997; Boyd and Bresser, 2008; Ethiraj and Zhu, 2008; Lee et al., 2000); it also shows, how the introduction of products (singles) was affected by digitization.

Finally, focusing on the music industry, our results indicate why music labels still choose to release singles, even as their direct revenue generating role has receded due to the digitization of the music market and the corresponding — almost total — unbundling of purchasable tracks from albums: Single releases still play an important role in generating consumer attention for the underlying album. Looking to the future, one of the central current trends in the listening behavior of consumers, individualized music streaming, may undermine one of the central channels through which singles generate attention. If the importance of radio airplay continues to decline, affecting the programme planning of stations through single releases will become an increasingly futile venture. Therefore Spotify may succeed where iTunes failed: Turning single releases into a truly unprofitable sideshow. The *Loudness War*, however, is likely to continue on different battlefields, such as automated or user-generated recommendations on online-platforms, i.e. blog posts (Dewan and Ramaprasad, 2012), playlists on Deezer and Spotify; likes, shares and retweets on Facebook and Twitter; videos on YouTube (Kretschmer and Peukert, 2014), and by continuing to turn live performances back into the lifeblood of the music industry (Tonon et al., 2014).

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Appendix

Table A.1: Descriptive statistics

	1990–2003				2003–2010			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Number of Singles	0.349	0.851	0	6	0.422	0.946	0	6
Time	87.797	147.228	0	728	73.001	132.645	0	728
Competition	5.291	5.116	1	36	5.543	4.537	1	31
Major Label	0.686	0.464	0	1	0.606	0.489	0	1
Track Count	12.838	4.935	1	50	12.905	4.752	1	50
Countries per Album	1.298	0.668	1	10	1.395	0.790	1	10
Observed Albums	8,543				9,209			
Observed Singles	3,927				4,489			

Table A.2: Descriptive statistics by genre

	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
	Alternative				*Metal*			
Number of Singles	0.358	0.789	0	4	0.239	0.644	0	4
Time	86.725	154.119	0	665	88.736	149.615	0	728
Competition	1.421	0.743	1	4	2.376	1.513	1	8
Major Label	0.526	0.501	0	1	0.288	0.453	0	1
Track Count	13.384	3.488	7	31	10.894	3.118	2	33
	Classical				*Other*			
Number of Singles	0.024	0.230	0	5	0.338	0.880	0	6
Time	49.667	83.367	0	366	80.761	147.607	0	704
Competition	7.805	6.493	1	31	5.205	3.314	1	13
Major Label	0.555	0.497	0	1	0.580	0.494	0	1
Track Count	11.800	5.394	2	42	14.115	5.651	2	50
	Electro				*Pop*			
Number of Singles	0.591	1.010	0	5	0.713	1.204	0	6
Time	87.390	149.945	0	721	58.882	114.542	0	700
Competition	2.648	1.788	1	11	5.296	3.622	1	18
Major Label	0.465	0.499	0	1	0.706	0.456	0	1
Track Count	12.592	5.070	1	49	13.090	3.615	2	36
	Hip Hop				*Rock*			
Number of Singles	0.522	1.004	0	6	0.622	1.084	0	6
Time	75.233	112.755	0	634	70.344	129.783	0	707
Competition	3.780	2.842	1	13	7.208	4.816	1	23
Major Label	0.771	0.420	0	1	0.712	0.453	0	1
Track Count	14.751	3.663	3	44	12.146	3.523	2	46

Note: Data refer to the period 2003–2010.

Table A.3: Pairwise correlations

	(1)	(2)	(3)	(4)	(5)
(1) Number of Singles	1.0000				
(2) Time	-0.3364	1.0000			
	(0.0000)				
(3) Competition	0.0832	-0.0468	1.0000		
	(0.0000)	(0.0215)			
(4) Major Label	-0.0563	-0.0239	0.0521	1.0000	
	(0.0056)	(0.2401)	(0.0105)		
(5) Track Count	-0.0467	0.0636	-0.0587	0.0680	1.0000
	(0.0218)	(0.0018)	(0.0039)	(0.0008)	

Note: p-values in parentheses. Data refer to the period 2003–2010.

Table A.4: Robustness checks: genre and artist popularity

	DV: Number of Singles		DV: Time between Releases	
	(1)	(2)	(3)	(4)
Competition	0.0338***	0.0372***	-1.291***	-1.105
	(0.00919)	(0.0124)	(0.406)	(0.887)
Competition^2	-0.00109***	-0.00126*		
	(0.000353)	(0.000649)		
Major Label	0.112	0.0435	-12.56*	-12.59
	(0.0731)	(0.0684)	(6.880)	(8.973)
Track Count	-0.00881***	-0.00693**	3.960***	3.756***
	(0.00289)	(0.00325)	(1.343)	(1.338)
Genre: Google Trends	-0.000746		-0.0684	
	(0.00148)		(0.439)	
Artist: Wikipedia Clicks		0.135***		-4.346***
		(0.00786)		(0.652)
Constant	0.452***	0.373***	62.56	72.36
	(0.157)	(0.130)	(47.79)	(43.55)
Observations	9,296	5,609	2,589	1,215
R^2	0.0784	0.243	0.0433	0.0829

Note: Reported coefficients are OLS point estimates. All specifications control for month, year, genre and album history fixed effects. Model (1) and (3) control for the Google Trends statistics of the particular genres. Models (2) and (4) control for popularity measured as the logarithm of cumulative clicks on Wikipedia for the artist in the month of album release. Standard errors are clustered on the level of parent labels. * p<0.1, ** p<0.05, *** p<0.01

Table A.5: Robustness check: time to measure competition

	DV: Number of Singles		DV: Time between Releases	
	(1)	(2)	(3)	(4)
Competition ±1	0.0155***		-1.050***	
	(0.00365)		(0.283)	
Competition ±1 sq.	-0.000189***			
	(0.0000528)			
Competition ±2		0.0106***		-0.845***
		(0.00258)		(0.242)
Competition ±2 sq.		-0.0000863***		
		(0.0000292)		
Major Label	0.102	0.106	-7.564	-7.356
	(0.0731)	(0.0735)	(6.928)	(6.809)
Track Count	-0.00758***	-0.00733***	3.348**	3.467***
	(0.00266)	(0.00267)	(1.279)	(1.273)
Constant	0.549***	0.516***	47.59*	49.90*
	(0.147)	(0.139)	(28.38)	(28.48)
Observations	10,494	10,404	2,400	2,390
R^2	0.0816	0.0820	0.0393	0.0406

Note: Reported coefficients are OLS point estimates. All specifications control for month, year genre and album history fixed effects. Standard errors are clustered on the level of parent labels. * p<0.1, ** p<0.05, *** p<0.01

Table A.6: Robustness checks: alternative estimation methods

	DV: Number of Singles			DV: Time between Releases	
	Tobit	Poisson	Ordered Logit	Tobit	Poisson
	(1)	(2)	(3)	(4)	(5)
Competition	0.143***	0.0795***	0.0896***	-2.933**	-0.0195***
	(0.0261)	(0.0241)	(0.0241)	(1.329)	(0.00663)
Competition^2	-0.00522***	-0.00261*	-0.00327**		
	(0.00157)	(0.00136)	(0.00142)		
Major Label	0.595***	0.250	0.441*	-6.502	-0.0975
	(0.0808)	(0.203)	(0.227)	(10.81)	(0.0884)
Track Count	-0.0435***	-0.0239***	-0.0263***	6.066***	0.0378***
	(0.00780)	(0.00887)	(0.00843)	(1.855)	(0.0137)
Constant	-2.041***	-0.854***		-73.32	3.945***
	(0.339)	(0.327)		(56.02)	(0.369)
σ	2.696***			201.7***	
	(0.0413)			(5.860)	
Cut1			1.316***		
			(0.407)		
Cut2			2.278***		
			(0.399)		
Cut3			3.076***		
			(0.410)		
Cut4			3.899***		
			(0.417)		
Cut5			5.177***		
			(0.440)		
Cut6			6.730***		
			(0.499)		
Observations	10,630	10,630	10,630	2,415	2,415
Log Likelihood	-8717.0	-9148.7	-8057.9	-9570.9	-198903.2

Note: All specifications control for month, year, genre and album history fixed effects. Model (1) are Tobit coefficients with a lower bound of zero, Model (2) is a Poisson regression and (3) estimates an Ordered Logit model. Columns (4) and (5) estimate a Tobit with lower bound of zero and Poisson model, respectively. Standard errors are clustered on the level of parent labels; except for the tobit models which do not allow for clustering. Here, we use robust standard errors instead. * p<0.1, ** p<0.05, *** p<0.01