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Online Music, Sales Displacement, and Internet Search: Evidence from YouTube

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Abstract

Digital content services have become an important means of enjoying music, and considerable debate exists over the performance rights of sound recordings. In this paper, we exploit the removal of Warner Music content from YouTube in January 2009, and its restoration in October 2009, as a plausible experimental design to investigate the impact of online content availability on music sales and Internet search. To this end, we obtained weekly sales figures for Billboard top 200 albums from Nielsen SoundScan and constructed a globally consistent index of artist keyword search using Google Trends. We find that the blackout had both statistically and economically significant positive effects on album sales, specifically the best-selling albums in a week as effects taper off into insignificance as the top 50 albums are dropped. We find no evidence that the blackout had any causal effects on Internet search for artists.

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1 Introduction

The Sound Recording Act of 1971 granted federal copyright protection to sound recordings, but only a subset of those rights that are usually granted to writing authors.[1] That is, while music artists were granted exclusive rights to reproduce, distribute, and adapt their sound recordings, they were not granted the public performance right. It was not until 1995 when the Digital Performance Right in Sound Recordings Act (DPRA) partially provided, for the first time, such a right that artists were able to get compensated for the public performance of their sound recordings. DPRA, however, set a limitation, which has become the center of debates in the market for digital content services.

Specifically, DPRA created a public performance right for sound recordings that are performed only by means of a digital audio transmission, which targeted the growing number of satellite radio and, increasingly today, internet companies. For instance, this meant that over-the-air FCC-licensed broadcasters are free to use the sound recordings without any payment to the artists or the record companies. The justification for this exemption was that over-the-air broadcasts promote the sale of records; however, "such a position is hard to justify today in light of recent technological developments and the alternative sources of music from other music services, and declining record sales" (Peters, 2007).

To our knowledge, there are few works investigating the rationale behind this policy. Liebowitz (2007) uses radio play (hours) data, and Nielsen SoundScan data both aggregated at the Designated Market Areas for the year 1998 and 2003. Liebowitz finds that radio play does not have a positive impact on record sales and instead appears to have an economically important negative impact. Our approach is complementary in the sense that we examine whether the digital content services have any promotional effect or simply displaces album sales. The findings in this paper therefore can inform the public policy debate on the copyright extension and licensing for online music services.[2]

[1] Sound recordings fixed before the effective date of the Act (February 15, 1972) would remain subject to state common law.

[2] The government has been supporting an equal treatment of terrestrial and online music services (De-

As we discuss in the next section, a growing number of authors have exploited quasi-experimental events to investigate the effects of digital content availability on consumer piracy and other related behavior. Our paper is similar in this regard, but the difference is that the literature has not exploited an experimental design in the context of music delivery, a large and rapidly changing industry. To be more precise, we are interested in finding out whether YouTube has promotional effect or merely displaces sales. In addition to its effect on sales, we use Internet search intensity to verify the claims of promotional effect; however, we fail to find evidence of promotional effect in either of these two dimensions.

Because YouTube is perhaps the most successful online content service, failing to find evidence in support of promotional effect means that free online content services are likely to be substitutes for consumer piracy in terms of industry profits. We find that the sales displacement effect is initially substantial although it falls into insignificance if we drop, say, the top 50 albums. For instance, using a six-month window before and after the blackout, the removal of content from YouTube is causally associated with an increase of 7375 units per week per album using the top 200 sample, 3155 units dropping top 10 albums, 1968 units dropping top 25 albums, and 555 units dropping top 50 albums.

However, we caution that the lack of promotional effect in our sample need not necessarily generalize to those outside of the top 200. In fact, Waldfogel (2012) assembles comprehensive data on albums released between 1980 and 2010 along with Billboard chart ranking and airplay on both traditional radio (since 1990) and Internet radio (2006-2011). Waldfogel finds some evidence that Internet radio play affects the number and kinds of products consumers have information on and an increasing number of albums find commercial success without substantial traditional airplay. This supports the view that Internet radio is a substitute for terrestrial broadcasters and has some role in promoting albums.[3]

On the other hand, Waldfogel's focus is on the extent of creative output (i.e., number

partment of Commerce 2013: 12).

[3]Relatedly, Hendricks and Sorensen (2009) find that consumers might not learn about new artists even with moderate levels of sales. Specifically, second albums sell on average 25% more than they would have if they had not been preceded by another album.

of new releases) and the concentration of top-selling albums, where sales are imputed from ranks. That is, Waldfogel does not directly test sales displacement effect. In fact, Bourreau et al. (2013) find some evidence that the number of new releases may increase without affecting sales. Thus, the results in this paper indicating a strong sales displacement effect at the top can be potentially consistent with online content services having some promotional effect for lesser-known artists, in a way that is consistent with the co-existance of a 'superstar' effect and 'long-tail' idea (Elberse and Oberholzer-Gee, 2007).

The remainder of this paper is organized as follows. Section 2 discusses relevant literature, and Section 3 explains the blackout episode. Section 4 describes the dataset, and Section 5 presents empirical findings. Section 6 concludes.

2 Related Literature

As one of the industries that were hit hard by the digital disruption, the music industry has received a great deal of attention in the past dozen or so years. Starting from the Napster case (*A&M Records, Inc. v. Napster, Inc.*), the sales displacement and the promotional effects of online file-sharing services have been at the center of debates. While there have been some anecdotal evidence and surveys indicating that file-sharing services help promote an artist's work, efforts to understand the promotional effect have been largely confined to theoretical works in the literature (e.g., Gopal et al., 2006; Peitz and Waelbroeck, 2006).[4] Absent independent empirical measures, the empirical literature evolved to focus heavily on sales displacement effect where promotional effect was regarded as the opposite of the sales displacement effect.

While we do not intend to survey this literature here (see, e.g., Liebowitz (2006) and Danaher et al. (2014) for details), most of previous works on music piracy made use of either individual-level survey data (e.g., Rob and Waldfogel, 2006; Zentner, 2006; Andersen

[4]Specifically, in a survey conducted by Pew Research Center, 43 percent of the artists agreed that "file-sharing services aren't really bad for artists, since they help to promote and distribute an artist's work to a broad audience" (Pew Internet & American Life Project. Press Release 12/5/2004).

and Frenz, 2010; Waldfogel, 2010; Hong, 2013) or country/city-level panel data (e.g., Hui and Png, 2003; Pietz and Waelbroeck, 2004; Liebowitz, 2008; Zentner, 2010). A couple of papers (Blackburn, 2004; Oberholzer-Gee and Strumpf, 2007) have attempted to assess consumer piracy using an album-week as the unit of observation. Although Blackburn and Oberholzer-Gee and Strumpf had direct measures of file sharing activities for albums, the difficulty they faced was to find a plausible instrumental variable, which was the key to identify the effect of file sharing on sales.[5]

In this paper, we contribute to the literature in two ways. First, instead of using instrumental variables, we apply quasi-experimental methods to more precisely identify the effect of free content availability on individual album sales. In fact, in a series of papers, Danaher et al. (2010), Danaher and Smith (2014), and Danaher et al. (2014) investigate the effects of copyright enforcement and content availability on digital content sales. For instance, Danaher et al. (2014) find that France's graduated anti-piracy law caused iTunes sales from major music labels to increase by over 20% relative to other European countries. Similarly, using pre-trend, cross-country variation, Danaher and Smith (2014) show that the US government's shutdown of a major piracy site caused digital revenues for major motion picture studios to increase by 7.5%.

The paper closest to ours in this regard is Danaher et al. (2010), which considers the removal of NBC content from Apple's iTunes store in December 2007, and its restoration in September 2008, as natural shocks to the supply of legitimate digital content. Their main finding is that the removal of content is causally associated with a more than 10% increase in BitTorrent activity for NBC's content but no change in NBC's DVD sales (imputed from sales rank) at Amazon.com. Our analysis is similar in style but the specific arguments are different because, for instance, their hypothesis is that users who are no longer able to purchase content through a paid channel (i.e., iTunes) would be more inclined to make a

[5]Oberholzer-Gee and Strumpf used the number of German secondary school students on vacation as an instrument, and Blackburn used the timing of the RIAA lawsuits against consumers as an instrument. Their conclusions, however, differ. That is, Oberholzer-Gee and Strumpf argue that downloading has had little effect on sales while Blackburn concludes that file sharing has had negative impacts on sales.

legal purchase, while ours is that users who can no longer view content free on YouTube would be inclined to do so.[6]

Unlike Danaher et al. (2010), however, we do not have a direct measure of piracy, but we use a novel measure that captures the user's interests in artists, providing a test of promotional effects from free content. Chiou and Tucker (2011) exploit the removal of all news articles by the Associated Press from Google News and find that users were less likely to investigate additional content in depth after the removal, relative to those who had used Yahoo! News, which continued to provide Associated Press content. Similarly, our hypothesis is based on changes in Internet user's behavior after seeing (or not seeing) online content, but the difference is that we focus on the intensity of search activity itself rather than user's web-browsing behavior (i.e., clickstreams data). We explain below how we measure search intensity by using Google Trends.

3 Event Description

YouTube was launched in November 2005 as a video-sharing website. The site grew rapidly, and a Reuters report on 16 July 2006 declared that YouTube is the leader in Internet video search with 29% of the U.S. multimedia entertainment market (according to Hitwise) and 20 million unique users per month (according to Nielsen NetRatings). According to data published by market research company comScore in 2010, YouTube's market share of online video content was 43.1% followed by Hulu (3.5%). Further, 84.8% of the total U.S. Internet audience viewed online video, where 144.1 million viewers watched 14.6 billion videos on YouTube (101.2 videos per viewer).[7] At least since 2010, the web information company Alexa ranks YouTube as the third most visited website on the Internet, behind Google and Facebook.

[6] Another difference is that we focus on the impact of content removal on relatively newly released albums while Danaher et al. (2010) had to remove all recent television episodes because NBC did not sell then-current season content on iTunes prior to the removal.

[7] The May 2010 comScore report is still a widely cited industry source. See http://www.comscore.com/Insights/Press_Releases/2010/6/comScore_Releases_May_2010_U.S._Online_Video_Rankings.

YouTube started as a platform to upload, view and share home-made, user-generated videos; however, soon the site contained many unauthorized clips of copyrighted content registered users could upload in an unlimited number and unregistered users can watch free. YouTube was basically used as an on-demand radio, where almost every song a user wanted to hear could be found. Because YouTube does not review videos before they are posted online, it was left to copyright owners to issue a takedown notice pursuant to the Digital Millennium Copyright Act.[8] However, in June 2007, Google, having acquired YouTube in November 2006, started resolving copyright infringement claims that characterized YouTube's early days both through licensing deals with major content providers and a content-management system, called Content ID.[9]

YouTube entered into a revenue-sharing partnership with the major content providers as early as 2006, and all the major labels had licensing agreements with YouTube in 2007. However, major labels were disappointed with those agreements having included a small fee for every video watched and a share of the advertising revenue, so they tried to renegotiate the terms. In late December 2008, when it was time for licensing renewal, multiple press releases confirmed that Warner and YouTube failed to agree to terms on a new licensing deal, and Warner began to remove its music videos (both professionally made music videos and amateur material that may include Warner content) from YouTube.[10] The Electronic Frontier Foundation says that thousands of Warner videos disappeared as YouTube muted the audio or pulled the video.

The removal of Warner content came at a time when the other three majors (i.e., Universal Music, Sony BMG, and EMI) were also renegotiating their licensing deals with YouTube, which was set to expire soon. Interestingly, however, YouTube and the remaining three

[8]In 2007, the media conglomerate Viacom filed a billion-dollar copyright-infringement suit against YouTube claiming that almost 160,000 unauthorized clips of Viacom's programming were made available on YouTube.

[9]When a video is uploaded, Content ID checks it against reference libraries of copyrighted audio and video material and alerts copyright owners whenever any part of their content went up on YouTube. Owners can then choose to remove the content or sell ads and share the revenue with YouTube.

[10]References for this fact include more than several online articles, too many to list here. However, they are available upon request.

major labels reached a renewal agreement with no reported case of content removal. On 29 September 2009, YouTube and Warner announced that they finally reached an agreement and Warner's artists (both the full catalog and user-generated content containing Warner acts) were returning to YouTube. This created a nine-month blackout period during which it was extremely unlikely to find Warner content on YouTube, providing a natural experiment as YouTube had licensing deals with all the majors (including Warner) for almost two years before and after the blackout.[11]

The licensing contracts between YouTube and record labels are not public information. Nonetheless, we believe the breakdown of renegotiation between YouTube and Warner is not likely to be an endogenous outcome for the following reason. A person familiar with the situation told a reporter that YouTube and Warner were close to an agreement until the last moment, when Warner changed its terms. In response, Google made the move to remove the label's content.[12] All licensing deals with the majors were set to expire within a narrow time window, and Warner was obviously the first to find the negotiation outcome. One interpretation is that Google might have been tough on the first negotiation, so that the other majors did not behave opportunistically. It seems plausible that the breakdown of negotiation with Warner, but not others, was a random event.

4 Data

The data sample in this paper comes from Nielsen Soundscan and is based on the 200, the US industry standard for album sales. The Billboard 200 is a ranking of the 200 highest-selling music albums from any genre. The chart is based solely on sales (both retail and digital) of albums in the United States. Technically, this sample is a restricted sample of

[11]This stands in contrast to the 2007 Viacom case, where there was no prior agreement; that is, users who posted Viacom's programming did so without authorization. In the Warner case, users posted Warner Music's songs for two years before suddenly their videos were taken down by the breakdown of renegotiation.

[12]This is consistent with the fact that Google did not say it is taking the music down at Warner's request. See http://allthingsd.com/20081220/warner-music-group-disappearing-from-youtube-both-sides-take-credit/.

albums; therefore, there is no guarantee that the findings in this paper generalize to those not making it into this chart. However, we believe the main issue here is to get sufficient and accurate variation in sales. That is, the Billboard chart omits any sales information making it impossible to determine, for instance, if the number one album this week sold as many as the number one from another week.

We thus obtained access to the weekly sales data for Billboard 200 albums from Nielsen SoundScan.[13] Looking at the sales, there is considerable variation within and across weeks. For instance, the 200th album tends to average only about .1% of the top 200 sales, so any albums below this are making up a very small percentage of the market. Importantly, top sales seem to vary considerably across weeks. In fact, we note here that our results changed qualitatively using the actual sales data compared to when we used only rank data. Thus, even though our sample is limited to albums in the Billboard 200, in this way we can take care of measurement issues. It would be impossible to get a complete listing of album sales without tremendous resources.

There are in total 2261 albums from 1663 artists in Table 1. This implies that there are a number of artists producing multiple albums on Billboard 200. We drop about 10-20 entries from every week because these are typically non-music albums and albums that are compilations (i.e., no artist fixed effects available). For each album, we construct the following variables: *twsales* is this week's sales, that is, the number of albums sold in a given week; *wkson* is the cumulative number of weeks on the chart, which increases by 1; and *wksonsq* is the square of *wkson*. Because demands for a new album often builds up before the premiere week, we include a variable, *firstweek*, that indicates the first week of each album in our sample.

The data includes both new and catalog albums, so we create an indicator for new albums: *firstalbum* is 1 if it is the first album of an artist found in our SoundScan database. Because the database contains only top 200 albums from year 2004, this variable indicates that an

[13]SoundScan is the official basis for the Billboard charts. Their sales data is collected from cash registers from some 14,000 retail outlets. We directly obtained access from Nielsen under a licensing agreement.

album is the first hit at least since 2004.[14] Because the level of previous album sales has been found to be correlated with second album sales (Hendricks and Sorensen, 2009), we include two additional variables: *previousalbumduration* and *previousalbumsales* are the length on the Billboard chart and total sales for the last album an artist placed on the Top 200. These are equal to 0 if they had no album on the charts in the database.

Our next step is to match with album genre and label information, which comes from the Discogs.com database, which is exceptionally extensive (see Waldfogel, 2012). We manually coded all major/indie labels: majors being either directly one of the majors, or a subsidiary of one of the majors. This involved following the path for each sublabel. If the label was under a major, the indicator for that label was coded 1. This also involved for some labels finding their website or an article about them. If we could find no connections anywhere, we labeled them as Indy. If Discogs.com labeled them as self-release or if the only releases under the label were of the artist, then we labeled it self-release. There are also 14 standard base genres.

The final step is to merge with radio chart ranking. Our source of data on radio airplay is the weekly USA Airplay Top 200 ("The most played tracks on USA radio stations").[15] Billboard also has a chart listing 75 most aired songs of the week in the US, but we preferred USA Airplay Top 200 because of its broader coverage. Notice that the radio chart is for songs, while the sales data is in albums. Further, in many instances a song will be played extensively before the album is released. Therefore, when matching each song to the album-week in our data, we matched for the weeks where an album was on the chart, but we took into account the fact that an album can appear on the radio chart several weeks before the album chart.

We do not have data on airtime minutes, but we believe using the rank for airtime may be less of a concern as control variables because the total number of slots for songs in

[14]We cross checked this indicator with the Billboard chart database (which goes back to 1998) and found very little change. That is, *firstalbum* indicates a first hit since 1998 for the vast majority of our sample.

[15]We scraped the radio chart from http://www.charly1300.com/usaairplay.htm.

radio stations would be relatively fixed over time. Specifically, we construct the following variables: *lastweekradiorank* is the last week's chart ranking for matched songs for all album-weeks. Next, *wocradio* is the number of weeks on the chart (and 0 if not on the chart); and *weeksinceradio* is the number of weeks since an album had a song on the radio chart for the last time (and 0 if active on the chart). These two variables capture the chart duration, but allow for differential effects. Finally, *noradio* is an indicator for albums that have never had a song on the radio chart.

We now describe how we constructed an index of search intensity (*twtrends*). Given the wide viewership of YouTube content, we wanted to measure and compare the level of interests in each artist among Internet users. Google Trends analyzes a percentage of Google web searches to determine how many searches have been done for the terms entered compared to the total number of Google searches done for a certain region within a category for a specified time period.[16] We decided to search for artists rather than albums because artist names are much likelier to give consistent results over time, and we also believe users are more likely to remember, and hence search on Google for artist names rather than album titles.

Specifically, we searched for each artist on Google Trends while restricting the search results to US in the 'Music & Audio' category from January 2008 to September 2010 (one year before and after the blackout). We chose the US region rather than, say, worldwide because while Google has been the dominant search engine in the US (with a consistent market share around 80%) its market shares in other countries are reportedly much lower. We also restricted our Trends search results to the Music & Audio category for more precise measurement because, for instance, some artists have generic names. Google explains that filtering Trends data by category means that Trends data is based on users who searched for the term in a related context.[17]

[16] Google Trends is increasingly used in academic research. For instance, medical researchers show that Google Trends data can predict changes in patient volume for individual hospitals. See http://healthland.time.com/2012/01/11/google-helps-emergency-room-docs-to-predict-flu-trends/.

[17] "For example, if you're searching for the term java in the Food & Drink category, you

For each search, Google Trends returns a weekly index for the search term, normalized by the highest search week, so that the peak in a series has a value of 100 (search terms with low volume would not appear). The major problem is that Google Trends allows only up to five terms to be searchable, hence comparable, at a time. To construct a globally consistent panel for our sample of artists, we made pairwise comparisons between a benchmark artist and all other artists for a given week. This would give a consistent cross-section of all artists in that week. The next step is to search artists, one by one, and download the normalized weekly search index for each term. This gives the weekly time-series for each artist in the sample.

We then scaled each individual artist's normalized index in the reference week, so that the index is equal to the above-mentioned cross-sectional value. Finally, this artist-specific scale factor is multiplied to each week's normalized index for that artist. This way we could obtain a globally consistent panel of search indices for each artist in our sample. To be more precise, because the search intensity varied a great deal across the artists, we in fact employed three benchmark artists (representing low, medium, and high search volume) to compare all the other artists in our sample against one of them. We then compared the three benchmark artists themselves for the same reference week, which added another layer of scale adjustment.

5 Estimation Results

We examine how the (un)availability of YouTube content affected album sales and Internet search. As Liebowitz (2005) explains, theoretically the so-called 'sampling' hypothesis can go in either direction with respect to sales. For instance, after listening to a song online consumers may like the music more or less than they did before. Thus, using sales as an outcome variable to identify the sampling effect may not be valid. To provide a less

won't see any information about searches done for java the computer programming language." See https://support.google.com/trends/answer/4359597?hl=en&ref_topic=4365600.

ambiguous test, we focus on changes in search volume. That is, we hypothesize that for sampling effects to be relevant, YouTube content must initially stimulate the user's interest, and this can manifest itself in the form of increased search activity in a context classified by Google as Music & Audio.

Existing empirical studies mostly focused on sales displacement effect. Theories often take into account the quality difference between a copy and the original; however, this concern becomes largely irrelevant in the content of digital copies. Although the bulk of these studies indicate positive sales displacement effect, one issue in the literature is that direct measures of illegal file-sharing activities are hard to come by, and proxies for file-sharing such as Internet penetration have the potentially confounding effect of being correlated with both the demand for legal services like YouTube and illegal downloading. By focusing on YouTube, we provide a direct test of whether sales displacement effect extends to legal channels.

To test these hypotheses, we model the effects of the policy change as follows:

$$Y_{it} = \beta_0 + \beta_1 \mathit{Warnereffect}_{jt} + \boldsymbol{X}_{jt}\boldsymbol{\beta}_2 + \beta_3 \mathit{Label}_j + \beta_4 \mathit{Genre}_j + \mathit{Week}_t + \mathit{Artist}_i + \epsilon_{ijt}$$

where Y_{it} is *twsales* in sales regressions, and *twtrends* in search regressions. Notice that we stacked the observations into an artist-week format for merging the data and analysis.[18]

Warnereffect is 1 for albums released by Warner Music (and its subsidiary) during the blackout, which runs from the first week in January 2009 to the last week in September 2009. $\boldsymbol{X}_{jt}$ is the set of album-level characteristics (including the radio chart-related characteristics matched to albums) described in the previous section. These can vary over time or within an artist if the artist has more than one album in our SoundScan database. Label and genre indicators are album-specific and can also vary from album to album within an artist. To account for the heterogeneity of artists with respect to album sales and Internet search, we included artist fixed effects; to capture nonlinear trends over time, we also included week

[18]There are a few simultaneous albums by the same artist in a week, in which case we simply added up the respective sales. The reason is that we cannot separately identify the effects on different albums in a week. In all such cases, label information did not change.

fixed effects.

If all artists in our sample had only one album on the Billboard 200 chart, no point estimates on the album-specific constant variables can be estimated in the artist fixed effects model, because artist fixed effects are perfectly collinear with those variables. In our case, these point estimates are identified by 598 artists (out of 2261 in our sample) having multiple albums in our database. We believe that the album-specific characteristics associated with multi-album artists provide a useful variation for our model. Below, we report our results using a full set of covariates. We also used a number of other specifications, and found that quantitative estimates are robust and significance often becomes stronger in simpler specifications.

Regression results from the fixed effects model of how the content removal affected album sales are presented in Table 2 through Table 5. The four columns' specifications only differ by the time period before and after the nine-month blackout. That is, column (1) limits the period to one year before and after the blackout; column (2) to nine month before and after; column (3) to six month before and after; and column (4) to three month before and after. On the other hand, the tables differ by the size of the sample. That is, Table 2 uses the full sample; Table 3 drops the top 10 albums, Table 4 drops the top 25 albums, and Table 5 drops the top 50 albums from the Billboard ranking. Standard errors are clustered by artists in all specifications.[19]

Table 2 shows that the Warner artists who had Billboard top 200 albums during the nine-month blackout sold on average larger quantities of albums, as opposed to the non-Warner artists during the same period. Looking across the four columns, the increase in sales (in unit) ranges from 5,718 per week using one-year (pre and post) window to nearly 10,000 per week using a three-month window. The estimates represent causal effects and thus render support for the sales displacement hypothesis. The pattern in which these point estimates

[19]We also bootstrapped standard errors following Bertrand et al. (2004), but it did not change any qualitative results. Specifically, the point estimates on *Warnereffect* often became more significant at 1 percent in sales regressions and no change at all in search regressions.

increase as we narrow the pre and post time periods shows that the results are stable and also consistent with the expectation that the policy effect would be stronger in a narrower time period.

The point estimates on the first week indicator show that sales are particularly high in the premiere week. The negative coefficients on the first album indicator suggest that new albums (either an artist's debut album or a new album in at least four year's time) tend to sell relatively small quantities even among those hitting the Billboard chart. This finding is consistent with the Hendricks and Sorensen (2009)'s finding that consumers are less likely to be aware of new artists even with moderate levels of sales. On the other hand, we do not find any positive significant effects from either the sales or the chart duration of an artist's previous album. This result may be interpreted as that there is little forward spillover effect in our sample.

We also find that the number of weeks on the radio chart is positively associated with album sales while the number of weeks on the Billboard chart is negatively correlated with sales. The latter may capture the fact that sales tend to naturally decrease over time while the former may indicate some positive effects of radio play especially since we count radio weeks before an album may appear on the Billboard chart. However, we caution that these are correlative effects, and we cannot provide a test of causal effects of radio play. Both the latest radio rank and the number of weeks since the last appearance on the radio chart are negatively associated with sales.[20] Albums with no radio rank tend to have lower sales all else equal.

Table 3 to Table 5 report the estimation results of the same specifications, dropping some outliers in terms of chart ranking. We do this because the distribution of album sales is highly skewed toward superstars' sales, and including interaction effects between the blackout and Billboard rank creates some endogeneity problems. The point estimates on *Warnereffect*

[20] This makes sense as the rank increases in absolute terms it is declining in terms of ranking. That is, this means that albums with higher ranked song(s) on the radio chart, conditional on having songs on the radio, are correlated with higher sales.

exhibit a marked decrease in the estimated causal effect of the content removal on album sales, relative to the full sample estimates. Specifically, dropping the top 10, the point estimates range from 2500 to 3700 albums per week; dropping 25, they range from 1400 to 2000 albums per week; and dropping 50, they are just a few hundreds with statistical insignificance.

This is perhaps not an unexpected result, but assessing quantitative relevance of this attenuation pattern is of interest. That is, our results suggest not only that the sales displacement effect can be very large on average but it also diminishes relatively quickly as one goes down the chart ranking. The rest of the coefficient estimates follow similar patterns. For instance, the coefficient on the first week decreases and eventually becomes negative in Table 5. This is because as we drop the top 50, the remaining albums premiering in the bottom 150 debut lower than the superstars. New albums continue to do better than those that are not, but the magnitude of the association keeps decreasing. Interestingly, in Tables 3 and 4, sales are negatively associated with the previous album's chart duration while in Table 5, they are positively correlated with previous album sales.[21]

Table 6 to Table 9 present the estimation results using the search intensity for artist names as the dependent variable, using the same specifications and independent variables as in Table 2 to Table 5. The point estimates on *Warnereffect* in Tables 6 to 9's regressions show that the blackout had no statistically significant effect on the level of Internet user's search activity although in all cases the estimates have a negative sign. Therefore, the hypothesis that a greater exposure to free online content increases the user's level of interests finds no support in our data. That is, whether or not the sampling effect leads to more or less album sales than without it, our results suggest that more exposure does not lead to additional search activities.

There are other notable differences. For instance, first albums are positively associated with search activity, where this relationship is statistically significant in Tables 8 and 9

[21]Tables 3 and 4 contain the superstars, so they cannot increase too much in all likelihood. On the other hand, lower ranks were likely lower ranks before, so they are more likely to increase in Table 5.

(whereas this variable was negatively associated with sales). On the other hand, the first week of the chart appearance is positively associated with search, but this is only significant using the full sample (in Table 6). Previous album sales are negatively associated with search activity, where the point estimates are often statistically significant. This indicates that Internet users search more for the artist when a debut album (or a new album in a few years) is ranked below say top 25, but they search less than they would have if an artist previously had a hit album.

6 Conclusion

Digital licensing revenue is growing in importance as a source of remuneration for artists. Free (or ad-sponsored) online content services such as YouTube have become a convenient source for experiencing music. While these services typically combine video and audio content, they serve as a prime music-listening portal with no software or subscription being required. While a great deal has been said about the potential role of these service in promoting and discovering new artists and music, our results cast some doubt on this widely believed notion, at least with regards to top selling albums, and our sales displacement results support laws that create digital performance rights for sound recordings.

We showed that the removal of content from YouTube had a causal impact on album sales by upwards of on average 10,000 units per week for top albums. If we take as an example 4,000 to be the average effect, then a rough back-of-the-envelope calculation results in 4,000 $\times$ \$12 (the average CD price) $\times$ 20 (the average *wkson*) $\approx$ \$1 million of lost sales for a top album. If we assume additionally that Warner had say 40 albums on Billboard 200 for a year, then the total lost sales become \$40 million per year. Although Google does not publish licensing agreements with music labels, this amounts to 1.6% of the Warner's revenues for the fiscal year of 2010.[22]

[22] According to 10-K, Warner Music Group's Recorded Music business generated revenues of \$2.455 billion during the fiscal year ended on September 30, 2010.

A priori there was little reason to expect that we would find total sales displacement in this range. Our findings suggest that sales displacement effect can be real without a promotional effect. That is, the people listening on YouTube appear to be, to some extent people who would know about this album anyway, but may not buy it because of Youtube. These results are largely driven by the top 50 or so highest-selling albums. Not only did we not find evidence for promotional effect in terms of sales, we were unable to detect a statistically significant effect on the level of user's interests in terms of Internet search activities, as measured by Google Trends.

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Table 1: Summary Statistics - Weekly Observations

Variable	Mean	Std. dev.
twsales	14016.101	30669.392
twtrends	948.447	2161.267
wkson	20.85	29.166
firstweek	0.12	0.325
firstalbum	0.244	0.429
previousalbumduration	17.39	28.424
previousalbumsales	564.427	1176.165
wocradio	5.183	8.436
lastweekradiorank	27.135	48.595
weeksinceradio	0.84	5.153
noradio	0.596	0.491
EMI	0.097	0.296
Sony	0.168	0.374
SonyBMG	0.081	0.273
Universal	0.247	0.431
Warner	0.145	0.352
Indy	0.245	0.43
Self-release	0.017	0.129
Blues	0.028	0.164
Children's	0.006	0.076
Christian	0.032	0.176
Classical	0.004	0.064
Electronic	0.09	0.287
Folk	0.165	0.371
Funk	0.093	0.29
Hip Hop	0.111	0.314
Holiday	0.015	0.121
Jazz	0.018	0.133
Latin	0.019	0.136
Pop	0.083	0.276
Reggae	0.002	0.04
Rock	0.334	0.472
N	20950	

The date range for this table is from January of 2008 to September 2010.

Table 2: Sales Regressions - Full Model

	(1) One year	(2) Nine months	(3) Six months	(4) Three months
Warnereffect	5718.5*	7864.3**	7375.6*	9829.2**
	(2965.5)	(3385.6)	(3776.8)	(4159.7)
wkson	-534.2***	-554.2***	-554.9***	-641.3***
	(72.93)	(75.05)	(70.21)	(91.58)
wksonsq	1.928***	1.947***	1.914***	2.316***
	(0.458)	(0.448)	(0.381)	(0.446)
firstweek	26869.8***	28465.7***	27553.5***	26767.7***
	(1737.6)	(1990.0)	(2023.1)	(2215.9)
firstalbum	-4535.5	-9233.1**	-10723.5**	-10918.6*
	(2901.4)	(3924.7)	(4749.8)	(5679.7)
previousalbumduration	35.75	29.01	37.07	-101.2
	(65.27)	(79.01)	(98.01)	(71.41)
previousalbumsales	-1.367	-1.513	-1.961	-0.191
	(1.185)	(1.422)	(1.878)	(2.487)
wocradio	163.5***	115.1*	56.37	21.13
	(62.98)	(61.43)	(69.72)	(74.51)
lastweekradiorank	-22.89	-23.64	-28.62**	-22.45
	(16.30)	(15.27)	(12.43)	(15.01)
weeksinceradio	-412.5***	-604.6***	-866.5***	-1030.4***
	(63.44)	(98.63)	(140.0)	(165.4)
noradio	-3969.6*	-4981.2**	-5301.7**	-7597.1**
	(2033.5)	(2323.6)	(2485.9)	(3366.5)
N	20950	17314	13398	9533

Standard errors in parentheses; genre, label, and week coefficients not shown for brevity.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3: Sales Regressions -Drop Top 10

	(1) One year	(2) Nine months	(3) Six months	(4) Three months
Warnereffect	2458.0**	2990.2**	3155.6**	3678.3**
	(1040.5)	(1197.0)	(1366.5)	(1738.0)
wkson	-166.7***	-179.0***	-198.4***	-247.4***
	(18.54)	(19.93)	(22.98)	(32.77)
wksonsq	0.540***	0.558***	0.632***	0.895***
	(0.114)	(0.111)	(0.116)	(0.169)
firstweek	3722.7***	4197.3***	4267.3***	4181.3***
	(412.5)	(473.9)	(562.2)	(709.7)
firstalbum	-958.9	-1514.9	-2427.8*	-4513.7**
	(901.6)	(1006.6)	(1310.2)	(1966.3)
previousalbumduration	-25.76*	-31.79**	-44.82***	-61.30**
	(15.03)	(14.66)	(16.90)	(25.43)
previousalbumsales	-0.0217	0.0735	0.374	0.749
	(0.285)	(0.321)	(0.432)	(0.780)
wocradio	120.0***	114.7***	122.3***	129.5***
	(23.77)	(26.09)	(29.73)	(35.50)
lastweekradiorank	-1.306	-3.280	-5.977	-7.441
	(3.536)	(3.602)	(3.990)	(5.021)
weeksinceradio	-154.4***	-235.3***	-333.7***	-496.6***
	(31.68)	(46.49)	(73.82)	(98.82)
noradio	-523.9	-1113.9	-1886.9**	-3108.6**
	(721.6)	(826.7)	(938.6)	(1415.3)
N	19809	16373	12671	9011

Standard errors in parentheses; genre, label, and week coefficients not shown for brevity.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4: Sales Regressions -Drop Top 25

	(1) One year	(2) Nine months	(3) Six months	(4) Three months
Warnereffect	1418.8**	1871.0**	1968.6**	1869.6*
	(713.6)	(760.6)	(828.5)	(1057.1)
wkson	-78.72***	-87.31***	-99.75***	-134.8***
	(10.04)	(10.69)	(13.02)	(18.79)
wksonsq	0.220***	0.226***	0.270***	0.444***
	(0.0539)	(0.0503)	(0.0577)	(0.0930)
firstweek	810.4***	908.8***	645.4**	329.5
	(231.5)	(267.9)	(309.5)	(394.6)
firstalbum	-1044.6*	-1524.3**	-2046.0***	-3247.9***
	(538.2)	(637.2)	(788.6)	(1118.2)
previousalbumduration	-23.75***	-22.71***	-24.35***	-28.53***
	(7.441)	(6.661)	(8.282)	(10.95)
previousalbumsales	0.164	0.237*	0.326*	0.520
	(0.132)	(0.127)	(0.173)	(0.331)
wocradio	79.65***	79.73***	93.30***	98.30***
	(15.06)	(16.86)	(19.22)	(22.18)
lastweekradiorank	-1.400	-3.147	-5.120**	-6.928**
	(1.928)	(1.943)	(2.270)	(2.910)
weeksinceradio	-94.21***	-158.2***	-225.9***	-356.4***
	(28.89)	(37.29)	(48.81)	(79.34)
noradio	291.3	-42.86	-451.8	-826.5
	(408.8)	(458.9)	(537.0)	(784.0)
N	18165	15006	11603	8243

Standard errors in parentheses; genre, label, and week coefficients not shown for brevity.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5: Sales Regressions -Drop Top 50

	(1) One year	(2) Nine months	(3) Six months	(4) Three months
Warnereffect	218.2	491.9	555.1	347.4
	(448.5)	(481.7)	(491.7)	(615.6)
wkson	-29.52***	-38.30***	-48.40***	-71.75***
	(5.275)	(5.850)	(7.259)	(9.083)
wksonsq	0.0710***	0.0873***	0.125***	0.248***
	(0.0204)	(0.0224)	(0.0273)	(0.0362)
firstweek	-329.5**	-362.1**	-560.6***	-851.0***
	(129.2)	(148.8)	(172.2)	(215.7)
firstalbum	-503.7*	-633.4*	-637.2	-1142.9*
	(276.9)	(364.8)	(454.6)	(684.6)
previousalbumduration	-8.585*	-4.704	-3.973	-5.019
	(5.002)	(5.265)	(6.521)	(7.230)
previousalbumsales	0.204***	0.194**	0.259*	0.548***
	(0.0761)	(0.0937)	(0.143)	(0.158)
wocradio	30.44***	28.91***	33.44***	40.58***
	(8.587)	(9.909)	(11.78)	(13.39)
lastweekradiorank	-0.601	-1.452	-1.844	-3.477**
	(1.322)	(1.331)	(1.482)	(1.660)
weeksinceradio	-53.83***	-92.89***	-117.7***	-179.3***
	(15.58)	(20.26)	(23.13)	(37.60)
noradio	-169.0	-396.5	-656.7**	-955.7**
	(244.1)	(270.5)	(318.1)	(458.7)
N	15360	12693	9800	6967

Standard errors in parentheses; genre, label, and week coefficients not shown for brevity.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 6: Trends Regressions - Full Model

	(1) One year	(2) Nine months	(3) Six months	(4) Three months
Warnereffect	-81.43	-52.87	-70.26	-39.28
	(155.9)	(152.2)	(153.0)	(134.6)
wkson	-3.447	-2.686	-2.137	-0.899
	(3.317)	(3.732)	(4.179)	(4.716)
wksonsq	0.00412	-0.00195	-0.00234	-0.00239
	(0.0142)	(0.0153)	(0.0158)	(0.0182)
firstweek	108.6***	132.4***	104.6**	105.0*
	(38.53)	(41.46)	(51.92)	(56.92)
firstalbum	-86.69	-93.68	-61.65	83.66
	(175.6)	(200.3)	(189.3)	(176.9)
previousalbumduration	2.415	2.835	3.157	6.845**
	(2.090)	(2.462)	(2.560)	(3.475)
previousalbumsales	-0.111**	-0.122*	-0.151*	-0.252*
	(0.0558)	(0.0656)	(0.0774)	(0.138)
wocradio	7.858*	6.672*	7.304*	5.228
	(4.039)	(3.829)	(4.026)	(4.082)
lastweekradiorank	-0.788**	-0.974**	-1.121**	-1.209**
	(0.357)	(0.445)	(0.462)	(0.538)
weeksinceradio	-23.15**	-34.03***	-33.88***	-35.81***
	(10.44)	(13.01)	(11.08)	(9.514)
noradio	44.64	23.78	27.06	-54.35
	(141.6)	(160.8)	(168.6)	(190.3)
N	20950	17314	13398	9533

Standard errors in parentheses; genre, label, and week coefficients not shown for brevity.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 7: Trends Regressions -Drop Top 10

	(1) One year	(2) Nine months	(3) Six months	(4) Three months
Warnereffect	-64.70	-45.34	-42.24	-54.71
	(84.15)	(87.84)	(90.80)	(84.32)
wkson	-0.506	-0.551	-1.605	-0.772
	(2.166)	(2.291)	(2.338)	(3.021)
wksonsq	-0.00293	-0.00567	-0.00259	-0.00417
	(0.00849)	(0.00920)	(0.00975)	(0.0130)
firstweek	16.96	20.95	-2.291	-8.568
	(25.47)	(28.12)	(33.88)	(40.00)
firstalbum	10.39	25.61	36.16	235.7
	(108.2)	(136.0)	(167.4)	(170.6)
previousalbumduration	-0.117	-0.165	0.0168	3.870**
	(1.102)	(1.395)	(1.436)	(1.775)
previousalbumsales	-0.0515*	-0.0540	-0.0759**	-0.178**
	(0.0293)	(0.0339)	(0.0323)	(0.0753)
wocradio	5.278**	5.076*	5.890*	6.102*
	(2.546)	(2.713)	(3.181)	(3.706)
lastweekradiorank	-0.376	-0.569	-0.586*	-0.772*
	(0.272)	(0.353)	(0.336)	(0.400)
weeksinceradio	-11.66***	-19.42***	-20.65***	-25.98***
	(3.916)	(5.271)	(5.639)	(5.377)
noradio	-20.23	-49.61	-54.12	-135.4
	(67.47)	(85.68)	(93.53)	(137.5)
N	18176	15006	11603	8243

Standard errors in parentheses; genre, label, and week coefficients not shown for brevity.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 8: Trends Regressions -Drop Top 25

	(1) One year	(2) Nine months	(3) Six months	(4) Three months
Warnereffect	-60.55	-40.65	-36.49	-57.75
	(78.97)	(83.11)	(83.80)	(80.09)
wkson	-0.150	-0.353	-1.717	-0.630
	(1.383)	(1.518)	(1.895)	(2.612)
wksonsq	-0.00371	-0.00572	-0.00239	-0.00475
	(0.00603)	(0.00652)	(0.00786)	(0.0114)
firstweek	25.84	27.81	-1.054	0.987
	(25.16)	(28.07)	(33.72)	(41.39)
firstalbum	164.2**	196.8*	248.0**	329.5*
	(72.32)	(104.4)	(124.7)	(187.9)
previousalbumduration	0.138	0.628	1.548	3.350**
	(0.867)	(1.171)	(1.057)	(1.416)
previousalbumsales	-0.0334	-0.0409	-0.0680**	-0.139**
	(0.0267)	(0.0362)	(0.0314)	(0.0616)
wocradio	1.957	2.516	3.361	3.880
	(1.717)	(1.777)	(2.294)	(3.198)
lastweekradiorank	-0.151	-0.299	-0.430*	-0.601**
	(0.219)	(0.241)	(0.244)	(0.303)
weeksinceradio	-9.013***	-16.70***	-20.17***	-28.03***
	(3.105)	(4.939)	(5.069)	(5.743)
noradio	-0.774	-21.57	-49.11	-126.4
	(69.80)	(84.53)	(98.14)	(136.5)
N	18176	15006	11603	8243

Standard errors in parentheses; genre, label, and week coefficients not shown for brevity.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 9: Trends Regressions -Drop Top 50

	(1) One year	(2) Nine months	(3) Six months	(4) Three months
Warnereffect	-51.12	-35.94	-37.88	-44.74
	(74.44)	(80.18)	(90.00)	(71.12)
wkson	-1.167	-1.879*	-3.249**	-1.979
	(1.027)	(1.044)	(1.506)	(1.680)
wksonsq	0.000331	-0.00103	0.00276	0.000833
	(0.00483)	(0.00470)	(0.00583)	(0.00875)
firstweek	21.59	20.76	-13.86	-19.22
	(26.05)	(26.70)	(30.18)	(29.51)
firstalbum	157.5**	196.3*	295.3**	282.5
	(70.50)	(100.1)	(146.2)	(185.5)
previousalbumduration	0.802	1.588	2.149*	2.788*
	(0.993)	(1.291)	(1.258)	(1.600)
previousalbumsales	-0.0486	-0.0681*	-0.0754**	-0.0960*
	(0.0299)	(0.0398)	(0.0325)	(0.0574)
wocradio	-0.385	-0.0690	0.313	-0.0262
	(1.479)	(1.281)	(1.199)	(1.657)
lastweekradiorank	-0.0888	-0.290	-0.344	-0.301
	(0.209)	(0.242)	(0.234)	(0.236)
weeksinceradio	-8.132**	-16.53***	-19.03***	-26.28***
	(3.606)	(6.304)	(6.700)	(7.899)
noradio	24.75	10.16	-7.729	-75.05
	(64.82)	(75.91)	(85.16)	(91.46)
N	15378	12692	9800	6967

Standard errors in parentheses; genre, label, and week coefficients not shown for brevity.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$