The Times They Are A-Changin:

Examining the Impact of Social Media on Music Album Sales and Piracy

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Abstract

The digital transformation of the music industry has changed the structure of the industry and consumers' consumption patterns. Social media have become an integral part of the strategic and tactical decisions of artists. The magnitude of their importance is depicted by the fact that most artist-fan interactions are channeled in these media. This study examines the effects of different social media measures, aggregated out of user-generated as well as artist generated content, on music album sales across both physical and digital channels. We collected data from various social media platforms including Twitter, Facebook, and Lastfm for all music albums released in June 2013 in the US. We found that the volume of user generated content positively impacts both sales channels, whereas the valence of the content (analyzed through sentiment analysis) and user engagement positively impact only the physical channel. In addition, we considered not only user generated content, but also artist generated content (i.e., artist broadcasting) and found its significant and positive influence on physical sales. Furthermore, we examined the impacts of these social media metrics on music piracy in terms of illegal downloads. Notably, for post-release, volume, valence, and user engagement *negatively* affect illegal download, suggesting consumers are more likely to purchase a music album instead of pirating when there is a large amount of social media buzz. Finally, we found that volume has a significant and positive influence on physical sales only for independent label releases but not for major labels, whereas for major label artists it is crucial to actively participate in social media as depicted in the significant and positive value for broadcasting. This is one of the first studies to empirically assess the influence of various social media metrics on the success of a music album (physical sales, digital sales, and piracy). Our study offers artists and their managers a rather holistic view of the effects of social media content on album performance, and helps them to identify an album's potential and to channel marketing budgets accordingly.

Keywords: electronic word of mouth, Facebook, Lastfm, music, social media, sentiment analysis, Twitter.

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1. Introduction

The music industry has been revolutionized by the emergence of social media. Artists can now communicate with their fans on a broader scale, promote their work, sell their albums, and keep their entire fan base up-to-date. As a result, a new class of artists has become popular and even exclusively operates within social media.[1] Music fans are not merely passive information recipients of traditional media (see radio, direct environment) but have gained access to a vast number of artists, which they can discover and actively assess (Dewan & Ramaprasad 2012; Salo et al. 2013). A closer look at the most popular social media, Facebook and Twitter, reveals that 50% and 60% (respectively) of the top-20 most liked or followed accounts globally belong to music artists (with an average of 60 million fans and 30 million followers).[2] Consumers (as fans) have online access to a large number of artists and directly interact with them bypassing all the traditional channels. These users produce content and spread their opinions across different social media channels and by making their preferences explicit to a large extent support (if not replace) traditional marketing activities. On weekly average the top 10 music artists have approximately 840.000 actively involved fans whereas they themselves do not update their page more than a few times per day.[3] Therefore, although artists attempt to cleverly promote their albums and get their fans engaged, their placement within social media largely depends on users' generated content.

Numerous studies have dealt with the predictive capability of social media across various contexts, such as stock market and movie industry (Bollen et al. 2011; Chintagunta et al. 2010; Dellarocas et al. 2007). Regarding the music industry, previous studies focused on the effect of volume of user-generated content within blogs mostly on physical music album performance (Dhar & Chang 2009; Dewan & Ramaprasad 2009). In this study, we included not only the *volume* of the user generated content, but also used sentiment analysis to examine the effect of *valence* on sales. In addition, we

[1] For example, Arctic Monkeys is one of the first bands that made full use of social media on their road to success (http://www.clashmusic.com/artists/arctic-monkeys).
[2] http://fanpagelist.com/
[3] http://www.insidefacebook.com/2012/01/10/people-talking-about-this-defined/

studied the effect of *engagement*, depicting interactions between fans and music artists, and artist generated content (artist *broadcasting*). We collected social media data from multiple sources including Twitter, Facebook, and Last.fm for all the albums in our sample. We investigated the effect of different social media measures on music album sales by looking at Twitter conversations about and from certain music artists, and artist popularity and fan engagement on Facebook, before and after the release date of a music album. We focused on the short period before and after the release of an album due to the short time span focus of Twitter. Further, we examined whether the social media measures can predict the performance of an album across various distribution channels, namely digital and physical album sales, as well as illegal downloads.

Our main results show that social media have a substantial predictive power on physical music album sales. User-generated volume, valence and engagement, and artist broadcasting have a positive impact on physical music album sales, whereas volume shows a significant and positive relationship with digital music album sales. Notably, for physical sales, we found a positive and significant influence of volume especially for independent label artists that have a higher need to create awareness of their existence than established major label artists. Interestingly, for post-release, volume, valence, and user engagement *negatively* affect illegal download, suggesting consumers are more likely to purchase a music album instead of pirating when there is a large amount of social media buzz. From a managerial perspective, our findings suggest ways for label management to evaluate the effect of social media on not only sales but also piracy. The measures we developed can help managers to assess the quality of artists with whom they want to potentially work with in the future.

In section 2 we present a review of literature and develop our hypotheses. Section 3 describes the data collection and Section 4 presents the main results and a set of additional analyses we conducted. We discuss our key findings in Section 5 and point out the major theoretical, managerial contributions, limitations, and future research.

2. Literature Review

2.1. Electronic Word of Mouth (eWOM) and Music Album Sales

The way users inform themselves about new products have dramatically changed. Traditionally, consumers used to get informed about products by consulting professional critics or personal acquaintances (Dhar & Chang 2009). Word of mouth (WOM) has major influence on consumer purchase decisions especially in the case of new products for which awareness needs to be created and product information must be distributed on the consumer side (Engel et al. 1969; Katz & Lazarsfeld 1955; Mahajan et al. 1984). Particularly in experience goods like music, WOM has been tagged as the most crucial element of long-term success and at a minimal cost (De Vany & Walls 1999; Tirunillai & Tellis 2012). Online channels now allow people to widely share their opinions and experiences on products through self-created content, in full geographical and temporal freedom (Jansen et al. 2009). Different studies have coped with the motivations behind user contributions and linked them to the wish to enhance influence and status as well as the intention to help other members of a community by offering meaningful input (Hennig-Thurau et al. 2004). Research has further shown the tremendous influence of user-generated content (UGC) on consumer decision-making. Findings provide evidence that consumers tend to prefer product reviews from peers to reviews from professionals (Dellarocas et al. 2007; Smith et al. 2005).

UGC ranges across all forms of word of mouth within various social media such as posts, comments or public disclosure of music consumption. The requirement is that these actions are publicly accessible and their creation demands some level of user effort (Tirunillai & Tellis 2012; Vickery & Wunsch-Vincent 2007). Most focus has been placed on assessing the effects of volume, valence, and dispersion of UGC on consumer decisions. Volume describes the amount of generated content whereas valence deals with the sentiment of this content (positive or negative). Dispersion is related to the variance across all generated content regarding a specific product/topic. Furthermore, some studies look at other measures of UGC such as duration and intensity (Godes & Mayzlin 2009; Eliashberg et al. 2000).

Numerous studies investigate the impact of eWOM on product sales in various contexts. Most focus has been placed on assessing the effects of volume, valence, and dispersion of UGC on consumer decisions. Volume describes the amount of generated content whereas valence deals with the sentiment of this content (positive or negative). Dispersion is related to the variance across all generated content regarding a specific product/topic. Findings in the movie industry seem to be contradictory where some studies find valence to be the most influential driver for movie success instead of volume when focusing on the sequential product rollout typical within the entertainment industry (Chintagunta et al. 2010). Also, the positive correlation between user and critic ratings is rather low encouraging the intention to investigate the impact of user-generated opinions instead of these of professionals (Dellarocas et al. 2007). The stock market has formed the base for several studies investigating the influence of different eWOM measures on stock performance. Especially, volume of chatter has been found to have a significant effect on abnormal returns and the volume of trading (Tirunillai & Tellis, 2012). Within the publishing industry book reviews are found to be in general more positive than negative (Chevalier & Mayzlin 2006).

Although predicting the success of music albums has long history (Lee 2003) the music industry came into focus of eWOM research relatively late (Appendix 1). Gathering sales data for music releases has been rather burdensome, since access to the industry benchmark for sales, Nielsen SoundScan, demands tremendous financial efforts, which has led to alternative measures calculated through sales ranks of retail websites (Dhar & Chang 2009). Within their work they control for popularity effects by including the amount of social media fans on the artists' Myspace profiles into their analysis. Chen et al. (2013) test the influence of artist-generated posts on Myspace on music album sales while controlling for traditional marketing measures. Personal artist posts have a strong influence on sales compared to automated messages. Other studies have addressed the long tail effect that explains the shift towards the popularity of niche products at the outer side of the demand curve (Dewan & Ramaprasad 2012). This phenomenon is mainly caused through the emergence of eCommerce and is especially present in the music industry. Findings suggest that blog posts have a stronger influence on the music sales in the long tail than within mainstream music whereas the influence on music sampling behavior is strong for both types of releases. Dewan and Ramaprasad (2013) investigate the relationship between blog buzz, radio play and music sales and find evidence for the bi-directional relationship of most variable pairs. While radio play positively influences song and album sales, blog buzz shows no significant relation to album sales but negatively influences song sales.

The bi-directional relationship between eWOM and music album sales has been addressed with a caution on the endogenous nature of eWOM (Dewan & Ramaprasad 2009). Reverse causality can be addressed by limiting the eWOM measures to occurring prior to release date. As the measures therefore occur temporarily before sales and user experience of the actual purchased product the reverse effect of sales on blog buzz is said to be negligible. This statement is disputatious as most retailers, including Amazon from which Dhar & Chang (2009) use the sales rank to estimate sales, allow customers to pre-order music albums. This prompts towards a more interdependent relationship in which sales also cause eWOM. A significant indication for the bi-directional relationship between blog buzz and music album sales is stronger for major releases compared to independent label releases.

2.2. Volume of eWom

Previous studies in the movie industry point towards a positive effect of the volume of eWOM on product sales (Duan et al. 2008; Yong 2006). The increase of awareness through high presence of a topic in media, positively affects sales. This relationship has been mostly addressed by looking at the volume of reviews about a product. Some recent studies limit this positive effect of eWOM volume claiming there is no significant relationship or sales do explain volume and not the other way round (Jungho & Byung-Do 2013; Roschk & Große 2013). These studies suggest that volume can only influence the success of niche items for which there is a higher need to create awareness and that effect is only present in the first week after the movie release.

An increase of consumer awareness is especially crucial for introductions of new products and associated with an increase in sales (Mahajan et al. 1984). In this study, we focus on posts on an external social media site about the artists instead of specific albums. This approach is comparable to content on brands and its influence on the sales of the respective products. We expect that a higher volume of eWOM about an artist increases the awareness about the artist and its upcoming or recently released music output. Further, we understand an increase in the volume of eWOM about an artist as an increase in the likelihood that users come across the artist, especially as social media feeds tend to change extremely fast because of the high frequency of new content generation. Within music industry, the use of volume of UGC within a microblogging platform differs than other media due to the fact that the effort to create a post is smaller[4]. Nevertheless, the volume of information rather increases, as microbloggers tend to update their sites with posts more frequently (Java et al. 2007). As a result, a higher volume signifies a higher buzz around the artist and therefore expected to be positively related to sales.

- H1: Higher eWOM volume about an artist leads to more physical (and digital) sales of a respective music album.

2.3. Valence of eWom

Regarding UGC, researchers should not underestimate the effect of negative chatter about an artist. Therefore, the focus is not only on how many posts are generated about a subject but also on the valence of these posts. Valence focuses on whether the generated content is perceived as positive or negative. Whereas volume has an informative effect creating product awareness, valence is rather focusing on the quality of a product and affects consumers' product perception and the attitude towards this product therefore creating a persuasive effect (Dellarocas et al. 2007; Liu 2006; Zufryden 1996). As a result, a more favorable attitude can lead to higher sales (Liu 2006). Positive attitudes foster product adoption of users that come across the content while negative attitudes prevent the adoption. This is in line with the fact that the extremity of the content increases its ability to be influential and that neutral messages are less memorable and perceived as less accurate. Some studies find valence to be even more influential on product sales than volume (Chintagunta et al. 2010).

By looking at the underlying tone of these messages researchers become able to test the direction of the contributor's opinion. Twitter offers the unique opportunity to collect a tremendous amount of these perceptions: "For eWOM, these microblogs offer immediate sentiment and provide insight in affective reactions toward products at critical junctions of the decision-making and purchasing process" (Jansen et al. 2009). As a result we expect a positive relationship between the valence of the UGC and the sales of a music album.

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[4] Twitter has a limitation of only 140 characters per post.

- H2: More positive eWOM sentiment about an artist leads to higher physical (digital) sales of a music album.

2.4. User Engagement

Engagement has previously been used to describe the dedication and positive attitude of an employee towards his employer (Macey & Schneider 2008). Customer Engagement Behavior (CEB) is a concept that includes "the total set of behavioral activities towards a firm" (Gummerus et al. 2012). Current research shows a shift from formerly proprietary brand communities to communities placed within other social media platforms (Gummerus et al. 2012). So far, studies have mainly focused on identification and engagement with brands and how the relationship towards brand communities impacts customer behavior (Algesheimer et al. 2005).

Theory states that engagement is an alignment between customer and firm goals (Van Doorn et al. 2010). Translating this into the case of music artists would mean that both artist and consumer have the goal to spread a positive image of the artist. In case both parties adhere to this goal the popularity and therefore also the record sales of the artist grow. Brands with increased equity are more likely to accommodate higher levels of engagement (Van Doorn et al. 2010). The dissemination of information through consumers influences the purchase decisions of other consumers. A high customer engagement can support brands to attract new and keep old customers (Wangenheim & Bayón 2007). Li et al. (2014) suggest that engagement in social media can be considered as a measure of an individual's cognitive response, personal or emotional connection, and/or actions.

The measure is different from the volume of user-generated content in two ways. First, the measure includes a far wider range of user interactivity than solely the creation of a post. Secondly, the user interaction covered by this measure is directly addressed to the artist. This is the case, as the interaction does not happen on the users profile but on the profile of the artist. While for UGC on a user's own profile there is a chance that the artist might come across this content, for engagement activity users accept that the artist and other users come across the content and its link to the contributor. We assume that fan engagement on social media positively impacts music album sales by supporting artists' goal to spread a positive image about them.

- H3: Higher eWOM engagement with an artist leads to higher physical (digital) sales of a music album.

2.5. Artist Broadcasting

Social media do not only allow monitoring the volume of eWOM about an artist but also the volume of content generated by the artist. This offers an additional perspective on volume as the artist can directly control the volume as well as the content of artist-generated posts themselves. Usually there is a separation of user- (e. g. on review sites) and artist-generated content (e. g. TV ads, radio broadcasting). Social media allows both sources to occur on the same platform pushing the control from advertisers to users. Social media has put artists in close contact with their fans and allow for more frequent and interactive communication (Kaplan, & Haenlein 2012). Although, artists can control the content that is distributed through their accounts there is still the danger that other users respond to their messages in a negative way. This risk cannot be fully diminished but only mitigated with adequate social media strategies. Kaplan & Haenlein (2010) advice that the utilization of social media in a corporate sense should be shaped by an active approach to ensure that a relationship between them and their followers can be build. Content needs to be kept fresh and engage followers in interaction. We consider the volume of artist-generated posts to be a good indicator for social media activeness.

Recent research looks into how artists can actually influence music sales with messages generated on their social media profiles (Chen et al. 2013). It has been shown that especially personal messages posted from artist social media accounts have a positive influence on music sales. As the artist is in control of the original messages that are spread through her profile we assume that the tone of the messages is favorable rendering an analysis of the sentiment behind artist broadcasting redundant. We tap into this field, termed artist broadcasting, when looking at the influence of the amount of artist-generated posts. Following similar research, we assume that more tweets generated by an artist increase the amount of physical and digital sales.

- H4: Higher artist broadcasting leads to more physical (digital) sales of a music album.

3. Methodology

3.1. Sample Selection and Data Collection

This research focuses on music albums released in the United States between the 11th and 25th of June 2013. To identify music album releases in this period, the "New Music Releases" section on Amazon.com is used. Under this section we find listings of music albums that are about to be released including their release date and a link to their specific product page. The final sample includes 65 music albums that belong to various music genres and include major as well as independent label releases and cover a rather complete spectrum of current music album releases. We gathered data from several sources. We used the Twitter search API as well as Topsy.com to track the volume and valence of eWOM. Moreover, we collected artist-generated tweets from Twitter to capture artist broadcasting. With the help of Facebook's graph API we got access to the platforms own "talking about this" (engagement) as well as the amount of "likes" to control for artist popularity. Last.fm allowed us to get access to the amount of listeners and plays at an artist level. We used these metrics to construct a control measure for consumption concentration. Finally, we crawl the Amazon sales ranks for both physical and digital music album releases in our sample on a daily basis.

3.2. Sentiment Analysis

The availability of methodological approaches in data mining (e.g. sentiment analysis) has facilitated the determination of "sentiments expressed within social media about particular topics" (Kennedy, 2012). Sentiment Analysis assesses text from a linguistic and textual perspective to often categorize messages into positive, negative, or neutral connotation categories. A measure for the sentiment of tweets about an artist is generated to capture the valence of UGC. We crawl up to 800 tweets mentioning an artist from the Twitter search API per day. These tweets are then categorized through the Sentiment140.com API. The classifier distinguishes between positive, neutral, and negative tweet messages using machine-learning algorithms through distant supervision (Go et al. 2009). As the classifier has been trained with tweet data from a different or not specific category we test the quality of the classifications received from Sentiment140 by putting 1000 tweets of each classification, positive, neutral, and negative, on the crowd-sourcing platform Crowdflower.com[5] to let the tweets be categorized manually. The subsamples used are drawn randomly from a total set of 608,254 tweets. To ensure an adequate representation we stratified the random tweets by genre category. Music genres have been obtained from iTunes Store (Business Wire, 2013). To reduce the dimensionality of genres we take the approach of Rentfrow & Gosling (2003) and aggregate the music genres in 4 main genre categories. For each sample we asked participants to categorize the tweets mentioning a certain artist into positive, neutral, or negative. The results of the surveys yield interesting insights in the quality of the sentiment analysis. Table 1 shows the percentages of tweets that were categorized into a different sentiment than the automated results. Especially interesting is the amount of false negatives: 14.7% of posts were true negatives within the subsample of 1000 tweets. We assume that this low accuracy stems from the fact that within the music scene a lot of irony and slang words are used and may mislead machine learning algorithms. To correct for this discrepancy, we updated the sentiment measures by taking the percentile adjustments obtained from the manual analysis. From these corrected measures we computed the share of each sentiment category within the subsample of maximum 800 tweets per day and artist and multiplied the share of each sentiment category with the absolute number of tweets per artist and day[6].

Table 1. Performance Evaluation of Sentiment Analysis

		negative	neutral	positive
Sentiment140	negative	0.147	0.547	0.306
	neutral	0.055	0.636	0.309
	positive	0.024	0.357	0.619

3.3. Variables

Sales. For the music albums in the sample we scrape the Amazon Sales Rank on a daily basis. There is a high correlation between the Amazon Sales Rank for both physical and digital versions of music sales with Billboard Chart listings when comparing them for Amazon top sellers (Chen et al. 2013). We assume that the sales ranks offer a good representation of the successfulness of an album in

[5] Crowdflower does not work with contributors directly but utilizes so-called "channel partners" through which tasks are distributed to contributors. A prominent example of these partners would be Amazon Mechanical Turk. The platform automatically tracks contributors' response velocity and answer distribution (CrowdFlower, 2013). Confidence measures are presented to indicate the consistency of answers given by the respondents.

[6] Source: Topsy.com

terms of sales. To obtain an absolute number for the sales, the sales rank is transformed based on the following formula[7] (Brynjolfsson et al. 2003; Dhar & Chang 2009; Goolsbee & Chevalier 2002).

$$\mathrm{Log}\,Sales_{it} = 10.526 - 1.61 * \mathrm{Log}\,SalesRank_{it}$$

Volume of eWoM. We measure eWOM volume with the daily aggregate (log-transformed) number of tweets generated about an artist (*Volume*).

Valence of eWoM. Based on the sentiment analysis, we focused on the messages that go into the positive or negative direction, not considering neutral messages that have rather an informative than persuasive character. We created a measure for the daily *Positiveness* of chatter per artist (Antweiler & Frank, 2004). Our measure is homogeneous of degree 0. As we also include a measure for eWOM volume in our models this is important and guarantees the independence of the two measures. Mathematically the measure is bound by +1 and -1 (*Postitiveness*).

$$Positiveness_{it} = \frac{PositiveVolume_{it} - NegativeVolume_{it}}{PositiveVolume_{it} + NegativeVolume_{it}}$$

User Engagement. We used the metric "talking about this" obtained from an artist's official Facebook profile to measure the volume of fan engagement. This metric is based on the last 7 days of interactions that occurred with a Facebook profile[8]. As the original measure from Facebook is aggregating the amount of interactions of the last 7 days, uniquely counting every user for 1 interaction the most, we use the difference of today's and yesterday's metric to depict the evolvement of the measure (*Engagement*).

Artist Broadcasting. To test the effect of artist broadcasting we collected tweets from an artist's Twitter account within our research sample on a daily basis and aggregate the tweet occurrences by day and artist. To account for the variables skewedness we again use the log-transformed version in our models (*Broadcasting*).

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[7] Although, especially the lower range values derived from the Sales Rank seem to look questionable and the utilized parameter values have not been established within the category of music album sales, the limitation for the absolute figures does not influence the direction of results. Because of the solely linear transformation the values can be utilized to estimate the effects of the different social media measures.

[8] The measure includes "liking a Page, posting to a Page's Wall, liking, commenting on or sharing a Page post (or other content on a page, like photos, videos or albums), answering a Question posted, RSVPing to an event, mentioning a Page in a post, phototagging a Page, liking or sharing a check-in deal, [and] checking in at a Place" (Search Engine Land, 2011).

Control Variables. We used the daily difference in likes on an artist's Facebook page to account for the influence of variations in popularity. We assume that a negative development of popularity might negatively influence sales (*DiffPopularity*). We measured the concentration of consumption per fan by using the total number of listeners and playcount obtained from Lastfm. We looked at the daily development per artist for both measures and calculated a measure for average concentration of consumption per listener. A higher consumption concentration indicates more dedicated fans that might produce a lot of social media buzz (*DiffConsump*).

$$DiffConsump_{it} = \frac{playcount_{it} - playcount_{it-1}}{listeners_{it} - listeners_{it-1}}$$

To control for a potentially different mechanism before and after the album release we created a binary variable that indicates whether a measurement was taken prior to release (*Pre-release=1*) or after release date. We collected the price for physical and digital album releases from Amazon product pages on a daily basis to control for their presumably negative effect *(PhyPrice, DigPrice)*.

3.4. Empirical Models

We develop 2 models to test our hypotheses for physical (Model 1) and digital (Model 2) sales. For every album i and days to/since release date t, we specify the following models:

$$\begin{aligned} LogPhySales_{it} &= \beta_0 + \beta_1\, Volume_{i,t-1} + \beta_2\, Broadcasting_{i,t-1} + \beta_3\, Positiveness_{i,t-1} \\ &+ \beta_4\, Engagement_{i,t-1} \\ &+ \beta_5\, DiffPopularity_{i,t-1} + \beta_6\, DiffConsump_{i,t-1} + \beta_7\, LogPhySales_{i,t-1} \\ &+ \beta_8\, Prerelease_{it} + \beta_9\, PhyPrice_{it} + \alpha_i + \varepsilon_{it} \end{aligned}$$

$$\begin{aligned} LogDigSales_{it} = {} & \zeta_{0i} + \zeta_1\, Volume_{i,t-1} + \zeta_2\, Broadcasting_{i,t-1} + \zeta_3\, Positiveness_{i,t-1} \\ & + \zeta_4\, Engagement_{i,t-1} \\ & + \zeta_5\, DiffPopularity_{i,t-1} + \zeta_6\, DiffConsump_{i,t-1} + \zeta_7\, LogDigSales_{i,t-1} \\ & + \zeta_8\, Prerelease_{it} + \zeta_9\, DigPrice_{it} + \omega_{it} \end{aligned}$$

The models are estimated with fixed effects specifications. Therefore, non-varying time constant factors like label type, genre, or if a release is an artists' first album are not included. A Hausman test points towards this fixed effects specification. We include 1-day-lagged values for all independent variables besides Price and *Pre-release.* We also include the 1-day-lagged versions of dependent variables in our models to control for the effects of former sales performance (*L1.LogPhySales*, *L1.LogDigSales*). The use of lagged predictors, accounts for the fact that the effects of social media elements (volume, valence & engagement) are observed after some time.

Time sequencing tests revealed that the effect of the 1-day-lagged versions of volume and broadcasting have the strongest effect among the 1 to 5-day-lagged variables. We further believe in our model specification as we are looking at a short time horizon of 36 days. This short period narrows done the potentially time varying album or artist specific factors and lets us rather control for further unobserved characteristics. Table 2 gives an overview of the variables included in our models.

3.5. Descriptive Statistics

After data cleaning, we used for all 65 albums, 36 consecutive daily measurement points gathered between 19 days before and 30 days after release date. We used releases of 19 different genres. The most popular music genre within our sample is *Rock* (21.5%), followed by *Alternative* (20%) and *Metal* (9.2%). Only 9.2% of the music album releases was the first release of an artist. 21 artists release their album on a so-called major label. Table 3 shows the summary statistics of the variables with which we form our measures for the models. Digital releases seem to be on average cheaper than physical releases. Artists receive daily up to 28,354 tweets while they themselves produce up to 20 tweets a day. In general, the results of our sentiment analysis shows that for all artists within our sample the amount of positive is higher than the amount of negative tweets.

Table 2. Summary of Variables

Variable	Description
LogPhySales	Logarithm of physical music album sales derived from Amazon sales rank
LogDigSales	Logarithm of digital music album sales derived from Amazon sales rank
LogIllDownloads	Logarithm of illegal downloads obtained from MusicMetric.com
Volume	Logarithm of volume of Twitter posts about an artist obtained from Topsy.com
Broadcasting	Logarithm of volume of Twitter posts generated on an artist account
Positiveness	Positiveness of tweets obtained with sentiment analysis on Sentiment140.com
Engagement	Difference in actual and prior day “talking about this” metric on Facebook
DiffPopularity	Difference in actual and prior day “likes” metric on Facebook
DiffConsump	Difference in actual and prior day average plays per listener obtained from Lastfm
Pre-release	Binary variable indicating pre- or post-release occurrence of dependent variable
PhyPrice	Price of physical music album on Amazon.com
DigPrice	Price of digital music album on Amazon.com

Table 3. Descriptive Statistics

Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
PhySalesrank	2181	37851.31	141868.30	3	2227936
DigSalesrank	1067	4360.93	10429.73	1	97705
Volume	2163	520.34	1427.76	0	28354
NegativeVolume	2134	26.52	75.57	0	1503.41
NeutralVolume	2134	286.83	797.82	0	15985.61
PositiveVolume	2134	201.14	551.41	0	10864.99
Engagement	2339	25.25	9265.45	-180334	140717
Broadcasting	2340	3.87	4.17	0	20
DiffPopularity	2273	968.73	2052.67	-88	15931
DiffConsump	2181	0.01	0.06	-0.57	0.95
PhyPrice	2213	11.33	2.27	6.85	18.66
DigPrice	1085	9.38	1.90	5	14.99

4. Results

4.1. Main Results

The following table shows the overall results of the earlier presented regression models. All models use a fixed effect specification with robust standard errors clustered around the album id. To gain further insights we split our dataset into major and independent label releases and pre- and post-release occurrence of measurements presented later in the additional analysis part.

Physical Sales. The volume of eWOM shows a significant and positive influence on physical sales. As expected it seems that an increase of volume leading to a higher consumer awareness of an album leads to higher sales. The measure for positiveness that we use to represent the eWOM dimension of valence in our models shows a positive and significant effect on physical sales supporting hypothesis H2. More positive eWOM buzz leads to a higher valuation of a music album and in consequence more physical music album sales. The effect of engagement is positive and highly significant supporting the notion that the interaction between users and artists creates a bond and increases their willingness to pay. Our models also show a positive relationship between artist broadcasting and physical sales.

Digital Sales. The volume of eWOM shows a significant and positive influence on digital sales. From a relative perspective the effect seems to be stronger for digital sales for which a 1% increase in eWOM volume leads to a 0.124% increase in digital sales while a 1% increase in eWOM volume leads to a slightly lower increase of 0.101% in physical sales. No other measure is found to have a significant influence on digital music album sales.

Looking at the control variables we find that the price for both physical and digital music album releases seems to negatively influence sales in the respective model. The 1-day lagged version of all dependent variables shows a significant and positive influence on the dependent variables. This effect is as expected as higher sales on a previous day are correlated with higher sales on a subsequent day. *Pre-release* has a negative effect on both channels, indicating that consumers tend to wait until a release really becomes available before ordering it. Finally, the difference in popularity has a positive effect on physical sales. Finally, consumption concentration has a positive relationship with digital sales. This may indicate that consumers that listen a lot to an artist are more likely to consume digital releases than physical versions.

Table 4. Results for Physical Sales and Digital Sales

	LogPhySales				**LogDigSales**			
	β	Robust SE	t	P>t	β	Robust SE	t	P>t
L1.Volume	0.101**	0.047	2.14	0.036	0.124**	0.051	2.45	0.017
L1.Positiveness	1.207**	0.584	2.07	0.043	1.706	1.184	1.44	0.155
L1.Engagement	0.000005***	0.000	2.90	0.005	0.000003	0.000	0.88	0.382
L1.Broadcasting	0.108***	0.039	2.77	0.007	0.038	0.040	0.95	0.346
L1.DiffPopularity	0.000095**	0.000	2.09	0.041	0.000005	0.000	0.15	0.883
L1.DiffConsump	-0.361	0.294	-1.23	0.224	0.803**	0.390	2.06	0.044
L1.*dependentvariable*	0.653***	0.041	15.90	0.000	0.729***	0.038	19.00	0.000
Pre-release	-0.358***	0.097	-3.68	0.000	-0.421***	0.031	-13.52	0.000
PhyPrice	-0.130***	0.041	-3.15	0.002				
DigPrice					-0.184***	0.061	-3.01	0.004
Constant	-0.452	0.711	-0.64	0.527	-0.220	1.029	-0.21	0.831
R-sq (within)	0.5916				0.6687			
R-sq (overall)	0.9025				0.9341			

*legend: * p<.1; ** p<.05; *** p<.01*

Table 5. Summary of the Hypotheses Testing

Model	**Hypotheses**	**Distribution Type**	**Confirmed**
Sales	H1 (Volume)	physical	**Yes**
		digital	**Yes**
	H2 (Valence)	physical	**Yes**
		digital	**No**
	H3 (Engagement)	physical	**Yes**
		digital	**No**
	H4 (Broadcasting)	physical	**Yes**
		digital	**No**

4.2. Additional Analysis

eWOM and Music Album Piracy. Focusing on legal sales channels in music industry is short-sighting given the recent changes in the field. A large part of users access music albums through alternative free sources. In 2009 only 37% of music consumed in the US was legally purchased (RIAA, 2013). Illegal download of copyrighted music material has been a subject of dispute over its relation to legal sales. The Internet provides consumers with the opportunity to illegally consume music for free through file sharing platforms and other sources. It is highly questionable whether eWOM measures affect illegal download behavior in the same way as legal purchase decisions.

Artists attempt with their social media appearances to strengthen the relationship between them and their fans and make them spread the word about their music therefore accomplishing work on the artist's behalf (Piskorski 2011). Further, these strategies also increase the bond among fans and create a community. If done right this leads to an increase in the willingness to pay for the artist's products on the consumer side. Consumer incentives can decrease piracy (Sinha & Mandel 2008) as they increase their willingness to pay.

The informative effect of eWOM volume (Zufryden 1996) allows consumers to come across new products. Nevertheless, the volume of eWOM does not affect consumers' valuation of a product and therefore their willingness to pay for it. Instead, eWOM volume also positively influences illegal downloads through an increased awareness of the presence of music albums. In contrast, the valence of eWOM has a persuasive effect on consumers influencing their attitudes towards a product and not their awareness about it (Zufryden 1996; Walker 2001). We assume that positive buzz leads to a higher valuation of a product and therefore increases the willingness to pay for it. This means that consumers tend to rather purchase than pirate a product and higher positive valence about a music album should lead to a lower number of illegal downloads. Further, through an increase in identification with the artist we assume that the relationship towards the artist is enhanced. Through this increase of willingness to pay we assume that consumers tend to rather purchase than pirate a music album with increasing fan engagement. Finally, we assume that encountering complementary artist posts positively influences the willingness to pay of consumers for the actual music albums. Through the personal touch of these messages a bond between the artist and the consumer is created. This bond increases consumers' valuation of the artist's music album resulting in a higher willingness to pay. Thus, it is likely that consumers tend to purchase a music album instead of pirating it when the artist broadcasts personal messages. Because of the high frequency of messages on Twitter we further assume that a higher volume of artist messages increases the likelihood that consumers encounter these artist messages among other tweets. Therefore, a higher volume of artist broadcasting should lead to more sales but less piracy of a music album.

We tested the role of social media metrics on illegal downloads through torrent sites. We collected data from Musicmetric.com and information aggregator for music artists on the amount of BitTorrent downloads per artist on a daily basis. Although, the direction of the influence of volume on illegal downloads does adhere to the presented assumptions the effect of eWOM volume is not significant.

Table 6. Results for Illegal Downloads

	β	**Robust SE**	**t**	**P>t**
L1.Volume	0.004	0.045	0.09	0.925
L1.Positiveness	-0.765	0.642	-1.19	0.242
L1.Engagement	-0.000002	0.000	-1.40	0.171
L1.Broadcasting	-0.023	0.027	-0.83	0.414
L1.DiffPopularity	0.000022*	0.000	1.88	0.070
L1.DiffConsump	1.694***	0.567	2.99	0.006
L1.*dependentvariable*	0.746***	0.032	23.43	0.000
Pre-release	-0.149***	0.045	-3.33	0.002
Constant	1.775	0.477	3.72	0.001
R-sq (within)	0.6372			
R-sq (overall)	0.9427			

Pre-Release vs. Post-Release. We further split our dataset into data occurring pre- and post-release to test the effect of our measures before and after release date of a music album. Due to a lack of pre-release values for digital music album sales we concentrate on physical music album sales as well as illegal downloads. We find that volume has a positive and significant relationship to physical sales only post-release. Buzz generation might be rather limited before the release of an album, and even less accessible and influential especially if we consider the lower social media savviness of the main target group of physical sales. We also find a significant and positive influence of engagement after release. This measure can be actively influenced by artists and suggests also keeping the amount of personal postings up after release.

For illegal downloads, we find significant and negative influences for volume, valence, and engagement (at 10%-level) on illegal downloads after the release date. The negative effect of volume contradicts our assumption that volume should lead to an increase of consumer awareness and not their valuation and subsequently higher illegal downloads. Looking at the negative effect of valence we assume that users tend to wait for peer opinions on music albums to then decide whether they purchase or illegally download an album. These opinions become available in a higher frequency after release date. The measure for engagement shows a negative influence on illegal downloads after release date significant at a 10%-level. Higher engagement with an artist negatively influences illegal downloads through an increase in the valuation of an artist's output. Further, we assume that the increase in significance of the measures arises to some extent due to the availability of pirated and legal music albums after release date. The shift from illegal to legal purchase forms can be explained through the potential availability of pirated album versions before release date. While legal distribution forms become only available on the release date illegal versions might allow consumers to get access to the content they are looking for at an earlier stage.

Table 7. Results for Pre-release vs. Post-release

	LogPhySales		**LogIllDownloads**	
Variable	Pre-release	Post-release	Pre-release	Post-release
L1.Volume	0.035	0.162***	0.151	-0.088**
L1.Positiveness	1.638	1.189	0.66	-1.612**
L1.Engagement	-0.000006	0.000007***	-0.000001	-0.000003*
L1.Broadcasting	-0.002	0.150***	-0.046	-0.018
L1.DiffPopularity	0.000057	0.000135*	0.000033*	0.000024
L1.DiffConsump	0.528	-0.266	2.965**	1.312***
L1.*dependentvariable*	0.571***	0.541***	0.695***	0.664***
PhyPrice	-0.470***	-0.094**		
Constant	2.699	-1.189	-0.039	3.335***
N	496	1267	247	536
R-sq (within)	0.393	0.424	0.521	0.508

*legend: * p<.1; ** p<.05; *** p<.01*

Comparing our results for illegal downloads with physical music album sales we find that the findings are more conclusive when we apply the release date split in our model. While the measures seem to positively influence physical sales post-release (significant for volume, engagement, and broadcasting) they do negatively influence illegal downloads (significant for volume, valence, engagement (10%-level)). Interestingly broadcasting has no significant influence on illegal downloads which from a managerial perspective limits the active role of artists to counteract piracy. Yet, as it positively influences physical music album sales artist involvement in social media is justified.

Major vs. Independent Label. We further split our dataset into major and independent label releases. We find that volume has a significant and positive influence on physical sales only for independent label releases. This makes sense, as it is more important for independent label artists to create awareness about themselves while major label artists enjoy a bigger marketing budget that already provides them with wider exposure in traditional marketing channels. Nevertheless, for major label artists the emphasis lays on different social media measures. Our analysis shows that the valence plays a really important role in their case indicated through a highly significant value that is twice as strong as the coefficient in our main analysis. Moreover, for major label artists it is crucial to actively participate in social media as depicted in the significant and positive value for broadcasting. We assume that this has also to do with the wider reach that major label artists usually have through their social media channels.

Table 8. Results for Major vs. Independent Label

	LogPhySales		**LogDigSales**		**LogIllDownloads**	
Variable	Indie Label	Major Label	Indie Label	Major Label	Indie Label	Major Label
L1.Volume	0.156**	0.002	0.169**	0.042	0.048	-0.100***
L1.Positiveness	0.717	2.809***	1.355	3.619	-0.937	-0.739
L1.Engagement	0.000006	0.000002	0.000001	0.000002	-0.000002	-0.000003**
L1.Broadcasting	0.049	0.190***	0.014	0.06	0.004	-0.059**
L1.DiffPopularity	0.000095**	0.00010	0.00006	0.00004	0.00001	0.00003
L1.DiffConsump	-0.254	-1.297	0.845**	0.133	1.716**	1.383
L1.*dep.variable*	0.590***	0.743***	0.693***	0.699***	0.745***	0.703***
Pre-release	-0.408***	-0.287*	-0.399***	(omitted)	-0.197***	-0.104
PhyPrice	-0.149***	-0.148				
DigPrice			-0.111	-0.698***		
Constant	-0.116	-0.998	-0.796	3.986	1.636***	2.681**
N	1143	620	568	353	479	304
R-sq (within)	0.539	0.687	0.6	0.745	0.677	0.558

*legend: * p<.1; ** p<.05; *** p<.01*

Our findings for digital music album sales are pretty much in line with the results presented in our main analysis. We find only one significant coefficient for the volume of eWOM in the case of albums released by independent labels. This again supports the assumption that for independent label artists it is crucial to create awareness about themselves whereas major label artists already enjoy a certain level of popularity. Finally, regarding illegal downloads, while we do not find significant influence of any measure for independent label releases in fact 3 measures significantly influence the illegal downloads for major label artists' output. For major label releases volume, engagement, and broadcasting show a negative relationship with illegal downloads. The negative effect of volume contradicts our assumption that the measure positively influences awareness and therefore not consumers' valuation of a music album. The finding is even more interesting as we are looking at the results for major label releases that already enjoy high exposure because of bigger marketing budgets. As hypothesized we find negative influence of both engagement and broadcasting for major label releases. We assume that the impact of the measures is significant for only major label artists as users do value interaction with these already popular artists extremely high.

5. Discussions and Conclusions

5.1. Discussions of Key Findings

Looking at the forecasting possibilities within the music industry several different models have been established emphasizing the importance of forecasting because of the fact that within the music industry several releases are scheduled simultaneously and it is hard to keep an overview of the potential of these product introductions (Lee, 2003). Nevertheless, research still struggles to identify clear patterns and metrics that influence music distribution. Nowadays, we have the opportunity to draw on tremendous information availability in terms of quality and volume, even prior to release, using bigger datasets consisting of user-generated data. Still, this data needs to be processed adequately.

Our study shows managers in the music industry the effect of eWOM measures on music album sales. As seen in the presented models these effects have proven to be significant especially for physical sales and only partly for digital distribution forms. This is a meaningful insight for managers and leads to the necessity to monitor social media chatter about the artists in their roster. Even more interestingly, we also looked at artist broadcasting in our models, which can be directly influenced, by artists and their management. This measure has proven to have significant and positive influence on physical sales and implicates the importance of artists and managers to personally engage in social media. Although, it is a characteristic of social media that users control the present conversation this also points towards the opportunity to partly trigger conversations or steer them into a more favorable direction. Looking at the distribution of illegal downloads we find an indication that a well-defined social media strategy might help managers to reduce the amount of illegal downloads consumed. By fostering the adequate direction of chatter, broadcasting, and engaging fans on social media, a shift from illegal downloads towards legal distribution channels might occur. Nevertheless, none of the measures in our model for illegal downloads has been significant limiting this statement and pointing to the necessity to further investigate these relationships. By including more fine grained and adequate data better recommendations can be drawn regarding marketing budgets, the amount of physical copies that need to be produced, and how social media marketing for music artists should be approached.

5.2. Theoretical Contributions

Consumers' decision making is influenced by communication with other individuals through whom they learn and develop attitudes that influence them in their purchase decisions (Ward, 1974). Our research focuses on the impact of four main types of eWOM influence factors: Volume, valence, engagement, and broadcasting. To our knowledge, no other study has so far combined these measures within one analysis. Furthermore, the nature of music being an information good allows us to address different distribution channels including the legal channels of physical and digital sales as well as the illegal channel of pirated downloads. This allows us to firstly look at the impact of the eWOM measures and secondly at the differences of effects across distribution channels. Looking at currently present literature in this field we see our contribution mainly in the following areas.

Most literature only measures the effect of eWOM on physical sound carrier sales or does not distinguish between different distribution forms and therefore neglects the significant share of digital sales. This is especially a shortcoming as consumers already find themselves within the digital online channel when consuming the eWOM content. In 2011 the share of digital sales within the amount of legally purchased music was estimated to account for 32% and growing (IFPI 2012). This leads to the necessity to test the influence of eWOM on this distribution channel as well and to control for the different effects of user-generated content on digital sales. We include the digital distribution channel in a separate model within our study to test for varying effect of eWOM across distribution channels.

We use a variety of measures to control for the influence of eWOM on music album distribution. Further, we obtain our dataset from a broad range of sources including the social media platforms Twitter, Facebook, and Lastfm. Therefore, we can provide a more complete picture of the social media world and the generated eWOM than former studies. The personal effort that needs to be undertaken to write about a music album in a blog is rather high whereas the effort to create a post within one's Twitter account or even just a so-called re-tweet can be seen as substantially lower, therefore creating more volume and variety of opinions. For this reason and concerning the fact that data from Twitter can be accessed relatively easy we decide to focus on Twitter as our main source of eWOM. Moreover, while Dhar & Chang (2009) control for popularity of music artists by looking at the variations of Myspace friends between different points of time we substitute this measure by using Facebook likes on artist profile pages. With Facebook claiming to have had one billion active users in October 2012 (Facebook, 2013) the platform has largely outgrown the number of Myspace users and can be seen as more representative.

Research often does not distinguish between different sentiments of UGC but rather just focuses on the volume of posts. With the help of sentiment analysis we categorized our posts into connotation categories: positive, neutral, and negative, to test for different effects regarding the valence of Twitter posts across models. In addition, we included a measure for fan engagement derived from Facebook in our models. This measure has to our knowledge so far not been investigated in a similar context allowing us to research the impact of eWOM from a new angle.

Although we cannot find significant relationships of our eWOM measures with our piracy measure we seem to be one of the first studies to address this distribution channel in such a context. Pirated music distribution accounts for a big amount of music consumption and the effect of eWOM on this part is mostly neglected by current literature. Current statistics state that in 2009 only 37% of music consumed by US inhabitants was paid for and between 2004 and 2009 there have been about 30 billion songs downloaded illegally (RIAA, 2013). Therefore, our study enhances the horizon of research by including the effect of eWOM metrics on music distribution in general, including pirated distribution, and controls for different effects across these distribution channels. By including a separate model for pirated music in our study we allow to test for the effect of eWOM on the amount of illegally obtained music. To our knowledge we are the first study to address this topic and find an indication of differently directed influence on illegal downloads of 3 of our 4 eWOM measures. Therefore, we lay the foundation for upcoming studies to further investigate these relationships.

Nevertheless, our study has to cope with some limitations. The sample size is relatively small, though based on some further analysis the sample can be considered rather representative. Especially for digital music album releases and illegal downloads for which because of further restrictions the sample size is even more limited. We see improvement opportunities in investigating bigger samples and widening our time scope in subsequent releases of the paper. In addition, the period of the data collection (in July) might be considered as one of the lowest selling periods within a year and hence, lacking some of the big releases of the peak periods (e.g. December, May)

Looking at the included eWOM measures we find improvement potential by considering the reach of the used social media metrics to construct the measures. As the effect of eWOM is highly dependent on its reach it makes sense to further evaluate the inclusion of the amount of subscribers to a message and weigh the constructed measure accordingly. Although we control for the popularity of an artist this might give further insights into especially the effect of volume, artist broadcasting, and valence that are all based on data gathered from Twitter, a platform on which the amount of followers heavily influences the reach of a message.

5.3. Managerial Implications

The main managerial implications of our study originate from the question: How can managers use the implications of social media measures on consumers' choice to or not to purchase a product? Further, how can consumers be kept away from pirating content and maybe even be transformed into buyers. Also interesting is the potential for managers to identify artists that are likely to be successful in the future to work with them.

With our research we present a more complete picture of the influence of UGC on product sales than prior studies. Because of data aggregation across several social media sources we can simultaneously investigate the effects of 4 different social media measures including volume, valence, engagement, and broadcasting. Despite the comprehensiveness of our measures we still perform sentiment analysis depicted in our measure for valence of eWOM. We show that the measures in our study can be expected to have the same effect on physical as well as digital sales. Further, our results give indication that valence, engagement, and broadcasting might have a negative effect on illegal downloads. We are able to investigate this amount of variables as we combine data from several sources including the social media platforms Twitter, Facebook, and Lastfm. By including a measure for engagement we investigate the effect of eWOM from a new perspective for the music industry. Our measure for artist broadcasting allows us to present insights into management or artist instead of user triggered social media activities.

Our study offers valuable insights for both artists as well as music management into the effect of social media on music album sales. The results of our analysis justify efforts that are undertaken to monitor social media activities around an artist. From a managerial perspective this justification applies to both already signed artists as well as artists that might be interesting for a collaboration in the near future. By giving management an indication of the successfulness of an artist marketing budgets can be adapted. Our broadcasting measure signals the positive effect of artist or respectively management engagement and stimulus of social media conversations. We show that broadcasting offers the potential to positively influence physical music album sales.

5.4. Limitations and Future Research

Theory still struggles with identifying the causation between the bi-directional relationship of UGC and product sales. UGC fosters more sales but more sales also foster the generation of UGC raising endogeneity concerns when researching this topic (Dewan & Ramaprasad, 2009). As suggested by other scholars it seems to be reasonable to use different sorts of models to investigate the research questions we are focusing on in our study. We advise upcoming research to follow the example of Dewan & Ramaprasad (2013) and Chen et al. (2013) that utilize a PVAR model to investigate a similar topic. This model copes especially well with the previously addressed endogeneity issues arising from potential reverse causality of dependent and independent variables. This model type better copes with the dynamic relationship between eWOM and sales or respectively illegal downloads.

5.5. Conclusion

Our study investigates the effect of a variety of eWOM measures including volume, broadcasting, valence, and engagement on music album distribution. Although, we find evidence for a positive impact of these measures on physical music album sales, only volume shows a significant and positive relationship with the digital distribution channel of music albums. We further postulate a different impact of eWOM on illegally distributed music albums. We assume that all eWOM measures discussed in this study, besides volume, negatively impact the number of illegal downloads. Our models indicate that our assumption goes into the right direction but offers only insignificant coefficients for the measures in focus. We advise scholars to undertake further research in the area of illegal music album distribution and detect the effects of eWOM and their direction in this field. By including a meaningful variety of eWOM measures and their impact on several distribution forms within the music industry we are confident to provide a more thorough picture than former research with this study.

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Appendix 1. Research Sample

ID	Artist Name	Album Name	Label	Major Label*	First Release**	Genre	Release Date
1	3OH!3	Omens	Atlantic	1	0	Pop	6/18/13
2	Amon Amarth	Deceiver of the Gods	Metal Blade	0	0	Metal	6/25/13
3	Aoife O'Donovan	Fossils	Yep Roc Records	0	0	Singer/Songwriter	6/11/13
4	August Burns Red	Rescue & Restore	Solid State Records	0	0	Metal	6/25/13
5	Big Time Rush	24/seven	COLUMBIA/ NICKELODEON	1	0	Pop	6/11/13
6	Bill Frisell	Big Sur	Masterworks	1	0	Jazz	6/18/13
7	Black Dahlia Murder	Everblack	Metal Blade	0	0	Metal	6/11/13
8	Black Sabbath	13	Universal Republic	1	0	Metal	6/11/13
9	Black Veil Brides	Wretched & Divine	Republic	1	0	Rock	6/11/13
10	Boards of Canada	Tomorrow's Harvest	Warp Records	0	0	Electronic	6/11/13
11	Bob Schneider	Burden of Proof	KIRTLAND RECORDS	0	0	Rock	6/11/13
12	Bosnian Rainbows	Bosnian Rainbows	Sargent House	0	1	Alternative	6/25/13
13	Bret Michaels	Jammin' With Friends	POOR BOY RECORDS INC	0	0	Rock	6/25/13
14	Bronze Radio Return	Up on & Over	Digsin	0	0	Alternative	6/25/13
15	Candye Kane	Coming Out Swingin	Vizzitone	0	0	Blues-Rock	6/25/13
16	Cheyenne Mize	Among the Grey	Yep Roc Records	0	0	Alternative	6/25/13
17	Children of Bodom	Halo of Blood	Nuclear Blast America	0	0	Metal	6/11/13
18	Chrisette Michele	Better	Motown / Universal	1	0	R&B/Soul	6/11/13
19	Da 'Unda' Dogg	Numbers Never Lie	Pushin Dope Productions	0	0	Hip-Hop/Rap	6/18/13
20	Deafheaven	Sunbather	Deathwish Inc	0	0	Metal	6/11/13
21	Donna the Buffalo	Tonight Tomorrow & Yesterday	Welk Records	0	0	Rock	6/18/13
22	Empire Of The Sun	Ice On The Dune	Astralwerks (Universal)	1	0	Alternative	6/18/13
23	Falling In Reverse	Fashionably Late (Deluxe Edition)	Epitaph	0	0	Rock	6/18/13
24	Forever the Sickest Kids	Jack	Fearless Records	0	0	Alternative	6/25/13
25	Gino Matteo	Sweet Revival	Rip Cat Records	0	0	Rock	6/18/13
26	Harry Connick Jr.	Every Man Should Know	Columbia	1	0	Jazz	6/11/13
27	Henry Santos	My Way	Universal Latino	1	0	Reggaeton & Hip-Hop	6/25/13
28	Hugh Cornwell	Totem & Taboo	Red River Entertaint	0	0	Rock	6/25/13
29	Hunter Hayes	Hunter Hayes (Encore) Deluxe	13STAR RECORDS	0	0	Country	6/18/13
30	Issac Carree	Reset	n/a	0	0	Religious	6/25/13
31	Jason Isbell	Southeastern	12TH STREET RECORDS	0	0	Singer/Songwriter	6/11/13
32	Jay Sean	Neon	Cash Money	1	0	Pop	6/25/13
33	Jillette Johnson	Water in a Whale	Wind-Up	0	1	Singer/Songwriter	6/25/13

34	Jimmy Eat World	Damage	RCA	1	0	Alternative	6/11/13
35	Joseph Arthur	Ballad of Boogie Christ	LONELY ASTRONAUT	0	0	Rock	6/11/13
36	Kelly Rowland	Talk a Good Game	Republic	1	0	R&B/Soul	6/18/13
37	Leslie Grace	Leslie Grace	Top Stop Music	0	0	Salsa & Tropical	6/25/13
38	Lou Doillon	Places	Universal Music/Video Distribution	1	1	French Pop	6/18/13
39	Mac Miller	Watching Movies With the Sounds Off	Rostrum Records	0	0	Hip-Hop/Rap	6/18/13
40	Middle Class Rut	Pick Up Your Head	Bright Antenna	0	0	Alternative	6/25/13
41	Moon Hooch	Moon Hooch	Megaforce	0	0	Jazz	6/25/13
42	Mr Del	Faith Walka	Dedicated Music Grp.	0	0	Gospel	6/18/13
43	Natalie Cole	Natalie Cole En Español	Verve	1	0	Baladas & Boleros	6/25/13
44	Philthy Rich	N.E.R.N.L.	Rbc Records	0	0	Hip-Hop/Rap	6/18/13
45	Queensryche	Queensryche	Century Media	0	0	Rock	6/25/13
46	Royal Canoe	Today We're Believers	Roll Call Records	0	1	Rock	6/25/13
47	Royksopp	Late Night Tales	Late Night Tales UK	0	0	Electronic	6/25/13
48	Scale the Summit	Migration	Prosthetic Records	0	0	Rock	6/11/13
49	Sensato	We Ain't Even Supposed 2 B Here	Sony U.S. Latin	1	1	Hip-Hop/Rap	6/25/13
50	Sigur Ros	Kveikur	XL Recordings	0	0	Alternative	6/18/13
51	Skillet	Rise	Atlantic	1	0	Rock	6/25/13
52	Slaid Cleaves	Still Fighting The War	Music Road Records	0	0	Country	6/18/13
53	Smith Westerns	Soft Will	Mom & Pop Music	0	0	Alternative	6/25/13
54	Statik Selektah	Extended Play	Duck Down Music	0	0	Hip-Hop/Rap	6/18/13
55	Stephen Kellogg	Blunderstone Rookery	Elm City (Universal)	1	0	Singer/Songwriter	6/18/13
56	Surfer Blood	Pythons	Warner Bros.	1	0	Alternative	6/11/13
57	The Goo Goo Dolls	Magnetic	Warner Bros.	1	0	Pop	6/11/13
58	The Mowgli's	Waiting For The Dawn	ISLAND / DEF-JAM	1	0	Alternative	6/18/13
59	Tiesto	Club Life 3: Stockholm	Musical Freedom	0	0	Dance	6/25/13
60	Treetop Flyers	The Mountain Moves	Partisan Records	0	1	Alternative	6/25/13
61	Tunng	Turbines	Full Time Hobby	0	0	Alternative	6/18/13
62	Valient Thorr	Our Own Masters	Volcom Entertainment	0	0	Rock	6/18/13
63	Walter Trout	Luther's Blues - A Tribute to Luther Allison	Mascot Records	0	0	Blues	6/11/13
64	Willie Nile	American Ride	Loud & Proud Records	1	0	Rock	6/25/13
65	Wrekonize	War Within	10 SPOT	0	0	Hip-Hop/Rap	6/25/13

* A "1" indicates that the album has been released on a major label.
** A "1" indicates that the release is the first album released by the artist.