Stars vs. Underdogs in Online Music Markets: The Effect of IT on Visibility, Artists' Broadcasting, and Fans' Activities[*]

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Abstract

In cultural markets, for books, music or movies, sales are concentrated on a small number of highly successful products. One explanation for the skewness of sales is incomplete information: consumers are poorly informed about most products, because only a small proportion of them are visible and promoted in the offline world. With digitization, as suggested by the Long Tail hypothesis, the increasing visibility of niche products could improve consumer information, and thus reduce sales concentration. In this paper, we study whether, in the music industry, online promotion improves the visibility of "underdog" artists or that of "stars". We use an original and large dataset of indicators for visibility, both offline (i.e., press coverage) and online (e.g., Facebook, Twitter, MySpace, YouTube, or LastFm), for about 1,000 artists over a 6-month period following a new album release. First, we investigate the extent to which the Internet democratizes access to visibility, and we examine the online promotional actions taken by artists and their fans to overcome a potential lack of visibility. We find that, while the most popular and visible artists offline are also the most visible online, audiences of underdog and debut artists are more strongly engaged to support their promotion efforts. Then, we use a panel vector autoregression (PVAR) model to explore the interplay between artists' broadcasting activities (artist-generated content), fans' activities (user-generated content), artists' online reputation (number of fans) and a free form of online consumption (music streaming), according to the artist's visibility in the traditional media channels. Our main results suggest that the promotion supported by online audiences has a positive effect on music streaming only for underdog artists, whereas artists' broadcasting activities in social media have no direct impact on music streaming.

Keywords: Social Media; Long Tail; User-Generated-Content; Music Industry; Panel VAR model.

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1. Introduction

In recent years, social media like Facebook, Twitter or YouTube have grown fast to attract millions of users. They have become an important channel for reaching consumers, alongside traditional media channels such as television, radio and newspapers, and companies have widely engaged in social media marketing to promote their products.

In cultural markets for books, movies or music, this new method of promotion may profoundly change consumer demand. In markets with frequent inflows of new products (hundreds of books, movies, or music albums are launched each week), the quality of which is difficult to evaluate *ex ante*, the process by which consumers are informed of the available products is central in determining the market demand.

Traditionally, consumers' awareness about products is primarily driven by product visibility in traditional media, such as radio, television or newspapers. As only a small share of the available products obtains visibility, consumers are often poorly informed about most of them. This is because traditional mass media face capacity and technical constraints that make visibility a scarce resource (e.g., scarce airtime on radio). As a consequence, firms in cultural industries have an incentive to concentrate their promotion efforts on a small number of products.

With digitization, product visibility is no longer defined by scarcity. Theoretically at least, information technologies (IT) provide unlimited space for promotion. A wider range of products, especially those ignored by the mass media, may benefit from visibility. The emergence of social media has also challenged the traditional bottleneck of promotion in two additional ways. First, the Internet has made self-promotion easier. For example, music artists are now able to promote their music and to reach a large audience, with great ease and at low cost, on platforms such as YouTube or Twitter. Second, decentralized promotion by the audiences has emerged on online platforms, with the diffusion of word-of-mouth on an unprecedented scale. Consumers can publicly review albums on Amazon, leave comments on artists' Facebook pages, or post on music blogs.

As suggested by the Long Tail hypothesis[1] (Anderson, 2004; Brynjolfsson et al., 2006), the increasing visibility of niche products in the digital world should allow them to make up a larger share of total sales than they would have achieved in the pre-digital age, and thereby reduce sales concentration, particularly in cultural markets.[2] Previous research on the music industry has shown that incomplete consumer information strongly contributes to the concentration of music sales (Hendricks and Sorensen, 2009): although consumers face a large choice set, demand remains concentrated on a small number of products due to the consumers' lack of information. If consumers are better informed about the set of available products, they may prefer to purchase a less popular product, more aligned with their tastes, than one of the few popular products they were aware of in the offline world.

In this paper, we study whether, in the music industry, online promotion tools allow "underdog" artists to compete for attention on a level playing field with the "stars". We first investigate whether online promotion tools democratize access to visibility for music artists, and then we study online promotion efforts made by artists and their fans to overcome a potential lack of visibility. Finally, we seek to determine who benefits from online promotion, using a panel vector autoregression model that disentangles the relationships between traditional promotion, online promotion (artist's broadcasting activities and fans' activities), and a free form of online consumption (music streaming).

Our contribution is to investigate the overall informational effect of IT in the music market. We thus contribute to the long tail literature by investigating both the supply-side drivers of the long tail, that is, whether IT enables artists to bypass the traditional bottleneck of promotion, and its demand-side drivers, that is, whether IT may improve consumers' information about their choice set of music.

Most of the long tail literature has focused mainly on the impact of IT on the distribution of product sales, providing mixed evidence of the long tail phenomenon (Brynjolfsson et al., 2003;

[1] The *Long Tail* is a term coined by Anderson (2004) to predict that digitization should allow a greater number of products to be brought onto the market (supply-side driver), while demand should switch from the hits towards a huge number of niche products in the tail of the distribution due to lower search costs online (demand-side drivers). See Brynjolfsson et al. (2010) for a literature review.

[2] Cultural markets are commonly described as "superstar" markets (Rosen, 1981; Adler, 1985) or "winner-take-all" markets (Frank and Cook, 1995): a small number of products, the best-sellers, claim a large share of the total sales.

Elberse and Oberholzer-Gee, 2007; Tan et al., 2012; Brynjolfsson et al., 2011). Brynjolfsson et al. (2006) argue that both supply-side and demand-side factors contribute to the long tail phenomenon. On the supply-side, IT has increased product variety (Brynjolfsson et al., 2003; Brynjolfsson et al., 2006), by lowering the cost of creating, storing and distributing niche products. On the demand-side, IT allow consumers to acquire product information more easily and at lower cost, leading to an increased demand for niche products. Previous research has studied the effects of online search (Brynjolfsson et al., 2011), personalization technologies (see, e.g., Oestreicher-Singer and Sundararajan, 2012; Fleder and Hosanagar, 2009), and user-generated content (see, e.g., Zhu and Zhang, 2010; Berger et al., 2010) on product sales.

As our focus is not only on product sales but also on product visibility, our paper is closely related to the seminal paper of Dellarocas et al. (2010), who study the distribution of user-generated content across hit and niche movies on the Amazon website. By contrast, we study both user-generated content and artist-generated content, and we retrieve data from several websites and social media. A recent paper by Chen et al. (2013) also investigates artist-generated content in social media with a panel VAR model, but they focus on the impact of artists' broadcasting activities on music sales and not on music streaming, and only use data from one social media website, MySpace.

We use an original dataset about visibility and promotion – both offline and online – of almost 1,000 artists who released a new album at the end of 2010. For each artist, the data were collected during a 6-month period following her new album release. Our dataset includes information about artists' characteristics, their offline visibility as measured by press coverage, and their online visibility and promotional activities on nine major online platforms, including Facebook, Twitter, LastFm and YouTube.

To begin with, we investigate whether IT has democratized access to visibility for music artists. While our preliminary findings provide weak evidence of democratization, we conduct an econometric analysis to further explore this issue, by controlling for artist-specific characteristics. Our results suggest that the most popular and visible artists offline are also the most visible online. Then, we study the effect of IT on promotion by considering both the artists' side and the consumers' side. We measure promotion efforts made by artists (i.e., artist-generated content) and their fans (user-generated content) in social media. We wish to test whether underdog artists and their fans make larger efforts than star artists and their fans, in order to overcome the asymmetry of visibility among artists in the offline world. Our econometric results suggest that, first, artists' broadcasting activities do not depend on their *ex ante* popularity, and second, that audiences of underdog and debut artists are more strongly engaged in their promotion.

Lastly, we conduct a dynamic analysis with a panel vector autoregression (PVAR) model to explore the relationship between artists' broadcasting activities in social media (artist-generated content), word-of-mouth (audience-generated content), artists' online reputations in social media (their number of fans), and digital consumption (music streaming). We study these relationships over the period surrounding an album release (i.e., 2 weeks prior to the release and 2 months after it), according to the artist's exposure in traditional media. Our main findings suggest that artists' broadcasting activities in social media only have a positive impact on fans' activities for underdog artists, and have no direct effect on music streaming for either underdog or star artists. We also find that promotion supported by fans (through word-of-mouth and by building up the artist's online reputation in social media) has a significant and positive effect on music streaming, but only for underdog artists.

The paper proceeds as follows. In Section 2, we discuss the effects of IT on the promotion of music artists, before moving on to describe the data in Section 3. We conduct our econometric analysis on cross-sectional data in Sections 4 and 5. We study the democratization of promotion, and then artists' broadcasting activities (artist-generated content) and consumers' activities (user-generated content). In Section 6, we study the dynamic relationships between social media promotion, by artists or their audiences, artists' online reputation and digital consumption, using a panel vector autoregressive model. Section 7 concludes.

2. The Effects of IT at the Promotion Stage

In this section, we discuss the effect of IT at the promotion stage, by considering first the visibility of artists, second their broadcasting activities, and third, user-generated content around them. We then develop our research hypotheses.

2.1 Visibility of Music Artists

Traditional mass media, such as television, radio and newspapers, have long been used as the main channels to reach a large audience, for brand communication and product marketing. In the music industry, where the marketing and promotion of artists is one of the largest items of spending in record company budgets, radio airplay has been for long considered as the most efficient way to promote songs (Peitz and Waelbroeck, 2005). Record companies therefore try to obtain large exposure for their artists in radio playlists through the leverage of costly marketing and PR campaigns.[3]

However, traditional media are characterized by capacity and technical constraints that make visibility a scarce resource. For example, in the music industry, the cost of providing airtime obliges radio stations to play only a very small fraction of newly released songs. As radio stations seek to reach the largest possible audience for their advertisers, they tend to focus on an even more limited selection of songs, especially those they expect to be very popular. As a result, mass media attention – and thus offline visibility – is mainly focused on an elite of "star" artists, who are already popular, well established and heavily promoted by major record companies.[4]

By contrast, the digital world does not face the same constraints: the space available to promote products is unlimited, at least theoretically. A wider range of artists can therefore benefit from visibility on the Internet, including those who lack exposure in traditional media. On the Internet, furthermore, artists can bypass the traditional promotion bottleneck by broadcasting

[3] An extreme case was the "Payola Scandal" during the 1950s in the United States. Payola is the illegal practice of payment or other inducement by record companies for the broadcasting of songs on music radio. Caves (2000) gives a broader definition of payola as "the bribe paid in order to influence a gatekeeper's choice among competing creative products." Between 2005 and 2007, the FCC conducted investigations on contemporary form of payola ("third-party loophole"), which involved major record companies (Sony BMG, Warner, Universal) and major broadcasters (CBS Radio, Citadel, Clear Channel, Entercom).

[4] For example in the United States, major label songs consistently securing about 80 percent of airplay between 2005 and 2008 (FMC Report, 2009: http://www.futureofmusic.org/sites/default/files/FMC playlisttrackingstudy.pdf).

themselves on social media such as Twitter, Facebook or YouTube. Because these online platforms reach millions of users, they represent a powerful alternative marketing tool for independent or unsigned artists who have no access to traditional media channels. As they can gain access to visibility with greater ease and at lower cost, they may be able to overcome the asymmetry of visibility.

We therefore hypothesize that in accordance with the demand-side drivers of the long tail hypothesis (Brynjolfsson et al., 2006), "underdog" artists may benefit from increased visibility in the digital world. In other words, IT may democratize access to visibility for artists who lack exposure in the offline world.

HYPOTHESIS 1 (H1). *Online media allow underdog artists, who lack exposure in traditional media, to access visibility.*

Since we consider several promotion channels, we test the democratization of visibility in Section 4 by comparing online media and traditional media in terms of product visibility. We determine the global level of online visibility of artists by studying nine major online platforms, including the six social media websites MySpace, Twitter, YouTube, DailyMotion, Lastfm and Facebook. Artists may seek to reach an optimal number of platforms to achieve visibility, given some complementarities or interdependencies between online platforms.

2.2. Artists' Broadcasting Activities in Social Media

Music artists can now directly reach a large audience at low cost, through social media. Because their mere presence on the web or on social media may not be enough to enhance consumers' awareness, artists may actively promote their music, and update their fans about their activities on various platforms. Artists' broadcasting activities on social media include various forms of artist-generated content like public messages, links, pictures or videos posted on social networks (e.g., Twitter or Facebook) and video-sharing websites (e.g., YouTube). As social media marketing has been widely adopted by music companies, artists' broadcasting activities may result from both their own self-promotion and their record company's marketing campaigns.

Few studies have analyzed the relationship between broadcasting activities in social media and product sales. Some studies (e.g., Dellarocas, 2006 or Godes et al., 2005) have examined how firms' online activities may play a role in influencing sales. In a recent paper, Chen et al. (2013) studied the impact of broadcasting activities on MySpace on music sales (using the Amazon sales rank of physical and digital music titles), and found that personal messages posted by artists on their official accounts have a positive impact on their sales. Interestingly, they show that the effect is larger for artists who also benefit from promotion in traditional media channels.

Therefore, while underdog artists may intensively broadcast in social media in order to overcome their lack of visibility, popular artists (stars) may also be largely involved in this new way of marketing, possibly even more intensively. This may reflect superior marginal revenues for stars, as well as synergies between traditional and online promotion channels. Since we want to study whether underdogs make relatively higher broadcasting efforts, compared with the stars, in order to bypass the promotion bottleneck, we posit the following hypothesis.

HYPOTHESIS 2 (H2). *On board a platform, underdog artists make higher online promotion efforts than stars in order to overcome their lack of visibility in traditional media.*

We study artists' broadcasting activities in Section 5. We consider the volume of artist-generated content in an artist's official account on two different social media sites,[5] because there may be some heterogeneity in broadcasting activities across platforms, reflecting the production costs of online content. The two social media sites are (i) Twitter, a micro-blogging website[6] that requires few skills from the publisher but frequent updates due to the short time span focus, and (ii) YouTube, a video-sharing website that calls for less frequent updates, but distributes video content that is more costly to produce.

[5] We exclude MySpace, the social network dedicated to music, because we cannot clearly distinguish between the broadcasting activities of artists and the content generated by their audience. Moreover, MySpace has declined since the late 2000s, overtaken by the rise of social media like Facebook and Twitter.
[6] Twitter enables users to send "tweets", which are text messages limited to 140 characters.

2.3. User-Generated Content on Online Platforms

Social media platforms reach millions of users: there were, for example, more than one billion users of Facebook and YouTube, and 500 million users of Twitter in 2013. In 2011, US consumers spent on average 3 hours per day on the Internet, including 30 minutes on social networks and 6 minutes on blogs.[7] On major social media, such as Twitter, Facebook or YouTube, music is a hot topic. On YouTube, for example, music artists' pages account for about half of the top 50 most popular pages.[8]

In contrast to traditional media channels, which push information towards passive consumers, online channels allow consumers to participate and interact, both with the content and between themselves. They can choose content that they like, follow or comment, and share their experiences, opinions and preferences with a large audience. User-generated content (UGC) on online platforms covers various forms of word-of-mouth (WOM), like consumer reviews, messages, blog posts, or video sharing. Although UGC may be displayed next to artist-generated content on online platforms, it differs in that the producer or the seller of the product does not directly create it.

For music artists, broadcasting on social media also represents an opportunity to foster fan-engagement in their marketing objectives: once consumers are aware and engaged, they may communicate their choice to other consumers online (e.g. through Facebook, Twitter, blogs, YouTube or Lastfm), which in turn may influence the decisions of other consumers. In online social networks, peers significantly increase music discovery, even in a network with extremely weak ties and where peers do not know each other such as Lastfm (Garg et al., 2011).

One stream of research studies the strategic use of UGC by firms. For instance, Aral and Walker (2011) examine how firms can generate word-of-mouth by designing viral features into their products and marketing campaigns. They compare information technology-enabled features like automated broadcast notifications and personalized invitations. Studying how firms can create viral campaigns, Godes and Mayzlin (2009) find that it may be more impactful for the firm to target less loyal customers to participate in a WOM campaign, contrary to the strategy of targeting loyal customers that is often advocated in the business and popular press. They show that for a product with

[7] Source: GfK/ IAB (2013), available at: http://www.iab.net/DigitalVideo45.
[8] See: http://vidstatsx.com/youtube-top-100-most-viewed; http://fanpagelist.com.

an initially low awareness level, a WOM campaign is primarily beneficial to the extent that it results in the spread of information.

Most studies have dealt with the positive effects on product sales of UGC in social networks, e-commerce websites and blogs (see, for example, Dellarocas, 2003; Chevalier and Mayzlin, 2006; Dhar and Chang, 2009; Berger et al., 2010; Zhu and Zhang, 2010), and stressed the importance of product reviews from peers in the consumer decision-making process (Dellarocas et al., 2007; Smith et al., 2005).

Within this stream of research, some papers are more closely related to the long tail hypothesis. In the video game industry, Zhu and Zhang (2010) show that the impact of the number of reviews is stronger for less popular video games and for those consumers who are more experienced in their use of the Internet, suggesting that the informational role of reviews is more important when there is hardly no alternative means of information acquisition. For books, Berger et al. (2010) underline that negative reviews hurt sales of books by well-known authors, but increase sales of books with lower prior awareness. Studying a free form of music consumption (sampling music in blogs), Dewan and Ramaprasad (2012) show that the marginal effect of blogs and music popularity (measured by album sales) is a stronger determinant of sampling music for niche music (i.e., albums ranked outside the top 5,000 on Amazon) than for mainstream music.

In this paper, we consider that UGC about the artist acts as a form of decentralized promotion by the audience. Rather than studying the effect of UGC on music sales, we are interested in its impact on the promotion of music artists. We explore this issue for stars and underdogs, whom we distinguish by their *ex ante* popularity and their visibility in traditional media (press coverage). Our aim is to determine the extent to which audiences help underdog artists to overcome their lack of visibility.

We focus on the volume rather than the valence (i.e., positive or negative) of UGC, since we are interested in its effect on the visibility of niche products. Volume has an informational effect by creating awareness (Zhu and Zhang, 2010), whereas valence has a persuasive effect, by informing about product quality. This is consistent with the findings of Chen et al. (2013), who show that for music artists, there is a high correlation between the sales rank and the number of both positive *and* negative reviews on Amazon.

We would expect the volume of UGC to be relatively larger for niche products. Consumers may have more incentive to support promotion efforts by underdog artists, who lack visibility in traditional media channels or who are making their debut in the music industry. However, this view has been challenged by the findings of Dellarocas et al. (2010). Analyzing consumer behavior in posting online reviews of movies after consumption, they find a U-shaped relationship between a population's average propensity to review a movie and that movie's success. Consumers may prefer to post reviews of niche products that are less available and less successful in the market, but they also post reviews of products that many other people have already commented on.

The question of whether fans are more involved in online promotion for underdog artists than for stars is an empirical issue. To determine whether this is indeed the case, we control not only for observable artists' characteristics but also for the potential audience addressed by the artist. We posit the following hypothesis.

HYPOTHESIS 3 (H3). *The online audience of underdog artists is more engaged and active in their support of promotion efforts than that of star artists.*

We study fan-engagement and UGC in Section 5, on three online platforms: the official pages of an artist on LastFm and Amazon (comments and reviews), and the blogosphere (blog posts).

3. Data

We collected data on the visibility and promotion – offline and online – of almost 1,000 artists, over a 6-month period following a new album release. Offline, we consider artists' radio and press coverage. Online, we consider their presence on the main online platforms where music artists can be visible: e-commerce websites (Amazon and iTunes), social media (MySpace, Facebook and Twitter), streaming music services (LastFm), video-sharing websites (YouTube and DailyMotion),[9] and blogs.

Our dataset includes artists who announced a new album release towards the end of 2010. To identify these artists, we used the "New Releases" tab on Amazon.com, which lists forthcoming album releases on a daily basis. We recorded all the new release announcements from 5 October to 21 December 2010, and stopped when we reached about 1,000 valid artists. We included an artist in the dataset only if the new album was announced on Amazon.com at least 15 days before the release, in order to observe promotional activity undertaken before the release.[10] About 94% of the artists in our dataset had a release date between November 2010 and January 2011 (see Table A1 in the Appendix). Re-editions and compilation albums were ignored to focus only on new album releases. We also excluded certain musical genres like Classical, Children's music, Christian, Broadway and Vocalists, and specific categories such as Imports, Music Deals, and Soundtracks.

We then collected data about artists' characteristics, as well as their visibility and promotion, both offline and online, over a 6-month period following the album release. Due to missing values on 29 artists, for which the online data collection failed, we reduced our sample to 966 artists. In the next subsections, we present our data and give some descriptive statistics about (i) artists' characteristics, (ii) promotion on online media channels, and (iii) promotion on traditional media channels.

3.1. Artists' Characteristics

Some of the characteristics of an artist may influence the promotion of their album, both offline and online. For example, US solo pop artists may, on average, be more promoted in the mass media than Korean-pop artists, given their appeal for the mass market. Similarly, female artists and *superstar* artists may be more visible offline and online, as suggested by their longer album survival in charts

[9] DailyMotion is a video-sharing website, similar to YouTube, created in France in 2005, and which operates internationally (it is available in 16 languages and 34 localized versions). Although it is ranked the 31st most visited website in the world, and one of the world's largest video-sharing websites, statistics reveal the large advantage of the leader YouTube: in 2012, the number of monthly unique visitors was 112 million on DailyMotion and more than 1 billion on YouTube, and the number of videos hosted is about 30 million on DailyMotion and 120 million on YouTube.
[10] Out of 7,717 new releases scheduled on Amazon, we selected 998 artists for whom the release date was announced at least 15 days before the release. Since releases by popular artists are often announced in advance, this methodology also ensured that we included stars in our sample (e.g., Rihanna, Kanye West, Adele, and Norah Jones).

(Bhattacharjee et al., 2007). We therefore collected a set of variables that we use as control and explanatory variables in the econometric analysis.

We have information, for the 966 artists, about their musical genre, their origin, gender, years in the music business, whether they are solo artists or bands, and the number of music awards obtained.[11] The descriptive statistics are provided in Table A2 in the Appendix. The artists in our dataset belong to various genres of music: Rock (30%), Pop-Dance (20%), Electronic (14%), Rap-RnB-Soul (12%), Jazz-Blues (10%), and World Music (6%). Artists from English-speaking countries constitute an overwhelming majority — 49% coming from the United States and 15% coming from other Anglo-Saxon countries[12] — while 25% come from Continental Europe.[13] Bands represent 43% of the artists, and 80% of the artists are male.[14]

Our dataset also reflects the variety of careers in the music industry. Only 5% of artists in the database (i.e., 48 artists) have already won a Grammy award, and 10 artists have won more than five Grammies, reflecting the fact that a small number of established artists have been acknowledged by their peers. We use the date of the first album release as a proxy for the start of the career.[15] We find that 25% of the artists are debut artists – they entered the music industry in the last two years (i.e., 2010 or 2011) – while around 38% of them have between 3 and 10 years of experience in the music business, and around one third have more than 11 years of experience.

Finally, we introduce a measure of the "popularity" of an artist, prior to the release of her new album. To assess the popularity of an artist, we compute the ratio of previous albums that entered a Billboard chart, especially the Billboard 200,[16] to the total number of previous albums released by the artist. We refer to this variable as the artist's *ex ante* popularity index:[17] a value of 1 implies that all of

[11] We collected information on various online databases, such as Wikipedia, iTunes, Facebook, MySpace Allmusic, and the Grammy search database (available at http://www.grammy.com/nominees/search).
[12] Anglo-Saxon countries include United Kingdom (11%), Canada (2.3%) and Australia (1.5%).
[13] We use the iTunes, Facebook and MySpace page of the artist to retrieve her origin.
[14] Bands are described as "male" (resp., "female") if their members are all male (resp., female), and as "mixed" otherwise.
[15] Note that this measure tends to underestimate the time spent in the music business as, for example, artists may change bands during their careers.
[16] Billboard is an international music trade magazine. It publishes several internationally recognized music charts that track the most popular songs and albums in various categories on a weekly basis. The two most notable charts are the Billboard Hot 100, for songs, and the Billboard 200, for album sales. The Billboard 200 is a weekly ranking of the 200 highest-selling music albums and EPs in the United States, based on sales (both retail and digital) of albums in the United States. It is frequently used to convey the popularity of solo artists and groups.
[17] This *ex ante* popularity index is similar to the one proposed by Hammond (2013), who uses the number of previous albums by an artist that sold more than 100,000 units in the United States as a measure of popularity.

the artist’s catalog albums hit the Billboard 200, while a value of 0 implies that none of them did so. About 14% of artists have had at least one album in the Billboard 200, and the average index is about 0.58, with a standard deviation of 0.31. As a robustness check, we also compute a variant of the index by considering sub-charts of the Billboard in which artists could have been ranked, like the Top Jazz Albums.

3.2. Traditional Media Channels

We measure the visibility of an artist in traditional media with the global press coverage she received over the observation period. We collected data on the worldwide press coverage of each artist by recording the total number of press articles that mentioned the artist from October 2010 to June 2011.[18] About 32% of artists (i.e., 306 artists) were quoted at least once in press articles over this period. On average, artists were quoted in 5 articles, with a maximum of 550 articles and a standard deviation of 28. Note that an article in the press about an artist might deal with the release of her new album, or about other types of event (e.g., a live concert). In any case, we consider that it increases the offline visibility of the artist (i.e., consumers’ awareness).

3.3. Online Media Channels

We collected daily data with a software robot on each artist’s official page on 8 online platforms, over a rolling 6-month window following the new release. These 8 platforms consist of two e-commerce websites (Amazon.com, iTunes.com), three social networking websites (MySpace, Facebook, Twitter), one streaming music service (LastFm), and two video-sharing websites (YouTube, DailyMotion). We also considered a ninth online platform, the "blogosphere".[19]

All the 966 artists were present on Amazon.com, since we constructed our dataset of artists using this platform. On the other online retailer, iTunes, 63% of artists were represented. The high participation rate on LastFm (90%) is due to the platform’s editorial policy, which creates artists’

[18] We used an aggregator called Factiva that lists more than 30,000 newspapers and magazines worldwide. For each of the 1,000 artists in the dataset, we searched for the artist’s name and album title while restricting our research to the music field (without filtering on languages and countries).
[19] The term “blogosphere”, coined in 2001 by the novelist and blogger William Quick, is commonly used to describe the community of blogs on the World Wide Web. Weblogs, or blogs, are self-publishing media on the Web, which can be linked to each other by hypertext links.

pages rather than letting them or their labels do so. By contrast, social networks like Facebook, Twitter and MySpace let artists create their own profile and gather an audience of "fans", "followers" or "friends". In our observation period, artists were using Facebook (74%) and MySpace (79%) more than Twitter (39%). As regards video-sharing websites, about 25% of artists had an official page on YouTube, and only 2% on DailyMotion. Finally, around 47% of artists were quoted at least once in a blog during the observation period.

We collected four types of information on the online platforms, according to the design of each platform: information about artist's visibility on online media channels (i.e., whether the artist is represented on the platform), information about artists' broadcasting activities in social media (artist-generated content), information about the activity of the artist's audience (user-generated content), and information about the artist's online reputation in social media (e.g., the number of fans or followers) and digital consumption (e.g., music or video streaming). Table A3 in the Appendix summarizes the online data collected and provides their descriptive statistics.

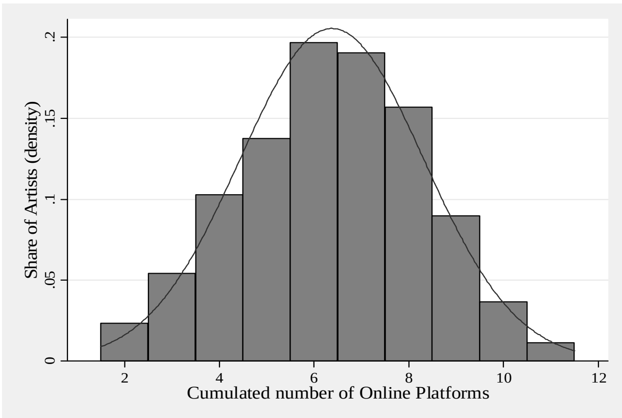
4. Toward the Democratization of Visibility?

In this section, we study whether online promotion democratizes access to visibility among music artists. The presence in offline media channels is very unevenly distributed among the artists in our dataset. We find that 68% of them (i.e., 660 artists) were not quoted in the press during the 6-month period following the new release. Moreover, the press focuses on a small number of artists: 6% of artists (and 16% of the artists who have been quoted at least once in the press) cumulated 80% of the press coverage.

Press coverage does not appear to be randomly distributed among artists either. An "elite" of star artists attracts most of the attention from offline media: the number of awards received and *ex ante* popularity are both positively and significantly correlated at the 1% level with press coverage (with correlation coefficients of 0.62 and 0.29, respectively). We also find positive and significant correlations at the 1% level between press coverage and the size of the artist's catalog (0.09), and whether the artist is female (0.14).

Does this elite also dominate the online channels, or do we observe a democratization of visibility in online media? To investigate this question, we evaluate the online visibility of an artist by counting the number of platforms she has joined. In other words, we view an online platform (such as YouTube, Facebook or Twitter) as a communication medium for an artist, equivalent to newspapers or radio channels. We find that the number of online platforms for an artist follows a Gaussian distribution, as illustrated in Figure 1, with most artists present on five to seven online platforms.

Figure 1. Gaussian distribution of online visibility



It therefore appears that IT have allowed almost all artists to become visible online to consumers. However, we still have to check whether the artists who are most visible offline are also the most visible online, or whether online visibility is independent of offline visibility.

In Figure 2, we plot the Lorenz Curve of visibility across offline platforms, showing a strong inequality in the distribution of visibility in traditional media; the Gini Coefficient[20] is estimated at about 0.93. For each artist of a given rank in offline media,[21] we then plot the number of online platforms they have joined on the lower graph. The solid curve is the moving average trendline (with period equal to 50).

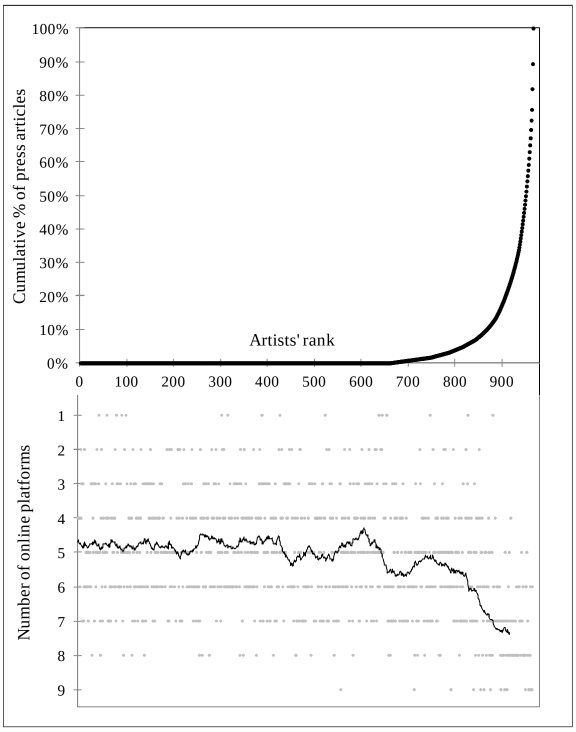
We find weak evidence of democratization of visibility, which suggests that H1 is valid. First, the Gini index of online visibility is estimated at about 0.19, suggesting a lower inequality in the

[20] The Lorenz Curve (Lorenz, 1905) and the Gini Coefficient (Gini, 1912) are often used to describe inequality in the distribution of assets. When assets are perfectly evenly distributed across products, the Lorenz Curve shows a 45-degree line, and the Gini Coefficient is equal to 0.

[21] In this figure, we view the press coverage of an artist as a proxy for the number of offline platforms (i.e., the number of newspapers or magazines) that they joined. We observe a high correlation between the number of articles and the number of outlets for an artist. For example, the most covered artist, Norah Jones, accounts for 160 articles from 100 different press sources, the band Weezer has 30 articles from 27 press sources, and Bear Hands has 4 articles from 4 sources.

distribution of online visibility among artists, compared with offline visibility. Second, IT allow underdogs to access visibility: two-thirds of artists, who were not visible offline, are on average visible on five online platforms.

Figure 2. Offline Visibility versus Online Visibility



However, visibility *per se* is not sufficient to achieve success. Artists compete for scarce consumer attention in the information-rich context (Anderson and de Palma, 2013). In Figure 2, the level of online visibility roughly reflects the hierarchies established in traditional media, and we find a significant and positive correlation (0.21) between the number of online platforms in which artists have a presence and the number of offline platforms (i.e., "articles"). Even if IT may democratize access to visibility, we want to assess whether underdogs compete on a level-playing field with the stars for online visibility, which requires analyzing visibility in relative rather than absolute terms.

Besides, the above analysis of the correlation between offline and online visibility is on average and does not control for artist-specific characteristics. We therefore now conduct an econometric analysis that controls for the observable characteristics of artists. With this analysis, we seek to determine who benefits from visibility in the offline and online worlds.

To begin with, we analyze the determinants of the visibility of an artist in traditional media. We estimate the following model:

$$ln(PressCoverage)_i = \beta_1 Popularity_i + \beta_2 \text{Awards}_i + \beta_3 Debut_i + \beta_4\ MusicalGenre_i + \beta_5 Origin_i + \beta_6 Female_i + \beta_7\ Band_i + \varepsilon_i. \quad (1)$$

As dependent variable, we use the logarithm of the total number of press articles about artist *i* over the 6-month period surrounding her new album release.[22] We include as explanatory variables the total number of awards received by the artist before the release of the new album and their *ex ante* popularity index relative to the Billboard 200.[23] The control variables are the artists' musical genre, their origin, gender, whether they are solo artists or bands and whether they are debut artist or not (i.e., have been active since 2010 or 2011 only).

We estimate model (1) with ordinary least squares. The estimation results are presented in Table 1 below. The coefficients for *Popularity* and *Awards* are both statistically and positively significant at the 1% level, suggesting that offline visibility is partly determined by the popularity and critical acclaim that artists have already received in the past. We also observe that the indicator variable *Debut* is negative and significant at the 5% level. Thus, everything else equal, star artists are more likely to obtain visibility in traditional media channels than underdogs or debut artists. In addition, we find that some artists' characteristics significantly influence mass media attention, either positively, like being female, or negatively, like the musical genres Hip-Hop-RnB-Soul and Electronic.

Likewise, we study the determinants of the visibility of artists in online media. We use the following ordered probit model:

$$y_i^* = X_i\,\beta + \varepsilon_i,$$

[22] As the dependent variable can take the value 0 (some artists have received no press coverage), we add 0.1 to the variable before the log transformation. The choice of different numbers does not influence the results.
[23] As a robustness check, we used other measures of "*ex ante* popularity" in our regressions. First, we used a dummy variable equal to 1 if the artist has already hit the Billboard 200, and to 0 otherwise. Second, we used the Billboard sub-charts in addition to the Billboard 200 (see Table A2 in Appendix for the descriptive statistics). We obtained similar qualitative results with these alternative measures of popularity.

where y_i^* is a latent variable measuring the online visibility of the i^{th} artist; X_i is a (k*1) vector of observed nonrandom explanatory variables; β is a (k*1) vector of unknown parameters; ε_i is the random error term. For any artist, it is reasonable to expect that a high probability of high online visibility is translated into a high level of observed online visibility y_i through the threshold values μ_n (where n = 2…9 is the number of online platforms where the artist has a presence). We estimate the following model by the method of maximum likelihood, with the same control and explanatory variables as in equation (1):

$$OnlinePlatforms_i = \beta_1 Popularity_i + \beta_2 \text{Awards}_i + \beta_3 Debut_i + \beta_4 MusicalGenre_i + \beta_5 Origin_i + \beta_6 Female_i + \beta_7 Band_i + \varepsilon_i . \quad (2)$$

We also estimate the following variant, where the artists' visibility in traditional media is included as an independent variable. The estimation results are presented in Table 1 below.

$$OnlinePlatforms_i = \beta_1 \ln(PressCoverage)_i + \beta_2 Popularity_i + \beta_3 \text{Awards}_i + \beta_4 Debut_i + \beta_5 Musical\ Genre_i + \beta_6 Origin_i + \beta_7 Female_i + \beta_8 Band_i + \varepsilon_i . \quad (3)$$

In both models (2) and (3), a higher *Popularity* is associated with a higher level of online visibility, while the indicator variable *Debut* is associated with *decreased* online visibility. In the estimation results for model (3), we also observe that higher *PressCoverage* is associated with higher online visibility. Everything else equal, artists who benefit from large press coverage also enjoy large coverage in online media. Therefore, although underdog artists benefit from a higher visibility online than offline, which supports H1, star artists still benefit from a higher visibility in both traditional and online media.

Table 1. Artist's Visibility in Offline and Online Media

	Visibility in Offline Media	Visibility in Online Media	
	Model (1)	**Model (2)**	**Model (3)**
Press Coverage			*0.227 ****
			(0.036)
Ex ante Popularity	*3.585 ****	*1.833 ****	*1.184 ****
	(0.262)	*(0.174)*	*(2.688)*
Awards	*0.203****	*0.075 ***	*0.037*
	(0.054)	*(0.036)*	*(0.036)*
Debut	*-0.302 ***	*-0.408 ****	*-0.362 ****
	(0.127)	*(0.079)*	*(0.079)*
Female	*0.672 ****	*0.110*	*-0.032*
	(0.140)	*(0.087)*	*(0.086)*
Band	*-0.035*	*0.044*	*0.059*
	(0.124)	*(0.077)*	*(0.077)*
Musical Genre:			
Rock	*-0.229*	*0.662 ****	*0.748 ****
	(0.245)	*(0.142)*	*(0.143)*
Pop/Dance	*-0.552*	*0.537 ****	*0.693 ****
	(0.246)	*(0.145)*	*(0.146)*
Jazz/Blues	*-0.176*	*-0.016*	*-0.021*
	(0.278)	*(0.163)*	*(0.163)*
Rap/RnB/Soul	*-0.855 ****	*0.812 ****	*1.060 ****
	(0.285)	*(0.164)*	*(0.166)*
Electronic	*-0.751 ***	*0.501 ****	*0.699 ****
	(0.240)	*(0.155)*	*(0.156)*
World	*0.320*	*0.426 ***	*0.378 ***
	(0.334	*(0.183)*	*(0.183)*
Origin Area:			
Continental Europe	*-0.145*	*0.333 **	*0.385 ***
	(0.213)	*(0.169)*	*(0.171)*
United States	*0.165*	*0.289 **	*0.266*
	(0.217)	*(0.164)*	*(0.165)*
Anglo-Saxon Countries	*0.643 ***	*0.389 ***	*0.267*
	(0.253)	*(0.176)*	*(0.177)*
Latin countries	*-0.010*	*0.064*	*0.071*
	(0.278)	*(0.202)*	*(0.202)*
# of obs.	958	958	958
R-sq.	0.32	0.07	0.10

Standard errors are in parentheses; *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

5. Artist’s Broadcasting Activities and Fans’ Activities

In this section, we study whether underdog artists and their fans make larger efforts than stars, to make up for the asymmetry of visibility among artists in the offline world. We first compare artist-generated content of stars and underdogs, and then proceed with the same type of analysis for user-generated content.

5.1. Artist-Generated Content

We study artist-generated content over the 6-month period following an artist’s new release on two social media sites: a social network, Twitter, and a video-sharing website, YouTube. We measure an artist’s activity by the number of tweets sent from their account on Twitter and the number of videos posted on the artist page on YouTube. On average, over the 6-month period, the 231 artists who had a YouTube page posted 6 videos each and the 372 artists with a Twitter account sent 893 tweets each (see Table A3 in the Appendix).

To explore artists’ broadcasting activities, we first divide up our dataset between the artists who have a presence in offline media (i.e., 306 artists who are quoted at least once in the press) and those who do not (660 artists). As Table 2 shows, artists’ broadcasting activities are similar in both groups. However, a *t*-test on the equality of means shows that the difference in the number of videos is statistically significant at the 5% level, while the difference is not statistically significant for Twitter.

Table 2. Artists’ broadcasting activities

		Obs.	Mean	Std.	Min.	Max.
Number of Videos posted (YouTube)	With press coverage	118	7.2	10.8	0	60
	Without press coverage	113	4.3	9.2	0	68
	Total	231	5.8	10.2	0	68
Number of Tweets sent (Twitter)	With press coverage	170	867	1,857.1	0	15,359
	Without press coverage	202	914.3	2,534.2	0	22,070
	Total	372	892.9	2,247.5	0	22,070

The key question is, conditional on joining a platform[24], whether underdog artists make relatively higher broadcasting efforts, compared to popular artists, to compensate for their lack of visibility in offline media. To investigate this question, we use a linear model where the dependent variable is the level of broadcasting activities in social media of artist *i* over the 6 month-period following the new album release: (i) on YouTube (using the logarithm of the total number of videos posted), (ii) on Twitter (using the logarithm of the total number of tweets sent).[25]

We estimate the following model, which includes the same control variables and explanatory variables as equation (3), with ordinary least squares:

$$ln(ArtistActivity)_i = \beta_1\, ln(PressCoverage)_i + \beta_2 Popularity_i + \beta_3 \text{Awards}_i + \beta_4 Debut_i + \beta_5 MusicalGenre_i + \beta_6 Origin_i + \beta_7 Female_i + \beta_8\, Band_i + \varepsilon_i. \qquad (4)$$

The estimation results are presented in Table 3 (see model (4)). We find that *PressCoverage* is statistically significant at the 5% level on both platforms, YouTube and Twitter, meaning that artists' visibility in traditional media is positively associated with their online promotion efforts. However, once the platform is joined, an artist's popularity has no significant effect on their broadcasting activities, suggesting that broadcasting activities of less-popular artists are similar to those of popular artists.[26] Yet, the costs of online promotion for less-popular artists are probably higher than for popular and established artists, for whom online promotion is likely to be financed by their record labels. Our findings therefore partially support H2 since online efforts made by less-popular artists could be higher than those made by popular artists, even though underdog artists are less engaged on platforms like YouTube or Twitter.

[24] Note that star artists are more committed to YouTube and Twitter than underdogs: among the artists who benefit from press coverage, 38% own a YouTube page and 55% have a Twitter account, while among the artists without press coverage, 17% own a YouTube page and 31% have a Twitter account.
[25] As the dependent variable *ArtistActivity* may be equal to 0 (some artists have not sent any messages on their Twitter account or uploaded any videos to their YouTube page), we add 0.1 to the variable before the log transformation.
[26] As a robustness check, we also estimated model (4) without *PressCoverage* as explanatory variable. With this alternative specification, *Popularity* is still not statistically significant.

Table 3. Artist-Generated Content and User-Generated Content

	Artist-Generated Content		User-generated Content		
	Model (4)		Model (5)		
	Posting videos (YouTube)	Micro-blogging (Twitter)	Reviews (Amazon)	Comments (LastFm)	Posts (Blogs)
Press Coverage	*0.163 *** *(0.065)*	*0.191 *** *(0.078)*	*0.001* *(0.056)*	*-0.041* *(0.046)*	*-0.079* *(0.063)*
Ex ante Popularity	*-0.283* *(0.467)*	*0.162* *(0.576)*	*-1.678 **** *(0.489)*	*-1.401 **** *(0.401)*	*-1.674 **** *(0.491)*
Awards	*-0.012* *(0.084)*	*-0.045* *(0.121)*	*-0.104* *(0.489)*	*0.040* *(0.075)*	*-0.061* *(0.095)*
Debut	*-0.575 ** *(0.329)*	*0.351* *(0.355)*	*1.801 **** *(0.235)*	*1.554 **** *(0.192)*	*1.880 **** *(0.262)*
Female	*-0.456* *(0.298)*	*0.158* *(0.343)*	*0.368* *(0.257)*	*0.481 *** *(0.210)*	*-0.567* *(0.550)*
Band	*0.283* *(0.313)*	*-0.053* *(0.357)*	*-0.045* *(0.224)*	*0.427 ** *(0.183)*	*0.180* *(0.262)*
Musical Genre:					
Rock	*0.155* *(0.641)*	*-0.250* *(0.660)*	*-1.019 *** *(0.416)*	*0.871 *** *(0.341)*	*-0.567* *(0.550)*
Pop/Dance	*0.234* *(0.638)*	*0.296* *(0.662)*	*-1.338 **** *(0.424)*	*0.122* *(0.347)*	*-0.471* *(0.563)*
Jazz/Blues	*-0.169* *(0.772)*	*-2.134 *** *(0.852)*	*0.978 *** *(0.480)*	*0.665 ** *(0.393)*	*0.374* *(0.655)*
Rap/RnB/Soul	*0.503* *(0.645)*	*0.223* *(0.663)*	*-0.262* *(0.469)*	*0.832 *** *(0.385)*	*0.473* *(0.550)*
Electronic	*0.451* *(0.780)*	*-0.594* *(0.764)*	*-1.719 **** *(0.449)*	*0.076* *(0.368)*	*-0.717* *(0.573)*
World	*0.613* *(0.736)*	*-0.754* *(0.793)*	*-0.314* *(0.540)*	*-0.267* *(0.443)*	*-0.238* *(0.714)*
Origin Area:					
Continental Europe	*1.540* *(0.922)*	*-1.281* *(0.844)*	*-0.240* *(0.415)*	*0.364* *(0.402)*	*0.951* *(0.649)*
United States	*2.271 *** *(0.888)*	*-0.602* *(0.779)*	*0.501* *(0.480)*	*0.380* *(0.394)*	*0.653* *(0.638)*
Anglo-Saxon Countries	*2.259 *** *(0.921)*	*-0.834* *(0.841)*	*0.324* *(0.513)*	*0.588* *(0.421)*	*1.132 ** *(0.667)*
Latin countries	*2.853 *** *(0.929)*	*-1.108* *(0.984)*	*-0.410* *(0.593)*	*-0.062* *(0.486)*	*0.064* *(0.797)*
# of obs.	230	371	868	868	423
R-sq.	0.14	0.08	0.16	0.15	0.19

Standard errors are in parentheses; *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

5.2. User-Generated Content

User-Generated Content (UGC) about an artist can be viewed as a form of decentralized promotion by their audience. Consumers actively promote the artist, for example by reviewing their new album on Amazon or by posting comments about the artist in social media and blogs.

Over the 6-month period, artists received on average 5 reviews on Amazon, 66 comments on LastFm and 37 blog posts, but some of them received 306 reviews on Amazon, 13,621 comments on LastFm and 1,807 blog posts (see Table A3 in the Appendix). We also note that there is no audience activity for a large proportion of the artists in the sample. For example, 63% of artists received no comments on Amazon (the corresponding percentages are 39% for LastFm and 52% for the blogosphere).

We split our sample between the artists who have a presence in traditional media (i.e., who are quoted at least once in the press) and those who have none. Table 4 below compares UGC for the two groups of artists and shows that UGC is much larger for the artists with a presence in the offline media (a *t*-test shows that all differences are statistically significant at the 1% level).

Table 4. User-generated content

		Obs.	Mean	Std.	Min.	Max.
Number of Reviews (Amazon)	With press coverage	306	14.5	33.9	0	306
	Without press coverage	660	0.8	7.1	0	172
	Total	966	5.1	20.9	0	306
Number of Comments (LatsFm)	With press coverage	288	177.9	987	0	13,621
	Without press coverage	586	11.3	56.8	0	894
	Total	874	66.2	573.2	0	13,621
Number of Posts (Blogs)	With press coverage	306	87.9	230.6	0	1,807
	Without press coverage	660	12.9	60.7	0	1,291
	Total	966	36.7	143.3	0	1,807

However, these absolute numbers do not control for an artist's audience, in particular online. Although audience activity is larger for the stars in absolute terms, the audience of underdog artists may be relatively more engaged and active.

To explore this question, we use a linear model where the dependent variable is the logarithm of the "audience activity ratio" of artist *i*. The audience activity ratio represents the ratio of the audience activity for artist *i* over the potential audience of the same artist. To evaluate the potential audience of an artist, we use the total number of listeners to artist *i* on the LastFm platform since the creation of the artist's page.[27] For the audience activity of the artist, we use the volume of user-generated content around artist i, over the 6-month period following the new album release, on the following online platforms: (i) LastFm (total number of comments on the artist's page), (ii) Amazon (total number of reviews on the artist's page), (iii) blogosphere (total number of blog posts about the artist over the 6-month period).[28] We use the following model, which includes the same control variables as the other models:

$$ln(\,AudienceActivityRatio)_i = \beta_1\, ln(PressCoverage)_i + \beta_2 Popularity_i + \beta_3 \mathrm{Awards}_i$$
$$+ \beta_4 Debut_i + \beta_5\, MusicalGenre_i + \beta_6 Origin_i + \beta_7 Female_i + \beta_8\, Band_i + \varepsilon_i. \qquad (5)$$

The estimation results are reported in Table 3 above (see model (5)). For the three online platforms, *Popularity* and *Debut* are statistically significant at the 1% level. An interesting finding is that *Popularity* has a negative effect on the audience activity ratio, while *Debut* has a positive effect. In other words, the audiences of less popular and debut artists are more engaged in their promotion, compared with the audiences of star artists, which is consistent with H3.

5.3. Summary of Findings

We now summarize in Table 5 below the results of the hypothesis testing, and discuss our major findings.

As regards to our first hypothesis about the democratization of visibility, our results suggest that underdog artists, who lack of exposure in traditional media, bypass the traditional promotion bottleneck and access visibility through online platforms. However, since artists compete for online attention, star artists, who are already popular and benefit from larger press coverage than underdogs, also enjoy a higher visibility in online media. In sum, though the barriers to visibility are much lower online than they are offline, it turns out that the most popular and visible artists in offline markets are also the most visible in online markets.

[27] Lastfm has a presence in over 200 countries, about 12 million artists (on major and independent labels, as well as unsigned artists) and more than 40 million users. We therefore assume that the total number of listeners of an artist on Lastfm (since the creation of their profile) is a consistent proxy for the potential online audience of the artist.
[28] We added 0.1 to the variable at the numerator before the log transformation, since some artists have received no audience activity on Amazon, LastFm or the blogosphere.

Turning to the second hypothesis, our results suggest that broadcasting activities of the artists in online media is independent of their *ex ante* popularity, but not of the press coverage they have received. Indeed, artists who benefit from visibility in traditional media are also the most represented on online platforms. Assuming a higher cost of online promotion for less-popular artists than for popular and established artists who are helped by their record labels, our second hypothesis would be partially supported: online efforts made by less-popular artists are higher than those made by popular artists in order to overcome their lack of visibility. At the same time, higher broadcasting activities is also associated with higher press coverage, which may suggest some synergies between offline and online promotion.

Finally, our results support the third hypothesis, that is, audiences of less popular and debut artists are more strongly engaged in their promotion, compared with the audiences of stars. Online audiences appear to support promotion efforts made by underdogs to bypass the traditional bottleneck of promotion, while they may feel less inclined to promote the stars, who are already very popular.

Table 5. Hypotheses Testing Results

H1	*Partially supported*	IT allow underdog artists to access visibility, but the most popular and visible artists in offline markets are also the most visible in online markets.
H2	*Partially supported*	Artists' broadcasting activities are independent of their *ex ante* popularity, but positively associated with their offline visibility.
H3	*Supported*	The online audience of underdog artists is more engaged and active in their support of promotion efforts than that of stars.

6. Dynamic Analysis

In this section, we exploit the cross-sectional and time-series variations of our data with two objectives. Our first objective is to study the causal relationships between artists’ broadcasting activities, fans’ activities and artists’ exposure in traditional media. More specifically, we wish to answer two questions. First, do the broadcasting activities of an artist stimulate her fans' activities and influence her exposure in traditional media? Second, is there a bidirectional relationship between the promotion by the fans and the coverage from traditional media? Do fans tend to promote what the mainstream media already promote? Conversely, do the online activities of an artist's fans attract the attention of traditional media towards the artist? Our second objective is to study the effects of online promotion on digital consumption for the artists who benefit from visibility in traditional media and for those who do not, by controlling for heterogeneity among artists (e.g., in terms of musical genre or quality).

6.1. Model Identification

We study the relationships between the promotion performed around an album release — artists' exposure in traditional media (press coverage) and artists' broadcasting activities in social media (artist-generated content) — audience activities (user-generated content), artist's online reputation (number of fans), and a free form of consumption of the artists' online contents (music streaming).

To overcome endogeneity issues between the time series variables used in our regression, we adopt a panel vector autoregression model (PVAR), as suggested by Chen et al. (2013) and Dewan and Ramaprasad (2014), which works especially well when there is a potential reverse causality of dependent and independent variables. The use of a panel VAR, with the GMM estimator, addresses the endogeneity issue, because this method treats all the time series variables in the system as endogenous, and employs lagged dependent variables as instruments.

We use the following time series variables in our model for artist *i* at day *t*: $ArtistPost_{it}$ (messages sent by the artist on Twitter), $ConsumReviews_{it}$ (consumer reviews on Amazon), $Fans_{it}$ (subscribers of the Facebook page), $MusicStream_{it}$ (music plays on LastFm), and $TradExposure_{it}$ (press articles).[29]

We estimate a panel vector autoregression (PVAR) model to examine the dynamic interactions between the promotional actions for a new album release (in a 75-day window, from 14 days pre-release to 60 days post-release), artists' online reputation, and digital consumption. We adopt the reduced form of the VAR model in which each dependent variable is endogenous and is a linear

[29] We also tested an alternative model with 7 variables, by counting $ConsumPosts_{it}$ (consumers' posts on Lastfm) as a proxy for user-generated content, and $Followers_{it}$ (subscribers to the artist's Twitter account) as a proxy for the online reputation of the artist. As Tables A4 and A5 in the Appendix show, it does not affect our qualitative results.

function of its own past values, the past values of all other dependent variables and an error term. The panel structure of the data also allows us to control for unobserved individual heterogeneity. We specify a first-order VAR model (6) as follows:[30]

$$y_{i,t}^{\tau} = \beta^{\tau} y_{i,t-1} + f_i^{\tau} + d_t^{\tau} + \varepsilon_{i,t}^{\tau}, \tag{6}$$

where $y_{i,t}^{\tau}$ is an $\tau \times 1$ vector of dependent variables for artist *i* at time *t*, containing the log transformation of {*ArtistPost*, *ConsumReviews*, *Fans*, *MusicStream*, *TradExposure*}; $y_{i,t-1}$ is an $\tau \times 1$ vector of lagged endogenous variables, β^{τ} is an $\tau \times 1$ vector of slope coefficients; f_i^{τ} is an $\tau \times 1$ vector of unobserved individual effects, characterizing artists' time-invariant attributes (such as music genre, quality, or *ex ante* popularity); d_t^{τ} is a vector of time dummies that control for any time effects, and $\varepsilon_{i,t}^{\tau}$ is a vector of the idiosyncratic errors.

In order to eliminate time and artist fixed effects, we make two transformations. First, we remove time fixed effects by subtracting from each variable their means for each day (i.e., the data are time-demeaned). Then, we transform all variables in the model to deviations from forward means (Helmert's transformation) to remove artists' fixed effects. Artist specific effects are correlated with the regressors by virtue of the lag dependent variable, so the mean differencing procedure commonly used to eliminate these fixed effects will create biased coefficients (Love and Zicchino, 2006). To avoid this issue, we use forward-mean differencing (see Arellano and Bover, 1995).

We include artists represented on Amazon, Facebook, Twitter, and LastFm in the regression only if we can observe data from 14 days before the new album release to 60 days after the release (T=75). Due to some missing data for the LastFm platform after March 13, 2011, we restrict our attention to artists who released a new album before January 13, 2011. We then estimate the model on a first subset of artists with a presence in traditional media channels (the stars) and a subset of artists who do not benefit from visibility in traditional media (the underdogs).

[30] The empirical analysis was conducted using the package provided by Love and Zicchino (2006).

6.2 Estimation Results

The estimation results are reported in Table 6 and 7. We first discuss the impact of artists' broadcasting efforts on fans' activities. It turns out that the results are different depending on whether we consider user-generated content (*ConsumReviews*) or the artist's online reputation (*Fans*). For all artists, broadcasting in social media tends to increase the artist's online reputation (i.e., her number of *Fans*). By contrast, the coefficient estimate for *ArtistPosts* in the *ConsumReviews* equation is significant only for the group of artists without exposure in traditional media. This suggests that only for underdog artists, broadcasting encourages fans to post reviews about their preferred artist. Let us now turn to the impact of artists' broadcasting activities on their exposure in traditional media. As can be seen from Table 6, the coefficient of *ArtistPosts* in the *TradExposure* equation is not significant. In other words, artists seem unable to attract more press coverage by broadcasting messages in social media.

We proceed by analyzing the bi-directional causal relationships between promotion by fans and promotion by traditional media, and focus on artists who benefit from visibility in traditional media. From Table 6, we observe that exposure in traditional media (*TradExposure*) influences positively artists' online reputation (*Fans*) and user-generated content about the artist (*ConsumReviews*). From the *TradExposure* equation, we can see that the relationships between these variables are bi-directional: an artist's coverage in traditional media is also influenced positively by her online reputation (*Fans*) and her fans' activities in social media (*ConsumReviews).* In sum, traditional media pay attention to what is happening in online media, especially in terms of online reputation.

Finally, we discuss the effects of online promotion on music streaming. We first observe that artists' broadcasting activities (*ArtistPosts)* have no direct impact on music streaming (*MusicStream*), for all types of artists. For the star artists (Table 6), exposure in traditional media (*TradExposure*) has a positive effect on digital consumption, while online reputation in social media (*Fans*) and user-generated content (*ConsumReviews*) have no effect. By contrast, online reputation and user-generated content have a positive effect on music streaming for underdog artists (see Table 7). Furthermore, the relationship between user-generated content and music steaming is bi-directional (the estimated coefficient for *MusicStream* is positive and significant in the *ConsumReviews* equation), which is consistent with the prior literature on the dynamic relationship between word-of-mouth and sales (word-of-mouth fosters more sales, which in turn generate more word-of-mouth).

Table 6. Panel VAR Coefficients for Artists *with* Visibility in Traditional Media (N=110)

Independent Variable	Dependent Variable				
	$ArtistsPosts_t$	$ConsumReviews_t$	$Fans_t$	$MusicStream_t$	$TradExposure_t$
ArtistsPosts $_{t-1}$	0.386 *** (0.019)	0.004 (0.014)	0.027 *** (0.007)	0.093 (0.066)	-0.012 (0.013)
ConsumReviews $_{t-1}$	-0.041 (0.022)	0.323 *** (0.022)	0.005 (0.017)	-0.021 (0.083)	0.097 *** (0.014)
Fans $_{t-1}$	0.086 (0.177)	0.455 *** (0.150)	0.438 *** (0.070)	-0.156 (0.652)	0.665 *** (0.012)
MusicStream $_{-1}$	-0.015 *** (0.004)	0.003 (0.003)	-0.003 (0.002)	0.155 *** (0.017)	0.019 *** (0.003)
TradExposure $_{t-1}$	0.052 (0.029)	0.073 *** (0.026)	0.032 *** (0.009)	0.238 *** (0.103)	0.228 *** (0.027)

Notes: Variables are logged and forward mean-differences; ** and * denote significance at 1% and 5% and number in parentheses are standard errors.

Table 7. Panel VAR Coefficients for Artists *without* Visibility in Traditional Media (N=142)

Independent Variable	Dependent Variable			
	$ArtistsPosts_t$	$ConsumReviews_t$	$Fans_t$	$MusicStream_t$
ArtistsPosts $_{t-1}$	0.256 *** (0.021)	0.010 *** (0.005)	0.038 *** (0.018)	0.065 (0.051)
ConsumReviews $_{t-1}$	0.048 (0.071)	0.402 *** (0.060)	0.037 (0.040)	0.506 *** (0.229)
Fans $_{t-1}$	0.041 (0.029)	0.025 *** (0.006)	0.270 *** (0.033)	0.240 *** (0.075)
MusicStream $_{t-1}$	0.008 (0.006)	0.003 *** (0.001)	0.005 (0.006)	0.240 *** (0.015)

Notes: Variables are logged and forward mean-differences; ** and * denote significance at 1% and 5% and number in parentheses are standard errors.

To sum up, for star artists, broadcasting and fans' activities have little effect on online consumption, which remains mainly driven by the level of exposure in traditional media. By contrast, for underdogs, broadcasting and fans' activities have a positive effect on digital consumption, either directly or indirectly. Thus, although all the artists, be they stars or underdogs, rely on social media to promote their music, it seems that the underdogs are the ones who benefit the most from online promotion.

7. Conclusion

In this paper, we have studied whether, in the music industry, online promotion (including online visibility, artists' broadcasting activities and user-generated content) benefits underdog artists. We used data about visibility and promotion – both offline and online – for a sample of 1,000 artists who released a new album at the end of 2010. On the one hand, we considered artists' visibility in print media (press coverage), and on the other hand, their presence on nine major online platforms (Amazon, iTunes, MySpace, Facebook, Twitter, LastFm, YouTube, DailyMotion and blogs).

Although our preliminary findings provide weak evidence of the democratization of visibility, when controlling for artist-specific characteristics our econometric results suggest that an elite of star artists still has a higher level of visibility in both the traditional world and the digital world. Yet, we find that the broadcasting activities of less-popular artists are similar to those of popular artists, even if the average cost of online promotion activity is probably higher for the former. We also showed that the audiences of underdogs and debut artists are more engaged and active in their promotion than the audiences of stars. Online audiences appear to support promotion efforts made by underdogs to bypass the traditional bottleneck of promotion, while they may feel less inclined to promote the stars, who are already popular.

Using a panel vector autoregression model (PVAR), we disentangled the dynamic relationships between online promotion, traditional promotion and online consumption (music streaming) for stars and underdogs. Our results suggest that the promotion supported by audiences, both through word-of-mouth and by building artists' online reputations, has a positive effect on music streaming for underdogs. Although artists' broadcasting activities in social media have no direct impact on music streaming (for either group of artists), it positively affects artists' online reputations (for both groups) and user-generated content (for underdogs).

We therefore suggest that the ongoing development of IT, especially of social media, could benefit underdog artists who suffer from incomplete consumer information, and may portend a shift towards the consumption of niche products.

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APPENDIX

Table A1. Distribution of Albums' Release Date

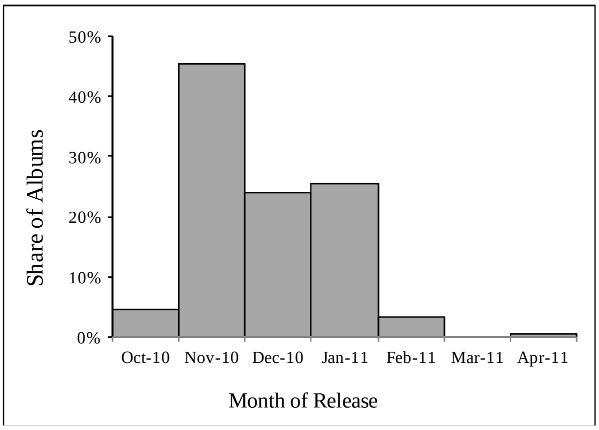

Table A2. Artists' Characteristics

Musical Genre		
Genre	# of Artists	Percent (%)
Rock	291	30
Pop/Dance	198	20
Electronic	134	14
Rap/RnB	112	12
Jazz/Blues	98	10
Others	73	8
World	60	6
Total	966	100

Gender and Formation				
Variables	Men	Female	Mixed	Total
Solo	444	98	0	542
Band	339	11	66	416
Total	783	109	66	958
Note: 8 artistes with missing values on gender and formation				

Origin		
Area	# of Artists	Percent (%)
United States	478	49
Continental Europe	232	25
Anglo-Saxon Countries	147	15
Latin countries	63	7
Others	46	5
Total	966	100

Career Duration		
Time since 1st	# of Artists	Percent (%)
1 year	58	6
2 years	178	18
3 to 10 years	370	38
> to 11 years	327	33
Missing values	33	3
Total	966	100

***Ex ante* Popularity**		
Charts	# of Artists	Freq.
Billboard 200	136	14%
Other Billboard Charts	71	7%
No Billboard Charts	759	79%
Total	966	100%

Awards Received	
# of Grammy	# of Artists
0	918
1	24
[2; 5]	17
(5; 18]	7
Total	966

Table A3. Online Promotion Data

Online platforms	Data Collected	Definition	Obs.	Mean	St. Dev.	Min	Max
Amazon	URL	Visibility	966				
	Comments	Audience Activity	966	5	21	0	306
Itunes	URL	Visibility	604				
Twitter	URL	Visibility	372				
	Followers	Online Reputation	372	54,673	297,417	0	4,185,716
	Following	Artists Activity	372	363	1,745	0	19,152
	Tweets	Artists Activity	372	893	2,247	0	22,070
Facebook	URL	Visibility	713				
	Fans	Online Reputation	713	177,394	1,338,331	0	27,900,000
YouTube	URL	Visibility	231				
	Friends	Artists Activity	231	215	1941	0	28,498
	Videos	Artists Activity	231	6	10	0	68
	Subscriptions	Artists Activity	231	0.6	2	0	19
	Views	Digital Consumption	231	7,727,860	40,000,000	0	538,000,000
	Suscribers	Online Reputation	231	7,288	25,314	0	283,963
Dailymotion	URL	Visibility	23				
	Videos	Artists Activity	23	0.3	1	0	4
	Views	Audience Activity	23	602,699	1,967,579	17	9,391,277
MySpace	URL	Visibility	764				
	Friends	Artists/Audience Activity	764	3,870	42,065	0	1,057,395
	Comments	Artists/Audience Activity	764	128	826	0	16,668
LastFm	URL	Visibility	874				
	Plays	Digital Consumption	874	218,772	1,255,552	0	17,700,000
	Comments	Audience Activity	874	66.2	573	0	13,621
Blogs	URL	Visibility	456				
	Posts	Audience Activity	456	37	143	0	1,807

Note: Data collected over the 6-months period of observation surrounding the new album release

Table A4. Panel VAR for artists *with* visibility in traditional media channels

Independent Variable	**Dependent Variable**						
	$ArtistsPosts_t$	$ConsumReviews_t$	$ConsumPosts_t$	$Fans_t$	$Followers_t$	$MusicStream_t$	$TradExposure_t$
ArtistsPosts $_{t-1}$	0.379 ***	-0.008	0.019	0.027 ***	0.042 ***	0.122	-0.025
	(0.20)	(0.015)	(0.017)	(0.007)	(0.013)	(0.068)	(0.013)
ConsumReviews $_{t-1}$	-0.042	0.319 ***	0.025	0.005	0.002	-0.007	0.091 ***
	(0.022)	(0.021)	(0.017)	(0.007)	(0.010)	(0.082)	(0.019)
ConsumPosts t-1	0.012	0.075 ***	0.377 ***	0.005	-0.009	-0.213	0.095 ***
	(0.031)	(0.026)	(0.024)	(0.009)	(0.012)	(0.120)	(0.025)
Fans $_{t-1}$	0.068	0.388 ***	0.405 ***	0.433 ***	0.017	-0.974	0.583 ***
	(0.159)	(0.134)	(0.137)	(0.066)	(0.087)	(0.578)	(0.124)
Followers t-1	0.089	0.157 ***	0.107	0.007	0.203 ***	-0.354	0.168 ***
	(0.072)	(0.060)	(0.058)	(0.027)	(0.039)	(0.249)	(0.053)
MusicStream $_{t-1}$	-0.016 ***	0.002	0.010 ***	-0.003	-0.011 ***	0.157 ***	0.018 ***
	(0.004)	(0.003)	(0.004)	(0.002)	(0.003)	(0.016)	(0.003)
TradExposure $_{t-1}$	0.054	0.073 ***	0.071 ***	0.032 ***	-0.008	0.243 ***	0.226 ***
	(0.029)	(0.026)	(0.023)	(0.008)	(0.013)	(0.103)	(0.027)

Notes: Variables are logged and forward mean-differences; *** and ** denote significance at 1% and 5% level, and number in parentheses are standard errors.

Table A5. Panel VAR for artists *without* visibility in traditional media channels

Independent Variable	**Dependent Variable**					
	ArtistsPosts $_t$	ConsumReviews $_t$	ConsumPosts$_t$	Fans $_t$	Followers $_t$	MusicStream $_t$
ArtistsPosts $_{t-1}$	0.255 *** (0.021)	0.008 (0.004)	0.005 (0.012)	0.041 *** (0.018)	0.088 *** (0.019	0.021 (0.050)
ConsumReviews $_{t-1}$	0.001 (0.069)	0.395 *** (0.060)	0.285 *** (0.076)	0.005 (0.037)	0.021 (0.050)	0.425 ** (0.229)
ConsumPosts t-1	0.124 *** (0.028)	0.012 (0.007)	0.307 *** (0.023)	0.079 *** (0.020)	0.003 (0.022)	0.071 (0.085)
Fans $_{t-1}$	0.027 (0.029)	0.022 *** (0.007)	0.135 *** (0.018)	0.257 *** (0.032)	0.011 (0.026)	0.153 *** (0.075)
Followers t-1	0.024 (0.037)	0.016 (0.010)	0.076 *** (0.024)	-0.006 (0.036)	0.154 *** (0.031)	0.265 *** (0.098)
MusicStream $_{t-1}$	0.005 (0.006)	0.002 (0.001)	0.019 *** (0.004)	0.003 (0.005)	-0.006 (0.005)	0.222 *** (0.015)

Notes: Variables are logged and forward mean-differences; *** and ** denote significance at 1% and 5% level, and number in parentheses are standard errors.