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From fewer blockbusters by more superstars to more blockbusters by fewer superstars: How technological innovation has impacted convergence on the music chart☆

Andrea Ordanini [a,*], Joseph C. Nunes [a,b]

[a] Department of Marketing, Bocconi University, Via Rontgen 1, 20136, Milan, Italy
[b] Department of Marketing, Marshall School of Business, HOH 604, University of Southern California, Los Angeles, CA, 90089-0443, USA

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ABSTRACT

The pace of change in recorded music technology has accelerated faster than ever during the past two decades with the shift from analog to digital. Digital recordings provide consumers the unimpeded ability to access, sample, learn about, acquire, store, and share vast amounts of music as never before. Supporters of *winner-take-all* theory believe lower search and transaction costs brought about by digitization have led to greater convergence with fewer extraordinarily popular songs (*blockbusters*) and a smaller number of artists who perform them (*superstars*). Supporters of *long-tail* theory believe the same factors have led to less convergence and a greater number of songs and artists becoming blockbusters and superstars. This work pits these opposing predictions against each other empirically. More specifically, we examine how the number of songs and artists appearing annually on *Billboard*'s Hot 100 singles chart has changed between 1974 and 2013 in relation to three major turning points in technology associated with digitization. These turning points mark consumers' shift: (1) from analog records and cassettes to digital audio with the advent of CDs, (2) from CDs to compressed digital audio MP3s, and (3) from P2P networks and illegal file sharing to legitimate online distributors of digital downloads. In general, we observe a growing winner-take-all effect for songs until the advent of MP3s in 1998, when this trend abated. This result appears largely due to greater convergence in the Top 10. The trend reverses itself as the number of songs making the chart increases steadily after the launch of legitimate online music sellers such as iTunes. The exact opposite pattern is observed for artists. Initially, an increasing number of artists made the chart, and this trend continued unabated until 2003. After the emergence of legitimate online resellers, the trend reversed as fewer and fewer artists made it onto the chart. The overall pattern is summarized as a transition from fewer blockbusters by more superstars to more blockbusters by fewer superstars.

1. Introduction

The development of audio recording and reproduction is arguably the most significant event to have affected the role music plays in people's daily lives. Only during the past century has recorded music allowed consumers to repeat a gratifying musical experience by hearing a song performed exactly the same way over and over again. Recorded music for home use was born with the phonograph. Phonograph records stopped being seen as a novelty in the 1920s, and by the 1930s, the "popularity" of music came to be measured by

☆ The authors contributed equally and are listed in reverse alphabetical order.

* Corresponding author at: Bocconi University, Via Rontgen 1, 20136 Milan, Italy.
E-mail addresses: andreaordanini@unibocconi.it (A. Ordanini), jnunes@marshall.usc.edu, joseph.nunes@unibocconi.it (J.C. Nunes).

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record sales (Frith, 1988). Yet the commercial market for recorded music didn't really take off until the late 1940s when the 33–1/3 long–playing record (LP) and 45–rpm were introduced (Salvaggio & Bryant, 1989). Vinyl records dominated the market until the late 1960s and early 70s, when affordable high-quality cassette decks hit the market. Better sound quality, a larger variety of offerings, and better artwork allowed records to coexist with cassettes until digital audio came along.

The pace of change in recording technology has accelerated faster than ever during the past two decades as the medium transitioned from analog to digital. The digitization of content, including music, film, TV shows, video games, and books has radically changed consumer behavior in the entertainment arena. Converting information into binary code has ultimately made it easier to store, access, and transmit large amounts of content faster and further than ever on a wider variety of media. During music's digital transformation, recording technology encountered three significant turning points. The first was the shift from analog to digital that led consumers to convert their music collections from records and cassettes to CDs. The second shift was from static to mobile music collections as consumers moved away from CDs (typically large .wav files) to compressed audio formats such as MP3s, files easily exchanged online. The third shift occurred as many consumers began moving away from peer-to-peer (P2P) networks and illegal file sharing to learning about and acquiring music from legitimate online distributors such as iTunes. A legitimized marketplace resulted in proprietary formats that came with digital rights management (DRM) protection. The most popular was Apple's AAC audio with FairPlay, but others including Rhapsody's AAC+ and WMA files with Helix DRM emerged as well.

Compressed digital files, the internet, P2P file sharing networks, and legitimate online sellers' extensive music catalogs each advanced consumers' ability to learn about, sample, acquire, save, and share vast amounts of music. A hyper-efficient digital market for music is believed by many to have intensified what is referred to as a *winner-take-all* effect, whereby a few winners (songs) capture a disproportionately large share of the market and go on to become *blockbusters*. This is because near-zero marginal costs, combined with effortless search and instantaneous delivery enable almost any consumer worldwide to identify and acquire what is presumed to be a small set of the very best products in terms of quality (Frank & Cook, 1995). The same efficiencies are believed to exert a similar effect on artists. *Superstar theory* refers to the idea that exposure to a greater number of artists results in fewer individuals coming to “dominate the fields in which they engage” (Rosen, 1983, p. 449).[1]

In contrast, proponents of what is known as the *long-tail* effect argue that the transition to digitized content has moved audiences away from a relatively small number of blockbusters toward a larger number of niche goods and away from a small cadre of superstars toward a larger stable of lesser-known artists (Anderson, 2006; Brynjolfsson, Hu, & Simester, 2011).

This research pits the predictions derived from these two conflicting viewpoints against each other and does so empirically. We rely on *Billboard*'s Hot 100 popular music chart to determine which songs are deemed blockbusters and which artists are deemed superstars. The Hot 100 is one of the industry's pre-eminent indicators of success in the music industry, and a song's ranking on the chart is considered the “best benchmark we have to measure the bigness of hits” (Molanphy, 2013). Proponents of winner-take-all effects and superstar theory predict any advances in market efficiency resulting from digitization would by and large lead to greater convergence, the end result being a greater concentration or smaller set of both songs and artists making it onto the Hot 100. Proponents of long-tail theory predict the opposite; advances in market efficiency result in less convergence resulting in less concentration and an expanded set of both songs and artists making it onto the Hot 100. Consequently, these two theories provide predictions that are diametrically opposed to each other with respect to how changes in market efficiency should impact the popular music charts.

1.1. Objectives of this research

At its broadest level, this research examines the impact of evolving technology on convergence in the entertainment market. More specifically, we examine how the concentration of songs and artists appearing annually on *Billboard*'s Hot 100 singles chart has changed over the course of the past 40 years (1974–2013) in response to shifts in recorded music technology. The technology shifts under investigation here have resulted in the recorded music market alternatingly becoming more and less efficient over time. Generally speaking, *more efficient* markets imply more convergence based on winner-take-all/superstar (long-tail) theory and should be reflected by a decrease in the number of songs and artists making the Hot 100. In contrast, *less efficient* markets imply the opposite. If inefficient markets make coalescing around a small set of winners and superstars more difficult, there should be relatively less convergence according to winner-take-all and superstar theory. If an inefficient market means consumers have difficulty identifying those idiosyncratic alternatives that would suit them better, there should be relatively more convergence according to long-tail theory.

1.2. Contribution

This research contributes to the extant literature on technological innovation and entertainment goods in several ways. First, we document the changing trends over time with respect to convergence in the music industry corresponding to major turning points in recording technology. Beginning with 1974, we observe convergence increasing annually, on average (i.e., fewer songs making the chart and thus becoming blockbusters), a trend that was halted by the advent and adoption of the MP3 format in 1998–99. Following the emergence of legitimate online music sellers in 2003–4, the trend reverses itself completely, and we observe greater divergence as more songs began making it onto the chart each year. Interestingly, almost the exact opposite pattern exists for artists. Beginning with

[1] In past work, concentration rates for products per se have frequently been described in terms of testing the “superstar” phenomenon. In this research, the term blockbuster is used exclusively with products such as songs and reflects a winner-take-all effect while the term superstar is used exclusively with people (i.e., performers) and reflects superstardom.

1974, we observe a trend toward decreasing convergence such that more artists made the chart (i.e., became superstars) each year, which continues unabated until 2003–4. At this point, the trend reverses, and fewer artists begin making it onto *Billboard's* Hot 100. Generally speaking, we find empirical evidence supporting both winner-take-all and superstar effects as well as long-tail effects but during different periods of time and with opposing effects at the song and artist level. The overall pattern can be summarized as a transition from fewer blockbusters by more superstars to more blockbusters by fewer superstars.

Historically, the winner-take-all, superstar, and long-tail literatures have remained largely separate. Recently, scholars in these areas have emphasized the need to study them simultaneously. For example, Brynjolfsson, Hu, and Smith (2010, p. 736) have asserted that in order for researchers to extend their insights and predictions with respect to these theories, they "can and should be analyzed as part of an integrated research agenda." It is critical, they argue, to understand how the phenomena relate as they may be influenced by common drivers such as increased supply side offerings and efficiency-enhancing software that lowers search costs for consumers. Our analyses and results tell a somewhat nuanced story that provides rich insights into how one common driver—changes in technology surrounding recorded music—have impacted convergence either consistent with or in opposition to predictions from all three literatures.

Second, the story is further unraveled to reveal what happens if we narrow our definitions of blockbusters and superstars to include only the Top 10 songs in the Hot 100. Considering only the Top 10, what we observe is more convergence for songs after CDs appeared and before compressed audio formats such as the MP3 became popular and less convergence for artists after MP3s moved music online. Digitization reduced the number of songs (blockbusters) and then increased the number of artists (superstars) who were able to make the Top 10. We share the opinion expressed by Hubbard and Murray Lindsay (2002), and by reporting these results, we hope to contribute to the search for empirical generalizations essential for moving theory forward.

Finally, our data extend until 2013, and thus our results provide more contemporaneous insights than past work (e.g., Bhattacharjee, Gopal, Lertwachara, Marsden, & Telang, 2007), an important point when looking at recent technological advances such as digitization. Further, by finding evidence of decreasing convergence for artists on the Hot 100 prior to 2004, our findings are in conflict and can be contrasted with past research presenting evidence supporting a superstar effect (Chung & Cox, 1994; Crain & Tollison, 2002; Strobl & Tucker, 2000).

It is likely our results differ from these past studies because our data come from the market for singles as opposed to albums and from the U.S. as opposed to the U.K. market. We also employ a metric of superstardom that is not dependent on sales exclusively (appearing on the Hot 100 depends on both sales and radio play). Using singles as the unit of consumption is critical given our focus is on the effects of digitization and its timing. Consider that online music downloads led CD sales to decline 50% and sales of full albums to drop 55% between 1999 and 2009 according to data from Nielsen SoundScan, all while sales of individual tracks soared from nearly zero to 1.2 billion. As Anderson (2004) put it, "online music has seen a return to the singles-driven business of the 1950s."

The remainder of the article proceeds as follows. We begin by briefly reviewing past literature on convergence as well as other work exploring music's lifecycle on the charts. We then more thoroughly explain the reasoning behind the three turning points we identified. Next, we describe our unique data set and present initial evidence supporting how the three turning points impact chart convergence. We conduct two separate sets of analyses, one for songs (blockbusters) and one for artists (superstars). First, we employ both ANOVA and spline regression to assess how the number of songs appearing on the chart has changed over time. With the number of positions fixed at 100, a decrease in the number of songs appearing on the chart within a fixed timeframe is indicative of greater convergence while an increase is indicative of decreasing convergence. In the second analysis, we compare the number of songs per artist in each period using ANOVA. A decreasing (increasing) number of "songs per artist" implies more (fewer) artists achieving superstardom and is indicative of decreasing (increasing) convergence. We conclude by discussing the implications of our findings for managers as well as for future research.

2. Past literature: superstars, blockbusters, and the charts

2.1. Superstardom and blockbusters

In 1947, economist Alfred Marshall observed that the correspondence between quality and remuneration was skewed in many fields of production but not in music. More than three decades later, Rosen (1981) presented an economic model based on Marshall's idea but with the exact opposite conclusion: a relatively small number of superbly talented artists achieve extraordinary levels of success while the vast majority struggle in relative obscurity. Hamlen (1991, 1994) tested the relationship between talent and earnings for artists appearing on the music charts empirically using sales data from the recording industry between 1955 and 1987. As a proxy for talent, Hamlen combined a measure of the harmonic quality for more than 100 singers' voices along with several other artist-specific measures (gender, race, appearances in movies, etc.). In the end, he found no empirical evidence supporting the Marshall-Rosen concept of superstardom based on talent.

However, many factors other than talent are assumed to play a role in determining the relative success of performers, including promotional support and the artist's charisma (Adler, 1985). While some of these factors are measurable and comparable, many contributory factors may never be identified, much less measured. Work by Chung and Cox (1994) shifted the focus away from differences in artists' abilities and proposed an alternative form of superstardom. Using data on the number of Gold Records earned by performers in the American popular music industry from 1958 to 1989 and applying a stochastic model that allows success to be concentrated in the hands of a lucky few; their findings support a distribution of successful artists in line with the notion of a more generalized superstar phenomenon.

Similarly, Strobl and Tucker (2000) offer empirical evidence consistent with both a winner-take-all effect and a superstar effect. These authors examined the British album chart listings from 1980 to 1993 and found the average and total number of weeks an album spent on the chart—as well as the total number of albums per artist—were skewed to the right. More recently, Crain and Tollison (2002) tested the idea of superstardom by focusing on two separate but nearly identical measures of music concentration. They examined the share of weeks during a given year between 1959 and 1988 that: (1) the top *four* and (2) the top *five* artists held the #1 spot in *Billboard*'s weekly ratings. They report an increasing concentration, consistent with a superstar effect, which they attributed to higher earnings over time. In general, much of the past research focusing on superstardom in music per se has found an effect but has tended either to take a static approach or focus on concentration levels prior to the profound transformations in the music industry brought about by digitization.

2.2. Long-tail theory

Since digitization, a number of researchers have acquired and presented evidence supporting a long-tail effect. In his article in *Wired* magazine, Anderson (2004) provided anecdotal evidence from the music industry to support a long-tail effect—the shift from hits to niches. His original claim was that enhanced distribution methods (e.g., the internet) and "infinite shelf-space" allow new artists and songs to find an audience, reversing what he called the "blanding" of music brought about by brick & mortar record stores' limited inventory, which he dubbed "distribution scarcity." To illustrate his point, he pointed to eCast, a digital jukebox company whose barroom players offer more than 150,000 tracks with 99% getting played. Contrast that with CDs, he added, where, according to the Recording Industry Association of America (RIAA), fewer than 10% are profitable. Of course, consumption of more obscure titles comes at the expense of more popular items, resulting in less convergence.

In support of Anderson's view, Brynjolfsson et al. (2011) analyzed data on women's clothing collected from a multi-channel retailer. They found sales over the internet exhibited a significantly less concentrated sales distribution compared to sales from the firm's more traditional catalog. In addition, Elberse and Oberholzer-Gee (2007) found evidence that a larger share of VHS and DVD sales shifted toward niche products from 2000 to 2005 in response to online retailing. Zhang (2013) collected data on 5,864 albums from 634 artists and observed that the removal of digital rights management (i.e., lowering the cost of copying and sharing) increased sales of lower-selling albums, a result attributed to a long-tail effect. Additionally, mixed evidence comes from Chellappa, Konsynski, Sambamurthy, and Shivendu (2007) who found the share of total sales generated from platinum albums dropped from 33% in 2002 to 23% in 2006. However, the number of albums released doubled in this period and thus sales became more concentrated at the top when using a measure of relative concentration.

2.3. Prior studies of convergence in music in response to digitization

Perhaps most related to this research is work by Bhattacharjee et al. (2007) that looked at convergence in the number of *albums* making the charts both before and after the P2P file sharing craze. Using survival analysis, their work contrasted turnover in the charts between the following two time periods: 1995–1997 and 2000–2002. They conclude an album's time on the chart declined an average of 42% (suggesting less convergence) in the post-file sharing period relative to the earlier period. The decline in convergence, however, was driven by increased churn at the bottom of the chart; albums that entered in higher positions did not see their survival rates decline. Further, they observed no decrease in chart life for albums by what they considered superstars (defined as artists having appeared on the chart for at least 100 weeks previously, looking back to 1991). These authors concluded "the superstar effect appeared to be alive and well, with albums by such performers surviving approximately 35% longer even after controlling for other variables" (p. 1372). Further, they state the superstar advantage remained unchanged after their event window.

Our work differs significantly from Bhattacharjee et al. (2007) in a number of ways. First, their focus was on chart success for albums. *Billboard* rankings for albums are based solely on sales as Nielsen Soundscan data indicates only what people buy. Our unit of analysis is singles, and the Hot 100 combines radio play with sales to assess overall success. Second, they compared survival rates for two years before and after a two-year gap (mid-1998 to mid-2000). In contrast, we take a much broader historical perspective, looking at how the chart has evolved over a 40-year time period. This allows us to document changes due to the commercial launch of digitization (CDs) before 1998 and changes due to legitimized downloads (e.g., iTunes) after 2002, periods Bhattacharjee and colleagues did not cover. Third, we focus on the number of songs *and* artists that appear on the chart annually, while they compared survival rates for albums alone, qualified for what they defined separately as superstars.

In direct contrast to Bhattacharjee et al. (2007) is work by Klein and Slonaker (2010) who examined how monthly turnover in *Billboard*'s Top 200 albums chart affected sales before and during the growth of the Internet as a music source. To accomplish this, they looked at chart turnover and music sales for new album debuts from 1990 through 2005 using monthly data from *Billboard*'s Top 200 albums chart. These authors concluded that higher turnover (shorter survival rates) has led to higher new album sales and claimed this association supports the long-tail phenomenon (albeit, they did not divide the chart any further). While they used turnover as a predictor of sales, we look at changes in technology as a predictor of turnover. Also, as mentioned earlier, the Hot 100 chart for singles relies on both sales and airplay for what we believe is a more comprehensive measure of extraordinary success.

3. Three turning points leading to four distinct periods

In accordance with the principles of periodization (Hollander, Rassuli, Jones, & Farlow Dix, 2005; Stowe, 1983), we identify three distinct technological "turning points" that occurred between 1974 and 2013 in the market for recorded music. These turning points are situated at the end of one year and the beginning of another—taking place in 1985–86, 1998–99, and 2003–04—and have been carefully identified based on both empirical evidence and prior literature.

The first turning point occurs when the CD initially popularized digital audio in line with market statistics (RIAA). The second turning point is anchored on the rise of MP3s and P2P file sharing in line with prior literature (Bhattacharjee et al., 2007). The third turning point marks the growing success of legitimate digital downloads, corresponding with the advent of the most important downloading music service (i.e., iTunes). These three turning points yield four distinct technological periods: 1974–1985, 1986–1998, 1999–2003, and 2004–2013. During each of these periods, consumer behavior with respect to recorded music changed profoundly, which we subsequently describe in more detail.

In any single period, more or fewer songs could potentially have made it into the fixed number of positions within the Hot 100, indicative of less and more convergence, respectively. Additionally, any decrease (increase) in the average number of songs per artist is synonymous with an increase (decrease) in the number of artists making the chart, and thus less (more) convergence. Accordingly, we look at the trend within each period and how these trends did or did not change at each turning point. We should mention upfront that we test the robustness of our results to alternative specifications of the dates of the turning points: while the pattern of results remains substantially unchanged, these additional analyses reveal that the original dates (i.e., periods) we propose best fit the data.

3.1. Turning point one: high quality digital recordings and the advent of the CD

The first turning point occurred in 1985–86 after digitization emerges in full force in popular music with the advent of the Compact Disc (CD). The impetus for change occurred in 1983 when a joint venture between Sony and CBS Records (formerly Columbia) introduced the first music CDs to American consumers. Prior to that, Americans listened primarily to records and cassettes. Consumers used blank cassettes to record individual songs off of albums as well as the radio and produce cheap and fairly reliable customized mix tapes. The decoupling of content (songs) from the recording mechanism (records) brought about by blank cassettes led their sales to surge past 150 million in 1975. In 1977, sales of pre-recorded cassettes surpassed vinyl for the first time. The introduction of the Sony Walkman in 1979 allowed consumers to make and take customized mixes of their favorite songs wherever they went. Customization and portability had made it easy for popular music fans to learn about a wider variety of songs and artists.

The CD was intended to replace easy-to-copy cassettes with a format providing much clearer sound, no need to rewind or fast forward, and no appreciable degradation in quality over time. The file size of digital recordings combined with relatively weak computing power at the time was also intended to make decoupling and moving music from the CD burdensome. This would make sharing more difficult, inhibiting access to information and reducing the ability of consumers to observe what others are consuming. By 1984, record companies had fully embraced digital audio, launching close to 2000 CD releases onto the market, and by the end of 1984, 4.3 million CDs had been sold (Sanjek, 1988). It didn't take long for CDs to catch on. In 1986, sales of CDs surpassed records and cassettes combined, according to the Recording Industry Association of America (RIAA). The significant shift in recorded music technology that occurred in 1985–86 marks our first turning point, representative of a decrease in market efficiency or the ease with which consumers could discover and share music. The trend continued, and by 1990, record stores had fully transitioned into CD stores as Americans replaced their aging vinyl and cassette recordings with compact discs (Shayo & Guthrie, 2005).

3.2. Turning point two: music moves online with the advent of the MP3

The second turning point occurred in 1998–99 after digitization enabled music to move about freely online. In 1993, the Moving Picture Experts Group, a subcommittee of the International Standards Organization/International Electrotechnical Commission, published the original MPEG-1 standard. The following year, the MP3, a file format created to reduce the amount of data required to represent an audio recording faithfully, became the internet audio standard (Sterne, 2012, p. 119). A 128 kilobyte MP3 version of a CD track is 10 to 12 times smaller than the original file. In 1997, WinAmp was distributed for free and allowed consumers to play MP3s on PCs. Originally, the music industry had intended for consumers to only be able to *decode* MP3 files, but as free encoding software rapidly became available, consumers used it to decouple songs from CDs and exchange music files online using peer-to-peer (P2P) networks.

By 1999, Napster software streamlined online music sharing significantly by providing directories of music available on its user network. After Napster was shut down in 2000, Morpheus, KazaA, Aimster, and other sites popped up to take its place (Shayo & Guthrie, 2005). The genie was out of the bottle, and CD sales plummeted. Piracy was rampant, and sales of legitimate recordings were in rapid decline after 1999; music sales plunged from $14.6 billion in 1999 to $6.3 billion in 2009 (Goldman, 2010). The way consumers interacted with music had shifted significantly again. A frustrated recording industry began suing American music fans in 2003 for sharing songs on P2P networks, creating a public relations nightmare. The recorded music industry was in a tailspin. By 2003, it was reported that 60 million Americans had shared music files online (OECD (Organization for Economic Cooperation and Development) Technology Outlook, 2004). Consumers could once again easily separate, store, and share musical recordings, this time even more easily than in the cassette era. The significant shift that occurred in 1998–99 as music sharing proliferated online marks our second turning point and is representative of an increase in market efficiency.

3.3. Turning point three: online resellers create a legitimate marketplace for music

The third turning point occurred in 2003–4 when iTunes and other legitimate online channels for music allowed consumers to acquire individual tracks legally. In 2003, Apple's iTunes Music Store officially opened as did similar channels for licensed digital music (e.g., Puretracks, which shut down in 2013). Unlike P2P sites that ignored copyright laws, Apple negotiated royalty-sharing agreements with the record labels. Demand for digital downloads really took off after Apple introduced the third generation of iPods in 2004 that were compatible with Windows PCs out of the box. On March 15, 2004, Apple announced iTunes customers had purchased and downloaded 50 million songs. Sales of digital singles grew by 163% between 2004 and 2005 (www.RIAA.com). As of 2008, digital music accounted for 32% of recorded music sales in the US, three quarters of which were sold on the iTunes Music Store (McAdoo, 2012). Apple's iTunes is the most popular legitimate reseller according to the International Federation of the Phonographic Industry's 2012 digital music report (available at www.IFPI.org), the most comprehensive and up-to-date directory of 500 legitimate music services in 78 countries.

Originally, AAC format songs purchased from iTunes were protected by Apple's proprietary FairPlay digital rights management (DRM) technology. Advanced Audio Coding (AAC) was developed by some of the same audio experts that created the original MP3 standard: the Fraunhofer Institute, Dolby, Sony, and AT&T. Protected content was locked within iTunes by FairPlay; the track could be played on up to five (originally three) authorized computers simultaneously. This severely limited the mobility of music associated with songs sold by Apple. It wasn't until 2009 that Apple announced that the entire iTunes library would be available without DRM. At the time, Amazon.com was making inroads as the dominant online music seller with its own DRM-free store. While overall music sales declined $1.3 billion in 2009, digital downloads grew $363 million to $4.3 billion with Apple's iTunes representing more than a quarter of total digital and retail U.S. sales, according to the *Recording Industry in Numbers* report issued by the IFPI (www.IFPI.org). The significant shift that occurred in 2003–4 as legitimate music sellers propagated and expanded online marks our third major turning point, a time of moderately decreasing efficiency when discovering new music became easier but sharing became much more difficult.

In Table 1, we provide a summary of how changes in technology across time impacted the efficiency of the market, and in turn, the overall concentration of songs and artists making the Hot 100. More formally stated, market efficiency is described in terms of the ease with which consumers would be expected to be able to learn about, sample, move, and share music.

We consider 1974–1985 the baseline and consider how convergence in the charts has been affected by changes in technology (i.e., our three turning points). Proponents of winner-take-all (WTA) and superstar theory (SST) would predict the exact opposite of what proponents of long-tail theory (LTT) would predict. We, however, remain agnostic in terms of our predictions as our objective is to pit the predictions derived from these conflicting viewpoints against each other empirically.

4. Data analysis

We collected data on the chart presence for every song (title, artist, week of entry, and peak rank achieved) appearing on *Billboard*'s Hot 100 for the 40-year period spanning from 1974 until 2013. The position a song takes on the Hot 100 music chart reflects a mixture of sales and airplay performance for a specific week. The information identifying all 15,976 songs that entered the Hot 100 was acquired initially from the music website www.umdbmusic.com before being cross-checked using a variety of sources including Whitburn (1996), the website www.bullfrogspond.com, and *Billboard* magazine's official website (www.billboard.com).

Table 1
Conflicting predictions regarding convergence based on how key characteristics of recorded music technology changed over time.

Era	1974–1985 Vinyl/cassette (analog)	1986–1998 CD (digital)	1998–2003 MP3 (compressed)	2004–2013 AAC (DRM)
Search	Terrestrial	Terrestrial	Online	Online
Bundling	Blank cassettes allow unbundling of songs from albums	Compact Disc Digital Audio (CDDA) files inhibit unbundling	Digital audio extraction software eases unbundling	Sales of singles online promotes unbundled content
Sharing	Inexpensive blank cassettes facilitate sharing music	Large lossless audio files inhibit sharing music	Compressed audio files and P2P facilitate sharing music	DRM and iTunes software attempt to inhibit sharing music
Portability	Sony Walkman makes music portable	CDs make portability cumbersome	MP3 players make music portable again	iPods, iTunes and smartphones increase portability
Market Efficiency	Baseline	Decreasing	Increasing	Mildly decreasing
Convergence in Songs	Baseline	WTA/SST: Less convergence (more songs) LTT: More convergence (fewer songs)	WTA/SST: More convergence (fewer songs) LTT: Less convergence (more songs)	WTA/SST: Less convergence (more songs) LTT: More convergence (fewer songs)
Convergence in Artists	Baseline	WTA/SST: More convergence (fewer artists) LTT: Less convergence (more artists)	WTA/SST: Less convergence (more artists) LTT: More convergence (fewer artists)	WTA/SST: More convergence (fewer artists) LTT: Less convergence (more artists)

4.1. Initial empirical evidence

The primary variable of interest in all of our analyses is “Tech Period,” a categorical variable designating in which of the four distinct technological periods a song first appeared on the Hot 100. Each song was assigned to a single period (Period 1, 1974–1985; Period 2, 1986–1998; Period 3, 1999–2003; or Period 4, 2004–2013) based on the week it first entered the chart. A summary of the number of songs appearing in each period is presented in Table 2.

We calculated the average number of songs per year because each period differs in terms of number of years. These averages are presented in Table 3. The averages are compared using ANOVA, and significant differences are highlighted using the superscripts a–c. Immediately apparent is how the average declined significantly in the Hot 100 from Period 1 to Period 2. It appears digitization and CDs brought about greater convergence. The decline reverses itself and the average increases significantly after online music sellers emerged at the beginning of Period 4. This suggests that legitimatization reduced convergence, albeit not to pre-CD levels.

We also examine two sub-categories within the Hot 100: Top 10 songs and the remainder of songs that peaked at #11 or below (henceforth Top 10 and #11–100). A total of 3,009 of the 15,976 songs (19%) in our sample made it into the Top 10, while the remaining 12,967 songs (81%) rose to #11 or below. By separating songs into these different sub-categories, we can test the extent to which our results are sensitive to a different definition of blockbuster. In other words, there may be two kinds of blockbusters: those defined by making it onto the Hot 100 and those defined by making it into the Top 10. In Tables 2 and 3, we also present summaries for the total number and average number of songs per period within these sub-categories. Looking at the averages across these two subcategories, it appears an increase in convergence occurred for Top 10 songs only after music moved online (Periods 3 and 4), and this trend never reversed itself even after online music sellers emerged (Period 4). For #11–100 songs, the changes across periods mirror those for the Hot 100, with an even stronger reversal in Period 4, raising the question of whether the results for the Hot 100 are especially influenced by the dynamics of songs in the lower echelons of the chart.

4.2. From means to trends: spline regression

While simple averages provide initial evidence of how chart convergence evolved over time, averages alone can hide potential heterogeneity in chart concentration within the four distinct periods (i.e., at the yearly level). In other words, evidence derived from averages might be too crude to adequately compare trends with respect to winner-take-all and superstar versus long-tail effects. Further, comparing simple means does not allow us to control for other factors that may have had an influence on the number of songs appearing on the chart. Consequently, we chose to analyze the data using spline regression, a technique used to analyze how a variable's trajectory can change smoothly over time in response to one or more events and can do so while also considering potential covariates (Marsh & Cormier, 2002).

Spline regression is essentially a dummy variable model subject to continuity restrictions; instead of estimating a unique trend of a variable of interest (in our case, chart concentration), it allows such a trend to change at certain points called knots (in our case, the three turning points at 1985–6, 1998–9, and 2003–4). A key assumption of spline regression models is that the trend *shifts* but does not break abruptly at each knot. Spline regression models thus provide a series of connected segments that capture smoothed transitions from one period to the other where only the slopes (and not the intercepts) change (Pindyck & Rubinfeld, 1991). This makes spline regression particularly appropriate in our case where the shifts in recording format technology change gradually and not instantaneously, affecting music consumption patterns gradually over time. Basically, by using spline models, we can observe to what extent chart data reflect smooth changes in the song concentration trend that correspond to the technology shifts we have identified. Moreover, by comparing the slope coefficients of the spline regression, it is possible to assess the predictions of the two main theories at each technology shift.

Clearly, the choice of the number of knots and their location represent key elements of spline regression models. In our case, we paid particular attention to our tech periods' definitions, motivating the turning points with both theoretical and empirical evidence. Second, we also provide robustness checks on both the number and location of the knots (see below), which largely support our original choices. Moreover, as spline regression permits the inclusion of covariates, it allows for adjustments to the spline coefficients, taking into consideration the effect that other variables may have on the trends (see section on alternative explanations below).

Spline regression can estimate both linear and higher-order functions such as quadratic or cubic. Higher-order polynomial functions generally improve the fit with the data but provide coefficients that are more difficult to interpret (Marsh & Cormier, 2002). The purpose of this research is not a curve fitting exercise but rather to contrast predictions made by enthusiasts from two opposing camps (winner-take-all/superstar theory versus long-tail theory) at particular points in time that align with major technology shifts.

Table 2
Summary statistics (*Billboard*'s Hot 100 from 1974 to 2013).

Tech period	Years	Number of songs (Hot 100)	Number of songs (Top 10)	Number of songs (#11–100)
P1 1974–1985	12	5,586	1,073	4,513
P2 1986–1998	13	4,730	1,059	3,671
P3 1999–2003	05	1,592	284	1,308
P4 2004–2013	10	4,068	593	3,475
Total number	40	15,976	3,009	12,967
Average per year		399	75	324

Table 3
Summary statistics (*Billboard*'s Hot 100 from 1974 to 2013).

Tech period	Years	Avg. number of songs per year (Hot 100)	Avg. number of songs per year (Top 10)	Avg. number of songs per year (#11–100)
P1 1974–1985	12	465.5 (46.6)[a]	89.4 (13.9)[a]	376.1 (43.7)[a]
P2 1986–1998	13	363.8 (30.2)[b]	81.5 (27.2)[a]	282.4 (11.4)[b]
P3 1999–2003	05	318.4 (19.8)[b]	56.8 (6.8)[b]	261.6 (18.9)[b]
P4 2004–2013	10	406.8 (61.9)[c]	59.3 (6.9)[b]	347.5 (63.0)[a]
Total Number	40	15,976	3,009	12,967
Average	10	399.4 (66.6)	75.2 (22.0)	324.2 (59.8)

Note: Standard deviations are presented in parentheses.
Different superscripts (letters a, b, and c) denote averages that differ significantly at $p < .05$.

Table 4
Billboard's Hot 100: Linear splines with knots at 1985–86, 1998–99, and 2003–4.

Hot 100	Coefficient	Std. Err.	T	P > |t|	95% Confidence interval	
Constant	532.59	15.734	33.85	0.000	500.65	564.53
Tech period						
P1 1974–1985	−10.34[a]	1.849	−5.59	0.000	−14.095	−6.589
P2 1986–1998	−6.22[ab]	1.418	−4.39	0.000	−9.097	−3.341
P3 1999–2003	−3.11[b]	3.838	−0.81	0.424	−10.898	4.685
P4 2004–2013	16.99[c]	2.346	7.24	0.000	12.230	21.755

Note: Different superscripts indicate slopes that differ significantly at $p < .05$; P3 differs from P1 at $p < .10$.

Moreover, considering that the gain in model fit obtained by a higher-order model is marginal in our case (see footnote number 2), we chose to focus on the linear splines results.

5. How technology shifts impacted convergence on the music chart for songs

All of our spline regression models utilize the categorical variable Tech Period as the independent variable. The dependent variable is the average number of songs appearing on the charts in a single calendar year. In our regression model, the coefficients describe the slope of the trajectory within each period. This analysis is at the song level and focuses on the blockbuster concept: a decreasing (increasing) number of songs appearing on the chart year after year is indicative of more (less) convergence and fewer (more) blockbusters. We also compare the slope coefficients to assess changes in convergence at the three turning points.

5.1. The Hot 100

Table 4 presents the results from our first regression. The model fit looks good (Adj $R^2 = 0.833$; RMSE = 27.22; AIC = 9.56), and the test of auto-correlation (Durbin Watson Statistic = 1.45) falls into the indifference zone, giving some assurance that the model has a minimum structure to represent the data adequately (Marsh & Cormier, 2002). The pattern across periods is consistent with the simple averages, while the parameters allow for deeper insight into how things changed within each period. Comparing coefficients, the number of songs appearing on the Hot 100 decreased precipitously in Periods 1 and 2 with large and negative slopes ($\beta_{P1} = -10.34$, $p < .01$ and $\beta_{P2} = -6.22$, $p < .01$). This trend abated in Period 3 ($\beta_{P3} = -3.11$, $p =$ N.S.), and the trend reversed completely in Period 4 when the number of songs grew dramatically year-over-year ($\beta_{P4} = 16.99$, $p < .01$). In summary, the regression parameters reflect increasing convergence from 1974 through 1993, a flattening out between 1994 and 2003, and a sudden reversal with a trend toward less convergence from 2004 onward. The average number of songs making the Hot 100 each year is plotted along with fitted lines for each period in Fig. 1.

This pattern suggests a trend of increasing convergence that ended when MP3s, P2P, and the internet took hold followed by a trend of decreasing convergence following the advent of iTunes and other legitimate online music sellers

5.2. The top 10 and songs #11–100

If we focus on a narrower and more restrictive definition of blockbuster songs, the picture is somewhat different. Looking at Top 10 songs only (see Table 5), the number of songs appearing on the Hot 100 did not change significantly in Period 1 ($\beta_{T10P1} = 1.38$, $p =$ N.S.) and decreased significantly only in Period 2 ($\beta_{T10P2} = -3.61$, $p < .01$) before flattening out in Periods 3 and 4 (See Fig. 2).[2] It seems that among Top 10 hits, convergence began to increase in the chart only after the advent of CDs (i.e., Period 2). While the

[2] While linear splines do a fairly good job in terms of fit, they do not capture the noisy trends in Period 1 for Top 10 songs with great precision (see Period 1 in Fig. 2). While a more flexible cubic spline model better accommodates the downward and then upward trends within Period 1 (Adj. R^2 of 0.822 vs. 0.569), the higher-order model provides results that are very similar to those of the linear spline after 1985. For the Hot 100 and songs #11–100, the fit measures are comparable with our original model using linear splines.

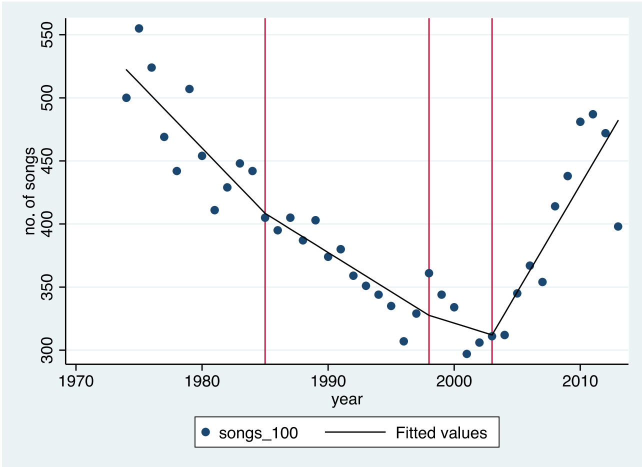

Fig. 1. *Billboard*'s Hot 100: Linear Splines with Knots at 1985–86, 1998–99, and 2003–4.

Table 5
Billboard's Top 10: linear splines with knots at 1985–86, 1998–99, and 2003–4.

Top 10	Coefficient	Std. Err.	T	P > |t|	95% Confidence interval	
Constant	85.61	8.332	10.27	0.000	68.693	102.525
Tech period						
P1 1974–1985	1.38^{a}	0.979	1.41	0.167	−0.607	3.368
P2 1986–1998	-3.61^{b}	0.751	−4.80	0.000	−5.130	−2.081
P3 1999–2003	1.06^{a}	2.032	0.52	0.605	−3.066	5.186
P4 2004–2013	-0.45^{a}	1.242	−0.36	0.721	−2.969	2.075

Note: Different superscripts indicate slopes that differ significantly at $p < .05$. P3 differs from P2 at $p < .10$.

change from CDs to MP3s still interrupted the trend toward increasing convergence, there is no evidence of a trend of decreasing convergence for Top 10 songs during Period 4.

These results suggest that the increasing chart turnover in Period 4 for all Hot 100 songs was driven by songs in lower positions in the chart (#11–100).

In Table 6, we present the results from a regression model looking at only songs #11–100. Here, we observe that the trend toward greater convergence diminishes in Period 2 ($\beta_{11-100P2} = -2.61$, $p = .06$), but the reversal in Period 4 that was absent in the Top 10 is present (See Fig. 3), substantial, and highly significant ($\beta_{11-100P4} = 17.44$, $p < .01$). It seems the emergence of legitimate online music sellers such as iTunes allowed more songs to make the chart but only in the lower echelons (i.e., those below the Top 10). In general, the spline regression results reinforce the overall pattern observed with the ANOVA and provide further evidence of the changing trends over time.

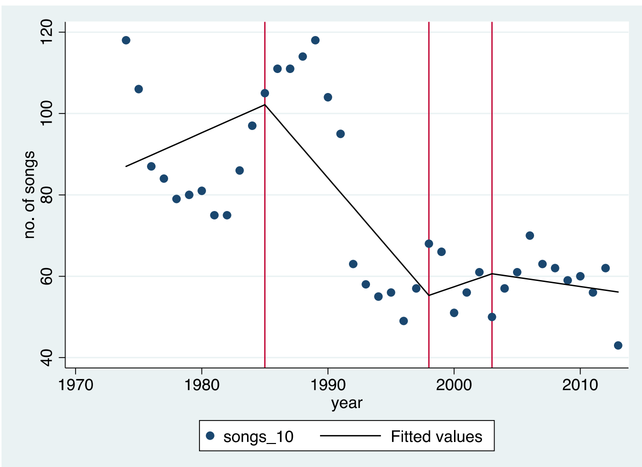

Fig. 2. *Billboard*'s Top 10: linear splines with knots at 1985–86, 1998–99, and 2003–4.

Table 6
Billboard's songs #11–100: linear splines with knots at 1985–86, 1998–99, and 2003–4.

	Coefficient	Std. Err.	t	P > |t|	95% Confidence interval	
Constant	446.98	15.250	29.31	0.000	416.021	477.938
Tech period						
P1 1974–1985	−11.72[a]	1.792	−6.54	0.000	−15.360	−8.085
P2 1986–1998	−2.61[b]	1.374	−1.90	0.065	−5.403	0.176
P3 1999–2003	−4.17[b]	3.720	−1.12	0.270	−11.718	3.385
P4 2004–2013	17.44[c]	2.274	7.67	0.000	12.823	22.056

Note: Different superscripts indicate slopes that differ significantly at $p < .05$.

Our findings reveal the shifts in technology for recorded music: (1) increased convergence in Period 1 but not for Top 10 songs, (2) increased convergence in Period 2 across the entire Hot 100 that halted in Period 3, and (3) dramatically decreased convergence in Period 4 driven by more songs appearing below #11 on the charts. In other words, fewer songs made it onto the chart below the Top 10 prior to CDs, fewer songs even made it into the Top 100 following CDs, MP3 and sharing stopped the convergence, and then more songs made the charts but didn't make the Top 10 following the advent of legitimate online sales.

6. Robustness checks

To test the robustness of our results to different time period specifications, we conducted a number of further analyses. For the sake of brevity, we summarize the results concisely here and provide tables presenting the detailed results in a web appendix.

6.1. Different time specifications

As our first robustness check, we reran our three linear spline regression models using equally-spaced knots (1984, 1994, and 2004) with four technological periods of comparable length (10 years). The pattern and significance of the coefficients does not change substantively; the only notable difference is that the significant change in rate of convergence (i.e., trend) between Period 1 ($\beta_{equal} = +0.61$) and Period 2 ($\beta_{equal} = -2.21$) among Top 10 songs and that between Period 1 ($\beta_{equal} = -11.10$) and Period 2 ($\beta_{equal} = -5.46$) among songs #11–100 are no longer significant. In addition, we compare the model fit of our original linear spline regressions (knots at 1985–86, 1998–99, and 2003–4) with models using three equally spaced knots (1983–4, 1993–4, and 2003–4). While the models seem substantially equivalent in the case of the Hot 100, our original model fits the data better in the case of Top 10 songs (Adj. $R^2 = 0.57$ versus 0.48 using three equally spaced knots).

As a second robustness check, we changed the number of knots and not their location. In light of Bhattacharjee et al. (2007), we reran the regressions using only one knot positioned at 1998–9, mimicking to some extent their division of time into before and after the introduction of the MP3, Napster, and P2P networks. This alternative model (linear spline, one knot) has a worse fit with the data when compared to our original model (linear spline, three knots), both for the Hot 100 (Adj. $R^2 = 0.83$ versus 0.80, respectively) and for the Top 10 (Adj. $R^2 = 0.57$ versus 0.47, respectively). As a third and more general check, we also estimated traditional polynomial regressions (nonspline) up to the cubic form (Marsh & Cormier, 2002; Carter & Signorino, 2010), although they are not strictly useful to compare our theories that include a discrete number of technology shifts. The linear, quadratic, and cubic models show a clearly worse fit than our original model (all Adj. $R^2 < .80$ for the entire Hot 100, and $< .48$ for Top 10), further suggesting

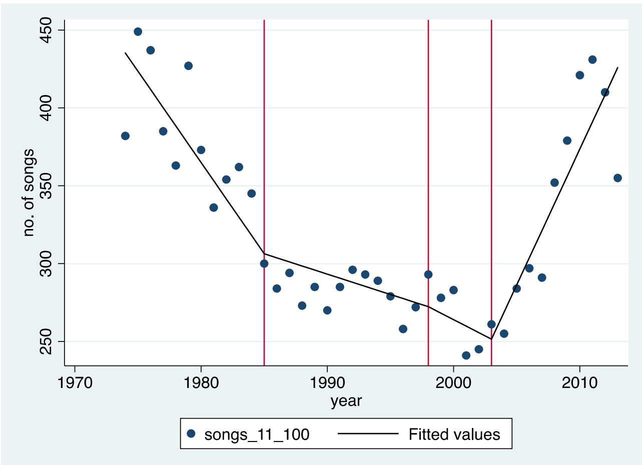

Fig. 3. *Billboard*'s songs #11–100: linear splines with knots at 1985–86, 1998–99, and 2003–4.

the spline modeling approach is appropriate. This first set of robustness checks supports the appropriateness of the originally chosen dates (1985–86, 1998–99, and 2003–4) as the relevant turning points, the choice of three as the number of turning points, and the use of turning points *per se* as opposed to curves associated with a polynomial model.

6.2. Alternative explanations: covariates

A second set of robustness checks involves the consideration of potential alternative explanations for the trends observed regarding song concentration. To this end, we collected additional data on the following covariates that allow us to control for the potential influence of several outside factors. The first variable measures annual expenditures on live concerts in the U.S. between 1987 and 2013. These figures were provided by Pollstar, a trade publication that tracks information about the concert tour industry. Ticket sales for concerts have increased profoundly in North America from $620 million in 1987 to $5.1 billion in 2013. To create the covariate “Live,” we calculated the ratio of annual expenditures on live concerts to annual sales for recorded singles obtained from the RIAA. This covariate allows us to control for changing habits among consumers vis-à-vis a shift from buying recorded music toward attending live performances.

The second and third covariates measure concentration within the recorded music industry as consolidation on the supply side may have affected the number of songs appearing in the charts. During the period under investigation, the market was dominated by a relatively few large players known as the “majors” that today consist of the “Big Three” (Universal, Sony, and Warner) with all other labels being known as the “independents.” Concentration in the industry typically has been assessed based on the percentage of Top 10 hit songs distributed among the top labels. Utilizing data available from *Bullfrogspond*, we followed the technique employed by Peterson and Berger (1975) and recorded the number of labels appearing in the Top 10 between 1974 and 2013. We then calculated a standardized Herfindahl–Hirschman Index based on label concentration. The covariate “Labels” refers to the absolute number of labels each year while the covariate “HHI” refers to an indexed score between 0 and 1. These covariates serve as proxies for industry concentration and allowing us to test the extent to which the number of songs and artists appearing in the chart is the result of structural changes on the supply side (Lopes, 1992).

The final covariates are intended to control for the evolution of musical artists' emergence on television shows, specifically singing competitions such as American Idol, and collaborations with other well-known artists who appear as “guest” performers on a particular track (i.e., a “featuring” effect). We collected the names of all the songs in the Hot 100 by artists who appeared on 12 major competition reality shows that aired between 1983, when *Star Search* was first broadcast, and 2013 (see Table 3 in the web appendix for a list of these shows). We also dummy coded all songs that included a “featuring” collaboration (e.g., the 2012 hit song “Payphone” by Maroon 5 featuring Wiz Khalifa). The covariates “TV Show” and “Featuring” allow us to control for the influence of both the effect of artists who emerge from reality television as well as collaborations that occur at the individual track level.

6.3. Alternative explanations: results

As the covariate data covered different timeframes (i.e., beginning in 1974 for “Label” and “HHI,” 1983 for “TV Show,” and 1987 for “Live”) and to avoid undesirable confounding effects related to the presence of multiple controls (Carlson & Wu, 2012), we reran our linear spline regression models in three iterations, incorporating the various covariates to control for the aforementioned possible confounding factors. The models adjust for: (1) a potential shift from buying recorded music toward attending live performances, (2) increasing industry concentration, and (3) the presence of artists who emerge from reality television as well as the “featuring” effect, respectively. The results are summarized concisely here while a full reporting of the results from each model is presented in Table 4 in the web appendix.

Because data for “Live” were only available from 1987 onwards, the three Tech Periods included in the first iteration align with Periods 2–4 in previous models. Therefore, we re-estimated the spline regression starting in 1987, maintaining two knots at 1998–99 and 2003–4. The covariate is never significant, and the pattern of results does not change substantially. Consequently, it seems unlikely that a different consumption orientation toward live concerts was significantly associated with the trends observed previously for the number of songs appearing on the chart.

Regarding consolidation in the industry, in the second iteration, only “Label,” the covariate reflecting the absolute number of labels, is significant and only for Top 10 songs. Moreover, the parameters of the regression do not change, except for Period 1 in which the parameter becomes significant ($\beta_{\text{Top10P1}} = 2.29$, $p < .05$). This suggests there was significantly less convergence in Period 1 among Top 10 songs. Despite this change, overall, we conclude the level of market concentration was not associated significantly with the trends and how the number of songs appearing on the chart changed over time from period to period.

Finally, the third category of covariates account for the evolution of artists emerging from television shows and increasing artist collaboration (i.e., the “featuring” effect), which primarily occurred in the final period. The two covariates “TV Show” and “Featuring” were included in the third iteration. The presence of TV Shows increased the number of songs that entered the Top 10, while featured artists increased the number of songs that entered below the Top 10 (#11–100). The spline coefficients are still very similar to those obtained for Top 10 songs. For songs #11–100, the coefficient for Period 4 changes in terms of significance and becomes marginal ($\beta_{\text{11-100P4}} = 6.95$, $p = .10$). This suggests that the featuring phenomenon that co-occurred with the entry of legitimate online sellers partially explains the increase in the number of songs making the chart in the last period. However, the overall pattern of results is generally supported even when controlling for these potential alternative explanations.

6.4. Summary of results for songs (blockbusters)

In summary, the totality of our results reveals there was increasing convergence toward fewer blockbuster songs on the Hot 100 up until 1998, the turning point when MP3s, the internet, and P2P file sharing conspired to halt the increase in convergence. Further, after legitimized online sellers came on board around 2003–4, the Hot 100 saw a renaissance in terms of more songs increasingly making it onto the chart, thus reducing convergence. What we observe during the transition to CDs (1986) was more in line with the prediction of long-tail theory, such that a less efficient market results in more convergence. The contrasting increase in market efficiency due to MP3s, P2P sharing, and the advent of music moving online led to a halt in convergence, which is also in line with long-tail theory. After legitimate online resellers emerged, market efficiency declined and there was a decrease in convergence, which is in line with the expectations of winner-take-all and superstar theory. Overall, the digital revolution in music seems to have shifted which theory more accurately explains convergence in terms of the number of songs appearing in the charts.

What happened in the Hot 100 can be further decomposed into what occurred in the Top 10 and what transpired with the rest of the chart. The convergence following the introduction of the CD, which one might describe as the industry's reclaiming some control over how consumers interacted with their music, occurred throughout the chart. However, the trend away from convergence following iTunes really took place only for songs #11–100 and away from the top tier as this phenomenon was not significant in the Top 10. This means that if we focus on blockbusters defined by reaching the extreme upper echelons of the chart, the impact of digitalization is still somewhat best captured by long-tail theory.

7. How technology shifts impacted convergence on the music chart for artists

Our second analysis focuses on artists whose songs make it onto the Hot 100. Making it onto *Billboard*'s Hot 100, if even for a short time, is indicative of superstardom, and we consider all 5996 artists who appear in our data set superstars when they made the chart. One might argue that a superstar is not a performer who makes it onto the chart only once or even two or three times. This argument holds that none of the 4,260 artists (63%) who appeared on the chart only one time, from Ray Charles to Charlie Pride, should be classified as having been superstars. Our argument, supported by past work on superstardom (e.g., Crain & Tollison, 2002), is that the number of unique artists appearing on the Hot 100 is a reasonable indicator of the concentration of superstars in popular music at any single point in time. However, for comparison's sake, we also employ a stricter definition of superstar in our analysis of the Top 10 places rather than the entire Hot 100.

The data allow us to examine the relationship between the categorical variable "Tech Period" and the number of artists, or superstars, appearing on the Hot 100. In the case of artists, we only provide a mean comparison across periods and not a spline regression analysis. The reasoning is as follows. If we take the artist data at the yearly level, the chance an artist enters more than once in the chart is quite low, and we would have spline regression results that largely mirror those already produced at the song level. Moreover, comparing the artists' presence in the chart across a longer period of time better reflects the process of superstar chart concentration (i.e., even the biggest superstars require more than one year to accumulate a significant number of chart successes).

7.1. Average number of songs per artist

To compare the number of artists across periods, we rely on the average number of songs-per-artist. The metric accounts for potential differences in the average length of time a song stayed on the charts, which could vary across periods while the number of artists alone does not. We began by counting the number of distinct artists appearing in each period. In our initial analysis, whenever an artist features one or more other artists, they are categorized differently (later analyses test the robustness of this approach). For our purposes, 6,736 artists were responsible for the 15,976 songs in our data set (see Table 7).

Note that 6,736 is derived by double counting artists whose songs appear in different periods (e.g., Elton John has hits in the '70s and '90s) and therefore is greater than 5996, the total number of unique artists who made it into the Hot 100 between 1974 and 2013.

Utilizing the number of songs entering the chart and the number of unique artists in each period, we calculated the average number of songs per artist per period (See Table 8). To compare averages across the four periods, we utilize ANOVA. The results, presented in Table 10, reveal that the average number of songs per artist fell from Period 1 to Period 2 with digitization and the popularization of the CD and again from Period 2 to Period 3 with the introduction of the MP3. This reflects a decline in convergence between 1986 and 2003; the declining number of songs per artist implies more superstars made the charts. It appears digitization allowed a greater number of artists the chance to achieve superstar status by appearing on the Hot 100 even though the artists did not appear as often. This result is in stark contrast to blockbuster songs, which saw increasing convergence across Periods 1 and 2.

Table 7
Summary statistics (*Billboard*'s Hot 100 from 1974 to 2013).

Tech period	Years	Number of artists* (Hot 100)	Number of artists* (Top 10)	Number of artists* (#11–100)
P1 1974–1985	12	1,944	532	1,365
P2 1986–1998	13	2,033	541	1,373
P3 1999–2003	05	865	206	581
P4 2004–2013	10	1,894	384	1,423
Total Number	40	6,736	1,663	4,742

* The total number of unique artists making the Hot 100 between 1974 and 2013, not separated by period, is 5996.

Table 8
Songs per unique artist in each period.

Tech period		Avg. # songs per artist (Hot 100)	Avg. # songs per artist (Top 10)	Avg. # songs per artist (songs #11–100)
P1	P1 1974–1985	2.87[a]	2.02[a]	1.58[a]
P2	P2 1986–1998	2.33[b]	1.96[a]	1.44[b]
P3	P3 1999–2003	1.84[c]	1.38[b]	1.51[ab]
P4	P4 2004–2013	2.15[b]	1.54[b]	1.59[a]

Note: Superscripts indicate averages differ significantly at $p < .05$.

Just as with songs, the trend for artists reverses itself after 2004 to pre-MP3 levels. It appears music's move online coalesced consumers around a smaller set of artists. We next separated the data into two sub-categories as we did for songs. Looking at the averages for Top 10 songs, we observe increasing convergence for Top 10 songs after 1998 that does not reverse itself in Period 4. There is little change across periods for songs #11–100 where the average was lower to begin with.

7.2. Robustness check for artists — the case of one-hit wonders

If, as our data indicate, the average number of songs per artist decreased, reflecting a greater number of artists making it onto the chart prior to 2004, we would expect to also observe an increase in the number of one-hit wonders (performers with only one song on the chart) across the first three periods as well. Stated another way, more artists with fewer songs per artist suggests more one-hit wonders. In Table 9, we present the number of artists with only one song and the number of artists with more than one song on the chart from 1974 to 2013 across the different time periods.

As expected, between 1974 and 2003, the percentage of artists with only one hit in the Hot 100 appears to increase (55%, 59%, and 69% per period, respectively) as the average number of artists making the chart increased (i.e., number of songs per artist decreased). This is further evidence that changes in recorded music brought about by technology (the internet, MP3s, P2P networks, and online distribution) contributed to a greater number of superstars, albeit many with only one blockbuster song.

Interestingly, the percentage of artists with only one hit (one hit wonders) also increased slightly (from 69 to 73%) in the final period (2004–13) when the average number of songs per artist increased as well (implying fewer artists making the chart). Ostensibly, more one hit wonders implies more artists making the chart, not fewer, and therefore may appear inconsistent with fewer artists actually making the chart after 2004. This anomaly may be the result of two different phenomena: (1) the emergence of mega-superstars and (2) a surge in collaborations or what we have labeled the “featuring effect.” First, after 2004, we witness the rise of a handful of what might be considered exceptional superstars (e.g., Taylor Swift) who possess an extremely large number of Hot 100 hits (55 in our data as “Taylor Swift”). The increase in convergence in the Top 10 and not songs #11–100 is consistent with the rise of mega superstars and may help explain why songs per artist increased, on average, despite more artists making the chart.

Second, there was an increase in the number of unique artists in our data set due to an unusually high number of collaborations between artists in which one artist is “featured” with another artist. This may explain why many artists appear as having had only one hit (e.g., “Taylor Swift featuring Ed Sheeran,” which is not counted in Taylor Swift's 55 Hot 100 hits). In fact, if we consider these collaborations as the product of the primary artist (i.e., a song by Taylor Swift featuring Ed Sheeran is a song by Taylor Swift), the overall pattern across time changes somewhat. By redefining unique artists in this way, we observe the percentage of artists with only one hit in the Hot 100 remaining close to constant across our four periods (54%, 54%, 56%, and 51%, respectively). Looking at the percentage of one-hit wonders in the Top 10 reveals a similar pattern (64%, 62%, 64%, and 62% of artists with only one song in the Top 10, across the four periods, respectively). On the one hand, collaborations are quite different from what one may think of as a one-hit wonder, yet on the other hand, artists compelled to include featured performers are reinventing themselves in a way that may or may not be attempted and/or succeed again.

The bottom line is that the average number of songs per artist and thus artists making the chart increases until 2003. But then, after 2004, fewer artists make the chart as a few mega-superstars fill the charts with more and more blockbusters. The impact of these mega-superstars is even greater if we consider the songs they produce with featured artists in their own portfolio rather than work done by a unique collaboration when counting the number of songs per artist.

Table 9
The number of one-hit-wonders by period.

	1974–1985		1986–1998		1999–2003		2004–2013	
	Hot 100	Top 10	Hot 100	Top 10	Hot 100	Top 10	Hot 100	Top 10
Artists with only one song on the Hot 100	1,078 (55%)	343 (64%)	1,199 (59%)	352 (65%)	596 (69%)	160 (78%)	1,387 (73%)	312 (81%)
Artists with more than one song on the Hot 100	866 (45%)	189 (36%)	834 (41%)	189 (35%)	269 (31%)	46 (22%)	507 (27%)	72 (19%)
Total # of artists	1,944	532	2,033	541	865	206	1,894	384

7.3. Summary of results for artists (superstars)

Using *Billboard*'s Hot 100 as an indicator of convergence for superstars, our results suggest a trend within the music industry resulting in more superstars in the Hot 100 producing fewer blockbuster songs. This trend increases significantly for songs below #11 with the advent of the CD and then in the Top 10 with the advent of the MP3. After 2004, with the emergence of legitimate online resellers, the trend appears to reverse itself; fewer superstars begin making the chart with more blockbuster songs per artist.

Interestingly, for artists, the transition to CDs around 1986 was more in line with the prediction of winner-take-all and superstar theory's premise that a less efficient market should result in less convergence (more artists coming in). And yet, the increase in market efficiency due to MP3s, P2P sharing, and the advent of music moving online after 1998 led to a decrease in convergence in line with expectations based on long-tail theory. This pattern is different from what occurred for songs. Additionally, in our fourth period, with the legitimization of online sellers, the trends for both songs and for artists are best described by winner-take all and superstar theory. It seems that in recent years, consumers have been looking for songs by the same artist (Taylor Swift) or featuring the same artist (e.g., B.O.B. featuring Taylor Swift). This could be a consequence of the internet and iTunes providing listeners the ability to find new songs more easily, yet consumers still looking for the tried and true stars.

8. Conclusion

8.1. Winner-take-all/superstar theory versus long-tail theory: is there a dominant theory?

At the outset, we pitted two theories against each other in order to test which would best predict how technological changes affected the Hot 100 chart. Which one dominates? It depends (see Table 10). Overall, if our focus is on the entire Hot 100 and thus a more liberal definition of blockbusters and superstars, we observe the following: the evolution of recorded music technology has changed the charts from fewer blockbusters by many superstars to more blockbusters by fewer superstars. Neither theory strictly applied with our empirical results being consistent with either one or the other depending on the type of technology change (increasing or decreasing market efficiency) and the unit of analysis (songs versus artists).

If, instead, we use a far more restrictive definition of blockbuster and superstar (i.e., only those appearing in the Top 10 of the chart), the implications of the observed changes in technology are less pronounced (i.e., more stability). As a consequence, the results are less contingent on the shift in technology and the only significant change in convergence was brought about by the turmoil of the MP3 and P2P revolution. When focusing on the top of the chart, the winning theory is much more straightforward as the changes we observe for songs are more in line with expectations articulated by long-tail theory while the changes observed for artists are more in line with winner-take-all/superstar theory.

8.2. Implications for theory

Based on the framework provided by MacInnis (2011), our study provides a conceptual contribution to marketing in the form of "revision." Contributions based on revising provide insight from the use of alternative frames of reference and are interesting because they suggest that what is seen, known, observable, or of importance can be seen differently. Contributions from revisions follow the context of theory justification, taking what is known or presumed to be known and seeing it differently through empirical analysis (Yadav, 2010). This research indeed uses alternative theoretical explanations (winner-take-all and superstar vs. long tail-theories) to gain a better understanding of a phenomenon—that is, how technology affects concentration in music charts. By taking a longitudinal perspective and relying on empirical data, we provide two main theoretical contributions in the vein of what MacInnis calls conceptual "revision."

First, we show that alternative theories can explain the effects of digitalization in music only when they are combined as each theory captures only a portion of the phenomenon. While long tail theory reflects the trend in concentration of both songs and artists when we focus on the top of the chart (Top 10), each theory captures only certain portions of the story as the definition of blockbuster and superstar becomes more inclusive (i.e., includes the entire Hot 100). It is only by integrating the two theories into a broader

Table 10
Theory best explaining observed changes in convergence resulting from shifts in technology.

Era	1974–1985 Vinyl/cassette (analog)	1986–1998 CD (digital)	1998–2003 MP3 (compressed)	2004–2013 AAC (DRM)
Market Efficiency	Baseline	Decreasing	Increasing	Mildly decreasing
Songs	Hot 100	Long-tail theory (fewer songs)	Long-tail theory (no change)	WTA/sstar theory (more songs)
	Top 10	Neither dominate	Long-tail theory (fewer songs)	Neither dominate
Artists	Hot 100	WTA/sstar theory (more artists)	Long-tail theory (more artists)	Long-tail theory (fewer artists)
	Top 10	Neither dominate	WTA/sstar theory (more artists)	Neither dominate

framework that allows for a greater understanding of digitalization's complex effects on chart concentration and helps to reconcile apparently inconsistent evidence existing in literature. In this light, we respond to the call for research invoked by Brynjolfsson et al. (2010) who argued that competing theories about the effect of digitalization should be analyzed as part of an integrated research agenda.

Second, exploring alternative theories allows for a better understanding of why the same shift in technology provides different effects in terms of convergence based on the focus of the investigation—songs or artists. One of the main reasons why extant evidence on a specific theory may be inconsistent is that some studies focused on artists while others focused on products (e.g., album or singles). Employing different theories helps not only to explain the existence of conflicting results but also shows that the value of each theory is contingent on the definition of the key constructs explored. Our findings reveal that each theory has different explanatory power for the same technology shift, depending on whether the focus is on the creator (the artist) or the creative output (songs).

8.3. Implications for managers

We believe our work has important implications for managers, agents, and other representatives of talent (e.g., publicity firms) within the music industry. Regarding superstardom, the decreasing number of performers who have gained access to the Hot 100 since 2004 suggests at least two noteworthy things. First, while more and more artists are vying for a spot on the chart, fewer are achieving their goal. On the one hand, this suggests talent management may have decreased the number of performers in their stables. Perhaps this is due to labels backing fewer artists or firms increasingly focusing their marketing efforts on fewer and fewer potential standouts (Elberse, 2008). Second, the trend toward featuring other artists on a song after 2004 should spur managers to think about possible collaborations as a way for superstars to help each other secure their place in the limelight. One might argue that technology has helped make finding another well-known artist and creating collaborations more advantageous.

The decrease in the number of songs making the charts that has accompanied initial shifts in technology likely corresponds to songs near the top (i.e., Top 10) holding their spots longer. This implies increasing returns associated with advancing up the ranks to a higher position. Managers may consider allocating more support, perhaps in terms of marketing spend, to songs that have entered the chart but are hovering at a lower rank. As a song moves up the charts, the time spent on the chart and thus the time it spends as a blockbuster is expected to increase. But more songs are being discovered and breaking out in the lower echelons of the chart post-2004, something that may be due to legitimate online music sellers helping consumers find new songs by the same stars or perhaps even commentary about such songs being published on their sites (i.e., curation to some extent).

Our results have implications for exploitation strategies concerning new songs by already famous artists. Technology advances appear to make the mass market more sensitive to “halo effects” or an artist's past successes in recent years. This should make it easier for managers—and the artists themselves—to leverage past chart success as evidenced by more blockbusters by fewer superstars. Managers should understand that digital technology changes have facilitated the grouping of people around hits and artists and that technology can facilitate reaching unexpected targets for those ultimately successful music acts. Changing technology may help explain the rapid diffusion of branding strategies in the music market according to which artists have become commercial brands and managers have activated social contagion mechanisms to launch new products (songs) under those brands (artists) and reach new customer targets.

Of course, managers—and artists—need to find a way to exploit the adoption opportunities spurred by new technologies related to launch strategies associated with new talent. The digitally mediated marketplace makes it easier to both keep interest up for an existing artist and get fans interested in new songs. However, they can also boost interest in new stars. For example, the increasing presence of singing competitions, talent shows, and related TV formats reflects how leveraging new technologies—and especially social networks—can be especially powerful when promoting and expanding the portfolios of the new stars. Consider that in Period 4 the Glee Cast had 167 songs on *Billboard*'s Hot 100, far more than any other artist in that period or any other period for that matter. And these songs are covers.

8.4. Implications for future research

Inextricably related to the number of songs appearing in the Hot 100 is the time each song stays on the chart. When songs are less enduring in popularity, they allow other songs to enter the chart. Observing more blockbusters would suggest shorter times on the chart. However, after we concluded our data collection, we observed that newer songs have begun shattering records in terms of time on *Billboard*'s Hot 100. Consider that “Radioactive” by Imagine Dragons exited the chart in May 2014 after 87 weeks, having broken the record for the longest life in the chart's 55-year history.[3] In Period 4, that record was held by Jason Mraz's hit single “I'm Yours” at 76 weeks on the chart. Further back, in Period 3, the record was held by LeAnn Rimes with her hit “How Do I Live” at 69 weeks. In terms of blockbuster songs, it appears that while more songs are making the chart (below #11) in recent years, as mentioned earlier for artists, there are true mega blockbusters that are appearing as they never have before and staying popular even longer. Our data does not indicate whether this extended popularity is due to more consumers catching on or some change in how consumers are interacting with the music they choose to listen to. This would be an interesting question for future research.

One immediate opportunity for future research involves a significant present-day shift in technology—music streaming services. We find advances enabled by the internet, P2P networks, and iTunes have affected the number of songs and artists making the

[3] In February 2013, *Billboard* announced it would begin incorporating YouTube data into their rankings. None of the results presented here change substantively when we exclude 2013 from our analyses.

chart. But how will streaming services like Spotify or Beats music (recently acquired by Apple) change the charts? Will they boost the convergence of superstars because of their similarity to the radio broadcasting approach? Or will they favor niche artists given these services also act as curators serving up samples from the long tail? Consider that Beats allows members to search for music in a variety of ways, including choosing among several alternatives to insert in the following sentence: "I am (at a party) & feel like (kicking back) with (the boys) to (pop)." The service then offers up songs, including new music, it believes the listener will like based on his or her insertions. By introducing listeners to new music that fits their mood in a customized way, curated services expand the breadth of artists and songs consumers are exposed to and are likely to enjoy, perhaps providing a boon for long-tail theory.

In the present research, we investigated how turning points in recorded music technology have impacted blockbusters at the individual song level of analysis. A third avenue for future research would be to extend the type of analysis to albums. Given that digital technologies have facilitated music unbundling (Elberse, 2010), it would be interesting to continue to investigate how technology has affected the album chart. It would be especially intriguing, from our perspective, to study the album chart and the singles chart simultaneously to determine how one impacts the other. One final potential research opportunity we might suggest results from our focus on the U.S. market. In the future, it would be informative to investigate the effects of similar technology shifts in foreign markets to determine whether cultural differences shape the effect of technology's impact on songs' chart-lives, turnover, and the concentration of artists.

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Appendix A. Supplementary data

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