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Does digitization lead to the homogenization of cultural content?

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This version: March 2021

Abstract. Using weekly music charts data in ten countries over the period 1990 to 2015, we analyze whether digitization leads to a trend of homogenization of music content or conversely to a greater acoustic disparity within music charts. Acoustic diversity measures the variance of a set of songs calculated across the following acoustic attributes: danceability, speechiness; valence; liveness; acousticness; energy; instrumentalness; loudness; tempo; duration. We consider the pre-digitization period (1990-1999) and split the digitization era in four periods: (1) the period characterized by unsanctioned music distribution via filesharing networks; (2) the launch of iTunes Music Store; (3) the emergence of social network services as powerful tastemakers; and (4) the emergence of global music streaming services, such as Spotify, as the dominant model for online music distribution. Our main result is that while acoustic diversity decreased during the iTunes and the YouTube periods, the period that begins with the introduction of audio streaming services, such as Spotify, represents a turning point and is marked by a significant increase in acoustic diversity.

Key-words. Music industry; Digitization; Content disparity; Cultural diversity.

1. Introduction

Has the digitization of the music industry led to a greater diversity or rather to a homogenization in music production and consumption? On the one hand, digitization seems to favor diversity: digital production tools, such as the home studio, offer the possibility to music artists to invent new music and to differentiate from their peers, while on the consumer side, recommendation systems allow music fans to discover new music niches matching their specific tastes. On the other hand, one might argue that digitization rather leads to homogenization. While it is less costly for an artist to invent new music, it is also less costly to imitate others.¹ For example, some artists specialize on the provision of cover songs that are successful on music streaming platforms such as Spotify.² Lawsuits over music plagiarism also abound nowadays.³ On the consumer side too, recommendations based on popularity may steer consumers towards a few hit songs, thereby reducing diversity. The impact of digitization on music diversity appears therefore *a priori* ambiguous. Our general objective in this paper is to provide new empirical evidence on the impact of digitization on music diversity.

Diversity in content industries is usually evaluated along two dimensions: *variety*, which increases with the number of products available, and *balance*, which decreases with the inequality in market shares across products. For instance, the debate between the “star system” hypothesis (Rosen, 1981; Adler, 1985; Hamlen, 1994) and the “Long Tail” hypothesis (Anderson, 2006) focuses on these two dimensions.⁴ However, as Stirling (1998) stressed, there is a third important dimension for diversity, *disparity*. Disparity measures how different two products are. Up to now, disparity has been measured using product categories such as the type of music label – small independent labels being supposed to release less conventional and commercial music than majors (see, e.g., Peterson and Berger, 1975; Bourreau et al., 2018) – the country of origin of the artist (see, e.g., Ferreira and Waldfogel, 2013; George and Peukert, 2016), or the musical genre (Lopes, 1992; Anderson et al., 1980). However, as pointed out by Askin and Mauskapf (2017), categories and their boundaries are dynamic and contested. For instance, the frontier between rock music and pop music is often seen as controversial. Likewise, the nationality of an artist could be either defined by her country of birth or by the country where she is making her career.

Hence, starting with Alexander (1996) and Dowd (2000), some authors have proposed to define relevant musical features to evaluate the disparity across songs. Alexander (1996) uses music scores and derives five binary variables (time and meter, form, accent, harmonic structure, and melody) to characterize songs. Dowd (2000) manually transcribes recorded songs in more than twenty dimensions. However, due to the amount of data that has to be manually collected, their samples are reduced to a few hundred songs. Thanks to music information retrieval (MIR) and machine learning, it is much easier today to reduce the high dimensionality of musical compositions to a set of discrete features for millions of songs. These features represent the best available approximation of what people hear when they listen to music (Askin and Mauskapf, 2017) and a robust representation of how listeners perceive music (Friberg et al., 2014). Moreover, these features were created to compare songs and measure their degree of proximity to improve the efficiency of recommendation

¹ The song “This Girl”, remixed by DJ Kungs in 2016 from an original song released by an Australian band in 2009, ranked #1 in the charts of several European countries. See [https://en.wikipedia.org/wiki/This_Girl_\(Cookin%27_on_3_Burners_song\)](https://en.wikipedia.org/wiki/This_Girl_(Cookin%27_on_3_Burners_song))

² See, e.g., “Sounds like a hit: the numbers game behind Spotify cover songs”, The Verge, September 2015, <https://www.theverge.com/2015/9/8/9260675/spotify-cover-songs-taylor-swift-adele>

³ “You stole my song! 4 historical examples of music plagiarism”, by Deana Sumanac-Johnson, CBC News, Jun 14, 2016, <http://www.cbc.ca/news/entertainment/music-plagiarism-analysis-1.3634429>

⁴ See Ordanini and Nunes (2016) for a recent contribution to this debate.

algorithms. In the present paper, we use song features to develop an indicator of acoustic diversity, which allows us to assess how different two songs are, from an acoustic point of view. We then evaluate how acoustic diversity has evolved in the digital era. However, different sub-periods exist in the digitization era with no reason to believe that they had the same impact on acoustic diversity. Besides the pre-digitization era, that ended in 1999, we consider four different periods for the digitization era: the period characterized by unsanctioned music distribution via filesharing networks; the period of the first efficient business model of digital music sales with iTunes Music Store; the period where social network services such as YouTube emerged as powerful tastemakers; and the period characterized by the development of music streaming services, such as Spotify, as the dominant model for online music distribution.

We use data from weekly charts in ten countries over the period 1990 to 2015 to analyze whether digitization has led to the homogenization of music content or to a greater acoustic disparity within music charts over the different periods. To measure music diversity, we compute an acoustic diversity measure that corresponds to the variance of a set of songs calculated across ten acoustic attributes (danceability, speechiness; valence; liveness; acousticness; energy; instrumentalness; loudness; tempo; duration), which we collected from Spotify for each song in our first data set. Using these two data sets, we find a small increasing trend over time in acoustic diversity in the era of unsanctioned music distribution via filesharing networks but a negative trend in for both the iTunes Music Store period and the period of the emergence of social network services (such as YouTube). Conversely, the streaming period displays an increasing and bigger trend for acoustic diversity. We argue that both supply-side and demand-side factors are at work to explain these trends. We provide some evidence that the development of IT had a positive impact on acoustic diversity when listeners display eclecticism in musical tastes, which suggests that IT tools help to explore the huge catalogue of recorded music.

A recent literature has studied whether digitization has led to a convergence of music consumption across countries, with a domination of US music, or rather to a divergence, with a larger weight for local music. Ferreira and Waldfogel (2013) study music charts from 22 countries for the period 1960 to 2007, and find that the market share of domestic music increases with Internet penetration, to the expense of US music. One explanation is that the online distribution of music and the local promotion of concerts are complements, and therefore the diffusion of Internet access tends to favor the consumption of domestic music. However, the period of their study ends in 2007, at the very beginning of the growth of YouTube and before the appearance of music streaming platforms such as Spotify. Studying the post-YouTube period, George and Peukert (2016) rely on weekly top singles charts from 2005 to 2013 in Germany, Austria, and the US. They find both a globalization effect (YouTube increases the overlap with US weekly charts) and a divergence effect (YouTube increases the domestic music market share). They stress that YouTube increases charts turnover, which expands the market for domestic products. They conclude that YouTube will not displace local culture. Our research question differs from this earlier literature. We ignore the (relevant) question of the convergence or divergence of cultures in the digital era, and instead, we study whether in each country digitization makes music sound more similar or more diverse, irrespective of the differences in the country of origin or musical genres. A second contribution of our paper is the introduction of a measure of similarity of music consumption, which goes beyond artists' nationality or musical genres.⁵

The remainder of the paper is organized as follows. In Section 2 we discuss the potential impact of digitization on music diversity using the relevant literature, and we also

⁵ This diversity measure could be used to investigate cultural convergence in music consumption across countries, but it is out of the scope of the present paper.

discuss further our contribution. Section 3 is devoted to the presentation of our datasets. In Section 4 we describe our empirical strategy and our estimation results. Section 5 discusses the results and Section 6 concludes.

2. The impact of digitization: homogenization or increased diversity?

Digitization can affect music diversity through the supply side and the demand side. First, the music that people purchase or listen to can be more or less diverse because artists tend to differentiate their creations more or less in the digital era than they used to in the pre-digital period. Music diversity can also be affected because consumers pick titles that are more or less different from what others decide to listen to. We discuss in more detail below how digitization can affect diversity through these two channels.

The impact of digitization on diversity on the supply-side

Digitization has substantially lowered the costs of bringing new music to the market for artists (Waldfoegel, 2013, 2014). It has lowered the fixed costs of creating music, with the advent of the home studio and other digital tools. It has also reduced distribution costs practically to zero with digital platforms, such as iTunes or Spotify, and promotion costs with social media. The question is whether this sharp reduction of the costs of creating new music for artists has led them to create music that is more or less differentiated from the music of their peers. If we take the analogy of R&D, digitization implies that the costs of inventing original and differentiated content are lower, but so are the costs of imitating the creation of others (see above the increase of cover songs on Spotify). Therefore, it is a priori unclear whether the digitization of music makes artists differentiate more from their peers or imitate more.

The literature has shown that digitization has led to an increase in the quantity of music produced and distributed (Handke, 2012; Waldfoegel, 2014). It has also shown that the quality of music has increased compared to the pre-digital era (Waldfoegel, 2012; Aguiar and Waldfoegel, 2016). However, it is silent on whether the music brought to the market in the digital era is more or less diverse than it used to be in the pre-digital era. In this paper, we aim to fill this gap and to provide some empirical evidence on the evolution of acoustic diversity for the subset of hit songs.

The impact of digitization on diversity on the demand-side

The diversity of the music consumed by people can also be affected by digitization for reasons that pertain to the demand side. The question is whether, taking as given the supply of music, digitization leads consumers to make more or less diverse music choices. The “long tail” hypothesis (Anderson, 2006) states that, if consumers have access to a large catalog of content (which we expect to happen with digitization), they will select content that best fits their taste, and possibly niche content that belongs to the “tail” of the distribution of sales, leading to less concentrated sales. The empirical evidence about the long tail hypothesis is mixed. For example, Elberse (2008) shows that for the period January 2005-April 2007, while the number of titles that come to the market increases with digitization, digital sales of music are more concentrated than physical sales. In other words, superstars still attract a large share of music sales in digital channels.

Since no clear picture emerges when we look at the aggregate effect of digitization on the diversity of music consumed, it is worth discussing the mechanisms through which digitization can affect consumer choices of music. First, digitization lowers search costs for

consumers. Online, consumers can easily read reviews of new music, sample new songs or artists, which reduces the costs of finding music that they like. The theoretical literature shows that a reduction of search costs allows consumers to make more informed choices and to select products that better fit their taste (see, e.g., Bakos, 1997; Peitz and Waelbroeck, 2006). Secondly, new digital tools can help consumers to choose what they want to purchase or listen to. Information about popularity (in the form of rankings, number of views, etc.) tends to steer consumers towards popular titles. Thus, we can expect this kind of information to reduce aggregate diversity. In line with this prediction, Salganick, Dodds and Watts (2006) provide empirical evidence that social influence negatively affects the diversity of music consumption. Providing information about the popularity of titles (in terms of number of downloads) leads to a larger concentration of downloads than when this information is not available. However, rankings can have countervailing effects. Sorensen (2007) argues that best-seller lists can generate a market-expansion effect that may dominate the business-stealing effect on niche products. Likewise, Tucker and Zhang (2011) show that popularity information can benefit proportionally more narrow-appeal (niche) products than broad-appeal (popular) products. The idea is that for consumers, the same level of popularity implies higher quality for a narrow-appeal product than for a broad-appeal product.

Digital music platforms also use recommendation systems (Resnick and Varian, 1997) to suggest music titles to their users. There are two different types of recommendation systems. Collaborative-filtering systems make recommendations to a consumer based on how similar users liked a product. Content-based filtering systems recommend products that are similar to products that the consumer liked. The effect of recommendation systems on music diversity is *a priori* ambiguous. On the one hand, recommendations help consumers discover new music or artists they might not have known before. In this vein, Datta Knox and Bronnenberg (2018) show that Spotify adoption increases the volume of music consumed, the variety of artists or genres of music, and the discovery of new music or artists. On the other hand, to the extent that they are based on sales, recommendations can lead to an increase in sales concentration, and hence, reduce diversity. For example, Fleder and Hosanagar (2009) propose a model of recommendations and show that collaborative filtering can generate a ‘rich gets richer’ effect and increase sales concentration. In support of this finding, Hosanagar, Fleder, Dokyun and Buja (2014) use data from iTunes and show that consumers exposed to recommendations purchase titles that are more similar to one another.

Network effects can also arise on the demand side when fans of a particular musical style form communities to exchange ideas or playlists, which is facilitated by digital technologies. The effect of such communities on the diversity of music consumption is unclear. While it could favor the development of more eclectic tastes, it could also have the effect of making people’s tastes more homogeneous.

To sum up, this discussion shows that taking the music offerings fixed, the impact of digitization on the diversity of music consumption is *a priori* ambiguous.

The impact of digitization on the diversity on music consumed

Ultimately, whether digitization leads to more homogenous or more diverse music consumption depends on the various effects at play on the supply side and the demand side, and their interaction in the market equilibrium. It is outside the scope of the present paper to build a formal model of these conflicting forces. Therefore, we discuss informally how digitization can affect the market equilibrium. Salop (1979) proposes a model of entry into a market with differentiated products, representing a good starting point. Salop shows that the number of products in the market equilibrium increases with the size of the market and

decreases with the fixed cost of entry.⁶ For the music industry, we have argued that digitization has reduced the fixed cost of entry on the supply side and search costs on the demand side, which can arguably lead to a larger market size. Salop's model would then lead us to predict that digitization increases diversity. But as discussed above, there are various countervailing forces, both on the supply side and the demand side, which can lead to the homogenization of music consumption instead of more diversity.

To sum up, the impact of digitization on the diversity of music consumption is *a priori* ambiguous. Whether it leads to homogenization or more diversity is an empirical question. All the empirical studies cited above use definitions of diversity that ignore the acoustic similarity or difference between two titles or artists. In these studies, introducing a new product increases diversity mechanically, even though it may be 100% similar, from an acoustic point of view, from an existing product. In this paper, we contribute to the literature by considering a more robust measure of diversity: acoustic diversity.

3. Data

The dataset used in this study has been generated by combining data of weekly music charts from ten countries with a dataset consisting of acoustic features of recorded music. These two datasets are introduced below.

Weekly music charts

The first dataset represents commercially successful music in a number of well-established music markets in North America, Europe and Australasia. Studies of music consumption have since decades back (e.g. Peterson and Berger 1975; Ferreira and Waldfogel 2013; George and Peukert 2016; Ordanini and Nunes, 2016) relied on "record charts" or "music charts" as a proxy for music consumption. These music charts list the best-selling or most-played songs (or albums) in a certain territory during a certain time period, normally a week. Charts play an important role in the music industry since they serve as a performance indicator, as a promotion tool, and as content for numerous media shows based on the chart as its fundamental structure (e.g. BBC's Top of the Pops in the UK aired between 1964-2006). Music charts have existed since the early days of the modern pop music industry and methodologies and practices for generating the charts have evolved along with the evolution of technologies and practices in the business for recorded music. Throughout these decades of change, major music markets across the globe have continued to publish a weekly chart, which the leading stakeholders in that market have collectively recognized as the "Official".

In this study, we are using such Official Charts from ten music markets as proxies of music consumption during the period 1990 to 2015. These markets represented 56% of worldwide recorded music sales in 2015 (including three of the top five markets), and thus can be considered as fairly representative of the whole industry. We built web scrapers for each chart and collected data from their online archives. The variables collected through this process were: Artist name (e.g. "Madonna"), Song title (e.g. "In My Feelings"), Chart title ("Nederlandse Top 40"), Chart date (e.g. "23-5-2012"), Chart position (e.g. 12). The charts vary in length between 40 to 100 songs per week,⁷ but in average there are 2,600 chart items per year and country. Table 1 below, presents the websites used and the size of the number of charts and chart items collected from these sites.

⁶ See Tirole (1988) for an exposition of Salop's model of circular differentiation with free entry.

⁷ Some charts contain a low number of songs (e.g., Norway had as few as 20 songs in the chart up until 2014).

Table 1 – The weekly charts

Country	Website addresses	Data source / Chart	Data points	Unique songs	Years available	Avg chart positions per song	Avg positions per chart
Austria	http://www.austriatop40.at/singles.php	Ö3 Austria Top 40	69,168	6,544	1990-2015	10.6	51.2
Australia	https://www.ariacharts.com.au/	ARIA Singles Chart	61,183	5,671	1990-2015	10.8	45.3
Belgium (Flemish)	https://www.ultratop.be/nl/ultratop50	BEA / Ultratop 50 Singles (Flemish)	58,057	5,936	1990-2015	9.8	42.9
France	http://www.snepmusique.com/tops-semaine/top-singles-megafusion/	Top Singles - SNEP	112,859	8,481	1990-2015	13.3	83.5
Netherlands	https://www.top40.nl/top40	Nederlandse Top 40	106,024	12,136	1990-2015	8.7	78.4
New Zealand	https://nztop40.co.nz/	The Official NZ Music Charts – Top 40 Singles	53,712	5,422	1990-2015	9.9	39.7
Norway	http://lista.vg.no/	VG-lista	21,542	2,473	1990-2015	8.7	15.9
Sweden	http://www.sverigetopplistan.se/	IFPI Sverige	58,799	5,800	1996-2015	10.1	56.5
United Kingdom	https://www.officialcharts.com	Official Singles Chart Top 100	49,024	10,983	1990-2015	4.5	36.3
USA	https://www.billboard.com/charts/hot-100	Billboard Magazine	127,365	8,783	1990-2015	14.5	94.2

Acoustic features of recorded music

The second dataset in this study contains data on “acoustic features” of recorded music. This data has been accessed from the world’s leading streaming music service, Spotify. The data is generated by an audio analysis algorithm developed by Berenszeig, Logan, Ellis and Whitman (2004) and commercialised by The Echo Nest (Whitman and Jehan 2011), a company that in 2015 was acquired by Spotify. Analysing acoustic features of recorded music is still a relatively novel research approach but generating a dataset from Spotify’s audio features API is becoming an established method as exemplified by Askin and Mauskapf (2017) or Chinoy and Ma (2018).

Spotify, and originally The Echo Nest, presents the audio analysis method as:

“...the world’s only ‘music listening’ API. It uses proprietary machine listening techniques to simulate how people perceive music. It incorporates principles of psychoacoustics, music perception, and adaptive learning to model both the physical and cognitive processes of human listening. The output of analyze contains a complete description of all musical events, structures, and global attributes such as key, loudness, time signature, tempo, beats, sections, harmony. It allows developers to create applications related to the way people hear and interact with music.” (Jehan 2014)

Based on this algorithm, Spotify has created a number of high-level dimensions in order to describe the acoustic features of a song. In this study we used ten of these features (“danceability”, “energy”, “speechiness”, “acousticness”, “instrumentalness”, “liveness”, “valence”, “loudness”, “tempo” and “duration”). Table 2 below presents Spotify’s definition of the ten dimensions.⁸

⁸ We are only considering those dimensions from the Spotify Audio Features API that are continuously distributed. This means that three dimensions – key, mode and time signature – are not included in this study.

Table 2 – Description of the ten dimensions of acoustic diversity

Feature	Description
<i>acousticness</i>	A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.
<i>danceability</i>	Danceability describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0.0 is least danceable and 1.0 is most danceable.
<i>duration</i>	The duration of the track in milliseconds. In this study, this variable has been normalised to the range 0.0 to 1.0.
<i>energy</i>	Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy, while a Bach prelude scores low on the scale. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.
<i>instrumentalness</i>	Predicts whether a track contains no vocals. “Ooh” and “aah” sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly “vocal”. The closer the instrumentalness value is to 1.0, the greater likelihood the track contains no vocal content. Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.0.
<i>liveness</i>	Detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live. A value above 0.8 provides strong likelihood that the track is live.
<i>loudness</i>	The overall loudness of a track in decibels (dB). Loudness values are averaged across the entire track and are useful for comparing relative loudness of tracks. Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). Values typical range between -60 and 0 db. In this study, this variable has been normalised to the range 0.0 to 1.0.
<i>speechiness</i>	Speechiness detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g. talk show, audio book, poetry), the closer to 1.0 the attribute value. Values above 0.66 describe tracks that are probably made entirely of spoken words. Values between 0.33 and 0.66 describe tracks that may contain both music and speech, either in sections or layered, including such cases as rap music. Values below 0.33 most likely represent music and other non-speech-like tracks.
<i>tempo</i>	The overall estimated tempo of a track in beats per minute (BPM). In musical terminology, tempo is the speed or pace of a given piece and derives directly from the average beat duration. In this study, this variable has been normalised to the range 0.0 to 1.0.
<i>valence</i>	A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry).

Source: <https://developer.spotify.com/documentation/web-api/reference/tracks/get-audio-features/>

Spotify’s song library contains approximately 40 million songs and the recordings span more than a century. The acoustic features have been calculated for all these songs and normalised across the entire library.

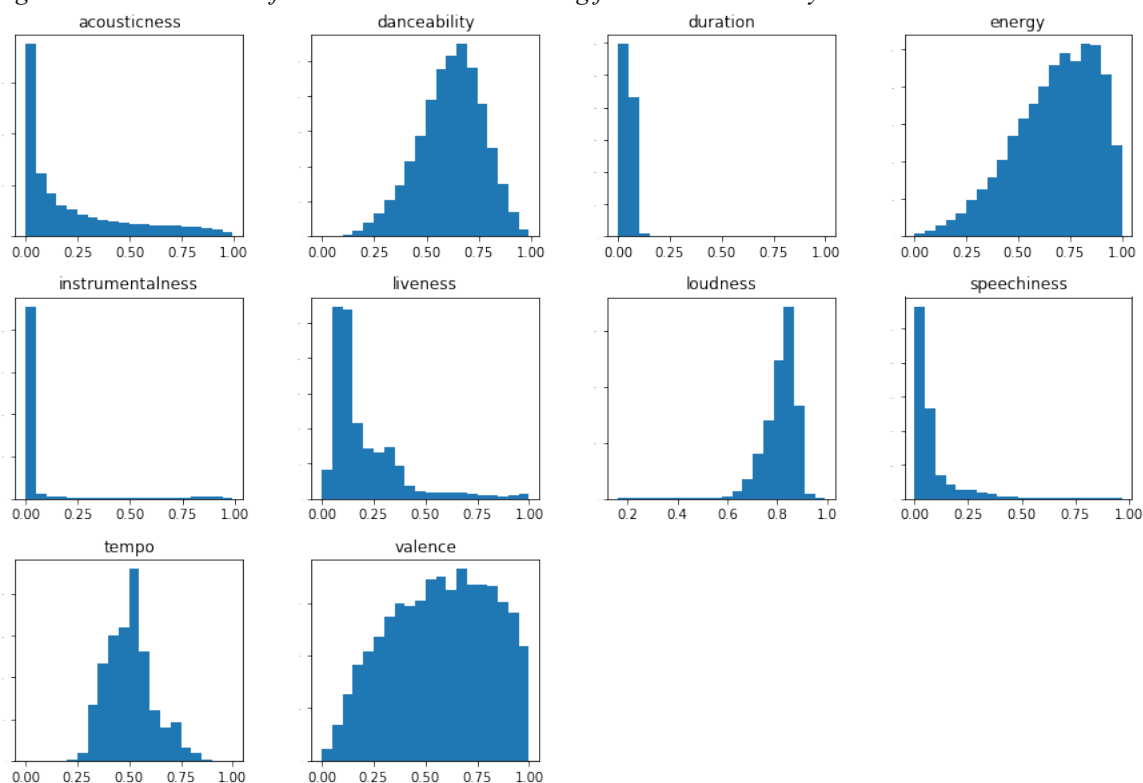
The distribution of the acoustic features for Spotify’s entire catalogue, or for the songs included in this study, is not normal. For instance, instrumental, acoustic songs are not as likely to enter mainstream weekly music charts as vocal, upbeat, pop and rock music. The histograms in Figure 1 illustrate the distribution of the ten acoustic features for the songs in the dataset and Table 3 presents some basic descriptive statistics for these distributions.

More about these features can be read at: <https://developer.spotify.com/documentation/web-api/reference/tracks/get-audio-features/>

Table 3 – Descriptive statistics of the ten variables accounting for acoustic diversity

	acousticness	danceability	duration	energy	Instrumentalness	Liveness	loudness	speechiness	tempo	valence
mean	0.23	0.61	0.05	0.68	0.06	0.20	0.82	0.08	0.50	0.57
std	0.26	0.15	0.02	0.20	0.19	0.17	0.06	0.09	0.11	0.24
min	0.00	0.00	0.00	0.00	0.00	0.00	0.16	0.00	0.00	0.00
25%	0.02	0.51	0.04	0.55	0.00	0.09	0.78	0.04	0.42	0.38
50%	0.11	0.62	0.05	0.71	0.00	0.13	0.83	0.05	0.51	0.58
75%	0.36	0.72	0.06	0.84	0.00	0.26	0.86	0.08	0.56	0.77
max	1.00	0.99	1.00	1.00	0.99	1.00	0.99	0.97	1.00	1.00

Figure 1 – Distributions of the ten variables accounting for acoustic diversity



In order to illustrate how the acoustic features work in practice, we present the data for eight songs in Table 4 (a & b) below and in the radar chart in Figure 2. Four songs are recorded by Britney Spears and four songs by John Denver. Table 4a shows when, where and by whom the songs were recorded and on what album the songs were released.

Table 4a – Details about the eight examples used to illustrate acoustic features

Song title & Artist	Album	Producer(s)	Studio	Released
Oops!...I Did It Again Britney Spears	Oops!...I Did It Again	Max Martin & Rami	Cheiron Studios, Stockholm	May 2000
Lucky Britney Spears	Oops!...I Did It Again	Max Martin & Rami	Cheiron Studios, Stockholm	May 2000
Toxic Britney Spears	In the Zone	Bloodshy & Avant	Murlyn Studios, Stockholm	Nov 2003
Someday (I Will Understand) Britney Spears	Britney & Kevin: Chaotic	Guy Sigsworth	Conway Studios, Los Angeles	Apr 2005
Sunshine on my Shoulders John Denver	Poems, Prayers & Promises	Milton Okun	RCA, New York	Apr 1971
Thank God I'm a Country Boy John Denver	An Evening with John Denver	Milton Okun	Universal Amphitheatre, Los Angeles	Feb 1975
I'm Sorry John Denver	Windsong	Milton Okun	RCA, Los Angeles	July 1975
Looking for Space John Denver	Windsong	Milton Okun	RCA, Los Angeles	July 1975

Table 4b below presents the values for the ten dimensions of the acoustic features for our eight song examples. The table shows among other things that the variability within the ten dimensions vary; for instance, there is very little variability in the ‘instrumentalness’, ‘duration’ or ‘speechiness’ dimensions.

Table 4b – The ten dimensions of the acoustic features of the eight song examples

Song title & Artist	acousticness	danceability	duration	energy	instrumentalness	liveness	Loudness	speechiness	tempo	valence
Oops!...I Did It Again Britney Spears	0.34	0.75	0.05	0.82	0.00	0.17	0.85	0.04	0.39	0.87
Lucky Britney Spears	0.24	0.77	0.05	0.82	0.00	0.15	0.85	0.03	0.39	0.97
Toxic Britney Spears	0.73	0.52	0.05	0.56	0.00	0.13	0.78	0.03	0.56	0.18
Someday (I Will Understand) Britney Spears	0.03	0.77	0.04	0.84	0.02	0.25	0.88	0.11	0.59	0.92
Sunshine on my Shoulders John Denver	0.86	0.45	0.05	0.27	0.00	0.18	0.71	0.03	0.53	0.50
Thank God I'm a Country Boy John Denver	0.89	0.43	0.02	0.16	0.00	0.19	0.74	0.03	0.42	0.42
I'm Sorry John Denver	0.90	0.40	0.05	0.22	0.00	0.70	0.71	0.05	0.28	0.18
Looking for Space John Denver	0.79	0.76	0.04	0.54	0.00	0.06	0.78	0.05	0.44	0.96

To further illustrate the concept of acoustic features and acoustic *proximity* between songs we present radar charts (Figure 2 below) for each song example, but for clarity, we are only using the dimensions with significant variability: acousticness, valence, tempo, liveness, energy and danceability. A naïve observation of the charts show that some songs are more acoustically similar than others. E.g. Spears’ *Oops!... I Did It Again*, *Lucky* and *Toxic* all have seemingly similar acoustic features and so is also the case for the pair of John Denver songs *I’m Sorry* and *Looking for Space*. Denver’s *Sunshine* however, seems intuitively to be an acoustic outlier in our sample of eight songs. We operationalise these similarities as the pairwise Euclidian distances between the eight songs where the songs are positioned in a 10-

dimensional space based on the song's acoustic features. The distance theoretically ranges from zero (0) which means that both songs are acoustically identical, to $\sqrt{10}$, which is only possible in the unlikely case that the two songs are positioned at maximum distance.

The Euclidean distance is 0.14 between Britney Spears' *Oops!...* and *Lucky*, which are both from Spears' second album, produced by Max Martin and are more or less identical in structure and sound. John Denver also has two cookie cutter songs (Euclidean distance 0.18), namely *I'm Sorry* and *Looking for Space*, both on the album *Windsong*, produced by Milton Okun. *Someday*, which is written by Spears and produced by a different team than used on most of her recordings during the first part of 2000s is an example of an outlier. The distance between this song and the three other Spears songs in the sample is actually greater than between *Someday* and the four Denver songs. All distances for the eight song examples are presented in Table 5 and the use of this metric to calculate *acoustic diversity* for a set of songs, will be explained in a subsequent section.

Figure 2 – Illustration of six acoustic feature dimensions for the eight songs.



Table 5 – Pairwise Euclidian distances calculated for the eight song examples

		Britney Spears				John Denver			
		Oops!	Lucky	Someday	Toxic	I'm Sorry	Looking	Sunshine	Country Boy
Britney Spears	Oops! (...I Did It Again)	-	0.14	0.89	0.39	0.92	1.03	1.26	0.55
	Lucky	0.14	-	1.01	0.33	1.02	1.13	1.37	0.63
	Someday (I Will Understand)	0.89	1.01	-	1.11	0.47	0.53	0.76	0.83
	Toxic	0.39	0.33	1.11	-	1.16	1.28	1.47	0.86
John Denver	I'm Sorry	0.92	1.02	0.47	1.16	-	0.18	0.67	0.64
	Looking For Space	1.03	1.13	0.53	1.28	0.18	-	0.59	0.76
	Sunshine (On My Shoulders)	1.26	1.37	0.76	1.47	0.67	0.59	-	1.14
	(Thank God I'm a) Country Boy	0.55	0.63	0.83	0.86	0.64	0.76	1.14	-

Merging the two datasets

The websites (see Table 1) where the charts used in this study are published, generally only present metadata such as the name of the charted songs and the name of the artist or band that made the recordings. There are no unique song identifiers available that would enable researchers to establish unambiguous links between a song in the chart data with its corresponding metadata accessible from other datasets. This means that when linking songs in our two datasets (Weekly music charts and Acoustic features) we are required to search for matching combinations of song name and artist name in each dataset. This is a straightforward and common approach, but due to typos, spelling ambiguities, etc., it is not one without flaws. Some of the songs in the chart dataset could for that reason not be confidently matched with acoustic features metadata, which led to our decision to delete the unmatched items (11%) from the original dataset. The final dataset used in the analysis therefore consists of 717,733 datapoints that pertain to 40,222 unique songs and 15,068 unique artists as presented in Table 1.

An aggregated measure of acoustic diversity

Diversity measures are per definition calculated over a set (or sets) of elements, in this case a set of songs. A song set in this study is defined as the songs that are listed in a chart in a specific country during a specific *Time Window*. Since the music charts in this study are published on a weekly basis, the minimum *Time Window* is one week. This *Time Window* is iteratively moved forward one *Time Step* at a time over the period of analysis (1990-2015) in order to build the time series representing the dynamics of the acoustic diversity measure.

In all calculations of the acoustic diversity measure, we used the smallest possible *Time Window* (1 week) and the shortest possible *Time Step* (1 week). This means that a complete time series that covers the entire period of analysis from 1 January 1990 to 31 December 2015 consists of (26 years x 52 weeks) 1,352 data points. Note that due to some data quality issues, resulting in missing data, approximately 5% of these data points were missing.

Acoustic diversity is calculated as the mean of all pairwise Euclidean distances between the songs in the song set, as discussed above⁹. Using the eight song examples to illustrate acoustic diversity, we calculate the acoustic diversity for all eight songs to 0.83, while the diversity metrics calculated separately for all Spears songs and all Denver songs are 0.64 and 0.66 respectively. To further illustrate the logic, we note that removing the Spears' outlier song *Sometimes*, the diversity metric for her remaining three songs in our sample falls to 0.29. Denver's outlier song is *Thank God I'm a Country Boy*, and if we remove that song from the sample the diversity metric for Denver's remaining three songs fall to 0.48.

4. Empirical strategy and results

We first provide a basic descriptive analysis of the evolution of acoustic diversity over the period on the whole dataset, and then an econometric analysis taking into account our panel of ten countries and the different periods of the digitization era. To account for the changes in distribution channels during the digitization era we argue that five periods, corresponding to four turning points, are significant and we run regressions that allow us to take into account the possible existence of different trends in these various periods. Note that we control for two dimensions that could have an impact on acoustic diversity within the music listened in a specific country: the dominant musical genres and the country of origin of songs that entered the tops.

Global trend of the evolution of acoustic diversity

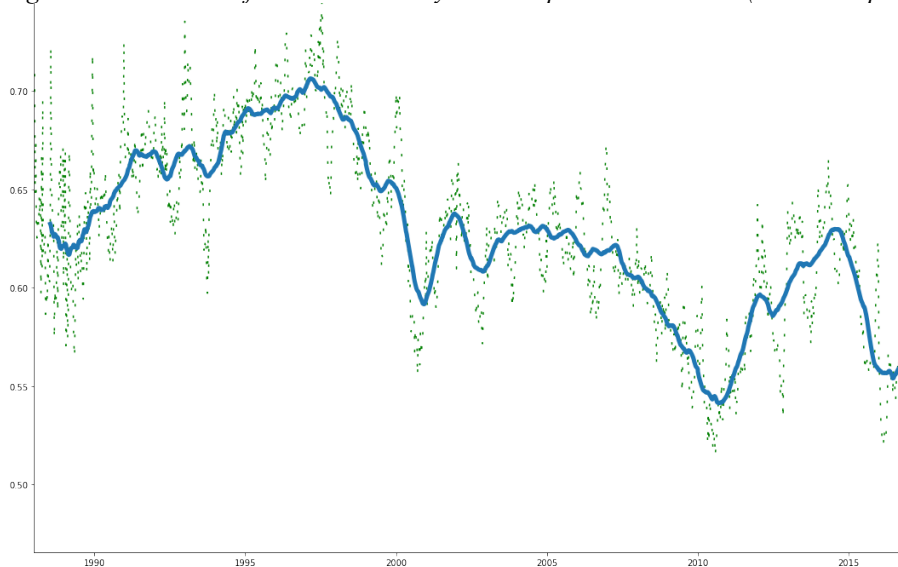
Plotting the evolution of the mean annual value of acoustic diversity over the period 1990-2015 in our whole sample highlights a seemingly negative trend (see Figure 3). While the acoustic diversity follows a similar overall trend in all ten countries (see Figure A.1 in appendix), there are nevertheless some distinct variations between individual countries. However, it is necessary to recognise that in this study we have no ambition to explain the variations between countries, but merely note that the data underscores the well-established idiosyncratic nature of national music markets.

Beyond the global trend of the evolution of acoustic diversity it is also interesting to study the evolution over the period of the ten individual acoustic features (Acousticness, Danceability, Energy, Instrumentalness, Liveness, Speechiness, Valence, Tempo, Loudness and Duration). It is by analysing all these features combined that allows us to produce a multidimensional and useful measure of the acoustic diversity of the songs over the time period in question. It is obviously possible to calculate the acoustic diversity based on fewer features than those that we are using. In Figure A.2 in Appendix we show charts of the acoustic diversity for all ten countries based on single attributes. It is vital to underscore the fact that these charts indeed show the diversity based on individual features and not the actual values of these features for the specific time period. The charts show that the trend on aggregate level can also be found for some of the individual features such as Liveness, Instrumentalness and, albeit somewhat less pronounced, also for Valence and Danceability. Other features however, such as Speechiness and Acousticness do not follow this trend but

⁹ Note that a larger set of songs mechanically increases acoustic diversity. Therefore, it makes sense to control for the number of songs that compose the song sets. However, in the present paper, acoustic diversity is measured for sets of songs of the same size (most of the time, charts are composed of the top-100 songs). Hence, our study does not suffer from the bias arising from different sizes of song sets.

rather remain fairly stable during the period. We note that the overall trend is generated by the former features having greater impact on aggregate level than the latter two, which produces the overall negative trend that can be observed. However, we will not take this observation further since our study is not aiming to explain the evolution of individual features of the time period but is focused on the analysis of aggregated data.

Figure 3 – Evolution of acoustic diversity over the period 1990-2015 (whole sample)



Note: The dashed line represents the actual weekly data, the solid line represents the rolling mean over 50 weeks.

The role of musical genres and of the country of origin of the songs entering the charts

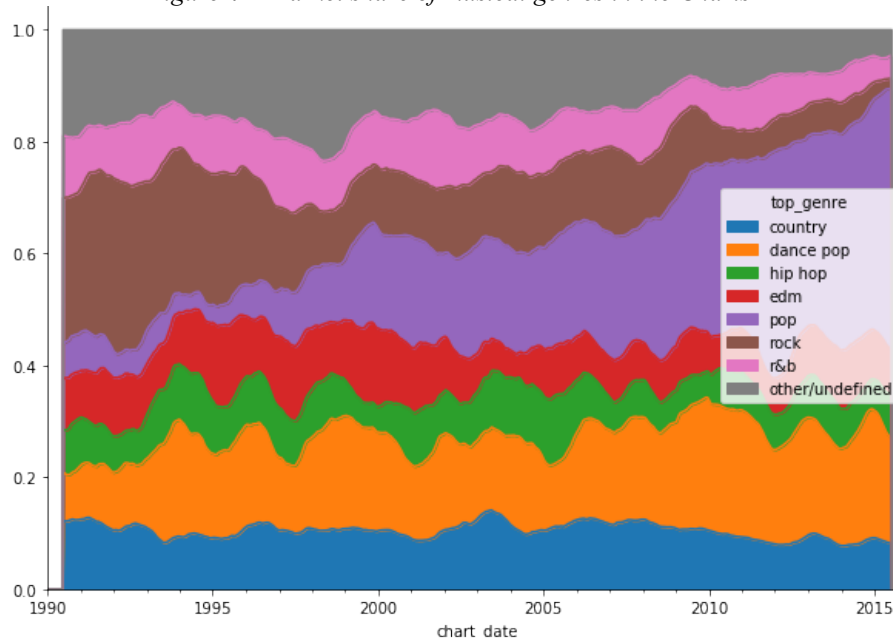
A first possible determinant of the evolution of acoustic diversity could stem from changes in popularity of musical genres over the period. Since diversity “within” a genre is expected to be lower than across genres, if the dominant genres in the 2000s have a lower within diversity than the dominant genres in the 1990s this would mechanically lead to a lower acoustic diversity in the 2000s than previously. In order to investigate whether this is the case or not, we need to check that the changes we observe in acoustic diversity do not simply capture the changing popularity of genres over the period.

Genre is however a challenging category to use when studying acoustic diversity over time. First, genres are obviously not as stable as a category as “countries”. Rather, the meanings of genres are constantly negotiated and evolve over time. What is considered “*rock*” in 2020s does not necessarily sound like what was considered to be “*rock*” in the 1990s. Second, genres are culturally specific. For instance, a song that is classified as “*latin*” in the USA may be classified as “*pop*” in Brazil. Third, a genre signifies much more than a song’s acoustic characteristics. E.g. “*punk*” without certain outfits and attitudes is not “*punk*”, even though it may share musicological conventions with what is generally considered as punk music. Finally, genres are not distinct. A song may be a mix of funk, pop and classical and debating whether it is more one genre than the other two quickly becomes a relatively meaningless exercise.

Due to the above, many music platforms choose not to focus excessively on genre. For instance, Spotify uses genres as labels attached to artists, rather than to songs and lists a number of very specific genres to assist music discovery and association. In this study, we are using this approach and collect data from Spotify about the genres associated with the artists in the dataset. Since these Spotify’s genres are very niche (e.g. Italian trance, chill groove, zapstep), we traced these back to a small number of well-established key genres that were

common in our dataset, namely *hip hop*, *electronic dance music (edm)*, *pop*, *dance pop*, *rock*, *rhythm & blues (r&b)*, *country*. Not all songs could be traced back to these genres, which required to add an “*other/undefined*” genre as well. Figure 4 plots the weekly market share of each musical genre within the charts of the whole set of countries. Deep changes have indeed occurred in the composition of the charts. “*Rock*” and “*other*” that accounted for about 40% of the songs entering the charts in 1990 have almost vanished at the end of the period. Conversely “*pop*” and (although at a lesser extent) “*dance pop*” songs have gained in popularity (the pop genre now represents about 40% of the songs that constitute the charts). We further observe that for the other main musical genres, namely “*country*”, “*edm*”, “*hip hop*” and “*r&b*” the market shares experienced only small changes over the period. We thus focus on the analysis of the evolution of the diversity within the musical genres that experienced significant changes in their market share, namely “*rock*”, “*other*”, “*pop*” and “*dance pop*”.

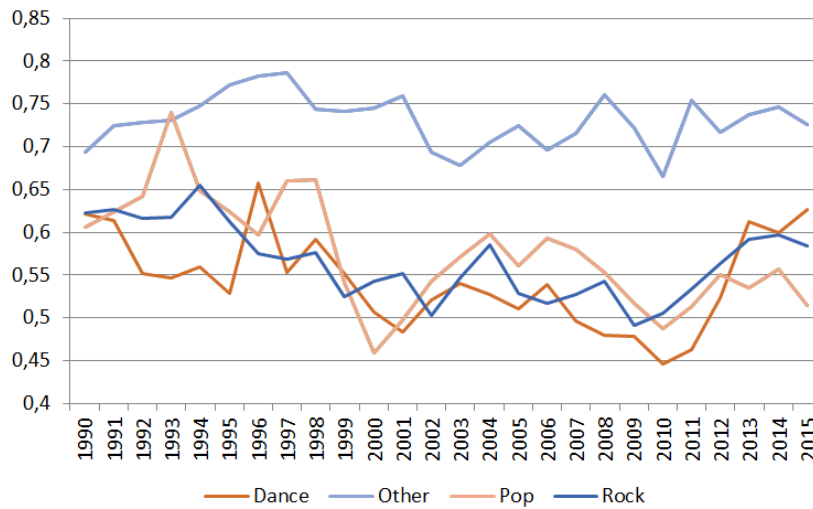
Figure 4 – Market share of musical genres in the Charts



Note: Rolling average – 50 weeks

Figure 5 presents the evolution of within diversity for these four genres. It shows that the diversity within the three dominant genres over the whole period (“*dance pop*”, “*pop*” and “*rock*”) follows a similar trend. It seems thus hard to explain the decrease in acoustic diversity over time by the increase of “*pop*” and “*dance pop*” songs at the expense of “*rock*” songs. However, the role of the “*other/undefined*” songs is potentially more important. On the one hand, the level of acoustic diversity is unsurprisingly higher for this genre than for the others. On the other hand, the market share of this genre has collapsed which has mechanically driven down the acoustic diversity in our dataset. However, if this can contribute to explain the decrease of acoustic diversity between 2000 and 2009, it cannot explain the increase in acoustic diversity at the end of the period! To sum up, we argue that the trend of acoustic diversity from the beginning of digitization could hardly be driven by the solely changes in dominant musical genres. To check the robustness of this claim, we will include in our regressions the weekly market share of our eight musical genres. This allows us to control for the impact on acoustic diversity of the changes in dominant musical genres all over the period.

Figure 5 – Evolution of the within diversity of musical genres which market share changes significantly over the period



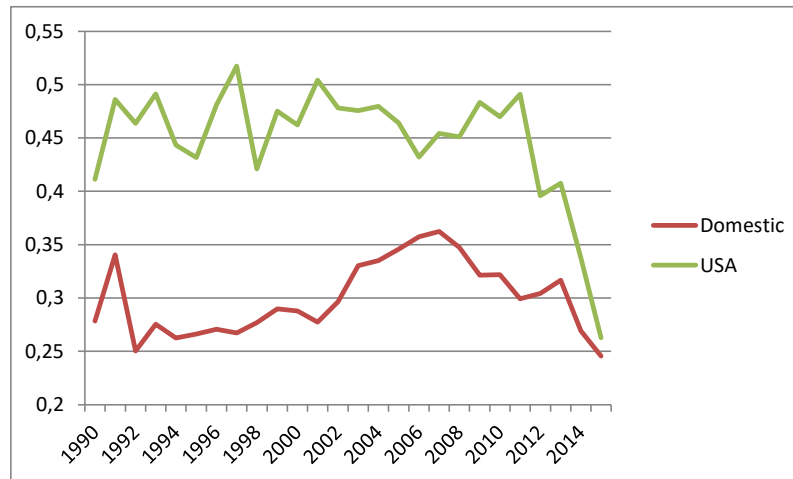
A second possible determinant of the evolution of acoustic diversity within the charts could be the country of origin of the songs that make the charts. We can reasonably imagine that songs from the same country are more acoustically similar to each other than songs from a different country. Since in most markets two origins are usually dominant: domestic songs and US songs, changes in the importance of these two repertoires could impact acoustic diversity. Ferreira and Waldfogel (2013) have shown that the market share of domestic music increases with Internet penetration during the first half of our time period. Could this increasing “home bias” be the main determinant of the decrease in acoustic diversity over that period?

Figure 6 displays the yearly average domestic and US music share over the whole sample. At a first glance it does not seem to be a clear relation between the country of origin and acoustic diversity: neither the US music market share nor the domestic market share present a pattern linked to the evolution of acoustic diversity displayed on Figure 3. However, we formally control for the role that the country of origin of the songs entering the Charts could have on acoustic diversity by including in our regressions the domestic market share as well as the US market share for each weekly chart of the ten countries. We thus use Musicbrainz, an online music database that collects music metadata¹⁰, to document the nationality of the artists. Musicbrainz mainly identifies the nationality of an artist from the “artist area” which indicates the area with which an artist is primarily identified with. It is often, but not always, its birth/formation country¹¹. We ended with a final manual step, mainly through Wikipedia, to document the nationality of the artists not founded in Musicbrainz.

¹⁰ See <https://musicbrainz.org>

¹¹ See <https://musicbrainz.org/doc/Artist#Area>

Figure 6 – Market share by country of origin in the Charts



Basic econometric analysis

To test how acoustic diversity evolves over the period 1990-2015 controlling for the panel nature of our sample that gathers data from ten countries, we ran an OLS regression with acoustic diversity as the dependent variable and time as a continuous independent variable. This regression includes ten country dummies to control for structural, time-invariant, specificities in the level of acoustic diversity in each country, as well as the weekly market share of musical genres in each country and the weekly domestic and US music market share in each country. We also include the GDP per capita as a control variable.

Table 6 – OLS regressions

Dependent variable: Acoustic_diversity		
	(1)	(2)
Time	- 0.0011*** (0.00025)	
Internet_users		- 0.1204*** (0.0055)
Country fixed effects	Yes	Yes
Control for musical genres	Yes	Yes
Control for GDP/Capita	Yes	Yes
Control for country of origin	Yes	Yes
Constant	2.95*** (0.4869)	0.517*** (0.023)
Adjusted R-squared	0.4108	0.4379
Observations	9,451	9,451

Standard error in parenthesis. *p<0.1; **p<0.05; ***p<0.01

The variable *time* is supposed to capture the development of IT that may have affected music diversity via the demand side and the supply side, as discussed in Section 2. We alternatively use as the main independent variable the share of internet users (*internet_users*) in each country for each year of the period 1990-2015.¹² This variable allows the development of IT over time to be specific to each country rather than uniform with time for all countries. Since the share of Internet users and time are almost perfectly correlated (correlation coefficient =

¹² The share of internet users by country is provided by ITU's World Telecommunication/ICT Indicators Database. This is the main source of global, and internationally comparable, telecommunication/ICT statistics.

0.94), we cannot use both variables in the regressions. Column (2) in Table 6 shows that results remain unchanged whatever the variable used. In the remaining of the paper, we use *time* instead of *internet_users* as the main independent variable.

The results displayed in column (1) in Table 6 confirm that acoustic diversity has significantly decreased over the period. We noticed above from Figure A.1 that the negative trend of acoustic diversity over time seems to exist in all countries. Table A.3 in appendix allows us to rigorously check for this conjecture. It turns out that this is indeed the case for all countries but Austria and Belgium. For these two countries it seems that the evolution in musical genres and in country of origin of the songs that enter the Charts better explain the decrease in acoustic diversity than time. However, as mentioned earlier it is beyond the scope of this paper to discuss the specificities of each country and the global impact of time, as a proxy for digitization, is not our main focus. Instead we aim at studying if the different periods of time of the digitization era, that correspond to different dominant distribution channels, had an homogeneous or conversely a specific impact on acoustic diversity.

Four turning points for the impact of digitization on acoustic diversity

Since the 1990's the music industry has experienced profound changes, moving from a situation where recorded music was sold and consumed as CDs to the emergence of streaming platforms. We argue that four main business and/or technological turning points occurred, which are especially relevant to define periods in the digitization of the music industry:¹³ the introduction of Napster in 1999, of iTunes Music Store in 2003, of YouTube in 2006 and of Spotify in 2009.

*Turning point 1: Napster.*¹⁴ Although the MP3 technology was developed in 1992, it became popular with the launch of Napster in June 1999, quickly followed by the introduction of various peer-to-peer (P2P) file exchange solutions (e.g., Kazaa). The MP3 technology allowed consumers to transform music into digital files, which could be downloaded and exchanged at almost zero costs. P2P networks also lowered search costs for consumers to find music, even though they did not provide any recommendation tools to discover music fitting one's tastes. Andersen and Frenz (2010) show that together with gratuity, music discovery was a key motivation for MP3 file-sharing. Therefore, we can speculate that the Napster era affected the demand side in a way that led to an increase in music diversity. On the supply side, artists were not able to monetize their music on these new distribution channels, and P2P downloads cannibalized their sales on legal distribution channels.¹⁵ Thus, the appropriability of artists' creations decreased, reducing their incentives to enter the music market with new works. Therefore, the overall effect of digitization in the Napster era on acoustic diversity remains ambiguous.¹⁶

Turning point 2: iTunes Music Store. In 2003, Apple launched the iTunes Music Store. It had a strong impact on the way music is consumed, and contributed to the decline of CDs. However the impact the potential impact of iTunes Music Store on the diversity of music produced and consumed is unclear. On the one hand, for the first time consumers had legally access to huge catalog of millions of songs which should foster discovery and thus diversity. On the other hand, the music was still sold at a unit price, in a similar way to the sales of CDs.

¹³ Ordanini and Nunes (2016) also rely on such a periodization approach.

¹⁴ Waldfogel (2017) speaks of Napster's entry as the start of "Round 1" of digitization.

¹⁵ See Waldfogel (2017).

¹⁶ A more structural approach could allow us to disentangle the demand side and supply side effects, but it is beyond the scope of the present paper.

That's why the overall effect of iTunes Music Store on acoustic diversity is difficult to forecast.

Turning point 3: YouTube. The second event that may have impacted the diversity of music produced and consumed is the launch of YouTube in April 2005. On the consumers' side, YouTube emerged as an easy and legal way of listening to music online, and surpassed file-sharing.¹⁷ Due to its popularity among consumers, YouTube also became an important medium for new artists to promote their music, which we expect to favor diversity. In addition, YouTube introduced recommendation tools to help users find (music) videos fitting their tastes. However, YouTube's recommender system mainly relied – at least in the early years – on the popularity of videos, which may lead to a concentration of consumption on a small set of music titles, as discussed in Section 2.

Turning point 3: Spotify. The third turning point is the emergence of Spotify. Spotify was launched in February 2009, and it is now the leading music streaming platform in the world. Spotify provides users with unlimited access to a catalogue of 40 million songs, either for free (and then advertiser-supported) or for a monthly subscription fee (without advertisement). From 2010 to 2017, the share of music streaming in total US music revenues rose from 7% to 65%. One of the key factors which explain Spotify's success and that of music streaming platforms in general is the quality of their personalized recommender systems, which offers users an easy and powerful way to discover new music. In particular, Datta, Knox and Bronnenberg (2018) show that Spotify adoption leads to more discoveries of new music or artists. We therefore speculate that the diversity of music has increased in the Spotify era.

OLS regression with non-linear effect of time on acoustic diversity

For the period 1990-2015, we first test the impact of the four turning points presented above on the evolution of music diversity. More precisely, we test empirically whether the evolution of *acoustic_diversity* changes significantly at the launch of Napster, the creation of iTunes Music Store, the introduction of YouTube and at the launch of Spotify.

However, we have to take into account that, except Napster, these various new music distribution channels did not appear at the same moment in each country. iTunes Music Store and Spotify had the possibility to block the access to their service depending on the country of residence to the consumers. Although YouTube was accessible everywhere in the world from the beginning, local versions that better fit the tastes of domestic consumers have been gradually released (see Table 7).

Table 7 – Date of launch of iTunes Music Store, YouTube and Spotify in the countries of the sample

<i>Distribution channel</i>	<i>Date of launch</i>
iTunes Music Store	April 28, 2003 (USA); June 15, 2004 (Austria, Belgium, France, Netherlands, UK); May 10, 2005 (Norway, Sweden); October 24, 2005 (Australia); December 6, 2006 (New Zealand)
YouTube	December 15, 2005 (USA); June 19, 2007 (Austria, Belgium, France, Netherlands, UK); October 22, 2007 (Australia, New Zealand); October 22, 2008 (Norway, Sweden)
Spotify	February 10, 2009 (France, Norway, Sweden, UK); May 18, 2010 (Netherlands), July 14, 2011 (USA); November 15, 2011 (Austria); November 16, 2011

¹⁷ In 2016, 19% of internet users illegally downloaded music, whereas 85% of YouTube users used it to listen to music. Source: Ifpi/Ipsos, Music Consumer Insight Report 2016.

We thus define five dummies for the five periods. The first period (pre-digitization) is identical for all the ten countries. The four digitization periods (*Napster*, *iTunes*, *YouTube* and *Spotify*) are country-specific and built from the information provided in Table 7. By interacting the period dummies the variable *Time*, we can assess how acoustic diversity evolves over time within each of the periods. Do note that this allows us to capture more precisely the impact of the various modes of distribution on acoustic diversity by including a country specific treatment.

The estimation results for this regression are displayed in Table 8. We find that during the pre-digitization era (*Time*) a small increasing trend appeared for acoustic diversity. This trend continued during the Napster era (*Napster*Time*). With the iTunes period began a decrease in acoustic diversity (*iTunes*Time*) with a small acceleration during the YouTube era (*YouTube*Time*). Conversely, the streaming era marked a real turning point and is associated with an opposite trend. Acoustic diversity increased during the streaming era (*Spotify*Time*).

Table 8 – OLS regression with interaction between time period and time trend

Dependent variable: Acoustic_diversity	
Time	0.00083** (0.00038)
Pre-digitization	Ref.
Napster	-3.373** (1.6438)
iTunes	8.417*** (2.6897)
YouTube	13.303*** (1.965)
Spotify	-36.695*** (1.6296)
pre-digitization*Time	Ref.
Napster*Time	0.00166** (0.0008)
iTunes*Time	-0.00422*** (0.00134)
YouTube*Time	-0.00666*** (0.00098)
Spotify*Time	0.0182*** (0.0008)
Constant	-0.973 (0.745)
Country fixed effects	Yes
Control for musical genres	Yes

Control for country of origin ¹⁸	Yes
Control for GDP/Capita	Yes
Adjusted R-squared	0.499
Observations	9,451

Standard error in parenthesis. *p<0.1; **p<0.05; ***p<0.01

However, the statistical significance of our results does not inform us about their economic significance. Hereafter, we thus propose some insights about the magnitude of the effects. From Table 8, we calculate how many standard deviations acoustic diversity evolves during each period. For the Napster, iTunes and YouTube period the magnitude of the effect on acoustic diversity remained limited (the changes in acoustic diversity represent respectively 0.216, 0.175 and 0.292 of a standard deviation during the respective period¹⁹. During the Spotify period, not only the trend is positive conversely to the iTunes and YouTube period, but the magnitude of the increase in acoustic diversity is much greater than during the previous periods: about 1.7 of a standard deviation of the acoustic diversity variable during that period²⁰. Hence the magnitude of the positive effect of digitization during the Spotify period dominates by large the negative impact during the two previous periods.

Robustness checks

Beyond exploiting variation in the time of entry of the various distribution channels into national markets to link changes in modes of distribution to changes in acoustic diversity, we propose an alternative approach to highlight the significance of our four turning points. We run a regression with acoustic diversity as the dependent variable and the following independent variables: countries dummies, month dummies, the market share of each musical genre, the market share of both domestic music and US music, and GDP per capita.

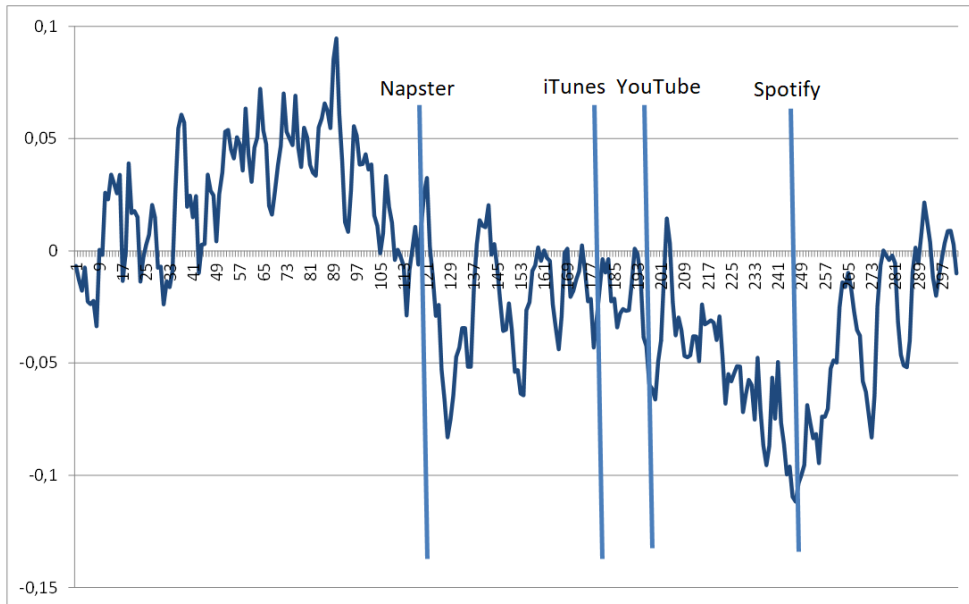
Figure 7 plots the coefficient of the more than 300 monthly fixed effects (January 1990 being the reference) with the four vertical lanes corresponding to our four turning points (creation of Napster, iTunes Music Store, YouTube and Spotify). Since these turning points are country specific, we report here the mean of the date of introduction of each mode of distribution in each of the ten countries. Figure 7 supports our definition of the different eras for digital music distribution. We observe discontinuities around the four turning points, with notably a clear decreasing trend beginning shortly after the creation of YouTube and an increasing trend starting after the creation of Spotify.

¹⁸ For the sake of brevity, we do not report below the coefficients of the variables accounting for country of origin. However it is worth noting that the coefficient of the domestic music variable is as expected negative and very significant suggesting that domestic songs seem to be acoustically closer from each other than from songs from different origin.

¹⁹ We consider for starting and ending points of each period the mean over the ten countries. For the Napster period, Table 8 shows that over all the period the changes in time has an impact of: $(2004.9323 - 1999.526) * (0.00083 + 0.00166) = 0.0135$ which represents 21.6% of the standard deviation of the acoustic diversity variable over the Napster period (0.06243). For the iTunes period we obtain $(2007.702 - 2004.9323) * (0.00083 - 0.00422) = -0.0094$ which is equal to 17.5% of the standard deviation of the acoustic diversity variable over the iTunes period (0.05374). For the YouTube we obtain $(2010.706 - 2007.702) * (0.00083 - 0.00666) = -0.0175$ which represents 29.2% of the standard deviation of the acoustic diversity variable over the YouTube period (0.05996).

²⁰ For the Spotify period we also consider for starting and ending points the mean over the ten countries. The impact on acoustic diversity caused by the time variable is $(2015.97 - 2010.706) * (0.00083 + .0182) = .1002$. This is nearly two times (1.69) the standard deviation of the acoustic diversity variable (0.0592).

Figure 7 – Monthly fixed effects coefficients

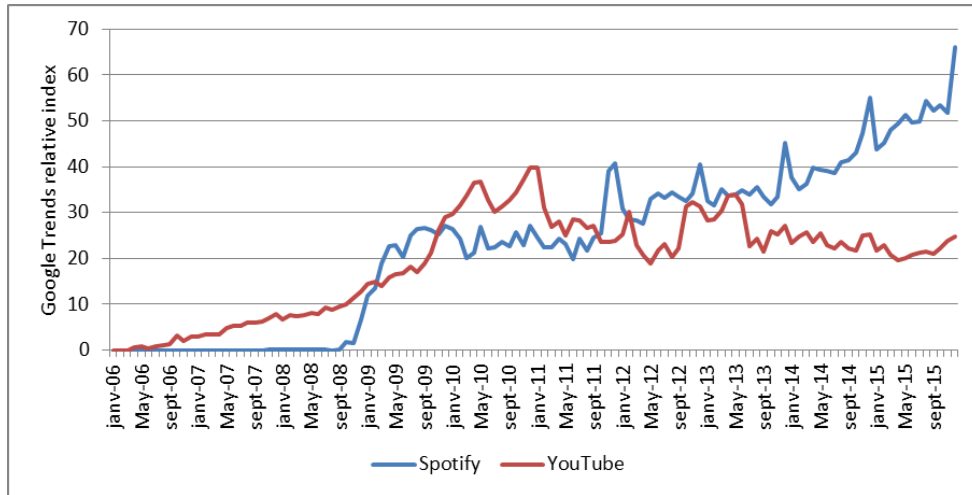


Considering the variation in date of introduction of the different distribution channels within the countries of our sample allowed us to include treatment at a week and a country level. However, this does not provide us with a tool for treatment intensity. To overcome this limitation, we propose a third empirical strategy to check for the robustness of our results²¹. We rely on Google Trends which is now a popular source of information for quantitative analysis (see, for instance, Choi and Varian [2012]). For each country the terms “YouTube Music” and “Spotify”²² were simultaneously entered. Google Trends provides us with the monthly relative popularity of these two terms over the period December 15, 2005 to December 31, 2019 with 100 being the maximum relative popularity over the whole period. We consider only results for the period December 15, 2005 to December 31, 2015, however taking into account a longer period allows us to account for differences in popularity across countries (in some countries the maximum relative popularity of these two terms is reached later than in others). Figure 8 displays, as an example, the relative popularity of the two terms for all the period and all countries together.

Figure 8 – Google Trends for “YouTube Music” and “Spotify” over the whole sample of countries

²¹ We thank an anonymous referee for suggesting us this idea.

²² Since Google Trends provide information from 2004 only, we focus on these two last periods.



We then use a *difference-in-difference* approach to explain for each country how a change in the popularity of the queries “YouTube Music” and “Spotify” in month m as compared to $m - 1$ impact the change in the mean of acoustic diversity in month m as compared to $m - 1$. This allows us to really capture a country specific treatment intensity. Table 9 displays the results of this diff-in-diff regression with the difference in acoustic diversity as the dependent variable and differences in popularity for both YouTube and Spotify as main independent variables. We also include as control the following variables: difference in market share of musical genres, difference in market share of country of origin, difference in GDP per capita and country dummies. The results of the diff-in-diff regression support our main conclusion: conversely to the YouTube period, the Spotify period had a positive impact on acoustic diversity.

Table 9 – Diff-in-diff regression (OLS)

Dependent variable: Diff in Acoustic_diversity	
Diff in “YouTube Music” popularity	0.00015 (0.00018)
Diff in “Spotify” popularity	0.00031** (0.00015)
Constant	0.00007 (0.0031)
Country fixed effects	Yes
Control for diff in musical genres	Yes
Control for diff in country of origin	Yes
Control for diff in GDP/Capita	Yes
Adjusted R-squared	0.061
Observations	1,039

Standard error in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

5. Discussion

At this point it remains unclear if the evolution of the acoustic diversity is rather a supply side or a demand side phenomenon (see Section 2). In the first case, digitization could help artists to find inspiration by discovering/exploring music on file-sharing websites, YouTube, or Spotify. If musicians tend to increasingly adopt a (conscious or unconscious) mimicking

behavior in their creation process, this could explain the global trend of decreasing acoustic diversity. In the second case, music tastemakers like recommender systems could be the main driving force of the evolution of music consumption, and thus of the evolution of acoustic diversity. If it turns out impossible to perfectly disentangle these two forces, we propose hereafter an approach that allows us to study if only supply forces matter or if demand side factors are also likely to be at work.

Should only supply-side forces matter, there is no reason to believe that the evolution of acoustic diversity would be different in the top or in the bottom of the charts. Since success is highly uncertain, artists decide *ex ante* on a creation strategy (if any), based on expected success. Therefore, if only supply-side forces are at work, there should not be any difference *ex post* between the top and the bottom of the charts in terms of diversity²³. To check for this conjecture, we have constructed a second dataset with only the weekly top 10 and the bottom 10 for each year and each country, and recalculated the average acoustic distance between each pair of songs within each top 10 and each bottom 10. We include a dummy variable *top10* that equals 1 if the data refers to the top 10 and 0 if it refers to the bottom 10. The interaction between time and the *top10* dummy variable should be insignificant if there is no difference between the evolution of acoustic diversity over time within the top 10 and within the bottom 10. The estimation results displayed in Table 10 show that the interaction term *Time*top10* is highly significant, and therefore, that there exists a difference in the way time impacts the acoustic diversity in the bottom and in top of the charts. Since the interaction term is negative, we observe that the decrease in acoustic diversity over time is more important in the top 10 than in the bottom 10. Hence, the songs that receive the greatest attention from the public have seen their acoustic diversity decrease more than less popular songs. These specificities in the evolution of acoustic diversity among the most popular songs suggest that the determinants of the evolution of acoustic diversity pertain – at least partially – to the demand side.

Table 10 – OLS regression with pooled dataset (top 10 and bottom 10)

Dependent variable: Acoustic_diversity	
Time	.00002 (.0004)
Time*Top10	-.001098*** (.00021)
Top10	2.1914*** (.4270)
Bottom10	Ref.
Country fixed effects	Yes
Control for musical genres	Yes
Control for country of origin	Yes
Control for GDP/capita	Yes
Constant	.840004 (.7296)
Adjusted R-squared	.1609
Observations	18,902

Standard error in parenthesis. *p<0.1; **p<0.05; ***p<0.01

²³ Of course, a song’s success is not purely random and specific efforts can be made to reach the top 100 (for instance, by hiring “hits writers”). In that case it might be that these specific efforts drive “hit writers” to release songs that use the same drivers of (possible) success and thus songs acoustically similar. The acoustic diversity would then decline at the top but not at the bottom of the distribution. However, we believe that these efforts cannot guarantee that a song will enter the top-10. Therefore, we assume that reaching the top-10 remains mostly unpredictable. In other words, if an artist can adopt a music production strategy that increases her probability to reach the top-100, we assume that there is no strategy that significantly increases her probability to enter the top-10.

If the demand side factors affect the evolution of acoustic diversity, what is the role played by taste making tools such as recommender systems and playlist generators? Our data do not allow us to straightforwardly address this issue. However, we propose to exploit the geographic origin of each artist in the charts to provide some insights: We argue that a high geographic diversity in music consumption signals eclectic preferences from music listeners. To measure this geographic diversity we use the market share of music which is neither domestic nor from US origin, the two dominant origins that makes more than half of the market in all countries but Austria. Since domestic artists and US artists are usually those the most broadcasted on radio and thus the easiest to scout, the more eclectic music consumers' tastes are, the more they should be prone to use IT tools to help them in their discovery process. We thus expect the impact of digitization on acoustic diversity to follow a specific trend when the geographic diversity of music consumption is high. Put in other words, the interaction term between the geographic diversity index and time should be significant and positive. This hypothesis is supported by the data as shown in Table 11. In countries where the geographic diversity of music consumption is high, and thus in which musical tastes seem to be eclectic, the development of IT is associated with a specific additional positive impact on acoustic diversity. We cannot claim any causal impact here, since digitization impacts both geographic diversity and acoustic diversity, and we are facing an endogeneity problem. Therefore, these results should be taken very cautiously and merely as a way to build the conjecture that recommendation systems allow the development of more eclectic tastes.

Table 11 – OLS regression with geographic diversity of music consumption as an independent variable

Dependent variable: Acoustic_diversity	
Time	-.00432*** (0.0003)
Geographic_diversity	-15.757*** (1.09253)
Time*Geographic_diversity	.00791*** (0.00055)
Country fixed effects	Yes
Control for musical genres	Yes
Control for GDP/Capita	Yes
Constant	9.318*** (0.662)
Adjusted R-squared	0.424
Observations	9,451

Standard error in parenthesis. *p<0.1; **p<0.05; ***p<0.01

6. Conclusion

Up to now, the impact of IT on content industries has been analyzed through the number of new releases, the quality of these releases or the weakening of the star-system through a more balanced distribution of success over songs. Using weekly music charts data in ten countries over the period 1990 to 2015, we analyze whether each of the different periods of digitization leads to a trend of homogenization of music content, or conversely, to a greater acoustic disparity within music charts. We thus split the music digitization era (starting in 1999) in four different periods: (1) the period characterized by unsanctioned music distribution via filesharing networks; (2) the period of the first legal alternative to piracy, the iTunes Music

Store; (3) the emergence of social network services as powerful tastemakers; and (4) the emergence of global streaming services, such as Spotify, as the dominant model for online music distribution. Acoustic diversity measures the variance of a set of songs calculated across ten acoustic attributes: Danceability, Duration, Tempo, Loudness, Speechiness; Valence; Liveness; Acousticness; Energy; Instrumentalness. The greater the variance, the greater the acoustic diversity.

Our main result is that a while a weak increasing trend in acoustic diversity exists in the era of unsanctioned music distribution via filesharing networks, during the iTunes and YouTube music periods we observe a decrease or a stability in acoustic diversity. Our most interesting result, is that the emergence of audio streaming as the dominant model of distribution is associated with a significant and robust increasing trend for acoustic diversity. We also argue that both supply-side and demand-side factors are at work to explain these trends. More specifically, we argue that in countries where musical tastes seem to be the more eclectic, the development of IT is associated with a stronger increase of acoustic diversity, since it helps to explore the huge catalogue of recorded music.

One of the limitations of this paper stems from our database. We only consider the top 100 songs for each week, and therefore, we are unable to analyze the possible homogenization of music consumption at a more granular level. Let us recall that the weekly charts constitute the bulk of music sales, and when studying the impact of digitization on the disparity of music consumption, it makes sense to focus on the tops. However, studying how acoustic diversity evolves beyond the charts is an interesting avenue for future research. Digitization facilitates entry of music suppliers due to lower costs of production, distribution, and promotion, allowing them to serve niche audiences better. In a theoretical setting, Bar-Isaac et al. (2012) show that digitization has an impact on the kinds of products offered, with some firms focusing on broad audiences and others targeting narrow niches. In future research, it would be interesting to study how digitization has affected acoustic diversity in the long tail too. Another limitation is that we do not deal with the convergence or divergence of charts across countries. This question could be a relevant follow-up to this paper. The convergence of music consumption across countries has been assessed using the nationality of artists (Ferreira and Waldfogel, 2013; Waldfogel, 2018) or the overlap of songs in charts from different countries (George and Peukert, 2016). Our measure of acoustic diversity would allow studying the dissimilarity of songs that enter the charts across countries, and therefore, to take into account that two songs from artists of different nationalities can, in reality, sound very similar.

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Appendix

Figure A.1 - Acoustic diversity based on ten features calculated for individual countries

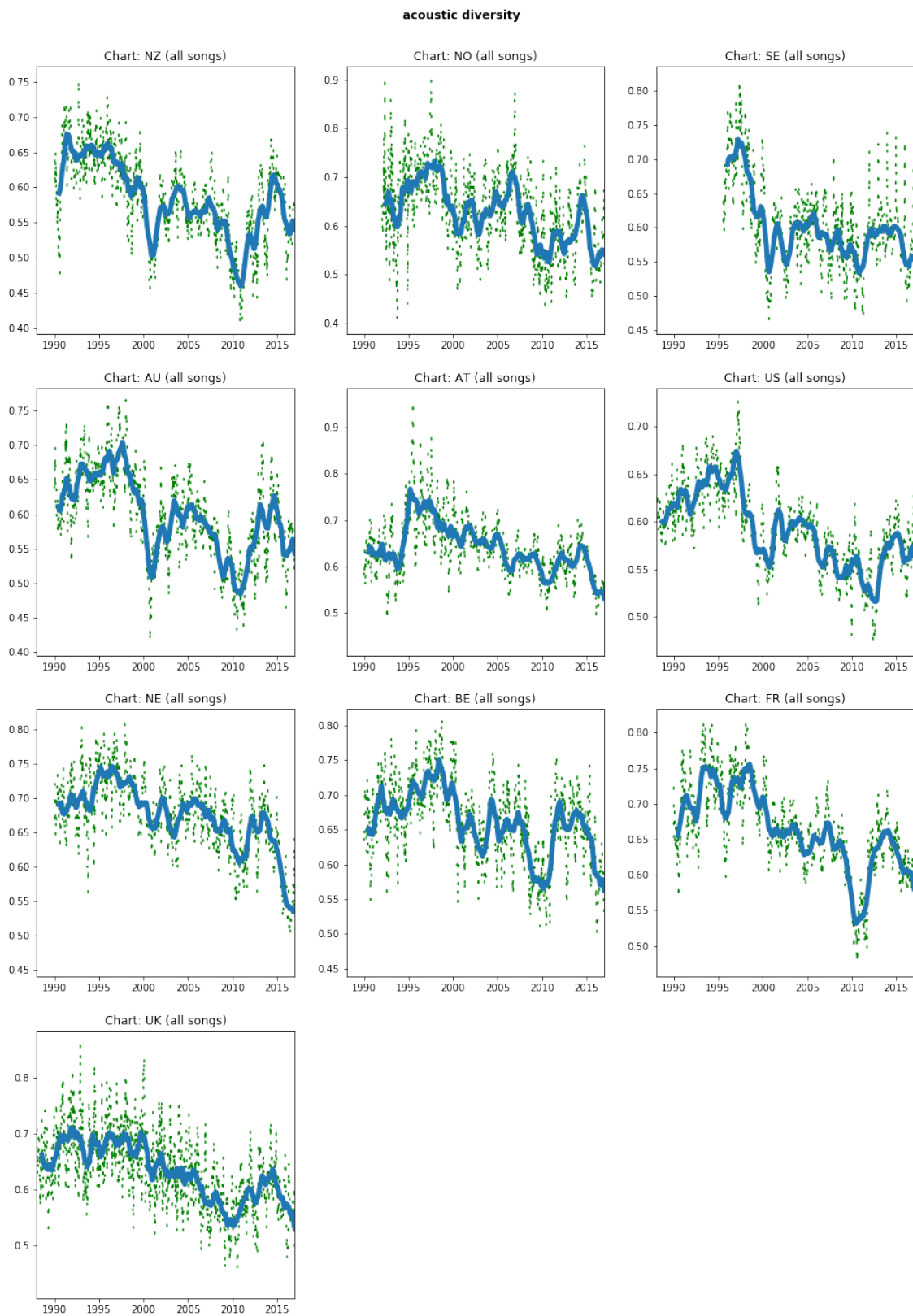


Figure A.2 - Acoustic diversity based on single features, calculated for all countries

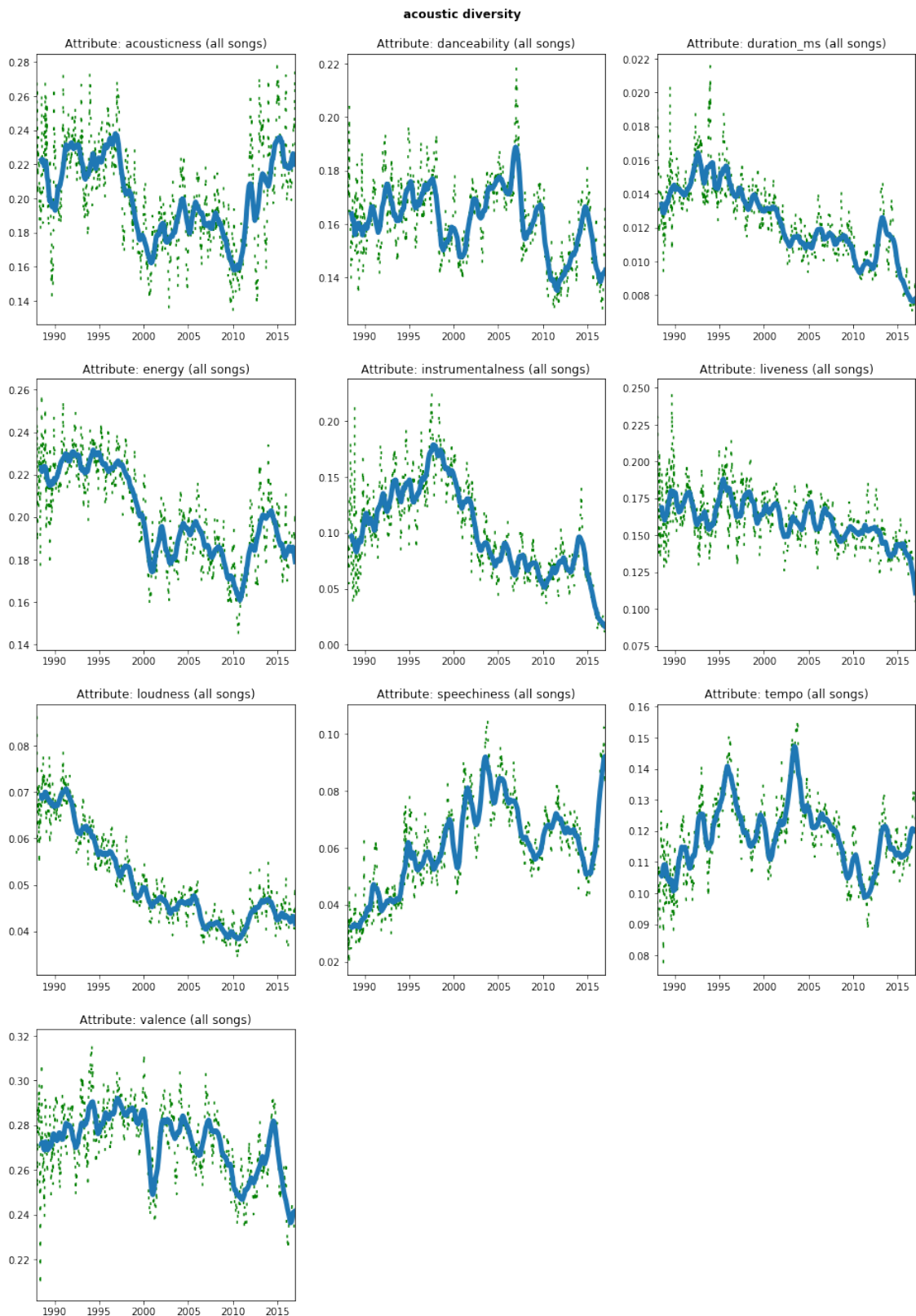


Table A.3 – OLS regressions with interactions between country dummies and time

Dependent variable: Acoustic_diversity	
Time	-.001807*** (.0003984)
Austria	-5.339417*** (.6988056)
Australia	-1.435137** (.6738305)
Belgium	-3.404684*** (.8582762)
Netherlands	-.4830819 (.7997593)
France	.4522588 (.8387406)
Norway	-.049393 (.757329)
New-Zealand	-1.111498 (.7007504)
Sweden	-.6635733 (.8479602)
UK	-1.410716** (.701803)
US	Ref.
Austria*Time	.0026474*** (.000349)
Australia*Time	.000695** (.000337)
Belgium*Time	.0016884*** (.0004284)
Netherlands*Time	.0002434 (.0003988)
France*Time	-.0002356 (.0004186)
Norway*Time	.0000224 (.0003806)
New-Zealand*Time	.0005243 (.0003502)
Sweden*Time	.0003146 (.0004232)
UK*Time	.0006952** (.0003507)
US*Time	Ref.
Constant	4.427131*** (.785587)
Control for musical genres	Yes

Control for country of origin	Yes
Control for GDP/Capita	Yes
Adjusted R-squared	0.4174
Observations	9,451

Standard error in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Note: for each country we have tested if the sum of the coefficients of (time + country*time) is negative and significant at least at the 5% level. This is the case for all the countries except for Belgium (no significantly different from zero) and for Austria (significantly positive).