11ème Séminaire MARSOUIN (2013) – Proposition
Axe : Pratiques Numériques

Information des consommateurs à l'ère numérique : Une analyse empirique des *spillovers* dans l'industrie musicale

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Resumé

Sur les marchés culturels, où l'offre de biens est extrêmement abondante, les choix des consommateurs dépendent, non seulement de leurs préférences, mais aussi de leur connaissance de l'espace des produits disponibles. Avec le développent des plateformes en ligne et des outils dédiés à la recommandation, les consommateurs pourraient être mieux informés, notamment concernant les biens les plus proches de leurs profils de goûts. L'objectif de cet article est de tester cette hypothèse, dans l'industrie de la musique enregistrée, en France. Notre approche s'appuie sur une estimation de l'évolution des « *backward spillovers* », définis pour un artiste comme l'impact de la sortie de son deuxième album sur les ventes de son premier album (Hendricks et Sorensen, 2009). Ces *backward spillovers* reflètent l'information imparfaite des consommateurs: certains consommateurs prennent seulement connaissance d'un artiste à l'occasion de la sortie de son second album, et corrigent alors inter-temporellement leurs décisions de consommation en achetant son premier album au moment de la sortie du second. A partir de données de ventes hebdomadaires d'albums physiques en France entre 2003 et 2011, nous comparons les *backward spillovers* de deux échantillons d'artistes. Le premier échantillon est constitué d'artistes débutant dans l'industrie musicale en 2003, et le second d'artistes débutant en 2007, lorsque les plateformes et les outils de recommandation en ligne sont devenus plus largement disponibles. Nos résultats montrent une baisse significative des *backward spillovers* entre 2003 et 2007, spécifiquement dans la deuxième fenêtre de diffusion de l'information, suggérant une amélioration de l'information sur le marché à l'ère numérique grâce à la propagation du bouche-à-oreille en ligne.

Mots clefs: information, numérique, spillovers, recommandation, bouche-à-oreille, industrie de la musique

Consumer Information in the Digital Age: Empirical Evidence from the Spillovers in the Music Industry

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Abstract

In cultural markets, consumer choices depend not only on preferences but also on knowledge of product availability. With the development of online recommendation tools and platforms, it is expected that consumers will be better informed about the products that fit their tastes. In this paper, we conduct an empirical test of this hypothesis for the music industry. We measure consumer information through *backward spillovers,* which are the impact of a second album's release on the first album sales by the same artist (Hendricks and Sorensen, 2009). Since backward spillovers reflect consumers' lack of information about an artist at the time of his first release, we study how the development of online recommendation tools affects backward spillovers. We use a dataset of weekly album sales in France for the period 2003-2010; we compare spillovers between a first sample of artists who released their debut album in 2003, at the early stage of the digital age, and a second sample of artists who debuted in 2007, when recommendation tools had become more widely available. We find that information spillovers have decreased between 2003 and 2007, in the second step of information dissemination, which suggests that online recommendation tools increase consumer information by more widely spreading word-of-mouth.

Keywords: Consumer information, digital age, music industry, spillover, recommendation, word-of-mouth, cultural markets.

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1. Introduction

In cultural markets, for books, movies or music, consumers face a very large supply of goods. For example in the music industry, more than 62,000 new albums were launched in 2010 in France.[1] This large amount of new releases entering the market makes it difficult for consumers to be informed about all products; consumer choices thus depend not only on their preferences but also on their knowledge of available products. Therefore, the process by which consumers obtain the knowledge of the products matters because it may determine market outcomes.

Traditionally, consumers are primarily informed by mass media, such as radio, or television. Not only because broadcasting space in mass media is limited, but also because cultural industries focus their promotional budgets on a few products, only a small set of products get visibility, even with some of them overexposed by mass media. In the music industry, around 3% of all the music available usually represents 76% of the radio plays in France.[2]

This informational bottleneck fosters imperfect consumer information and may contribute to skewness in the distribution of sales. We observe that sales in cultural markets are indeed highly concentrated on a few bestsellers good. This common pattern of sales concentration, also called the Pareto principle or the 20/80 rule, underlines that only a small part of the products which flow into the market turn out to be profitable.[3] On 3,000 albums released in 2001 in France, only 30 albums were on radio playlists and they accounted for 80% of market outcomes.[4]

However, the development of the Internet has been changing the process by which consumers obtain information. According to a national US survey (*Edison Research*, 2010) the internet is narrowing the gap with radio as the leader for learning about new music. In 2002, radio was cited by 53% of respondents as the first media to discover new music, followed by television (14%), Internet (9%), and newspapers (2%); in 2010, radio was only cited by 39%, closely followed by the internet with 31% of respondents, before television (12%) and newspaper (3%).

Over the last decade, platforms and tools allowing music recommendation have grown faster (as illustrated in Figure 1 in Annex) to reach millions of users today.[5] MySpace, the first music social network was created in 2003. The social network Facebook was opened to everyone in 2006, and the micro-blogging platform Twitter also emerged in 2006. Video-sharing websites like YouTube and Dailymotion were launched in 2005. Online radio and music communities such as LastFm and Deezer which were created respectively in 2006 and 2007, use similar users' music profiles to generate dynamic playlists and charts. Lastly, the number of music blogs has been constantly increasing since 2002 with the success of

[1] Observatoire de la Musique/GfK (2010).
[2] Observatoire de la musique (2003-2010).
[3] This pattern is also described by the *SuperStar theories* (Rosen, 1981; Adler, 1985).
[4] Le Guern, Philippe (2003), Présentation, *Réseaux* (n°117), p. 9-44.
[5] In 2012,the number of Unique Monthly French Visitors was (in millions): 6 to SkyBlog, 10.4 to Blogger, 28.4 to Facebook, 3 to MySpace, 23.5 to YouTube, 11 to Dailymotion, 5 to Deezer, 3 to Twitter.

publisher like Blogger or Skyblog in France, up to the creation of the music blogs aggregator the Hype Machine in 2005.

On the supply side, the digital world has been giving other spaces of visibility and promotion to the products. Distributors can carry a much larger product selection online than with traditional retailers, as shown by Brynjolfsson *et al.* (2003). They also often use recommender systems to help customers discover new products, leading to the emergence of visible product networks (Oestreicher-Singer and Sundararajan, 2012). Besides, artists can directly reach their audience and make themselves visible on the online platforms (Bastard et al., 2011). For artists ignored by mass media, this could be an opportunity to circumvent the bottleneck of the music industry.

On the demand side, the internet has offering a way to extend word-of-mouth.[6] Advices from relatives and friends are usually one of the three main sources of influence for music consumers to purchase recorded music with radio and television (Peitz and Waelbroeck, 2005). Online, individuals can easily contribute to the exchange of information and interact both with the content but also with each other. This is shown through blogging, discussion forums, product ratings and consumer reviews, comments and content sharing in social networks, and collaborative recommender systems as well. Recommendations from acquaintances or opinions posted by consumers online are now the most trusted form of advertising, according to a survey of 25,000 Internet consumers from 50 countries (*Global Advertising*, 2009).

Finally, we can assume that consumers will be better informed about the products that fit their tastes with the development of recommendation tools and platforms on the internet. In this paper, we conduct an empirical test of this hypothesis in the music industry. We measure the impact of imperfect information on consumers' music purchases, at two stages of the digital development: in 2003, the early stage, and in 2007, when online recommendation tools and platforms had become more widely available.

Our empirical strategy to measure consumer information is based on that of Hendricks and Sorensen (2009). In the music market, they consider that the presence of uninformed consumers leads to an under-selling of albums of high quality which do not benefit from the exposure by mass media. The information bottleneck created by mass media, by overexposing a small numbers of artists, leads some consumers not to buy the "good" album at the "right" time. Empirically, they quantify albums "lost sales" due to consumer's lack of information by measuring the effect of a second album's release on the sales of the first album.

They called this effect the "backward spillover", meaning that any promotional activity associated with a newly released album enhances consumer awareness about the artist and may cause some consumers to discover and purchase the artist's past albums. Since the backward spillovers reflect consumers correcting initial mistakes and buying the first album at the time of the second release, they give us a measure of consumers' lack of information.

We use a data set of weekly album sales in France for the period 2003-2010 to compare the backward spillovers between a first sample of artists who released their debut album in 2003, and a second sample of artists who debuted in 2007. This allows us to estimate

[6] Defined by Arndt (1967) as an oral form of interpersonal non-commercial communication among acquaintances.

the evolution of the backward spillovers with the development of online recommendation tools and platforms.

The rest of this paper is organized as follows. Section 2 provides a summary of related literature. Section 3 describes our data and Section 4 describes our empirical strategy. Section 5 presents our empirical results and discusses our findings. Section 6 underlines some remarks and limitations, and Section 7 concludes.

2. Related Literature

Our paper is related to the literature on information spillovers. They have already been studied in theoretical models: in the personal computer market where the rapid pace of technological change makes consumers less than fully informed about the set of available products (Goeree, 2008); in the firms' decision to release new products under existing brand names when consumers are uncertain about product qualities (Choi, 1988; Cabral, 2000). In the latter case, high-quality new products can improve brand reputation and thus increase existing products' sales.

Our paper is most closely related to that of Hendricks and Sorensen (2009), who made the first empirical contribution on information spillovers between products. They find a substantial and persistent increase in sales of an artist's catalog albums due their discovery during the release of an artists' new album. Backward spillovers created by the release of a second album increase first album sales from 40 to 55%. But contrary to our paper, they estimate spillovers in the music industry only in the pre-digital age, between 1993 and 2002.

More broadly, our paper also contributes to the growing literature about the impact of information provision on market outcomes in cultural industries. Previous studies found that consumer choices can rely on observable characteristics such as genres and stars (De Vany and Walls, 1999), on advertising and promotion (Prag and Casavant,1994), on prices and awards received (Litman, 1983), or on expert reviews (Reinstein and Snyder, 2005). Individuals may also draw inferences from mere observation of others consumers' behavior, summarized by rankings and sales chart. This may influence consumers to purchase from the bestseller lists (Sorensen, 2007), and may lead to informational cascades and herd behavior (Bikhchandani and al., 1992; Banerjee, 1992). Word-of-mouth traditionally also contributes to consumers' discovery process (Arndt, 1967) and affects the diffusion of new products (Mahajan *et al.*, 1990).

In the digital age, researchers have especially studied the impact of consumers' reviews and ratings – as a proxy for electronic word-of-mouth, online rankings, recommender systems, and file-sharing technologies. Rather than focusing on a particular mechanism, our paper assesses the overall impact of online recommendation tools and platforms on information provision.

Previous research has found that online consumer reviews have a positive impact on product sales and influence consumer choices (Senecal and Nantel, 2004; Chevalier and Mayzlin, 2006). Dellarocas *et al.* (2010) show also that consumer reviews could increase informational inequality between popular and niche products, since the volume of consumer reviews are even more skewed towards popular products than they are offline. To study

online rankings, Salganik *et al.* (2006) built an artificial online music market where participants could listen and download previously unknown songs, either with or without knowledge of previous participants' downloading choices. They showed that increasing the strength of social influence improved both inequality and unpredictability of market outcomes.

For collaborative recommender systems, while Fleder and Hosanagar (2009) showed they contribute to reduce sales' diversity, Hervas-Drane, (2012) found they reduce sales' concentration by allowing consumers to obtain product information from other consumers with similar preferences. Lastly, academic papers related to the digital piracy in the music industry underline that consumers can discover new products with file-sharing technologies (Peitz and Waelbroeck, 2006). This "consumer sampling" may replace costly marketing and promotion, and seems to prevail for lesser-known artists (Gopal *et al*., 2006).

Finally, our paper is also related to the empirical work on the Long Tail hypothesis in cultural industries. With online distribution, Anderson (2006) argues that the *Superstar effect* (Rosen, 1981; Adler, 1985) tends to be offset by a *Long Tail effect*. As predicted by the economic theory, the exposure to a greater variety of products could lead consumers to easily find the variety closest to their most preferred choice. Nevertheless, empirical studies provide conflicting evidence about the existence and the magnitude of the Long Tail (Brynjolfsson *et al.*, 2003; Anderson, 2006; Elberse and Oberholzer-Gee, 2007; Tucker and Zhang, 2007). From a theoretical perspective demand–side factors should help drive the sales to the tail, and some argue that online recommendation tools would help consumers to find the products that better fit their tastes (Anderson, 2006; Brynjolfsson *et al.*, 2006). Our paper may contribute to this literature by studying their impact on consumer information.

3. Data

We use a data set of weekly physical album sales history recorded in France between 2003 and 2010.[7] Music sales are tracked at the point of sale by monitoring cash registers at over 3,500 retail outlets. This panel is representative of album sales in France, and includes various distribution channels, including supermarkets specialized in cultural products, food stores, record shops, online retailers, or other specialized stores. Therefore, we can observe weekly sales for each album from the time of its release through the end of 2010; and each album is linked to an artist name, genre, sales volume and sales values.

To construct our sample, we exclude albums relating to film soundtracks, recordings of comedy shows, children's stories and audio books, in order to only study spillovers in the music industry. Also, as our objective is to measure demand responses to newly released albums, we restrict our attention only to full-length studio releases and exclude singles, EPs, maxis, recordings of live performances, holiday albums, anthologies or compilations.

[7] Data have been retrieved from the GfK Marketing Institute, which is the principal source of sales data for the French music industry and the basis for national charts and rankings of artist popularity.

After narrowing our selection, we need to identify artists who debuted in 2003 and in 2007, but no charts or other tools exist in France that list the upcoming new artists.[8] Therefore, we select from the whole weekly sales album database a set of artists who match our restriction period and conditions, and then examine their discographies.

Firstly, we keep all the albums for which the first weekly sale date happened in 2003 or 2007. We also keep albums for which the artists did not appear in the database before 2003, and respectively before 2007, to ensure they made their first record in 2003 or 2007. Secondly, we exclude artists who did not release another album over the period. Lastly, since a lot of artists have sold a few units of their debut album, we restrict our attention to the artists who sold at least 1,000 units of their debut album to avoid getting a lot of weekly sales at zero.

For each of these artists, we consult various online databases for auxiliary information,[9] especially to check the accuracy of the artists' discographies and the release dates of their first and second albums. After dropping a small number of artists who did not release a second full-length album, and others who have already released an album before 2003 or 2007, we obtain our sample: 145 new artists for 2003 and 127 new artists for 2007, who sold more than 1,000 units of their first album and who released at least one other album over the period.

The descriptive statistics of our sample underlines some relevant characteristics for the econometric model.

First, we need to take into account the diversity of artists in the sample. It is made up of six genres of music (see in Table 2 in Annex): Pop Rock (40%), Hip Hop-Soul-R&B (19%), French variety (16%), Electronic (9%), Jazz -Blues (7%), Classical (5%) and World Music (4%). Around 50% of the artists are French,[10] 25% come from America and 25% from the European Union (see Table 3 in Annex).

Also, some artists are signed to major or independent labels, and they cover a broad range of commercial success: from the most successful like American metal group *Evanescence* or French singer *Thierry Amie*l in 2003, and international pop singer *MIKA* or French R&B group *Tragedie* in 2007, to relatively unknown and obscure artists like French singer *Anis* or Irish rock band *The Thrills* in 2003, and Australian electronic group *Midnight Juggernauts* or English soul band *Belleruche* in 2007.

We also observe a strong heterogeneity in sales across albums, and a concentration on a few successful artists. Figure 2 shows the distribution of total first year sales across artists in each sub-sample. We observe that around 20% of the artists in both samples account for

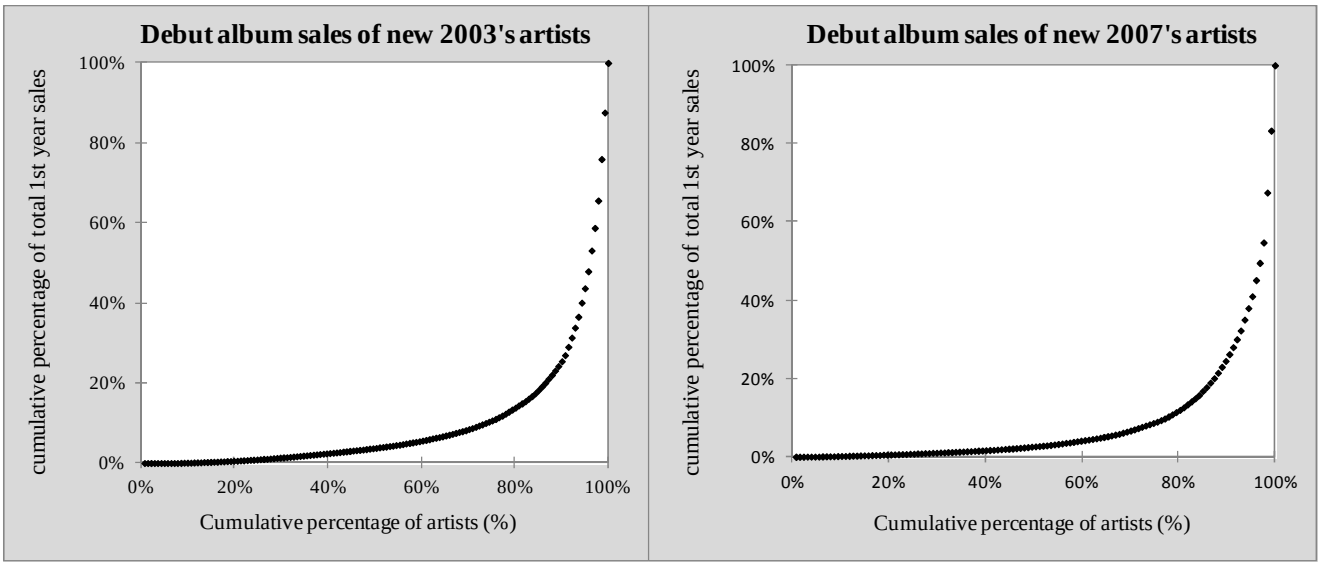
[8] Hendricks and Sorensen (2009) used the "Heatseekers Billboard charts", which is the weeks' top-selling albums by new or developing acts, defined as those who have never appeared on the top 100 of the Billboard 200 or the top 10 of R&B/Hip-Hop Albums, Country Albums, Latin Albums, Christian Albums, or Gospel Albums.

[9] We use five different online sources: an online database of information about audio recordings *Discogs*, an online music guide service *AllMusic*, the music website *LastFm*, the online collaborative encyclopedia *Wikipedia*, and the website of a french retail chain specialized in cultural products *Fnac*.

[10] The French music industry benefits from trade and government support, especially for the national live scene and non mainstream music. Also, radio stations must abide by the Domestic Quota which has encouraged investments in national production and strengthened the local market.[10]

almost 85% of the first year sales. Median sales are about 4,300 units and average sales of 34,000 units, with a maximum of roughly 900,000 units. About a quarter of artists sell between 5,000 and 17, 000 units, and only 10% sell more than 50,000 units during the first year following the release of their debut album.[11]

Figure 2. Distribution of First Year Debut Album Sales



Sales data analysis also shows that a large proportion of debut album sales occur during the first year following the release: on average, about two-thirds of debut album sales are done over the first year following the release. Most albums' sales paths exhibit an early peak followed by a steady decline. Table 3 below displays the distribution of the week of first albums' sales peaks across the artists. During the first year following the release, sales peak on average during the 12th week. More precisely, 75% of the artists in both samples exhibit peak sales within the first 16 weeks, and only 10% after more than 35 weeks.

Table 3. Peak Sales Week

Peak sales week								
	N	MEAN	ST. DEV.	0.10	0.25	0.50	0.75	0.90
2003 Sample	*145*	11.27	13.72	1	2	4	14	35
2007 Sample	*127*	11.89	13.39	2	3	6	16	33

[11] According to SNEP (Syndicat National de l'Edition Phonographique), a commercial success in France is equivalent to a gold record certification (100,000 units sold, in 2003) or a silver record certification (50,000 units sold, in 2006). Sales between 10,000 and 50,000 may characterize a medium commercial success, while weak sales between 1,000 and 5,000 copies may reveal a critical success. The crisis of the music industry led to a subsequent review of level of gold record certification (75,000 units, from May 1st, 2005) and silver record certification (35,000 units, from May 1st, 2005).

We also need to consider the seasonality of albums sales and releases dates. As expected, we observe that album sales are highly seasonal, like their releases dates: sales are strongest in spring and fall, and there is a huge increase in December in which sales are two to three times larger than average sales in other months of the year. Table 4 below shows the distribution of releases across months. Spring and fall appear to be the most popular periods to release a new album, whereas labels seem to avoid releasing new albums during the summer and in December or January.

Table 4. Seasonal Variation in Release Date

PERCENTAGE OF RELEASES OCCURING					
MONTH	2003-Sample		2007-Sample		Overall *(N=269)*
	Album 1	Album 2	Album 1	Album 2	
1 - January	6.4	4.1	8.7	4.5	5.9
2 - February	9.2	6.9	7.8	7.1	7.8
3 - March	9.9	13.1	12.6	12.5	12.0
4 - April	4.9	8.3	5.5	12.5	7.8
5 - May	7.8	11.0	11.8	8.0	9.7
6 - June	10.6	7.6	3.9	6.2	7.1
7 - July	9.2	4.1	2.4	1.8	4.4
8 - August	3.5	6.2	6.3	8.9	6.2
9 - September	8.5	10.3	7.1	13.4	9.8
10 - October	12.1	10.3	24.4	12.5	14.8
11 - November	13.5	14.5	7.9	8.9	11.2
12 - December	4.3	3.4	1.6	3.6	3.2

Table 5 below summarizes some statistics for the album releases in our two samples. The first part of Table 5 shows the distribution of albums' release dates (a). The median debut date for artists in the in 2003 Sample is June 23, and July 9 for artists in 2007 Sample. For artists with a debut in 2003, the median second album release date is November 1st, 2005, with a mean at February 13th, 2006. Some released their second albums as early as September, 2004 and others as late as October, 2007. For new artists starting in 2007, the median second album release date is November 2nd, 2009, with a mean at December 11th, 2009. Some released their second albums as early as November, 2008 and others as late as March, 2011.

The second part of Table 5 displays the delay between the releases of first and second albums (b). Overall, the median elapsed time before the release of the second album is more than two years (120 weeks), and the low end of the distribution is more than one year (66 weeks). Figure 2 below shows precisely the histogram distribution of the lags between first and second album. Around 80% of the artists exhibit an elapsed time under 3.5 years (186 weeks) between the first and the second album release.

Table 5. Album Release Statistics

ALBUM RELEASES STATISTICS									
					PERCENTILE				
		N	MEAN	ST DEV.	0.10	0.25	0.50	0.75	0.90
a. Date Of Release									
Album 1	*2003 Sample*	*145*	25-Jun-03		17-Feb-03	17-Mar-03	23-Jun-03	20-Sep-03	27-Oct-03
	2007 Sample	*127*	30-Jun-07		5-Feb-07	19-Mar-07	9-Jul-07	1-Oct-07	12-Nov-07
Album 2	*2003 Sample*	*145*	13-Feb-06		14-Sep-04	6-Mar-05	1-Nov-05	14-Oct-06	18-Oct-07
	2007 Sample	*127*	11-Dec-09		14-Nov-08	20-Apr-09	2-Nov-09	7-Jul-10	14-Mar-11
b. Weeks Between Releases									
Album 1→2	*2003 Sample*	*145*	134.6	69.0	66	90	113	163	221
	2007 Sample	*127*	127.1	42.6	75	102	124	152	188
	Overall	*269*	131.0	58.8	66	94	120	158	205

Figure 2. Histogram Distribution of Release Time

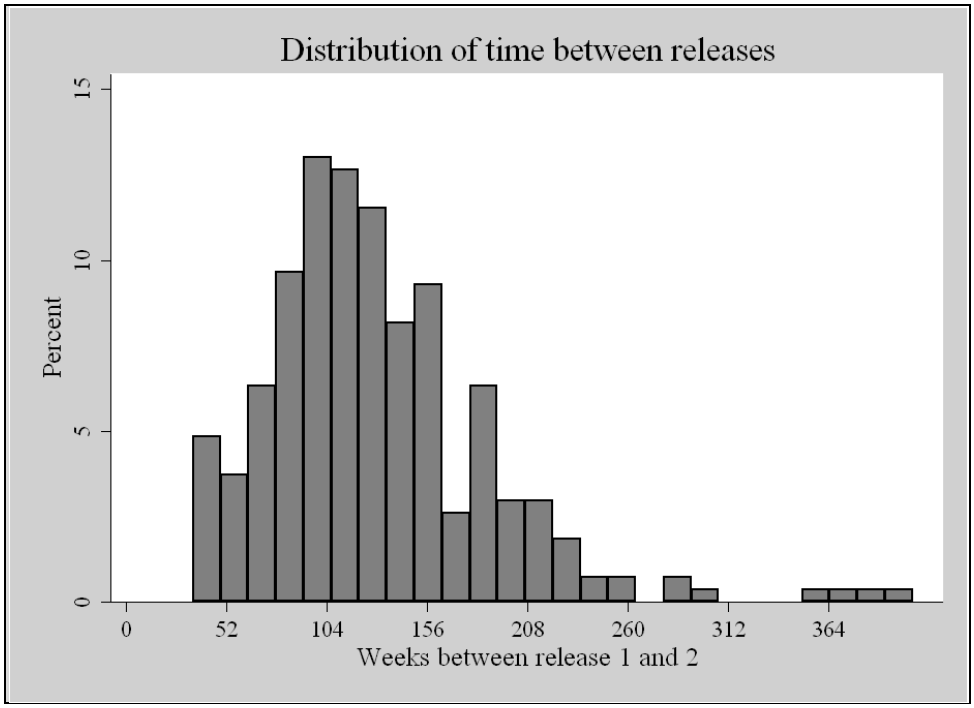


Figure 3 and Figure 4 illustrate backward spillovers for two artists from the 2003 Sample. These two graphs plot the logarithm of weekly total sales over time for the artists' first album from the time of the artists' debut release, and the dashed vertical lines indicate the date of the release of their second albums.

Figure 3. Debut Album Sales for Amy Winehouse

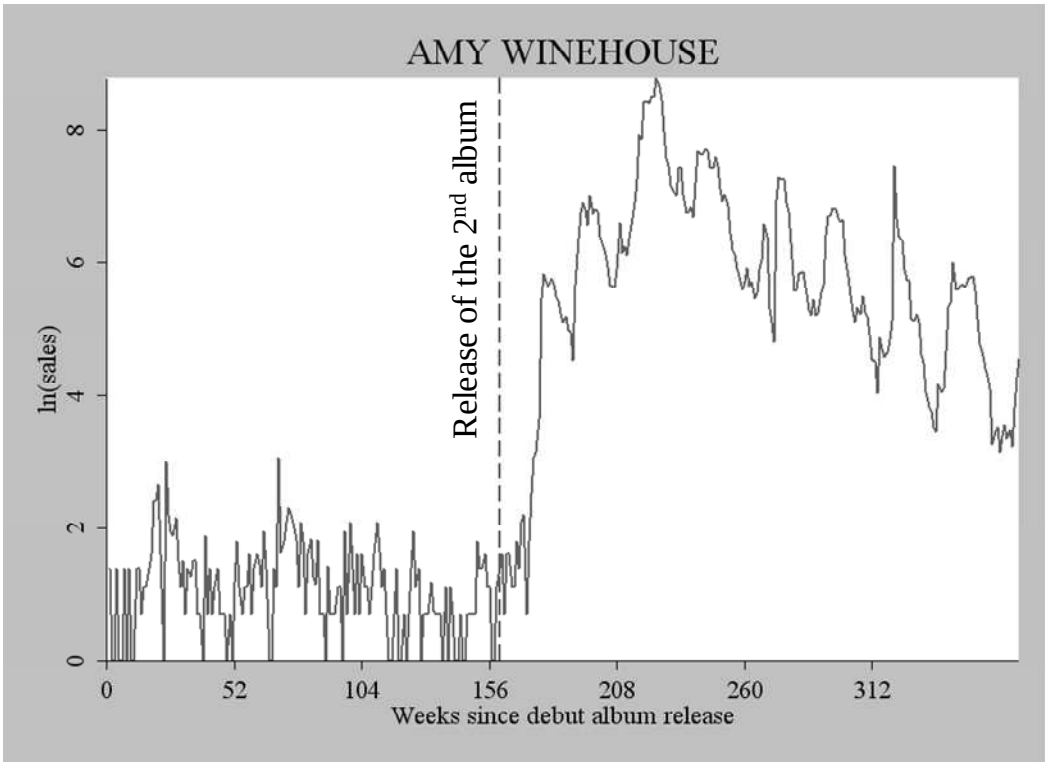
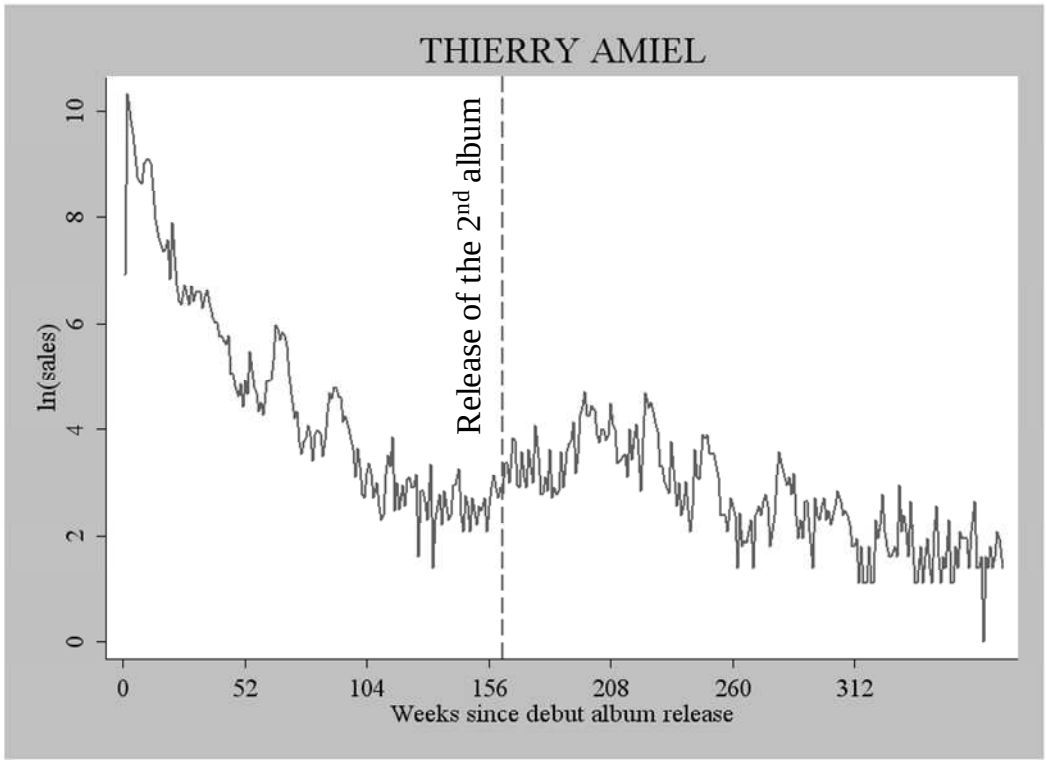


Figure 4. Debut Album Sales for Thierry Amiel



In Figure 3, which follows the first album sales of the soul singer Amy Winehouse, we observe a strong impact of her hit second album "Black to Black", released in October, 2006 (week 157), on the sales of her debut album "Stronger than me" which failed to gain success

in France at first. First album sales increase dramatically after the new release and peak almost one year later, remaining at a higher level than before releasing her second album.

As Figure 4 shows, the first album sales of the French singer Thierry Amiel, runner-up on TV show Pop Idol in France, exhibit a very different path. His debut album "Paradoxes" was an early success and awarded a gold record in France a few weeks after being released. Sales of the first album reached their peak in the early weeks following the release, and started decreasing from this point until the release of his second album "Thierry Amiel". In the weeks surrounding the second release, sales of the debut album experienced a surge for one year.

4. Empirical Strategy

We follow the methodology used by Hendricks and Sorensen (2009). We observe the flow of sales for prior albums at the time when a new album is released, and both cross-sectional and time-series variations can be used to measure the sales responses. The release of a second album by an artist represents the "treatment" of the first album's sales, and the treatment is an irreversible act.

We define S as a binary treatment indicator, where $S = 1$ with treatment and $S = 0$ with no treatment. The aim is to estimate the effect of the treatment, the second album release, on sales of the debut album during *s* periods of treatment.

We estimate the average treatment effect on the population treated ("*ATT*") for each period of the treatment window, which is the difference: $y_{it}^{s} - y_{it}^{0}$. The treatment effect is the difference between two potential outcomes: the potential outcome with treatment for the treated album sales (that we observe) and the potential outcome for the album sales without treatment. The problem is that we do not observe this last outcome, the sales of an album in the absence of treatment. To estimate the counterfactual sales, we use albums that have not yet been treated as a control group, by exploiting the exogenous variation between release dates of albums.

Two key assumptions in the model also need to be underlined. First, we assume that prices are constant over time and across albums. This assumption is valid when we check the price of the first album overt the period: if the first album can be discounted, it is not systemically related to the period surrounding the second release of the artist. Second, we assume that the preferences are additive across albums by the same artist, so that there is no complementarities in consumption between the first and the second album.

Following this approach, we run the following regression for our sample (1):

$$y_{it} = \alpha_0 + \alpha_i + \lambda_t + \sum_{m=2}^{12} \gamma_m D_{it}^{m} + \sum_{s=-5}^{26} S_{it}^{s} . (\beta_s + \delta_s W_i) + \epsilon_{it}$$

,where y_{it} is the log of album sales of artist i at time *t*, and *t* is the number of weeks since the first album's release. The dependent variable is log-transformed to handle the positive skewness in the sales distribution.

α_i is an artist fixed effect which does not vary over time. The fixed-effects model controls for all time-invariant differences between the individuals, so the estimated coefficients of the fixed-effects models cannot be biased because of omitted time-invariant characteristics. We assumed this is the time-invariant effect that impacts the treatment indicator, and not the idiosyncratic shock of the time-varying error term. Indeed, we need the treatment to be random across artists to ensure that the estimation of the average treatment is still valid. Like Hendricks and Sorensen (2009), we assume that the main determinant of the length of time between albums releases is essentially an artist's creativity and personal effort, which are time-invariant and controlled by the artist fixed effect.

λ_t's are time dummies to control the decay path of sales, and $D^{m\prime}$s are month dummies to control for seasonality.

S_{it}^{s} is an indicator equal to one if the release of artist *i*' s second album was *s* weeks away from period *t*, so β_s measures the second album's release impact on the artist's first album sales in week *s* of the treatment window. We allowed for a 32-week treatment window (7 months), beginning 5 weeks (1 month) before the week of the new release (in $t = 0$) and 26 weeks (6 months) after the new release. The pre-release periods allowed us to estimate some promotional activities done before the new release.

W_i is a dummy variable, equal to 0 if the artist's entry into the music industry was in 2003, and equal to 1 if the artist's debuts was in 2007, when online recommendation tools had become more widely available. The interaction term between dummies *W* and *S* allows us to test that the impact of the second album's release on first album sales depends on the stage of digital development, so δ_s measures a change in the coefficient of the treatment effect *S* over *W*. In other words, we want to test the backward spillovers' variation between 2003 and 2007, assuming that a negative variation could suggest an improvement of consumer information in the music market with online recommendation tools.

We include in the sample for each *t*: artists who have released their second album and artists who have not yet released one, and exclude artists whose catalogs have been already treated by releasing a second album. We start to include debut album sales at *t* equal to 35 weeks (i.e. 8 months) to ensure we do not model an early peak in album sales and that the λ_t's better control for the time decay dynamic. We stop including albums at *s* equal to 17 in order to eliminate post-estimation treatment in our regression.

After performing a Breush-Pagan test and a modified Wald test, we corrected standard errors to take into account some heterosckedasticity across individuals, because some artists' sales are more volatile than others. We also corrected for serial correlation within individuals, after detecting auto-correlation of the stochastic errors of the first order auto-regressive form. So the $\hat{\rho}$'s are the estimated AR(1) coefficients, reflecting the degree of serial correlation in demand shocks for a given album.

5. Results

Table 6 in Annex presents the estimates from the regression. The rows list the estimated coefficients β_s and δ_s for the 32 weeks of the treatment window. Time and month

dummies were included in the regressions but estimated coefficients were suppressed for ease of reading.[12]

Figure 5 and Figure 6 summarize the results graphically, showing the estimated effect along with 95% confidence interval bands.

Figure 5. Time Patterns of Backward Spillovers

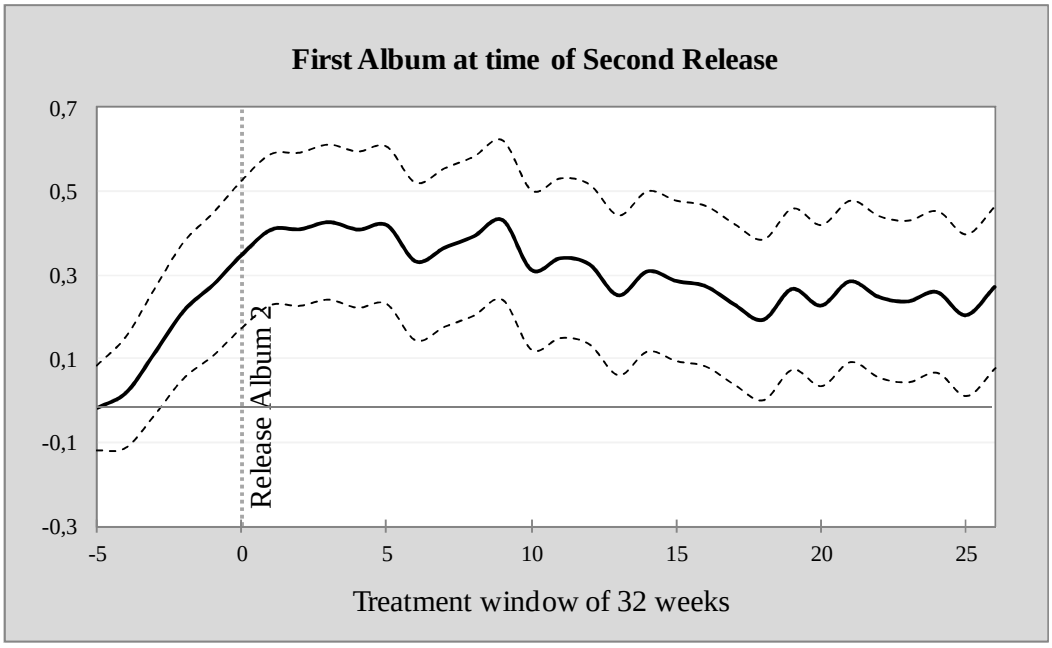
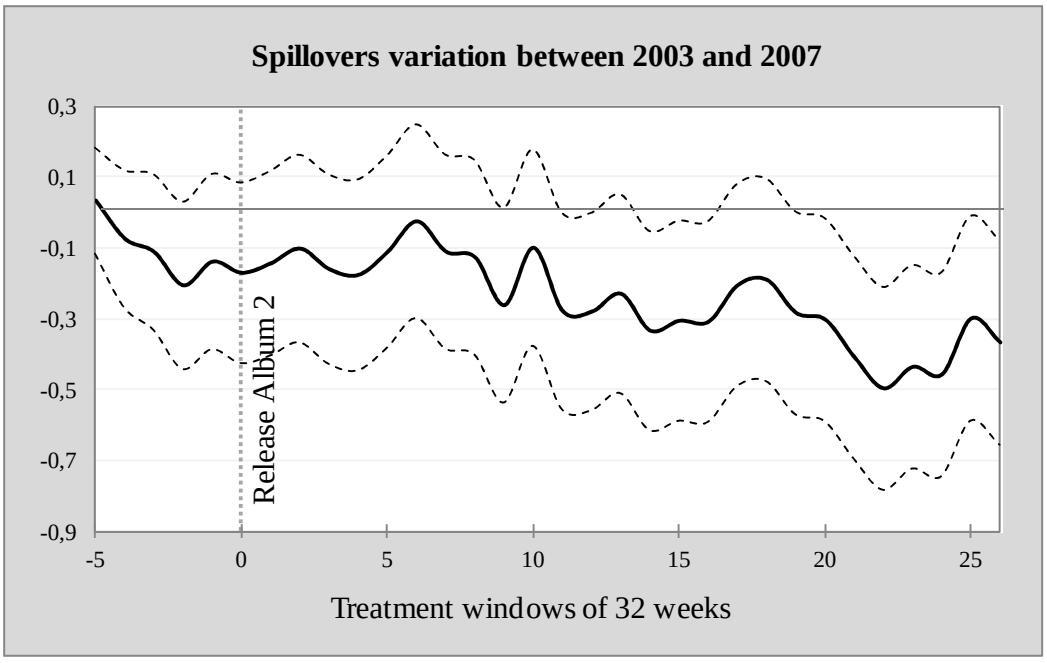


Figure 6. Variation of the Backward Spillovers



[12] They appeared all statistically significant, and time dummies *t* reveal a steady and monotonically decline over time.

Figure 5 shows the estimated effects of the second release on sales of debut albums. Since the dependent variable is the logarithm of sales, the coefficients can be interpreted as approximate percentage changes in sales of the first album resulting from the second release. In general, small (but statistically significant) increases start showing up 2 weeks prior to the new album's release (*t=0*), growing in magnitude until 5 weeks after the release (*t=5* in the table). Overall, backward spillovers are between 12% and 43%, on average about 31%, and their effects for each of the weeks following the release of the second album are always positive and statistically significant.

Figure 6 shows the estimated coefficients of the interaction term between the 32 weeks of the treatment window and the indicator variable *W* of digital development. We find a significant and negative statistical effect of the spillovers' variation between 2003 and 2007 for the 15 weeks between the 9th and the 26th week of the treatment window, and all the coefficients are negative in each period of the treatment window. On average, the decrease of the backward spillover is about 34%.

We test for the joint significance of the interaction term in the overall period, and find no statistically significant effect ($\chi^2_{(32)}$ = 40.6, *p-value* = 0.14), which suggests that the effect of the second album release is the same in 2003 and 2007. Nevertheless, after testing for different windows, we found a statistically significant effect at the 5% level ($\chi^2_{(23)}$= 35.77, *p-value* = 0.04) when starting with the 5th week following the second release. This last result suggests that backward spillovers are lower in the advanced stage of digital development, from one month after the second album's release.

The decrease in information spillover from one month after the second release could be a result of the different ways in which consumers obtain information about an artist, since both traditional promotion and word-of-mouth contribute to consumer information in cultural markets.

Academic literature distinguishes these two stages of information dissemination in the diffusion of new products in a market. Literature on new products diffusion[13] assumes that new adopters join the market as a result of two types of influences: external influences, such as advertising and other communications initiated by the firm, and internal influences that result from interactions among adopters and potential adopters, in terms of word-of-mouth and personal communications. Goldenberg et al. (2001) show that, beyond a relatively early stage (i.e. 16% of the market becomes informed), the effect of external marketing efforts or advertising quickly diminishes and word-of-mouth becomes the main factor driving the diffusion of new products.

We are not aware of prior literature that specifically estimates the temporal dynamic of word-of-mouth and mass media promotion on music demand. However, some empirical papers give evidence that word-of-mouth takes time to spread information and become influential. In computer science literature, Leskovec et al. (2007) show that the probability of purchasing a music dramatically increases when an individual has received recommendations

[13] based on the framework developed by Bass (1969). A new product growth model for consumer durables. *Management Science* 15 (5): p215–227.

of at least five other individuals in his networks, and that recommendations are more efficient for cultural niche products.

Building on this idea of the process of information dissemination, our results are summarized in Table 7 below.

Table 7. Test for Joint Significance

Windows	Weeks	F-Test	Effect of digital technologies on consumer information
Full window (32 weeks)	From 5th week pre-release to 26th week post-release	$\chi^2_{(32)} = 40.59$ p-value = 0.14	**None**
Traditionnal promotion (9 weeks)	From 5th week pre-release to 4th week post-release	$\chi^2_{(9)} = 6.33$ p-value = 0.71	**None**
WOM window (23 weeks)	From 5th week post-release	$\chi^2_{(23)} = 35.77$ p-value = 0.04	**Positive** (decrease of backward spillovers)

In the period surrounding the album's release, mass media visibility enhances consumers'awareness about the artist. This traditional form of promotion includes advertising and marketing expenditures, mass media cover, radio airplay and television broadcasting as well. According to our results, backward spillovers are the same in 2003 as they are in 2007 with respect to this first step of information dissemination, which is estimated from 5 weeks prior to 4 weeks after the second release. The impact of the second album's release on the artist's first album sales — because of consumers' discovery due to the promotion of the second album — does not fluctuate with the development of online recommendation tools. Content selection by mass media keeps playing an important role in consumer information, giving visibility to a small part of products.

In the second period, consumers' awareness about an artist may increase as word-of-mouth spreads about the second release. Therefore, the backward spillovers will occur later after the second release. It is in this second stage of information dissemination, estimated to start approximately one month following the release of the second album, that we observe a negative variation of backward spillovers. Our results suggest that word-of-mouth about the second album has a lower impact on the first album's sales for artists who debuted in 2007 than for those who debuted in 2003. Indeed, one can expect that word-of-mouth is more widely diffused through the internet and may improve consumer information by allowing more consumers to learn about the artist right after his first release.

Exchange communities have been developed on the internet, far beyond personal relationships, in which individuals share the experiences they have lived with products and services among people of various backgrounds (Van Alstyne and Brynjoflsson, 2005). Forums, online communities, social networks, peer-to-peer technologies, or collaborative

recommender systems, give an opportunity to extend word-of-mouth, even giving it "*a new significance due to the unique property of the Internet*" (Dellarocas, 2003 p. 1407). The decrease of the backward spillovers in the second stage of information dissemination suggests that digital technologies improve consumer information through the effects of online word-of-mouth.

Our results are also supported by early findings in sociology from the "strength of weak ties" theory (Granovetter, 1973). Weak ties are acquaintances or loose relationships; they act as bridge links and are more effective at disseminating information because the information they transmit to one another is more likely to be new. On the other hand, strong ties, often defined as close friends and family, usually possess similar information and this limits the gathering of new information. With the rise of social networks and online communities, the Internet should increase the number of weak ties across individuals (Donath and Boyd, 2004), which in turn could increase the speed of information dissemination (Goldenberg et al., 2001).

6. Remarks and Limitations

A first remark is that our estimation of the backward spillovers' decrease may reflect the aggregation of two opposite effects. Indeed, we assumed that artists who debuted in 2007 benefit from better information dissemination than artists who debuted in 2003. Indeed, more consumers know about the artist right after his first release, leading to a decrease of the backward spillovers. However, a larger portion of the remaining part of uninformed consumers may learn about the artists at time of the second release, thus leading to an increase in backward spillovers. Overall, our estimation of the backward spillover's variation aggregates these two opposite effects and suggests that the first effect dominates.

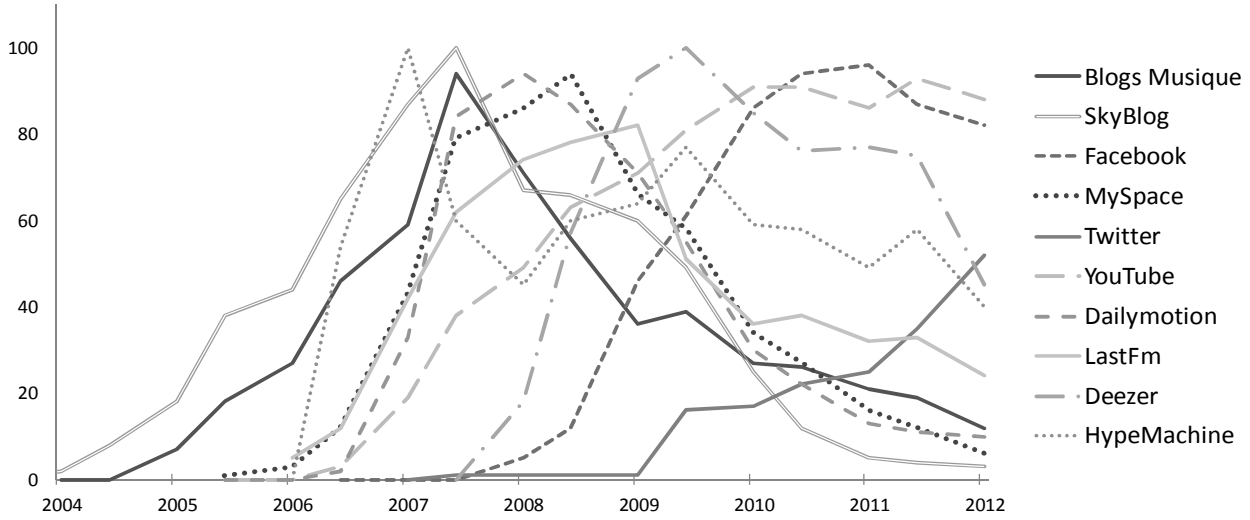
Several limitations come from our dataset. First, we use only weekly physical album sales, even from online retailers, but not online digital album sales. Second, sales from digital piracy are obviously "shadow" sales for which we also cannot account for. Although these missing sales could lead to under-estimate backwards spillovers, some evidence mitigates this assumption. Market figures show that digital sales represent only from 7% to 15% of the music market between 2003 and 2010. Also, the effect of digital piracy on spillover variation could be limited: some studies show that pirates are also the ones who buy more cultural products (Bounies *et al.,* 2012) and that the "consumer sampling effect" of file-sharing technologies helps consumers to discover new products and improve consumer information (Peitz and Waelbroeck, 2006).

7. Conclusion

Annex

Figure 1. The rise-and-rise of online recommendation tools and platforms

Evolution of Google search terms in France between 2004 and 2010 (*source: Google Trends*)



Note:
Google Trends designates a certain threshold of traffic for search terms, so that those with low volume won't appear and are equal to zero . The graph reflects how many searches have been done for a particular term, relative to the total number of searches done on Google over time. Data are normalized and presented on a scale from 0-100.

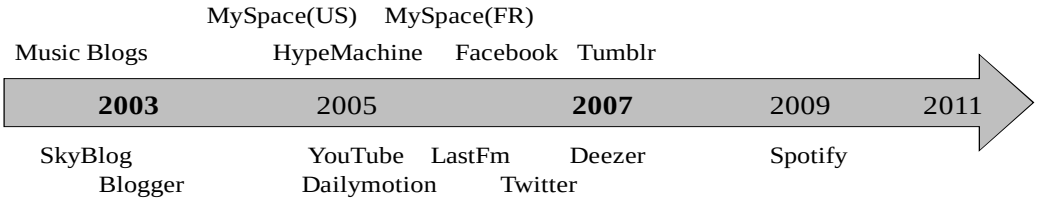


Table 1. Distribution of musical genre (in %)

Genre	2003-Sample *(N=145)*	2007-Sample *(N=127)*	Overall *(N=272)*
Pop Rock	32.4	47.2	39.8
Hip Hop RnB Soul	17.9	20.5	19.2
French variety	22.8	9.4	16.1
Electronic	9.7	8.7	9.2
Jazz Blues	8.3	6.3	7.3
Classical	4.8	4.7	4.8
World Music	4.1	3.1	3.6
Total	100	100	100

Table 2. Distribution of artists' origin

Origin	2003-Sample *(N=145)*	2007-Sample *(N=127)*	Overall *(N=272)*
France	50%	42%	46%
America	32%	21%	26%
European Union	14%	30%	22%
Others	5%	7%	6%
Total	100%	100%	100%

Table 6. Regression results for the 32 weeks

Week relative to release date of second album *(t=0)*	β_s	δ_s
t=-5	*-0.018* *(0.725)*	*0.302* *(0.667)*
t=-4	*0.019* *(0.778)*	*-0.075* *(0.448)*
t=-3	*0.116* *(0.130)*	*- 0.112* *(0.317)*
t=-2	*0.216**** *(0.009)*	*- 0.206* *(0.087)*
t=-1	*0.277**** *(0.001)*	*-0.140* *(0.269)*
t=0	*0.349**** *(0.000)*	*-0.171* *(0.189)*
t=1	*0.408**** *(0.000)*	*-0.144* *(0.278)*
t=2	*0.409**** *(0.000)*	*-0.103* *(0.447)*
t=3	*0.426**** *(0.000)*	*-0.161* *(0.239)*
t=4	*0.408**** *(0.000)*	*-0.177* *(0.198)*
t=5	*0.419**** *(0.000)*	*-0.112* *(0.419)*
t=6	*0.332**** *(0.001)*	*-0.026* *(0.852)*
t=7	*0.365**** *(0.000)*	*-0.111* *(0.426)*
t=8	*0.392**** *(0.000)*	*-0.127* *(0.364)*
t=9	*0.431**** *(0.000)*	*-0.262** *(0.062)*
t=10	*0.311**** *(0.001)*	*-0.100* *(0.478)*
t=11	*0.340**** *(0.000)*	*-0.279*** *(0.050)*
t=12	*0.325**** *(0.001)*	*-0.281*** *(0.049)*
t=13	*0.251**** *(0.010)*	*-0.230** *(0.100)*
t=14	*0.308**** *(0.002)*	*-0.334*** *(0.020)*
t=15	*0.285**** *(0.003)*	*-0.306*** *(0.034)*
t=16	*0.273**** *(0.005)*	*-0.309*** *(0.033)*
t=17	*0.229*** *(0.019)*	*-0.206* *(0.158)*
t=18	*0.192*** *(0.049)*	*-0.191* *(0.191)*
t=19	*0.266**** *(0.007)*	*-0.284*** *(0.050)*

t=20	*0.226*** *(0.021)*	*-0.303*** *(0.039)*
t=21	*0.284**** *(0.004)*	*-0.409**** *(0.005)*
t=22	*0.247*** *(0.012)*	*-0.497**** *(0.001)*
t=23	*0.236*** *(0.016)*	*-0.436**** *(0.003)*
t=24	*0.259**** *(0.008)*	*-0.457**** *(0.002)*
t=25	*0.203*** *(0.039)*	*-0.300*** *(0.043)*
t=26	*0.271**** *(0.006)*	*-0.367*** *(0.013)*
# of artists	268	
# of observations	31,835	
$\hat{\rho}$	0.827	

Model follow a GLS estimation, corrected for heterosckedasiticity and serial correlation (AR1). Standard errors are in parentheses; *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

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