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Let the music play? Free streaming and its effects on digital music consumption☆

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ABSTRACT

The tremendous growth in interactive music streaming is raising questions about its effects on the music industry. While premium subscriptions offer unconstrained access to music streaming, free services typically offer limited mobility in their usage. If streaming enhances product discovery, and if consumers value mobility, then free streaming could stimulate the use of channels that allow mobile consumption. I exploit the introduction of a listening cap by the platform *Deezer* to identify the effect of free and mobile-restricted streaming on the music purchasing and piracy behavior of a large set of individuals. Results show that users visited licensed and unlicensed downloading websites around 2% less than they would have had the restriction not been introduced, showing a positive effect of free streaming on these alternative sources of consumption. Results also indicate heterogeneous effects of the restriction, and back of the envelope calculations suggest that the purchasing and piracy activities of lighter streamers are stimulated by free streaming to a larger extent.

1. Introduction

Interactive music streaming services have recently gained in popularity and generated heated debates around their effects on the recorded music industry. At the heart of the issue lies the potential of these services to curb music piracy and, to a larger extent, the fear that they may negatively affect recorded music sales, and therefore decrease revenues to music right holders. These concerns have led some artists - claiming relatively low levels of streaming royalties - to remove their products from online streaming services altogether.[1]

In the wake of digitization, analyzing the effects of music streaming on alternative consumption channels is crucial to understand the tumultuous transformation of the recorded music industry. On the one hand, online streaming services are often described as product discovery tools, which could potentially stimulate digital music sales and consumption.[2] According to *Spotify*, for instance, their service “makes it easier than ever to discover, manage and share music [...]”[3] Likewise, *Deezer* describe themselves as “music lovers at heart, on a mission to help you discover artists that rock your world.”[4] On the other hand, streaming could also serve as a substitute to alternative consumption channels, decreasing both music sales and piracy.

Recognizing the importance of this issue, the empirical evidence on the effects of music streaming on recorded music sales has now been growing. However, and perhaps more importantly, the debates surrounding this question often fail to distinguish between the various types of online music streaming services and their corresponding functionalities. They often do not, for instance, differentiate between interactive and non-interactive platforms, or between free and premium subscriptions services when considering their effects on alternative music consumption channels.

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1 See for instance Taylor Swift’s decision to pull her music away from Spotify in November 2014 (http://uk.businessinsider.com/taylor-swift-explains-why-she-left-spotify-2014-11?r=US&IR=T) or Adele’s decision to withhold her album “25” from streaming services (http://www.nytimes.com/2015/11/20/business/media/adele-music-album-25.html?_r=0).

2 Because music is an experience good (Nelson, 1970), a consumer may like to sample a song before deciding whether to purchase it. See for instance Shapiro and Varian (1999); Peitz and Waelbroeck (2006a, 2006b); Dewan and Ramaprasad (2012)and Zhang (2016) for various accounts of how sampling and reduced search costs could stimulate demand.

3 https://press.spotify.com/us/2013/05/29/hello-music-discovery-spotify-here/.

4 http://www.deezer.com/features.

http://dx.doi.org/10.1016/j.infoecopol.2017.06.002

Economic theory does not provide any clear predictions on the effects of these functionalities; each one of them could a priori serve as either a substitute or a complement to digital sales and piracy. Yet there are reasons to believe that not all types of online music streaming would have the same effects on these alternatives consumption channels.

Consider, for instance, the services offered by a *premium* subscription to an interactive music streaming platform.[5] These would typically provide users with on-demand, advertisement-free listening on fixed and mobile devices, both online and offline. For a monthly fixed-fee, premium subscribers can therefore have access to the complete platform's repertoire whenever and wherever they want. In that case, it seems natural to expect subscribers to have little incentives to acquire digital music via other channels of consumption such as licensed or unlicensed downloading. Put differently, interactive premium streaming would a priori be likely to displace both digital sales and piracy.

Alternatively, consider the case of *free* interactive streaming. These advertisement-supported services naturally offer a more limited access to music. First, consumer listening is interrupted by advertisement. Second, and most importantly, on-demand streaming mobility is not accessible or drastically restricted. Until recently, consumers were typically only offered the possibility to freely stream from a fixed device - such as a PC - as no mobile access was available. The recent introduction of mobile apps for free users has somehow changed this situation, but the limited on-demand listening capabilities that they offer (e.g. limited repeated listening, no ability to skip tracks within playlists, imposition of shuffle mode) are still preventing free users from flexibly accessing music everywhere.[6] So while free streaming allows consumers to discover and learn about new products, it does not offer them the possibility to freely and easily access these products through a mobile device. Digital sales and piracy, on the other hand, naturally offer fully interactive mobile consumption within an individual's personal library.[7] Consider an individual who discovers a (set of) new product that she likes through a free streaming account. Because the latter would prevent her from consuming that product unrestrictedly on a mobile device, she may decide to further acquire it through purchase or piracy. It follows that if consumers want to add mobility to their music listening, then *free* and, more specifically, *mobile-restricted* streaming may well stimulate consumption through both of these alternative channels.[8] This is in contrast with *premium* streaming since the latter would already offer unconstrained (mobile and otherwise) consumption.

These considerations suggest that while it is easy to imagine a circumstance in which *premium* streaming would displace digital sales and piracy, the effects of *free* and mobile-restricted streaming are - a priori - less clear.[9] Learning about these potential differences has important implications for the various actors of the recorded music industry. For instance, understanding the effects of free streaming is important for practitioners who contemplate its integration into a windowing strategy.[10] Because the settlement of music streaming royalties also evolves around the effect of streaming on alternative consumption channels, a good understanding of these relationships is crucial for the various parties involved in the settlement of royalty rates and from a public policy perspective (See Strickler, 2015).

The objective of this paper is to identify the causal effect of online *free* and *mobile-restricted* music streaming on music purchasing and piracy behavior. This is an inherently difficult task, mainly for two reasons. First, it is usually hard to access data on music consumption through streaming, sales, and piracy. Second, even with access to such data, the lack of clean experimental settings naturally challenges the identification of a causal effect of streaming on alternative consumption channels. By focusing on the introduction of a listening cap on free streaming by the French leading streaming platform *Deezer*, the empirical strategy followed in this paper allows to tackle this particular question. The analysis relies on Internet clickstream data, which allow to precisely follow the online behavior - including visits to licensed and unlicensed digital music consumption websites - of a representative sample of 5000 French Internet users during the year 2011. The empirical approach therefore exploits *Deezer*'s introduction of a listening cap on June 6, 2011 as a source of exogenous variation in free streaming. I rely on a difference-in-differences strategy to identify the causal effect of free and mobile-restricted streaming on the usage of licensed and unlicensed music downloading platforms. Because individuals in the sample are naturally not randomly assigned into using *Deezer*, self-selection may still be a potential cause for concern. I tackle this issue by selecting a control group of individuals by means of a propensity score matching algorithm and pair each of the *Deezer* users in the sample with a comparable individual who did not use the French music streaming platform.

The results from the empirical analysis show a negative effect of the imposition of the free streaming cap on visits to both licensed and unlicensed music downloading websites. In particular, I find that users of *Deezer* who were directly affected by the cap imposition visited licensed and unlicensed downloading websites around 2% less than they would have had the restriction not been imposed. I also exploit the variation in pre-cap levels of *Deezer* usage to identify heterogeneous effects of the restriction. Results show that heavier users of *Deezer* - who were naturally more importantly affected by the restriction - decreased their visits to downloading websites to a larger extent. Individuals in the top of the *Deezer* intensity distribution decreased their visits to licensed and unlicensed websites by 3.5% and 3.1%, respectively. For individuals located in the middle of the intensity distribution, the corresponding figures equal 1.86% and 2.31%. Individuals in the bottom of the *Deezer* intensity distribution show no significant effect of the cap on their visits to these alternative music consumption websites.

[5] Online streaming services can broadly be divided into two distinct categories: interactive and non-interactive platforms. The non-interactive platforms (such as *Pandora* or *iHeartRadio*) offer services that are similar to a radio broadcast in that the end user is offered a pre-programmed set of songs, and consumers cannot select the songs they want to listen to or even observe the order of the tracks to be played. This is in contrast with interactive platforms (such as *Deezer* or *Spotify*), which offer consumers the liberty to pick the songs they want to listen to. The analysis will focus exclusively on interactive music streaming services. For simplicity and ease of exposition, I therefore refer to these services simply as "music streaming service" in the remainder of the text.

[6] From that perspective, mobile apps offered by free interactive streaming platforms resemble the services provided by non-interactive platforms (see footnote 5). See, for instance http://tinyurl.com/Deezer-free-mobile for the case of *Deezer*'s mobile app and http://tinyurl.com/Spotify-free-mobile for the case of *Spotify*'s mobile app.

[7] Any MP3 file obtained via either a licensed or unlicensed provider can presumably be played on any mobile device.

[8] There is now increasing evidence showing that consumers indeed value mobility in their music consumption. *Spotify*, for instance, announced that mobile consumption now accounts for the majority of listening (http://techcrunch.com/2015/01/10/music-is-a-mobile-linchpin/). Empirical evidence in Leung (2015) also shows that pirated music files are complements to mobile devices such as the iPod, indicating that music consumers indeed value mobility in their digital music consumption.

[9] A similar theoretical argument would lead to the same conclusions when considering the effects of non-interactive music streaming services, where users do not have full control over the songs they can listen to.

[10] One could for instance imagine that new releases be first made available on premium streaming services during periods of high demand (e.g. around release) and later on free ad-supported tiers. See for example http://www.billboard.com/articles/business/6882769/sony-entertainment-chief-streaming-windowing-spotify-response.

Back of the envelope calculations also allow me to compute the streaming elasticity of visits to alternative music consumption websites. These calculations suggest that for the average *Deezer* user, a one percent increase in *Deezer* streaming leads to increases of about 0.1% in visits to licensed and unlicensed downloading websites. However, the results indicate that heavier *Deezer* users present much lower elasticities than lighter users. In other words, the purchasing and piracy behaviors of lighter *Deezer* users appear to be more sensitive to streaming.

A now growing literature has analyzed the effects of streaming on recorded music sales.[11] However, a very limited set of papers has focused on the potentially heterogeneous effects of different types of streaming services. In particular, the effects of their various functionalities have hardly been studied.[12] This paper aims at filling this gap and provides evidence on the causal effect of free and mobile-restricted streaming on music purchasing and piracy behavior. The study contributes to the growing debate surrounding the effects of music streaming and to the empirical literature on the effects of digitization in the recorded music industry. It has several implications. First, the results are consistent with online music streaming serving as an information channel for consumers to discover and learn about new products they would otherwise not have been aware of. Second, the results indicate that *free* streaming - because it only allows for very limited mobility in consumption - can lead to a stimulation in alternative digital music consumption channels that offer mobility, such a licensed and unlicensed downloading. Finally, this study highlights the importance of taking the specific functionality of each streaming service into account when analyzing its effects on alternative consumption channels. In particular, the results should not be extrapolated to other types of streaming services providing users with alternative functionalities, such as services offering full mobility of consumption (i.e. premium subscriptions) or non-interactive streaming services. From that perspective, this study serves as a first step toward understanding the heterogeneity of effects that streaming platforms may have on the rapidly changing recorded music industry.

The remainder of the paper is composed of 5 sections organized as follows. Section 2 presents the existing literature on the effects of streaming as well as some descriptive facts about the French music streaming market and *Deezer*. Section 3 presents the data for the study and Section 4 presents the empirical approach and identification strategy. Section 5 turns to the results of the estimations of the various effects of the cap imposition on music purchasing and piracy behavior. It also presents robustness checks as well as back of the envelope calculations that measure the streaming elasticity of visits to licensed and unlicensed downloading websites. Section 6 concludes and discusses the implications of the results.

2. Background

2.1. Existing literature

In the past few years, online music streaming services have become an increasingly important segment of the recorded music industry, expanding music consumption opportunities and making music ubiquitously available for consumers. According to the International Federation of the Phonographic Industry (IFPI), streaming revenues from both premium and add-supported services increased 45.2% in 2015 and grew more than four-fold over the period 2011–2015. These revenues accounted for 43% of digital revenues in 2015, up from 32% in 2014 and 25% in 2013.[13]

The growing importance of online streaming platforms in the music market has naturally triggered an increasing body of empirical research regarding their effects on alternative digital music consumption channels, and in particular recorded music sales. However, a very limited set of studies has focused on the differentiated effects of interactive and non-interactive streaming, or on the effects of their various functionalities.

A first set of papers has analyzed the effects of music consumption on interactive streaming services. Some recent studies have analyzed the effects of music consumption on *YouTube* on digital sales of music.[14] Exploiting the removal of Warner Music content from *YouTube* between January and October of 2009, Hiller (2016) finds a substantial sales displacement effect of *YouTube* consumption on the best-selling albums. His results also show that this effect diminishes quickly with the album's ranking. In particular, he finds no evidence of sales displacement when focusing on the albums below the top 50. Kretschmer and Peukert (2014) also analyze the effect of *YouTube* music consumption on digital music sales by exploiting a royalty dispute between *YouTube* and the German collecting society and performance rights organization *GEMA*. They find that online music videos trigger sales of album, but have no effect on the sales performance of individual songs. Aguiar and Waldfogel (2017) make use of the streaming growth during the years 2013–2015 to measure their collective impact on unpaid consumption and on the sales of recorded music. They show a displacement effect of streaming on both sales and piracy. Their analysis does not, however, differentiate between free and premium streaming. Datta et al. (2017) study the effects of *Spotify* adoption on individual music consumption and discovery. While they do not distinguish between free and premium subscriptions, they find that the adoption of *Spotify* cannibalizes consumption on *iTunes* and increases overall music consumption. Their results also show that adopting *Spotify* leads to an increase in the variety of music consumed and to more discovery of music. The paper by Wlömert and Papies (2015) is, to my knowledge, the only paper to distinguish between free and premium streaming when analyzing the effects of streaming on online recorded music purchases. They rely on a survey panel of music consumers to analyze the effect of on-demand streaming services adoption. They find that consumers who adopt such services purchase significantly less recorded music, with a larger cannibalization effect for paid streaming adoption. Nguyen et al. (2013) also focus on free interactive streaming, but they only study its effect on offline music sales and live music performances. Their results, which rely on a representative survey of 2000 French individuals, show that free streaming has no effect on CD sales but affects positively live music attendance. They conclude that free streaming acts like a tool for discovering music. Finally, Aguiar and Martens (2016) use Internet clickstream data on a sample of more than 16,000 individuals to look at the relationship between different music consumption channels. Using a host of variables to control for many forms of unobserved individual heterogeneity such as music preferences, they find a positive relationship between online music streaming and visits to licensed downloading websites. Their analysis does not, however, distinguish between the various types of streaming services.

Recent research also shows how interactive and non-interactive streaming services can differently affect music sales. Danaher (2014) argues that while interactive services can serve as perfect

[11] See for instance Kretschmer and Peukert (2014); Aguiar and Waldfogel (2017); Hiller (2016); Aguiar and Martens (2016); Datta et al. (2017).

[12] Wlömert and Papies (2015) is currently the only paper that distinguishes between the effects of free and premium streaming services on online recorded music sales.

[13] See http://ifpi.org/news/IFPI-GLOBAL-MUSIC-REPORT-2016 and IFPI (2015).

[14] *YouTube* offers a different music consumption experience than interactive streaming services like *Deezer* or *Spotify*. However, it allows users to access music in an almost unrestricted way, making this service rather similar to the premium subscriptions offered by fully interactive streaming services.

substitutes for music purchases, non-interactive services can act as a complement to paid digital downloads by exposing individuals to songs they would otherwise not have heard or by allowing sampling of music. Using data from an Internet consumer panel tracking company, he shows that the use of non-interactive webcasting services has a significantly more positive impact on digital song purchases than interactive webcasting services. In a similar vein, McBride (2014) looks at the effect of *Pandora* on sales of songs. By manipulating the availability of certain songs in certain geographical locations, he shows that *Pandora* increases music sales by around 2%, providing evidence that non-interactive music streaming services can stimulate sales.

2.2. The French music streaming market and Deezer

Online streaming has developed rapidly in France in recent years. According to the French National Syndicate of Phonographic Publishing (SNEP), the share of France's digital revenues coming from streaming (subscription and advertisement-based combined) grew from 36% in 2011 to 54% in 2014, and up to 79% in 2016.[15]

Within this growing market, *Deezer* is undoubtedly the major online streaming platform in France. In 2011, *Deezer* accounted for nearly 70% of overall streaming revenues. This share decreased to 65% in 2012 and remained stable in 2013.[16] In 2013, about two thirds of French streaming revenues came from premium subscriptions, and one third from advertisement. Until the end of 2011, *Deezer* was only available in France, Belgium and the United Kingdom. The platform basically offered three types of services at that time: one for free users and two for premium subscribers. Free users initially had access to unlimited streaming - interrupted by advertisement - on their PC, but had no access to mobile streaming. At the same time, two premium subscription plans were available. For € 4.99 a month, users could get rid of advertisement and keep enjoying unlimited streaming on their desktop exclusively. The second subscription plan added unlimited mobile streaming for € 9.99 a month.[17]

As in the case of most streaming services providers, *Deezer*'s customer base is mainly composed of free users. In a July 2011 press release, *Deezer* claimed to have more than a million premium users for a total of 20 million members and the share of premium users did not reach 10% as of June 2012.[18] The number of paying users has nevertheless been growing significantly in recent years. In November 2013, *Deezer* announced that they had multiplied their subscriber base by 2.5 in one year, reaching 5 million subscribers.[19] In January 2015, they claimed to have 16 million monthly active users and 6 million paid subscribers worldwide.[20] While *Deezer* naturally serves as a music consumption platform, many of its characteristics also define it as a powerful product discovery tool. In particular, users (free or premium) are given personalized music recommendations, information about musical events and new artists, all of which may spur their interest into acquiring more music.

While free streaming on *Deezer* was initially unlimited, the platform introduced a restriction that imposed a monthly 5 hours limit on free streaming starting June 6, 2011. In this paper I exploit this change to identify the causal effect of free and mobile-restricted streaming on digital music purchasing and piracy behavior.

3. Data

The basic data for this study come from Nielsen NetView - Nielsen's Internet audience measurement service - which monitors the online activity of representative panels of Internet users and tracks their usage across websites. The original sample includes 5000 French individuals who are voluntarily followed over the period going from January 1, 2011 to December 31, 2011, providing detailed information on their website visits.[21] The data also reports demographic information on the users, such as gender, age, household income, education, and employment.

For each visit made by an individual in the sample, I observe the precise URL of the webpage visited, the time at which it was visited, and the duration spent on that specific URL. Nielsen also classifies webpages in different categories according to their content. This allows me to identify specific types of websites within these different categories. Because I am interested in the effects of online music streaming on other digital music consumption channels, I identify all major music streaming websites, websites that (legitimately) sell digital music, and piracy websites that provide access to unlicensed downloading of music. It is worth noting that contrary to studies that rely on individual surveys to measure individual-level music consumption, the data are based on actual usage patterns rather than subjective assessment from Internet users.[22] It is also important to note that since the data is composed of a representative sample of Internet users (in terms of gender and age), the results from the analysis need not be restricted to a particular subset of the population (e.g. college students).

3.1. Music consumption websites

The identification of music consumption websites was performed by manually checking each of the top 1500 websites registered in Nielsen's music category. I also identified the URLs that correspond to digital music purchases within large online retailers like *Amazon* and *FNAC*. Each of these music websites was then classified into one of three distinct groups according to their purpose: music streaming websites, licensed music downloading websites, and unlicensed music downloading websites.[23]

15 See http://tinyurl.com/snep-shares-2011 and http://www.snepmusique.com/actualites-du-snep/bilan-2016-marche-de-la-musique-enregistree/.

16 See http://tinyurl.com/snep-market-2014-pdf.

17 Since 2014, *Deezer* dropped its € 4.99 subscription plan. *Deezer* has also expanded internationally and is now available in 182 countries.

18 See "Dossier de Presse Deezer: Juillet2011", July 2011. http://www.slideshare.net/deezer_com/le-dossier-de-presse-deezer-juillet2011. And see Pichevin, Aymeric. "Deezer CFO/COO Simon Baldeyrou on Music Streaming Service's Global Expansion, Spotify, Avoiding The U.S." Billboard, June 12, 2012. http://www.billboard.com/biz/articles/news/1093736/deezer-cfocoo-simon-baldeyrou-on-music-streaming-services-global-expansion.

19 See http://tinyurl.com/guardian-deezer-5m-subscribers.

20 See http://tinyurl.com/blog-deezer-com-paidsubscriber.

21 According to Nielsen, the sample is weighted to be nationally representative of the age and gender of France's online population.

22 See, for instance Rob and Waldfogel (2006) and Waldfogel (2010), which rely on surveys of college students to identify the effect of piracy on music sales. See also Nguyen et al. (2013) and Wlömert and Papies (2015), which use individual surveys to study the effect of online music streaming on music purchases.

23 I define the set of licensed webpages as the websites that allow for downloading of digital music files. While these naturally include in-browser digital music stores, they also include licensed websites that allow free downloading. An example is the now gone French ad-supported download store *Beezik*, which offered users the possibility to download digital songs in exchange for the visioning of video advertisement. The set of unlicensed websites includes websites that allow for the direct downloading or ripping of MP3 files. While the data also allows to observe visits to *Torrent* websites, I unfortunately cannot identify whether the visit was made to download a music file or an alternative type of file (e.g. a book or a movie). These websites are therefore not included in the unlicensed downloading websites category. In a 2011 study, however, Envisional (2011) analyze the top 10,000 pieces of content available on *PublicBT*, the largest and most popular bittorrent tracker worldwide at the time. Their results show that the relative popularity of music was low within this content, with music files accounting for only 2.9% of the content available. This suggests that the unobserved share of music piracy that happens through *Torrent* websites is limited, therefore alleviating the potential concern that the levels of piracy captured through the list of unlicensed downloading websites could importantly understates true piracy levels.

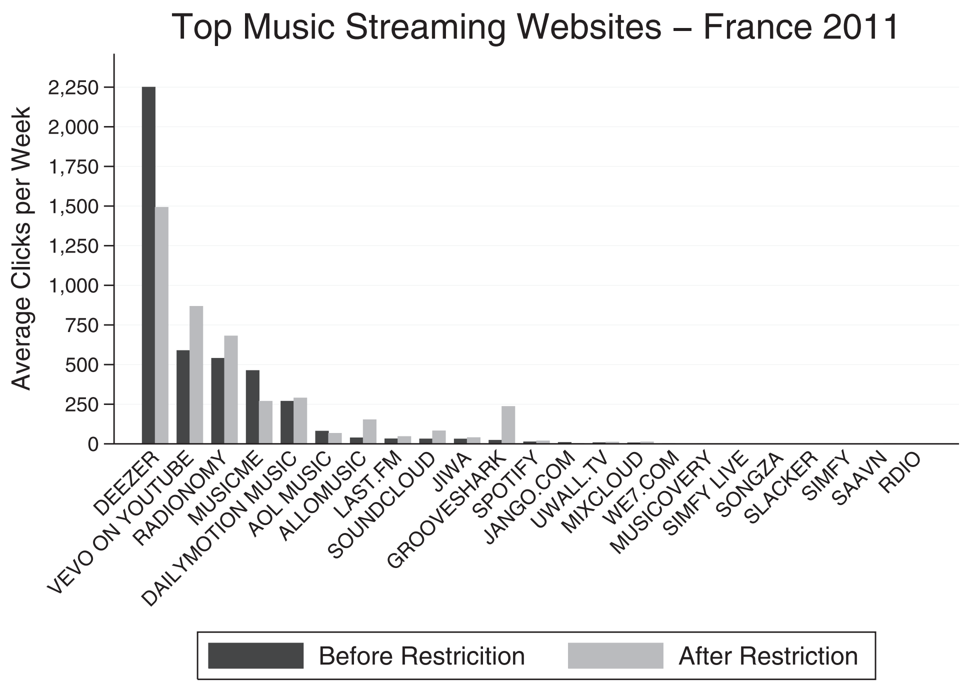


Fig. 1. Top Streaming Websites in France, 2011.

Because *Deezer* is a streaming service that is used within the web browser, the data provide an excellent measure of its usage.[24] For each of the 5000 individuals in the sample, I can observe the number of weekly visits made to the *Deezer* webpage, which provides me with a proxy for music streaming consumption on this platform. Because individuals have the opportunity to use their *Deezer* account through Facebook, I also identify the visits made to *Deezer* through the social media platform. The data also include the time spent during each domain's visit. However, Nielsen's measurement tool only records the time spent on websites that are in focus (i.e. the time spent on a given webpage stops being recorded once the users switches to another tab). The recorded duration will therefore clearly underestimate the actual time spent on *Deezer* if the individual is streaming music in the background while focusing on another website.[25]

Fig. 1 shows the average weekly visits for all the music streaming websites identified in the data. It clearly shows that *Deezer* was the dominant music streaming platform in France at that time, with almost 4 times as many average visits as the second most visited domain, *Vevo on YouTube*.[26] Note that *Deezer* maintained its leading position after its free streaming restriction was imposed. Fig. 2 shows the set of websites included within the categories of licensed and unlicensed downloading websites.

At the outset, it is important to note that the data only allow to observe the number of clicks on a given URL, but does not allow to observe the precise individual's behavior on the URL. Rather than measuring actual streams, licensed, and unlicensed downloads, the data therefore give a proxy for the actual consumption of digital music through these different channels. Because this naturally implies an imperfect measure of digital music consumption, understanding whether biases could occur as a result of this feature is nevertheless important. It is of course natural to expect some visits not to translate into consumption, if for instance individuals went on licensed or unlicensed downloading websites with other purposes than to consume music. Within the setting of this study, a bias could naturally occur if the ratio of site visits to actual consumption is systematically related to streaming behavior. For instance, a concern could arise if people who stream more were also more inclined to visit purchasing or piracy websites without actually consuming music. If this were the case, the proxy measure would overestimate purchases for heavy streamers relative to lighter streamers. The most likely motive for individuals to visit downloading websites without consuming music is perhaps to obtain information about certain products (e.g. albums, songs, artists), using them, in essence, as discovery tools. However, given that *Deezer* - like most interactive streaming services - offers powerful search functions and product discovery options built-in, it seems unlikely that users of the service would need to browse licensed or unlicensed downloading websites to discover new products. Moreover, even if some users were to behave that way, it is hard to see why such behavior should be related to their intensity of streaming usage. Note also that aside from licensed and unlicensed downloading websites, many alternative music websites are also likely to be used for discovery purposes (e.g. websites providing information on music charts).

Another potential issue relates to the fact that the Nielsen NetView application only captures traffic within the browser, which prevents the measurement of visits to standalone applications. While this could lead to a lower quality proxy in cases similar to the one of *iTunes* (see footnote 24), the remaining top licensed websites that appear in the left-hand side of Fig. 2

[24] The fact that the Nielsen NetView application only captures traffic within the browser imposes some limitations to the analysis. In particular, I cannot observe purchases on *iTunes* given that it is a standalone software. I am therefore only able to observe the visits to the *iTunes* webpage, which is nevertheless an individual proxy for signing up to the service making later purchases. As a robustness check I also performed the empirical analysis below removing *iTunes* from the category of licensed downloading websites. The results are robust to this exclusion.

[25] The measures of clicks and duration are nevertheless strongly correlated in the sample (e.g. see Fig. 3 below). For these reasons, the duration variable does not provide much more information than the clicks. I have nevertheless checked the robustness of my results by replicating the empirical analysis below using the duration as an alternative to clicks. The results are all robust to using the duration as an alternative measure of consumption.

[26] This numbers are in accordance with the figures provided by the SNEP in their 2012 annual report on the French musical market. See http://tinyurl.com/french-market-snep-2012.

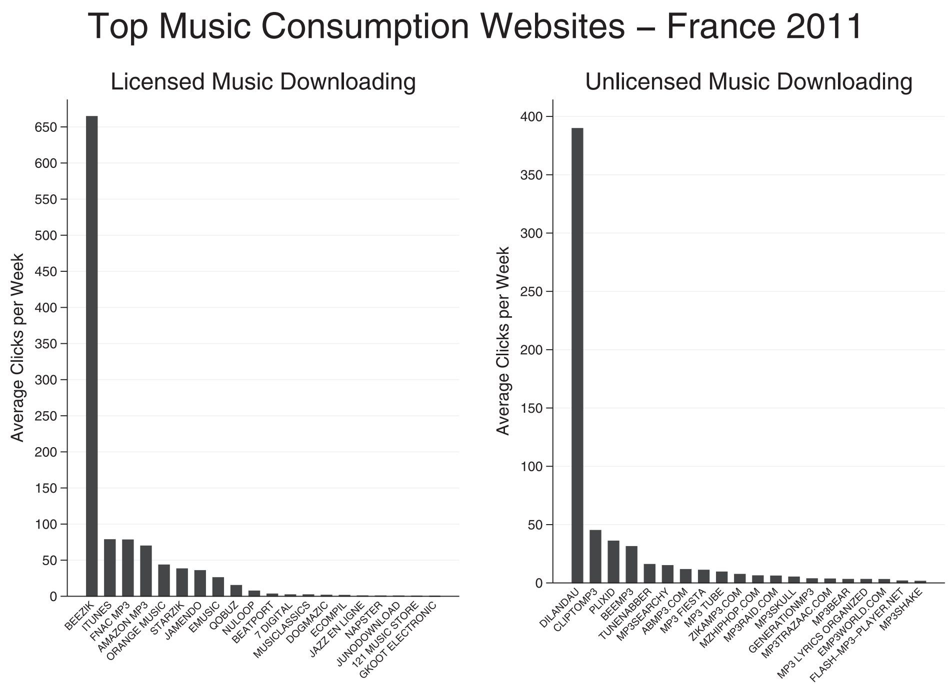


Fig. 2. Top Music Consumption Websites in France, 2011.

fortunately operate within the browser.[27] Beyond the explanations presented above, these websites additionally do not present any particularity that would lead one to expect individuals to visit such online stores without intent to buy.

Similar considerations hold regarding unlicensed downloading websites. The websites included in this category correspond to sites that allow for direct downloading of MP3 files (for instance *Dilandau* and *BeeMP3*), for ripping *YouTube* clips into MP3 format (for instance *CliptoMP3*) or sites that provide direct links to downloads from other websites (for instance *Plixid*). Because the MP3 files obtained through these websites need to be reached through the web browser, it is reasonable to assume that individuals would visit such sites mainly for consumption. The final dataset consists of an individual-level panel dataset of 5000 French Internet users and their weekly visits to *Deezer* as well as licensed and unlicensed music consumption websites throughout 2011. A total of 1410 individuals (28% of the sample) visited *Deezer* before the free listening cap was introduced.

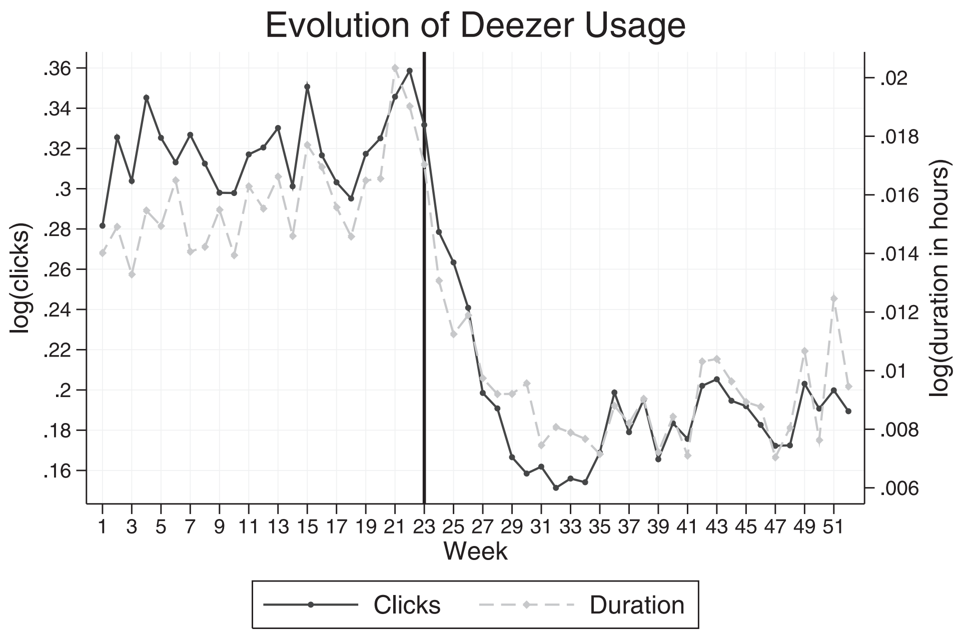
4. Empirical approach

The main interest of this paper lies in the identification of the effect of free and mobile-restricted streaming on digital music purchasing and piracy behavior. For a given individual, one would ideally like to compare her music consumption through digital purchases and piracy when she has access to online streaming services with her music consumption in the hypothetical case in which she has no access to these services. However, since the data naturally only allow to observe individuals when they have access to online streaming, there is no way of knowing how they would have behaved in this counterfactual state. In a world where consumers all have access to online streaming services, an ideal experiment would consist in removing access to streaming services to a set of randomly chosen individuals. The effect of online free music streaming on digital purchases and piracy would then be identified as the change in purchases and piracy for the individuals who were denied access compared to the individuals whose use of streaming platforms remained unchanged. Because this type of experimental design is often not feasible, one needs to rely on alternative sources of variation in the consumers' ability to use online streaming services. In this paper, the empirical strategy relies on the introduction of a 5 hours free listening cap introduced by *Deezer* on June 6, 2011. Because this restriction provides exogenous variation in free and mobile-restricted streaming, it ca be used to identify its effect on purchasing and piracy behavior.

Given that free listening was unlimited before that date, the cap imposition represents a very important restriction for consumers. Fig. 3 shows the overall evolution of usage (in terms of clicks and duration) of *Deezer* for the 1410 individuals who were using the platform before the cap was imposed. The graph shows that the free streaming restriction had a clear impact on usage for the average user of *Deezer*.

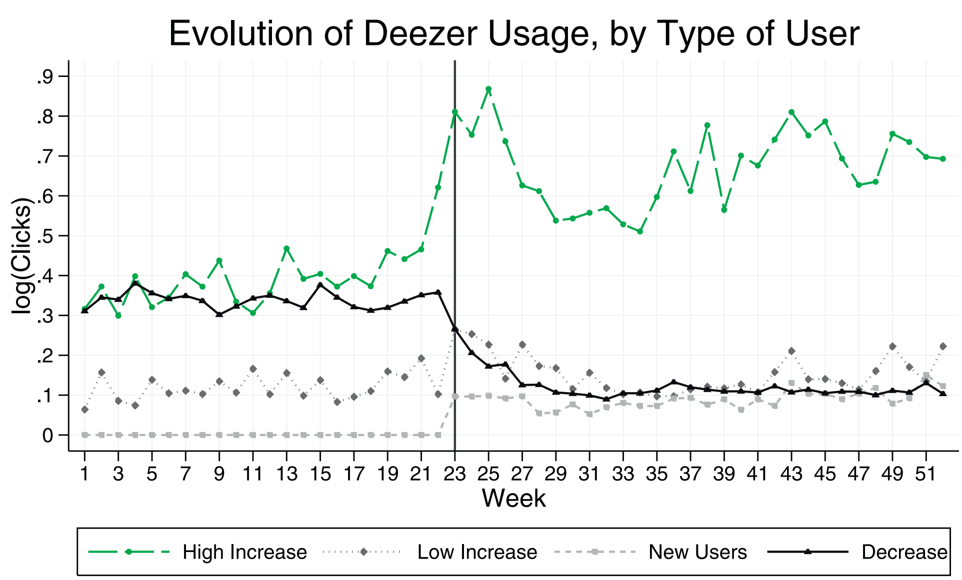
While informative, Fig. 3 masks the fact that not all individuals in the sample were necessarily affected by the restriction in the same way. First, the restriction was exclusively aimed at free subscribers, and premium subscribers were therefore not affected by the cap imposition. Likewise, free users with lower levels of *Deezer* usage (i.e. below the cap) were not directly affected by the restriction. Second, some free users may have decided to switch to a premium account as a response to the cap imposition, which could have even resulted in an increase in their usage of the platform. Third, the announcement of the cap imposition could have raised awareness about *Deezer*, which may in turn have led some new individuals to start using the platform only after the restriction was imposed. The data do not directly provide information on whether a given individual uses *Deezer* through a free or premium account, but I can infer the type of subscription individuals were using by looking more closely into their *Deezer* usage. Fig. 4 presents the evolution of *Deezer* usage for different types of individuals in the sample. In particular, it distinguishes between individuals who decreased and increased their usage of

[27] For instance, *FNAC MP3* and *Amazon MP3*, *FNAC*'s and *Amazon*'s online music stores, respectively, both had to be reached within the browser. As in the case of *Beezik* (see footnote [23]), they allowed users to directly download songs from their webpage at a given price.



Note: Includes individuals who visited Deezer at least once before the cap imposition.

Fig. 3. Evolution of Deezer Usage in France, 2011.



Note: High (Low) Increase individuals are users of Deezer whose usage increase is above (below) the median increase in usage of Deezer users (171 and 172 individuals, respectively). Decrease individuals are users who decrease their usage of Deezer after the cap (1067 individuals). New users are defined as individuals who start using Deezer after the cap (591 individuals).

Fig. 4. Evolution of Deezer Usage by Type of User in France, 2011.

the platform after the free streaming cap imposition.[28] Out of the 1410 individuals who used *Deezer* before the cap was imposed, 1067 presented a reduction in their usage of the platform. As shown in the figure, this decrease is substantial for these users, which strongly suggests that they were and remained free subscribers of *Deezer* throughout the sample period.

The remaining 343 users of *Deezer* increased their consumption on the platform after the cap imposition. Note that this group of individuals may broadly comprise two sets of users. On the one hand, individuals who were premium subscribers before the cap could increase their usage since they would not face any restrictions. Likewise, some free users may have decided to subscribe to a premium account following the cap imposition, which would again not face any restriction.[29] On the other hand, some individuals who sticked to their free account may simply have increased their visits to *Deezer* following the announcement of the cap

[28] For each individual in the sample, the changes in usage are calculated by comparing the simple average usage of *Deezer* in the periods before and after the cap imposition.

[29] Note that if the pre-cap levels of *Deezer* usage are above or equal to the 5 hours per month limit, the levels of post-cap usage can only be higher if the user was already a premium account subscriber or switched to one.

imposition, provided their pre-cap level of usage was not above the restriction limit. Within the set of individuals who increased their usage, Fig. 4 differentiates users according to the intensity of this increase. In particular, it splits the set of 343 users into two groups of equal size by considering users whose increase in *Deezer* usage is above and below the median usage increase. The 171 users whose increase is above the median present higher levels of *Deezer* usage, both before and after the cap. This suggests that these individuals (about 12% of the total number of *Deezer* users in the sample) were using *Deezer* through a premium account before the cap or converted to one after the restriction was imposed.[30] The 172 users whose increase is below the median present a pre-cap level of usage that is much lower than the one corresponding to the set of free users who decreased their usage. Their post-cap level of usage is also similar to the one from the latter group, which suggests that these individuals were free users whose consumption levels were not directly affected by the cap.[31]

Finally, an extra group of 591 individuals who were not initially using *Deezer* started doing so after the imposition of the cap. Fig. 4 suggests that these new consumers also mainly used the platform through free subscriptions, as their post-cap level of usage of *Deezer* remained close to the level of the other set of free users.

Deezer's policy change can be used together with the information provided in Fig. 4 to identify the effect of free and mobile-restricted streaming on digital purchasing and piracy behavior. I focus on the set of individuals who used the free version of *Deezer* both before and after the cap imposition and use the latter as a source of exogenous variation in the ability of individuals to use *Deezer*'s free streaming services.[32] In particular, I follow a difference-in-differences strategy and compare how *Deezer* users changed their use of alternative music consumption channels as a results of the streaming cap, compared to a control group of individuals who were not users of *Deezer*. The construction of the control group is described in more detail in the next sub-section. The empirical strategy therefore consists in estimating the following difference-in-differences equation:

$$\ln(Clicks_{it}^{A}+1) = \alpha + \beta(Deezer_i * Cap_t) + \gamma X_{it} + \eta_i + \nu_t + \varepsilon_{it}, \tag{1}$$

where $Clicks_{it}^{A}$ measures the sum of clicks to the set of alternative consumption websites A for individual i in week t, with $A \in$ {*Licensed Downloading, Unlicensed Downloading*}. I use the logarithm of the number of clicks to account for the fact that the individual-level clickstream data tends to be dispersed and because I am interested in relative changes.[33] The variable $Deezer_i$ is an indicator variable equal to 1 if individual i visited *Deezer* before the free streaming cap was imposed, and Cap_t is a dummy variable taking value 1 during the weeks that follow the listening cap restriction. I include a vector of individual fixed effects η_i to control for variation in alternative consumption across individuals that is constant over time, resulting for instance from time-invariant differences in musical tastes.[34] The set of week fixed effects ν_t controls for variation in alternative consumption that is common to all individuals, X_{it} includes individual and time specific control variables (such as visits to other types of websites and user-specific time trends), and ε_{it} is an individual and time specific error term. Under the assumption that changes in alternative consumption would have been similar for users and non-users of *Deezer* absent the imposition of the listening cap, the coefficient β estimates the effect of free *Deezer* streaming on alternative consumption channel A.[35] Eq. (1) is estimated using OLS and clustering standard errors at the individual level since the error term ε_{it} is likely to be correlated over time within individuals.

4.1. Deezer users and control group

The empirical approach consists in comparing changes in music consumption (through licensed or unlicensed downloading websites) for individuals who used *Deezer*'s free streaming services and for a control group of individuals that did not use *Deezer*. Because individuals in the sample are naturally not randomly assigned into using the French platform, my identification strategy still faces a self-selection issue. One may indeed worry that individuals who decide to use *Deezer* form an inherently different group than individuals who decide not to. Table 1 presents demographic characteristics for these two groups of individuals, together with a measure of total online activity, measured by the average (log of the) total number of clicks during the period prior to the cap imposition. The set of *Deezer* users (second and third columns) includes 1201 free users identified in Fig. 4 for whom I have information available on age, gender, education, income, and employment.[36] The second part of thetable (fourth and fifth columns) considers the 2878 individuals who do not use *Deezer* throughout the sample period and have information available on the same demographic variables.

Differences in these variables across *Deezer* users and individuals who never use the platform are presented in the sixth column of the table. Perhaps unsurprisingly, individuals who use *Deezer* are on average more active online. The group of *Deezer* users also includes a larger share of females and is younger on average. These differences are all statistically significant. There are no significant differences in terms of income. In terms of education, the set of *Deezer* users includes a significantly larger share of individuals with tertiary education and a significantly lower share of individuals with primary education. Finally, there are also important differences in terms of occupation. In particular, *Deezer* users are employed or students to a larger extent. The share of individuals out of the labor force is significantly larger for the group of individuals that never used *Deezer*.

The differences found between users and non-users of *Deezer* naturally raise concerns about the self-selection issue discussed above. In order to ensure better comparability, I select a control group of individuals by means of a propensity score matching algorithm and pair each of the 1201 free *Deezer* users in the sample with a comparable individual who did not use the French music streaming platform. In particular, I estimate each individual i's probability (or propensity) of using *Deezer* as a function of

[30] In particular, note that their post-cap level of usage remained higher than the level of pre-cap usage that corresponds to the set of free users.

[31] One may wonder why individuals who should not be directly affected by the cap increased their *Deezer* usage. Note that the increase appeared mostly around the weeks directly following the cap imposition for this set of users, and that their overall post-cap level of usage otherwise remained relatively close to their pre-cap level. One possible explanation for this pattern could be that these users simply experimented with their level of usage around the cap announcement to see whether the restriction would be binding for them.

[32] I therefore focus on the 1067 individuals who decreased their usage as well as on the 172 individuals who increased their usage in a more moderate fashion (see Fig. 4).

[33] Because I often do not observe a user visiting an alternative music consumption website in a given week, I follow the prior literature and take the log over $Clicks_{it}^{A}+1$.

[34] Note that the term $Deezer_i$ is not included in specification (1) as it is absorbed by the individual fixed effect η_i.

[35] More precisely, the effect of free *Deezer* streaming on alternative consumption channel A is given by $e^{\beta}-1$.

[36] The total number of free users identified in Fig. 4 is equal to 1,067 + 172 = 1,239. However, 38 of these individuals have missing values in some of the demographic characteristics used during the construction of the control group. In the final estimation sample, the corresponding numbers of *Deezer* users are 1033 and 168, respectively.

Table 1
Demographic characteristics by type of individual.†

	Deezer Users		Non-Users of Deezer							
	(N = 1201)		Full sample (N = 2878)				PSM sample (N = 1201)			
	mean	s.d.	mean	s.d.	Diff.	t-stat	mean	s.d.	Diff.	t-stat
Log(total clicks + 1)	5.47	2.40	4.04	2.72	−1.43***	(−15.80)	5.28	2.51	−0.18	(−1.70)
Age	38.78	14.98	42.47	17.49	3.695***	(6.82)	39.74	15.27	0.96	(1.55)
Female	0.53	0.50	0.49	0.50	−0.0487**	(−2.84)	0.52	0.50	−0.01	(−0.53)
Income (in euros)										
0–18,000	0.11	0.31	0.11	0.31	0.00	(−0.02)	0.11	0.31	0.00	(−0.07)
18,001 – 27,000	0.19	0.39	0.18	0.39	0.00	(−0.19)	0.18	0.38	−0.01	(−0.32)
27,001 –36,000	0.20	0.40	0.21	0.41	0.01	(0.87)	0.20	0.40	0.00	(−0.05)
36,001 – 54,000	0.29	0.45	0.27	0.44	−0.02	(−1.28)	0.29	0.45	0.00	(0.05)
54,001 – 72,000	0.14	0.35	0.14	0.35	0.00	(0.10)	0.15	0.36	0.01	(0.64)
72,001 And Over	0.08	0.27	0.09	0.29	0.01	(0.99)	0.08	0.27	0.00	(−0.30)
Education										
Primary	0.25	0.44	0.34	0.47	0.0852***	(5.55)	0.25	0.43	0.00	(−0.19)
Secondary	0.12	0.32	0.14	0.35	0.02	(1.88)	0.11	0.32	0.00	(−0.19)
Tertiary	0.63	0.48	0.52	0.50	−0.106***	(−6.34)	0.63	0.48	0.01	(0.30)
Employment										
Employed	0.63	0.48	0.57	0.50	−0.0604***	(−3.61)	0.65	0.48	0.02	(1.15)
Out of labor force	0.21	0.41	0.30	0.46	0.0857***	(5.88)	0.21	0.41	0.00	(−0.10)
Self employed	0.03	0.18	0.03	0.17	0.00	(−0.24)	0.03	0.17	0.00	(−0.12)
Student	0.07	0.26	0.05	0.23	−0.0211*	(−2.43)	0.05	0.23	−0.0208*	(−2.08)
Unemployed	0.05	0.22	0.05	0.22	0.00	(−0.36)	0.05	0.22	0.00	(0.09)

† Users of Deezer are defined as individuals who visited *Deezer* at least once before the free streaming cap was imposed. * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

observed characteristics:

$$\text{Prob}(Deezer_i = 1 \mid Z) = \text{Prob}(\delta_0 + \delta_1 Z_i + \mu_i > 0 \mid Z), \qquad (2)$$

where Z_i includes a set of observable individual characteristics and the error term μ_i is assumed to follow a standard logistic distribution. For each individual i, the variables included in vector Z_i correspond to the variables presented in Table 1. The observed self-selected users of *Deezer* are then matched to control users having the same propensity scores. In particular, I perform a one-to-one matching and match each *Deezer* user with the most similar non-user in terms of propensity.[37]

Table 2 reports the results of estimating Eq. (2), where the dependent variable is equal to one for the individuals who used *Deezer* prior to June 6, 2011. As expected, individuals who spend more time online are more likely to use *Deezer*. Individuals with higher levels of income and education, as well as younger individuals, are more likely to use the streaming platform. Finally, individuals who are students are more likely to use the French platform.

The completion of the matching procedures leads to a total of 1201 free users of *Deezer* and 1201 individuals who never used the platform. Descriptive statistics on the latter group are presented in the last part of Table 1. The matched control group is now statistically indistinguishable from the group of *Deezer* users in terms of the various characteristics presented in the table (except for the student indicator). Recall also that the difference-in-differences strategy allows to remove any time-invariant unobservable individual effect that may affect the outcome variable of interest. Descriptive statistics on visits to the different categories of music consumption websites, both before and after the cap imposition, are presented in Table 3 for the two groups of individuals.

4.2. Identification assumption

The identification strategy assumes that being a user of *Deezer* is uncorrelated with week to week changes in usage of alternative channels of music consumption. In other words, it relies on

Table 2
Propensity Score Matching model - Probit.†

	(1) Coef./s.e.
Log(total clicks + 1)	0.3197***
	(0.016)
Age	−0.0145***
	(0.002)
Female	0.0658
	(0.045)
Income: 18,001–27,000 euros	0.0843
	(0.085)
Income: 27,001–36,000 euros	0.1132
	(0.084)
Income: 36,001–54,000 euros	0.2216***
	(0.082)
Income: 54,001–72,000 euros	0.1903**
	(0.092)
Income: 72,001 euros an over	0.1836*
	(0.105)
Secondary education	0.0156
	(0.078)
Tertiary education	0.2103***
	(0.059)
Out of labor force	−0.0211
	(0.058)
Self employed	0.0038
	(0.130)
Student	0.2445**
	(0.099)
Unemployed	0.0011
	(0.105)
Constant	−3.0069***
	(0.170)
Pseudo-R^2	0.121
Nb. of Observations	4079

† The dependent variable is equal to 1 for users of *Deezer* and equal to 0 for non-users during the weeks preceeding the cap imposition. The total number of clicks is calculated over the period prior to the cap imposition. Standard errors are in parenthesis. * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

[37] See Leuven and Sianesi (2003) for details on the implementation using Stata.

Table 3
Descriptive Statistics.†

	Deezer Users (N = 1201)				Control Group (N = 1201)			
	Before Cap		After Cap		Before Cap		After Cap	
	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
Deezer	1.469	3.460	0.494	1.371	0.000	0.000	0.000	0.000
Log(Deezer + 1)	0.302	0.452	0.128	0.257	0.000	0.000	0.000	0.000
Licensed Websites	0.511	2.812	0.331	1.531	0.169	1.058	0.092	0.518
Log(Licensed Websites + 1)	0.075	0.206	0.056	0.151	0.029	0.091	0.020	0.055
Unlicensed Websites	0.230	1.647	0.233	1.630	0.070	0.629	0.128	1.004
Log(Unlicensed Websites + 1)	0.036	0.179	0.036	0.175	0.014	0.099	0.019	0.112
Alternative Streaming Websites	0.805	4.763	1.083	5.653	0.394	5.442	0.431	6.020
Log(Alternative Streaming Websites + 1)	0.177	0.325	0.186	0.348	0.076	0.241	0.074	0.238

† The table presents statistics on the number of clicks (or log of clicks) to the corresponding type of website. Alternative streaming websites correspond to the websites listed in Fig. 1, excluding *Deezer*.

the assumption that usage of alternative channels for both users of *Deezer* and the control group would have followed similar trends had the listening cap not been introduced.[38] The data fortunately allow to partially test this identification assumption by looking at the trends in alternative channels of consumption in the period before the restriction was introduced.

4.2.1. Pre-trends comparisons

Estimating the following model is a possible way to test whether trends in the usage of alternative consumption websites are statistically different for users of *Deezer* and the control group before the cap imposition:

$$\ln\left(Clicks_{it}^{A}+1\right)=\alpha_0+\alpha_1^t Week_t+\alpha_2^t(Week_t*Deezer_i)+\eta_i+\varepsilon_{it}, \tag{3}$$

with $t=1,\ldots,22,$ and where, as above, the dependent variable measures the logarithm of the number of visits to the set of alternative music consumption websites A for individual i in week t, with $A \in$ {*Licensed Downloading, Unlicensed Downloading*}. $Week_t$ is a vector of week dummy variables, $Deezer_i$ is again an indicator variable equal to 1 if individual i visited *Deezer* before the free streaming cap was imposed, η_i is an individual fixed effect, and ε_{it} is an error term. The α_2^t coefficients therefore reflect the difference in the trends in visits to the corresponding set of alternative websites between users and non-users of *Deezer*, before the cap is imposed.

Eq. (3) is estimated using ordinary least squares (OLS) and clustering standard errors at the individual level since the error term ε_{it} is likely to be correlated over time for a given individual. The second column of Table 4 presents the resulting α_2^t coefficients from estimating Eq. (3) using the logarithm of visits to licensed downloading music websites as a dependent variable. The reference week is week 22, which is the last week before the cap was introduced. As indicated in the last two rows of the table, a test of joint significance rejects the null hypothesis that the trends are equal (F-test= 1.24; p-value= 0.204). This indicates that users of *Deezer* and individuals in the control group follow indistinguishable licensed downloading trends in the period preceding the introduction of the restriction, giving support to the identification strategy.

The last column of Table 4 presents the estimates of the α_2^t coefficients obtained from the estimation of (3), using now the logarithm of visits to unlicensed music downloading websites as a dependent variable. The p-value for the joint significance test is equal to 0.137, so the null hypothesis that the trends are equal can

[38] This assumption requires the absence of other shocks contemporaneous to the listening cap imposition that may have affected alternative consumption channels for *Deezer* users exclusively.

Table 4
Licensed and Unlicensed Websites Visits - Deezer Users vs Control Group.†

	(Licensed) Coef./s.e.	(Unlicensed) Coef./s.e.
Deezer × Week = 1	−0.002	−0.008
	(0.020)	(0.013)
Deezer × Week = 2	0.019	−0.023*
	(0.019)	(0.012)
Deezer × Week = 3	0.019	−0.019*
	(0.018)	(0.012)
Deezer × Week = 4	0.026	−0.022*
	(0.020)	(0.012)
Deezer × Week = 5	0.016	−0.018
	(0.019)	(0.012)
Deezer × Week = 6	0.006	−0.007
	(0.016)	(0.013)
Deezer × Week = 7	−0.013	−0.024**
	(0.019)	(0.011)
Deezer × Week = 8	0.009	0.002
	(0.020)	(0.013)
Deezer × Week = 9	0.020	−0.016
	(0.019)	(0.012)
Deezer × Week = 10	0.015	−0.003
	(0.021)	(0.013)
Deezer × Week = 11	0.028	0.005
	(0.019)	(0.011)
Deezer × Week = 12	0.030*	0.001
	(0.018)	(0.013)
Deezer × Week = 13	0.029	−0.002
	(0.019)	(0.013)
Deezer × Week = 14	0.022	0.002
	(0.018)	(0.013)
Deezer × Week = 15	−0.012	0.002
	(0.019)	(0.012)
Deezer × Week = 16	−0.015	−0.002
	(0.017)	(0.012)
Deezer × Week = 17	0.009	0.015
	(0.017)	(0.013)
Deezer × Week = 18	−0.003	0.001
	(0.017)	(0.012)
Deezer × Week = 19	0.010	0.010
	(0.017)	(0.011)
Deezer × Week = 20	0.017	0.006
	(0.017)	(0.010)
Deezer × Week=21	0.007	0.006
	(0.016)	(0.011)
R^2	0.223	0.345
No. of Individuals	2402	2402
No. of Observations	52,844	52,844
F-test: joint significance	1.24	1.34
P-value	0.204	0.137

† Standard errors are in parenthesis and clustered at the individual level. All specifications include individual fixed effects. The reference week is week 22, corresponding to the last week before the cap imposition. * Significant at the 10% level. ** Significant at the 5% level.

Table 5
Effect of Free Streaming on Visits to Licensed and Unlicensed Websites.†

	Licensed Websites				Unlicensed Websites			
	(1) Coef./s.e.	(2) Coef./s.e.	(3) Coef./s.e.	(4) Coef./s.e.	(5) Coef./s.e.	(6) Coef./s.e.	(7) Coef./s.e.	(8) Coef./s.e.
Deezer × Cap	−0.0099**	−0.0104**	−0.0179**	−0.0187***	−0.0052	−0.0058	−0.0166**	−0.0174**
	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)	(0.005)	(0.007)	(0.007)
Log(Alternative Music Streaming + 1)		0.0545***		0.0545***		0.0526***		0.0526***
		(0.006)		(0.006)		(0.006)		(0.006)
Linear Group Trend	✗	✗	✓	✓	✗	✗	✓	✓
R^2	0.161	0.166	0.161	0.166	0.278	0.285	0.278	0.285
Nb. of Individuals	2402	2402	2402	2402	2402	2402	2402	2402
Nb. of Observations	124,904	124,904	124,904	124,904	124,904	124,904	124,904	124,904

† Standard errors are in parenthesis and clustered at the individual level. All specifications include individual fixed effects and week fixed effects. * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

again be rejected. Note that the overall pattern of the coefficients is nevertheless less clear. In particular, it seems that, relative to the control group, visits to music piracy websites were trending upwards for *Deezer* users. If not accounted for, these differences in music piracy trends may bias the estimation results. Note, in particular, that they will bias the estimates positively, and therefore go against finding a negative impact of the restriction on piracy. I will therefore relax the identification assumption in the analysis below and account for *Deezer* user specific trends in some specifications, asking whether users of *Deezer* deviate from their pre-restriction trend more so than non users of *Deezer*.

5. Results

I now turn to the main question motivating the paper, asking how free and mobile-restricted streaming affects digital music purchasing and piracy behavior. I start by presenting the main estimates from the difference-in-differences model. After performing some robustness checks to test the validity of the results, I explore the heterogeneity in these effects and turn to some back of the envelope calculations.

5.1. The effect of the cap on purchasing and piracy behavior

Columns (1)–(4) in Table 5 present the results of estimating (1) using the logarithm of visits to licensed downloading websites as a dependent variable. The first specification in the table shows that imposing a free streaming cap leads to a statistically significant 1% decrease in visits to licensed music downloading webpages. Because users of *Deezer* may decide to switch to alternative music streaming services after the listening cap was imposed, specification (2) includes the logarithm of visits to alternative streaming websites as a control variable. The websites included in this category are the ones listed in Fig. 1, excluding *Deezer*. The results remain unchanged by the introduction of this control variable. Specifications (3) and (4) replicate the exercise by adding *Deezer* user specific time trends. This results in slightly larger coefficient in absolute value, with decreases in visits to licensed downloading websites of about 1.8%. These figures indicate that free and mobile-restricted music streaming has a positive effect on digital music purchasing behavior.

Columns (5)–(8) turn to the effects of online free streaming on digital music piracy behavior. It therefore presents the results of estimating (1) using the logarithm of visits to unlicensed music downloading websites as a dependent variable. Specifications (5) and (6) - which exclude *Deezer* user specific time trends - show a negative but non statistically significant effect of the cap imposition on visits to music piracy websites. As discussed in the previous subsection, and as the last column of Table 4 showed, visits to piracy websites were trending upwards for users of *Deezer* compared to the control group before the listening cap was imposed. This could bias the estimates against finding a negative impact of the restriction on piracy. I relax the assumption that piracy trends are independent of the *Deezer* usage status by including linear *Deezer* user specific trends in specifications (7) and (8). I therefore ask whether users of *Deezer* deviate from their pre-restriction trend more so than non users of *Deezer*. As expected, the results present coefficients that are larger in magnitude. In particular, I find that the imposition of the free streaming cap leads to a statistically significant 1.7% decrease in visits to unlicensed music downloading webpages.

5.2. Constrained vs unconstrained Deezer users

The above results show that the cap on free streaming imposed by *Deezer* had a negative and significant impact on both music purchasing and piracy behavior. In fact, the only individuals affected by the restriction are the ones that were freely streaming more than 5 hours a month prior to June 6, 2011. Free users who were using the service for less than 5 hours a month should not have been affected. As illustrated in Fig. 4, the subset of 172 users who increased their usage in a moderate fashion were not directly affected by the restriction. Indeed, these individuals display relatively little change in their usage of the platform. Moreover, their level of usage was lower before the cap - relative to individuals who decreased their usage - and similar after the imposition of the restriction. This suggests that this group of individuals were free users whose consumption levels were not directly affected by the cap. If the results from Table 5 are effectively driven by the listening cap imposed by *Deezer*, then no effect of the restriction on this last group of users should be observed.

To test this implication, I modify specification (1) above and estimate the following equation to allow for different effects on these two distinct groups of individuals:

$$\ln(Clicks_{it}^{A}+1) = \alpha + \beta_U\left(Deezer_i^U \times Cap_t\right) + \beta_C\left(Deezer_i^C \times Cap_t\right) + \gamma X_{it} + \mu_i + \nu_t + \varepsilon_{it}, \quad (4)$$

where $Deezer_i^C$ is an indicator variable equal to 1 if individual i was directly constrained by the cap imposition. The set of constrained individuals therefore corresponds to the group of users who decreased their *Deezer* usage following the restriction (see Fig. 4). Similarly, $Deezer_i^U$ is equal to 1 if individual i is part of the group of users who were unconstrained by the cap imposition. Eq. (4) is again estimated using OLS and clustering standard errors at the individual level.

Columns (1)–(4) of Table 6 present the results of estimating (4) using the logarithm of visits to licensed downloading websites as a dependent variable. Columns (1) and (2) confirm that the effect of the listening cap only affects individuals who were directly constrained by the restriction, with a statistically significant 1.3% decrease in visits to licensed downloading websites. Columns (3)

Table 6
Effect of Free Streaming on Visits to Licensed and Unlicensed Websites - Constrained vs Unconstrained Users.†

	Licensed Websites				Unlicensed Websites			
	(1) Coef./s.e.	(2) Coef./s.e.	(3) Coef./s.e.	(4) Coef./s.e.	(5) Coef./s.e.	(6) Coef./s.e.	(7) Coef./s.e.	(8) Coef./s.e.
Constrained *Deezer* × Cap	−0.0129**	−0.0131**	−0.0211***	−0.0215***	−0.0089*	−0.0091*	−0.0186**	−0.0190**
	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)	(0.005)	(0.008)	(0.007)
Unconstrained *Deezer* × Cap	0.0089	0.0060	0.0015	−0.0013	0.0172*	0.0144	−0.0048	−0.0075
	(0.013)	(0.013)	(0.024)	(0.024)	(0.009)	(0.009)	(0.012)	(0.012)
Log(Alternative Music Streaming + 1)		0.0545***		0.0545***		0.0525***		0.0525***
		(0.006)		(0.006)		(0.006)		(0.006)
Linear Group Trend	✗	✗	✓	✓	✗	✗	✓	✓
R^2	0.161	0.166	0.161	0.166	0.278	0.285	0.278	0.285
Nb. of Individuals	2402	2402	2402	2402	2402	2402	2402	2402
Nb. of Observations	124,904	124,904	124,904	124,904	124,904	124,904	124,904	124,904

† Standard errors are in parenthesis and clustered at the individual level. All specifications include individual fixed effects and week fixed effects. * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

and (4) add group specific linear time trends (i.e. trends for constrained and unconstrained individuals). The effect of the cap remains insignificant for the unconstrained users and display a significant 2.1% decrease for the constrained users.

Columns (5)–(8) turn to the estimation of Eq. (4) using the logarithm of visits to unlicensed music downloading websites as a dependent variable. Columns (5) and (6) show a negative and marginally significant effect of the listening cap on constrained users. The effect is positive but only significant in one case for the unconstrained users. Specifications (7) and (8) include group specific linear time trends to relax the common trend assumption. The results show that the decrease in visits previously observed in the corresponding columns of Table 5 is indeed only driven by individuals who were directly affected by the restriction. In particular, the results show that the cap imposition led to a 1.9% decrease in visits to music piracy websites for individuals who were constrained by the restriction.

5.3. Robustness checks

Before further exploring the effects of the cap imposition, some robustness checks are warranted. First, one may worry that the estimations results presented above could be driven by *Deezer* users decreasing their overall online activity following the cap imposition. If these individuals decided to stay away from their computer after the cap, for instance substituting offline for online activities, it could translate into a decrease in visits to licensed and unlicensed downloading websites. To rule out this possibility, I estimate the effect of the cap imposition within the same difference-in-differences setting using the total online activity as a dependent variable. Performing these estimations results in statistically insignificant effects.[39] Estimating Eq. (4) using the same alternative dependent variable also results in statistically insignificant effects for constrained *Deezer* users. These results allow to rule out the possibility that the effects of the cap are driven by an overall decrease in online activity.

A second potential concern relates to the fact that many individual-week observation show no visits to licensed or unlicensed downloading websites. For instance, out of the 1201 *Deezer* users included in the final sample, 484 users never visited any websites included in the licensed downloading category during the sample period. The corresponding number of individuals who never visited any websites included in the unlicensed downloading category is equal to 850. To assess whether these inactive users could potentially bias the estimation results, I re-estimate Eqs. (1) and (4) excluding them from the current sample. The coefficients corresponding to specifications (4) and (8) in Table 5 are equal to −0.0292 (*s.e.* = 0.0132) and −0.0847 (*s.e.* = 0.0351). The coefficients for the constrained *Deezer* users corresponding to specifications (4) and (8) in Table 6 are equal to −0.035 (*s.e.* = 0.0132) and −0.0904 (*s.e.* = 0.0367). It is perhaps not surprising that excluding inactive users leads to larger estimates in magnitude. I conclude that the results are robust to the exclusion of inactive users.[40]

5.4. Heterogeneous effects of the cap

The set of *Deezer* users that were constrained by the cap were naturally not all equally affected by the restriction. Individuals who were heavier users of *Deezer* before the cap naturally experienced a stronger decline in their streaming usage. One may therefore expect a stronger effect from the cap imposition on individuals that were using *Deezer* more intensively. To test this hypothesis, I split the set of constrained *Deezer* users into three equal-sized groups corresponding to low, medium, and high pre-cap *Deezer* usage. I then expand Eq. (4) by interacting the $Deezer_i^C$ dummy with an indicator variable for each distinct group.[41] The equation to be estimated is therefore given by:

$$\begin{aligned}\ln\left(Clicks_{it}^A + 1\right) = \alpha &+ \beta_U\left(Deezer_i^U \times Cap_t\right)\\ &+ \beta_C^{Low}\left(Deezer_i^C \times Low_i \times Cap_t\right)\\ &+ \beta_C^{Medium}\left(Deezer_i^C \times Medium_i \times Cap_t\right)\\ &+ \beta_C^{High}\left(Deezer_i^C \times High_i \times Cap_t\right)\\ &+ \gamma X_{it} + \mu_i + \nu_t + \varepsilon_{it}, \qquad (5)\end{aligned}$$

[39] I have considered visits to all websites as well as visits to all but music websites (i.e. excluding visits to licensed and unlicensed downloading as well as streaming websites) as a dependent variable separately. The estimations presented statistically insignificant results in both cases.

[40] Notice that for each type of downloading website (licensed or unlicensed), the corresponding set of inactive individuals naturally includes users and non-users of *Deezer*, which means that excluding these individuals results in uneven treated and control groups. To deal with this potential issue, I have also constructed an alternative control group via propensity score matching focusing only on active users. In the case of visits to unlicensed downloading websites, the set of active non-users of *Deezer* is unfortunately smaller than the set of active *Deezer* users, and I therefore use the full set of active non-users of *Deezer* as controls. Estimating Eqs. (1) and (4) on these alternative samples again leads to negative and significant effects which are in magnitude larger than the ones presented in Tables 5 and 6. Estimating a negative binomial model on these same samples also results in negative estimates that are larger in magnitude.

[41] For each individual in the sample, the intensity of *Deezer* usage is measured as the cumulative number of visits made to *Deezer* before the restriction was imposed. High intensity users are then defined as individuals whose pre-cap intensity usage falls above the 66th percentile of the usage intensity distribution. Medium intensity users are defined as individuals whose pre-cap intensity usage falls in the 66th and above the 33rd percentile of usage intensity distribution. Low intensity users are defined as individuals whose pre-cap intensity usage is in the 33rd percentile of usage intensity.

Table 7
Effect of Free Streaming on Visits to Licensed and Unlicensed Websites - by Intensity of *Deezer* Usage.†

	Licensed Websites				Unlicensed Websites			
	(1) Coef./s.e.	(2) Coef./s.e.	(3) Coef./s.e.	(4) Coef./s.e.	(5) Coef./s.e.	(6) Coef./s.e.	(7) Coef./s.e.	(8) Coef./s.e.
Unconstrained *Deezer* × Cap	0.0089	0.0060	0.0015	−0.0013	0.0172*	0.0144	−0.0048	−0.0075
	(0.013)	(0.013)	(0.024)	(0.024)	(0.009)	(0.009)	(0.012)	(0.012)
Constrained *Deezer* × Low × Cap	0.0004	0.0018	−0.0112	−0.0106	0.0001	0.0015	−0.0040	−0.0034
	(0.005)	(0.005)	(0.009)	(0.009)	(0.005)	(0.005)	(0.011)	(0.011)
Constrained *Deezer* × Medium × Cap	−0.0147**	−0.0158**	−0.0188*	−0.0188*	−0.0159**	−0.0169**	−0.0234***	−0.0234***
	(0.008)	(0.007)	(0.011)	(0.011)	(0.007)	(0.007)	(0.008)	(0.008)
Constrained *Deezer* × High × Cap	−0.0256**	−0.0267**	−0.0340**	−0.0360**	−0.0119	−0.0130	−0.0297**	−0.0317**
	(0.012)	(0.012)	(0.014)	(0.014)	(0.011)	(0.011)	(0.014)	(0.014)
Log(Alternative Music Streaming + 1)		0.0546***		0.0546***		0.0526***		0.0526***
		(0.006)		(0.006)		(0.006)		(0.006)
Linear Group Trend	✗	✗	✓	✓	✗	✗	✓	✓
R^2	0.161	0.166	0.161	0.166	0.278	0.285	0.278	0.285
Nb. of Individuals	2402	2402	2402	2402	2402	2402	2402	2402
Nb. of Observations	124,904	124,904	124,904	124,904	124,904	124,904	124,904	124,904

† Low, Medium, and High refer to the corresponding groups of pre-cap *Deezer* usage as described in the text. Standard errors are in parenthesis and clustered at the individual level. All specifications include individual fixed effects and week fixed effects. * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

where Low_i, $Medium_i$, and $High_i$ are indicator variables equal to 1 if individual i's level of *Deezer* usage falls into the low, medium, or high category, respectively.

Columns (1)–(4) of Table 7 present the results of estimating (5) using the logarithm of visits to licensed downloading websites as a dependent variable. The estimates show that the effect of the cap is indeed larger for individuals who were using *Deezer* more intensively before the restriction was imposed. Higher intensity users significantly decreased their visits to licensed downloading websites by 3.5% following the cap, while medium intensity users did so by about 1.9%. The corresponding estimate is not statistically significant for the low intensity users. Columns (5)–(8) present the results of the same estimations using the logarithm of visits to unlicensed music downloading websites as a dependent variable. The results are similar, with a decrease in visits of 3.1% for higher intensity users, and 2.3% for medium intensity users. The corresponding estimate is again not statistically significant for low intensity users.[42]

5.5. Back of the envelope calculations

While free online music streaming services provide access to vast amounts of new musical products, they still lack an important feature of digital music consumption: mobility. If free streaming services allow sampling and the discovery of new products, and if consumers value mobility in their music consumption, then one could expect a positive effect of these services on alternative music channels that allow for mobile consumption. The evidence presented above is consistent with this mechanism, as the estimation results show a negative effect of *Deezer*'s free streaming cap on visits to both licensed and unlicensed music downloading websites.

While these findings indicate a stimulating effect of free music streaming on music purchases and piracy, measuring the size of this effect is difficult given the nature of the data. Because actual sales, unlicensed downloads, and streams are not observed in the data, it is particularly hard to estimate, say, the number of *Deezer* streams that it would take to stimulate an extra sale. Despite these limitations, I can construct a more direct measure of the effect of free streaming on purchasing and piracy behavior. In particular, the estimation results allow to calculate the streaming elasticity of visits to licensed and unlicensed websites.

5.5.1. Streaming elasticity of visits to licensed and unlicensed websites

The estimation results from Table 6 allow to measure the percentage change in visits to licensed and unlicensed downloading websites following a 1% increase in visits to *Deezer*. In line with the heterogeneous effect of the cap estimated in Table 7, differences in this elasticity are likely to exist for different types of individuals. In particular, if the mechanism through which streaming stimulates sales and piracy is one of product discovery, one should perhaps expect these consumption channels to be more sensitive to streaming for lighter streamers. While these individuals would, by definition, consume less music through streaming overall, they are also likely to be aware of a more limited set of products to start with and therefore more likely to discover new products.

Computing the streaming elasticity of visits to licensed and unlicensed downloading websites requires measuring the percentage change in *Deezer* streaming following the cap imposition. The set of *Deezer* users that was effectively constrained by the cap imposition decreased its amount of *Deezer* streaming by 18.8 percent overall. Within this set of individuals, low, medium, and high intensity users decreased their amount of streaming by 4, 10.6, and 37.14% , respectively.[43] Given these figures, the visit elasticity for each corresponding subset of individuals can be calculated as the ratio between the corresponding coefficients from Tables 6 and 7 and the percentage decline in *Deezer* streaming.

When considering all constrained *Deezer* users indistinctively, the results show an overall streaming elasticity of visits to licensed downloading websites of 0.11.[44] The corresponding elasticity for unlicensed downloading websites is equal to 0.10. When looking at elasticities by type of users, the results indicate higher elasticities for medium intensity users than for high intensity users. For high intensity users, a 1% increase in *Deezer* streaming leads to a 0.10%

[42] Similar robustness checks as the ones performed in Section 5.3 show that the heterogeneity results hold when excluding inactive users from the sample. Likewise, estimating (5) using total online activity as a dependent variable shows no statistically significant effect for any on the three categories of *Deezer* users.

[43] Using the sample of 1033 *Deezer* users who were directly constrained by the restriction, I obtain this measure by regressing the log(clicks to Deezer +1) on a dummy variable equal to 1 during the weeks following the cap imposition. I perform a similar exercise to obtain a direct measure of the decline in *Deezer* usage for the different groups of low, medium, and high users.

[44] Recall from Table 6 that constrained users of *Deezer* decreased their visits to licensed downloading websites by 2.1% following the cap imposition. Given that the restriction led them to decrease their *Deezer* usage by 18.8%, the elasticity of visits to licensed downloading websites is calculated as $\frac{-2.1}{-18.8} = 0.11$.

and 0.08% increase in visits to licensed and unlicensed downloading websites, respectively. For medium intensity users, the corresponding elasticities are equal to 0.18 and 0.22. At 0.26, the estimated elasticity of visits to licensed downloading websites is even larger for low intensity *Deezer* users. The corresponding elasticity for visits to unlicensed downloading websites is 0.08. These last two elasticities should nevertheless be interpreted with more caution given that the coefficients from Table 7 presented non-significant effects of the cap for the low intensity *Deezer* users. Overall, the results suggest that free and mobile-restricted streaming stimulates purchasing and piracy behavior to a larger extent for lower intensity streamers.

6. Conclusion

The popularity and usage of music streaming services has dramatically increased in recent years, generating heated debates around their contribution to the transformation of the recorded music industry. Recognizing the importance of this issue, the empirical evidence on the effects of music streaming has now been growing. However, current debates seem to overlook the fact that the effects of music streaming platforms may differ according to their functionality. While interactive services offering full mobility in consumption leave users with little incentives to purchase or unlawfully download music, the effects of services that restrict mobility may affect music sales and piracy differently. Understanding how these distinct services may affect alternative channels of music consumption is crucial to understand the overall impact of streaming on the music industry.

This paper focuses on the French leading streaming platform *Deezer* and exploits the introduction of a listening cap to identify the effect of free and mobile-restricted streaming on music purchasing and piracy behavior. The findings present a negative effect of the free streaming cap on visits to both licensed and unlicensed music downloading websites. In particular, the results show that following the imposition of the streaming cap, *Deezer* users who were constrained by the restriction visited licensed and unlicensed downloading websites around 2% less than they would have had the restriction not been introduced. Taken at face value, these results therefore indicate a positive effect of free streaming on these alternative channels of music consumption. Additionally, the results indicate important heterogeneity in these effects according to the pre-cap levels of *Deezer* usage, with heavier users decreasing their visits to downloading websites to a larger extent.

Back of the envelope calculations allow to compute the streaming elasticity of visits to alternative music consumption websites and suggest that heavier *Deezer* users present much lower elasticities than lighter users. In other words, the purchasing and piracy behavior of lighter *Deezer* users appear to be stimulated by streaming to a larger extent. These results are consistent with a mechanism through which streaming services allow for the discovery of new products and stimulate alternative music channels that allow mobile consumption.

This study contributes to the important debate around the effects of music streaming and to the empirical literature on the effects of digitization in the recorded music industry. It has several implications. First, the results show that music streaming services can serve as a channel of music discovery. Second, the results show that free streaming services - because they do not offer users full mobility in their music consumption - can lead to a stimulation in alternative music consumption channels that offer mobility, such as licensed and unlicensed downloading. While the results are consistent with this mechanism, I highlight that they should not be extrapolated to streaming services that offer alternative functionalities. In particular, the results do not imply a positive effect of premium subscription services - which offer full mobility in consumption - on digital sales or piracy. From that perspective, this study serves as a first step toward understanding the heterogeneity of effects that distinct streaming platforms - interactive, non-interactive, free, premium - may have on the recorded music industry.

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