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Alternative payment models in the music streaming market: A comparative approach based on stream-level data

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ABSTRACT

Music streaming platforms' models for sharing revenues with content providers have been the subject of intense debate for nearly a decade. The dominating model involves pooling platform revenues and allocating these funds to songs based on a song's share of the total number of platform streams. Since this model has several controversial consequences, alternative models have been proposed. This paper uses a novel approach to assess the two most discussed models – the "user-centric" and the "artist-centric". Our approach relies on a unique data set of 154,505 streaming platform users (890 million streams) and simulates how a large-scale implementation of these models may reallocate revenues across different songs and rightsholders. We disentangle the static effects of a transition to a "user-centric" or an "artist-centric" model across each of six different song characteristics. We then compare the results of the two models. We show that contrary to its objective, an artist-centric payment system does not significantly improve remuneration to professional artists while the user-centric payment system would generate more significant changes in revenue reallocation, mainly at the expense of Rap & Hip-hop songs, superstars and new releases. Finally, we analyze the positions of the various stakeholders with regard to each of them.

1. Introduction

For over twenty years, digitization has profoundly changed the music industry, and music streaming platforms have become the dominant mode for recorded music distribution and listening. One of the understudied aspects of the music streaming economy is how platform revenues are shared among rightsholders (UNESCO, 2023). In the pre-streaming era, consumers purchased a song or an album, and the rightsholders to these songs received a share of the sales revenues. This is entirely different in the music streaming economy. The revenue-sharing model dominating the streaming economy since its infancy is known as the *pro-rata* payment model. The model dictates that each user's monthly subscription fee should *not* be distributed among the rightsholders whose music they have listened to. Instead, subscription fees from all users are pooled, and each rightsholder receives a payment proportional to their share of the total number of streams. While the model has an appealingly simple structure, it also has some problematic consequences. One such consequence is that intensive music listeners – those who listen to more music than the average user – have a disproportionate influence over the distribution of revenues compared to users who use the service less, even though all users pay the same monthly subscription fee (e.g., Page and Safir, 2019).

Different payment models have been proposed as solutions to these problems, especially the *user-centric* payment system (UCPS)[1] and the artist-centric payment system (ACPS). The UCPS model[2] returns to the pre-streaming revenue-sharing principles and prescribes that a user's monthly subscription fee is only distributed to the songs a user has listened to. In March 2021, SoundCloud, a music streaming service, became the first platform to implement such a payment model (Ingham, 2021). SoundCloud states, as an example of the consequences of the new

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[1] Many music streaming platforms offer both a free (ad-based) and a premium (subscription based) service. The user-centric payment model is only considered for the premium subscription service.

[2] The literature uses both *system* and *model* to refer to these phenomena. In this paper we are using *model*, even though we also use the established acronym for the user-centric payment model, which is UCPS.

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model, that the British band Portishead's release of their ABBA "SOS" cover earned 500 percent higher revenue under their new model. A few months later, the US streaming platform Tidal announced that it also intended to implement a user-centric payment model. Even the major music labels raise concerns about the pro-rata payment model and call for a new approach. In 2023, Lucian Grange, Chairman and CEO of Universal Music Group, stated that "*there is a growing disconnect between, on the one hand, the devotion to those artists who fans value and seek to support and, on the other, the way subscription fees are paid by the platforms. Under the current model, the critical contributions of too many artists, as well as the engagement of too many fans, are undervalued.*[3]" Yet, according to PRS[4] Council member Crispin Hunt,[5] "*No definitive modeling has shown the true outcome of user-centric [sic], but clearly it'll redistribute revenue according to fans. [...] However, the significant factor is user-centric's [sic] secondary effects [on musicians and on record companies] which no model has considered.*"

The uncertainties surrounding the consequences of the user-centric payment model have led to propositions of a range of other payment models. According to some major stakeholders, while the pro-rata model is flawed, the user-centric payment model "*isn't the answer either as it creates a different set of imbalances*[6]". Hence, the largest music streaming platform, Spotify, announced in late 2023 that they are moving away from the status quo payment model and will implement changes that reallocate revenues away from "functional noise recordings," fraudulent and "artificially inflated streams," and songs with <1000 streams per year.[7] The intention behind Spotify's initiative is quite different from the user-centric payment model as it focuses on incentivizing "professional artists," addressing fraud, and reducing the platform's operational costs.

Only a few months before Spotify's announcement, in September 2023, the music streaming platform Deezer and the world's largest music company, Universal Music Group, announced that they are exploring another model, referred to as an "artist-centric" model. This model also reallocates revenues to "professional artists," defined as those artists with a minimum of 1000 streams per month by a minimum of 500 unique listeners. The model includes features such as double payment to streams by songs recorded by professional artists *and* to all streams not initiated as part of an algorithmic recommendation sequence (with the aim to reduce the remuneration to songs not actively chosen by the users).[8] The model also involves a "streaming cap" for individual users so that the weight allocated to specific streams will be gradually reduced for users who stream >1000 streams per month. The intention of the artist-centric model to favor professional artists is in line with Alaei et al. (2022), who stress that superstar artists on streaming music platforms are necessary for lesser-known artists to get exposure to large audiences on mainstream music streaming platforms. However, some stakeholders claim that such a "reverse Robin Hood" mechanism would be unfair (Mulligan, 2023; Dredge, 2023). Since Spotify's model is still imprecisely defined, which makes it challenging to simulate, we will only focus on evaluating the more clearly defined artist-centric payment model.

This paper thus aims at simulating and comparing the consequences of implementing a user-centric payment model and an artist-centric payment model in a subscription-based music streaming service. We follow a three-step approach. The two first steps focus on UCPS and the third compare both models. First, we examine the relative importance of two user characteristics (listening intensity and listening concentration) that the theoretical literature identified as significant revenue reallocation determinants under UCPS (Page and Safir, 2019; Alaei et al., 2022). In the second step of our analysis, we examine how listening intensity and listening concentration differ by song characteristics. This allows us to understand why the revenue payouts change and, thus, which songs benefit more or less from implementing a user-centric payment model. Finally, in a third step, we disentangle the effect of each of the various song characteristics on revenue reallocation and calculate, for each characteristic, the average percentage of increase or decrease in revenue that the implementation of a user-centric payment model would generate.[9] We then replicate the approach for the artist-centric payment model and compare their consequences. In our discussion, we address the potential for different music industry stakeholders to accept a change to these alternative models. Finally, we compare the user-centric and the artist-centric payment models to evaluate how they achieve their stated purpose.

To conduct this analysis, we rely on data from Deezer, France's leading music streaming platform, containing the listening history of 154,505 anonymized subscribers of the premium version of the Deezer service model during 2020. The dataset represents 890 million individual streams listened to by these users. It includes details of which user listened to what song and at what time and a range of metadata, further contextualizing each stream. This stream-level dataset enables us to calculate the payments allocated by different payment models to individual streams and aggregate these payments to the song level. Our key findings are the following. We first focus on user characteristics and show that the reallocation of revenues following the implementation of a user-centric payment model is primarily driven by individual users' *listening intensity* and, secondly, by the users' *listening concentration*. Then, we connect these user characteristics to song characteristics and show that users' listening intensity varies significantly across song characteristics, such as music genres and artist popularity. It is thereby reasonable to assume that an implementation of a user-centric payment model will have very different consequences for songs in different categories of these two characteristics: music genres and artist popularity. We confirm this assumption in the third step of our analysis. We analyze the change in revenues for all song characteristics and show, among other things, that a user-centric payment model would decrease the share of the revenues allocated to the most popular artists (−6 percent) and to Hip-hop & Rap music (−13 percent) while increasing the revenues for Pop and Rock songs (+10 and +7 percent respectively). An artist-centric payment model would generate considerably smaller changes. The corresponding changes for this model would be +0.2 (popular artists), −4 (Hip-hop & Rap genre), +3 (Pop genre) and +4 (Rock genre) percent. Likewise, the revenue allocated to a recently released song will decrease by 3 percent with a user-centric payment system, and a song that is more than ten years old will experience a 5.1 percent gain. The corresponding values for the artist-centric payment model is −0.6 and +1.4 percent.

Our main contribution is as follows. First, we empirically test the

[3] https://variety.com/2023/music/news/universal-music-lucian-grainge-slams-streaming-economy-spotify-1235486063/

[4] PRS for Music Limited is a British music copyright collective which undertakes collective rights management for musical works on behalf of its 140,000 members.

[5] Crispin Hunt (@crispinhunt) / X

[6] https://variety.com/2023/music/news/universal-music-lucian-grainge-slams-streaming-economy-spotify-1235486063/

[7] https://pitchfork.com/news/spotify-officially-announces-new-policy-for-royalty-payouts-artificial-streams-and-functional-noise

[8] https://newsroom-deezer.com/2023/09/universal-music-group-and-deezer-to-launch-the-first-comprehensive-artist-centric-music-streaming-model/

[9] Note that this is a comparative *static* analysis, which means we do not consider potential dynamic effects that may emerge when various stakeholders react to a new payment model. Our analysis is based on real-world data, and since no major music streaming service has yet implemented a user-centric payment model, real-world data that allows such analysis does not yet exist. However, our static approach remains highly relevant since it enables the detailed prediction of which content types will benefit from a user-centric payment model. Our findings contribute to the literature, and they provide crucial insights for industry decision-makers as they plan for a music streaming economy that follows a new logic for royalty distribution.

relative importance of the two user characteristics identified by the theoretical literature as critical drivers for revenue reallocation caused by the implementation of a user-centric payment model (Page and Safir, 2019; Alaei et al., 2022). Secondly, we also contribute to the literature by extending the analysis of which song characteristics significantly determine the impact of a user-centric payment model (e.g., Meyn et al., 2023). Finally, from a managerial perspective, we discuss the potential for a new payment model to be accepted by the industry and contrast the user-centric payment model with the artist-centric model. We thereby contribute to the debate on the necessary evolution of music streaming payment models by reducing some of the current uncertainty in the industry debate.

The paper is organized as follows. The next section provides the background and introduces the research questions we set out to address. Section 3 presents the dataset, and Section 4 presents our empirical strategy and results. Lastly, in Section 5, we discuss our results, conclude, and identify opportunities for future research.

2. Background and research questions

2.1. The distribution of revenues from music streaming platforms to rightsholders is a contested issue

The rise of music streaming as the dominant music distribution mechanism has profoundly transformed music consumption and has led to significant net increases in industry revenues (e.g., Wlömert and Papies, 2016; IFPI, 2023). Despite these increases, streaming platforms have received strong criticism, mainly from artists unhappy with their compensation levels. In large music markets, such as France and the UK, governments have responded to this pressure and initiated investigations of what is framed as a lack of fairness and transparency in the streaming music economy (e.g., Digital, Culture, Media and Sport Committee, 2021).

A question that somewhat surprisingly receives limited attention by these initiatives is how the audiences' music listening practices are translated into rightsholder revenues. Most music streaming platforms use the pro-rata model to govern this translation (introduced in the previous section). As discussed above, this model has some problematic consequences, most glaringly the fact that the sharing of revenues becomes inherently biased towards the artists whose fans, on average, are more avid listeners, at the expense of artists whose fans have more casual listening practices.[10] The user-centric payment model, which is the focus of this analysis, aims to address the problems with the pro-rata payment model. User-centric payment models are not a new phenomenon in the music economy and have been debated for many years by academia (e.g., Maasø, 2014; Dimont, 2018) and the industry (e.g., Ingham, 2021). The model resembles the pre-streaming principle for revenue sharing, as the users' monthly fee is only shared by the artists they listen to. The user's payment is distributed proportionally to these artists based on the artists' share of the user's total number of streams during the month.[11] While the debates about alternative payment models have been ongoing for many years, it was not until 2021 that the music streaming platforms SoundCloud and, later, Tidal implemented a version of a user-centric payment model. Later, in 2023, there were announcements from larger platforms, such as Deezer, followed by Spotify, that changes to their payment models were afoot, with the emergence of the artist-centric payment system. Even though several changes are in the works that will potentially impact how billions of dollars from streaming platforms are distributed to rightsholders, there are very few empirical studies of the consequences of these alternative models on the music economy. We will discuss the small number of extant studies in the next section.

2.2. Related literature

We identify two streams of literature examining the impact of alternative payment models on music industry stakeholders, one theoretical and one empirical. Both streams are relevant to our paper, and we also contribute to both.

Theoretical contributions have been made by scholars such as Dimont (2018), Page and Safir (2019), Alaei et al. (2022) and Lei (2023). Dimont (2018) was among the first scholars to point out that the pro-rata model leads to cross-subsidization between low and high streaming users, streaming fraud, and inequity in compensation for artists. Page and Safir (2019), on the other hand, analyzed which artists would benefit from the implementation of a user-centric model based on the characteristics of the individual artists' audiences. Page and Safir highlighted two audience behavior dimensions, which are crucial in driving revenue reallocation following a change from a pro-rata to a user-centric payment model: listening intensity and listening concentration. The authors concluded that an artist whose audience is constituted of users with both a low listening intensity and a high listening concentration would benefit the most from a user-centric payment model. Following in the footsteps of Page and Safir (2019), Alaei et al. (2022) also used a theoretical approach to arrive at a similar conclusion. However, they also argue that users are likely to start using a platform primarily to listen to music by superstars. This benefits less popular artists on the platform who can get discovered by the superstars' fans. The authors find that a benefit of the pro-rata payment model is that the superstars are remunerated for this positive externality they generate.[12]

A key conclusion from these theoretical inquiries is that it is crucial to examine the role of users' behavior when assessing and determining the optimal revenue-sharing allocation strategy (Page and Safir, 2019; Alaei et al., 2022). We build on their conclusion and contribute to this literature by being the first empirical study to provide a detailed analysis of how users' listening behavior impacts the reallocation of revenues at the song level after implementing a user-centric payment model.

The first empirical study on this topic was published by Maasø (2014). Maasø's study did break new ground, but it used a very limited sample and followed a descriptive approach, making it difficult to conclude the impact across user behaviors or song characteristics. Deloitte (2021) published the results of another descriptive study using a dataset from the same streaming platform we used in this study but with the same limitations as Maasø (2014). The last paper in this second stream of literature, Meyn et al. (2023), presents an empirical study with an ambition closely aligned with our research. Like our paper, Meyn et al. try to assess the financial consequences of a user-centric payment model. However, lacking the access that we have to platform users' data, their paper relies on a survey on music preferences of German streaming users and examines revenue reallocation with music genre as the unit of analysis. Their analysis concludes that a user-centric payment model has significant financial consequences for rightsholders and that the model

[10] Imagine a music streaming market with two users (A and B) and two artists (1 and 2). Both users pay the same monthly subscription, but A listens ten times a month to a song of artist 1, and B listens 90 times a month to a song of artist 2. Despite that A and B have devoted the same amount of money to their favorite artist, with the pro-rata model 10 percent of the revenues will be disbursed to artist 1 and 90 percent to artist 2.

[11] In the previous example, under a User-Centric payment system artists 1 and 2 would receive the same revenue since user A only listens to artist 1 and user B only listens to artist 2.

[12] In a third theoretical paper, Lei (2023) concludes that the system level benefits more from the pro-rata payment model than the user-centric payment model as pro-rata stimulates the artists to increase the quality of the songs they release. However, Lei's reasoning is based on two assumptions that are inconsistent with empirical evidence – that artists can predict the market performance of their songs and that all users have a uniform listening intensity – which limits the relevance of the conclusions proposed by the paper.

reallocates revenues from mainstream genres (e.g., Rap, Hip-hop, Pop) to niche genres (Classical, Jazz, Metal). We extend this work by relying on a different kind of empirical data and by explicitly examining the impact of a range of song characteristics on the reallocation of revenues after implementing a user-centric payment model.

Following this overview of literature relevant to our paper, we are ready to define our research questions.

2.3. Research questions

The fundamental gaps in the literature we are addressing in this paper concern which songs benefit financially (or not) from implementing a user-centric payment model or an artist-centric payment model. The answer to this question underpins a range of other issues raised by the implementation of an alternative payment model, such as whether such a reform is acceptable to the various industry stakeholders or how stakeholders should strategically respond to the impact of the change. Our approach to addressing this question is structured into three phases (already discussed in previous sections) and corresponding sub-questions.

As discussed in the section above, Page and Safir (2019) and Alaei et al. (2022) have theoretically found that users' listening intensity and concentration are significant drivers of revenue reallocation after implementing a user-centric payment model. However, the theoretical literature does not tell us about the relative importance of these two dimensions in explaining revenue reallocation. Hence, our first research question is:

RQ1. What is the relative importance of users' listening intensity and concentration in determining the revenue reallocation caused by implementing a user-centric payment model?

To explain why some songs, and thus some artists, benefit more or less from a user-centric payment model, we must understand if the users who listen to specific types of songs also have some specificities regarding their listening intensity and concentration. To deal with this issue, we rely on song characteristics commonly considered in academic analyses of structural changes in the music industry: *artist popularity* (Hamlen, 1991; Chung and Cox, 1994; Rosen, 1981; Adler, 1985), *type of music label* ("major" vs. "independent") that released the song (Bourreau et al., 2017; Aguiar and Waldfogel, 2016; Handke, 2012; Mariuzzo and Ormosi, 2020), *music genre* which is a fundamental structure used by both the music companies and the listeners to categorize songs and artists (Negus, 1999; Lena and Peterson, 2008; Meyn et al., 2023), *artist nationality* since the domination of domestic music, on the one hand, and US music, on the other, can be observed in most national markets (Aguiar et al., 2018; Waldfogel, 2017; Bourreau et al., 2022; Kjus et al., 2021). We also consider two additional dimensions: *song vintage*[13] and *listening context*. Both variables are defined in detail in Section 3.3. Our second research question is thus:

RQ2. How are users' listening intensity and listening concentration linked to song characteristics?

To assess the real-world consequences and the acceptance of such a reform by stakeholders, it is necessary to disentangle and measure how the six song characteristics separately drive the reallocation of revenue for both the user-centric and the artist-centric payment systems. Our third research question can thus be formulated as follows:

RQ3. How does implementing a user-centric or an artic-centric payment model impact revenue reallocation for each of the six song characteristics?

[13] The streaming era has shifted revenues from new songs ("frontline") to the old ("back catalog"). A song from the back catalog repeatedly played on a streaming platform by a user continues to generate revenues for the rights holders year after year. In the pre-streaming era, however, revenues were only generated when a song was purchased on a CD or similar, and no revenues were generated when the user played the song on their stereo.

3. Empirical strategy

This section presents the empirical strategy used in the study. We first present an overview of the analytic approach, followed by the dataset used in the study, and lastly, we define dependent and independent variables.

3.1. High-level structure of the analysis

To answer our three research questions, we calculate the revenue per stream for the pro-rata and the user-centric payment models and aggregate these results to the song level for each month.

Formally, the monthly revenue per song i in the pro rata payment system writes:

$$r_i^{pr} = \frac{\sum_{j=1}^{p} s_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{p} s_{ij}} \times pF \quad (1)$$

with p the total number of users, s_{ij} is the monthly total number of streams of a song i made by a user j, and F the share of the monthly fee paid by each user that accrues to rights holders.

Likewise, the monthly revenue per song i in the user-centric payment system writes:

$$r_i^{uc} = \sum_{j=1}^{p}\left[\frac{s_{ij}}{\sum_{i=1}^{n} s_{ij}} \times F\right] \quad (2)$$

While the monthly revenue per song in the artist-centric payment system writes:

$$r_{i'}^{ac} = \frac{\sum_{j=1}^{p}\left(4s_{i'j}^{na} + 2s_{i'j}^{a}\right)}{\sum_{j=1}^{p}\left[\sum_{i'=1}^{v}\left(4s_{i'j}^{na} + 2s_{i'j}^{a}\right) + \sum_{i''=1}^{w}\left(2s_{i''j}^{na} + s_{i''j}^{a}\right)\right]} \times pF \quad (3)$$

or

$$r_{i''}^{ac} = \frac{\sum_{j=1}^{p}\left(2s_{i''j}^{na} + s_{i''j}^{a}\right)}{\sum_{j=1}^{p}\left[\sum_{i'=1}^{v}\left(4s_{i'j}^{na} + 2s_{i'j}^{a}\right) + \sum_{i''=1}^{w}\left(2s_{i''j}^{na} + s_{i''j}^{a}\right)\right]} \times pF \quad (4)$$

Where i' denotes one of the v songs released by a "professional" artist, i'' one of the w songs released by a "non-professional" artist ($v + w = n$), and the subscripts na and a denote respectively non-algorithmic and algorithmic streams ($s_{ij} = s_{ij}^{na} + s_{ij}^{a}$). Recall that for each user j, the total number of streams taken into account is caped at 1000. This means that for any j, if $\sum_{i=1}^{n} s_{ij} > 1000$, then $s_{i'j}$ and $s_{i''j}$ in the above equations should be weighted by the coefficient $1000/\sum_{i=1}^{n} s_{ij}$.

Following the empirical strategy proposed by Brynjolfsson et al. (2011), we then pool data on revenue per song in a pro-rata model and data on revenue per song in a user-centric model in a single data set, creating a dummy (*ucps*) indicating whether an observation is for the user-centric or the pro-rata payment model. Interacting this dummy variable with the various variables of interest allows us to highlight the heterogeneity of the impact of a user-centric payment model. These calculations and data manipulations result in 52,045,144 observations, where each observation represents a specific song in a particular month, with revenues either calculated based on the pro-rata or the user-centric payment model.[14] Each song can then be associated with the variables we want to focus on, both for user characteristics (listening intensity,

[14] There are 10,989,055 unique songs streamed during the year and 26,022,572 song-month observations in the dataset. The reason why the number of song-month observations is not simply twelve times the number of unique songs in the dataset is that not all songs are streamed every month. The creation of the dummy *ucps* which represents which payment model has been used for a specific observation, doubles the number of observations to 52,045,144.

listening concentration) and for song characteristics (artist popularity and nationality, musical genre, music label type, song vintage, and listening context). To test the artist-centric payment system we replicate the same approach with a dummy *acps* indicating whether an observation is for the artist-centric or the pro-rata payment model.

Our analysis is structured into three steps, discussed above, each addressing one of our three research questions. To reiterate: In the first step, we examine how the revenue reallocation at the song level depends on the characteristics of the audience of each song, especially the audiences' listening intensity and concentration. Then, in the second step, we identify the song characteristics that correlate to the user characteristics examined in step one. Thus, we can identify the characteristics of songs that should be positively or negatively affected by implementing a user-centric payment model. In the third step, we assess how each specific song characteristic contributes to the magnitude of the revenue reallocation after implementing the user-centric as well as the artist-centric payment models.

The conceptual difference between the first and the third step is that in the first step, we rely on users' characteristics to understand why the revenue payouts would change when switching from the pro-rata to the user-centric payment model. In the third step, we rely on song characteristics to understand how the revenue would change at the song level. The second step serves as a bridge between user and song characteristics. Before embarking on our analysis and presenting our results, we introduce the dataset and the variables used in the empirical approach.

3.2. Data

The dataset used in this study is provided by Deezer, a European music streaming service with 14 million users worldwide. Deezer is based in Paris, and while the service is available in 170 countries, France was the territory where the platform had its largest market share during the relevant period (37.5 percent in 2019, followed by Spotify with 25.2 percent[15]). With its history as a large mainstream online music platform in the French music market, it is reasonable to assume that the profile of the platform's user base is similar to other large international platforms such as Spotify, Apple Music, or Amazon Music Unlimited. France was also, in 2020, the world's fifth-largest music market. While all national music markets are idiosyncratic, France shares many characteristics with other similar-sized markets, such as Germany, the UK, or Canada, which makes it reasonable to assume the findings from this study are transferable to other advanced music markets worldwide.

For this study, the music platform initially created a random sample of 100,000 active premium service subscribers in March 2020, all based in France. When users in this initial sample shared their subscriptions with their families, the family members were added to the sample for completeness.

The study focuses on the users' music listening activity in 2020. The total number of unique users in the dataset who listened to a song at least once during the period of analysis is 154,505, and the average number of active users per month is 131,100.

The users initiated 1390,115,937 streams during the period of analysis. Of these streams, only 889,929,685 are at least 30 s, the minimum duration for a stream to be counted as "a listen" and to be included in the distribution of royalties to rights holders.

The ~890 million streams are distributed across 10,989,055 unique songs. As mentioned above, the music economy is very top-heavy, and a small number of songs and artists typically generate a significant share of the streams and capture an equally significant share of the revenues. For example, the most popular song in the sample was streamed 2425,740 times, while 91.6 percent of all the songs generated fewer than 100 streams during the entire year.

[15] https://snepmusique.com/wp-content/uploads/2019/07/DP-SNEP_-Bilan-1er-semestre-2019.pdf

The detailed stream level data allows us to calculate user behavioral data on the individual user level, such as the monthly number of streams per song for each user, their preferred listening context, song genre preferences, and the two key variables representing users' listening *intensity* and *concentration*. Each month, a user in our sample listens to 570 streams across 263 unique songs on average. However, these averages hide a significant variation in the users' listening practices. The 10 percent most intensive users listen to at least 1178 streams a month, while the 10 percent least intensive users listen to <61 streams per month. Likewise, the 10 percent of users with the most concentrated listening behaviors listen to <39 unique songs per month. In contrast, the users with the least concentrated listening practices listen to 515 distinct songs per month on average. User data on gender and age is provided by the users when signing up for the streaming service. We have been advised by the streaming platform that this data is not entirely reliable and is therefore not included in our analysis.

The initial dataset did not include metadata about the name of the song, the recording artists involved, the music label that released the song, or the date of release. These metadata were therefore added to the dataset by scraping from various music public music databases, such as MusicBrainz.[16]

3.3. The variables

This section introduces the main variables used in this study.

3.3.1. log(rev)

The dependent variable is the natural logarithm of the revenues generated by a song during a specific month and for a specific payment model (user-centric or pro-rata). The revenues are unitless (like a fictitious currency) for confidentiality reasons, and they correspond to the net payments owed by the platform to the rightsholders (net of VAT and operating costs). Revenues are first calculated at the stream level to account for the various contexts for specific streams. Secondly, the payments to all streams of a song are added, generating the total revenues of a song for a specific month. The payment to a stream in the pro-rata model is calculated by dividing the sum of the subscription fees paid by all active users during a month by the total number of streams by these users. The payment to a stream in a user-centric payment model is calculated one user at a time by dividing a user's monthly subscription fee by the user's total number of streams.[17]

3.3.2. ucps and acps

ucps and *acps* are dummy variables that is one if the observation represents a payment under the user-centric (resp. artist-centric) payment model and is zero if it pertains to the pro-rata payment model.

3.3.3. log(intensity)

To capture the average user listening intensity for a specific song in a specific month, we first calculate the total number of streams (S_{nt}) for each user *n* and each month *t*. Then, for each song *i* and month *t*, we identify the *N* users who have listened to this song during the month. Lastly, for each song *i* and month *t*, the average value of S_{nt} is calculated: $intensity_{\text{it}} = \sum_{n=1}^{N} S_{nt}/N$. The variable log*(intensity)* is the natural logarithm of this value.

[16] MusicBrainz (https://musicbrainz.org/) is an open music encyclopedia that collects music metadata and makes it available to the public.

[17] Note that the payment per stream in the user-centric payment model will differ from one user to the next based on the user's stream count for the month. A user who only plays a few streams a month will split their subscription fee across fewer streams and make a higher contribution per stream than a high-intensity user who frequently uses the service and plays many streams.

3.3.4. log(concentration)

To capture the average user listening concentration for a specific song in a specific month, we first calculate a Herfindhal Hirschman Index representing the distribution of streams over distinct songs for month t for each user n. The index is calculated as follows: $HHI_{nt} = \sum_{i=1}^{M} ms_{nit}^2$ where ms_{nit} is the share of a user's (n) total number of streams during a month t, attributed to song i. The index varies, between close to zero, when a user (hypothetically) has listened to many songs only once, to one, if a user has only listened to a single song that month. Then, for each song i on a month t, we identify the N users who have listened to this song during the month. Lastly, for each song i and month t, the average value of HHI_{nt} is calculated: $concentration_{it} = \sum_{n=1}^{N} HHI_{nt} / N$. The variable log*(concentration)* is the natural logarithm of this value.

Variables representing the six song characteristics are defined as follows:

3.3.5. Artist popularity

A set of five dummies accounts for the popularity of the artist who recorded a particular song. An artist's popularity is measured by the total number of streams of all songs recorded by the artist in a particular month. We consider five different ranges of popularity: rank 1st to 10th, rank 11th to 100th, rank 101st to 1,000th, rank 1,001st to 10,000th, and rank > 10,000th. The dummies are labelled *rank1–10, rank11–100, rank101–1k, rank1k-10k, rank>10k*. The last category gathers a large number of artists (we have around 167k different artists in the dataset), but they represent only a small share of the total number of streams (10.5 %).

3.3.6. Music label

We distinguish between music labels that are distributed by one of the three "majors" (Universal Music Group, Sony Music Group, Warner Music Group) or one of their subsidiaries, music labels distributed by a digital provider (such as Believe[18]), and music labels distributed by an independent provider.[19] We thus include three dummies, labeled *major, digital*, and *indie*, that account for the type of music label that supplied the song to the platform. The three major labels have released 47 percent of all songs (representing 70 percent of the total number of streams). Hundreds of independent labels that are either direct suppliers to the platform or distributed by a digital music label have provided the songs that constitute the remainder of the dataset.

3.3.7. Music genre

the dataset provided by the streaming platform distinguishes ten music genres (*Classical, Electro, Jazz, Latin, Pop, Rock, RnB & Soul, Rap & Hip-hop, Unknown*, and *Other*) that are each accounted for with a dummy. The dominating music genre is "Rock" (24.5 percent of all songs), followed by "Pop" (15.4 percent) and "Rap & Hip-hop" (12.5 percent).

3.3.8. Artist nationality

We create four dummies to represent the different categories of artist nationality (*France, US, UK, Other*) .[20] Approximately 22.4 percent of all the songs are recorded by French artists, while US artists recorded 34.6 percent.

3.3.9. Vintage

The ISRC[21] provides information about what year the song was recorded, and this data was used to establish whether the song was released <18 months ago (defined as "frontline") or if it was released from 18 months to ten years ago, or more than ten years ago. We create three dummies labeled *frontline, backless10,* and *backmore10* that account for the vintage of the songs. 16.8 percent of all songs in the dataset are frontline songs, 45.9 percent are recent back catalog, and the remaining 37.3 percent were released more than ten years ago.

3.3.10. Listening context

We also include four variables derived from a stream's "listening context." Streaming platforms identify a very large number of different listening contexts. For instance, a stream can be initiated from an artist's list of top songs, a user's list of favorite songs, an algorithmically curated song sequence, etc. In this study, we aggregate these contexts into four main categories: The first context is the case where a user actively selects a specific song to stream (*organic*); the second context is the case where the stream is initiated from a user-generated playlist (*ug_playlist*); the third context is the case where the stream is initiated from a branded playlist curated by the platform or, sometimes, by a partner (e.g., record label or festival) (*platform_playlist*); and the fourth context is the case where the stream is initiated as part of a personalized music feed generated by the platform's automated recommendation mechanism (*reco*). Each variable represents the share of streams corresponding to a specific context for a given song in a given month. The most common context is "organic" (50.9 percent), followed by *ug_playlist*, with 30.4 percent. Algorithmic recommendations and platform playlists only generate 18.7 percent of all streams (13.0 percent and 5.7 percent).

Table 1 below presents descriptive statistics for our main variables.

4. Results

This section presents the results from the analysis, structured into the three steps introduced earlier in this paper.

4.1. Analysis of user characteristics (Step 1)

The theoretical literature has highlighted users' listening intensity and concentration as critical determinants of revenue reallocation following the implementation of a user-centric payment model (Page and Safir, 2019; Alaei et al., 2022).[22] However, no insight is provided about the relative importance of these two characteristics. To disentangle the impact of the listening intensity from the impact of listening concentration, we run the following fixed effect OLS regression:

$$\begin{aligned} log(rev_{itr}) \;=\; \beta\, log(intensity_{it}) \;+\; \delta\, log(concentration_{it}) \;+ \gamma ucps \\ +\, \sigma ucps^{*} log(intensity_{it}) + \tau ucps^{*} log(concentration_{it}) + \lambda_i + \mu_t + \varepsilon_{itr} \end{aligned} \quad (5)$$

with i a specific song, t a specific month, and r a specific payment model (ucps or pro-rata). λ_i is the *song* fixed effect and μ_t is a set of month dummies. We include song fixed effect to account for potentially song-specific omitted variables (advertising, radio airplay, live performances, etc.). Furthermore, we include month dummies. Firstly, because we compute the data at the month level since the payments are made on a monthly basis. Secondly, because the monthly revenue of a

[18] *Believe Label & Artist Solutions* is a Paris-based music company (https://www.believemusic.com)

[19] We manually checked that the music labels that account for >1 percent of the total market were correctly categorized.

[20] The nationality of an artist is inherently challenging to determine automatically. In this study, we combined data from MusicBrainz with the country code embedded in the songs' ISRC.

[21] International Standard Recording Code (https://isrc.ifpi.org/en/)

[22] Of course, age and gender are also user characteristics that probably play a role in users' listening behavior. As mentioned earlier, the data available on user demographics is not used in this study. However, with a song fixed effect, the specificities of songs in terms of mean age or main gender of their audience songs are taken into account. Moreover, the impact of age and gender in the revenue reallocation following an implementation of a user-centric payment model is indirect and is captured through listening intensity and listening concentration.

Table 1
. Descriptive statistics of the dependent and main independent variables.

	Variable	Obs	Mean	Std. dev.	Min	Max
	revenue (ucps)	26,022,572	5.999476	104.3368	.1653077	81,204.31
	revenue (acps)	26,022,572	5.999476	106.4049	.0039398	91,730.39
	concentration	26,022,572	0.005522	.0105154	.0001188	1
	intensity	26,022,572	1554.199	1175.63	1	70,719
Music genre	classical	26,022,572	0.0530721	0.2241772	0	1
	electro	26,022,572	0.1173894	0.3218838	0	1
	jazz	26,022,572	0.0547855	0.227561	0	1
	latin	26,022,572	0.0436099	0.2042256	0	1
	other_genre	26,022,572	0.1607693	0.367318	0	1
	pop	26,022,572	0.1543027	0.3612387	0	1
	rnb	26,022,572	0.0387429	0.1929817	0	1
	rock	26,022,572	0.2453136	0.430273	0	1
	unknown_genre	26,022,572	0.0073216	0.0852528	0	1
	rap&hip-hop	26,022,572	0.1246929	0.3303703	0	1
Artist nationality	FR	26,022,572	0.2239892	0.4169149	0	1
	UK	26,022,572	0.1487616	0.3558533	0	1
	US	26,022,572	0.3456742	0.4755876	0	1
	other_nationality	26,022,572	0.281575	0.4497672	0	1
Artist popularity	rank1–10	26,022,572	0.0009878	0.0314131	0	1
	rank11–100	26,022,572	0.0124613	0.1109323	0	1
	rank101–1k	26,022,572	0.1015144	0.3020087	0	1
	rank1k-10k	26,022,572	0.323041	0.4676382	0	1
	rank>10k	26,022,572	0.5619956	0.4961417	0	1
Vintage	frontline	26,022,572	0.1683765	0.3742003	0	1
	backless10	26,022,572	0.459009	0.4983169	0	1
	backmore10	26,022,572	0.3726146	0.4835007	0	1
Music label	digital	26,022,572	.1947671	.3960213	0	1
	indie	26,022,572	.332438	.471087	0	1
	major	26,022,572	.4727949	.4992593	0	1
Listening context	organic	26,022,572	.5093051	.430768	0	1
	ug_playlist	26,022,572	.3035736	.3889446	0	1
	platform_playlist	26,022,572	.0566183	.1942277	0	1
	reco	26,022,572	.1305029	.280835	0	1

Note: For confidentiality purposes, revenue per song data is unitless. .

specific song depends on the total number of streams played that month.

The interpretation of coefficients σ and τ allows us to quantify the significance of listening intensity and listening concentration in determining the revenue reallocation at the song level caused by a user-centric payment model. Since both the dependent and independent variables are in log form, it is straightforward to interpret the results of this OLS regression (Table 2).

Table 2
. How users' listening intensity and listening concentration impact change in revenue in a UCPS as compared to a prorate payment system**.

Dependent variable: log(rev) at the song_month level	
log(intensity)	0.314***
	(0.000391)
log(concentration)	0.270***
	(0.000405)
ucps	6.367***
	(0.00105)
ucps*log(intensity)	−0.754***
	(0.000209)
ucps*log(concentration)	0.218***
	(0.000256)
Song fixed effect	Yes
Time fixed effect	Yes
N	52,045,144
R-square (within)	0.316

Notes: Standard errors in parentheses are clustered at the song level.[23].
[*] $p < 0.05$.
[**] $p < 0.01$.
[***] $p < 0.001$.

The table should be interpreted as follows. If users listening to a particular song increase their listening *intensity* by 10 percent (as an example), the revenues allocated to this song, under a user-centric payment model, decrease by 7.54 percent compared to a pro-rata model. Another way of phrasing this relationship is that songs with high-intensity audiences benefit less (or lose) from an implementation of a user-centric payment model compared to songs with low-intensity audiences. With a parallel reasoning for listening concentration, we find that if users listening to a particular song increase their listening *concentration* by 10 percent, the revenues allocated to this song, under a user-centric payment model, increase by 2.18 percent, compared to a pro-rata model. In other words, songs with high-concentration audiences benefit more from the implementation of a user-centric payment model than songs with low-intensity audiences.

These findings allow us to conclude whether it is primarily a song's audience listening intensity or its audience listening concentration that determines whether the song benefits or loses from the implementation of a user-centric payment model. The answer to this question is *listening intensity*, since listening intensity results in a revenue reallocation that is three times the impact of a change of the same magnitude in listening concentration.

4.2. Linking song characteristics with audience listening intensity and concentration (Step 2)

In this second step of our analysis, we build on the conclusion in step one and calculate the average user listening intensity (Fig. 1) and concentration (Fig. 2) for different song characteristics. The six characteristics yield 29 categories in total, illustrated in Figs. 1 and 2. For the purpose of these tables, we transform the four listening context ratio

[23] It has been shown that cluster adjustments may still be necessary in fixed-effects regressions (e.g., Bertrand et al., 2004). However, Abadie et al. (2023) show that while the robust variance can underestimate the true variance, the cluster variance is generally too large. Hence, our results are conservative.

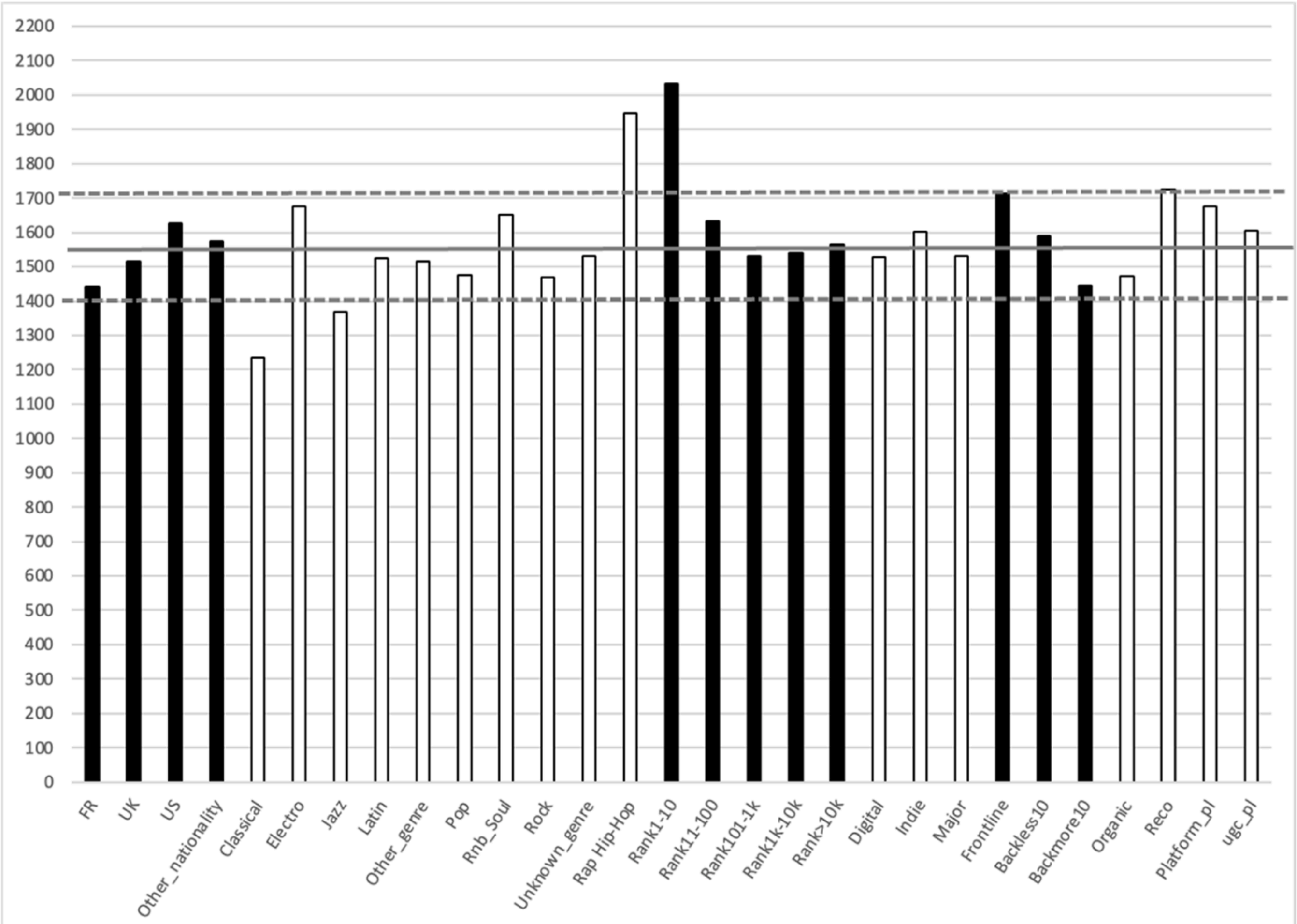

Fig. 1. . Heterogeneity of audience listening intensity by song characteristics
Note: On the vertical axis, the unit is the monthly number of streams per user. The bold grey line shows the mean of this variable for all the users, and the dashed lines represent the interval of 10 percent around the mean.

variables into binary categories by setting the category variable to one if the ratio is equal to or exceeds 50 %. 94.5 percent of all songs have such a dominating listening context. The remaining songs for which a dominating listening context cannot be determined are dropped from the figures.

Fig. 1 shows the average user listening intensity across the six characteristics and the 29 categories. Song characteristics with an average audience listening intensity above the mean will experience a decrease in revenue following the implementation of a user-centric payment model. Of course, the opposite is true for song characteristics below the mean. Fig. 1 shows that while listening intensity is relatively stable across different types of music labels, this is not the case for different music genres or between the “superstars” and artists in lower popularity ranks. The figure shows that Rap & Hip-hop songs, as well as songs recorded by “superstars,” will experience a significant negative impact from the implementation of a user-centric payment model.

Conversely, Classical or Jazz songs and songs from medium-popularity artists will benefit. We also observe, although, to a lesser extent, some variation of listening intensity between older and newer songs, songs recorded by artists with different nationalities, and songs primarily listened to within different contexts. Fig. 1 shows that frontline songs and songs streamed within the contexts “Platform playlists” and “Algorithmic recommendations” are likely to experience a reduction in revenue. On the other hand, songs that are more than ten years old, as well as songs that users tend to listen to as “organic streams,” are likely to benefit financially from the implementation of a user-centric payment model.

Fig. 2 confirms the less important role played by users’ listening concentration in explaining revenue reallocation after implementing a user-centric payment model. In step one of our analyses, we concluded that the impact of listening concentration is more than three times smaller than listening intensity. In this second step, we find that the variation of listening concentration across song characteristics is also smaller. Fig. 2 shows that the listening context displays a significant variation in listening concentration. We find that users who primarily listen to songs from user-generated playlists tend to relisten to the same songs many times (i.e., a high listening concentration). The opposite is true for users who listen to music primarily via algorithmic recommendations.

Further, we note that listeners of songs recorded by superstars also exhibit high-concentration listening behaviors. This observation ought to mitigate, to some extent, the negative impact of a user-centric payment model that these songs experience due to their audience’s high listening intensity (see Fig. 1). We are indeed able to confirm this assumption in a regression where we correlate audience listening intensity and listening concentration with song characteristics (See Table A1 in the appendix).

The figure also shows that songs with an *unknown* genre have an audience with high listening concentration. Since this category only represents 0.7 percent of all songs in our dataset, we ignore this finding.

To summarize the main conclusion from the analysis in step 2 above, we note that four song characteristics are significantly associated with a song’s audience listening intensity: music genre, artist popularity, and,

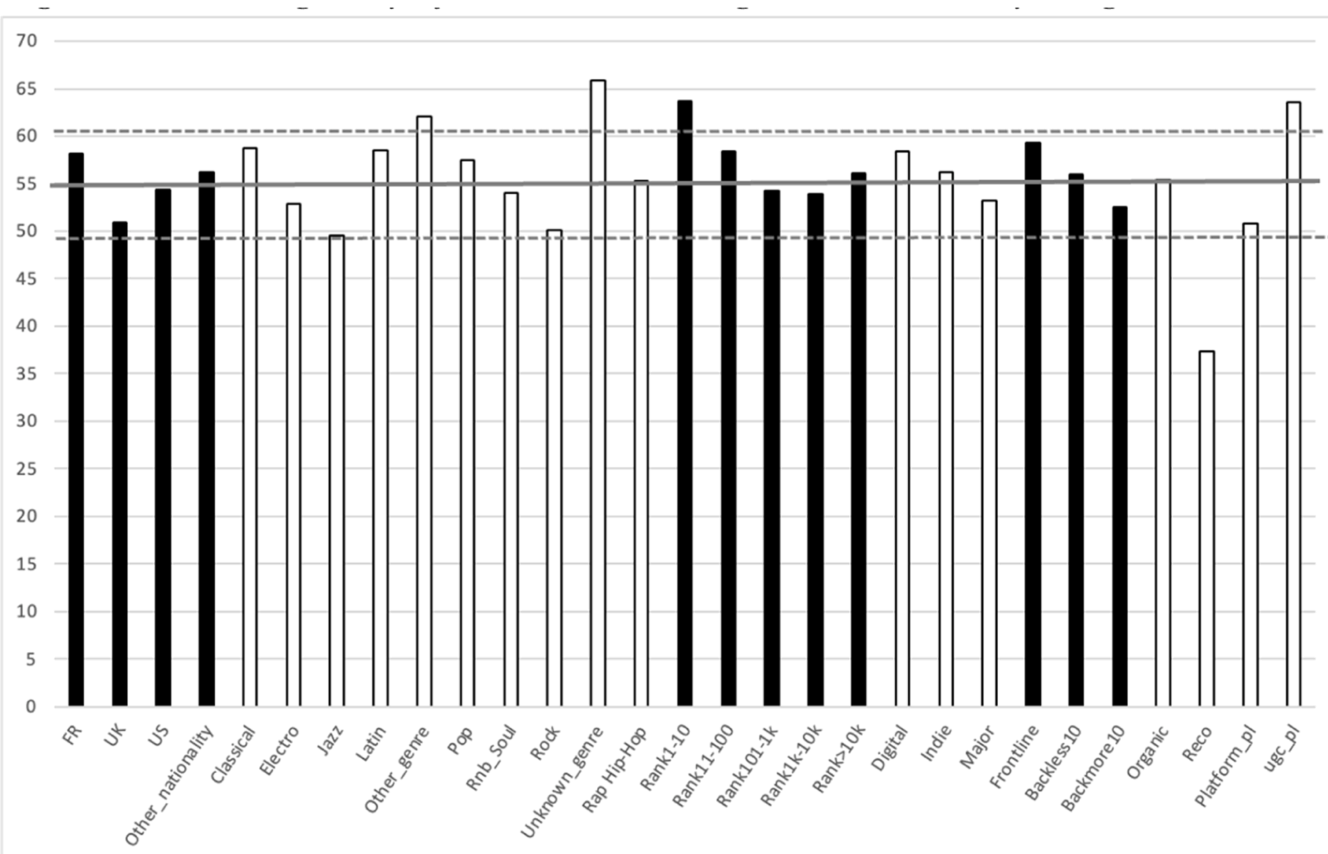

Fig. 2. . Heterogeneity of audience listening concentration by song characteristics
Note: On the vertical axis, the songs' HHI values are multiplied by 10,000. The bold grey line represents the mean of the monthly songs' HHI per user, and the dashed lines represent the interval of 10 percent around the mean.

albeit to a lesser extent, song vintage and listening context. Therefore, it is reasonable to expect these four song characteristics to be the main determinants of the revenue reallocation caused by implementing a user-centric payment model.

4.3. Assessing the magnitude of the revenue reallocation following an implementation of a user-centric payment model or of an artist-centric payment model across song characteristics (Step 3)

The descriptive analysis above does provide some interesting findings on its own. However, it does not allow us to assess and isolate the magnitude of revenue reallocation at the song level for individual song characteristics. To formally test the impact of a user-centric payment model and of an artist-centric[24] payment model on the distribution of payments across different categories of artist popularity, music genre, music label type, artist nationality, song vintage, and listening context, we run the following fixed effect linear regressions:

$$log(rev_{itr}) = \beta X'_{it} + \delta ucps + \gamma ucps^{*} X'_{it} + \lambda_i + \mu_t + \varepsilon_{itr} \tag{6}$$

$$log(rev_{itr}) = \beta X'_{it} + \delta acps + \gamma acps * X'_{it} + \lambda_i + \mu_t + \varepsilon_{itr} \tag{7}$$

with *i* a specific song, *t* a specific month, and *r* a specific payment model (alternative model or pro-rata). μ_t is a set of month dummies and λ_i is the *song* fixed effect. The vector X'_{it} captures the six song characteristics introduced in Section 3.3: artist popularity (5 categories), music genre (10 categories), music label (3 categories), artist nationality (4 categories), song vintage (3 categories), and listening context (4 categories).

In this third step, we drop the two user characteristics, log(intensity) and log(concentration), that contribute to explaining revenue reallocation after implementing a user-centric payment model. The user characteristics were useful in the first step of the analysis to explain the logic behind the revenue reallocation. In this third step, we aim to determine how this revenue reallocation impacts songs with different characteristics, which is necessary to establish the consequences of implementing an alternative payment model on industry stakeholders.

Table 3 reports the results of the regression for both alternative models. The song fixed effect and the month dummies eliminate bias from unobservable variables that change over time but are constant over songs, and it also controls for factors that differ across songs but are constant over time. In such a fixed-effect regression model, any constant variables within every song are redundant and will be omitted. All individual song characteristics variables are thus omitted, and only the interactions remain.[25] However, our main interest in Eq. (2) is γ, which represents the set of coefficients of the interaction between *ucps* and all

[24] To assess the artist-centric payment model, we adjust the thresholds announced by Deezer to our sample of 100,000 accounts. Deezer had 3.9 million active paying accounts in France during the fiscal year 2020 (source: https://www.deezer-investors.com/wp-content/uploads/2022/10/Deezer-2022-Investor-Day-Oct-4.pdf). Our sample being made up with 2.6 percent of all Deezer's paying accounts, the thresholds for "professional artists" are adjusted to 26 streams per month from 13 unique users.

[25] Actually, the results for the coefficients of the three dummies that account for the vintage of the songs and for the variables that account for the listening context are not omitted since these variables can change over time for the same song. To simplify the presentation of Table 3, we choose not to report these results. However, the full table is presented in appendix (Table A.2).

Table 3
. Determinants of revenue reallocation with alternative payment systems as compared to pro-rata**.

Dependent variable: log(rev) at the song_month level		User-Centric x = ucps		Artist-Centric x = acps	
		(1)	(2)	(3)	(4)
	x	0.849***	0.840***	0.887***	0.854***
		(0.00111)	(0.00108)	(0.000683)	(0.000689)
Artist nationality	x*FR	1.137***	1.139***	1.075***	1.078***
		(0.000851)	(0.000854)	(0.000488)	(0.000519)
	x*UK	1.010***	1.009***	1.028***	1.023***
		(0.000789)	(0.000790)	(0.000497)	(0.000526)
	x*US	0.986***	0.986***	1.017***	1.012***
		(0.000636)	(0.000637)	(0.000421)	(0.000442)
	x*other_nationality	Ref.	Ref.	Ref.	Ref.
Music genre	x*classical	1.129***	1.131***	1.108***	1.121***
		(0.00143)	(0.00143)	(0.000837)	(0.000883)
	x*electro	0.948***	0.942***	1.113***	1.060***
		(0.000896)	(0.000892)	(0.000702)	(0.000703)
	x*jazz	1.041***	1.040***	1.116***	1.107***
		(0.00125)	(0.00125)	(0.000820)	(0.000850)
	x*latin	1.015***	1.014***	1.131***	1.111***
		(0.00136)	(0.00136)	(0.000982)	(0.00103)
	x*pop	1.038***	1.036***	1.112***	1.087***
		(0.000952)	(0.000954)	(0.000633)	(0.000650)
	x*rnb_soul	0.956***	0.956***	1.097***	1.070***
		(0.00132)	(0.00133)	(0.000905)	(0.000941)
	x*rock	1.013***	1.011***	1.128***	1.095***
		(0.000815)	(0.000814)	(0.000589)	(0.000598)
	x*unknown	1.035***	1.036***	0.981***	0.977***
		(0.00328)	(0.00330)	(0.00210)	(0.00217)
	x*rap&hip-hop	0.820***	0.820***	1.045***	1.015***
		(0.000757)	(0.000755)	(0.000642)	(0.000649)
	x*other_genre	Ref.	Ref.	Ref.	Ref.
Music label	x*digital	1.008***	1.008***	1.016***	1.009***
		(0.000749)	(0.000751)	(0.000480)	(0.000501)
	x*indie	Ref.	Ref.	Ref.	Ref.
	x*major	1.032***	1.030***	1.054***	1.044***
		(0.000611)	(0.000611)	(0.000396)	(0.000414)
Artist popularity	x*rank1–10	0.909***	0.912***	0.966***	0.978***
		(0.00402)	(0.00397)	(0.00140)	(0.00192)
	x*rank11–100	1.029***	1.029***	0.994***	0.991***
		(0.00202)	(0.00203)	(0.000657)	(0.000845)
	x*rank101–1k	Ref.	Ref.	Ref.	Ref.
	x*rank1k-10k	0.924***	0.925***	1.002***	1.009***
		(0.000743)	(0.000744)	(0.000321)	(0.000390)
	x*rank>10k	0.885***	0.888***	0.766***	0.777***
		(0.000716)	(0.000718)	(0.000299)	(0.000345)
Vintage	x*frontline	Ref.	Ref.	Ref.	Ref.
	x*backless10	1.033***	1.031***	1.039***	1.004***
		(0.000716)	(0.000713)	(0.000488)	(0.000488)
	x*backmore10	1.087***	1.083***	1.065***	1.021***
		(0.000810)	(0.000805)	(0.000515)	(0.000515)
Listening context	x*organic	Ref.		Ref.	
	x*ug_playlist	1.024***		1.003***	
		(0.000693)		(0.000383)	
	x* platform_playlist	0.885***		0.931***	
		(0.00107)		(0.000759)	
	x*reco	0.903***		0.520***	
		(0.000664)		(0.000223)	
	Song fixed effect	Yes	Yes	Yes	Yes
	Month dummies	Yes	Yes	Yes	Yes
	N	52,045,144	52,045,144	52,045,144	52,045,144
	R-square (within)	0.034	0.031	0.084	0.044

Notes: Exponentiated coefficients; Standard errors in parentheses are clustered at the song level. In such a fixed-effect regression model, any constant variables within every song are redundant and will be omitted. All individual song characteristics variables are thus omitted, and only the interactions remain. The results for the coefficients of the three dummies that account for the vintage of the songs and for the variables that account for the listening context are not omitted since these variables can change over time for the same song. To simplify the presentation of the table, we choose not to report these results.

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

the categories of the song characteristics. By interpreting the coefficients of interacted terms in Table 3, this model allows us to identify how the various features of a song would impact the gain or the loss of revenue generated by the song in an alternative model. The coefficients are exponentiated in Table 3 to facilitate the interpretation of the results. This means, as an example, that all other variables being put at their reference, the coefficient of *ucps* × (*ucps*classical)* should be interpreted as the multiplier coefficient of revenues to a classical song under UCPS compared to its revenues under a pro-rata payment system.

In Table 3, the results are presented with the "listening context" variables (columns 1 and 3) and then without these variables (columns 2 and 4). Isolating these variables is useful for understanding how organically played streams are remunerated in the alternative models. Hence, with both UCPS and ACPS, organic streams are better remunerated than streams resulting from an algorithmic recommendation or a playlist created by the platform. On the other hand, from the point of view of artist remuneration, it is preferable not to consider the context in which streams are listened to, and to stick to the variables that define each song. To facilitate the interpretation of our results, we present the marginal effects for all our variables of interest in Table 4. For each variable, we report the revenue reallocation caused by the implementation of an alternative payment model. The comparison is made to a fictitious average song with all the variables set at their mean.[26] The first row of Table 4 should be interpreted as follows: Consider a fictitious song with all six characteristics set at their mean as reference. A song with the only distinction from this fictitious song being that its music genre is "Classical" would earn, on average, 19.7 percent more with a user-centric (6.4 percent more with a artist-centric) than a pro-rata payment model.

Table 4 shows that in our comparative static approach of the user-centric payment model, the revenue generated by a Rap & Hip-hop song would decrease by 13.2 percent. In contrast, the revenue of songs from niche genres such as Classical or Jazz would increase by 19.7 and 10.1 percent, respectively. The payments to songs recorded by a top 10 artist and songs recorded by artists ranked below the 1,000th rank would experience a significant decrease, to the benefit of artists ranked from 11th to 1,000th. We also observe that frontline songs would experience a reduction in their revenue (−3 percent), at the benefit of songs from the back catalog that are at least ten years old (+5.1 percent). As far as the artist-centric payment system is concerned, songs recorded by artists ranked below the 10,000 ranks ("*rank>10k*") are the most likely not to meet the "professional artist" criteria and experience a decrease in revenue of 20.4 percent compared to the pro-rata model. However, combined with the fact that songs streamed as part of an algorithmic recommendation sequence ("*reco*") lose half of their revenue in the artist-centric payment model, the reallocated amounts are relatively small since these two categories constitute a minor share of the total market. In the pro-rata model, songs by artists ranked below the 10,000 ranks and songs streamed as part of an algorithmic recommendation sequence are allocated 10.5 percent of the total revenues. Hence, reallocating revenues from the "losing categories" amounts to minor absolute additions to "winning categories." This can be seen in Table 4, as the reallocations to other artist popularity categories do not exceed 3 percent.

Finally, it should be noted that the impact of the various characteristics is cumulative. To calculate the effect of how some variables are conditioning on others, it is possible to simulate several typical situations from our results. We propose hereafter three of these typical situations: most of the artists from the top 10 are Rap & Hip-Hop French artists, a large number of US and French pop stars from the late 90s or early 2000s belong to the top 11–100, and current French pop stars also belong to the top 11–100. Hence, an average frontline Rap & Hip-hop song by a top ten French artist would experience a 26.2 percent revenue reduction following the implementation of a user-centric payment model but only 5.8 percent with the artist-centric payment model. An average Pop song that is more than ten years old, recorded by a French artist whose popularity is between rank 11 and 100, would experience a 13.6 percent revenue increase while only +4.3 percent with ACPS (−1.7 and −2.1 percent respectively for a US artist). An average new release Pop song recorded by a French artist whose popularity is between rank 11 and 100 would experience a 4.7 percent revenue increase (+2 percent with ACPS).

[26] Means are also calculated for binary variables.

4.4. Robustness

Our dataset contains all streams (~890 million) made over one year by a sample of 154,505 unique users randomly sampled from the several million subscribers of this platform. With such a large sample, we are confident that our analysis does not suffer from any systematic bias. A possible issue could be that our time period (2020) comprises two periods of lock-down that France experienced from March 17th to May 3rd and from November 1st to December 15th due to the COVID-19 pandemic. There is indeed evidence that music consumption has changed during that period. In the US and Europe, music streaming consumption decreased with the widespread social distancing, likely because the time spent in public transportation is often dedicated to listening to music (Sim et al., 2021). Since we include a time fixed effect, we partially control for that. However, to rule out any possible issue, we also ran our main regression excluding the months of lock-down, and our results remain unchanged (see column 2 in Table A2 included in the Appendix). We also check that our results are not too dependent on all the deep-tail songs representing only a minuscule part of streaming revenues.[27] This check involves dropping the songs that are only streamed once during the month. These songs constitute 39.3 percent of all the observations but only 1.3 percent of all streams. Column 1 in Table A2 in the Appendix shows that our results remain globally unchanged.

5. Discussion and conclusion

This section discusses our results and their implications for industry stakeholders. Among other things, we discuss the potential for the industry to accept both alternative payment models, and we identify some limitations of this study and suggest opportunities for future research.

5.1. A deeper understanding of the impact of alternative payment models

The first contribution of this paper is to propose an empirical test of the theoretical propositions from Alaei et al. (2022) and Page and Safir (2019). Page and Safir (2019) have formally shown that two user-level dimensions are essential to assess the impact of a user-centric payment model on a rightsholder's revenues: the intensity and the concentration of the user's listening habits. We contribute to this finding by showing that listening intensity is the most significant driver of revenue reallocation and that listening concentration plays a more marginal role.

We also expand the empirical knowledge about the profile of the songs and artists that a user-centric payment model would positively or negatively impact. Meyn et al. (2023) have shown from survey data from Germany that Hip-hop, Rap, and electronic dance music (EDM) would be the music genres that would be most negatively impacted, while genres such as International Rock, Metal, and Classical music would benefit the most. We confirm these results for the case of France. However, above all, we expand the analysis to other song characteristics (e.g., artist popularity, song vintage, listening context) that prove to be highly relevant to disentangle the losers from the winners of an implementation of the model. For instance, our results enrich the conclusion from Meyn et al. (2023) that international rock and metal would benefit from the user-centric payment model. Our results suggest that this is probably mainly because those genres (aggregated as "Rock" in our analysis) are overrepresented in the catalog that is more than ten years

[27] This robustness check echoes Spotify's announcement in 2023 that, from 2024, songs that do not meet the threshold of 1,000 streams a year will not qualify for payouts. https://www.musicbusinessworldwide.com/confirmed-next-year-tracks-on-spotify-1000-plays/

Table 4
. Marginal effects on songs' revenues following a UCPS or a ACPS implementation compared to the current pro-rata system.

		User-Centric			Artist-Centric		
		Marginal change (in percent)	*95 percent confidence interval*		**Marginal change (in percent)**	*95 percent confidence interval*	
Music genre	Classical	**19,7**	19,6	19,8	**6,1**	6,1	6,2
	Electro	**−0,2**	−0,2	−0,2	**0,4**	0,3	0,4
	Jazz	**10,1**	10,0	10,1	**4,8**	4,7	4,8
	Latin	**7,4**	7,3	7,5	**5,2**	5,2	5,3
	Other_genre	**5,9**	6,0	5,7	**−5,3**	−5,2	−5,4
	Pop	**9,7**	9,7	9,7	**2,9**	2,9	2,9
	Rnb_Soul	**1,2**	1,1	1,3	**1,3**	1,3	1,4
	Rock	**7,0**	7,1	7,0	**3,7**	3,7	3,7
	Unknown	**9,7**	9,2	10,2	**−7,6**	−7,8	−7,3
	Rap&Hip-hop	**−13,2**	−13,2	−13,2	**−4,0**	−4,0	−3,9
Artist nationality	FR	**7,7**	7,7	7,8	**3.3**	*3.2*	*3.3*
	UK	**−4,5**	−4,6	−4,5	**−1.2**	*−1.3*	*−1.2*
	US	**−6,7**	−6,7	−6,7	**−2.3**	*−2.3*	*−2.3*
	other_nationality	**−5,4**	−5,3	−5,5	**−3.9**	*−3.8*	*−4*
Music label	Digital	**−1,4**	−1,4	−1,3	**−2,2**	−2,3	−2,2
	Indie	**−2,2**	−2,1	−2,3	**−3,1**	−3,0	−3,1
	Major	**0,8**	0,8	0,8	**1,2**	1,2	1,2
Artist popularity	rank1–10	**−5,7**	−6,4	−5,1	**0,2**	−0,1	0,5
	rank11–100	**6,4**	6,1	6,6	**1,6**	1,5	1,7
	rank101–1k	**3,3**	3,5	3,1	**2,4**	2,5	2,4
	rank1k-10k	**−4,4**	−4,4	−4,4	**3,4**	3,4	3,4
	rank>10k	**−8,3**	−8,3	−8,3	**−20,4**	−20,4	−20,4
Vintage	Frontline	**−3,0**	−2,9	−3,1	**−0,6**	−0,6	−0,7
	Backless10	**0,0**	0,0	0,1	**−0,2**	−0,3	−0,2
	Backmore10	**5,1**	5,0	5,1	**1,4**	1,4	1,5

Note: Each value corresponds to the percentage of change in the song's revenue following a user-centric payment model implementation, taking as reference a fictitious song with all variables being set at their mean (including binary data) and changing only the mentioned characteristic. Changes have been normalized to make the gains compensate for the losses within each set of song characteristics.

old.[28] Our results show that due to the preferences of highly intensive users and, more marginally, of users displaying a high concentration at the song level, the main winners of implementing a user-centric payment model would be rightsholders of songs in niche genres (Classical, Jazz), songs over ten years old, and domestic (French in our case) songs. Conversely, the biggest losers would be rightsholders of songs by both top artists and deep-tail artists, of Rap & Hip-hop music, of frontline songs, and of songs frequently listened to as part of platform playlists or algorithmic recommendations. Finally, we find that the type of music label only has a marginal impact on the revenue reallocation difference following the implementation of a user-centric payment model.[29]

At a macro level, we observe changes in terms of the concentration of revenues across songs. Hence the average revenue of the top 10 songs is higher in both the user-centric (+5.6 %) and the artist-centric (+8.6 %) payment systems than in the current system. This is also observable for the top 100 songs (+7.6 and +7.2 % respectively). However, beyond these changes, we show that the artist-centric payment model does not lead to a significant improvement in the remuneration to professional artists. Moreover, we note that most of the changes caused by an implementation of ACPS would go in the same direction as the changes induced by UCPS but with a much smaller impact.

5.2. Policy and managerial implications: how can any new payment model be accepted by key stakeholders?

Based on back-of-the-envelope calculations, we can estimate an order of magnitude of the revenue reallocation that an implementation of a user-centric payment model would generate. The gross value of the French subscription streaming market amounted to €351.3 million in 2020.[30] Hence, assuming that our sample is representative of the whole French subscription streaming market, we can roughly estimate the revenue reallocation from the top 10 artists to the rest of the distribution. According to our data, the top 10 artists account for 6.1 percent of the value of the whole market, and they experience a decrease in revenue of 5.7 percent (see Table 4). This revenue reallocation would correspond to around €1.2 million for the French market alone. Following the same approach, the loss in revenue for the tens of thousands of artists ranked beyond 1,000th amounts to €7.3 million. Hence, €8.5 million would transfer from both ends of the distribution to the artists ranked between 11th and 1,000th. Revenue reallocation between music genres and song vintages would be even more significant. For instance, in the pro-rata model, Rap & Hip-hop music accounts for 32.8 percent of the revenue to rightsholders from the streaming subscription market, and the drop in revenue for this music genre following the implementation of a user-centric payment model amounts to 13.2 percent (see Table 4). This means the revenue reallocation from Rap & Hip-hop to other genres amounts to €15.2 million. Finally, frontline songs represent 40.2 percent of the revenue, and we predict that the revenue allocated to these songs will decrease by 3 percent (see Table 4) with the implementation of the user-centric payment model, which amounts to €4.2 million. These changes are not massive but remain significant without introducing a dramatic disruption in the distribution of revenues within the industry. This could be considered favorable by multiple key stakeholders and make the user-centric payment model an acceptable approach for distributing revenues more in accordance with users' actual listening behavior.

Implementing a new payment model is a fundamental change for a music streaming platform ecosystem. It would require the agreement of

[28] The genre "Rock" amounts to 18.6 percent of the total number of streams in our dataset but to 31.9 percent of the total number of streams in the back catalog >10 years old.

[29] In Moreau et al. (2023) it is shown that adopting a user-centric payment model with a temporis based measurement of revenue share (based on the total time spent to listen to a song instead of the number of times a song has been listen to) would not lead to tremendous changes as compared to a "per stream" user-centric payment model that does not take listening time into consideration.

[30] https://snepmusique.com/wp-content/uploads/2021/03/DP-Bilan-2020.pdf

all the stakeholders – the platform and all its content providers. Jeffrey Sachs debates in an unpublished paper whether a policy reformer "*should strive for a consensus with affected groups*" (cited in Rodrik, 1996, p. 33) and whether this is at all achievable. Answering this question for our particular case is beyond the scope of our paper. However, we provide some initial thoughts hereafter. For music streaming platforms, the implementation of a new payment model is neutral from a financial perspective. Their total revenue distributed to rightsholders would not be changed, and they might even expect an increase in the willingness-to-pay of subscribers because of a fairer payment for artists, similar to "fair-trade" products benefit from a price premium (e.g., Hainmueller et al., 2015; Bürgin et al., 2021).

The question is more sensitive to rightsholders who receive less revenue under any new model. We have shown above that the artists we refer to as "superstars" constitute a stakeholder group that will lose about 6 percent of their revenues with UCPS. Disputes between superstars and platforms about the income they get from streaming platforms, especially Spotify, are frequent. For instance, in the early days of the streaming economy, Taylor Swift removed her entire catalog from Spotify in 2014, complaining about the revenues she received from the ad-supported service. However, Taylor Swift quickly rejoined Spotify because "*she and her team are smart enough to see how the tides have changed […]. Spotify is simply too large and far too important these days to ignore, no matter what an artist looking to be No 1 feels about their financial ethos*" (McIntyre, 2017). If this case illustrates the superstars' dependence on music streaming platforms, it seems unlikely they would oppose such a reform, even though they lose some streaming revenues. According to Vianney, one of the most popular musicians in France, "*when I ask my baker for a baguette, I find it normal that the euro I give her does not go to the bakery next door. The user-centric principle seems to me to be fairer and more logical.*"[31]

While independent labels have long criticized the pro rata remuneration system (Jenssen, 2024), it is interesting to observe that they would not benefit neither from the implementation of UCPS nor ACPS. They would experience respectively −2.2 and −3.1 percent decrease in revenue as compared to the current system. Another stakeholder group with what is most likely the strongest bargaining position is the group of major music labels: Universal Music, Warner Music, and Sony Music. Any change to agreements with rightsholders is only possible with the approval of these three giants. Overall, the revenue per song for major labels, controlling for all other variables, would slightly increase (see Table 4), which might indicate that an acceptance of the user-centric payment model is possible. However, major music companies are susceptible to how they are perceived by music creators, and reallocating revenues from Rap & Hip-hop music to the back catalog could be a very controversial change. "*A new model where young Black hip-hop artists (not just the superstars but emerging and independent musicians) may be 'losers' is enough to raise red flags*" (Dredge, 2023). Hence the proposition from the largest music company, Universal Music Group, to implement the artist-centric payment system, which would not have such important negative impacts on specific profiles of artists (superstars, Rap & Hip-Hop music, etc.). However, our analysis shows that the user-centric payment model achieves the aims of the artist-centric model just as well or even more effectively. The user-centric payment model leads to decreased revenues to deep-tail artists and superstars, benefitting mid-tier artists, which is precisely what the artist-centric model is designed to do. Further, the user-centric payment model also decreases the payment to algorithmically recommended streams and to streams played as part of a platform playlist. The model also does not suffer from the problematic threshold effects, which burdens the artist-centric model with its ad hoc definitions of a "professional artist."

While the artist-centric payment model has significant limitations, we note that by lowering the "streaming cap" parameter, the model becomes increasingly "user-centric-like." If the artist-centric model becomes used more widely in the streaming economy, one can hope that the streaming cap parameter becomes part of the negotiations between rightsholders and platforms and that the cap will eventually be lowered. While this is a potentially positive development of the artist-centric payment model, the user-centric payment model still has the advantage of being a simple rule based on the fundamental principle that a subscriber's payments to the platform are only distributed to the artists they have listened to.

5.3. Limitations and future research

The main limitation of our study is that our analysis is based on a comparative static approach. We have simulated the implementation of a user-centric and an artist-centric payment models with the assumption that the payment model will not change the behavior of either content providers or users. We have no reason to believe that users will change their music listening practices because of the implementation of a new payment model. For instance, an online survey on music streaming users shows that making users aware of a popularity bias has no impact on their song selection (Ingesson, 2022).[32] However, if such a model were to be implemented, rights holders most likely would adjust their strategy to the new conditions. There are examples of how content providers previously have responded to changing business conditions caused by the rise of music streaming platforms. For instance, since the payment to an individual stream is not dependent on the song's duration, content providers have increasingly released shorter songs (Kopf, 2022).[33] Another example is the increasing interest in back catalogs, especially songs released over ten years ago. For example, Bob Dylan sold the rights to his entire song-writing catalog (about 600 songs) to Universal Music Group,[34] while Bruce Springsteen did the same to Sony Music.[35] The founder of Hipgnosis Songs Fund Ltd., an investment company focused on heritage song catalogs and associated musical intellectual property rights, argues that "*great, proven songs have predictable, reliable income. It is better than gold or oil*".[36]

Hence, we can hypothesize that should a user-centric payment model be implemented, music labels would probably rationally decide to focus more on the musical genres that benefit from the user-centric payment model at the expense of Rap & Hip-hop music (which is tailored for the pro-rata payment model with young and highly intensive users). They would also probably invest less in superstars and look more for artists with a large audience constituted by low- or medium-intensive users. All these moves, which are rational reactions to the implementation of a user-centric payment model, will reinforce our results. Yet, a dynamic analysis that would study the strategic moves that rights holders might undertake in reaction to the implementation of a user-centric payment model remains an avenue for future research.

Meyn et al. (2023) propose an ambitious agenda for future research on music streaming platforms' remuneration models, and the authors note that the topic so far has largely been ignored by academic research.

[31] https://www.leparisien.fr/culture-loisirs/musique/streaming-musical-la-repartition-des-revenus-me-parait-injuste-reconnait-vianney-18-04-2021-TFYSRWNUGBGIPGLEJUW63SHEQM.php

[32] Note that this is not in contradiction with the idea that a user-centric payment model could be valuable to users. Users could have a higher willingness-to-pay for a platform that implements such a payment model but with a consumption pattern identical to what it would be in a pro-rata platform.

[33] The average duration of a song released in the 90s was 259 seconds, 243 seconds in the 2000s and only 197 seconds in the 2020s (https://ucladatares.medium.com/spotify-trends-analysis-129c8a31cf04).

[34] https://www.nytimes.com/2020/12/07/arts/music/bob-dylan-universal-music.html

[35] https://www.nytimes.com/2021/12/15/arts/music/bruce-springsteen-sells-music-catalog.html

[36] https://www.ft.com/content/71c2be62-b823-47d9-9f43-ab322883aa8c

This paper responds to some of the opportunities identified by Meyn et al., and our findings facilitate future studies on the topic. For instance, there is a parallel between our results on music genre and those of Meyn et al. (2023), which indicates that it is reasonable to expect that our findings are transferable to other markets beyond France. Moreover, our identification of listening intensity as the main user-level driver of revenue reallocation after implementing a user-centric payment model enables the translation of our results to other jurisdictions.

Finally, our findings show that while the basis for suggesting a user-centric payment model is the fundamental idea that users' payments should only be distributed to the artists they listen to, it also has consequences that are well-aligned with industry stakeholders' views of how the distribution of payments from streaming platforms should change. An opportunity for future research is to examine how the principles of a user-centric payment model can be combined with other principles, for instance, with the increased weight of organic streams, which is one component of artist-centric payment model.

CRediT authorship contribution statement

François Moreau: Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Conceptualization. **Patrik Wikström:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Data curation, Conceptualization. **Ola Haampland:** Writing – review & editing, Methodology, Conceptualization. **Rune Johannessen:** Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix

Table A1, Table A2, Table A3

Table A1
Regressions correlating audience listening intensity and concentration with song characteristics*,**.

	Dependent variable:	log(intensity)	log(concentration)
Music genre	classical	0.821***	0.958***
		(0.000969)	(0.00118)
	electro	1.115***	0.928***
		(0.000991)	(0.000869)
	jazz	0.894***	0.851***
		(0.00102)	(0.000962)
	latin	0.999	1.000
		(0.00128)	(0.00128)
	pop	0.994***	0.980***
		(0.000858)	(0.000870)
	rnb_soul	1.082***	0.919***
		(0.00144)	(0.00126)
	rock	0.989***	0.884***
		(0.000746)	(0.000706)
	unknown_genre	0.999	1.051***
		(0.00310)	(0.00329)
	rap&hip-hop	1.322***	0.936***
		(0.00115)	(0.000868)
	other_genre	Ref.	
Artist nationality	FR	0.950***	1.074***
		(0.000666)	(0.000774)
	UK	1.000	0.951***
		(0.000731)	(0.000725)
	US	1.039***	0.999
		(0.000632)	(0.000633)
	other_nationality	Ref.	
Artist popularity	Rank1–10	1.284***	1.241***
		(0.00441)	(0.00418)
	Rank11–100	1.088***	1.123***
		(0.00173)	(0.00193)
	Rank101–1k	Ref.	
	Rank1k-10k	0.973***	0.914***
		(0.000707)	(0.000687)
	Rank>10k	0.898***	0.829***
		(0.000665)	(0.000629)
Vintage	frontline	Ref.	
	backless10	0.933***	0.938***
		(0.000596)	(0.000635)
	backmore10	0.877***	0.890***
		(0.000596)	(0.000636)
Music label	digital	0.985***	1.017***
		(0.000695)	(0.000748)
	indie	Ref.	

(*continued on next page*)

Table A1 (*continued*)

	Dependent variable:	log(intensity)	log(concentration)
	major	1.007***	1.007***
		(0.000563)	(0.000582)
Listening context	organic	Ref.	
	ug_playlist	1.093***	1.214***
		(0.000710)	(0.000811)
	platform_playlist	1.259***	1.009***
		(0.00133)	(0.00107)
	reco	1.249***	0.746***
		(0.000905)	(0.000495)
	N	26,022,572	26,022,572
	R-sq	0.047	0.046

Notes: Exponentiated coefficients; Standard errors in parentheses clustered at the song level; Regressions include month dummies.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table A2
Regressions from Table 3 with all the coefficients displayed.

	Dependent variable: log(revenue) per song	User-Centric x = ucps	Artist-Centric x = acps
Music genre	classical		
	electro		
	jazz		
	latin		
	pop		
	rnb_soul		
	rock		
	unknown		
	rap&hip-hop		
	other_genre		
Artist nationality	FR		
	UK		
	US		
	other_nationality		
Artist popularity	rank1–10		
	rank11–100		
	rank101–1k		
	rank1k-10k		
	rank>10k		
Vintage	frontline	Ref.	
	backless10	0.871***	0.923***
		(0.00218)	(0.00156)
	backmore10	0.916***	0.991***
		(0.00306)	(0.00265)
Music label	digital		
	indie		
	major		
	x	0.840***	0.854***
		(0.00108)	(0.000689)
Music genre	x*classical	1.131***	1.121***
		(0.00143)	(0.000883)
	x*electro	0.942***	1.060***
		(0.000892)	(0.000703)
	x*jazz	1.040***	1.107***
		(0.00125)	(0.000850)
	x*latin	1.014***	1.111***
		(0.00136)	(0.00103)
	other_genre	Ref.	Ref.
	x*rnb_soul	1.036***	1.087***
		(0.000954)	(0.000650)
	x*pop	0.956***	1.070***
		(0.00133)	(0.000941)
	x*rock	1.011***	1.095***
		(0.000814)	(0.000598)
	x*unknown	1.036***	0.977***
		(0.00330)	(0.00217)
	x*rap&hip-hop	0.820***	1.015***
		(0.000755)	(0.000649)
Artist nationality	x*FR	1.139***	1.078***
		(0.000854)	(0.000519)

(continued on next page)

Table A2 (*continued*)

	Dependent variable: log(revenue) per song	User-Centric x = ucps	Artist-Centric x = acps
	x*UK	1.009***	1.023***
		(0.000790)	(0.000526)
	x*US	0.986***	1.012***
		(0.000637)	(0.000442)
	x*other_nationality	Ref.	Ref.
Artist popularity	x*rank1–10	0.912***	0.978***
		(0.00397)	(0.00192)
	x*rank11–100	1.029***	0.991***
		(0.00203)	(0.000845)
	x*rank101–1k	Ref.	Ref.
	x*rank1k-10k	0.925***	1.009***
		(0.000744)	(0.000390)
	x*rank>10k	0.888***	0.777***
		(0.000718)	(0.000345)
Vintage	x*frontline	Ref.	Ref.
	x*backless10	1.031***	1.004***
		(0.000713)	(0.000488)
	x*backmore10	1.083***	1.021***
		(0.000805)	(0.000515)
Music label	x*digital	1.008***	1.009***
		(0.000751)	(0.000501)
	x*indie	Ref.	Ref.
	x*major	1.030***	1.044***
		(0.000611)	(0.000414)
	Song fixed-effect	Yes	Yes
	Month dummies	Yes	Yes
	N	52,045,144	52,045,144
	R-square (within)	0.031	0.044

Notes: Exponentiated coefficients; Standard errors in parentheses clustered at the song level; In such a fixed-effect regression model, any constant variables within every song are redundant and will be omitted. All individual song characteristics variables are thus omitted, and only the interactions remain. The results for the coefficients of the three dummies that account for the vintage of the songs and for the variables that account for the listening context are not omitted since these variables can change over time for the same song.

Table A3
Robustness checks**.

	Dependent variable: log(revenue) per song	(1)	(2)	(3)
	ucps	0.855***	0.863***	0.840***
		(0.00134)	(0.00126)	(0.00108)
Music genre	ucps*classical	1.155***	1.150***	1.131***
		(0.00197)	(0.00168)	(0.00143)
	ucps*electro	0.962***	0.946***	0.942***
		(0.00111)	(0.000997)	(0.000892)
	ucps*jazz	1.042***	1.045***	1.040***
		(0.00162)	(0.00145)	(0.00125)
	ucps*latin	1.022***	1.006***	1.014***
		(0.00171)	(0.00151)	(0.00136)
	ucps*pop	1.049***	1.041***	1.036***
		(0.00117)	(0.00107)	(0.000954)
	ucps*rnb_soul	0.961***	0.948***	0.956***
		(0.00158)	(0.00147)	(0.00133)
	ucps*rock	1.028***	1.018***	1.011***
		(0.00102)	(0.000917)	(0.000814)
	ucps*unknown	1.031***	1.028***	1.036***
		(0.00426)	(0.00367)	(0.00330)
	ucps*rap&hip-hop	0.825***	0.812***	0.820***
		(0.000919)	(0.000831)	(0.000755)
	ucps*other_genre	Ref.	Ref.	Ref.
Artist nationality	ucps*FR	1.146***	1.140***	1.139***
		(0.00103)	(0.000957)	(0.000854)
	ucps*UK	1.024***	1.011***	1.009***
		(0.000984)	(0.000892)	(0.000790)
	ucps*US	0.986***	0.984***	0.986***
		(0.000792)	(0.000711)	(0.000637)
	ucps*other_nationality	Ref.	Ref.	
Artist popularity	ucps*rank1–10	0.900***	0.901***	0.912***
		(0.00391)	(0.00432)	(0.00397)
	ucps*rank11–100	1.021***	1.022***	1.029***
		(0.00201)	(0.00220)	(0.00203)
	ucps*rank101–1k	Ref.	Ref.	
	ucps*rank1k-10k	0.931***	0.921***	0.925***
		(0.000799)	(0.000828)	(0.000744)
	ucps*rank>10k	0.872***	0.883***	0.888***

(*continued on next page*)

Table A3 (*continued*)

	Dependent variable: log(revenue) per song	(1)	(2)	(3)
		(0.000791)	(0.000799)	(0.000718)
Vintage	ucps*frontline	Ref.	Ref.	Ref.
	ucps*backless10	1.036***	1.032***	1.031***
		(0.000847)	(0.000806)	(0.000713)
	ucps*backmore10	1.104***	1.088***	1.083***
		(0.000971)	(0.000909)	(0.000805)
Music label	ucps*digital	1.012***	1.006***	1.008***
		(0.000922)	(0.000836)	(0.000751)
	ucps*indie	Ref.	Ref.	
	ucps*major	1.047***	1.034***	1.030***
		(0.000753)	(0.000686)	(0.000611)
Listening context	ucps*organic	Ref.	Ref.	
	ucps*ug_playlist	0.966***	1.016***	
		(0.000859)	(0.000773)	
	ucps* platform_playlist	0.880***	0.867***	
		(0.00138)	(0.00121)	
	ucps*reco	0.927***	0.899***	
		(0.000996)	(0.000774)	
	Song fixed-effect	Yes	Yes	Yes
	Time fixed-effect	Yes	Yes	No
	N	31, 613,176	34,256,128	52,045,144
	R-square (within)	0.0458	0.0337	0.0242

Notes: Exponentiated coefficients; Standard errors in parentheses clustered at the song level; In such a fixed-effect regression model, any constant variables within every song are redundant and will be omitted. All individual song characteristics variables are thus omitted, and only the interactions remain. The results for the coefficients of the three dummies that account for the vintage of the songs and for the variables that account for the listening context are not omitted since these variables can change over time for the same song. To simplify the presentation of the table, we choose not to report these results.

Column (1): Determinants of the difference in revenue per song between pro-rata and user-centric payment systems eliminating the least popular songs each month (39.3 percent of all the observations that correspond to songs that have been streamed just once by one user during the month and that all together cumulate only 1.3 percent of all streams).

Column (2): Main regression for UCPS (see Table 3) with exclusion of the data from March, April, November, and December 2020 (corresponding to the two lock-down periods of the COVID-19 pandemic in France).

Column (3): Main regression for UCPS (see Table 3) without month dummies.

* $p < 0.05$.

** $p < 0.01$.

*** $p < 0.001$.

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