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On-demand streaming services and music industry revenues — Insights from Spotify's market entry

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ABSTRACT

On-demand streaming services that rely on subscription fees or advertising as a revenue source (e.g., Spotify) are a topic of ongoing controversial debate in the music industry because their addition to the distribution mix entails the risk of cannibalization of other distribution channels (e.g., purchases of downloads or CDs) and might reduce overall revenues. To date, no research has assessed the effect of streaming services on revenue, and whether cannibalization indeed takes place. Our research fills this void and assesses the impact of free and paid streaming services on music expenditures and on total music industry revenue. To this end, we constructed a research design in which we observed a panel of more than 2500 music consumers repeatedly over more than one year. This approach allows us to eliminate individual-specific unobserved effects that may otherwise confound the identification of a cannibalization effect. Our results show that the adoption of a free streaming service as well as the adoption of a paid streaming service cannibalizes consumers' music expenditures. The net effect of paid streaming services on revenue, however, is clearly net positive. In contrast, the net effect of free streaming services on revenue is only positive for consumers who were relatively inactive before the adoption. On the industry level, our findings suggest that the negative effect of free streaming on industry revenue is offset by the positive effect of paid streaming in the context that we analyze. Hence, in the market that we study and under the assumptions that we make, we estimate that the overall effect of streaming on industry revenue is positive.

1. Introduction

Since the rise of digital channels for media distribution, the music industry has undergone a major transformation process, which was characterized by plummeting revenues (Elberse, 2010) and a strong growth in digital sales in recent years (IFPI, 2015). In the wake of these turbulent developments, marketers and academics are searching for viable business models to address the legitimate demand for online music (IFPI, 2015; Papies, Eggers, & Wlömert, 2011; Schlereth & Skiera, 2012; Sinha & Mandel, 2008). The most controversial and intensively debated topic in this industry has recently been and still is the on-demand streaming model (Sisario, 2014). For some industry representatives it represents nothing less than a part of the "music industry's digital revolution" (IFPI, 2015). This business model deviates from the music industry's traditional business model and allows customers to access a comprehensive library during a subscription period rather than purchase individual music products (e.g., CDs or downloads). The streaming service providers (e.g., Spotify, Deezer) earn revenue either by charging a monthly flat fee to consumers

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(i.e., paid streaming service — PSS), or by offering the service free of charge to consumers and, instead, generating revenue through advertising (i.e., free streaming service — FSS).

The consequences of adding streaming channels to the music industry's distribution mix are unclear and a topic of ongoing debate. On the one hand, free streaming in particular could attract new customers who were previously inactive or who obtained music primarily via illegitimate channels. Accordingly, some industry representatives believe that "the presence of access services can expand the whole market" (IFPI, 2012). Streaming services may, for example, be an attractive legal alternative to illegal file sharing (Sinha & Mandel, 2008). Furthermore, music is an experience good that consumers typically want to sample before they purchase to reduce the uncertainty that is associated with unobservable product quality (Chellappa & Shivendu, 2005; Dewan & Ramaprasad, 2012; Nelson, 1970). Hence, free streaming services may serve as a convenient sampling device.

On the other hand, free as well as paid streaming services may appeal to existing customers who then turn to the streaming service and reduce their expenditures in existing channels. This cannibalization will be harmful to the publisher's profits if consumers generate less revenue in the new channel compared to the established channels. In support of this, Edgar Bronfman, the former chairman of Warner Music, noted that "free streaming services are clearly not net positive for the industry" (Youngs, 2010), and Taylor Swift, one of the most successful artists in recent years, questioned the sustainability of the current streaming model and made her entire catalog unavailable for some streaming services (e.g., Spotify in 2014; Sisario, 2014).

In sum, it is unclear whether streaming services are beneficial or harmful for the industry, and the conflicting voices from the industry suggest that the cannibalizing effects of channel additions and their influence on the industry revenue are not well understood. The present research therefore contributes to the literature on channel cannibalization and entertainment marketing by estimating how the shift from a purchase-based model to an access-based model affects the distribution of revenues as well as the overall revenue in the music industry while taking potential cannibalization into account.

Some popular press articles report that adopters of a free ad-funded streaming service "are much more likely to buy music downloads" compared to non-adopters (e.g., Chen, 2013). This type of comparison is confounded by the fact that consumers with a strong affinity to music have a higher probability of both spending money on music *and* adopting a free streaming service, i.e., the preferences for the channels are correlated. We therefore constructed a research design that avoids this problem by relying on longitudinal variation. That is, we obtained access to a large-scale panel of music consumers in the German market and repeatedly interviewed these music consumers over a period of 13 months in 2012 and 2013. We then employ a difference-in-difference approach to estimate the effect of the adoption of streaming services on music purchases, i.e., we assess the changes in consumers' behavior after the adoption compared to the pre-adoption time and relative to non-adopters. The difference-in-difference estimator is a common method for estimating treatment effects in pseudo-experimental settings because it removes time-invariant unobserved individual differences that may be correlated with the adoption decision and the dependent variable (Ailawadi, Zhang, Krishna, & Kruger, 2010; Bronnenberg, Dubé, & Mela, 2010; Wooldridge, 2002). The underlying intuition is that individual differences are relatively stable over time, and potential endogeneity is thus concentrated in the cross-sectional dimension rather than in the time dimension (Ebbes, Papies, & van Heerde, 2011; Leenheer, van Heerde, Bijmolt, & Smidts, 2007), which is controlled for by the estimator.

Our results demonstrate that consumers who adopt a streaming service purchase significantly less recorded music after the adoption, and this cannibalization effect is stronger for paid compared to free streaming adoption. Despite their cannibalistic effect on other channels, we find a positive net effect for paid streaming services on revenue. Free streaming services – in contrast – only positively affect revenue for consumers who previously spent little money on music purchases. Consequently, managers in the industry must expect that demand in other channels will decrease as streaming services proliferate, in particular if paid streaming services become more popular. At the same time, music labels may benefit from this situation because – although the net effect of free streaming services is negative – we find an overall positive effect on industry revenue because the positive effect of paid streaming overcompensates for the negative effect of free streaming. Artists, however, must expect that their established revenue sources lose importance and should therefore have a strong interest in negotiating contracts that adequately reflect revenues from streaming channels.

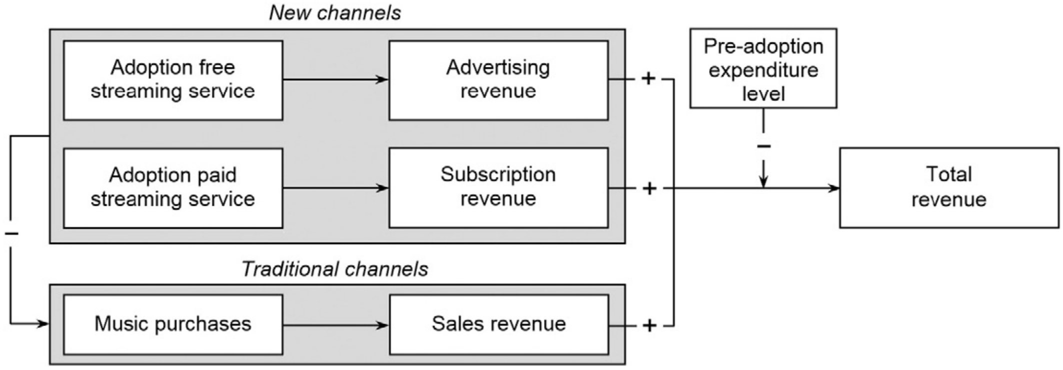

Fig. 1. Conceptual framework.

Next, we describe our conceptual framework. We then discuss our research design and the estimation in Sections 2.2.1 and 3. Section 4 contains the results, and Section 5 the conclusion.

2. Conceptual framework

Consumers in the market for recorded music can obtain music by following the industry's traditional business model, for instance by ordering a CD or by downloading an album at a commercial download store (e.g., Amazon, iTunes). In both cases, consumers purchase an item, and there is no contract beyond the purchase of that particular item. In contrast, consumers nowadays increasingly have the opportunity to stream music, i.e., consumers obtain access to a library of music titles for the period of their membership or subscription. The growing popularity of streaming services (e.g., Deezer, Spotify, Apple Music) is evidence of a paradigm shift in the music industry that – similar to other online service industries – increasingly relies on revenues from access services (Essegaier, Gupta, & Zhang, 2002; IFPI, 2014). Firms that offer such access-based streaming services can earn revenue in two ways: they can charge consumers a subscription fee (e.g., 10 EUR per month), or they can rely on advertising as a revenue source (Halbheer, Stahl, Koenigsberg, & Lehmann, 2014). Many firms (e.g., Spotify, Deezer) use both revenue sources and operate a two-tiered service that simultaneously offers a free ad-based version and a fee-based version (Riggins, 2003). Fig. 1 summarizes how labels and artists can earn revenue from the recorded music market.

Our main goal is to investigate how the new set of distribution channels (i.e., free ad-based and paid streaming services) affects the revenue that record companies and artists can earn. To decompose the total effect of streaming services on revenue, it is necessary to first consider to which extent streaming services affect expenditures in other channels.

2.1. Direct effect on expenditures in other channels

Music is an experience good whose true utility is only revealed to the consumer after it has been consumed. Hence, consumers need to sample music prior to purchase (Dewan & Ramaprasad, 2012; Holbrook & Hirshman, 1982; Lal & Sarvary, 1999). On the one hand, one can argue that the increased convenience of sampling through streaming services will strengthen the relationship between consumers and their preferred artists. This may make it more likely that consumers will purchase music. This argument suggests that there may be a positive effect of streaming on music purchases.

On the other hand, other theoretical arguments suggest a cannibalistic effect on purchases in other channels. Previous research on channel choice in the entertainment industry has argued from a utility theory perspective (Bhattacharjee, Gopal, Lertwachara, & Marsden, 2006; Hennig-Thurau, Henning & Sattler, 2007). Similarly, one can conceptualize the choice of how to obtain and enjoy music as a trade-off between costs and benefits (Konus, Neslin, & Verhoef, 2014). Following this reasoning, a consumer, when confronted with the choice between streaming, purchasing, or forgoing the opportunity to obtain an album or a song, will opt for the alternative with the highest expected net utility or the highest benefit (Prasad, Mahajan, & Bronnenberg, 2003; Schoemaker, 1982). This utility maximization perspective suggests that if obtaining and consuming music through streaming services is perceived as a close enough substitute for purchasing music products, the streaming channel will displace sales from traditional channels to the extent that consumers now rely on a streaming service instead of purchasing music products to fulfill their consumption needs. Several arguments suggest why streaming services offer a higher utility compared to traditional distribution channels for some consumers. For example, they offer easy access to a comprehensive music library and alleviate consumers from the often tedious task of storing music files and transferring them between devices. Further, consumers can conveniently discover and share music (e.g., through public playlists and recommendation engines). For ad-funded services, these features are free of charge. If they offer sufficient utility to consumers, they may not see the need to purchase music via CDs or downloads. This argument suggests that there should be a negative (i.e., cannibalistic) relationship between the adoption of a streaming service and music sales.

Similar to our theorizing above, previous research has weighed theoretical arguments regarding sampling and utility maximization (e.g., Bhattacharjee et al., 2006; Hennig-Thurau, Henning and Sattler, 2007). Empirical evidence, however, for sampling when consumers choose between different channels for recorded music is weak (e.g., Danaher, Smith, & Telang, 2013).

While we expect a cannibalistic effect for free *and* paid services, we expect this negative impact to be even stronger for paid streaming services because the expenditures for such services compete against expenditures in other channels for consumers' limited budgets. That is, consumers who pay a monthly subscription fee for a service may not be able to justify a constant level of expenditures in other channels. Therefore, in sum, we expect that adopting a streaming service cannibalizes demand from other channels, and we expect this cannibalization effect to be stronger for the paid streaming channel.

2.2. Total effect on revenue

Our main research aim is to analyze the effect of the new set of channels on the total music industry revenue. As shown in Fig. 1, streaming services generate revenue through advertising and subscription fees that may offset potential cannibalization effects that arise for consumers who purchased music before the adoption.

For the case of *free streaming services*, we argue that a consumer's usage of a free service reflects the utility that s/he derives from the service. Because the revenue labels receive from free streaming services depend on the number of songs (streams) a consumer listens to, we expect that the higher the utility a consumer derives from a free streaming service, the higher the payouts that the streaming service makes to labels. Hence, the net effect of *free* streaming services will depend on the utility consumers derive from the service. Accordingly, our focal dependent variable (total revenue) captures the revenue that is generated through the usage of a free streaming service.

The net effect on the industry level, however, also depends on the streaming services' potential to attract new, previously inactive customers because the adoption made by these consumers does not lead to cannibalization. We argue that *free* streaming services are particularly likely to re-activate consumers who may have been inactive in the past because, e.g., prices for music exceeded their willingness-to-pay. If streaming services appeal to these consumer types, the net effect of streaming services will be positive for these consumers. Previous research suggests that this is particularly likely if consumers are no longer able to justify the use of illegal file sharing when legal and free alternatives are available (Papies et al., 2011). Based on these arguments we expect that *free* streaming services compensate for at least some of the losses that they generate in other channels, but we do not have a clear prediction of whether the net effect of free streaming adoption will be positive or negative.

Following the utility argument, one can expect that consumers adopt a *paid* streaming service if the expected utility exceeds the price they have to pay. This consumer decision then creates a constant stream of revenue of substantial magnitude. Although we expect substantial cannibalization effects due to the adoption, we expect that revenues from paid streaming over-compensate for the reduction in expenditures in other channels. The reason is that consumers often make the decision in favor of a “flat-rate” type of payment model despite the fact that they would be economically better off if they opted against the flat-rate. Previous research coined this phenomenon the “flat-rate bias” (Lambrecht & Skiera, 2006). Reasons for this flat-rate bias include the consumers' desire to reduce fluctuations in recurring expenditures and the overestimation of future use of a service. Because this type of behavior has been observed in other markets, we expect a similar behavior in the market for music access services. Hence, we expect that the net effect of paid streaming adoption on revenue will be positive.

One critical factor that determines whether the effect on revenue is positive or negative are contractual arrangements between labels and streaming services. When we assess the total effect on industry revenue, we will investigate to which extent the effect depends on assumptions one makes regarding the payments made to labels.

2.2.1. Moderating effect of pre-adoption expenditure level

We argue that a consumer's contribution to total revenue will depend on her level of activity in traditional music distribution channels prior to the adoption decision. On the one hand, streaming services may attract inactive users who usually do not purchase any music. This “re-activation” will generate revenue for labels without any cannibalization. The net effect may also be positive for users with low levels of expenditures because the cannibalization can be easily offset by the payouts that the streaming services make to labels. Similarly, consumers who relied on illegal piracy channels before adopting a streaming service will generate income for the industry after the adoption; e.g., Papies et al. (2011) find that free streaming services may attract consumers who would otherwise use no commercial music services.[2] On the other hand, active consumers who buy multiple albums per month only need to cut their expenditures by one album, and the total effect may well be negative. Hence, we expect that the total effect of adopting a streaming service on revenue will be negatively moderated by the pre-adoption expenditure level such that the net effect will be positive for consumers with low pre-adoption expenditure levels and negative for consumers with high pre-adoption expenditure levels.

3. Research design

3.1. Data collection

When one observes that the increase in demand from one channel (say, a free streaming services) is positively correlated with demand from another channel (say, CDs), one could conclude that these two channels are complements. However, this correlation may merely be a correlation in preferences that is due to an unobserved variable that drives demand in both channels (Gentzkow, 2007). We therefore use a research design that allows us to utilize the within-person variation to identify the effect of streaming service adoption on music purchases and revenue. To this end, we conducted a panel survey, in which we repeatedly interviewed the same respondents between January 2012 and February 2013 regarding their music expenditures and listening behavior. We recruited respondents via the online consumer panels of three major media distributers that are active in Germany, which is one of the four largest markets for recorded music worldwide (IFPI, 2013). These online panels are designed to keep track of developments in the media consumption of music consumers. In total, we conducted nine surveys during the observation period.[3]

Almost three months after the first survey, the largest international music streaming service at that time (Spotify) entered into the German market, just before the third survey (in March 2012). Until then, only a small number of consumers used streaming services (BVMI, 2012).[4] Although some rumors regarding a possible market entry started circulating two weeks prior to the launch date, the exact timing remained confidential until one day before the launch, which was also when the press started reporting about the imminent launch. The press reports and Spotify's advertising campaign generated momentum and ensured public

[2] While Papies et al. (2011) provide information on the potential effects of free streaming services, they cannot quantify the cannibalization effect and the net effect on revenue. In this respect, the current research makes a contribution above and beyond existing research. Further, they analyzed behavioral intention (choice) when the streaming market was still in its infancy, and consumers had no experience with the product.

[3] A comparison of our data with external market research data can be found in Table 1, which will be discussed in the next section in more detail.

[4] Streaming revenues amounted to only 1.7% of the industry's total revenues in 2011 (BVMI, 2012).

awareness around the launch of the service.[5] Therefore, this market entry is a unique quasi-experimental shock to the market that makes it more likely for consumers to adopt a streaming service and thus induces variation in our focal independent variables.

In each of the nine surveys, respondents indicated their expenditures, respectively, on physical music products (e.g., CDs or vinyl), downloads from commercial download stores (e.g., iTunes), and paid music subscription services (e.g., Napster) over the past 30 days. This approach, asking respondents about their spending behavior, is comparable to the consumer expenditure survey (e.g., Du & Kamakura, 2008) and has been used in previous research (e.g., Lohse, Bellman, & Johnson, 2000). To minimize response error, we provided explanations for each channel (e.g., brand names of the most important players in each channel).

The payments from streaming services to labels depend on the number of songs that are streamed by consumers. We therefore asked the participants how many hours they had spent listening to music via the respective services over the past seven days. To facilitate ease and accuracy in answering these questions, we provided detailed explanations and the brand names of all relevant services. Furthermore, respondents indicated their weekly usage levels via easy to use sliders in increments of 30 minutes.

To ensure that our variables are not affected by systematic biases that may arise because of self-reported measures, we made sure that respondents were unaware of which variables were of particular interest to us (i.e., we did not ask respondents directly for the adoption of a streaming service, but inferred it from their answers). Further, as we will explain below, our estimation approach allows us to eliminate unobserved individual factors, such as the potential inclination to over- or underreport.

3.2. Variable definitions

3.2.1. Streaming service adoption

The focal independent variable is the adoption of a free or paid streaming service. If respondent i indicated that she had used a (free or paid) streaming service (e.g., Spotify) in the tth month of the survey, we counted this respondent as an adopter of a free streaming service, i.e., ($D_{it}^{FSS} = 1$), or paid streaming service ($D_{it}^{PSS} = 1$), respectively. Note that we provided the brand names of all free and paid streaming services that were available in the market during each survey to avoid consumers providing inaccurate answers. Hence, this variable does not only capture the adoption of Spotify, but any other streaming service in the market.

3.2.2. Monthly expenditures

We added up all expenditures for music across channels per respondent to obtain the dependent variable required to assess cannibalization through streaming services, i.e., the total expenditures of consumer i for music purchases in month t, which we denote as E_{it}. As we estimate the effect of streaming adoption on expenditures in other channels, we excluded expenditures for paid streaming from this dependent variable.

3.2.3. Total revenue

Our main contribution pertains to the net effect of streaming adoption on revenue when the revenue that streaming services generate is taken into account. We therefore define a variable that captures the revenue that a consumer contributes to labels' and artists' revenue when she adopts and uses a streaming service. Although the detailed arrangements of revenue sharing are part of confidential contracts between labels and streaming services, we reconstructed the key elements of how labels and artists obtain revenue from streaming services from publicly available sources (e.g., Ingham, 2015; Jones, 2015; Singleton, 2015) and validated these in conversations with industry representatives. In general, ad-funded streaming services pay royalties to music labels on a per-stream basis. Publicly available sources suggest that the payout that labels typically receive for ad-supported streaming is around \$1 per 900 streams, i.e., approximately 0.001 EUR per stream (Jones, 2015).[6] To obtain an estimate of revenue generated through *free* streaming, we divided the time (in minutes) in which a respondent used free streaming services in a given month by the average song length (3.5 min), and multiplied the resulting number of plays by a payout of 0.001 EUR. For *paid* streaming services, consumers pay a subscription fee (e.g., 10 EUR per month). It is common that the streaming service pays a part of this subscription fee to the music labels to ensure a minimum payout. We follow industry sources and use 50% of consumer expenditures for streaming services as a consumer's revenue contribution from paid streaming (70% of the price that is net of taxes; Ingham, 2015).

These calculations for streaming services consider the *revenue* that consumers contribute to the music labels by using a streaming service. To make consumer *expenditures* comparable to these revenue contributions, we have to consider that only a part of the expenditures that consumers make in other channels are revenue for music labels. We therefore deduct an average retailer margin of 30% from expenditures consumers make for music purchases to obtain revenue from other channels. We then compute the total revenue contribution from respondent i at time t (R_{it}) as the sum of (1) revenue from music purchases, (2) revenue from free streaming services, and (3) revenue from paid streaming services.

[5] Data from Google Trends that reflect public awareness of the service indicate a sharp increase in search volume at the launch date in Germany while the search volume prior to the launch was very low (see Appendix A).

[6] We note that other sources cite different payout rates. For example, a recently leaked contract between Sony Music and Spotify suggests a payout of \$0.00225 per ad-funded stream. However, our conversations with industry representatives revealed that the actual payout rate is lower (around 0.001 EUR per stream), which has also been publicly confirmed by the CEO of Sony Music in a recent interview (Jones, 2015). Because payouts may vary between labels and over time, we conduct sensitivity analyses that use different payout rates to establish under which conditions we can expect certain net effects.

Table 1
Descriptive statistics of model variables.

Variable	Description	Mean	SD	Min	Max
$\log R_{it}$[a]	Log of monthly total revenue from purchases, free and paid streaming at time t for respondent i	1.83	1.57	0	5.79
$\log E_{it}$[b]	Log of sum of monthly expenditures excluding paid subscriptions at time t for respondent i	2.18	1.70	0	6.14
D_{it}^{FSS}[a]	= 1 if a FSS is adopted at time t by respondent i, 0 else	0.06	0.24	0	1
D_{it}^{PSS}[a]	= 1 if a PSS is adopted at time t by respondent i, 0 else	0.01	0.11	0	1
$\text{Log}\overline{E}_i$[a]	Log of mean expenditures across the first two observations in the panel for respondent i	2.68	1.51	0	5.46

[a] N = 2224, number of observations: 20,016.
[b] N = 2058, number of observations: 18,522.

3.2.4. Pre-adoption expenditure level

We follow previous research and use the first time periods from our panel as a calibration period (e.g., Konus et al., 2014) and define each respondent's average monthly expenditures for music in the first two waves of the panel, when the focal streaming service was not yet available in the market, as the pre-adoption expenditure level ($\overline{E}_i$). All remaining periods then serve as the estimation period in models that utilize this variable. Table 1 contains the model variables and descriptive statistics.

3.3. Sample

We invited all members of the respective online access panels to participate in a series of surveys. Respondents who participated in all of the surveys received a CD of their choice as an incentive at the end of the final survey and participated in a lottery with additional prizes (e.g., mobile music players). A total of 2756 respondents completed all nine surveys.[7] To ensure that our results are not contaminated by inaccurate answers, we excluded the following cases. First, we deleted 137 respondents who reported unrealistically high expenditures over the observation period, using the highest fifth percentile as the cutoff. After consultation with industry experts, we excluded these respondents as outliers who most likely provided wrong answers or did not purchase for private use. Second, we asked respondents at two different times during the observation period (in the sixth and ninth wave) whether they felt that they had provided accurate answers to our questions in the respective questionnaires. We made it clear that providing fully honest answers to these control questions was vital for the validity of the study results and that the answer to these questions would have no influence on the participation reward. We dropped 132 (89) respondents who provided answers below the eighth category on a 11-point rating scale from 0% (only random answers) to 100% (always fully accurate) in the sixth (ninth) survey. Third, we excluded 174 respondents, who had already adopted a streaming service before the first survey. This is recommended when applying a difference-in-difference estimator because for these consumers we cannot observe the behavioral change (Wooldridge, 2002, p. 283).[8] Finally, for estimating the effect on expenditures, we excluded 166 cases with no variation in the dependent variable (i.e., those who never spent during the observation period). This approach leaves us with a valid sample of 2058 respondents to assess the effect on expenditures in other channels and 2,224 cases to assess the effect on revenue. Note that dropping any of the sample restrictions does not alter the conclusions of our study.

Table 2 shows that our sample is very similar in terms of key demographic variables compared to the entire German music buyer population (BVMI, 2013). However, it shows a somewhat higher affinity to music consumption (time spent listening to music and music expenditures), which is not surprising because the participants were recruited via media distributors panels, which consist of highly involved music consumers. According to the IFPI, these consumers are intensive music buyers, who represent the most important consumer group that accounts for almost 50% of the music industry's overall revenue in Germany (BVMI, 2015). We provide additional descriptive statistics for our model variables in Table 1.

3.4. Validation of the quasi-experimental approach

Table 3 displays the development of streaming service adoption over time. The figures show that 27.3% of all respondents (i.e., 654 participants) at some point adopted a free streaming service. Paid streaming services are adopted less frequently, with an overall adopter rate of 7.3% among the survey participants (i.e., 175 participants). Thus, the share of paying customers is approximately 21% (i.e., 175/829). This figure represents a realistic ratio of paying to non-paying users in the "freemium" business model, in which the average paid user share was found to be 24% across different industries (Mulligan, 2013).

Similar to other field studies (e.g., Bronnenberg et al., 2010), it is impossible to assign respondents randomly to treatment and control conditions. Rather, some respondents choose to adopt a streaming service while others do not. To assess whether adopters fundamentally differ from the control group of non-adopters, we compared both groups on several key variables (Bronnenberg et al., 2010). We used information from the first survey to compare those who adopt at some later point with those who never adopt during the observation period. In some cases, the comparisons (i.e., t-tests and Wilcoxon rank sum tests) indicate differences for the absolute values of variables. In all cases, however, these differences are removed by taking first-differences (Table 4). Hence, the groups on which we will base our analysis later do not significantly differ in their key variables, which we view as reassuring.

[7] In Appendix B, we show that panel attrition is not a reason for concern.
[8] One can also argue that it is important to keep these early adopters in the sample (we thank an anonymous reviewer for making us aware of this interpretation). We will therefore report our results also for a sample that contains those respondents who had already adopted in the first period.

Table 2
Comparison of sample with population of music buyers.

Variable	German music market	Sample[a] M	Sample[a] SD
Age (mean)	38[b]	37	12.00
Gender (male)	60%[b]	57%	0.49
Music listening (hours:min per day)	3:42[c]	3:58 (3:11)[d]	3:02
Monthly music expenditures (EUR)	4.66[b]	23.21 (12.99)[d]	32.90

[a] N = 2398. Refers to the valid cases in our sample including the group of non-spenders and participants who adopted a FSS in the first survey.
[b] BVMI (2013).
[c] Van Eimeren and Frees (2012); excludes digital music.
[d] Number in parentheses is the median.

4. Analysis

4.1. General estimation approach

Our identification strategy exploits the panel structure of our data to identify the effect of streaming adoption on music expenditures and revenue contribution, respectively. The main identifying assumption is that unobserved preferences that are related to the adoption behavior as well as the spending behavior in other channels are relatively stable, in particular over the time period that we analyze. Our point of departure is the following baseline model:

$$Y_{it} = \beta_i + \xi_t + \delta D_{it} + \varepsilon_{it} \tag{1}$$

where Y_{it} represents the expenditures for music products (revenue contribution) of individual i in period t. β_i and ξ_t are individual and time intercepts, respectively, and ε_{it} is the idiosyncratic error. D_{it} denotes the adoption of a streaming service by respondent i at time t. The main goal of our analyses is to obtain a consistent estimate of δ, which is the effect of the adoption of a streaming service on expenditures and revenue. We deploy a difference-in-difference estimator that removes the individual intercept by taking the difference for each individual between adjacent periods, such that:

$$\Delta Y_{it} = \xi_t + \delta \Delta D_{it} + \Delta \varepsilon_{it} \,, \tag{2}$$

where $\Delta Y_{it} = Y_{it} - Y_{i,t-1}$, $\Delta D_{it} = D_{it} - D_{i,t-1}$, and $\Delta\varepsilon_{it} = \varepsilon_{it} - \varepsilon_{i,t-1}$. By removing the individual effects through first differencing, we obtain a consistent estimator under the assumption that there are no time-variant omitted variables contained in the error ε_{it} that are correlated with D_{it}. Our model accounts for general individual differences, e.g., heterogeneous probabilities to adopt, heterogeneous preferences for digital music, or different tastes in music. To account for time-varying shocks that are homogenous across the sample, we include a time-specific intercept ξ_t (Bronnenberg et al., 2010; Wooldridge, 2002, p. 284). This difference-in-difference estimator is a standard estimator to assess the effect of policy changes (e.g., Ailawadi et al., 2010; Bronnenberg et al., 2010; Wooldridge, 2002, p. 283) or treatments when a true experimental manipulation is not feasible.

4.2. Streaming service adoption and music expenditures

To obtain an estimate for the effect of the adoption of a streaming service on music expenditures, we use the log of the monthly music expenditures as the dependent variable, $\log E_{it}$. Taking the log has the advantage that δ (the effect of the streaming service adoption) can be interpreted as a percentage change in spending. We therefore estimate:

$$\Delta \log E_{it} = \xi_t + \delta_1 \Delta D_{it}^{FSS} + \delta_2 \Delta D_{it}^{PSS} + \varepsilon_{it}, \tag{3}$$

where ΔD_{it}^{FSS} (ΔD_{it}^{PSS}) denotes the adoption of a free (paid) streaming service.

Table 3
Streaming service adoption rates.

	t1	t2	t3	t4	t5	t6	t7	t8	t9
Absolute FSS[a]	4.7%	5.7%	9.2%	8.7%	8.1%	8.0%	10.0%	9.5%	9.8%
Cumulative FSS[b]	4.7%	8.0%	14.0%	16.7%	18.8%	20.5%	23.9%	25.7%	27.3%
Absolute PSS[a]	2.9%	2.9%	2.9%	2.8%	3.0%	3.6%	3.7%	4.0%	4.3%
Cumulative PSS[b]	2.9%	3.6%	4.2%	4.8%	5.3%	5.9%	6.5%	6.9%	7.3%

Notes. Percentages are based on all valid cases in our sample including the group of non-spenders and participants who adopted a FSS in the first survey (N = 2398).
[a] Refers to the percentage of respondents that used the respective streaming service in a given period.
[b] Refers to the cumulative share of respondents that used the respective streaming service at least once up to a given time period.

Table 4
Comparison of streaming service adopters with non-adopters.

Variable	Non-adopters Mean (SD)	FSS adopters Mean (SD)	PSS adopters Mean (SD)	t-Test FSS t (p)	t-Test PSS t (p)	Wilcox. FSS z (p)	Wilcox. PSS z (p)
Expenditures (Euro per month)	39.09 (43.00)	38.19 (40.47)	45.55 (44.14)	0.041 (0.683)	−1.390 (0.165)	−0.178 (0.858)	−2.012 (0.044)
ΔExpenditures (Euro per month)	−11.40 (36.99)	−9.62 (33.47)	−13.604 (31.75)	0.944 (0.345)	.556 (0.578)	0.432 (0.666)	0.904 (0.366)
Digital usage (hours per week)	11:02 (14:38)	16:07 (17:08)	14:58 (13:55)	6.405 (0.000)	2.447 (0.015)	7.736 (0.000)	4.021 (0.000)
ΔDigital usage (hours per week)	−0:12 (13:11)	0:16 (17:39)	−0:48 (13:17)	−0.626 (0.531)	0.417 (0.677)	−0.504 (0.614)	0.171 (0.242)
Physical usage (hours per week)	7:22 (9:52)	6:58 (9:49)	5:39 (6:20)	0.783 (0.434)	.642 (0.101)	.824 (0.068)	0.995 (0.320)
ΔPhysical usage (hours per week)	−0:55 (8:51)	−0:20 (10:10)	−0:31 (6:47)	−1.246 (0.213)	−0.435 (0.664)	−1.291 (0.197)	−0.408 (0.683)

5. Streaming service adoption and total revenue

To assess the net effect of streaming service adoption on revenue, we rely on $\log R_{it}$ as our dependent variable, which is the log of the sum of consumer expenditures, revenues from free ad-based streaming services, and revenues from paid streaming services for a consumer i at time t, as defined in Section 2.2.1. Furthermore, the conceptual framework proposes that the total effect on revenue is moderated by the consumers' pre-adoption level of music expenditures. The estimation therefore considers interactions between the adoption variables and each consumer's baseline expenditure level:

$$\Delta \log R_{it} = \xi_t + \delta_1 \Delta D_{it}^{FSS} + \delta_2 \Delta D_{it}^{PSS} + \beta_1 \log \overline{E}_i \Delta D_{it}^{FSS} + \beta_2 \log \overline{E}_i \Delta D_{it}^{PSS} + \varepsilon_{it}, \tag{5}$$

where $\overline{E}_i$ denotes the mean expenditure level of consumer i in the first two periods. We estimate (5) on a larger number of respondents (N = 2224) because this analysis considers also those respondents who have not purchased at all.

6. Results

6.1. Streaming service adoption and music expenditures

Table 5 displays the estimation results. Model 1 shows the effects of streaming service adoption on expenditures in other channels. Although the standard errors around the estimates are substantial, both the adoption effects for free and paid streaming are significant at the 5% level and have a negative sign ($\delta_1 = -0.114$, $p < 0.05$; $\delta_2 = -0.274$, $p < 0.05$). The magnitude of the coefficient for δ_1 implies that the adoption of a free service reduces the expenditures for recorded music products from other channels by 10.8%.[9] As expected, consumers who adopt a paid service reduce their expenditures in other channels to an even larger extent, i.e., δ_2 suggests a cannibalization by 23.9% due to the adoption of a paid streaming service.[10]

In sum, these results provide an indication that streaming services cannibalize demand from other channels because those users who adopt spend significantly less on music products after the adoption compared to the control group of non-adopters, i.e., consumers treat streaming services as a substitute to music purchases.[11]

6.2. Streaming service adoption and total revenue

To assess whether the negative effect of cannibalization may be compensated by revenue from streaming services, the estimation results reported in Model 2 (Table 5) rely on $\log R_{it}$as the dependent variable, which is the sum of consumer expenditures, revenues from free ad-based services, and revenues from premium streaming.

In contrast to the analysis in the previous section, the main effect for free streaming adoption is negative but insignificant ($\delta_1 = -0.022$, $p > 0.05$). This finding suggests that – although free streaming services cannibalize demand from other channels – the revenue that the services generate has the potential to largely offset this cannibalization effect. In addition, we observe a significant interaction effect with the pre-adoption expenditure level for free streaming adoption ($\beta_1 = -0.076$; $p < 0.01$). The negative sign of the interaction implies that with increasing pre-adoption expenditure levels, the adoption effect becomes increasingly

[9] The effect is calculated as follows (Halvorsen & Palmquist, 1980): the log multiplier −0.114 of δ_1 corresponds to a percentage change of $100 * [\exp(-0.114) - 1] = -10.8\%$.

[10] While we cannot estimate the initial adoption effects for the early adopter who had already adopted before our first survey, including this potentially important consumer group in the estimation sample leads to similar estimates and does not influence the conclusions (i.e., $\delta_1 = -0.0767$, $p < 0.10$; $\delta_2 = -0.2413$, $p < 0.05$).

[11] When re-estimating Eq. (3) using the adoption of other web-based, free music consumption channels as the independent variables (e.g., online radio with non-interactive programming), we fail to identify a cannibalistic effect for these less convenient services, which is face valid and increases our confidence in the effects we find (Appendix C).

Table 5
Estimation results.

Model	Model 1		Model 2	
	ΔLog of monthly expenditures		ΔLog of revenue per customer	
	Est. (se)	*p* (CI)	Est. (se)	*p* (CI)
ΔFSS adoption (δ_1)	−0.114	0.014	−0.022	0.624
	(0.049)	(−0.205/−0.023)	(0.045)	(−0.110/0.066)
ΔPSS adoption (δ_2)	−0.274	0.023	0.430	0.004
	(0.120)	(−0.510/−0.038)	(0.123)	(0.190/0.670)
ΔFSS adoption × expenditure level (β_1)			−0.076	0.010
			(0.029)	(−0.133/−0.018)
ΔPSS adoption × expenditure level (β_2)			−0.043	0.660
			(0.097)	(−0.232/0.147)
Time period fixed effects	Yes		Yes	
No. of respondents	2058		2224	
No. of observations	16,464		13,344	

Note: Difference-in-difference estimator.

negative such that for consumers with high expenditure levels, the adoption effect of free streaming services is negative, even when advertising revenues are considered. This finding provides support for our expectation that the adoption effect will be stronger for intensive buyers, for whom the cannibalization potential is higher. In contrast, for consumers with low (or no) pre-adoption expenditures, the adoption of a free streaming service has a strong positive effect on revenue. This finding is in line with our expectation that free streaming services may re-activate consumers who have not been purchasing music. Through their usage of the free streaming service, they generate new (advertising) revenue. The same reasoning applies to low-volume consumers, who generate more revenue through their usage of a free streaming service than they would have spent through music purchases. Furthermore, the free streaming service may appeal to consumers who mostly (or only) relied on illegal piracy channels before and shift their preferences towards a legitimate service. Fig. 2 shows the interaction between adoption and expenditure level and displays the marginal effects over different levels of pre-adoption expenditures.

For paid streaming, we find a substantial positive direct effect of adoption ($\delta_2 = 0.430$, $p < 0.01$). This finding implies that although the adoption cannibalizes demand from other channels, the subscription fees outweigh the cannibalization effect, which is in line with our expectations. Furthermore, we do not find a significant interaction between the adoption and the pre-adoption expenditures, which means that the effect is substantial and positive, regardless of pre-adoption expenditure levels ($\beta_2 = -0.043$; $p > 0.10$).[12]

6.3. Aggregate level prediction and external validation

So far, we have focused on the effects of streaming service adoption on consumer-level revenue. However, to make tentative inferences about the overall monetary consequences that streaming services have on the industry, we complement our individual-level parameter estimates from the previous analyses with an aggregate-level revenue equation on the industry level. Consistent with our previous analyses, we differentiate between four different groups of consumers. (1) We distinguish between adopters of free and paid streaming services, respectively. (2) For each service, we calculate the monetary effect for the group of previously inactive consumers and previously active consumers separately. The reason is that – as our analyses revealed – previously inactive adopters are particularly profitable for the industry because this group generates income without cannibalizing expenditures. For previously active consumers, in contrast, streaming services are a double-edged sword because they not only generate income but also cannibalize expenditures for music products.

Eq. (6) summarizes our approach, and our results are presented in Table 6:

$$\Delta Revenue = \widetilde{ad}^{FSS}_{inactive} \times \overline{R}^{FSS}_{inactive} + \widetilde{ad}^{PSS}_{inactive} \times \overline{R}^{PSS}_{inactive} + \widetilde{ad}^{FSS}_{active} \times \overline{R}^{FSS}_{active} + \widetilde{ad}^{PSS}_{active} \times \overline{R}^{PSS}_{active} + \widetilde{ad}^{FSS}_{active}\left(\delta^{FSS}_{active} \times \overline{E}\right) + \widetilde{ad}^{PSS}_{active}\left(\delta^{PSS}_{active} \times \overline{E}\right). \quad (6)$$

To estimate the change in aggregate (market) level revenue ($\Delta Revenue$), we proceed as follows. We multiply the share of previously inactive adopters from our sample, i.e., 14% (9%) for the free (paid) streaming service, by the number of adopters of free and paid on-demand streaming services in the German market in 2014, when 6.4 million (1.4 million) people had used a free (paid) streaming service (BVMI, 2015), i.e., we estimate that $\widetilde{ad}^{FSS}_{inactive} = 896{,}000$ ($\widetilde{ad}^{PS}_{inactive} = 126{,}000$) of the free (paid) streaming adopters were inactive, while the remaining $\widetilde{ad}^{FSS}_{active} = 5.504$ million ($\widetilde{ad}^{PSS}_{active} = 1.274$ million) adopters were active buyers before the adoption.

To calculate the revenue contribution of each group, we use the average monthly revenue ($\overline{R}$; advertising revenue or subscription fees) per user in the respective group from our sample and multiply this value by the number of consumers per group

[12] In the calculation of the dependent variable in Model 2 (total revenue), we make assumptions regarding the retail margin in sales channels (30%) and the labels share of revenues from paid streaming services (50%). To test the sensitivity of our estimates in Model 2 regarding these assumptions, we vary the percentages by +/−10 percentage points and re-estimate Eq. (5). The results are very similar and do not change any conclusions.

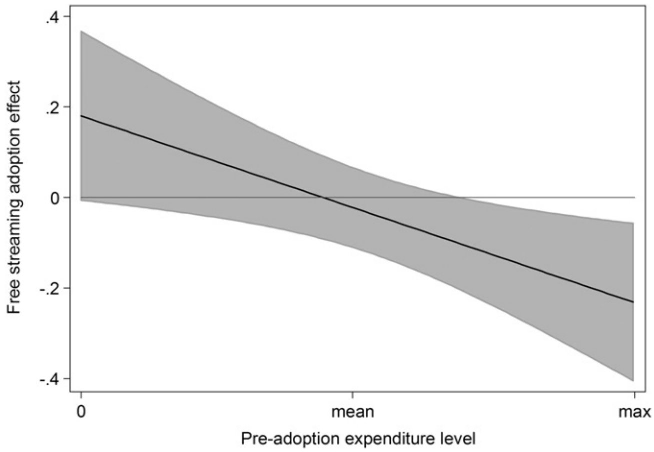

Fig. 2. Interaction of pre-adoption expenditures and free streaming adoption. Note: The black line is the estimated effect of free streaming adoption across different levels of pre-adoption expenditures, the gray area represents the 95% confidence interval.

(summands 1–4 from Eq. (6)). Table 6 shows that, although the group of paid streaming adopters is much smaller compared to the group of free adopters, the revenue that the paid adopters generate (5.8 million EUR) by far exceeds the revenue that free users generate (2.1 million EUR) due to the higher average revenue per user. Overall, we predict that on-demand streaming services generate income of approximately 7.8 million EUR per month. This figure compares well with the observation that free and paid on-demand streaming services generated monthly revenue of 9 million EUR in the German market in 2014 (BVMI, 2015).

Next, we calculate the aggregate level cannibalization due to free and paid streaming adoption for the groups of active adopters (summands 5 and 6 from Eq. (6)) based on the average monthly expenditures of an active music consumer in the German market in 2015 (i.e., $\overline{E} = 5$ EUR; BVMI, 2015). By multiplying the average monthly expenditure with the cannibalization rates (δ^{FSS} and δ^{PSS})[13] that we estimated in our sample for the previously active adopters, it is possible to infer the approximate monthly cannibalization. Table 6 shows that the aggregate market level cannibalization due to the adoption of free streaming (3.9 million EUR) exceeds the cannibalization due to the adoption of paid streaming (1.3 million EUR). When we compare this cannibalization with the revenue that the services generate, it becomes clear that free streaming services are likely to have a negative influence on industry revenue (-1.8 million EUR),[14] while paid streaming services have an overall positive effect on revenue (4.4 million EUR). Thus, because the increase in revenue due to paid streaming overcompensates for the decrease in revenue due to free streaming, the overall monetary effect is positive with an increase of 2.6 million EUR per month, which represents approximately 2.1% of the overall music industry revenue in Germany in 2014.

A direct comparison of this prediction with market level outcomes is not possible because the net effect of streaming service is – as the conflicting voices from the industry that we cite above show – generally unknown and our study provides a first estimate. However, to tentatively assess the validity of the magnitude of our prediction, we compare our estimate with the average monthly market growth in the German market in 2014 (i.e., the difference in total market revenue between 2014 and 2013, divided by 12), which was 2.25 million EUR. This requires the assumption that revenue in the market remained constant, except for streaming induced changes. Our figure of 2.6 million EUR compares well to this monthly growth and suggests that the overall positive effect in the German market in 2014 was to a large extent driven by an increase in streaming revenues (BVMI, 2015).

Because free streaming services tend to have an overall negative effect on revenue, the question arises, what managers can do to increase the profitability of free streaming services. To address this question, we investigate how the overall revenue effect changes when two critical factors in the aggregate-level revenue equation of the free service are changed: (1) the payout rate per stream, and (2) the share of previously inactive adopters. As indicated before, the payout may change over time and vary across labels and countries. We therefore performed a sensitivity analysis and vary the per-stream payout up to a maximum payout of 0.005 EUR.[15] Regarding the share of previously inactive adopters, our analyses above show that free streaming adoption is particularly beneficial for previously inactive consumers. Hence, the share of previously inactive consumers is a candidate for increasing the profitability of free streaming.

Fig. 3 shows the net negative effect of free streaming on overall revenues at a payout rate of 0.001 EUR and the inactive adopter share from our sample of 14%. It can be seen that the profitability increases with increasing payout rates and that to at least break even, the payout rate would need to double to around 0.002 EUR. Interestingly, this amount approximately coincides with the payout rate specified in the leaked contract between Spotify and a major record label, suggesting that if this specified amount was paid, the losses caused by the free streaming service on the labels' side on average would be offset by the ad-

[13] We obtain the cannibalization rates for free and paid streaming by estimating Eq. (3) on the sample of respondents who had spent money on music products in the calibration period (i.e., the previously *active* consumers). We then convert the estimated coefficients for δ_1 and δ_2 to percentage rates.

[14] Note, however, that the main effect of free streaming on overall revenue in Model 2 (Table 5) is insignificant, suggesting that this estimate should be interpreted with caution.

[15] We could not find any source that gives an estimate of larger than 0.005 EUR for ad-funded streaming.

Table 6
Aggregate level prediction.

	Free streaming service			Paid streaming service	
	Inactive	Active		Inactive	Active
User share inactive/active[b]	14%	86%		9%	91%
Overall adopters in DE 2014[a]	6,400,000			1,400,000	
Number of adopters by group	896,000	5,504,000		126,000	1,274,000
Revenue contribution by user/month[b]	0.33€	0.32€		5.14€	4.01€
Revenue contribution by group/month	295,680€	1,761,280€		647,640€	5,108,740€
Overall revenue/month			7,813,340€		
Mean music expenditures DE/month[a]	–	5.00€		–	5.00€
Cannibalization rate[b]	–	14%		–	21%
Cannibalization by user/month	–	−0.70€		–	−1.05€
Cannibalization by group/month	–	−3,852,800€		–	−1,337,700€
Overall cannibalization/month			−5,190,500€		
Net revenue effect/month	−1,795,840€			4,418,680€	
Overall net effect/month			2,622,840€		

[a] BVMI (2015).
[b] This study.

revenue (Singleton, 2015; Jones, 2015). Furthermore, the profit contribution of free streaming increases when a higher share of previously inactive adopters can be attracted and reaches a break even at an inactive adopter share of approximately 50%.

7. Conclusion

7.1. Discussion

This research contributes to the literature by assessing the effect of the adoption of a free or paid streaming service on music industry revenue when taking into account potential cannibalization of other distribution channels and revenue that streaming services generate. To make this contribution, we use a research design, in which we observed a panel of more than 2500 consumers over more than a year. Based on a conceptual framework that shows how labels and artists can generate revenues on the market for recorded music, we estimate the effect of streaming adoption on expenditures and on revenue. Consistently, we find a negative effect of the adoption of free and paid streaming services on consumer expenditures for music in other channels. The magnitude implies that the adoption of a free streaming service reduces expenditures by approximately 11%, while cannibalization due to the adoption of a paid streaming service reduces expenditures in other channels by approximately 24%. These results suggest that consumers rely less on streaming services as a tool for sampling or exploring music that they may later purchase. Rather, on average, the use of streaming services as a substitute for consuming and obtaining music from other channels appears to dominate. This dark picture, however, becomes lighter when one considers revenue generation through streaming services. The adoption of paid streaming services has a significant and substantial positive net effect on revenue. Using a payout rate of 0.001 EUR, we find that the effect of free streaming tends to be negative but insignificant, while it is clearly negative for those users who were active music buyers before the adoption and positive for those who were inactive before the adoption. Our

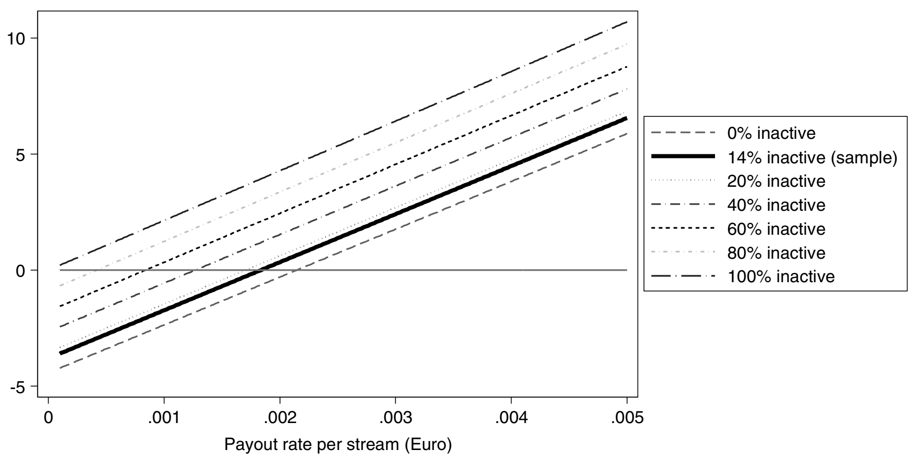

Fig. 3. Sensitivity of aggregate level free streaming adoption effect regarding payout and share of previously inactive adopters.Note: The lines show the estimated monetary net effect of free streaming adoption on aggregate level music industry income across different levels of payout per stream and different shares of previously inactive adopters.

aggregate level calculations suggest that – given the current number of adopters of free and paid streaming services – streaming services are net positive for the industry. This positive effect, however, only occurs because of the strong positive revenue contribution of paid streaming that offsets the net negative impact of free streaming. These findings have important implications for several actors in the market.

7.1.1. Music labels

Our industry-level calculations suggest that the net impact of paid streaming on market revenue is positive, while the impact of free streaming is not. The clear implication from this finding is the recommendation that music labels should focus on paid streaming and ensure that sufficient numbers of consumers choose paid streaming services over free streaming services. If firms are successful in attracting many consumers into the paid streaming model, they can expect the music market to grow due to the substantial revenue contribution of these services. They cannot expect similar growth when active consumers choose the free streaming services instead. Free streaming services are only profitable for consumers who did not spend money on music products before the adoption. Managers should therefore target the business model of free streaming to inactive consumers or those with very low level of expenditures for music. This would for example imply that promotions for free streaming services should not happen where one can expect to meet primarily active music buyers (e.g., music festival, record stores). This should rather be the place to attract consumers into paid streaming.

Firms may also boost the positive effects of streaming through more pronounced product differentiation. The cannibalization effects indicate that the utility consumers derive from streaming is substantial, i.e., streaming suffices as the primary tool for music consumption. Our industry-level predictions further show that free streaming services are net negative because they currently attract also many active music buyers. Therefore, one option is to decrease the utility of the free streaming service, e.g., by reducing the numbers of free hours, limiting the duration of free membership, increasing the amount of advertising, or reducing the amount of free content. Further, one could make the content available in the ad-funded channel with a time delay through windowing (Hennig-Thurau, Henning, Sattler, Eggers & Houston, 2007). We speculate that this may decrease the share of active adopters in the free channel and provide incentives to adopt the profitable paid channel. Recent developments, however, suggest that streaming providers keep increasing the utility of their free versions to attract customers and to enhance the position in the market (e.g., Spotify improved the utility of the free version that now includes mobile use and unlimited hours; Murray-Morris, 2014). This may not be in line with the artists' and labels' interests, who should maintain a stronger focus on the relationships between different channels.

7.1.2. Artists

Traditionally, artists obtain a share of the revenue that originates from the music that consumers purchase (download purchases and CDs). This research finds that revenue from these sources will become smaller as streaming is on the rise. Hence, artists should be strongly interested in negotiating contracts that reflect these shifting weights in revenue sources, i.e., they should strive to negotiate contracts in which the growing relevance of streaming is adequately reflected. Consider the so called "blanket licenses" in which labels license their entire catalog to a streaming service. In these cases, some artists do not receive any payments from streams that are made under this blanket license (e.g., Resnikoff, 2014). Given the cannibalization effect of streaming on music purchases, such a contract would be very disadvantageous for artists. Hence, artists who operate under such a contract should have a strong interest in adequately including streaming revenues into their contracts.

7.1.3. Retailers

Adding the new set of distribution channels leads to a shift in weights in the distribution mix of music labels, which may result in channel conflicts because the labels' activities in the streaming channel are disadvantageous for other channels where consumers might purchase music, such as Amazon or other record stores. Based on findings from this research, these outlets must anticipate a declining relevance and less revenue, and labels may expect conflicts among their distribution channels. Retailers that still operate a purchase-based business model should thus consider to extend their business and offer a streaming channel. Although this step would cannibalize their current business, it would increase their relevance in the future music market.

7.1.4. Managers in adjacent industries

Our study also bears important lessons for other industries (e.g., movies or books) where access services are becoming more prevalent. Specifically, our findings suggest that firms should not expect that consumers use a tool such as free streaming for sampling. Rather, one must expect a displacement of expenditures in other channels. Firms should only use these offers to lock consumers into streaming services and trigger conversions to premium streaming services because – although they cannibalize expenditures from other channels – their net effect on revenue is clearly positive. Hence, firms from other industries should design their streaming offers from the outset such that the free version is clearly inferior to the paid version with the goal of fostering conversion.

7.2. Caveats, limitations, and future research opportunities

By estimating the effects of streaming services on demand in other channels and on total revenue, our research makes an important and implementable contribution to the literature. It is, however, subject to limitations, which open avenues for future research. First, our analysis looks at one of the largest markets for music, but it only considers one country. Second, we conduct our research based on a sample of intensive music buyers. While this group represents the most important consumer group in the German music market, which accounts for approximately 50% of the music industry's revenues, one has to exercise caution when generalizing the findings to all potential buyers. Third, our observation period covers more than one year, and it will therefore contain most respondents' basic reaction to the adoption of the service. However, it would be interesting to assess long-term effects that encompass several years. One could speculate that the degree of cannibalization becomes stronger over time, which would also change the effect of streaming on revenue, e.g., because consumers need to become accustomed to the new service, and once they are accustomed, they may stop purchasing music altogether. Additional analyses (not reported in the paper), however, did not yield a significant interaction between adoption and time of adoption. Fourth, our unit of analysis is the individual consumer and her expenditures for recorded music. It is possible that some artists benefit from streaming services because consumers may learn about new music from new artists, which may lead to an increase in demand in other channels (e.g., for concert tickets). Exploring these spillovers would be a fruitful avenue for future research. Fifth, introducing a free channel may negatively affect the perceived value of the content (e.g., Brynjolfsson, Hu, & Smith, 2003) and reference prices (e.g., Winer, 1986). Hence, the long term cannibalization effect may be stronger than the effect that we find. Future research should investigate the effect of streaming services on these constructs. Sixth, we rely on stated behavior because there is no consumer-level panel that combines purchase data with consumer-level information on the adoption of streaming services, as was confirmed to us by industry representatives. Although our approach of using stated behavior is established, it may be subject to measurement error. Further, our interpretation of the coefficients as causal effects rests on the assumption that unobserved factors that are related to the adoption variable are relatively stable over time. While we believe that this is a realistic assumption, it may be interesting to analyze our research questions in a setting in which this assumption is not necessary. It was our intention to actively induce exogenous variation in the adoption decision by randomly inviting a part of the sample to join a streaming service. We used this variable as well as the interaction between a dummy variable that indicated Facebook membership and a dummy variable that indicated the point in time when Spotify did no longer require a Facebook account for signing up as instruments for the adoption decision. Unfortunately, these were not sufficiently strong (i.e., their impact on the adoption decision was weak), which resulted in large standard errors and a large variability in the estimated coefficients depending on the exact specification. Hence, these are no suitable instruments. Other instruments that fulfilled the necessary requirements (i.e., exogeneity, strength, varying across time and across individuals) were not available to us. We therefore decided not to use instrumental variables in this case, which is in line with renewed calls to use instrumental variables with caution (Rossi, 2014). However, it is important to keep in mind the identifying assumption when interpreting the effects as causal. In addition, it is important to note that – regardless of this assumption – the estimates provide a *prediction* of how the revenue distribution will likely change when streaming services proliferate (Ebbes et al., 2011). Finally, in our sample we were not able to detect significant conversion from free to paid streaming, which may be either due to the relatively short term nature of the data or the utility difference between the free and paid service being too low. Thus, identifying the optimal utility level of free streaming services (e.g., through field experiments) and ways to enhance conversion should be at the top of the music industry's agenda. Despite these limitations, we believe that our research makes a useful contribution to the literature's understanding of how the music market works and how consumers behave in this important entertainment market.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.ijresmar.2015.11.002.

References

Ailawadi, K. L., Zhang, J., Krishna, A., & Kruger, M. W. (2010). When Wal-Mart enters: How incumbent retailers react and how this affects their sales outcomes. *Journal of Marketing Research*, *47*(4), 577–593.

Bhattacharjee, S., Gopal, R. D., Lertwachara, K., & Marsden, J. R. (2006). Impact of legal threats on online music sharing activity: An analysis of music industry legal actions. *Journal of Law and Economics*, *49*(1), 91–114.

Bronnenberg, B. J., Dubé, J. -P., & Mela, C. F. (2010). Do digital video recorders influence sales? *Journal of Marketing Research*, *47*(6), 998–1010.

Brynjolfsson, E., Hu, Y. J., & Smith, M. D. (2003). Consumer surplus in the digital economy: Estimating the value of increased product variety at online booksellers. *Management Science*, *49*(11), 1580–1596.

BVMI (2012). *Musikindustrie in zahlen 2011.* (Berlin).

BVMI (2013). *Musikindustrie in zahlen 2012.* (Berlin).

BVMI (2015). *Musikindustrie in zahlen 2014.* (Berlin).

Chellappa, R. K., & Shivendu, S. (2005). Managing piracy: Pricing and sampling strategies for digital experience goods in vertically segmented markets. *Information Systems Research*, *16*(4), 400–417.

Chen, B. X. (2013). *Apple enters Net radio's busy field.* The New York Times ((accessed January 7, 2014), available at: http://www.nytimes.com/2013/06/10/technology/apple-enters-busy-field-of-streaming-radio.html).

Danaher, B., Smith, M. D., & Telang, R. (2013). Piracy and copyright enforcement mechanisms. In J. Lerner, & S. Stern (Eds.), *Innovation policy and the economy*. *14*, Chicago, IL: University of Chicago Press.

Dewan, S., & Ramaprasad, J. (2012). Music blogging, online sampling, and the long tail. *Information Systems Research*, *23*(3), 1056–1067.

Du, R. Y., & Kamakura, W. A. (2008). Where did all that money go? Understanding how consumers allocate their consumption budget. *Journal of Marketing*, *72*(6), 109–131.

Ebbes, P., Papies, D., & van Heerde, H. J. (2011). The sense and non-sense of holdout sample validation in the presence of endogeneity. *Marketing Science*, *30*(6), 1115–1122.

Elberse, A. (2010). Bye bye bundles: The unbundling of music in digital channels. *Journal of Marketing*, *74*(3), 107–123.

Essegaier, S., Gupta, S., & Zhang, Z. J. (2002). Pricing access services. *Marketing Science*, *21*(2), 139–159.

Gentzkow, M. (2007). Valuing new goods in a model with complementarity: Online newspapers. *American Economic Review*, *97*(3), 713–744.

Halbheer, D., Stahl, F., Koenigsberg, O., & Lehmann, D. R. (2014). Choosing a digital content strategy: How much should be free? *International Journal of Research in Marketing*, *31*(2), 192–206.

Halvorsen, R., & Palmquist, R. (1980). The interpretation of dummy variables in semilogarithmic equations. *The American Economic Review*, *70*(3), 474–475.

Hennig-Thurau, T., Henning, V., & Sattler, H. (2007a). Consumer file sharing of motion pictures. *Journal of Marketing*, *71*(4), 1–18.

Hennig-Thurau, T., Henning, V., Sattler, H., Eggers, F., & Houston, M. B. (2007b). The last picture show? Timing and order of movie distribution channels. *Journal of Marketing*, *71*(4), 63–83.

Holbrook, M. B., & Hirshman, E. C. (1982). The experimential aspects of consumption: Consumer fantasies, feelings, and fun. *Journal of Consumer Research*, *9*(2), 132–140.

IFPI (2012). *Digital music report 2011.* (London).

IFPI (2013). *The recording industry in numbers 2012.* (London).

IFPI (2014). *Digital music report 2013.* (London).

IFPI (2015). *Digital music report 2014.* (London).

Ingham, T. (2015). *Major labels keep 73% of Spotify premium payouts — Report.* Music Business Worldwide ((accessed February 4, 2015), available at: http://www.musicbusinessworldwide.com/artists-get-7-of-streaming-cash-labels-take-46/).

Jones, R. (2015). *Sony music: Doug Morris backs streaming but cools on ad-supported models.* Music Ally ((accessed June 7, 2015), available at: http://musically.com/2015/06/07/sony-music-doug-morris-streaming-midem/).

Konuş, U., Neslin, S. A., & Verhoef, P. C. (2014). The effect of search channel elimination on purchase incidence, order size and channel choice. *International Journal of Research in Marketing*, *31*(1), 49–64.

Lal, R., & Sarvary, M. (1999). When and how is the internet likely to decrease price competition? *Marketing Science*, *18*(4), 485–503.

Lambrecht, A., & Skiera, B. (2006). Paying too much and being happy about it: Existence, causes, and consequences of tariff-choice biases. *Journal of Marketing Research*, *43*(2), 212–223.

Leenheer, J., van Heerde, H. J., Bijmolt, T. H. A., & Smidts, A. (2007). Do loyalty programs really enhance behavioral loyalty? An empirical analysis accounting for self-selecting members. *International Journal of Research in Marketing*, *24*(1), 31–47.

Lohse, G. L., Bellman, S., & Johnson, E. J. (2000). Consumer buying behavior on the internet: Findings from panel data. *Journal of Interactive Marketing*, *14*(1), 15–29.

Mulligan, M. (2013). *Making freemium add up.* Music industry blog ((accessed December 5, 2013), available at: http://musicindustryblog.wordpress.com/2013/05/21/making-freemium-add-up).

Murray-Morris, S. (2014). *Spotify removes time restrictions on free desktop player.* The Independent ((accessed March 7, 2014), available at: http://www.independent.co.uk/life-style/gadgets-and-tech/spotify-removes-time-restrictions-for-desktop-listening-9062361.html).

Nelson, P. (1970). Information and consumer behavior. *Journal of Political Economy*, *78*(2), 311–329.

Papies, D., Eggers, F., & Wlömert, N. (2011). Music for free? How free ad-funded downloads affect consumer choice. *Journal of the Academy of Marketing Science*, *39*(5), 777–794.

Prasad, A., Mahajan, V., & Bronnenberg, B. (2003). Advertising versus pay-per-view in electronic media. *International Journal of Research in Marketing*, *20*(1), 13–30.

Resnikoff, P. (2014). *How streaming services are screwing Lady Gaga (and every other artist).* Digital Music News ((accessed August 8, 2014), available at: http://www.digitalmusicnews.com/permalink/2014/06/10/streaming-services-screwing-lady-gaga-every-artist).

Riggins, F. J. (2003). Market segmentation and information development costs in a two-tiered fee-based and sponsorship-based web site. *Journal of Management Information Systems*, *19*(3), 69–86.

Rossi, P. E. (2014). Even the rich can make themselves poor: A critical examination of IV methods in marketing applications. *Marketing Science*, *33*(5), 655–672.

Schlereth, C., & Skiera, B. (2012). Measurement of consumer preferences for bucket pricing plans with different service attributes. *International Journal of Research in Marketing*, *29*(2), 167–180.

Schoemaker, P. J. H. (1982). The expected utility model: Its variants, purposes, evidence and limitations. *Journal of Economic Literature*, *20*(2), 529–563.

Singleton, M. (2015). *This was Sony music's contract with Spotify.* The Verge ((accessed May 20, 2015), available at: http://www.theverge.com/2015/5/19/8621581/sony-music-spotify-contract).

Sinha, R. K., & Mandel, N. (2008). Preventing digital music piracy: the carrot or the stick? *Journal of Marketing*, *72*(1), 1–15.

Sisario, B. (2014). *Chief defends Spotify after snub by Taylor Swift.* The New York Times ((accessed November 14, 2014), available at: http://www.nytimes.com/2014/11/12/business/media/taylor-swifts-stand-on-royalties-draws-a-rebuttal-from-spotify.html).

Van Eimeren, B., & Frees, B. (2012). Ergebnisse der ARD/ZDF-Onlinestudie 2012. *Media Perspektiven*, *2012*(7–8), 362–379.

Winer, R. S. (1986). A reference price model of brand choice for frequently purchased products. *Journal of Consumer Research*, *13*(2), 250–256.

Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data.* Cambridge, Mass.: MIT Press.

Youngs, I. (2010). *Warner retreats from free music streaming.* BBC (accessed November 27, 2013), available at: http://news.bbc.co.uk/2/hi/8507885.stm.