Competition for Exclusivity and Customer Lock-in: Evidence from Copyright Enforcement in China

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Abstract

Copyright enforcement in China since 2015 has heightened competition among music streaming services for obtaining exclusive licenses. The competition is driven by the existence of multi-homing and switching costs for consumers in choosing among services. I specify and estimate a structural model that allows consumers to tradeoff between multi-homing and switching. I use estimates to simulate market outcomes had a compulsory licensing provision been enforced. I find that with compulsory licensing, the market will evolve to a "tipping" equilibrium in which all users choose to exclusively subscribe to a same service that is of better quality. Although providing more music content, small services would lose significant market shares. This is because multi-homing users of small services would switch away from their services when the music content were less differentiated from others. The result suggests that a compulsory provision does not benefit the small services and may lead to a higher market concentration.

Keywords: Platform Competition, Two-sided Markets, Switching Costs, Multi-homing Costs, Exclusive Content Provision, Music Industry
JEL classification: L13, L42, L51, L82, L86

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1 Introduction

Music streaming is growing around the world, providing ways of legitimate distribution and regaining revenue for the recorded industry. The music streaming market is competitive - as of 2019, more than three hundred services are competing with each other either domestically or internationally [1]. Services compete with one another by negotiating licenses with labels (music producers) in order to get their repertoires distributed via their platform. No two services have the identical music library - a service often has certain content exclusively available on its platform. Why platforms often prefer to use exclusivity is an open question and has been actively addressed in the literature in a wide range of industries. Most of the work has focused on firms' incentives to lock out competitors (i.e. market foreclosure). This paper, however, is studying whether exclusivity can also be used as an alternative strategy to introductory (penetration) pricing. That is, platforms invest heavily in exclusivity early in its life cycle to capture customers until they have established a substantial user base, and then "harvest" from the locked-in customers by raising the price. Platforms might be more likely to do so when consumers' willingness to pay are low but switching costs are high.

Switching costs often incur when a customer switches to a new product or a new service and exist in various important industries, including computer software and hardware, cable television, internet, and telecommunications. Although most prevalent switching costs are monetary in nature, in the case of streaming music, the reason why switching costs arise is most likely because the personalized functions provided by streaming services. As most services offer users personalized music discovery service through learning users' personal tastes, a user who has created personalized playlists and connected with friends on a service has to consider the advantages she/he will forgo when switching to other services. Although exclusive provision, which limits consumers' choice by preventing them from accessing exclusive content of other platforms, makes streaming less appealing to consumers when compared with download services or physical CDs, multi-homing may moderate this issue and it indeed becomes a common practice for having universal access to music. However, multi-homing costs might exist in many instances, which not only include the monetary costs of paying subscription fees, but also include the efforts required to manage playlists across services, remember passwords, periodic logins, and connecting to friends on different platforms.

The development in the Chinese music industry is a good setting to study consumer switching and multi-homing behavior interacting with exclusive provision. The music industry in China has historically been hindered by rampant piracy that has resulted in a lower willingness to pay for music. China's online music services paying ratio was only 3.9% which is significantly lower than that of the other online entertainment formats, such as online video (with a paying ratio of

[1] See https://www.fool.com/investing/2019/03/09/why-did-it-take-so-long-for-spotify-to-turn-a-prof.aspx

22.5% in 2017) and online games (with a paying ratio of 14.1% in 2017).[2] For the past decade, the Chinese government has increased its efforts to enforce copyright protection. Accordingly, streaming music platforms joined such efforts by investing in negotiating licenses with labels and independent copyright owners. The copyright enforcement also led to a heightened competition in the streaming market - fierce price gouging and bidding wars among services for getting exclusive licenses.[3] Tencent became the dominant company standing out from the competition, not only because it has the largest market share - over 40 percent, but also because it owns the largest exclusive content relative to other services. From 2014 to 2017, the company sealed exclusive licenses from Warner Music Group, Sony Music, Universal Music Group, South Korean label YG Entertainment and other domestic labels, artists and independent producers[4]. The company's exclusive album titles increased from less than 10 percent to more 30 percent of its repertoire. Smaller services, on the contrary, have less exclusive content which make up less than 1 percent of their own repertoires.

The first goal of this paper is to estimate switching and multi-homing costs from the aggregate data. To motivate this, I first look into important statistics from the data and reduced form regressions to show that the data is consistent to substantial multi-homing costs and switching costs. I find that multi-homing users are almost doubled from August 2016 to June 2017 indicating that exclusive provision induce multi-homing. I also find that the market share of multi-homing users cannot be explained by independent random choice of each service which suggests the existence of multi-homing costs. From the reduced form regressions, I find that current period exogenous variables affect not only contemporaneous aggregate market shares of services but also future market shares, which implies the existence of switching costs.

I then develop a structural model of consumer service adoption, usage, multi-homing and switching behavior. Consumers are forward looking and face an infinite horizon dynamic problem. That is, they recognize their current decision of adopting services affects not only their contemporary utilities but also their future utilities due to the existence of the switching costs and rapidly changing service characteristics. Within each period, consumers face a two-stage decision problem: they pick which streaming services to subscribe to in stage I and then determine hours spent on each service in stage II. I estimate the model using the aggregate data on monthly active users and aggregate usage time of each service ranging from January 2014 to July 2017. The identification of multi-homing costs is leveraged on overlapped users data that is observed for part of the

[2] According to iResearch's music market report. See Form F-1 Registration Statement of Tecent Music Entertainment Group, available at https://www.sec.gov/Archives/edgar/data/1744676/000119312518290581/d624633df1.htm.

[3] Qijun Zhou & Jing Xuan Teng, Copyright Authority Takes Aim at Exclusive Licenses for Music, Caixin (Sep. 15, 2017, 6:14 AM), https://www.caixinglobal.com/2017-09-15/101145826.html.

[4] Thanks to Streaming Services, China's Consumers Have Begun Paying for Music, The Economist (July 29, 2017), https://www.economist.com/news/21725529-market-dominated-one-company-tencent-biggest-countrys-online-giants.

sample period (August 2016 to June 2017). And I estimate the switching costs by leveraging the dependence of current period aggregate decisions on exogenous variables of the previous period. The intuition is that if switching costs were absent, previous period decisions should be irrelevant for current period choices.

Using parameter estimates from the structural model, I then examine the impact of a counterfactual policy that mandates a compulsory license provision. Such a provision would prohibit exclusive content by letting streaming services offer a copyrighted song to the their users without negotiating permission from the copyright owner, while the interests of copyright owners are protected by royalty payments. And usually independent music rights organizations set the royalty rates [5] and collect payments from services. Compulsory license provision is commonly used as a license arrangement of many important industries. In particular, in many countries, license fees paid by radio broadcasts for the right to broadcast music are set by a regulatory authority, rather than relying on a process of negotiation between the parties. This is because broadcasts of music are seen to be a service of significant social value, while copyright holders have the incentive to demand for a monopoly fee without internalizing the positive externalities. Assessing the impact of compulsory licensing on the streaming music industry is also at the heart of debate in the literature of legal issues. McKay (2010) argues that the US recording industry has abused its power to deny uses of copyrighted music and has failed to satisfy the constitutional purpose of copyright of providing for the public benefit. As a result, this power should be removed and replaced with a compulsory license system similar to the Section 115 Reform Act of 2006 (SIRA) [6], which would create a blanket collective license covering digital reproduction and distribution rights for musical works. Richardson (2014) suggests a compulsory license system with capping license fees. The article points out that royalty rate sets by Copyright Royalty Board verges to punitive for webcasters such as Pandora, although the service qualifies for compulsory licensing under the Digital Millennium Copyright Act.

Base on simulations, I find when a compulsory licensing provision were enforced, the market would evolve to a “tipping” equilibrium, in which almost all consumers exclusively join a same platform. This is because when services are less differentiated in their music content due to the compulsory licensing provision, the market will tip the platform providing a better service. Similar results are also discovered in other industries. For example, Augereau et al. (2006) finds that internet service providers deliberately choose the modem standard incompatible to their local competitors which prevents the market from “tipping” toward the more popular product. While unlike standards that may complement each other, music content is not only differentiated but is also each

[5] In the United States, the royalties are based on a "statutory rate" set by the U.S. Congress. This rate is increased to follow changes in the economy, usually based on the Consumer Price Index. See https://entertainment.howstuffworks.com/music-royalties6.htm

[6] Section 115 Reform Act, H.R. 5553, 109th Cong. (2006) (the bill was never enacted, and thus expired).

other's complement. With exclusive provision, multi-homing usage is prevalent as services complement each other, while when a compulsory provision were enforces, multi-homing users would switch away from the small service as their music content were less differentiated from other services and their service quality is lower than the others.Therefore, I also find small services would lose significant market shares under the compulsory licensing, although providing more content. Finally, I find no evidence showing that small services would lose shares is due to the lock-in effect caused by switching costs. The results combined show that a compulsory licensing provision does not benefit the small services and might lead to a less competitive market.

This paper is related to the literature in threefold. First, this paper contributes to the empirical work on understanding the cause of exclusivity. Most of the previous empirical literature on exclusivity has been focused on the firms' incentives for foreclosure and entry deterrence in both "up-stream" and "down-stream" competition (see Chipty (2001) and Asker (2004) for up-stream competition and Lee (2013) for down-stream competition). Theoretically, exclusivity may arise for several reasons other than the incentive to lock out competitions especially in a two sided market: Armstrong and Wright (2007) shows that a platform uses exclusive contract to persuade agents of one side to stop subscribing to the rival platform and, consequently, is able to exploit positive network effect of the other side; Hagiu and Lee (2011) shows that exclusivity is more likely to arise if a content provider has sold their content outright and have no control of pricing to consumers. Ishihara and Oki (2017) argues that a monopolistic content provider leverages the strategy of setting different number of content to be exclusively provided to each platform to balance the two opposite effects on its bargaining power: the positive effect caused by increase in multi-homing consumers and the negative effect caused by restriction of distribution channels. In contrast, this paper emphasizes the effect of switching costs and focuses on the incentive of using exclusivity to lock in customers.

Second, this paper is related to literature on switching cost estimation. Switching costs have been estimated in many markets leveraging on various estimation strategies. Schiraldi (2011) studies auto-mobile replacement. The author argues the existence of switching costs due to the transaction costs and estimates the costs by observing consumers who have switched and consumers who retain their existing choices. Both Handel (2013) and Nosal (2012) study switching costs in health insurance market, but different identification strategies are used. The former paper leverages on the observations of "passive" decisions due to plan menu change and forced re-enrollment to identify the switching costs, while the latter identifies the switching costs through the impact of the entry of new plans on market shares of existing plans. The estimation strategy implemented in this paper is closely related to Shcherbakov (2016) in which the identification of the switching costs relies on the state dependence of consumer choices, i.e. the relationship between past purchases and current choice probabilities (see Dubé et al. (2010) for a discussion).

Finally, this paper also addresses important policy question in the music industry. Since the advent of digitalization, the music industry has generated fierce debates on numerous questions related to economics and legal issues. One strand of research has addressed concerns of digital music on its advantage of cost reduction and displacement to physical music sales(see Waldfogel (2010), Aguiar and Waldfogel (2018) and Waldfogel (2017) for a survey). This paper is related to another strand of research which is on measuring on the effects of anti-piracy interventions in music industry. Bhattacharjee et al. (2006) tracked online file-sharing behavior of over 2,000 individuals to assess the impact of RIAA's pursuing legal action against individual participants of P2P file-sharing networks. Adermon and Liang (2014) studies the effect of a copyright protection reform in Sweden in April 2009 to internet traffic and music sales. However, few paper have studied the effects of such interventions on market competition. This paper addresses a novel issue by focusing on competition in music streaming market in the background of anti-piracy campaign in China.

2 Industry Background

In this section, I provide a brief summary on global recorded music industry and background on music streaming services in China. Since 1999, the industry has experienced significant revenue decline (Figure 1). According to IFPI report, music sales had fallen by 40 percent to $14.3 billion in the 15 years since 1999, when the rise of digital revenues failed to offset the declines of physical sales as a result of piracy[7]. After peer-to-per (P2P) illegal file-sharing services such as Napster was banned by the court [8] and anti-piracy campaign, the recorded industry has been through a long journey of fighting against piracy and seeking for options of distributing music legally and profitably. The appearance of streaming music services such as Spotify and Pandora raises various optimism and concern about their impacts on recorded music revenue. Unlike the services using download model (e.g. Apple's iTunes), streaming services use the subscription model of which the underlying idea is selling access to vast collections of musical content instead of using the download-and-own model - selling each recording separately for downloading and let users own the downloads. There are two types of streaming services: interactive and non-interactive streaming. The interactive streaming (e.g. Spotify) provides users complete flexibility to choose what content they would like to play at a time of their own choosing; while the non-interactive streaming (e.g. Pandora) provides pre-determined programming, a resemblance of traditional broadcast radio where users can select the type of provider or style of music, but do not have control over specific content. Generally, those services induce consumers to listen to streaming music on demand and generate revenues from paid subscriptions for premium services or advertising (Thomes, 2013). Since appearance,

[7]International Federation for Phonographic Industry's Digital Music Report, 2017, p. 11.
[8]A&M Records, Inc. v. Napster, Inc.

streaming services have developed rapidly and attracted users to switch from download service and illegal listening. Several researches in the existing literature have indicated that music streamings displaces music piracy (Aguiar, 2017; Aguiar and Waldfogel, 2018) .

2.1 Chinese Market and Anti-Piracy Campaign

The Chinese market is dominated by one leading firm followed by several small services. After aggressive horizontal and vertical integrations, Tencent, one of the largest China's internet giants[9], became the leading service taking up the largest market share in China. Tencent started its streaming service named QQMusic in 2005, then acquired Kugou and Kuwo, when it bought majority stakes in their parent company, China Music Corporation (CMC) in 2016. Other small services include: Netease, a company with origins as a gaming platform; Xiami, owned by e-commerce giant Alibaba and Baidu Music, owned by search giant Baidu. All these services offer both free and ad-supported interactive streaming services.

Music streaming also becomes the major source of the industry revenue in China: from 2012 to 2016 digital-music revenues in China nearly quadrupled, to $195m; most of that amount comes from music streaming (Figure 2). Music piracy was rampant in China, especially in the era of physical music, with large scale infringement against both local and global rights owners by selling counterfeits discs. In 2015, Chinese government undertook an anti-piracy campaign "Sword Net" to enforce copyright legislation and the collection of digital royalties. National Copyright Administration of China (NCAC) set a July 2015 deadline for all Chinese music services to take down their catalogs of unlicensed songs, then promptly removed 2.2 million unlicensed songs (Tang and Lyons, 2016).

The copyright enforcement in China also led to a heightened competition in the streaming market. Services compete with each other by biding for exclusive licensing from record labels. For example, Tencent sealed exclusive licenses from Warner Music Group, Sony Music, Universal Music Group, and South Korean label YG Entertainment, by paying each label with a big, but unknown, payout[10]. Services also compete with each other by filing lawsuits for copyright violations. In August, Tencent Music and NetEase sued each other for the second time in the two years over alleged copyright infringement after China banned unlicensed music streaming[11]. In 2015, Kugou

[9]Tencent is also best known for its WeChat messaging service.

[10]Thanks to Streaming Services, China's Consumers Have Begun Paying for Music, The Economist (July 29, 2017), https://www.economist.com/news/21725529-market-dominated-one-company-tencent-biggest-countrys-online-giants.

[11]Eva Yoo, Tencent Files Lawsuit Against Netease Music Over Copyright Infringement, Technode (Aug. 25, 2017), https://technode.com/2017/08/25/tencent-files-lawsuit-netease-music-copyright-infringement/.

[12]and Alibaba were also involved in a legal back-and-forth over music rights[13].

2.2 Personalization, Multi-homing and Switching

The most prominent feature of streaming services is the ability to discover new and listen to music digitally, without having to download song files or pay-per-track. By utilizing technology to understand customers' tastes, services are able to recommend a specific user more comparable songs on a timely basis. Spotify, for example, acquired the music intelligence platform The Echo Nest in 2014 and started to offer Discover Weekly, a signature weekly music recommendation service based on users' previous playlists and personal preferences[14]. Pandora, the largest non-interactive service, allows consumers to seed their own stations with a song or an artist they like. The station then plays songs and artists similar to the seed, according to various criteria, including musicological similarity and evidence about which music is liked in common among consumers (Aguiar and Waldfogel, 2018). Similarly, Chinese services also offer personalized services in various forms. For instance, users of QQMusic can establish his/her personal homepage and share their songs or playlists via Weixin/WeChat or QQ and other major social platforms[15].

Because of the personalized services that fit each person's music taste, active users homing on a service, having created their own playlists, and building relationships with other users are less likely to switch to other services frequently, i.e., substantial switching costs arise when a user switches from one service to another. An anecdotal evidence was that when Taylor Swift spoke out against platforms like Spotify for unfair compensation, and Prince pulled content from some services only to offering exclusives on others, few users did switch except for some hardcore fans. In an interview with Tech Times, a music expert Gary Sinclair commented " Because the switching costs ... are actually really high—I don't mean switching costs in terms of financial, but in terms of the amount of work they put in to develop their playlists, maybe their friends are on Spotify, and even the hassle of switching providers"[16]. That consumers who are accustomed to multi-home also explain why Taylor Swift and other artists' exit has no significant impact on Spotify's user base[17]. Indeed, consumers' incentive to multi-home is largely depending on how diversified and exclusive content are across services.

[12] At then, Kugou was not acquired by Tencent.

[13] Josh Jorwitz, China's Major Music Streamers Are Suing the Hell Out of Each Other – and That's a Good Thing, Quartz, July 22, 2015. https://qz.com/459551/a-whirlwind-of-lawsuits-among-chinas-internet-giants-might-tear-through-the-nations-piracy-habit-too/.

[14] http://static.echonest.com/enspex/

[15] See Page 140-142, Registration Statement of Tencent Music Entertainment Group, https://www.sec.gov/Archives/edgar/data/1744676/000119312518290581/d624633df1.htm#rom624633_18.

[16] https://www.techtimes.com/articles/81895/20150910/business-music-streaming-services-deals-record-labels.html.

[17] See Sandy Gill's article: "Stay, Stay, Stay": How worried should spotify be about Taylor's exit? http://www.onlineeconomy.org/stay-stay-stay-how-worried-should-spotify-be-about-taylors-exit/index.html

2.3 Exclusive Licensing

Although with differences across countries or areas in interpretation and execution of copyright protection, copyright law usually allows labels or independent artists to license their recording copyright via negotiation as opposed to the composition copyright which is subject to a statutorily mandated compulsory license rule (Schwemer et al., 2014). Streaming services, in particular the smaller entrants, seek for exclusive deals as a differentiation strategy to compete with market incumbents. Tidal, which entered the market since 2014 and is owned by a high profile artist, Jay-Z, and a variety of other successful music artists since 2015, leverages on its advantage of being as an artist-owned streaming platform offering exclusive content already available and expected for the future from the company owners, as well as others.[18] Apple Music, in the early stages after its launch, attempted to win paying subscribers with proprietary content. It paid several artists including Dr. Dre and Frank Ocean an agreed upon sum for exclusively premiering their latest albums on its service. [19]As mentioned above, services in China also aggressively bid for exclusive licenses after the anti-piracy campaign led by the Chinese government resulting in skyrocket licensing fee.

However, many services in the industry appear to be abandoning the exclusive practice either for profit maximization, or as a collusive practice against monopoly power hold by major labels or copyright collectives. Both Spotify and Apple Music announced to stop the expensive war for exclusive releases in 2017[20]. As quoted from Troy Carter, former global head of creator services of Spotify, "Exclusive audio content, specifically with albums, is ... bad for the music industry, it's not that great for artists because they can't reach the widest possible audience, and it's terrible for consumers".

There is also another scope for license setting based on fairness that needs government regulation. The best example is that many countries including U.S., Canada and New Zealand set regulated rate paid by radio stations for the right to broadcast music, because radio broadcasts of music are seen to be a service of significant social value (Watt 2010). Similarly in China, in response to vicious competition and copyright disputes between music-streaming services, Chinese National Copyright Administration came forward, seeking to stop exclusive licenses in the music industry and to promote the "widespread dissemination" of music by regulation[21]. The exact form of regulation might be either mandatory or market based policy (e.g. price ceiling), the objective is pushing license fee to be fair and equitable to both the copyright holders and the streaming services.

[18] Young, Alex (March 31, 2015). "TIDAL debuts with exclusive releases from The White Stripes, Daft Punk, and Arcade Fire". Consequence of Sound. Retrieved March 31, 2015.

[19] See https://www.forbes.com/sites/natalierobehmed/2016/08/23/frank-ocean-just-ignited-a-streaming-war-with-apple-and-universal-music/#26f4eb69c636.

[20] Daniel Sanchez, Spotify Makes It Clear: No More Album Exclusives (June 13, 2017), https://www.digitalmusicnews.com/2017/06/13/spotify-timed-exclusives/

[21] Qijun Zhou & Jing Xuan Teng, Copyright Authority Takes Aim at Exclusive Licenses for Music, Caixin (Sep. 15, 2017, 6:14 AM), https://www.caixinglobal.com/2017-09-15/101145826.html.

3 Data

In this section, I provide a description of the data used for this study. The data set is compiled from several sources. The first source is *Analysis Qianfan* - a Chinese consulting company providing services in app analytics, data mining and business intelligence for the mobile industry in China. The data set I collected from this source includes aggregate information on monthly subscriptions and usage of each music streaming service from Jan. 2014 to June 2017. Specifically, the variables are number of active users and aggregate hours spent on each service. The consulting company collected and generated the data set by tracking individual SDKs that are installed on the apps of major service providers and operation systems.[22].

One advantage of using the data collected by SDKs is that the usage behavior (e.g. listening hours) is directly observed. Unlike the survey data, my data does not rely on the accuracy of individual report. Table 1 presents the summary statistics of users and usage behaviors for each service. The number of overlapped users is also directly observed for part of sample periods from Aug. 2016 to June 2017. The overlapped users between two services is defined as the consumer who subscribed on two services and has stable usage of both services within a month.

Each observation in the aggregate data set is a service-month combination. The total services observed in each month varies across the sample period: there were approximately 20 service providers observed at the beginning periods, while the number increased to more than 100 in the later periods. For this study, I choose the six leading services that are QQMusic, Kugou, Kuwo, Xiami, Netease and Baidu. I create the market share for each service by dividing the number of their active users over the number of internet users in each year. The data of total internet users is collected from China Internet Network Information Center (CNNIC).

Although the aggregate data collected by SDKs is reliable, it does not provide information on whether the user is using a freemium or a premium service, while almost all music streaming services are operating under a freemium business model in which basic services are free while enhanced features are available on a subscription. Moreover, there is also a lack of enough data on the subscription fee. Therefore, there is no enough information or variation in the data that helps to identify users price sensitivity. However, being lack of the information on subscription fee may not affect to my analysis, as the paying ratio of music streaming services grew slowing and stayed below 4% from 2013 to 2017.[23] As a comparison, video streaming market had a merely 1.5 percent of users paying for subscriptions in 2013, while the paying ratio grew fast in the following years and reached to 22.5 percent by 2017 (Figure 3).

The most important aspect of music streaming market is the content that are available on each

[22]More details of their SDK technology are available on the website http://qianfan.analysyschina.com/view/help/rules.html.
[23]According to the report of iResearch, a market research and consulting company for online business in China.

service. To get information on this, I collected the second data set, which contains an exhaustive information on licensed albums. The data is directly collected from the website of above-mentioned services. Each observation is at the album level and has the following attributes: the album title, artist's name, record label, language and release date. The data was collected between Dec. 2017 and Jan. 2018, however many record labels licensed heir copyrighted music to services at different times before that. To address this issue, I tack the press released and company announcement to retrieve the date that a record label signed a deal with a service. By doing this and focus on the major labels only[24], I am able to recover the date when the music content from those labels became available on each service. Finally, I use the dataset to create attribute variables for services, the variables include the number of exclusively and non-exclusively licensed albums, labels and artists. Because a consumer is allowed to choose a bundle of streaming services, the music content of a service might be unique within some bundle choices but not others. Therefore, I created attribute variables for each service and bundle combination [25]. In the end, I combined both data sets described above for demand estimation and the descriptive statistics of the data are presented in Table 2a and 2b. In total, there are 252 service-month observations and 4032 service-bundle-month observations.

4 Preliminary Analysis

In this section, I provide a preliminary analysis of the data to illustrate the subscription patterns that are consistent with consumer switching cost and multi-homing cost. To show the evidence of switching cost, I apply the reduced-form method in Shcherbakov(2016) . That is, I first run the following linear regression,

$$s_{jt} = Z_t\beta + \hat{s}_{t-1}\alpha + \varepsilon_{jt},$$

where Z_t is a vector of exogenous variables and $\hat{s}_{t-1}$ is a vector of market shares instrumented using Z_{t-1}. Then I examine the state dependence in consumer decision by a joint test on the statistical significance of the lagged market shares. The test is based on the simple idea that if switching costs are substantial, current period choice is a function of the previous period decision. Because market shares are representations of the aggregated consumer decisions, one can regress the contemporaneous market shares on the lagged market shares instrumented with exogenous state variables. The data is consistent with consumer switching costs in the industry if the lagged market

[24]Major labels are the Big Three labels: Sony, Warner and Universal; and big domestic labels such as Huayi, Taihe Rye, Rock Records and EE-Media

[25]In the empirical application, there are six services studied in the analysis and I further assume that a bundle contains no more than two services. Therefore, there are 22 choices in total including the outside option.

shares of the above linear regression are jointly significantly different from zero.

Table 3 shows the estimation results of above regression by using the usage hours per active users of each services as the exogenous state variable. I choose the usage hours as an exogenous state variable because it is a good proxy for service quality. The regression results show that, for all service, the lagged market shares are jointly different from zero (inferred from the F-test). The signs of own lagged market shares are positive suggesting that larger own market share in the previous period ceteris paribus results in larger current period own market share. Although a larger competitor's market share in the previous period does not always imply lower own market share, it is consistent with the fact that consumer multi-homing. Moreover, the level of state dependence is varying across services, as values of the test statistics are different. This implies heterogeneous switching costs across services.

To show the evidence of multi-homing costs and benefits, and get a sense of their magnitudes, I compare the share of multi-homing users observed in the data to the share simulated from the independent random choice model. The underlying idea of this test is to examine whether a consumer adopts a service independently from its decision to adopt another. For example, suppose that the probability of a consumer subscribe to service A and B is 20% and 40% respectively. If the consumer makes independent choices of adopting services, the rate of subscribing to both services should be close to 8% (=20% $\times$ 40%). An actual rate of subscribing to both services that is smaller (larger) than the predicted rate indicates the existence of incremental costs (benefits) of multi-homing. Four examples presented in figure 4 show the share users that simultaneously subscribe to QQMusic and another service. In these examples, observed multi-homing rates are significantly smaller than the rates simulated from independent random choices, suggesting the multi-homing costs are dominating the multi-homing benefits. In another two examples presented at the top graphs of figure **??**, which show the users subscribing to both Xiami and QQMusic, and Xiami and Kuwo, multi-homing benefits were almost equal to costs in earlier periods, from August to September in 2016 , as the observed and simulated rates were roughly equal at those periods. Observed rates were then dominated by the simulated rates from January 2017, suggesting the costs became dominating the benefits after then. Finally, the two graphs at the bottom of figure **??** show the examples that multi-homing costs can be dominated by multi-homing benefits, as simulated rates are larger than observed rates.

Whether or not multi-homing benefits are greater than the costs depends on whether music content provided by each service in the bundle are substitutes or complements. For instance, the benefits of subscribing to both service A and B is greater if the music content provided by these two services are less similar. That is, a consumer subscribing to both service can access to a wider span of music, therefore multi-homing could be more beneficial than costly. To verify whether this is the case, I further run a regression letting the difference of share of users subscribing to a bundle between observed and predicted depend on the number of exclusive and non-exclusive album titles available on both services within the bundle. Table 4 lists the regression results under different specifications. As the number of exclusive album titles of services in a bundle increases, the difference between observed and predicted subscription rate of the bundle shifts towards positive suggesting that the incremental multi-homing benefits increases. In contrast,the incremental multi-homing benefits decreases when services in the bundle have more overlapped content, as the number of non-exclusive album titles is negatively affecting the difference between observed and predicted subscription rate.

5 Model

In this section, I develop a dynamic model of consumer adoption and use of music streaming services. The model proceeds in two stages: In stage I, the consumer picks which streaming service providers to subscribe to; In stage II, the consumer solves a time allocation problem to determine hours spent on each service. The model allows for forward-looking consumer decisions, strategic behavior of streaming service providers, vertical product differentiation across service providers and persistent consumer heterogeneity in preferences.

I index consumer by i and time by t. The set of streaming service providers is denoted as J with a particular service provider denoted as j. I further use B to represent a set of all possible subset of J. I assume that in each period, consumers' decisions are made according to the following timing: Stage I, consumer i subscribes (including both freemium and paid subscription) to a bundle of streaming services $b \in B$. The out side option, indexed by o is the "download music" that are free of charge yet require searching efforts. Stage II, consumer spends time on listening music. The bundle b chosen by the consumer at the first stage is a union of service providers. I proceed to describe details of each stage and further assumptions by reversing the order of the timing.

In stage II, I model the time allocation problem faced by consumers following Crawford and Yurukoglu (2012) who study the television market. Specifically, I let a consumer i allocate its time $\ell_{ibt} \equiv \left\{\ell_{ijt}\right\}_{j \in b \cup \{0\}}$, where ℓ_{ijt} is the time spent on listening music of service j, to solve the following maximization problem:

$$\max_{\ell_{ibt}} V_{ibt}(\ell_{ibt}) = \gamma_{i0t} v(\ell_{i0t}|\eta_0) + \sum_{j \in b} \gamma_{ijbt} v(\ell_{ijbt}|\eta_j) \tag{1}$$

$$s.t.\ \ \ell_{ijbt} \geq 0 \ \ \forall j \in b,$$
$$\sum_{j \in b \cup \{0\}} \ell_{ijbt} \leq T.$$

Parameter γ_{ijt} represents individual tastes for music that are available on service provider j and governs the level of marginal utility of the consumer listening music on service provider j. I further parameterize γ_{ijt} as follows:

$$\gamma_{ijbt} = \begin{cases} exp(l_{jbt}\gamma^{l}) \cdot \xi^{u}_{ijt} & j \neq 0 \ and \ j \in b \\ \xi^{u}_{0t} & j = 0 \end{cases}, \tag{2}$$

$$where \ \xi^{u}_{ijt} \sim Exponential(\rho_j),$$

where l_{jbt} is the set of observable characteristics including time fixed effects, and the number of album titles and performers that are exclusively or non-exclusively available on service provider j with respective other services in bundle b. The consumer also observes ξ^{u}_{ijt} which represents the quality that consumer i perceives for music content on service provider j whereas is not observed by researchers, in which superscription u stands for usage. Finally, I assume function $v(\cdot|\eta_j)$ as an increasing and concave function, where the level of concavity is governed by η_j. In other words, parameter η represents the speed that marginal utility from a service provider diminishes with additional time spent on listening. I define optimized value from the time allocation problem in equation 1 as the *usage value* and denote it by $\nu^{*}_{it}(b)$.

The specification of *usage value* brings several advantages. It allows me to make use of the listening hours to infer service qualities on each service provider that the consumer perceives. Since I observe only the number of music titles, labels and performers that are available on each service provider, while many other features such as audio quality, algorithm of recommendation, interface design and so on are hardly observable to researchers, I assume those to be captured in the *usage value* via ξ^{u}_{ijt}. More usage time spent on a service provider implies better services provided and raises the probability of higher draws in ξ^{u}_{ijt}.

Now consider the stage I. In this stage, I use the random-coefficients logit model (Berry, 1994; Berry et al., 1995) to model subscription choices. Specifically, I let a consumer i choose a bundle of services. I assume the consumer can subscribe to at most two services provider at each period. I also assume that the consumer knows all information required in the stage II. Thus, the consumer knows $\nu^{*}_{it}(b)$ for each possible bundle $b \in B$. I specify the utility function conditional on subscribing to bundle b as

$$u_{it}(b_{it},b_{it-1}) = \sum_{j\in b_{it-1}} -\psi_j I(j\notin b_{it}) + \beta^s v^*_{it}(b_{it}|d_{it},l_{jt}) + \underbrace{\sum_{j\in b_{it}} \lambda_{ijt}}_{\lambda_{ibt}} + D(b) + \varepsilon_{ib_t}, \tag{3}$$

where ψ_j is provider-specific switching cost and $I(\cdot)$ is an indicator function. Parameter λ_{ibt} represents the subscription benefits in excess of the utility of listening music, which could include easiness/cost to use the interface, extensiveness of catalog, compatibility of applications, etc. that are observable to the consumer but may not to researchers. I assume the subscription benefits λ_{ibt} as the sum of λ_{ijt} the subscription benefits received from each service provider that is included in the bundle b. I allow the interactive effect of jointly subscribing to multiple services through a scalar function $D(b)$. This term represents multi-homing cost in utility of this stage or complementary benefits if it is positive. More details on econometric specification of equation 3 is delayed until the following section. The utility of the outside option, i.e. when $b=\emptyset$, is denoted as u_{io}. Vector $\varepsilon_{it} \equiv \{\varepsilon_{ibt}\}_{b\in B}$ is idiosyncratic shock and i.i.d across periods, consumers and service bundles.

The consumer maximized the expected present discounted value of flow utilities over an infinite horizon. Let Ω_t denote information set that includes current service characteristics and any other factors affecting future service characteristics. Assume that Ω_t follows a first-order Markov process, the value function for the consumer is:

$$V_i(\Omega_t,b_{it-1},\varepsilon_{it}) \equiv E\left\{ \max_{\{b_{i\tau}\in B\}_{\tau=t}^{\infty}} \sum_{\tau=t}^{\infty} \gamma^{\tau-t} E\left[u_{it}(b_{i\tau},b_{i\tau-1})|\Omega_\tau,b_{i\tau-1},\varepsilon_{i\tau}\right]|\Omega_{it},b_{it-1},\varepsilon_{it}\right\}, \tag{4}$$

where $\gamma\in(0,1)$ is a discount factor. Since ε_{it} are i.i.d. across time, the consumer dynamic maximization problem 4 is simplified and written in the form of a Bellman equation:

$$V_i(\Omega_{it},b_{it-1}) = \max_{b_{it}\in B}\left\{u_{it}(b_{it},b_{it-1}) + \gamma E\left[V_i(\Omega_{t+1},b_{it})|\Omega_t,b_{it-1}\right]\right\}. \tag{5}$$

The state space is further simplified by defining an inclusive value as:

$$\delta_{ibt} \equiv \beta^s v^*_{ibt}(b_{it}|d_{it},l_{jt}) + \lambda_{ibt}.$$

The approach of reducing dimensionality of the state space is the same spirit of Melnikov (2013) and Hendel and Nevo (2006). Note that the inclusive value does not include the switching costs and multi-homing cost since parameters in both cost functions are deterministic and innocuous to be exclude from state variable vector Ω_t. The inclusive value is service bundle specific, therefore it is defined differently as in Schiraldi (2011) and Gowrisankaran and Rysman (2012) where a single log inclusive value is defined as expected utility received from the optimal choices[26]. I further simplify the model using the following assumption:

Assumption 1. *Each consumer i perceives that inclusive value δ_{it} can be summarized by a first-order Markov process:*

$$F(\delta_{ibt+1}|\Omega_t) = F(\delta_{ibt+1}|\Omega_t'),\ if\ \delta_{ibt}(\Omega_t) = \delta_{ibt}(\Omega_t')\ \forall b \in B.$$

Assumption 1 implies that $\delta_{it} \equiv \{\delta_{ibt}\}_{b\in B}$ is a sufficient statistics for marginal distribution of flow utilities received from service bundle b conditional on state variable vector Ω_t . Given this assumption, I rewrite equation 5 as:

$$V_i(\delta_{it}, b_{it-1}) = \max_{b_{it}\in B}\left\{\delta_{ibt} + \sum_{j\in b_{it}} -\psi_j I(j \notin b_{it-1}) + D(b_{it}) + \gamma E\left[V_i(\delta_{it+1}, b_{it})|\delta_{it}, b_{it-1}\right]\right\}.$$

I close this section by defining the firms' strategies. Instead of modeling the dynamic profit maximization problem explicitly that makes all service characteristics endogenous, I assume consumers perceive the next period's δ according to following simple linear autoregressive specification:

$$\delta_{ibt+1} = \gamma_{ib1} + \gamma_{ib2}\delta_{ibt} + \gamma_{ib3}(\delta_{ibt})^2 + \zeta_{ibt+1}, \forall b \neq \emptyset\ , \tag{6}$$

where ζ_{ibt+1} is independently normally distributed with mean 0 and variance σ^2_{ib} . I include flow utility received from each of the individual service provider into the linear regression to capture the competition effect. Notice that streaming service providers take the outside option, "download music" as one of the competitors, while the outside option does not as the easiness of getting free "download music" usually depending on exogenous policy rules.

6 Aggregation and Estimation

In this section, I provide the further parametric assumption, aggregation across consumers and estimation strategy. In the first stage (the subscription stage), the subscription benefits for each service provider λ_{ijt} is assumed to have the following parametric form:

$$\lambda_{ijt} = Z_{jt}\beta^Z_{it} + \xi^s_{jt},$$

[26]The log inclusive value in these two paper is not only depending on optimal choice in current periods but also optimal choices in the future.

where Z_{jt} is a vector of observed characteristics of each service providers and ξ^s_{jt} represents the service-specific characteristics that are observable to consumers but not observable to researchers. Each consumer has a random preference for each observed characteristics, β^Z_{it}, that is drawn from an independent multivariate normal distribution i.e. $\beta^Z_{it} \sim N(\beta^Z_t, \Sigma^Z)$. Note that I cannot observe individual level price paying to the service and listed price schedules are almost identical across service providers. Hence instead of using price, I use service fixed effect to capture the costs of using the service and let random coefficients to capture heterogenous disabilities of price. Assuming the idiosyncratic error ε_{ibt} is distributed Type I extreme value, the probability of bundle b chosen by consumer i given last period choice b_{it-1} is:

$$s_{ibt}(b_{it-1}) = \frac{exp(\delta_{ibt} + \sum_{j \in b_{it}} - \psi_j I(j \notin b_{it-1}) + D(b_{it}) + \gamma E\left[V_i(\delta_{it+1}, b_{it}) | \delta_{it}, b_{it-1}\right])}{exp(V_i(\delta_{it}, b_{it-1}))}.$$

As I only observe the subscription rate for each service provider, I further calculate the probability that consumer i subscribe to service provider j as a summation of choice probability of bundles that include service provider j:

$$s_{ijt}(b_{it-1}) = \sum_{b \in B_j} s_{ibt}(b_{it-1}),$$

where B_j denotes the set of choice bundles that include service provider j. The aggregated subscription rate of service provider is integration of individual choice probability across consumer types. Denote $G_t(\cdot)$ as the joint density function of consumer tastes β^Z_{it} , usage value V^* and last period subscription rate of each service bundle, the aggregated subscription rate of service provider j is:

$$S_{jt} = \int s_{ijt}(b_{it-1}) \, dG_t(\beta^Z_{it}, v^*_{it}, s_{ibt-1}).$$

In the second stage (the time allocation stage), I assume the parameters η_j that govern the speed of marginal utility decaying to be constant across service provider and assume the function $v(\ell_{ijt}|\eta_j)$ to be an iso-elastic utility function, that is

$$v(\ell_{ijt}|\eta) \equiv \frac{\ell_{ijt}^{1-\eta} - 1}{1-\eta}.$$

Denote ℓ^*_{ijbt} as the optimal time allocated to listening music on service provider j when the consumer is subscribing to service bundle b. Given the functional form assumption the solution to the time allocation problem describe in equation 1 is

$$\ell_{ijbt}^{*}=\begin{cases}\frac{\gamma_{ijbt}^{\eta}}{\sum_{k\in b\cup\{0\}}\gamma_{ikbt}^{\eta}}\times T & if\ j\in b,\\ 0 & if\ j\notin b.\end{cases}$$

The expected time that consumer i spends on service provider j is the weighted sum of optimal time spent on that service provider across subscription bundles and the weight is the probability that the consumer subscribes to bundle b:

$$\ell_{ijt}^{*}=\sum_{b\in B}s_{ibt}\cdot\ell_{ijbt}^{*}.$$

Similarly, the expected usage time averaging across subscribed users is

$$\ell_{jt}^{*}=\int\sum_{b\in B}s_{ibt}\cdot\ell_{ijbt}^{*}\ dG_{t}(\beta_{it}^{Z},\nu_{it}^{*},s_{ibt-1}).$$

The estimation is to recover the parameters of subscription value $\theta_1\equiv\left\{\beta^{s},\beta^{Z},\Sigma^{Z}\right\}$ and parameters of usage value $\theta_2\equiv\left\{\gamma^{l},\eta,\left\{\rho_{j}\right\}_{j\in J}\right\}$. I estimate those parameters using simulated GMM by constructing two sets of moments.

The first set of moment condition utilizes the difference between the listening hours in the data and predicted by the model. Specifically, the moment is

$$\mathbb{E}\left[\ \tfrac{1}{ns}\textstyle\sum_{i}\ell_{ijt}^{*}-\bar{\ell}_{jt}\ \ |Z_{t}\right]=0\ , \tag{7}$$

where Z_t is the set of exogenous variables affecting usage time, and ns denotes the number of consumers. $\bar{\ell}_{ij}$ is the time spent on service j averaged over service users.

The second set of moment conditions are:

$$\mathbb{E}\begin{bmatrix}\xi_{jt}^{s}H_{t}\\ \xi_{jt}^{s}H_{t-1}\\ \frac{1}{ns}\sum_{i}s_{ibt}\cdot 1(\#b=k)-s_{t}(\#b=k)\end{bmatrix}=0, \tag{8}$$

where H_t is the vector of instruments which are exogenous shifters for the contemporaneous market shares and H_{t-1} is the lagged exogenous shifters for the lagged period decisions, $\#b$ denotes the number of services included in the subscription bundle b and k is an integer that is great and equal than 2. The first and second moments are constructed based on the orthogonality between the contemporaneous and lagged instruments H_t and the unobserved characteristics ξ_{jt}^{s} and the last moment is matching the share of multi-homing users.

7 Identification

Because identifying the discount factor in a dynamic discrete choice model is notoriously difficult (Rust, 1994), I don not attempt to estimate the discount factor in this study rather than set the discount rate $\gamma = 0.99$. The primary concern in this study is then separately identifying multi-homing and switching cost parameters from consumer preference heterogeneity.

The identification of the switching costs relies on the state dependence in the aggregate market shares even that the choice probabilities that govern the amount of users switching in and switching out are not directly observed. Two sets of assumptions are needed. First I make assumptions on serial property of individual level preferences. In particular, I assume the idiosyncratic shock in the first stage, ε_{ibt}, to be serially independent. I also assume the unobserved preference shock in the second stage, ξ^{u}_{ijt} , and coefficients on observed service attributes are constant over time. This assumption is, to some extent, strong as it abstracts away any persistent consumer-specific preference that is unobservable to researchers. But the assumption becomes less strong when I consider consumers' heterogenous preferences, in particular, the random coefficients. This is because the model with random coefficients allows the persistent market share to be attributed to the persistent consumer-specific parts in flow utilities. The second set of assumptions emphasize on the serial properties of observed and unobserved service attributes. Specifically, I assume that ξ^{s}_{jt} to be a temporary shock to the service quality and mean independent to both contemporaneous and lagged market share shifters, i.e., $\mathbb{E}\left[\xi^{s}_{jt}|H_t\right] = \mathbb{E}\left[\xi^{s}_{jt}|H_{t-1}\right] = 0$, which are corresponding to the first and second moment conditions in equation 8. The same conditions are imposed in many applications that estimate switching costs through the aggregate market share data (e.g. see Nosal, 2012; Shchebakov, 2016; and see Yeo and Miller, 2018 for other possible conditions). None of the above assumptions imply that the unobserved service attributes, ξ^{s}_{jt}, are transitory. Therefore, the level of switching costs is determined by the persistency in market shares unexplained by the persistency in both observed and unobserved service attributes.

For the identification of the multi-homing cost, I use the last moment condition in equation 8 which levies on the data of overlapped users between services. Note that the identification of the switching costs also affects the identification of the multi-homing cost, because of the trade off between switching and multi-homing.

To identify consumers' preference heterogeneity in the first stage, I assume that the random coefficients follow normal distributions with unknown means and standard deviations and, as discussed above, are constant over time. Therefore, the variation of observables across time identifies the parameters of preference heterogeneity.

Finally, the identification of preference parameters in the second stage depends on the first set of moments presented in equation 7 which matches the usage time predicted by the model and observed from the data. To be specific, the parameter for the distribution of ξ^u_{ijt} , ρ_j , is identified by the first moment condition in equation 7 that matches the mean in hours spent on each services; the parameter that governs the speed of marginal utility decaying, η, is identified by the third moment condition that matches the average hours spent on all services; and the parameters of the demographic characteristics, γ^d, are identified by the second moment condition that matches the mean hours by demographic group.

8 Results

In this section, I first present the parameter estimates from the structural model, then I discuss the implication of the results. Table 5 presents estimates of important parameters in the structural model.

The top left panel of the table reports coefficient estimates of the time allocation stage. The coefficients for music content are all positive and significant, suggesting the more music music content a service possesses the more time users choose to spend on that service. However, the estimates are small indicating the model is saturated with year fixed effects. For coefficients from the service adoption stage, I find significant substantial variance for random coefficients that govern heterogeneous tastes of consumers. Most importantly, I find switching costs are heterogeneous in across services. The estimates for switching costs of dominant services - QQMusic, Kugou and Kuwo - are significant and statistically larger than the estimates of small services - Xiami, Netease and Baidu. Specifically, among all services, Kugou has the largest switching costs, while Xiami has the smallest switching costs. It worth noting that the estimate for switching costs of Xiami is small and insignificant, which is consistent to the reduced form evidence reported in table 3.

Of particular interest to this study is assessing the magnitude of switching costs. Ideally, one need to transfer the switching costs into a monetary value and compare it with services' subscription expenses. However, I cannot estimate the price coefficient as neither the subscription price of each service nor the ratio of paid subscriptions is observable. A heuristic way is comparing the estimates of switching costs to mean utilities of services by assuming those mean utilities were totally attributed to disutility from subscription expenses. For example, given that the mean utility of Kugou is -5.29 on average over the sample period, the costs of switching away from Kugou are equivalent to the expenses of subscribing to the service for more than one month, suggesting its switching costs are substantial. As a comparison, the costs of switching away from Baidu is approximately a percent of of its mean utility which is -15.04, which indicates its switching costs are relative small. However, this way of assessment is less convincing when the mean utility of a service includes many other factors related to its service quality. Instead, I use the following two approaches to assess the magnitude of switching costs.

In the first approach, I simulate the counterfactual market outcomes by assuming zero switching costs, and compare the counterfactual market shares to those observed in the data. This assessment is based on the same idea of identifying the switching costs. That is, without the switching costs - current choices of consumers are not depending on exogenous payoff-relevant variables in the last period - the persistence in market shares is solely accounted by the persistence in consumer preferences. Thus, the difference in time series persistence between the counterfactual and realized market share of a service reveals the significance of its switching costs. Figure 6 plots the realized and counterfactual market shares of Kugou and Baidu respectively, and Figure 7 plots the month-over-month change of their market shares. When switching costs were absent, market share of Kugou fluctuates more dramatically than the market shares with the switching costs, suggesting substantial costs of switching away from Kugou. In contrast, switching costs of Baidu is less significant as its counterfactual and realized market shares exhibit a similar time series pattern - both fluctuate in similar frequencies and magnitudes.

The second approach mimics the assessment on price elasticities. Except that I examine the percentage change of market shares in response to a change in music content. I compare a temporary 1 percent decrease in both album titles and number of performers on each service to a permanent 1 percent decrease in those content. The music content decreased at time t_d and it is unexpected to consumers before then. I assume at time t_d consumers know whether the decrease in music content is temporary or permanent. To simulate the counterfactual market outcomes I treat consumers' expectations in the same way that price elasticities were calculated in Gowrisankaran and Rysman (2012). For the temporal case, I compute the time t_d expectations of the inclusive values, δ_{ibt_d+1} , using the baseline δ_{ibt_d} realized in the case of no decrease in content; for the permanent case, I use the counterfactual δ_{ibt_d} realized under the decrease in content. For both cases, I compute the expectations of inclusive values via equation 6 by keep the estimated coefficients.

I compute the elasticities and make the comparison between two services, Kugou and Baidu, in figure 8 with t_d set to August 2016. An important result learned from this figure is that less users would switch away from Kugou in the case of temporary content drop than in the case of permanent drop, while Baidu would lose the same amount of users in both cases. For Kugou, a permanent content drop by 1 percent reduces its market share by 0.28 percent, while a temporary content drop leads to a drop in its users by 0.32 percent. For Baidu the temporary and permanent content leads a drop in users by a same amount which is around 0.08 percent. The result is consistent to the fact that Kugou has a larger estimate for the switching costs - users would be more likely to stay at Kugou when they expect the content drop is temporary.

Table 6 reports cross elasticities of all service to a temporary content drop of Kugou and Baidu. Each row indicates a change of users of the corresponding service listed in the first column. I report the percentage change of total users, both multi- and single-homing, in panel A. Then I decompose the percentage changes of users into multi- and single-homing and report those respectively in panel B and C. The first column in panel A of the table shows that the content drop of Kugou not only reduces its own users, but also reduces users of the small services such as Xiami, Netease and Baidu. In fact, the content drop of Kugou has larger impacts on the small services - with 5 percent drop in users on average - than on Kugou itself. As further shown in panel B and C, although the content drop of Kugou reduces its multi-homing users by more than 1 percent, its single-homing users are increased by almost 1 percent. In contrast, small services lose their multi-homing users by 5 percent on average, while their single-homing users increase by only 0.003 percent. Together these results suggest that users who were subscribing to both Kugou and another small service are more likely to switch away from the small service in response to the content drop in Kugou. This is also consistent to the fact that small services have lower switching costs - when multi-homing becomes less favorable, multi-homing users would firstly switch away from the service with lower switching costs.

The panel at the bottom reports the estimate for coefficient related to mulit-homing costs. Although the coefficient estimate is small, it does not indicate that the costs for multi-homing are less important. In fact, this coefficient is not separately identified from the constant term in the mean utility of all services, given that the utility received from a bundle of services in the model is defined as the sum of utilities received from each service within the bundle (see equation 3). Thus, the estimate for the constant is negative reported in the top right panel where the coefficients from service mean utility are reported, indicating that a user adopting two services simultaneously will receive twice as big the negative utility from the constant term as a user will receive when adopting on a single service.

9 Counterfactual: An Evaluation of Compulsory Licensing Provision

In this section, I simulate the counterfactual market outcome under compulsory licensing provision. The main goal of this counterfactual exercise is to examine the impact of counterfactual policy that mandates a compulsory license provision. Such a provision would prohibit exclusive content by letting streaming services offer a copyrighted song to their users without negotiating permission from the copyright owner, as long as the interests of copyright owners are protected by royalty payments. In addition, by comparing the counterfactual market outcome to the market outcome in reality, I can examine whether the exclusive provision favors the dominating services (QQMusic, Kugou and Kuwo) or the small services (Xiami, Netease and Baidu).

Two aspects are changed in the counterfactual environment of compulsory licensing. First, consumers have an universal access to music via using any service. Second, no service in the market has exclusive content. I first compute the steady state market shares of services under the compulsory provision keeping the estimated switching costs from the baseline. An important assumption made in this counterfactual exercise is that service quality in excess of its music content and switching costs were not changed in the counterfactual environment. This assumption exclude the possibility that services might make tradeoffs from different dimensions with respect to the change from exclusive to compulsory licensing. For example, services might invest more in a better UI interface or more advanced algorithms to learn users' preference and construct play lists based on individual taste.

Next, I redo the calculation by assuming way the switching costs. However, as illustrated in Figure 6, services' market shares would mechanically increase when the switching costs were zero, as the utilities are improved by removing the costs of current and future periods. Therefore, in order to make a better comparison between these two counterfactual scenarios, I assume that switching costs were removed unexpectedly by consumers. That is, although consumers would be free from the switching costs in current periods, they still expect the one time costs will occur if they switch away from a service in the future.

I compute the steady state variables by taking sample averages of mean utilities and music content variables. The simulation results are presented in table 7, where the baseline results are present in the first column. Column 2 and 4 respectively present the counterfactual results of compulsory licensing with and without the switching costs. Column 3 and 5 present the percentage change of counterfactual results with respect to the baseline.

Under the exclusive licensing provision, I find the CMC services including QQMusic, Kugou and Kuwo are dominating the market, which is not surprising as those services have more exclusive content than the rest of services. I also find multi-homing usage are dominating under the exclusive provision for all services. Indeed, as music content is not only a differentiated product but also a complement good to each other, when services are more differentiated by their exclusive content, multi-homing usage will be prevalent.

Under the first counterfactual environment in which a compulsory licensing provision were enforced, I find that market shares of all services except Kuwo would drop by more than 90 percent compared to the baseline. On the contrary, the market share of Kuwo would be almost twice as big as its market share in baseline. Stated another way, the market under the compulsory licensing would evolve to a tipping equilibrium in which consumers would exclusively join a same platform. This is because under the compulsory licensing provision, services are less differentiate by their exclusive content, while the only factor that is different across services is the service fixed effect embedded in the service mean utility. The mean utility of Kuwo in the steady state is -7.37 which is larger than mean utilities of the small services that are lower than -10. Although Kuwo does not have the large mean utility among all services in the CMC group, it has smaller switching costs than the other two services. Because the level of the mean utility is representing the service quality in excess of music content, the result implies that consumers would be more likely to switch to a service that is of better quality. For the small services, single-homing users would increase under the compulsory licensing by at least 25 percent compared to the baseline, although the shares would be very small. As illustrated in panel C, without exclusivities, multi-homing would become the least favorable choice, thus the share of multi-homing users were close to zero, suggesting a compulsory licensing provision would steer multi-homing users to switch away from the small service.

It is also worth noting that the share of users choosing the outside option under compulsory licensing would be about 3 percent lower than under the exclusive licensing. Thus, while the compulsory licensing would encourage more streaming music users, the influence would be very limited. In term of welfares, if the licensing were switching from exclusive to compulsory, consumer welfare would increase by 5 percent from 218.52 utils to 230.35 utils on average per person.

Finally, by comparing the counterfactual result of compulsory licensing when switching costs were removed temporarily for one period, I find market shares of services were not much different from results of the first counterfactual simulation. Although a small share of users would switch to the small services when switching costs were removed, the market shares of the small services under the compulsory licensing would still be much smaller than under the exclusive licensing. Hence, the lock-in effect by switching costs is not the main reason why small services would lose market share under the compulsory licensing. All these results combined suggest that a compulsory licensing provision would not benefit the small services.

10 Conclusion

This paper specifies and estimates a structural model that allows consumer to tradeoff between multi-homing and switching. With model estimates, I simulate the market outcomes had a compulsory licensing provision been enforced. I find with the compulsory licensing enforced, the market will tip the service with a better service quality. Although providing more music content, small services would lose significantly market shares.

Enforcing a compulsory licensing provision in the streaming music market receives increasing supports recently, especially in China. The pro-compulsory side believes such a provision will reduce services burden of paying expensive licensing fees and benefit suers by increasing their access to more music content. However, my analysis shows such a provision might lead to a higher market concentration.

My analysis also shows a compulsory licensing would not benefit the small services and might force those services to exit. Although providing more content under the compulsory provision, small services would lose a significant market shares as the multi-homing users would switch away from their platforms when their content were less differentiated from others. Again, my analysis highlights the fact that a compulsory licensing might lead to a less competitive market.

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Table 1: Summary Statistics of Users and Listening

	Variables	QQMusic	Kugou	Kuwo	Netease	Xiami	Baidu
Platform Users	Avg. MAU (M)	125.302	116.464	63.098	16.067	6.239	12.924
	Avg. Market Share (%)	17.635	16.081	8.936	2.160	0.852	0.019
	Avg. Total Listening Hours (MM hrs.)	321.045	521.295	145.300	87.143	18.122	21.959
	Avg. Listening Hours/MAU ($hrs.$)	2.329	4.073	2.275	3.914	2.085	1.699

Notes: Statistics are calculated from the aggregate data set described in Section 3. Total sample period is from Jan. 2014 to June 2017. MAU stands for monthly active users.

Table 2a: Summary Statistics of Music Contents

	Variables	QQMusic	Kugou	Kuwo	Netease	Xiami	Baidu
Album Titles	Total # Title Released	97764	97834	98320	63221	66464	17432
	# Titles Released /Month	2273.581	2275.209	2286.512	1470.256	1545.674	405.395
	(Min,Max)	(1100, 3612)	(912, 3775)	(1058, 3775)	(815, 2530)	(999, 2489)	(249, 692)
Labels	Total # Labels	39233	39351	39533	37204	38534	24483
	# Labels/Month	912.395	915.140	919.372	865.209	896.140	569.372
	(Min,Max)	(174, 1295)	(165, 1301)	(172, 1303)	(132, 1288)	(162, 1271)	(54, 1023)
Performers	Total # Peformers	1303825	1273588	1286292	929410	1055338	313218
	# Performers/Month	30321.510	29618.330	29913.770	21614.190	24542.740	7284.140
	(Min,Max)	(1221, 63418)	(1062, 62931)	(1264, 63112)	(903, 45849)	(1065, 48737)	(272, 15560)

Table 2b: Album Titles over Years

Variables	Year	Tencent	Kugou	Kuwo	Netease	Xiami	baidu
# Album Titles (Monthly Average)	2014	1371.250	1369.417	1409.917	1456.167	1203.333	309.750
	2015	2230.250	2136.250	2136.250	1456.167	1613.000	425.500
	2016	2941.583	2956.083	2956.083	1872.000	1900.250	471.333
	2017	2750.429	2899.000	2899.000	1669.857	1409.286	421.857
# Exclusive Album Titles(Monthly Average)	2014	133.833	150.667	170.000	1.000	0.667	21.083
	2015	451.333	401.000	401.000	0.917	1.417	1.083
	2016	670.250	742.333	742.333	0.500	0.750	0.833
	2017	875.571	963.286	963.286	1.571	0.143	0.857

Notes: The top table shows the summary statistics of albums, labels and performers that are available on each services. The bottom table shows the statistics of total and exclusive albums titles by services by year. Statistics are calculated for the variables generated from music licensing data set described in Section 3. Total sample period is from Jan. 2014 to June 2017. Variables of each service in the top table have 252 service-month observations. Variables in the bottom table have 12 observations for each service and years from 2014 to 2016 and 7 observations for each service in 2017.

Table 3: Reduced-Form Evidence of State Dependence in Aggregate Consumer Decisions

		QQMusic	Kugou	Kuwo	Xiami	Netease	Baidu
	QQMusic	0.456***	-0.044	-0.305***	-0.004	-0.010	-0.059*
		(0.156)	(0.218)	(0.105)	(0.024)	(0.037)	(0.035)
	Kugou	-0.003	0.736***	0.120	-0.043	-0.028	0.037
		(0.156)	(0.220)	(0.104)	(0.028)	(0.038)	(0.038)
	Kuwo	0.127	0.066	0.098	-0.087	-0.060	-0.094
		(0.368)	(0.384)	(0.213)	(0.053)	(0.081)	(0.077)
$\hat{s}_{t-1}$	Xiami	2.749	-6.712**	-0.175	-0.041	-2.020***	-0.131
		(2.050)	(2.782)	(1.303)	(0.313)	(0.507)	(0.456)
	Netease	-1.355**	-0.131	0.707*	0.057	0.696***	0.149
		(0.536)	(0.844)	(0.390)	(0.082)	(0.157)	(0.122)
	Baidu	-1.321	-2.967**	-0.948	-0.151	-0.127	0.154
		(0.969)	(1.354)	(0.656)	(0.201)	(0.317)	(0.259)
	Observations	42	42	42	42	42	42
	Year FE	Yes	Yes	Yes	Yes	Yes	Yes
	R^2	0.970	0.997	0.943	0.982	0.999	0.857
	F-test	24.940	45.890	39.770	6.690	52.270	16.640
	(p-val.)	(0.000)	(0.000)	(0.000)	(0.351)	(0.000)	(0.011)

Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Notes: The dependent variable is the contemporaneous market share of each service. Only the lagged market shares are presented in the table, other characteristics of services such as the usage hours per active users, number of album titles, etc., are included in the regressions but not reported. The exogenous state variable is the usage hours per active users which is taken as a proxy for service quality. The lagged market shares are instrumented by the lagged exogenous state variables. F-test is used to test the joint significance of lagged market shares.

Table 4: Dependence of Multi-homing on Exclusive and Non-exclusive Contents

	Specification 1	Specification 2	Specification 3	Specification 4
# exclusive albums	0.0025**	0.0022**	0.0006***	0.0004*
	(0.0010)	(0.0010)	(0.0002)	(0.0002)
# non-exclusive albums	-0.0039	-0.0049	0.0073**	-0.0095**
	(0.0028)	(0.0033)	(0.0026)	(0.0038)
Service FE	No	No	Yes	Yes
Time FE	No	Yes	No	Yes
N	135	135	135	135
R^2	0.3557	0.4170	0.8957	0.9297

Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Note: The dependent variable is the difference between multi-homing users observed and predicted by the independent random choice model. Each observation is at the bundle level and each bundle contains two services. Exclusive albums are the album titles exclusively available on services in the bundle. Non-exclusive albums are the album titles commonly available on both services. All explanatory variables are in logarithmic form except for the constant and fixed effects.

Table 5: Estimation Results for the Dynamic Model

Time Allocation:		Service Adoption:	
γ_{cons}	-5.485	β_{cons}	-6.024
	(0.219)		(0.240)
γ_{album}	0.086	β_{trend}	-0.158
	(0.039)		(0.034)
γ^E_{album}	0.431	β_{trend^2}	0.002
	(0.015)		(0.001)
$\gamma_{performer}$	0.457	σ_{cons}	1.054
	(0.024)		(0.023)
$\gamma^E_{performer}$	0.650	σ_{cmc}	0.657
	(0.018)		(0.083)
η	0.960	β^s	1.401
	$(3.166x10^{-4})$		(0.033)
Switching Cost (ψ):			
$\psi_{QQMusic}$	-3.819	ψ_{Xiami}	-0.177
	(0.144)		(0.368)
ψ_{Kugou}	-6.581	$\psi_{Netease}$	-1.035
	(0.455)		(0.514)
ψ_{Kuwo}	-2.852	ψ_{Baidu}	-0.163
	(0.573)		(0.031)
Multi-homing Cost:			
θ_{mc}	-0.610		
	(0.180)		

Note: The estimation results are from simulated GMM which are based on the moment assumptions listed in equation 7 and 8. The random coefficients are the standard deviations of normal distributions, where σ_{cmc} is the random coefficient for constant and σ_{cmc} is the random coefficient for the dummy variable indicating services of CMC group. The CMC group has QQMusic, Kugou and Kuwo. Both service and time fixed effects are included, but the estimates of those are not reported.

Table 6: Elasticity to a temporary change in music content

Panel A: %△ of all users

	Kugou	Baidu
Ouside	0.073	4.44×10^{-4}
QQMusic	-0.015	0.001
Kugou	-0.279	0.000
Kuwo	0.070	0.000
Xiami	-4.936	0.005
Netease	-4.223	0.005
Baidu	-6.575	-0.079

Panel B: %△ of multi-homing users

	Kugou	Baidu
QQMusic	-0.025	0.001
Kugou	-1.276	-0.002
Kuwo	0.064	-4.08×10^{-4}
Xiami	-4.940	0.005
Netease	-4.226	0.005
Baidu	-6.576	-0.072

Panel C: %△ of single-homing users

	Kugou	Baidu
QQMusic	0.010	2.07×10^{-4}
Kugou	0.997	0.002
Kuwo	0.006	1.54×10^{-4}
Xiami	0.003	3.19×10^{-5}
Netease	0.003	1.45×10^{-5}
Baidu	3.74×10^{-4}	-0.007

Note: This table reports percentage changes in users of all services in response to a temporary 1% drop in content of Kugou and Baidu. Each row indicates the change in users of the corresponding services listed in the first column. Panel A reports the percentage change of both multi- and single-homing users; Panel B and panel C respectively reports the change of multi-homing users and single-homing users as a percentage of all users (multi- and single-homing) in the baseline model.

Table 7: Market Shares in Steady State: Exclusive and Compulsory Licensing

Panel A: Multi- and Single-homing

	exclusive (baseline)	compulsory			
		w/ switching costs	% △ to the baseline	w/o switching costs	% △ to the baseline
Outside	0.6129	0.5930	-3.2364	0.5884	-3.9892
QQMusic	0.2326	0.0145	-93.7615	0.0221	-90.5198
Kugou	0.2237	0.0167	-92.5401	0.0114	-94.9141
Kuwo	0.1378	0.3749	171.9537	0.3740	171.2956
Xiami	0.0166	0.0003	-98.3986	0.0011	-93.1045
Netease	0.0647	0.0006	-99.0700	0.0028	-95.7158
Baidu	0.0117	0.0001	-99.5055	0.0003	-97.4924

Panel B: Single-homing

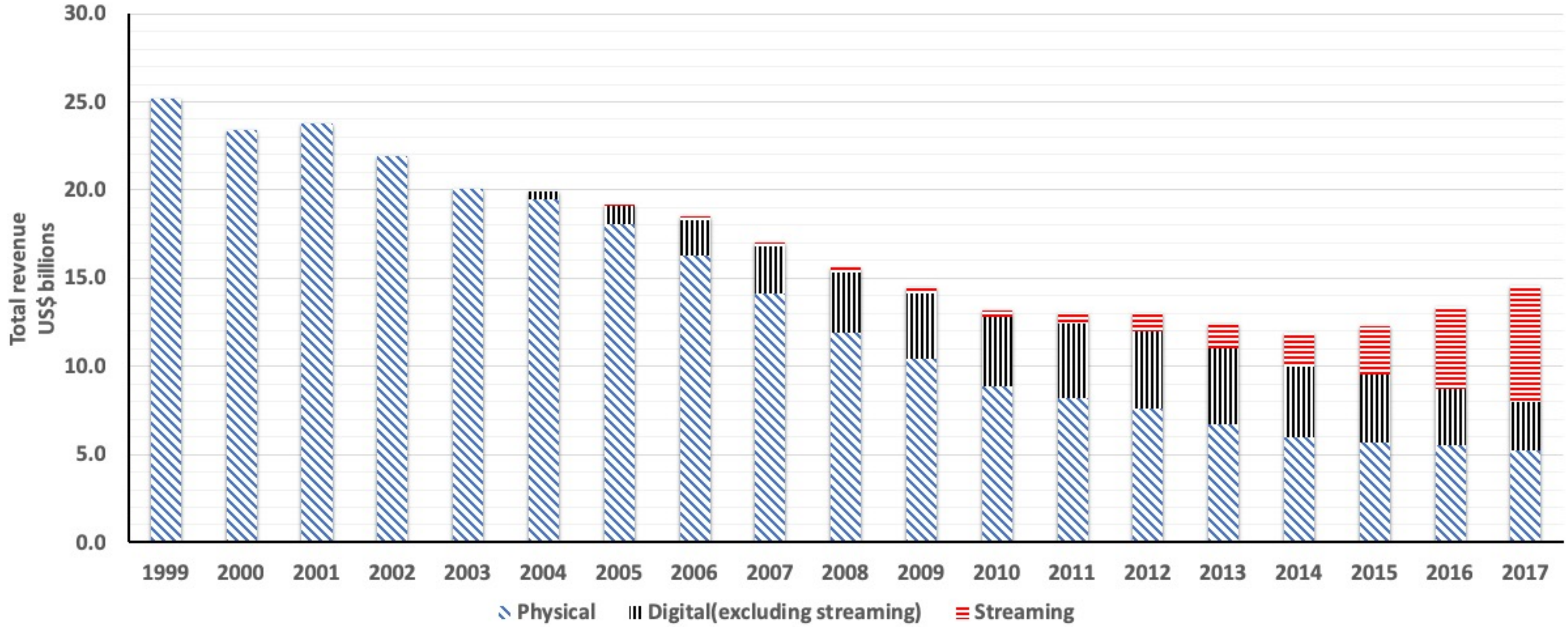
	exclusive	compulsory			
		w/ switching costs	% △ to the baseline	w/o switching costs	% △ to the baseline
QQMusic	0.0108	0.0145	34.4358	0.0221	104.6335
Kugou	0.0562	0.0167	-70.3731	0.0114	-79.7616
Kuwo	0.0195	0.3749	18.2167	0.3740	1817.1745
Xiami	0.0002	0.0003	25.8587	0.0011	446.0109
Netease	0.0004	0.0006	46.9672	0.0028	581.9781
Baidu	0.0000	0.0001	121.7924	0.0003	1032.2739

Panel C: Multi-homing

	exclusive	compulsory			
		w/ switching costs	% △ to the baseline	w/o switching costs	% △ to the baseline
QQMusic	0.2219	0.0000	-99.9891	0.0000	-99.9899
Kugou	0.1675	0.0000	-99.9894	0.0000	-99.9947
Kuwo	0.1184	0.0000	-99.9625	0.0000	-99.9702
Xiami	0.0163	0.0000	-99.9879	0.0000	-99.9877
Netease	0.0643	0.0000	-99.9932	0.0000	-99.9931
Baidu	0.0117	0.0000	-99.9967	0.0000	-99.9967

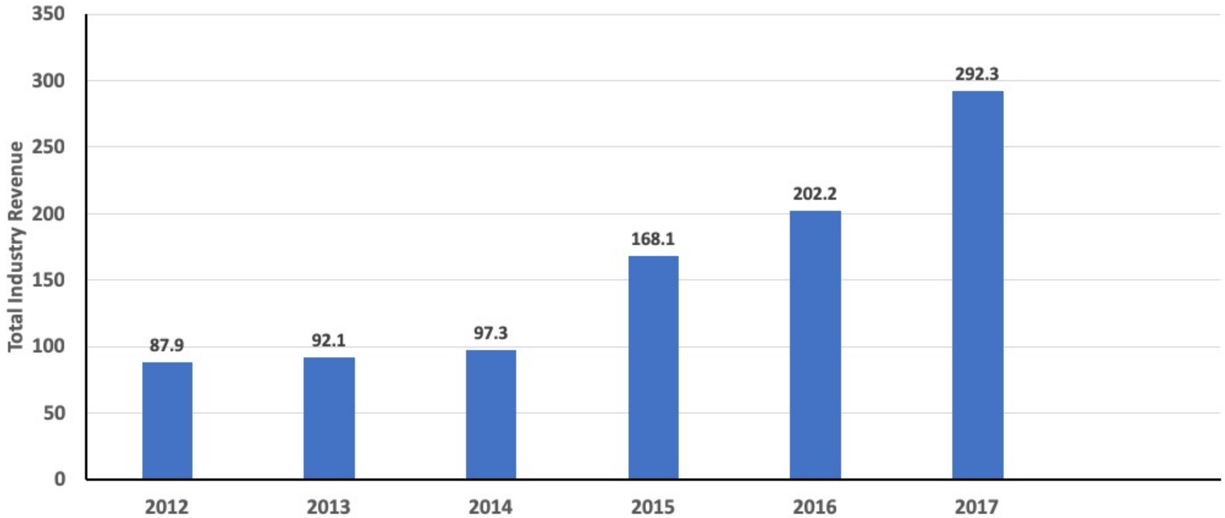
Note: This table reports steady state market shares of services under exclusive and compulsory licensing. Panel A reports the shares of both single- and multi-homing users. Panel B and C respectively reports the steady state shares of single-homing and multi-homing.

Figure 1: Global Recorded Music Industry Revenues 1999-2017 (US$ Billions)



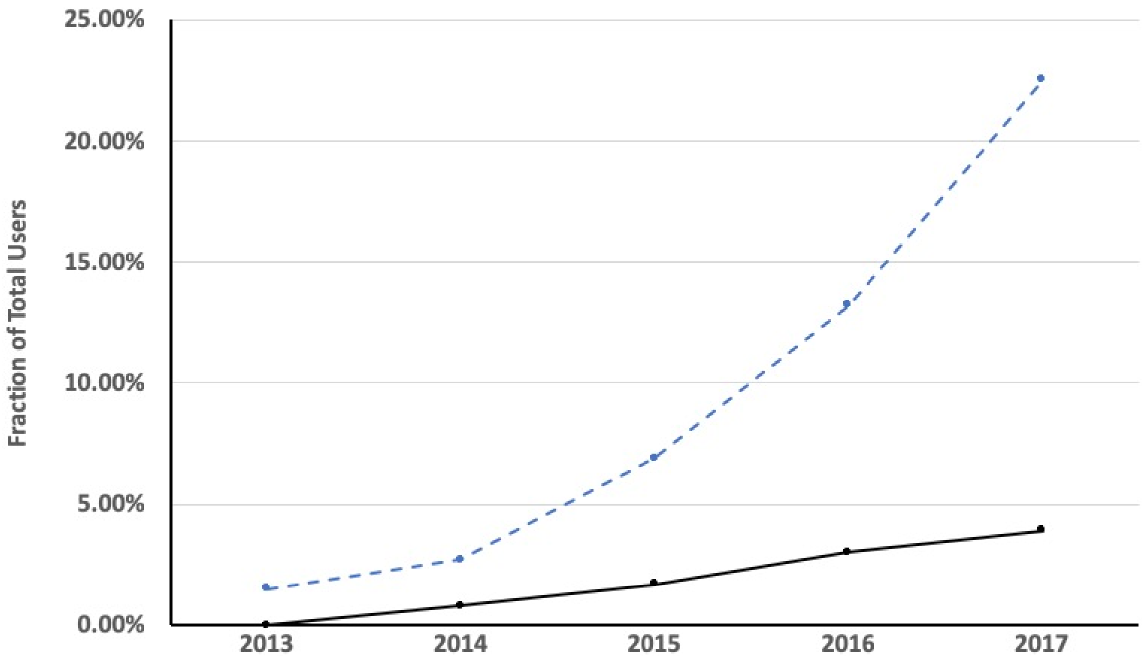
Notes: The graph plots the total revenues of the global recorded music industry from 1999 to 2017 and the breakdown of revenue by different sources. Adapted from "Global Music Report 2018" by IFPI, 2018.

Figure 2: China's Recorded Music Industry Revenues 2012-2017 (US$ Millions)



Notes: The graph plots the total revenue of recorded music industry in China from 2012 to 2017. Adapted from "Global Music Report 2017" by IFPI, 2017.

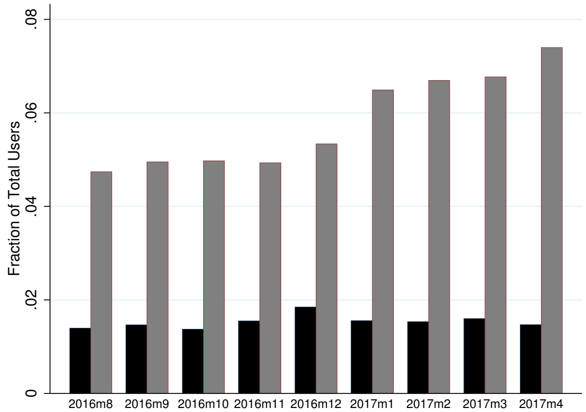
Figure 3: Paying Ratios of China's Music Streaming vs. Video Streaming



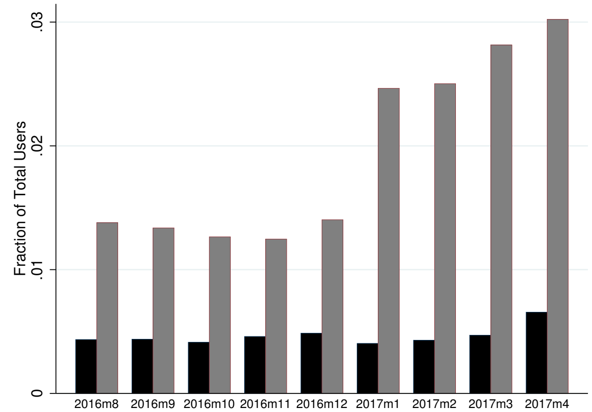
	2013	2014	2015	2016	2017
Video Streaming	1.50%	2.70%	6.90%	13.20%	22.50%
Music Streaming	0.00%	0.80%	1.70%	3.00%	3.90%

Notes: The graph at the top plots the ratio of paid subscriptions to total subscriptions in the music streaming market and video streaming market. And the table below shows the figures of those paying ratios. Adapted from "2018 China Online Music Report" by iResearch consulting company, 2018.

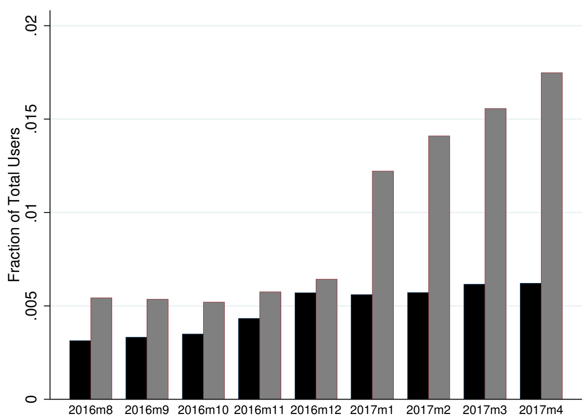
Figure 4: Example of Multi-homing I



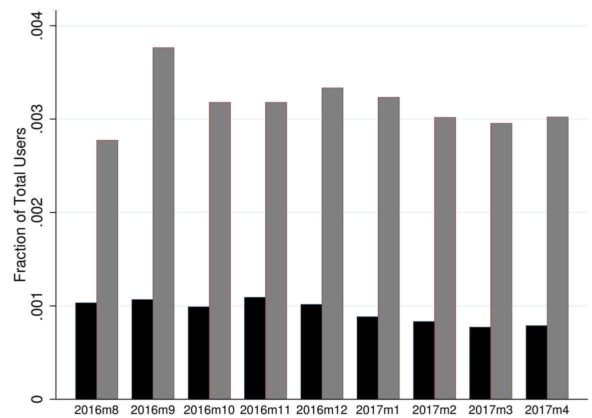
(a) QQMusic and Kugou



(b) QQMusic and Kuwo



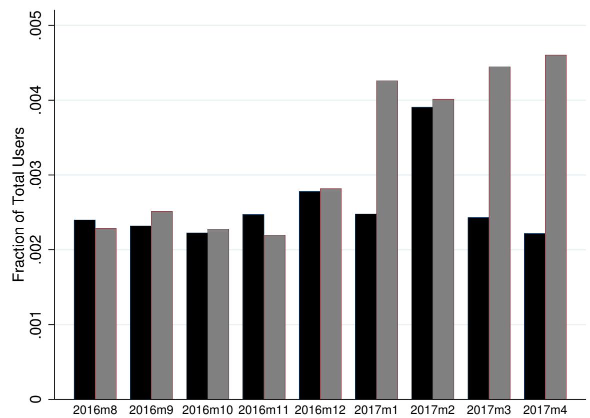
(c) QQMusic and Netease



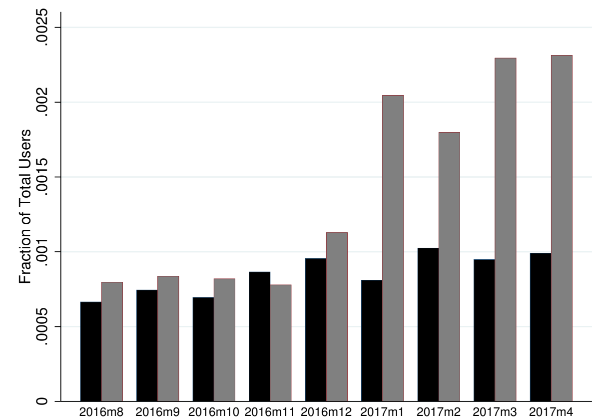
(d) QQMusic and Baidu

Notes: The graphs above plot the share of multi-homing users. The top left graph plots users subscribing to QQMusic and Kugou simultaneously; The top right graph plots users subscribing to QQMusic and Kuwo simultaneously; The bottom left graph plots users subscribing to QQMusic and Netease simultaneously;The bottom right graph plots users subscribing to QQMusic and Baidu simultaneously. In all graphs, the black bar represents the share of multi-homing users observed in the data; the gray bar represents the share simulated by independent random choice model.

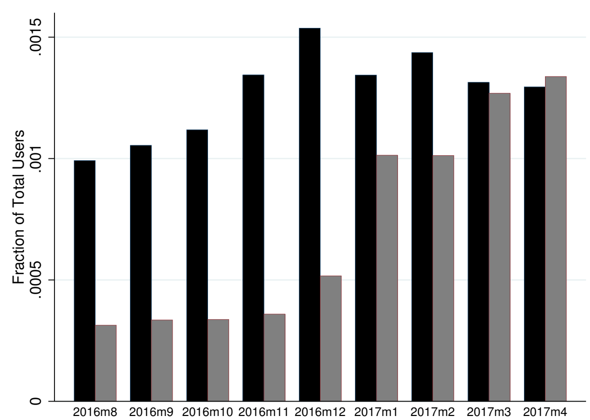
Figure 5: Example of Multi-homing II



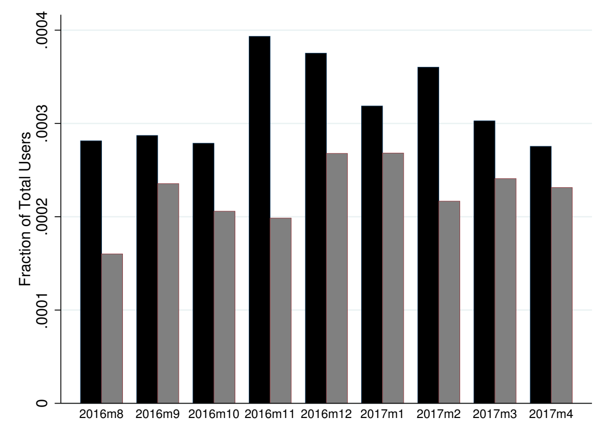
(a) Xiami and QQMusic



(b) Xiami and Kuwo



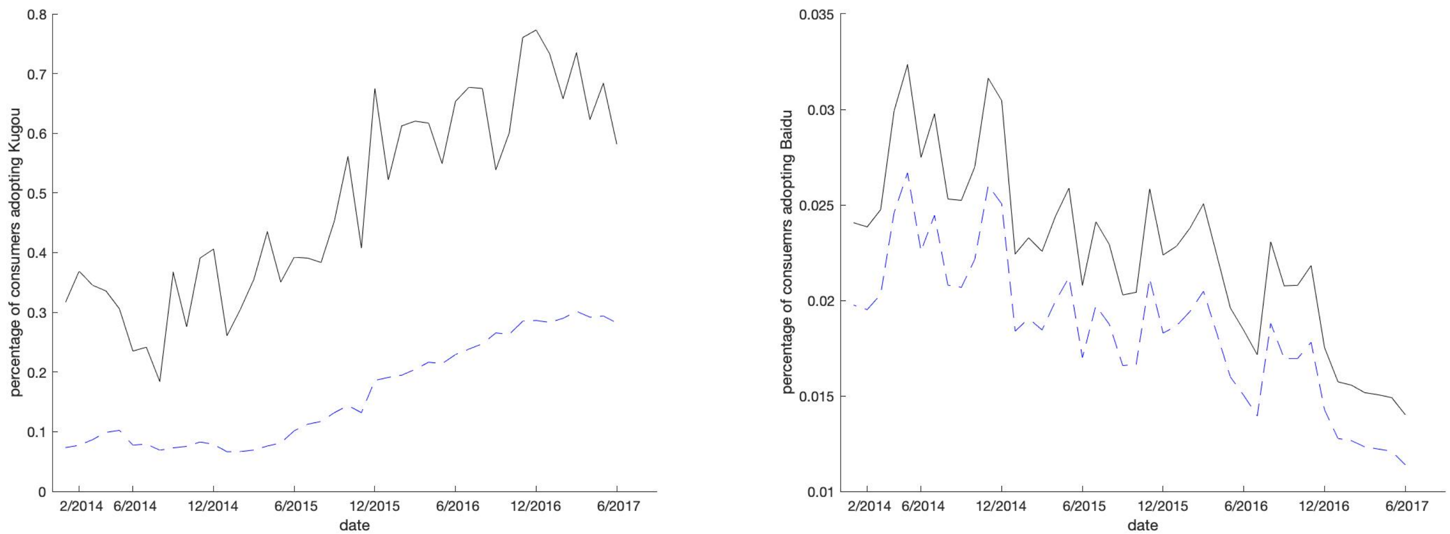
(c) Xiami and Netease



(d) Xiami and Baidu

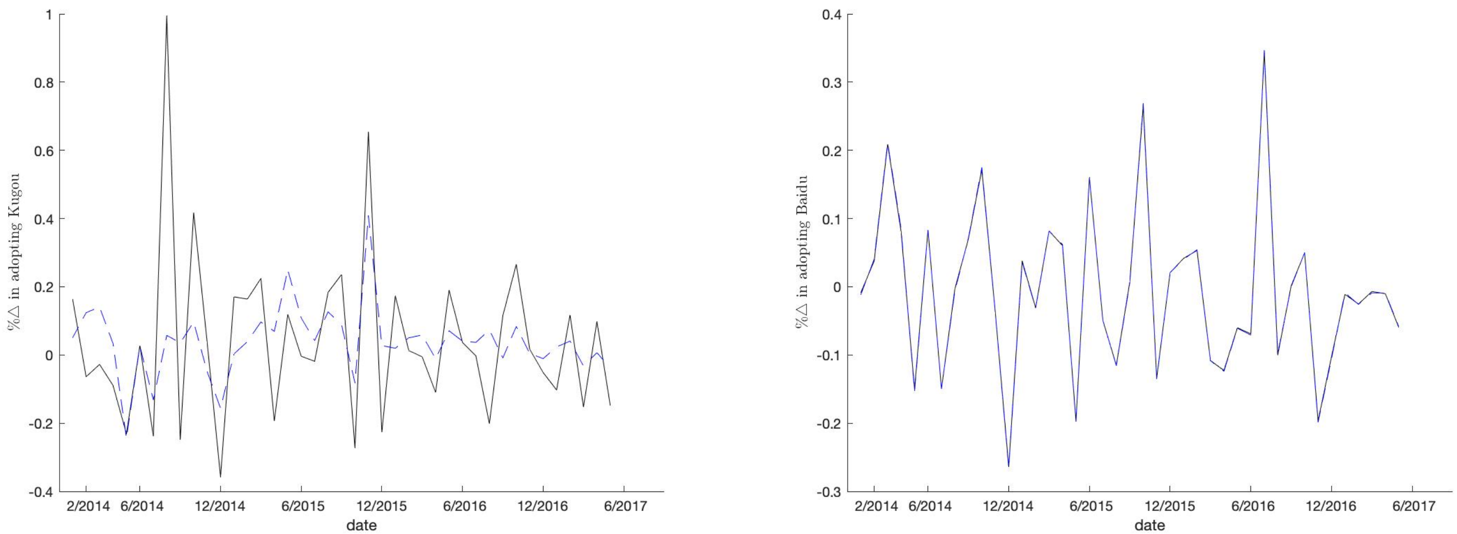
Notes: The graphs above plot the share of multi-homing users. The top left graph plots users subscribing to QQMusic and Xiami simultaneously; The top right graph plots users subscribing to Kuwo and Xiami simultaneously; The bottom left graph plots users subscribing to Xiami and Netease; The bottom right graph plots users subscribing to Xiami and Baidu. In all graphs, the black bar represents the share of multi-homing users observed in the data; the gray bar represents the share simulated by independent random choice model.

Figure 6: Model Prediction of Service Adoptions



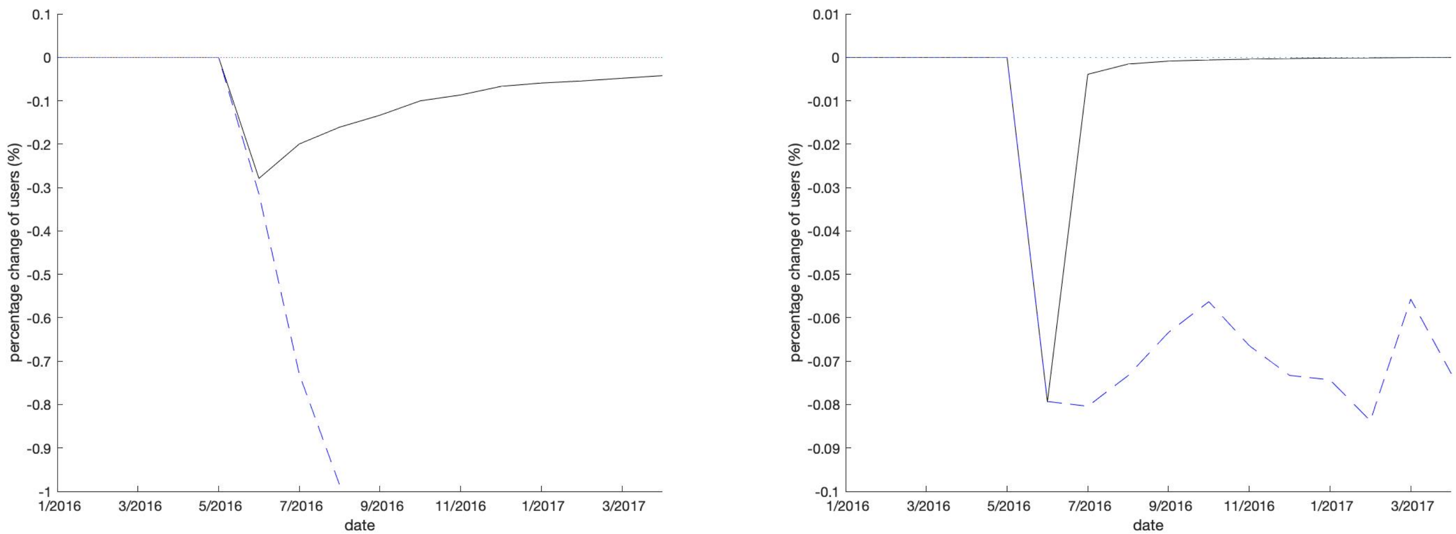
Notes: The left graph plots the adoption rates of Kugou and the right graph plots the adoption rates of Baidu Music. Solid lines are the adoption rates observed from the data. Dashed lines are adoption rates predicted from the model assuming zero switching costs.

Figure 7: MoM change in Service Adoptions



Notes: The left graph plots the month to month change in adoption rates of Kugou and the right graph plots the change in adoption rates of Baidu Music. Solid lines are the adoption rates observed from the data. Dashed lines are adoption rates predicted from the model assuming zero switching costs.

Figure 8: Dynamic elasticities to a change in music content



Notes: The left graph plots the percentage change in adoption rates of Kugou in response to a 10% decrease in its music content; and the right graph plots the change of Baidu Music. Solid line indicates market response to a temporary change; dashed line indicates market response to a permanent change.