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

Youming Liu *

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Abstract

Copyright law grants the exclusive right to copyright owners so that they have adequate financial incentives to create and innovate. However, when firms are copyright owners, they can leverage the exclusive right to sell or distribute products exclusively. This paper studies the music streaming industry, where streaming services compete for exclusive licenses from music labels. Service providers use exclusive content to attract users, tailoring their services to individual preferences that create switching costs leading to user lock-in. I first use theoretical analysis and descriptive empirics to show that exclusivity confers advantages in competition to a service that can generate larger lock-in effects. I then construct a dynamic structural model in which consumers face switching costs when making subscription decisions. I estimate the model using the monthly data from China's music streaming market over 2014-2017. Finally, I simulate market outcomes under two alternative policies, a compulsory licensing provision, and a mandatory data portability policy. The policy simulation shows that compulsory licensing that enforces non-exclusive distribution would not improve market competition by "leveling the field" between dominant and small services as intended. On the contrary, the policy increases market concentration, enlarging the gap in market share between dominant and small services. In contrast, mandatory data portability that reduces switching costs would reduce market concentration, bringing more users to smaller services.

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1 Introduction

Since the revolution of digitization, piracy has been a constant issue, making copyright enforcement a priority in many industries that rely on intellectual property, such as music, books, movies, television, and computer software. With numerous enhanced enforcement actions taking place in the past two decades[1], illegal downloading and file-sharing services have started to fade away. However, while enforcing intellectual property rights tends to improve market performance, copyright enforcement might also lead to exclusive dealing, due to the exclusive provision in copyright law of many countries that grants right-holders exclusive right to control the reproduction and distribution of music works. It is potentially problematic when exclusivity is used to foreclose rivals (Rasmusen et al., 1991; Bernheim and Whinston, 1998). On the other hand, exclusivity can also be leveraged by small entrants to compete with big incumbents for customers, therefore promoting market competition (Lee, 2013).

The copyright campaign in China provides a vivid example of this enforcement dilemma. The music industry in China has historically been hindered by rampant piracy.[2] Starting from 2012, the Chinese government began to increase its efforts to enforce copyright protection on the internet.[3] The campaign forced music streaming services to negotiate licenses with labels or independent copyright owners, leading to heightened competition in the market with fierce bidding wars among services for getting the exclusive deals. Importantly, an exclusive deal between a music label and the streaming service provider does not necessarily mean the service distributes the label's content exclusively. The copyright owner usually grants sublicensing, which allows a service provider to supply the copyrighted songs to other providers. Despite that, service providers often choose to withhold some musical works from their rivals. Consequently, no service in this market currently can distribute a universal set of music.

Understanding what drives exclusive distribution is crucial to addressing the copyright enforcement dilemma, especially whether exclusivity takes place as a mechanism to drive market share to the largest firms. However, it is not obvious what is the incentive for a service to withhold some content from its rivals. A service that chooses exclusive distribution will face a significant opportunity cost of forgoing the sublicense revenue collected from other service providers. At the same time, it has to pay expensive licensing fees to the labels. It is also not clear that a service can use exclusive content to steer users away from rival services. Consumers with heterogeneous preferences can subscribe to multiple services simultaneously, i.e., multihoming. Indeed, with exclusive con-

[1]Examples in the U.S. include A&M Records, Inc. v. Napster, Inc; RIAA v. The People. Internationally, the International Federation of the Phonographic Industry (IFPI) has filed more than 11,000 lawsuits in countries including China, Japan, Netherland, Finland, Ireland, and Iceland (Tang and Lyons, 2016).

[2]The piracy rate was as high as 90 percent at the end of the 20th century. See IFPI Piracy Report 2000

[3]The campaign named as "Sword Net" has lasted for several years from 2012.

tent distribution, multihoming becomes common practice among streaming users in getting access to broader music content.

My paper studies the practice of exclusivity by focusing on a dynamic incentive of streaming services: exclusivity facilitates a service to penetrate the market in the initial stage. After establishing a substantial user base, the service can harvest profit by exploiting its locked-in customers. Essential to this strategy is that consumers face a substantial switching cost that prevents them from changing their subscription decisions. The switching cost arises because streaming services learn consumers' tastes and recommend the right song on a timely basis by using a mix of human curation, proprietary algorithms, and integration with social media (Harding, 2015). A user who has created personalized playlists and connected with friends on service has to consider the advantages she/he will forgo when switching to a different service. Because each offers a proprietary blend of human editorial and algorithmically generated selections (Popper, 2015), services are differentiated by the ability to deliver a high standard of customer service. The differentiation in quality also leads to an asymmetry in services' ability to retain its users, and therefore leads services to have different incentives for exclusive content distribution.

In this paper, I first examine the interaction between exclusivity and the switching cost in a theoretical model where service can access different content and endogenously choose whether to distribute the content exclusively. In a static analysis of the model in which services compete for one period only, I find they always choose distribution the content non-exclusively. A service will always choose to supply its content to the rival because it can choose the per-subscriber fee to maximize the joint profit of both services and choose the lump-sum fee to extract all the profit up to the amount that the rival could gain if choosing the exclusive distribution. However, in a dynamic analysis in which services compete for two periods and services can create switching costs to their users that lead to consumer lock-in. The exclusive distribution naturally arises if one service can generate a significantly larger lock-in effect than the other service. Intuitively, the service will choose to withhold the proprietary content from its rival to capture more users in the current period, gaining a higher market share and advantageous position in the next period because of the switching cost.

The empirical analysis relies on a consistent estimate of consumers' switching costs and other coefficients affecting the subscription decision. The estimation is based on a dynamic structural model of consumer subscription and usage decisions. A key ingredient of the model is a service-specific cost consumers face in switching from service to service. Because services can be complements or substitutes, the model allows consumers to multihome. In this way, consumers can gain access to more music content by multihoming across services.

I estimate the model using aggregate data from China's music streaming market. The data includes active users and aggregate usage time of six important streaming services in China from

January 2014 to July 2017. In estimating switching costs, I extend the method of Shcherbakov (2016) that leverages the dependence of current period aggregate decisions on exogenous shifters in the previous period's decisions. The identification is based on the idea that if switching costs were absent, consumers' subscription decisions of current period should not depend on their subscription decisions of previous period. Because a service's market share represents its users' aggregated decisions, one can infer the switching cost of the service from the persistence in its market share. For each service, I use its rival services' lagged usages as exogenous shifters of market shares to exclude any other unobserved persistence in service quality and consumer preferences from the serial-correlation in market share.

The main findings in the empirical analysis are that switching costs are important - the dynamic model fits the data well, and particularly for the theoretical prediction. Specifically, dominant services in the market have a significant and statistically larger estimate of switching cost coefficients than the small services. Because the dominant services also distribute more exclusive content than the small services, the empirical finding is consistent with the theoretical prediction that a service's incentive for exclusive content distribution depends on its ability to retain users. In addition, the analysis also finds that a service's switching cost is positively correlated with the service quality that is estimated as the service fixed effect in service usages. This finding is consistent with the intuition for switching cost: A service provider that offers a high quality music-listening experience to its users can encourage more usage and, therefore, can better retain those users.

Using parameter estimates from the structural model, I then examine the impact of two counterfactual policies. The first counterfactual analysis studies an alternative copyright enforcement policy that mandates a compulsory licensing provision. Such a provision would prohibit exclusive content by letting streaming services offer a copyrighted song to the users without negotiating permission from the copyright owner while using the regulated royalty payments to protect copyright owners' interests. Compulsory licensing provision is commonly used as a license arrangement in many important industries. For example, in many countries, including the US and China, 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 a monopoly fee without internalizing the positive externalities. In China, because of the competition for exclusive licenses and copyright disputes among services, the Chinese National Copyright Administration came forward, seeking to stop exclusive licenses in the music industry and promote the "fair use" and "widespread dissemination" of music by regulation. The authority also notices the market is highly concentrated and is potentially monopolized by the dominant company. Therefore, they expect mandating compulsory licensing to improve market competition.

The second counterfactual analysis focuses on a mandatory data probability policy. An example of this policy is the General Data Protection Regulation (GDPR), which came into effect in the European Union in May 2018. GDPR sets a regulation in EU law on data protection and privacy in the European Union (EU) and the European Economic Area (EEA). A mandated data portability is included in the regulation as a right of data subject [4]. One possibility for implementing the policy would be allowing users to transfer their personal data, including playlists and streaming history, to another service. Thus, the policy directly reduces the switching cost by enabling users to move their playlists, favorite settings, and other personal data related to music listening to a new service. The policy can further reduce the switching cost if services are allowed to use the data that are transferred users from other services to learn users' tastes so that they can tailor their service features to individual preferences.

The counterfactual exercise finds that using compulsory licensing would not improve market competition and reduce market concentration as intended. In contrast, when a compulsory provision is enforced, the market is even more concentrated: the dominant service's market share under the compulsory provision would be larger than 70%, an increase of 14% from the market outcome under the exclusive provision. Although small services provide more content, they would lose significant market share under the compulsory provision than the exclusive provision. The result is driven by the fact that when services are less differentiated in their music repertoire, service quality becomes the dominant factor in consumers' decisions. Service quality is assumed to be exogenously determined, and refers to the features, such as audio quality and the effectiveness of the music recommendation system, that are relevant to music listening experience in excessive of the music content of a service. The dominant services offer better service quality than smaller services; therefore, in the counterfactual scenario where services have a uniform set of songs, consumers will switch to the dominant service. The switching of multihoming users also contributes to the reduction in users of small services. Under the exclusive provision, multihoming users account for more than 20 percent of small services' market shares. However, under the compulsory scenario, multihoming users would become singlehoming users due to the existence of the switching cost, switching away from small services. The counterfactual analysis results suggest that a compulsory licensing provision does not 'level the field' between dominant and small services. On the contrary, it would harm the small services and lead to a more concentrated market.

In the second counterfactual analysis, I model the mandatory data portability as a full reduction in switching costs. The results show that enforcing data portability will boost the growth of streaming users because the policy improves the overall streaming experience by allowing users to switch "freely" between services, leading to extensive growth in streaming users that benefits all

[4]Data subject refers to any individual person who can be identified, directly or indirectly, via an identifier such as a name, an ID number, location data, or via factors specific to the person's physical, physiological, genetic, mental, economic, cultural or social identity. The right to data portability is provided by Article 20 of the GDPR.

services in this market. The policy also reduces market concentration by bringing more users to small services – users who do not switch from dominant services to small services because of the switching cost will choose to switch when the cost is removed. Specifically, under the policy, small services will expand their user base to be more than twice as large as the baseline scenario without the policy. Therefore, my paper suggests using a mandatory data portability policy to reduce market concentration.

The contributions of my paper are as follows. First, my paper addresses important policy issues regarding copyright protection. The common purpose of copyright law across countries is ensuring adequate incentives for creation and innovation. Albeit straightforward, there is no consensus on the proper way to enforce copyright protection. My paper adds to the discussion by analyzing the effect of copyright enforcement on market competition under the exclusive provision and alternative provisions, including compulsory licensing and mandatory data portability. Secondly, my paper stresses the importance of using a dynamic framework in explaining the implications of exclusive content distribution. The analysis uses a dynamic model to show that streaming services have incentives to choose exclusivity, while a static analysis shows streaming services will always choose non-exclusive distribution (Armstrong, 1999; Katz and Shapiro, 1985; Weeds, 2016). In the dynamic incentive for exclusivity, the switching cost is the most important ingredient relevant to the service's ability to provide high-quality customer service and retain customers. Policymakers should be aware of this dynamic incentive when investigating and evaluating the possible impact of exclusivity on the competition.

The relevance of my paper is not limited to music streaming. Its implication applies to many sectors, such as computer software and hardware, cable television, internet service, and telecommunications. A common feature of these industries is the "bottleneck" product, of which the distribution has a significant impact on downstream competition. Also, switching costs often exist in those industries.

2 Literature Review

My paper addresses important policy questions on copyright protection. Economic analysis of intellectual property traditionally focuses on whether reconciling incentives for private producers to invest in innovation (Arrow, 1962). Economics research studying this question has focused extensively on patent innovation, where it is easier to define and measure creative contributions (Budish et al., 2015; Galasso and Schankerman, 2018; Sampat and Williams, 2019; Scotchmer, 2004). The evidence that copyright improves creations is scarce regarding the music industry, partially due to the lack of exogenous variation in modern copyright laws (Giorcelli and Moser, 2020). Waldfogel (2012) finds no evidence that piracy can lead to a reduction in the quality of music released using the exogenous shock of the unprecedented growth of piracy introduced by the Napster. In contrast, Giorcelli and Moser (2020) uses the history data of Italian operas and finds that copyright protection at then increased the number and quality of opera produced.

My paper contributes to the literature by comparing different approaches to protect intellectual property that includes using compulsory licensing. Compulsory licensing allows someone to use intellectual property without the consent of patent owners. Previous research has studied compulsory licensing centered on the pharmaceutical industry, where the government often uses compulsory licensing to enforce wide access to patented drugs or vaccines that can significantly impact society. Bond and Saggi (2014) finds theoretical evidence that using compulsory licensing can raise welfare by improving access to patented foreign products. Baten et al. (2017) uses the data of chemical patents in German after World War I to show that the imposition of compulsory licensing increased inventions by German firms.

Assessing the impact of compulsory licensing on the streaming music industry is at the heart of the debate in the literature of legal studies. 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 the copyright to provide 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) [5], which would create a blanket collective license covering digital reproduction and distribution rights for musical works. Richardson (2014) suggests a compulsory license system with capped license fees. The article argues that the royalty rate set 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.

The previous empirical literature on exclusivity has been focused on measuring the effect of exclusive contracting on competition (see Chipty (2001) and Asker (2004) for up-stream competition and Lee (2013) for down-stream competition). The incentives of a service provider to distribute exclusive content is studied mostly in theory. Armstrong and Wright (2007) shows that a platform uses exclusive contracts to persuade agents of one side to stop subscribing to the rival platform and, consequently, can exploit the 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 its content outright and have no control of pricing to consumers. Ishihara and Oki (2017) shows a monopolistic content provider leverages exclusivity to balance two opposing effects on its bargaining power: a positive effect caused by the increase in multihoming consumers; a negative effect caused by the restriction of distribution channels. My paper differs from the literature by focusing on the downstream firms' incentive to exclusive distribution. My paper also differs in emphasizing the effect of switching costs on the firms' incentive for exclusive content distribution. A similar theory result is also

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

discovered in the pay-TV sector(e.g., Weeds (2016)). Similar empirical evidence is found in the internet service industry. Augereau et al. (2006) finds that internet service providers (ISP) deliberately choose the modem standard that is incompatible to their local competitors because doing this prevents users from switching to a more popular product. One of the empirical implications in my paper is that exclusivity benefits small services. A similar result is also discovered in the literature. Lee (2013) finds that exclusive software enables small entrants to differentiate themselves from the incumbent and gain traction in the video gaming console market.

There is emerging literature on the economic impact of the General Data Protection Regulation (GDPR) (Johnson et al., 2020; Jia et al., 2018). My paper supplements this strand of literature in three respects: First, my paper addresses this regulation's mandatory data portability. Previous literature has focused on the privacy protection of GDPR. Second, this is the first paper, to my knowledge, that uses a structural model in the empirical evaluation of this policy on market competition. Finally, my paper explores the possibility of implementing this policy in a developing country.

My paper also relates to the topics on digitization of the music industry. One strand of research has addressed concerns of digital music on its advantage of cost reduction and displacement of physical music sales(see Waldfogel (2010), Aguiar and Waldfogel (2018) and Waldfogel (2017) for a survey). My paper is related to another strand of research that is on measuring the effects of anti-piracy interventions in the 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 on internet traffic and music sales.

Switching costs have been estimated in many markets, leveraging various estimation strategies. Schiraldi (2011) studies auto-mobile replacement. The author argues the existence of switching costs due to 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 the health insurance market, but use different identification strategies. The former paper leverages " passive" decisions due to plan menu change and forced re-enrollment to identify the switching costs, while the latter identifies switching costs through the impact of the entry of new plans on market shares of existing plans. The estimation strategy implemented in my 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).

The demand model in my paper contributes to the literature on the dynamic demand estimation. Several studies in the literature have shown the importance of applying a dynamic model to study economic phenomenons or data patterns that cannot be explained in a static framework (e.g., Rust (1994); Hendel and Nevo (2006)). In my paper, I specify and estimate a two-stage dynamic discrete-continuous model for estimating the demand for complementary goods. The model combines the dynamic discrete choice model and its solution introduced in Gowrisankaran and Rysman (2012), and the discrete-continuous demand model developed in Crawford and Yurukoglu (2012).

3 Roadmap

The rest of the paper is structured as follows: Section 4 presents a brief overview of a theoretical model that implies that the existence of switching costs can lead to exclusive distribution. Section 5 describes the institutional details of copyright law and the music industry. Section 6 describes the datasets employed in the empirical analysis. Section 7 provides preliminary evidence for the existing switching costs and multihoming behavior. Section 8 describes the dynamic structural model, the empirical specification, and discusses the identification assumptions and intuitions. Section 10 presents the main model estimates. Section11 describes and discusses counterfactual analysis. Finally, Section 12 concludes.

4 Theoretical Illustration: Exclusivity with Consumer Lock-in

Before proceeding to the empirical analysis, I first show an illustrative and stylized theory model that shows consumer lock-in can lead to exclusive content distribution. This section presents a brief overview of the theoretical model and its predictions. The details of the model and formal proofs of the results are presented in Appendix A.

4.1 The Model

The theoretical analysis proceeds from a Hotelling-style competition model with two service providers and a continuum of consumers. Service providers are differentiated vertically: one of the service providers has vertically integrated with a monopoly content provider and the provider is referred to as an integrated service provider due to the vertical arrangement. The other provider is referred to as a non-integrated service provider.

The competition takes place in multiple stages. Before setting the subscription price and letting consumers make their subscription decisions, both service providers participate in a contract negotiation. The contract is about sub-licensing the integrated service's content to the non-integrated service. It entails a take-it-or-leave-it offer from the integrated service provider demanding a sub-licensing fee paid by the non-integrated service provider. The sub-licensing fee is set in the form of a two-part tariff which includes a lump-sum fee and a per-subscriber fee. After negotiating the contract, both services set their subscription prices. Consumers choose one service provider to subscribe to after observing services' prices and their content in distribution. Both services can generate revenues from users' subscriptions and endogenously set their subscription prices through a Bertrand competition. The integrated service provider may also receive revenue in terms of a sub-licensing fee paid by the non-integrated service provider if a sub-license contract is made in the negotiation.

I then take the above game into analysis in a static and dynamic framework respectively. In a static framework, the game takes place only for one period, while in a dynamic framework, the game takes place for two periods repeatedly. Service providers make separate sub-license contract and set separate subscription prices in each period. Consumers are new to the services at the beginning of the first period. However, in the dynamic framework, consumers face a decision of whether to switch to a different service in the second period. A consumer will receive an extra utility if he/she chooses to continue the subscription to the same service as in the previous period; Whereas, a consumer who switches to another service in the second period will forgo this additional surplus. The continued subscription surplus represents the benefit a streaming service provider can offer to its existing users by curating its service based on the user's first-period usage. For example, a streaming service usually provides a customized playlist list of songs based on individual users' search history patterns and revealed music preferences. The continued subscription surplus serves the same purpose as a switching cost, which captures the lock-in effect created by a service provider.

The analysis focuses on whether exclusive content distribution will occur in the equilibrium. An equilibrium outcome is exclusive if only the integrated provider distributes the content, while the equilibrium outcome is non-exclusive if both services distribute the content.

4.2 Theoretical Predictions

The first result from the theoretical analysis (Proposition 1) shows service providers always negotiate to distribute the same content in a static equilibrium. Because of the static setting and that consumers have not subscribed to any service in the beginning of the period, switching costs do not affect either services' or consumers' decisions. In this equilibrium, the integrated service provider can always find a contract that the non-integrated service will accept. The integrated service can also use the contract to set a collusive price with the non-integrated service and gain a joint monopoly profit. Intuitively, because of the two-part tariff sub-licensing fee, the integrated service can choose the per-subscriber fee to maximize the joint profit and choose the lump-sum fee to extract the profit from the non-integrated service provider up to the amount that it could gain in the situation of exclusive distribution. For that reason, non-exclusivity is a preferred choice because it enables a soft price competition and extra profits.

The main result (Proposition 2) drawn from the theoretical analysis is that exclusive equilibrium arises when introducing consumer lock-in and dynamic competition to the model. Due to the existence of customer lock-in, a higher market share in the current period to a firm means an advantageous position in the price competition of the next period. Moreover, by price discriminating against existing users, a service provider can exploit the existing continue subscription surplus to achieve higher profit in the second period, which in turn gives the integrated service provider more incentive to distribute the content exclusively in order to capture more users in the initial market penetration period. A necessary condition for the exclusive equilibrium is the integrated service provider creates a sufficiently larger lock-in effect than the non-integrated service provider. This condition is necessary because the sub-licensing contract enables the integrated service to extract the surplus of non-integrated service's users. Therefore, if the non-integrated service provider creates a larger lock-in effect or both services create similar lock-in effects, the integrated service provider may still prefer a non-exclusive distribution of the content.

4.3 Relation to the Literature

The theoretical analysis shows when per-user fees can be used in the sub-licensing contract, non-exclusivity is the unique outcome. A similar result is also discovered in the literature studying the exclusive content distribution in the pay TV market (Armstrong, 1999). Weeds (2016) overturned the non-exclusivity result by adding consumer lock-in and dynamic competition into the model, while in her framework the licensing contract only uses a per-user fee. My analysis shows when a two-part tariff fee is used in the contract, non-exclusivity might be still the only equilibrium unless there is an asymmetry in the lock-in effects between services. The following empirical analysis on the Chinese music streaming market is going to show this important evidence that services' abilities to lock in users are positively correlated with their exclusive content in distribution.

5 Industry Background

This section summarizes the 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 the 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.[6] The recorded industry has been through a long journey to fight against piracy and seek options to distribute the music legally and profitably. The emergence of streaming services such

[6]International Federation for Phonographic Industry's Digital Music Report, 2017, p. 11.

as Spotify and Pandora raises optimism and concern about their recorded music revenue impacts. Unlike the services using the download model (e.g., Apple's iTunes), streaming services use the subscription model. The underlying idea is selling access to vast musical content collections instead of using the download-and-own model is selling each recording separately for downloading and letting 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 choosing. In contrast, 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, streaming services have developed rapidly and attracted users to switch from download service and illegal listening. Several studies in the existing literature have indicated that music streamings displace music piracy (Aguiar, 2017; Aguiar and Waldfogel, 2018).

5.1 Chinese Music Streaming Market, Anti-Piracy Campaign and Competition for Exclusivity

The Chinese music market is one of the single fastest-growing markets in the world in terms of recorded music sales, which is surprising because piracy was rampant in China. Especially in the age of physical music, the market had a large scale infringement against both local and global rights owners by selling counterfeits discs. Two changes drive the growth took place in the market: A governmental-leading anti-piracy campaign and the emergence of increasingly popular music streaming services.

From 2012, the Chinese government undertook an anti-piracy campaign "Sword Net" to enforce copyright legislation and 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 and promptly removed 2.2 million unlicensed songs (Tang and Lyons, 2016). The campaign also banned illegal downloading services, leading to an increase in music streaming revenue. Since 2012, music streaming has become the primary source of the industry revenue in China (Figure 2).

China's music streaming market consists mainly of local services due to the absence of global competitors.[7] After aggressive horizontal and vertical integrations, the market has one dominant firm, followed by several smaller services. Tencent Music Entertainment (henceforth TME), one

[7] As in many other digital markets of the country, the Chinese government takes a protectionist policy to the streaming music market. There is no Spotify, Tidal, or Deezer in Mainland China; Apple Music is available since 2015, with next to no success.

of the largest China's internet giants[8], became the leading firm taking up the largest market share in China. Tencent started its streaming service named QQMusic in 2005, then acquired Kugou and Kuwo in 2016.[9] 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.

In China, copyright enforcement also forced services to negotiate with licensing contracts with labels, leading to heightened competition for exclusivity in the streaming market. Services compete with each other by bidding for exclusive licensing from record labels. For example, Tencent sealed exclusive deals with Warner Music Group, Sony Music, Universal Music Group, and South Korean label YG Entertainment, by paying each label with a hefty, but unknown, licensing fee.[10]

A typical exclusive deal between a label and a service permits sub-licensing, enabling the service to choose which set of songs its competitors can play. For example, Universal Music Group (UMG), one of the world's largest label companies, distributed their copyrighted songs via Tencent starting from 2017. It also allows Tencent to sublicense UMG's content to third-party music service providers in the region. [11] Although there are several cases that services share licensed songs with each other, they also choose to withhold a broad set of songs, which perceived as highly popular to users, from their rivals. [12] The competition for exclusivity results in a fragmented distribution that no service nowadays can offer universal access to music as each is distributing a set of exclusive content.

The dominant position of Tencent has received regulators' attention in China, especially because it has signed exclusive deals with most labels. In 2019, the State Administration for Market Regulation (SAMR) imitated an anti-trust investigation into Tencent. [13]

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

[9]The two services were owned by the same company, China Music Corporation (CMC), at the time of merging.

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

[11]See the article "Universal Signs Major Licensing Deal with Tencent in China," available at https://www.musicbusinessworldwide.com/universal-signs-major-licensing-deal-with-tencent-in-china/.

[12]There are many lawsuits filed for a dispute in a sub-licensing contract. In August 2017, Tencent Music and NetEase sued each other for the second time in the two years over alleged copyright infringement violating their music sharing agreement. See the article "Tencent Files Lawsuit Against Netease Music Over Copyright Infringement", Technode (Aug. 25, 2017), available at https://technode.com/2017/08/25/tencent-files-lawsuit-netease-music-copyright-infringement/. In 2015, Kugou and Alibaba were also involved in a legal back-and-forth over music rights. See the article "China's Major Music Streamers Are Suing the Hell Out of Each Other and That's a Good Thing", Quartz, July 22, 2015. Available at https://qz.com/459551/a-whirlwind-of-lawsuits-among-chinas-internet-giants-might-tear-through-the-nations-piracy-habit-too/.

[13]See the NYSE investor notice. Available at https://finance.yahoo.com/news/nyse-tme-investor-notice-lawsuit-123500022.html

5.2 Personalization and Switching Costs

The most prominent feature of streaming services is discovering new songs and listening to music digitally without downloading song files or pay-per-track. Utilizing technology to understand customers' tastes can recommend a specific user more comparable songs on a timely basis. For example, Spotify 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. Pandora, the largest non-interactive service, allows consumers to seed their stations with a song or an artist they like. According to various criteria, the station then plays songs and artists similar to the seed, including musicological similarity and evidence about which music is liked in common among consumers (Aguiar and Waldfogel, 2018). Like their counterparts in the U.S., Chinese music streaming services also offer personalized services in various forms. In addition to the music discovery feature, they offer users more personalized experience users utilizing social networking apps. For instance, QQMusic allows users to establish a personalized homepage and share their comments via WeChat and QQ.[14]

Because of the personalized services that fit each person's music taste, active users of a service, having created their 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. 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".[15] Similarly, in China, the evidence of existing switching costs was shown when services started charging for more of its content in 2019, while users did not transit away from those services.[16]

[14] WeChat and QQ are the two most popular social networking apps in China. See Page 140-142, Registration Statement of Tencent Music Entertainment Group. Available at https://www.sec.gov/Archives/edgar/data/1744676/000119312518290581/d624633df1.htm#rom624633_18.

[15] See the article "The Business Of Music-Streaming Services: How Deals With Record Labels And Publishers Are Made", September 2015. Available at https://www.techtimes.com/articles/81895/20150910/business-music-streaming-services-deals-record-labels.html.

[16] See the article "Tencent Music charges for more content as paying users drive profit beat", Reuters, May 2019. Available at https://www.cnbc.com/2019/05/14/tencent-music-charges-for-more-content-as-paying-users-drive-profit-beat.html.

5.3 Copyright Law

Although with differences across countries or areas in interpretation and execution of copyright protection, the common purpose of copyright regulation in the music industry is ensuring adequate incentives exist for the creation and dissemination of musical subject-matter.[17] Albeit straightforward, there is a divergence in the way of achieving this simple objective.

The first approach uses the exclusive provision that protects copyright owners' exclusive rights in distribution, reproduction, adaption, and performance. This approach is rooted in the economic concept of the "tragedy of the commons" (Hardin, 1968) in which a common resource will be overused because anyone can consume it without internalizing the cost to others. In the same spirit, inefficiency can arise in music distribution, when musical works are taken as common resources. Those who use the musical works illegally will eventually reduce the producers' incentive for creating new works or publishers' investments in disseminating the works, putting negative externalities to those who use the works legally.

While this exclusive provision gives copyright owners extensive control to protect their copyrighted works from unauthorized reproduction and thus protect their financial benefits, it also enables them the monopoly power over the use of their works. And monopoly generates inefficiency as it creates deadweight loss to society. Record labels are the especial group in the market have used their exclusive right to control the reproduction and distribution of musical works that enlarges their markup to consumers and markdown to artists. 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".

A second approach to the regulatory purpose of the copyright law uses the compulsory licensing provision. This approach relies on a third-party fee collector.[18] A copyright owner who wished to collect revenue from his/her work would register it with the third-party agent. The agent would then make the work available to the public via charging an efficient fee that sufficiently compensates the copyright owner. Overall, the compulsory provision grants non-exclusionary access to the music works from the public while guaranteeing the minimal incentives for creating new works. For that reason, this approach balances the dissemination purpose of copyright law against the benefits of providing incentives to create new works.

There is also another scope for compulsory licensing provisions based on social welfare and fairness. The best example is that many countries, including U.S. and China, set regulated rate paid

[17] For example, Article I of the U.S. Constitutional Law states the copyright law is "to promote the progress of science and useful arts." China's copyright law also states:"The spirit of the law was to encourage the creation and dissemination of works which would contribute to the spiritual and material well being of society as well as the promotion of culture and sciences."

[18] The third-party agent can be a governmentally administrated organization, see Fisher (2001).

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). In U.S., non-interactive streaming services such as Pandora are granted to obtain a compulsory license to distribute copies of phonorecords under the Digital Performance Right in Sound Recordings Act (DPRA) enacted in 1995. The discussion on whether an interactive streaming service should also be granted for a compulsory licensing is still undergoing. [19] 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 "fair use" and "widespread dissemination" of music by regulation[20]. The exact form of regulation might be either mandatory or market-based policy (e.g. price ceiling). The objective is pushing license fees to be fair and equitable to both the copyright holders and the streaming services.

6 Data

This section describes the data used for this study. The data set is compiled from several sources. The first source is *Analysis Qianfan* - a 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 the number of active users and aggregate hours spent on each service. The consulting company collected and generated the data set by tracking individual SDKs[21] that are installed on the apps of major service providers and operation systems.[22]

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 in the market which are QQMusic, Kugou, Kuwo, Xiami, Netease and Baidu. I compute a market share for each service by dividing the number of active users over the number of internet users each year. The data of total internet users is collected from China Internet Network Information Center (CNNIC).

One advantage of using the data is the direct observation of overlapped users (multihoming)

[19] The Section 115 Reform Act of 2006 (SIRA), for example, one of several recent attempts to modify Section 115 of the United States Copyright Act to provide compulsory licenses to all digital delivery of musical works.

[20] 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.

[21] SDK stands for Software Development Kit. It brings pre-built functionality that a developer can use directly without building from scratch. One of the functions is tracking users and usages behaviors.

[22] More details of their SDK technology are available on the website `http://qianfan.analysyschina.com/view/help/rules.html`.

between services. The overlapped users are consumers who subscribed to multiple services simultaneously and regularly used both services within a month. The variable is available for services with user base larger than one million and is available each month between Aug. 2016 and Apr. 2017.

Table 1a reports the summary statistics of users and usage behaviors for each service. The number of active users of dominant services is more than ten times larger than that of small services through all sample periods. As of 2017, the three dominant services, QQMusic, Kugou, and Kuwo have more than 500 million active users, while the small services have active users close to 80 million. Users also spend more time on dominant services than the small: user usage of dominant services accounts for more than 90 percent of all services' usage. Multihoming users are an essential component of small services' users, accounting for more than 10 % of their users. For Xiami, one of the small services, multihoming users account for close 50% of its users. For the other two small services, Netease and Baidu, multihoming users also account for more than 20 % of their users. The change of active users over time is plotted in Figure 4 . Overall, streaming users are increasing over time from around 200 million in 2014 to nearly 600 million in 2017. Users of small services are growing as well, although the dominant services hold the largest market share over the entire sample period.

Although SDKs' aggregate data is reliable, it does not provide information on whether the user uses a freemium or a premium service. The freemium service offers basic features without a paid subscription, while the premium service includes some enhanced features such as downloading, accessing premium content, and creating smart playlists. Moreover, there is also a lack of enough data on the subscription fee. Therefore, there is no enough information or variation in the data to identify users' price sensitivity. However, being lack of the information on subscription fee may not be an essential issue that biases the model estimates, as the paying ratio of music streaming services grew slowly and stayed below 4% from 2013 to 2017.[23] As a comparison, the 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).

Content distribution is crucial in studying the music streaming market. I collected the second data set to get information on this, which contains exhaustive information on content distribution. The data is a snapshot from the website of the services mentioned above. 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 in Dec. 2017, however, many record labels licensed heir copyrighted music to services at different times before that. I track back to the press and company announcement to retrieve the exact date that a service signed a deal with a record

[23] According to the report of iResearch, a market research and consulting company for online business in China.

label to address this issue. By doing this and focus on the major labels only[24], I recover the date from which the music content of those labels started being available on each service. Finally, I use the dataset to create attribute variables for each service. Those variables include the number of exclusively and non-exclusively licensed album titles. These two variables change over time with the assumption that each album's release date is the date that album became available on service. Because a consumer is allowed to choose a bundle of streaming services, a service's music content might be unique within some bundle choices but not others. Therefore, I created attribute variables for each service and bundle combination [25]. The descriptive statistics of the data are presented in Table 2a and 2b. In the end, I combined both data sets described above for demand estimation. There are 252 service-month observations and 4032 service-bundle-month observations.

The content distribution is asymmetric among services, as each service has signed exclusive licensing contracts with a different set of record labels. Table 2b reports a selected list of labels and their corresponding exclusive deal partners (services), and a comparison of the album titles released by labels is presented in Figure 6. The parent company of dominant services, TME [26] has the most exclusive deals sealed with record labels, including the Big Three: Sony, Warner, and Universal. The total number of albums published by the Big Three within the sample period accounts for almost 60 % of the entire set of albums in the data. Although there are many exclusive deals signed, services still have much commonly-possessed music content. For dominant services, the exclusive content takes approximately 20% of their entire repertoire. The existing shared content is due to two reasons: First, services can sublicense the music content to the others, which is generally allowed in an exclusive contract; Second, there exist several small labels or independent artists that distribute their songs via all services.

7 Preliminary Analysis

This section provides a preliminary analysis of the data to illustrate the subscription patterns consistent with consumer switching costs. I also provide a reduced-form analysis to show that services can be complements to each other.

[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.

[26]or CMC before the merge of QQMusic, Kugou, and Kuwo in 2016

7.1 Reduced-form Evidence of Switching Costs

The method I apply in my paper in estimating switching costs is an extension of Shcherbakov (2016). The main idea of the method is testing the persistence in an aggregated market share. The intuition is as follows: if switching costs are substantial, consumers in each period should weigh the benefits of changing their subscriptions against the switching cost. Thus consumer decisions are state-dependent, which means the current period decision is a function of the previous period decision. Because market shares are representations of the aggregated consumer decisions, testing the persistence in market share can also be used to test if the switching cost does exist and is substantially large. Therefore I conduct a preliminary analysis of the market-level data using the following regression:

$$\log s_{jt} = Z_{jt}\beta + \alpha_j \log s_{j,t-1} + \varepsilon_{jt}, \tag{1}$$

where s_{jt} is the market share of service j at period t, Z_{jt} are control variables including a time trend, service attributes (number of album titles), service usages, and rivals' market shares and usages.

The regression is a simple autoregressive model in which α_j is the autoregressive coefficient. The significance level, sign, and magnitude of the coefficient reflect the degree of persistence in market share. Moreover, the coefficient is expected to be positive if the service's switching cost is substantial. Intuitively, with the switching cost, an increase in the previous period user base implies more users in the current period.

However, switching costs might not be the only cause of market share persistence. There exist many other confounding factors affecting the market share that is also persistently changing over time. For that reason, a significant autoregressive coefficient cannot be attributed to the existence of switching costs. Those confounding factors can be unobserved investments (e.g., advertisement) or consumer preference (e.g., brand loyalty).

To exclude unobserved persistence in market share driven by factors other than the switching cost, the lag market share in the regression is instrumented by rivals' lagged period usages. Service usage is a good proxy for service quality. Because a service competes with other services in the same market, its rivals' service quality will significantly affect its market share. However, a service's persistent demand shock should be uncorrelated with its rivals' quality. Therefore, with the lagged service's market share instrumented by rivals' usage hours, the test shows whether a change in previous market share due to some exogenous shocks will have a long term impact on its market share. Note that the regression also includes rivals' current period usages. Thus the persistence in those variables will not affect the estimate of the autoregressive coefficient α_j.

Table 4 shows the estimation results of the above regression with and without using the instruments for the lag market share. A comparison of autoregressive coefficients across services is presented in Figure 7. When predicted lag market share is used, autoregressive coefficients for all services have expected positive signs suggesting that a larger own market share in the previous period ceteris paribus results in a larger current period's market share. Coefficients of dominant services are statistically significant and more massive than those of small services. That level of persistence in market share varies across services, implies services are asymmetric in switching costs.

7.2 Substitutes and Complements

This section provides an analysis of the substitution or complementarity relationship between services. The relationship depends on the existing multihoming costs and bundling benefits. The multihoming costs can arise in many instances, including the costs of paying subscription fees, the efforts required to manage playlists across services, remember passwords, periodic logins, and connecting to friends on different platforms. Bundling benefits arise when subscribing to those services gives access to a broader set of music content.

Services are substitutes when the multihoming cost is dominating. In contrast, two services are more likely to be complements if the bundling benefit is much higher. If neither the multihoming cost nor the bundling effect exists, subscribing to one service should be independent of the decision of subscribing to another service. Based on this idea, it is straightforward to test whether an independent choice model can explain the observed size of multihoming users.

Taking a simple example to illustrate: suppose that a consumer subscribes to service A and B with probability equals to 20% and 40%, respectively. If subscribing to one service is independent of the decision to subscribe to the other, the probability that the consumer subscribing to both services is 8% (=20% $\times$ 40%). When the multihoming cost is high - services are substitutes - the observed share of multihoming users should be lower than 8%. On the contrary, when the bundling benefit is high - services are complements- the observed share of multihoming users should be greater than 8%.

Four examples of service bundles are presented in Figure 8. In these examples, the observed multihoming user is significantly less than predicted by the independent choice model. These examples indicate the existence of the multihoming cost. The four examples presented in Figure 9 show evidence of the existing bundling benefit. Two service bundles presented at the top of Figure 9 show that bundling benefit and multihoming cost can be equal. In those examples, the observed multihoming user size is roughly equal to the size predicted by independence service choice. Finally, the examples presented at the bottom of Figure 9 show that the bundling benefit can be greater than the multihoming cost.

All examples presented above reject that subscription decision is independent. The next question is when the bundling benefit will arise and become more significant than the multihoming cost? Intuitively, the benefits of subscribing to both service A and B is substantial if the music content provided by these two services are less similar with each has its exclusive content that the other service does not offer. This intuition is justified in the following regression.

The dependent variable is the difference between multihoming users as observed in the data and as predicted by the independent choice model. Following the same intuition as above, the dependent variable is likely to be positive if services are close to being complementary. The independent variables on the right include the number of exclusive and non-exclusive album titles available on both services within the bundle.

Table 5 summarizes the regression results under different specifications. After controlling both service fixed effects and time fixed effects, the number of exclusive album titles of services in a bundle increase. The difference between the observed and predicted subscription rate of the bundle shifts towards positive, suggesting that the incremental multihoming benefits increases. In contrast, the incremental multihoming benefits decrease when services in the bundle have more overlapped content, as the coefficient estimates for non-exclusive album titles are negative.

8 A Dynamic Model of Service Demand

This section develops a dynamic model of consumer subscription and usage decisions of music streaming services.

Consumers are indexed by i, and time is indexed by t. The set of streaming service providers is J with a particular service provider denoted as j. I further use B to denote a collection of subsets of J. In each period, I assume that a consumer makes the following two-stage decision: In stage I, consumer i subscribes to a bundle of streaming services $b \in B$. The outside option, indexed by $\emptyset$, represents the non-streaming services. In stage II, the consumer picks a length of time spent listening via each service in the bundle b. I proceed to describe details of each stage and further assumptions by reversing the order of the timing.

8.1 Stage II: Time Allocation

In stage II, I model the time allocation problem faced by consumers. Specifically, I let a consumer i make a decision of spending a length of time $\ell_{ibt} \equiv \sum_{j \in b \cup \{0\}} \ell_{ijt}$, on each service of bundle b, where ℓ_{ijt} is decision made for individual service j. The consumer can also choose a length of time for not listening $j = 0$. The consumer maximizes the following utility:

$$
\begin{aligned}
\max_{\ell_{ibt},\ell_{i0t}} \quad & v_{ibt} = \phi_{ibt} v^1(\ell_{ibt}|\eta) + \phi_{i0t} v^0(\ell_{i0t}) \\
s.t. \quad & \ell_{ibt}, \ell_{i0t} \geq 0 \;\; \forall j \in b, \\
& \ell_{ibt} + \ell_{i0t} \leq T.
\end{aligned} \tag{2}
$$

In the above utility function, the parameter ϕ_{ibt} captures the marginal utility of listening to music. I specify the utility function of listening $v^1(\ell_{ibt}|\eta)$ as an increasing and concave function, where the level of concavity is governed by η,

$$
v^1(\ell|\eta) = \frac{(\ell+1)^{1-\eta} - 1}{1-\eta}, \tag{3}
$$

where parameter η captures the speed of marginal utility diminishing with additional time spent on listening to music. The utility received from non-listening is specified in a log utility form:

$$
v^0(\ell) = \log(1+\ell). \tag{4}
$$

Note that the difference between v^1 and v^0 is the rate of marginal utility diminishing. As $\eta \to 1$, the utility function converges to a log utility.

I define the optimized value from time allocation problem in equation 2 as the *usage value* and denote it by $v_{it}^*(b)$.

I further specify the marginal utility ϕ_{ibt} and ϕ_{i0t} as follows:

$$
\begin{aligned}
\phi_{ibt} &= exp(x_{bt}\gamma^J)\varepsilon_{ibt}^u, && (5)\\
\phi_{i0t} &= \varepsilon_{i0t}^u, && (6)
\end{aligned}
$$

where x_{bt} is the set of observable characteristics of the service bundle, which includes a constant, annual time fixed effects, and the number of album titles that are available on services within the bundle b. Both ε_{ibt}^u and ε_{i0t}^u are idiosyncratic error terms. The specification and distribution assumption of those error terms are as follows:

$$
\begin{aligned}
\varepsilon_{ibt}^u = \sum_{j \in b} \varepsilon_{ijt}^u, \text{ where } \varepsilon_{ijt}^u &\sim \text{Exponential}(\rho_j), && (7)\\
\varepsilon_{i0t}^u &\sim \text{Exponential}(\rho_0).
\end{aligned}
$$

The specification of *usage value* uses the listening hours to infer service qualities on each service provider that the consumer perceives. Since only a finite set of observable service features, while many other features such as audio quality, the algorithm of recommendation, and interface design are hardly observable to researchers. Those will be captured in the *usage value* via ε^u_{ijt}. More usage time spent on a service provider implies better services and raises the probability of larger draws in ε^u_{ijt}.

8.2 Stage I: Subscription Decision

Now consider the stage I. In each period, a consumer decides to subscribe to a bundle of services. In making the decision, the consumer considers characteristics of the service bundle, including the utility from the second stage $v^*_{it}(b)$. As in the theory model, the "switching cost" enters the utility in this stage as an additional benefit received from a continued subscription. That is, a consumer gets an extra utility ψ_j by subscribing to service j if the consumer has subscribed to the same service in the previous period. For that reason, a consumer's utility depends on his/her decision of the last period.

I use a random-coefficients logit model (Berry, 1994; Berry et al., 1995) to describe consumes' subscription decisions. Given the last period choice as b_{it-1}, the utility function of subscribing to service bundle b_{it} is specified as follows:

$$u_{it}(b_{it}, b_{it-1}) = \underbrace{\sum_{j \in b_{it-1}} \psi_j I(j \in b_{it})}_{\text{"Switching Cost"}} + \underbrace{\beta^s v^*(b_{it}|\varepsilon_{ibt}, l_{bt}) + \underbrace{\sum_{j \in b_{it}} \lambda_{ijt}}_{\lambda_{ibt}}}_{\text{Inclusive Value } \delta_{ibt}} + \underbrace{D(b)}_{\text{Multihoming Cost}} + \varepsilon^s_{ibt}, \quad (8)$$

where ψ_j is the service-specific "switching cost" and $I(\cdot)$ is an indicator function. The parameter λ_{ibt} represents an intrinsic value of using services in bundle b beyond listening to music. The parameter captures individual tastes of the service's attributes such as user interface, compatibility to devices, etc. Those attributes might be observable to consumers but may not to researchers. I further assume λ_{ibt} as an additive sum of service fixed effect, λ_{ijt}, of each service j that is included in the bundle b. Note that price is not explicitly included in the utility function because there are not enough variations in subscription prices across services or across time. However, the price is likely captured by the service fixed effect.[27] Moreover, few users choose to pay for a subscription in the market - the percentage of premium service users is lower than 5 % (see Figure3).

Finally, the multihoming cost is added via a scalar function $D(b)$. The utility received from the

[27] Streaming services set the same subscription price during the sample period, and they also set the same price across services, which is also observed in the U.S. market, where major services charge a \$ 9.99 monthly membership fee. See the article "Why Is Every Streaming Service Using the Same Pricing Model?", available at https://hbr.org/2019/11/why-is-every-streaming-service-using-the-same-pricing-model.

outside option, i.e. when $b = \emptyset$, is denoted as u_{i0}. Vector $\varepsilon_{it}^{s} \equiv \{\varepsilon_{ibt}\}_{b \in B}$ denote idiosyncratic errors. They are i.i.d across periods, consumers, and service bundle choices. I defer more details on the econometric setting to the next section.

8.3 Consumer Dynamic Optimization

The consumer maximizes the expected present discounted value of flow utilities over an infinite horizon. Let Ω_t denote an 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:

$$V_i(\Omega_{it}, b_{it-1}, \varepsilon_{it}) = \max_{\{b_{i\tau} \in B\}_{\tau=t}^{\infty}} \sum_{\tau=t}^{\infty} \mu^{t-\tau} \mathbb{E}\left[u_{i\tau}(b_{i\tau}, b_{i\tau-1}) | \Omega_{i\tau}, \varepsilon_{i\tau}\right], \tag{9}$$

where $\mu \in (0,1)$ is a discount factor and $u_{i\tau}(b_{i\tau}, b_{i\tau-1})$ is defined in equation 8.

Because ε_{ibt}^{s} are i.i.d. across time, the consumer dynamic maximization problem 9 is simplified and written in the form of a Bellman equation:

$$V_i(\Omega_{it}, b_{it-1}) = \max_{b_{it} \in B} \left\{u_{it}(b_{it}, b_{it-1}) + \varepsilon_{ibt} + \mu E\left[V_i(\Omega_{t+1}, b_{it}) | \Omega_t, b_{it}\right]\right\}. \tag{10}$$

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

$$\delta_{ibt} \equiv \beta^{s} v_{ibt}^{*}(b_{it} | d_{it}, l_{jt}) + \lambda_{ibt}. \tag{11}$$

The approach to reducing the dimensionality of the state space is in the same spirit of Melnikov (2013) and Hendel and Nevo (2006). Note that the inclusive value does not include the switching costs and multihoming cost. Both parameters are deterministic and excluded from the state variable vector Ω_t. The inclusive value, which is the expected utility received from the optimal choice in each period, is bundle specific.[28]. 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 δ_{ibt} 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 10 as:

[28] Note that the inclusive value is defined differently in Schiraldi (2011) and Gowrisankaran and Rysman (2012) where it depends not only on the optimal choice in current periods but also the optimal decisions in the future.

$$V_i(\delta_{it}, b_{it-1}) = \max_{b_{it} \in B} \left\{ \delta_{ibt} + \sum_{j \in b_{it}} -\psi_j I(j \notin b_{it-1}) + D(b_{it}) + \mu E\left[V_i(\delta_{it+1}, b_{it}) | \delta_{it}, b_{it-1}\right] \right\}, \quad (12)$$

where $\delta_{it} \equiv \{\delta_{ibt}\}_{b \in B}$.

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

$$\delta_{ibt+1} = \gamma_{ib1} + \gamma_{ib2}\delta_{ibt} + \gamma_{ib3}(\delta_{ibt})^2 + \zeta_{ibt+1}, \forall b \neq \emptyset \ , \quad (13)$$

where ζ_{ibt+1} is independently normally distributed with mean 0 and variance σ_{ib}^2 .

9 Econometric Setting

In this section, I provide the further parametric assumption, aggregation across consumers and estimation strategy.

9.1 Parametric Assumption

In the first stage (the subscription stage), the subscription benefits for each service provider λ_{ijt} is assumed to have the following parametric form:

$$\lambda_{ijt} = Z_{jt}\beta_i^Z + \xi_{jt}^s, \quad (14)$$

where Z_{jt} include a constant, time trend, service fixed effect, and ξ_{jt}^s. The last term represents the service-specific characteristics that are observable to consumers but not observable to researchers. Each consumer has a random preference for Z_{jt}. The coefficient β_i^Z, is random that follows an independent multivariate normal distribution i.e. $\beta_i^Z \sim N(\bar{\beta}^Z, \Sigma^Z)$. In estimation, I choose the constant and dominant services fixed effect as random. [29] Note that I cannot observe individual-level price paying to the service, and there is no time variation in services' listed subscription price schedules. Hence instead of using the price, I use a service fixed effect to capture the costs of

[29] Adding random coefficient to dominant service dummy is motivated by the observation that a different set of users potentially chooses the dominant services. For instance, Tencent, the parent company of the dominant services, is also the developer of the most popular social media app, WeChat. Only the dominant streaming services are compatible with WeChat that has more than 1000 million active users by the end of 2019. For that reason, users of dominant service are also likely to be the users of WeChat.

using the service and let random coefficients in constant to capture heterogeneous disutility from the price.

Assuming the idiosyncratic error ε^{s}_{ibt} is distributed Type I extreme value, the probability of bundle b chosen by consumer i given last period choice b_{it-1} is:

$$s_{ibt}(b_{it-1}) = \frac{exp(\delta_{ibt} + \sum_{j\in b_{it}} -\psi_j I(j \notin b_{it-1}) + D(b_{it}) + \gamma E\left[V_i(\delta_{it+1}, b_{it})|\delta_{it}, b_{it-1}\right])}{exp(V_i(\delta_{it}, b_{it-1}))}. \tag{15}$$

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:

$$s_{ijt}(b_{it-1}) = \sum_{b\in B_j} s_{ibt}(b_{it-1}), \tag{16}$$

where B_j denotes the set of choice bundles that include service provider j.

The multihoming cost is captured by a scalar function $D(b)$, which depends on number of services included in service bundle b. The function is specified as follows:

$$D(b) = (n(b) - 1)\theta_{mc}, \tag{17}$$

where $n(b)$ is the cardinality of set b, and θ_{mc} is the constant marginal cost of multihoming.

Finally, the switching cost ψ_j is parametrized as follows:

$$\psi_j = \tilde{\Gamma}_j \theta_{sc}, \tag{18}$$

where $\tilde{\Gamma}_j$ includes a constant, a dummy for the dominant services, and service j's user base and usage averaged over time. The last three variables are used to capture potential cross-sectional heterogeneity in switching costs among services.

In the second stage (the time allocation stage), the optimal decision gives the solution of time,ℓ^{*}_{ibt}, allocated to listening to music using services in the bundle b. The set of variables l_{bt}, which is included in the parameter governing marginal utility of listening (equation 5), describes characteristics of service bundle b. The variables include a constant, annual time fixed effect, and the number of album titles available in the service bundle b. Specifically, the number of album titles include all albums that are distributed before.

$$\# \text{ titles}_{b,t} = \sum_{s \le t} (t-s)^{\gamma^\alpha} \left(\# \text{ non-excluisve titles}_{b,s} + \sum_{j \in b} \# \text{ excluisve titles}_{j,s} \times \gamma^E \right), \tag{19}$$

where γ^α is negative and represent the rate of decaying popularity of albums. The coefficient γ^E adds extra weight to exclusive albums, which are supposed to be more popular than non-exclusive albums.

Because only the service-specific usage is observed, I further calculate the time allocated to each service given service j's characteristics as x_{jt} by the following equation:

$$\ell^*_{ijbt} = \frac{\phi_{ijt}}{\sum_{j \in b} \phi_{ijt}} \times \ell^*_{ibt},$$
$$\text{where } \phi_{ijt} = \exp(x_{jt}\gamma^\ell)\varepsilon^u_{ijt}.$$

The variable x_{jt} is the number of album titles available in that service.[30]

9.2 Aggregation

The aggregated subscription rate of service j is an 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:

$$S_{jt} = \int s_{ijt}(b_{it-1})\, dG_t(\beta^Z_{it}, v^*_{it}, s_{ibt-1}). \tag{20}$$

The expected time that consumer i spends on service j is a weighted sum of optimal time:

$$\ell^*_{ijt} = \sum_{b \in B} s_{ibt} \cdot \ell^*_{ijbt}, \tag{21}$$

where s_{ibt} is the choice probability of consumer i choosing service bundle b.

Similarly, the expected usage time averaging across subscribed users is

$$\ell^*_{jt} = \int \sum_{b \in B} s_{ibt} \cdot \ell^*_{ijbt}\, dG_t(\beta^Z_{it}, v^*_{it}, s_{ibt-1}). \tag{22}$$

[30]Adding a constant or time trend into x_{jt} will not change the result because they are canceled out in calculating the allocated time of each service.

9.3 Estimation

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

$$\mathbb{E}\left[\ \tfrac{1}{ns}\textstyle\sum_i \ell^*_{ijt} - \bar{\ell}_{jt}\ \ |Z_{jt}\right] = 0\ , \tag{23}$$

where Z_{jt} is the set of exogenous variables affecting service j's usage , and ns denotes the number of consumers. $\bar{\ell}_{ij}$ is the time spent on service j averaged over service users. I choose a set of instrument variables in Z_t including a constant, year dummy variable, and the total number of album titles distributed by service j.

The second set of moment conditions are:

$$\mathbb{E}\begin{bmatrix} \xi^s_{jt} H_{jt} \\ \xi^s_{jt} H_{jt-1} \\ \frac{1}{ns}\sum_i s_{ibt}\cdot 1(\#b=k) - s_t(\#b=k) \end{bmatrix} = 0, \tag{24}$$

where H_{jt} is the vector of instruments which are exogenous shifters of the contemporaneous market shares, H_{jt-1} is the lagged period exogenous shifters, $\#b$ denotes the number of services included in the subscription bundle b and k is an integer that is at least greater than 2. The first and second moments are constructed based on the orthogonality assumption that unobserved characteristics ξ^s_{jt} are mean independent to both contemporaneous and lagged exogenous variables. The set of exogenous variables H_{jt} includes the sum of services' usages except for service j's usage, which is $\sum_{k\neq j}\bar{\ell}_{kt}$. The exogenous variables also include the number of album titles newly distributed by that service in period t and the number of album titles newly distributed by the rivals' services. The rival service of service j is defined as a service that is not owned by the same parent company of service j. Based on the definition and the specific market structure in the Chinese music streaming market, a dominant service's rivals include all small services. In contrast, a small service's rivals include all the dominant services plus the rest two small services.[31]

[31] Note that the number of album titles newly distributed in period t include only the albums published in that period. This variable is different from the total number of album titles included in the exogenous variables Z_{jt}, which includes all albums published in and before that period.

9.4 Identification

Because identifying the discount factor in a dynamic discrete choice model is notoriously difficult (Rust, 1994), I do 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 to identify the switching cost from consumer preference heterogeneity separately.

Identifying the switching costs relies on state dependence in the aggregate market shares when the individual decision cannot be directly observed. The identification strategy relies on two sets of assumptions. First, the idiosyncratic shock in both stages, including ε^{u}_{ibt} and ε^{s}_{ibt}, are assumed to be i.i.d over time. To some extent, this assumption is strong as it does not allow any persistence in consumer-specific preference heterogeneity that is unobservable to researchers. But the assumption becomes less binding when the random coefficients,β^{Z}_{it}, are used to represent consumers' heterogeneous preferences. Each draw of the random coefficients represents a type of consumer preference that is assumed to stay the same over periods. Those random coefficients capture the persistence in the market share that is explained by consumer preferences. The second assumption emphasizes on the orthogonality condition of the unobserved service attributes. Specifically, I assume that ξ_{jt} is mean independent to lagged market share shifters, i.e., $\mathbb{E}\left[\xi_{jt}|H_{t-1}\right] = 0$, which are corresponding to the second moment condition in equation 24. The exogenous shifters of the lagged market share include rival services' usages and album titles. Those variables are proxies for rivals' service qualities and attractiveness. Intuitively, holding current service characteristics fixed, an increase in current market share due to the increase of previous market share driven by a change in rival services' quality and attractiveness can only be explained by switching costs. Finally, to justify the use of instruments selected in H_t, the number of album titles distributed and unobservable characteristics should not be jointly determined. Indeed, because when to publish an album is a joint decision of performers, producers, and record labels, it should not be endogenous to consumers' subscription decisions. Similar conditions are also used in many applications that estimate switching costs through the aggregate data (e.g. see Nosal (2012), Shcherbakov (2016); and see Yeo and Miller (2018) for other possible approaches).

Identifying the multihoming cost relies on the last moment condition in equation 24 which leverages the data of overlapped users between services. I further restrict a consumer can subscribe to at most two services at a time to make the model more tractable.

Finally, the identification of preference parameters in the second stage (time allocation) relies on the first set of moments presented in equation 23 that matches the usage time predicted by the model and observed from the data. The mean independence assumption gives the identification of coefficients for service arr tributes, γ^{J}, and the distribution parameter of the idiosyncratic error term, ρ_j. One can take those distribution parameters ρ_j as service fixed effect. Because a constant is included γ_{ibt}, not all ρ_j including ρ_0 are identified. For that reason, the coefficient γ_0 is normalized to 1.

9.5 Computation

The procedure of recovering unobserved characteristics ξ_{jt} combines BLP contraction mapping algorithm with the algorithm as in Lee (2013) that solves consumers' dynamic optimization problems by assuming a terminal period. With the unobservable characteristics recovered, I then compute the GMM objective function constructed via moment conditions in equation 23 and 24.

Given a parameter set $\theta \equiv \{\theta_1, \theta_2\}$, the procedure begins by obtaining the starting values for $v^*(b_t)$ for all possible service bundles by solving the optimal time allocation decision problem for each consumer type. To reduce the computation burden, I further restrict each service bundle to include at most two services.[32] With the starting value of $v^*(b_t)$, I solve the service adoption decisions and calculate the market share of each service in each period via an initial guess of unobservable characteristics ξ_{jt}.

Solving a consumer's subscription decision involves solving the consumer's dynamic programming problem in equation 10. To solve the problem, I assume service utility decays to 0 ten years after the initial sample period of January 2014. This assumption is motivated by the coming 5G technology revolution that is expected to reshape the current streaming format.[33]

Once the dynamic problem is solved, an updated unobservable characteristics are calculated using the BLP contraction mapping.[34] Finally, I search over the parameter space to find the parameters that minimize the objective function.

10 Estimation Results and Implications

In this section, I first present the parameter estimates for the structural model. Then I discuss the implications of the estimation results.

Table 6 reports the coefficient estimates for observed services attributes. The coefficients for albums titles are all positive, suggesting more music content available on a service induces more usages of that service. The result also suggests exclusive content may have a greater influence on usage than non-exclusive content, as the coefficient estimate for γ^E is greater than 1. However,

[32] The data also justifies that there rarely exists a consumer who subscribes to more than two services simultaneously.

[33] For example, virtual concerts hold the potential for major growth due to the emergence of 5G speeds. See the article "Is the Music Industry Ready for 5G? Embracing the Future of Music Beyond Streaming", available at https://medium.com/hackernoon/is-the-music-industry-ready-for-5g-embracing-the-future-of-music-beyond-streaming-18867590a2e5.

[34] I assume all consumers are new to streaming services at the beginning of the sample period.

the evidence is relatively weak as the coefficient estimate has a large standard error. Album titles also depreciate quickly with a polynomial decay rate at -2.91, implying the influence of a hundred album titles distributed by a service will decay to almost zero in about three months. The estimate for η shows that the marginal utility diminishes at a rate of less than 1, implying using streaming service has a slower rate of marginal utility diminishing than the rate of non-listening, which is normalized to 1. Note that η is estimated via a parameter transformation $\eta = \frac{exp(\theta)}{1+exp(\theta)}$, its 95% confidence interval of η is from 0.56 to 0.97, of which the upper bound is still strictly less than 1.[35] Results from Stage I show that the upward popularity of using the streaming services, which is potentially due to the gradually enhanced copyright enforcement. There is also heterogeneity in consumer preference as the standard deviation of both random coefficients are significant.

Estimates for switching costs are reported in Table 8. The switching cost estimate (interpreted as the continue subscription benefit) is positive and significant for all services. Moreover, the estimates for the dominant services - QQMusic, Kugou, and Kuwo, are significantly larger than that of small services - Xiami, Netease, and Baidu. In the same table, estimates for service quality are reported. The service quality is captured by the mean of idiosyncratic error term following an exponential distribution with parameter ρ_j. The result suggests that switching cost is positively associated with service quality. Table 7, which reports estimates for switching costs coefficients, further suggests that the asymmetric switching costs are positively correlated with the unevenly distributed user base among services. The last result is consistent with the intuition that switching cost arises from a service feature in learning users' tastes. For example, data collected from a large user base of service allows the service to train their algorithms with big data, significantly improving the overall better musical experience.

The last column in Table 7 reports the estimate for the coefficient related to multihoming cost. The estimate for the marginal cost of multihoming is negative as expected. However, the estimate is insignificant with a large standard error. Compared with the switching cost, the estimate for multihoming cost is relatively small, implying consumers are more likely to choose to multihome than switch.

In the next, to test the intuition on estimating the switching cost, I make a comparison of the full model estimated with two alternative models that have different assumptions on the switching cost. The estimates for alternative model specifications are presented in Appendix C. The first alternative specification holds the switching costs fixed at zero. Without the switching cost, the model degenerates into a static model. In this setting, a consumer's payoff received from each choice decision does not depend on the last choice. However, the coefficients are estimated via the full set of moment conditions listed in Equation 23 and 24. The estimates are reported in Table C.1. Neglecting the switching cost has a significant impact on the estimates. The standard deviation of the random

[35] The confidence interval is calculated by transforming the 95% confidence interval of θ.

coefficient for a dominant service dummy becomes more than four times larger than the estimate for the same coefficient in the full model. The result is consistent with the intuition that dominant services' market shares evolve more persistently than smaller services'. When the switching cost is absent, the estimation adds more heterogeneity in consumers' preference dominant services to match the persistence in market shares of dominant services.

The second alternative specification assumes homogeneous switching costs among services. The estimation results are reported in Table C.2. In this specification, the estimate for the switching cost is in between the highest and lowest estimate for services switching costs estimated in a full model that allows asymmetric switching costs. Including the switching cost significantly reduces the preference heterogeneity. The standard deviation for the dominant service dummy is almost halved compared with the estimate for the same coefficient in the first alternative specification. Therefore, both alternative specifications justify the identification intuition of the switching cost. That is, the switching cost is identified by the persistence in market share that cannot be explained by the persistence in consumers' preferences.

Evaluating the Switching Cost Of particular interest to this study is assessing the magnitude of switching costs. Ideally, one needs to transfer the switching costs into a monetary value and compare it with services' subscription expenses. However, it is hard to estimate the price coefficient because neither the subscription price of each service nor paid subscriptions are 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 the price disutility. For example, given that the mean utility of Kugou is -4.60 on average over the sample period, the switching cost of Kugou is equivalent to a half of the subscription fee. As a comparison, the costs of switching away from one of the small service Xiami is approximately 20 percent of its mean utility that is about -7, which indicates its switching cost is relatively small. However, this assessment method is less convincing when the mean utility of 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 share of service by assuming zero switching costs. I then compare the counterfactual market share to that observed in the data. This assessment is based on the same idea of identifying the switching costs. That is, without the switching cost, the consumer's decision in the current period does not depend on his/her choice of the previous period. Therefore, the persistence in market share has been solely driven by the persistence in consumer preferences. Figure 11 plots the realized and counterfactual market shares of Kugou and Baidu, respectively. Figure 12 plots the month-over-month change of their market shares. When switching costs were absent, the market share of Kugou fluctuates more dramatically than the market shares with the switching costs, suggesting that without the switching cost, the market share of Kugou would become less persistent. In contrast, Baidu's switching costs are less high as its counterfactual and realized market shares exhibit a similar time-series pattern - both fluctuate in similar frequencies and magnitudes.

The second approach evaluates the switching cost via content elasticities: the percentage change of market shares in response to a percentage change in the service's music content. Specifically, I compare a temporary to a permanent content elasticity. The temporary content elasticity corresponds to a temporary reduction in service's album titles, while the elasticity corresponds to a permanent reduction in album titles. For both elasticities, the change in service album titles is unexpected to consumers before then. I also assume that at the time of change, consumers know whether it 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 13 by keeping the estimated coefficients.

I compute the elasticities and make the comparison between two services, Kugou and Baidu, in Figure 13 with t_d set to August 2016. Whether there is a significant difference between the temporary and permanent elasticity suggests if the switching cost plays a role in preventing users from switching. Indeed, for a dominant service such as Kugou, fewer users would switch away in response to a temporary content drop than a permanent drop. Nonetheless, for a small service such as Baidu, almost the same number of users would switch in temporary and permanent cases. The difference in switching costs between the services also results in different consumer dynamic behaviors in response to a change in their music content. It takes almost six months for the dominant service Kugou to regain those lost users due to a temporary drop in content, while the small service Baidu can recover its users shortly in two months. Because switching the subscription of a service forgoes the continued subscription benefit, a user is less likely to resubscribe to the service after he/she choose to switch. The result suggests that the switching cost plays a vital role in retaining users of a dominant service such as Kugou.

To evaluate the effect of switching cost on exclusivity, it is necessary to construct a model depicting services' choices in exclusive and non-exclusive distributions. In Appendix B, I develop a simple dynamic supply-side model assuming services make a decision over number of album titles distributed in each period. Each service faces a constant marginal cost that comes from paying for licensing fees and managerial costs. The idea of estimating the marginal cost is based on calculating the dynamic response of the market change to a change in content. The model is fairly stylized and should be treated as a partial equilibrium analysis. However, the model is designed to show important implications of consumer switching costs for the optimal content distribution decisions.

11 Counterfactual Analysis

In this section, I simulate the market outcome under two counterfactual scenarios. The goal is to find an effective policy that promotes the use of streaming services while maintaining market competition. The analysis also shows the key factors driving the high market concentration.

11.1 Compulsory Licensing

This counterfactual exercise is aimed to examine whether the government should enforce copyright law with a ban on exclusive dealing between streaming services and record labels to improve market competition. Using compulsory licensing 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 royalty payments protect copyright owners' interests. Besides, I also examine whether the exclusive provision favors the big services (QQMusic, Kugou, and Kuwo) or small services (Xiami, Netease, and Baidu).

Two aspects are changed in the counterfactual environment of compulsory licensing. First, consumers have universal access to music via using any service. Second, no service in the market has exclusive content. The counterfactual exercise proceeds holding services' quality and switching costs fixed in the counterfactual environment. This assumption excludes the possibility that services might make tradeoffs from different dimensions concerning the change from exclusive to compulsory licensing. For example, services might invest more in a better user interface or more advanced learning algorithms to improve user experience.

The simulation assumes variables are in a steady-state. For those time-varying variables are either set at the average sample level or assumed to stay constant. For example, I set services' album titles, exclusive album titles, and unobservable ξ_{jt} at the sample averages and set time variable and time fixed effect at the value of the last month of the sample (July 2017). I compute the steady-state market shares of services under the compulsory provision by keeping the estimated switching costs from the baseline with the treatment to the variables. Because the three big services are similar in characteristics, I treat the three dominant services as one single big service (Tencent) in the simulation. [36]

The steady-state market outcome is calculated in iterations. The simulation procedure starts from an initial user distribution R^0 with all non-streaming users new to the streaming services. By computing choice probability of each consumer type in choosing among service bundles using

[36]The conclusion of the counterfactual stay the same if the dominant services are treated as separately.

equation 15, the updated aggregate user distribution R^{k+1} is computed by using user distribution of the last iteration R^k and equation 20. The algorithm proceeds in this way until the convergence of user distribution.

The simulation results are presented in Table 9, where the baseline results are present in the first column. The second column of the table gives the counterfactual services' market shares under the compulsory licensing provision. The percentage change of the counterfactuals compared with the baseline is shown in the third column.

The counterfactual results suggest the market would be more concentrated under the compulsory licensing scenario: the market share of the dominant service under the compulsory licensing provision would be greater than 70% that is increased by 14% from the steady-state under the exclusive provision. On the contrary, compulsory licensing would lead to a significant drop in small services' market shares, although they would distribute more content. The market share of small service would be 3%, reduced by 11% from the exclusive provision. The compulsory licensing provision would improve market concentration because services are differentiated in their service quality, as shown in Table 8. When services are less differentiated in content distribution, the service that provides the best quality will attract the most users.

Small services would lose market share when a compulsory licensing was enforced. More than 10% of small services' singlehoming users would have switched out and started to use a dominant service. Small services also lose 13% of their multihoming users. Users of small services would switch to the dominant service because the cost of doing so is relatively small. Similarly, because services become less likely to complement each other due to the compulsory licensing, multihoming users under the exclusivity would choose to singlehome under the compulsory licensing provision. In deciding which service to stop the subscription, a user would choose the one with smaller switching costs, which is likely to be a small service.

11.2 Data Portability

To examine the effect of existing switching costs on market competition, I conduct another simulation by assuming users can receive the continued benefits regardless of subscribing to the same or different service in the next period, which happens when they can transfer his/her personal data to a new service at the time of switching. This data portability setting in this counterfactual analysis is motivated by the General Data Protection Regulation (GDPR) that came into effect in the European Union in May 2018. The regulation protects natural persons regarding the processing and free movement of their personal data.[37] With this specific clause on the free movement of data,

[37] Regulation (EU) 2016/679 of The European Parliament and of the Council on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing (2016) Official Journal L119, p.13.

GDPR allows users of streaming services to carry their personal data, including the playlists and streaming histories, to different services he/she can subscribe to, which reduces the switching cost significantly.[38]

The simulation follows the same algorithm as in the previous counterfactual analysis to compute the steady-state market outcome. The simulation also proceeds by holding services' quality unchanged in the counterfactual environment. The only difference in this setting is the switching cost (continued subscription benefit). The setting assumes all users are new to the streaming services initially; thus, no one can receive the continued subscription benefit. Once a user starts to use a service, he/she can keep receiving the continued subscription benefit of that service no matter whether the user chooses to switch or not. A user can receive an accumulated continued subscription benefit if he/she subscribed to a dominant service and small service simultaneously or sequentially. However, the user can receive the benefit from at most one of the small services that offers the largest benefit among those small services he/she has subscribed to previously. For example, suppose there are two small services A and B in the market. Service A offers larger continued subscription benefit to users. if a user subscribe to a small service B in the current period, and has subscribed to service A previously, the user can receive only the continued subscription benefit from A in the next period.[39]

Table 10 presents the counterfactual result. The main finding of the analysis shows that enforcing data portability promotes the use of streaming services significantly. If the regulation is enforced, non-streaming consumers will decrease by more than 70 % in a steady state, implying more consumers choose to use a streaming service in this scenario. The increase in streaming users results in an increase in users of all services. Although the big service is still dominating the market with its users increase by 7 %, users of small services will be more than twice as large as their user base in the baseline scenario with existing switching costs. Reducing the switching cost can confer better user experience of streaming, persuading more consumers to use the streaming service, thus, benefiting all services in the market.

Although the market share gap between the leading and small services with data portability is smaller than the baseline scenario, the leading service still has a larger userbase than small services. As shown in the previous counterfactual analysis, the uneven distribution of users is largely driven by the differentiation in service quality. Unlike the compulsory licensing provision that will force the small services to exit by reducing their market shares, pushing the market closer to the edge

[38] GDPR also affects music streaming services in many ways. However, they are out of the scope of this counterfactual analysis. For example, if a service's recommender system needs to process private data of users, the user's affirmative consent is required. The user also has the right to erasure. (Krämer and Stüdlein, 2019)

[39] This treatment is ad hoc but is reasonable for this market. It is based on the observation that small services have the same capability in learning users' tastes, thus subscribing to different small services will not gain extra benefits. This setting also excludes any outcome that is mechanically driven by benefits accumulation.

of monopoly, the mandatory data portability policy enables small services to have more users and stay in the market likely.

Finally, I examine the counterfactual market outcome when both compulsory licensing and data portability jointly take place. Table C.4 presents the simulation result. Because both policies are pro-streaming, the number of streaming users are further increased in this counterfactual scenario. With both policies enacted, the market is less concentrated than the baseline scenario with the exclusive provision but more concentrated than the policy implementing only the data portability. The result is as expected. Dominant services would create a larger lock-in effect than small services, and they provide service with better quality. Removing switching costs induces more consumers to switch from dominant to small services. In contrast, removing small services' exclusive content undermines their attractiveness due to their inferior service qualities.

12 Conclusion

The purpose of copyright law is promoting the dissemination of intellectual work while ensuring adequate incentives for creation and innovation. Albeit straightforward, there is no consensus on how to enforce the copyright law properly. For some developing countries where copyright enforcement was weak, copyright infringement was a perennial issue. With the strengthening regulation, the situation is much improved in recent years. However, a new issue regarding exclusive dealing arises along with the enhanced enforcement. Although the copyright law grants exclusive arrangements under certain circumstances, it often raises competition concern for its use in an anticompetitive practice such as entry deterrence.

My paper provides both theoretical explanations and empirical evidence on the role of exclusive in a foreclosure strategy. A firm has the incentive to choose exclusivity if it can incur switching costs to its customers because it captures more users in the early period of market penetration and gains a higher profit in the future by exploiting switching costs as a lock-in device.

My paper simulates the market outcomes with model estimates that had a compulsory licensing provision or regulation on data portability been enforced. The empirical analysis finds that the market will tip the service with better service quality with the compulsory licensing enforced. Although providing more music content, small services would lose significant market shares. However, the analysis suggests that enforcing data portability between services using the regulation such as GDPR will promote the use of streaming services and maintain moderate market competition. Both the dominant and small service will benefit from the increase in data portability. Because the regulation as GDPR grants users the right to transfer their personal data using the streaming service to another service, the switching cost is greatly reduced. Reducing the switching cost makes streaming services more attractive to users, thus benefiting the entire music streaming market's development.

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 users by increasing their access to more music content. However, the analysis shows such a provision might lead to a higher market concentration. The analysis also shows a compulsory licensing provision would not benefit the small services and might force those services to exit. Overall, the results suggest that the ongoing anti-trust investigation in China into Tencent Music should be wary of pushing the market toward compulsory licensing. In U.S., there is a debate on whether to expand the compulsory license scope for distributing phonorecords outlined by Section 115 of the Copyright Act to music streaming. My paper also sheds light on the debate, drawing on empirical evidence that implementing a compulsory licensing can exacerbate competition issues.

Table 1a: Descriptive Statistics of Users

Variables	Statistics	Streaming Services QQMusic	Kugou	Kuwo	Netease	Xiami	Baidu
Monthly Active Users (M.)	Mean	125.30	116.46	63.10	16.07	6.24	12.92
	Std	33.79	68.92	14.83	17.81	4.68	2.11
	(Max,Min)	(189.31, 79.45)	(232.89, 44.73)	(101.99, 48.64)	(57.89, 1.52)	(14.70, 0.04)	(17.31, 8.80)
Service Usage (M. hrs.)	Mean	321.04	521.29	145.30	87.14	18.12	21.95
	Std	239.92	404.74	145.30	98.59	22.14	25.06
	(Max, Min)	(737.97, 39.42)	(1353.71, 69.09)	(463.89, 1.49)	(262.74, 0.22)	(69.85, 0.01)	(109.77, 1.95)
Service Usage/ Total Usage (%)	Mean	31.28	49.62	11.36	4.91	0.93	1.89
	Std	5.19	7.54	5.22	4.64	0.96	1.10
	(Max, Min)	(41.56, 21.15)	(66.58, 38.25)	(32.78, 1.33)	(13.92, 0.17)	(2.79, 0.01)	(4.80, 0.50)
Multihoming Users/ Users (%)	Mean	13.51	9.38	13.38	25.85	46.28	20.46
	Std	1.69	0.65	2.74	6.16	8.34	2.91
	(Max,Min)	(17.54, 12.43)	(10.62, 8.29)	(17.29, 9.49)	(36.84, 18.87)	(59.38, 35.23)	(26.02, 16.33)

Table 1b: Active Users by Years

Variables	Year	QQMusic	Kugou	Kuwo	Netease	Xiami	Baidu
Monthly Active Users (M.)	2014	94.43	53.68	52.08	2.33	3.14	16.88
	2015	124.68	90.86	68.61	6.85	3.18	14.55
	2016	136.92	208.48	54.81	25.11	11.00	13.02
	2017	188.50	226.74	101.66	57.89	12.63	9.34
Service Usage (M. hrs.)	2014	89.13	134.15	33.30	1.88	0.05	7.97
	2015	164.67	250.44	41.83	7.83	2.21	5.09
	2016	634.09	1078.40	301.99	182.19	46.03	57.32
	2017	450.02	694.24	246.05	206.32	28.56	14.22
Service Usage/ Total Usage (%)	2014	0.34	0.36	0.10	0.00	0.00	0.01
	2015	0.36	0.38	0.16	0.01	0.01	0.02
	2016	0.21	0.54	0.13	0.06	0.01	0.02
	2017	0.26	0.41	0.15	0.13	0.02	0.01

Notes: The top table shows summary statistics of active users, multihoming users and usages of each streaming service. The bottom table shows services users and usages by year. Statistics are calculated from the aggregate data set described in Section 3. Total sample period is from Jan. 2014 to June 2017 for all variables except for multihoming users. Sample period of multihoming users is from Aug. 2016 to Apr. 2017. There are two measure of service usages are presented. Service Usage is total hours spent by users of each service in each month. Service Usage / Total Usage is hours spent by users of each service over total hours spent on all six services presented in the table. 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 2a: Descriptive Statistics of Content Distribution

Variables	Statistic	QQMusic	Kugou	Kuwo	Netease	Xiami	Baidu
Album Titles	Total	97,764	97,834	98,320	66,464	66,464	17,432
	Mean	2,273.58	2,286.51	2,286.51	1,470.26	1,545.67	405.40
	Std	738.72	750.60	750.60	437.56	340.83	98.68
	(Max,Min)	(3,612; 1,100)	(3,775; 1,058)	(3,775; 1,058)	(2,530; 815)	(2,489; 999)	(692; 249)
Exclusive Album Titles	Total	21127	22361	22361	176	127	277
	Mean	491.33	520.02	520.02	4.09	2.95	6.44
	Std	316.35	347.69	347.69	3.12	3.21	10.96
	(Max,Min)	(1,620; 78)	(1,775; 103)	(1,775; 103)	(12; 0)	(12; 0)	(36; 0)

Table 2b: Album Titles by Years

Variables	Year	QQMusic	Kugou	Kuwo	Netease	Xiami	Baidu
# Album Titles (Monthly Average)	2014	1,371.25	1,409.92	1,409.92	1,456.17	1,203.33	309.750
	2015	2,230.25	2,136.25	2,136.250	1,456.167	1,613.000	425.500
	2016	2,941.58	2,956.08	2,956.08	1,872.00	1,900.25	471.33
	2017	2,750.43	2,899.00	2,899.00	1,669.86	1,409.29	421.86
# Exclusive Album Titles(Monthly Average)	2014	150.67	150.67	170.00	1.00	0.67	21.08
	2015	451.33	401.00	401.00	0.92	1.42	1.08
	2016	670.25	742.33	742.33	0.50	0.75	0.83
	2017	875.57	963.29	963.29	1.57	0.14	0.86

Note: The top table shows the summary statistics of albums, labels and performers that are available on each services. The middle 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: Exclusive Content Distribution by Labels

Record Label	# of albums	Percent (%)	Service w/ Exclusive License
Sony	11,043	21.89	TME, CMC
Warner	9,467	18.77	TME, CMC
Universal	9,297	18.43	TME, CMC
Kdigital	7,888	15.64	TME, CMC
Huayi	376	0.75	TME
Emperor Entertainment	270	0.54	TME
Linfair Records	253	0.5	TME
JVR	27	0.05	TME
Avex Trax	815	1.62	Netease
EE-Media	132	0.26	Netease
Rock	655	1.62	Xiami
Media Asia	188	0.37	Xiami
B'in Music	68	0.13	Xiami
Taihe	1,367	2.71	Baidu

Note: The table shows exclusive deals made between service and labels. The second column is number of albums published by the label in the data. The third column is percentage take total number of album titles published by that label takes up in entire set of album titles in the data. The last column is the corresponding service that signed an exclusive contract with the label. CMC is the parent company of Kugou and Kuwo before 2016. TME is the parent company of QQMusic. TME also has acquired services of CMC after 2016.

Table 4: Reduced-Form Evidence of Switching Cost

		QQMusic	Kugou	Kuwo	Xiami	Netease	Baidu
s_{t-1}	OLS	0.47***	0.60***	0.50***	-0.22	0.12	0.20
		(0.15)	(0.20)	(0.16)	(0.19)	(0.20)	(0.17)
	2SLS	0.48***	0.80***	0.58***	0.06	0.12	0.27
		(0.15)	(0.17)	(0.18)	(0.18)	(0.19)	(0.20)
	Observations	42	42	42	42	42	42
$R^2(\%)$	OLS	95.50	98.65	84.33	96.52	98.87	86.19
	2SLS	95.50	98.57	84.07	96.17	98.87	86.10

Notes: The dependent variables are time trend, service's attributes, usages and rivals' market contemporaneous market shares and usages, and lag market share. Only the lag market shares are presented in the table, other characteristics of services such as the usages, number of album titles, etc., are included in the regressions but not reported. The lag market share is instrumented in the 2SLS estimation, in which rivals' usages are used as instruments. Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Dependence of Multihoming on Exclusive and Non-exclusive Contents

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

Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Note: The dependent variable is the difference between multihoming 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 6: Coefficient Estimates for the Dynamic Model

Stage I: Service Adoption:		Stage II: Time Allocation:	
β_{cons}	-5.56	Constant	-8.24
(se)	(0.20)	(se)	(2.29)
β_{trend}	0.05	# of Album	0.94
(se)	(0.03)	(se)	(0.14)
σ_{cons}	1.05	# of Exclusive Album γ^E	1.58
(se)	(0.02)	(se)	(1.47)
$\sigma_{Dominant}$	0.66	Album Depreciation γ^α	-2.91
(se)	(0.08)	(se)	(0.25)
β^S	1.40	Diminishing Marginal Utility η	0.88
(se)	(0.03)	(se)	(0.14)

Note: The estimation results are from simulated GMM which are based on the moment assumptions listed in equation 23 and 24. The standard error (se) is reported in the parenthesis. Note that η is estimated via transformation $\eta = \frac{exp(\theta)}{1+exp(\theta)}$, its 95% confidence interval of η is $(0.56, 0.97)$. The random coefficients are the standard deviations of normal distributions, where σ_{cons} is the random coefficient for constant and $\sigma_{Dominant}$ is the random coefficient for the dominant service dummy. The dominant service are QQMusic, Kugou and Kuwo. Service fixed effects are included, but the estimates of those are not reported.

Table 7: Estimates for Switching Cost and Multihoming Cost Coefficient

Switching Cost Coef.				Multihoming Cost Coef.
θ_{sc}				θ_{mc}
Constant	Dominant Service Dummy	Average User base	Average Usages	# of services-1
0.06	0.10	0.199	0.01	-1.18
(0.58)	(0.23)	(0.08)	(0.83)	(1.10)

Note: The estimation results are from simulated GMM which are based on the moment assumptions listed in equation 23 and 24. The standard error is reported in the parenthesis. The last to coefficients of switching cost is the service's user base and usages averaged across time.

Table 8: Estimates for Switching Costs and Service Quality

	QQMusic	Kugou	Kuwo	Xiami	Netease	Baidu
Service Quality $1/\rho_j$	2.20	3.83	1.01	0.15	0.65	0.25
(se)	(0.80)	(0.86)	(0.74)	(0.68)	(0.74)	(0.73)
Switching Cost ψ_j	2.03	2.02	1.90	1.34	1.53	1.49
(se)	(0.08)	(0.07)	(0.10)	(0.12)	(0.11)	(0.12)

Note: The estimation results are from simulated GMM which are based on the moment assumptions listed in equation 23 and 24. The standard error (se) is reported in the parenthesis. The service quality $1/\rho_j$ is the mean of exponential error term ε^u_{ijt} defined in equation 7. The switching costs are estimated using the parametric assumption in equation 18. The estimates of coefficients for switching cost is reported in Table 7.

Table 9: Market Shares in Steady State: Exclusive and Compulsory Licensing

	exclusive (baseline)	compulsory	
	Market Share	Market Share	% △ to the baseline
Panel A: Active Users			
Tencent	0.637	0.727	0.142
Xiami	0.018	0.015	-0.197
Netease	0.070	0.064	-0.095
Baidu	0.013	0.011	-0.168
Outside Option	0.287	0.206	-0.283
Panel B: Singlehoming Users			
Tencent	0.613	0.706	0.152
Xiami	0.013	0.011	-0.195
Netease	0.053	0.048	-0.092
Baidu	0.009	0.008	-0.162
Total	0.688	0.772	0.123
Panel C: Multihoming Users			
Tencent	0.024	0.021	-0.130
Xiami	0.005	0.004	-0.202
Netease	0.017	0.015	-0.105
Baidu	0.004	0.004	-0.182
Total	0.05	0.04	-0.120

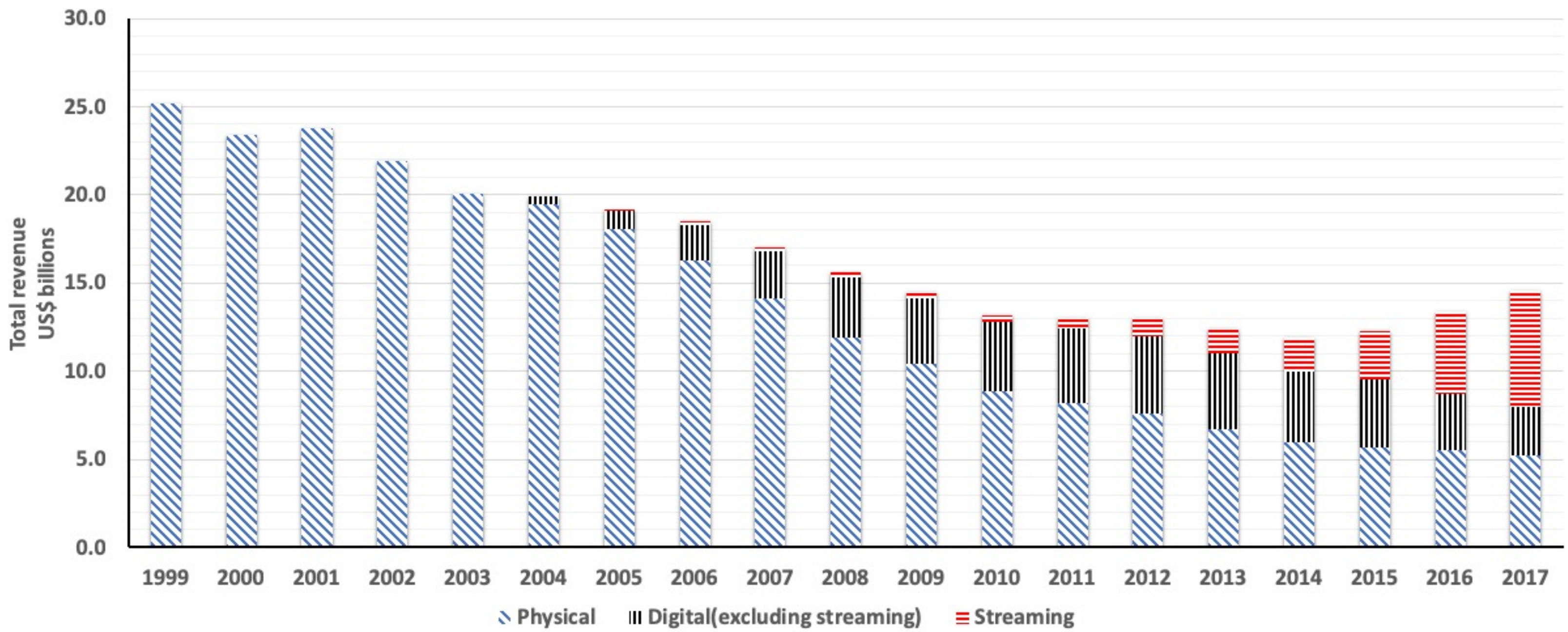
Note: This table reports steady state market shares of services under exclusive and compulsory licensing. Panel A reports the shares of all active users. Panel B and C respectively reports the shares of single- and multihoming.

Table 10: Market Shares in Steady State: Baseline, Compulsory Licensing, and Data Portability

	Baseline w/ Switching Costs	Compulsory Licensing w/ Switching Costs		Data Portability w/o Switching Costs	
	Market Share	Market Share	% △ to the baseline	Market Share	% △ to the baseline
Tencent	0.637	0.727	0.142	0.684	0.073
Xiami	0.018	0.015	-0.197	0.055	1.993
Netease	0.070	0.064	-0.095	0.158	1.246
Baidu	0.013	0.011	-0.168	0.043	2.390
Outside Option	0.287	0.206	-0.283	0.083	-0.709

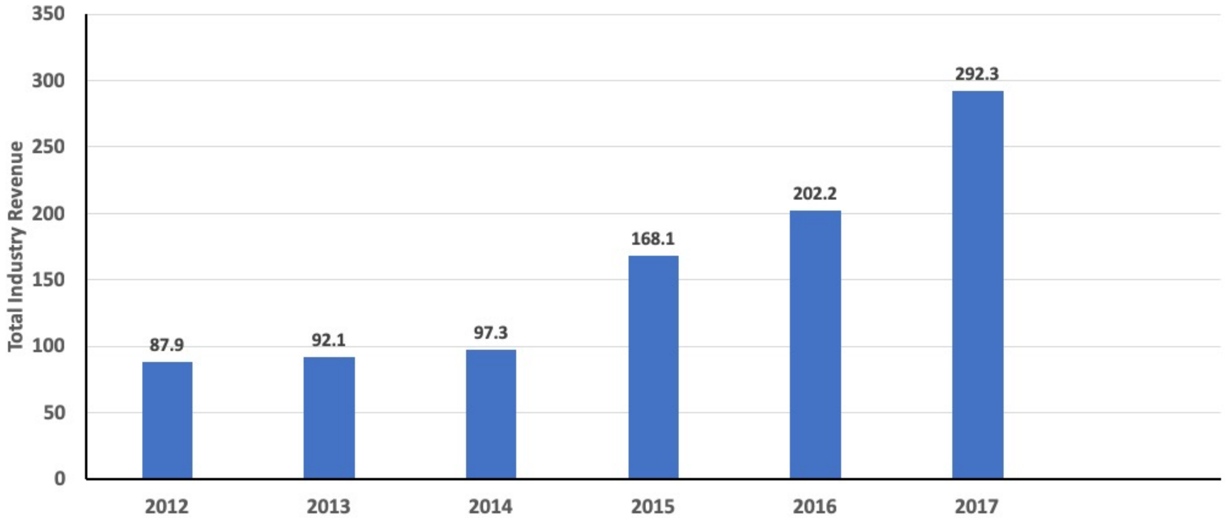
Note: This table shows a comparison in market outcomes between the scenario with exclusive provision and switching costs, the scenario with compulsory licensing and switching costs, and the scenario without switching costs under the mandatory data portability.

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



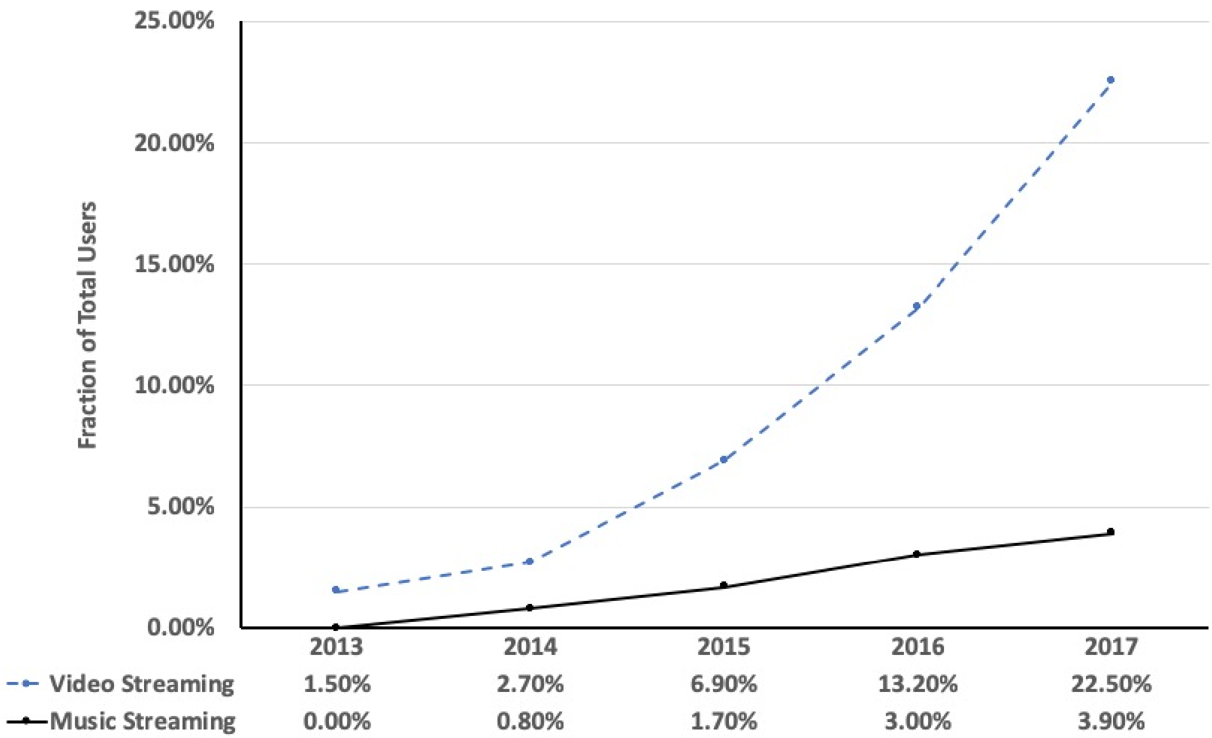
Notes: The figure presents the total revenues of the global recorded music industry from 1999 to 2017 and the breakdown of revenue by different sources. Adapted from "Global Music Report 2018" by IFPI, 2018.

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



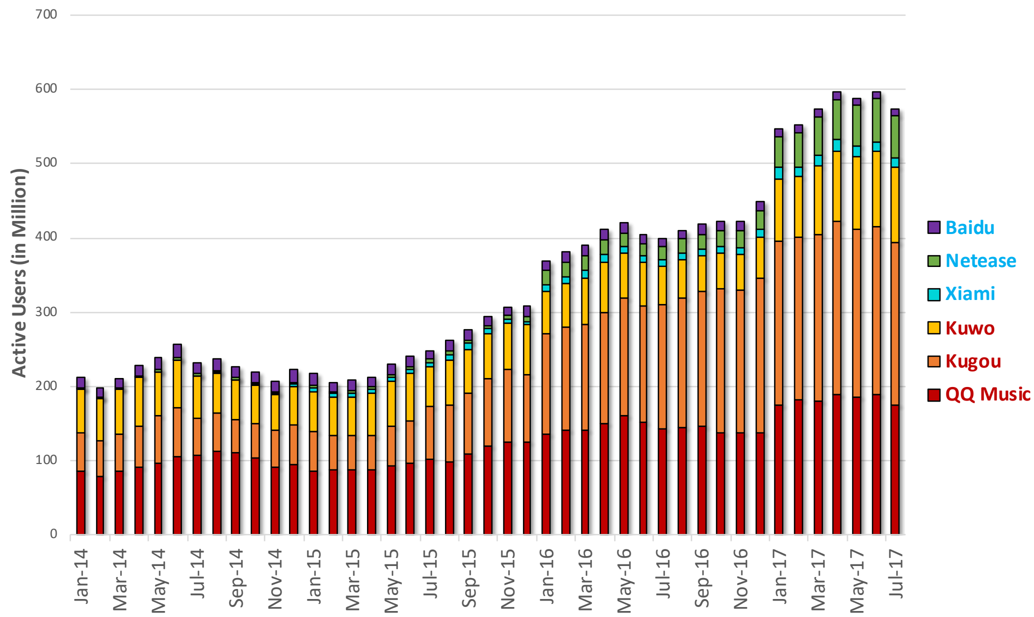
Note: The figure presents the total revenue of recorded music industry in China from 2012 to 2017. Adapted from "Global Music Report 2017" by IFPI, 2017.

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



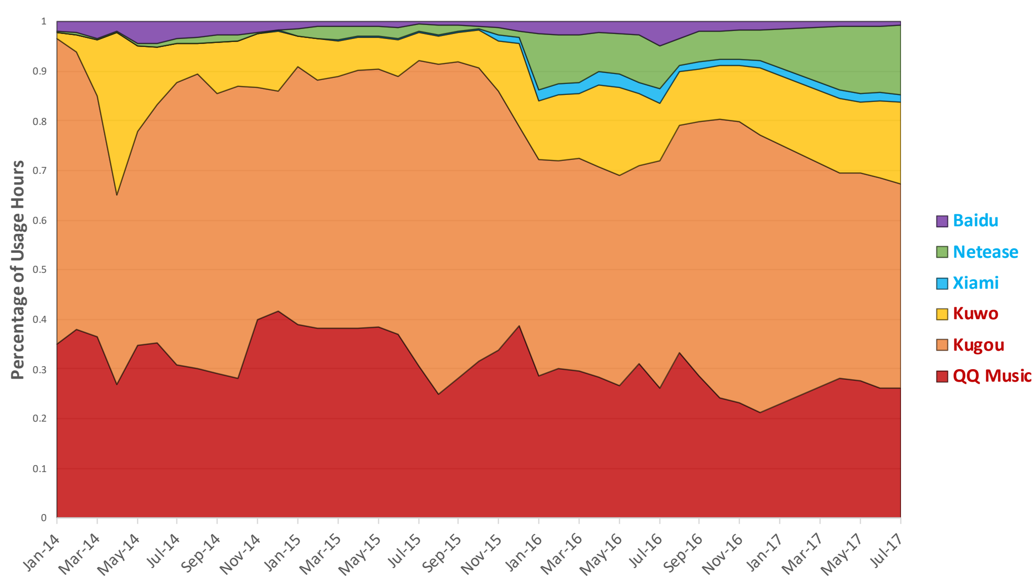
Note: The figure at the top plots the ratio of paid subscriptions to total subscriptions in the music streaming market and video streaming market. And the table below shows the figures of those paying ratios. Adapted from "2018 China Online Music Report" by iResearch consulting company, 2018.

Figure 4: Monthly Active Users of Streaming Services



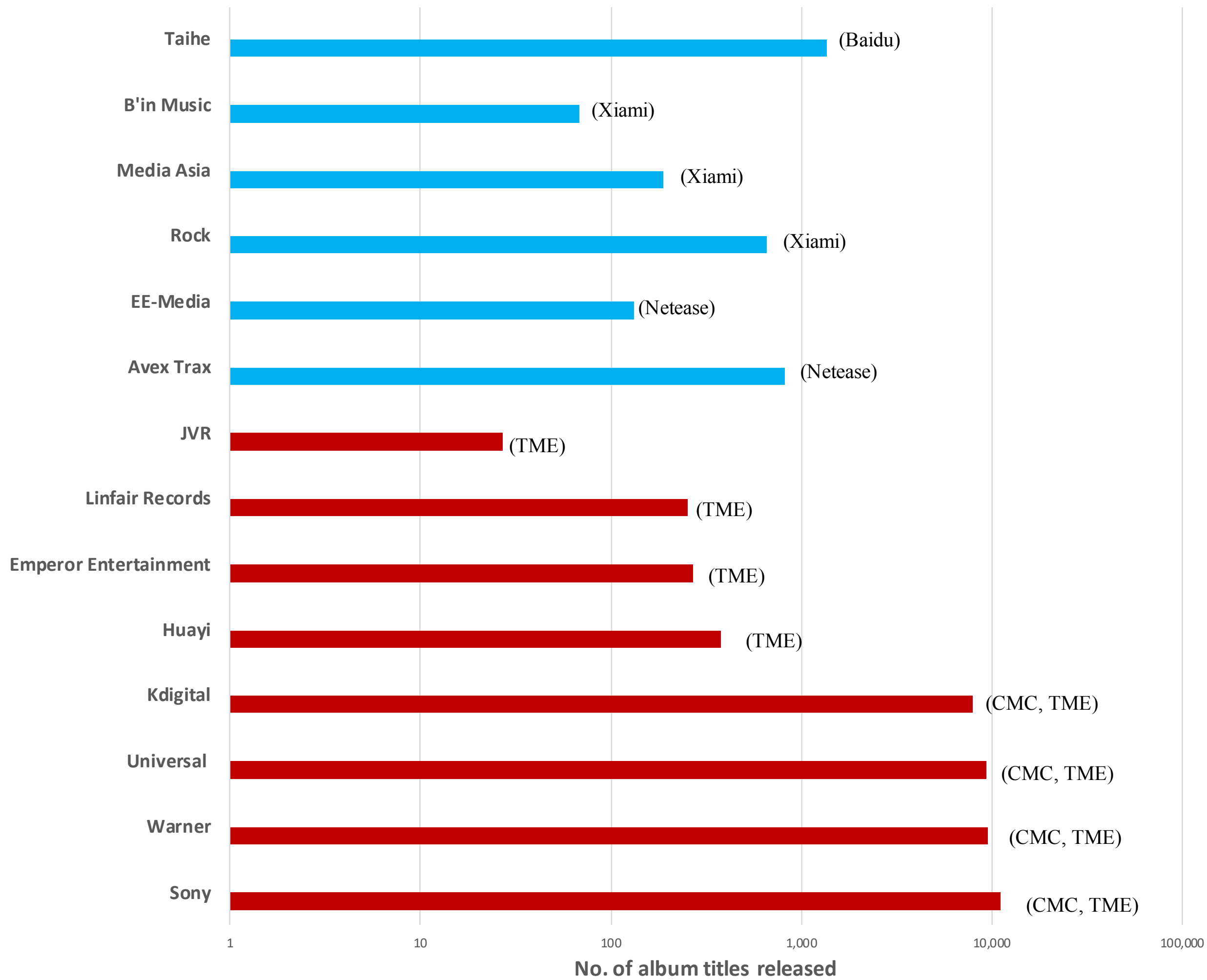
Note: The figure presents the dynamic of monthly active users (MAU) of each service. Summary statistics of MAU is presented in Table 1a.

Figure 5: Percentage of Service Usage Hours



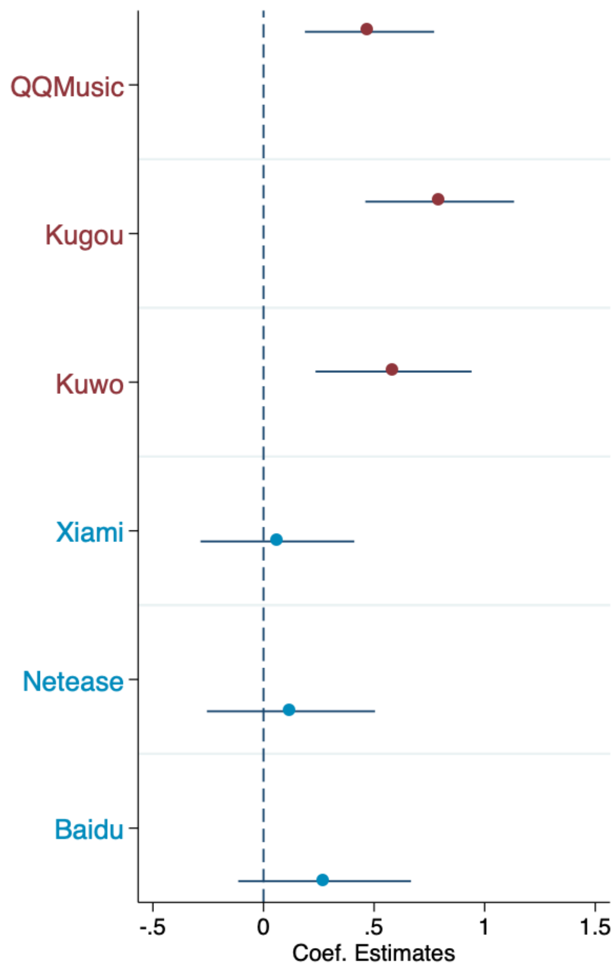
Note: The figure present the dynamic of percentage of service usage that is defined as the total hours spent by a service's users over total hours spent by users of all services. Summary statistics of this usage measure is presented in Table 1a.

Figure 6: Album Titles Released of Record Labels



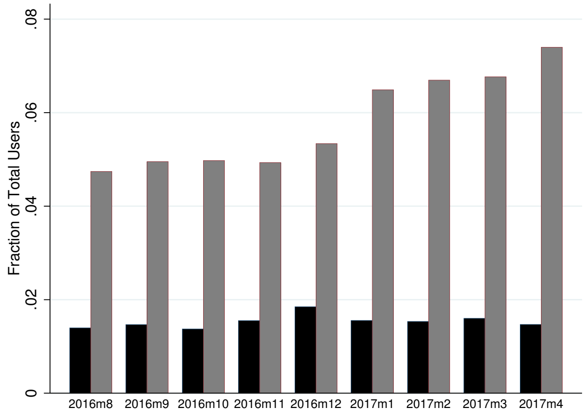
Note: The figure corresponds to Table 2b. It plots total album titles released by each record label that has signed an exclusive deal with a streaming service. The corresponding service name is presented in parenthesis. Red bars correspond to the dominant services owned by TME or CMC. Blue bars correspond to small services.

Figure 7: Plot of Autoregressive Coefficients

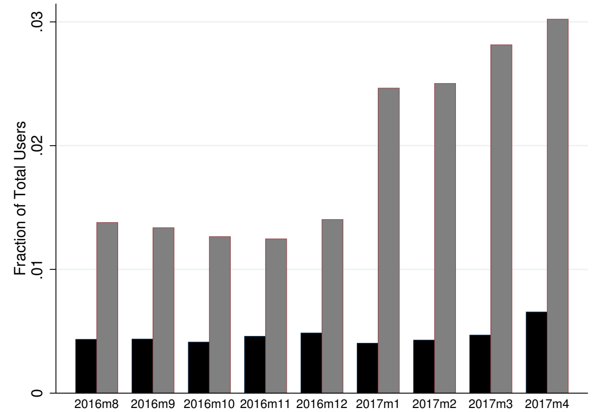


Note: The figure plots a comparison of the autoregressive coefficients across market share of different services, with their 95% confidence interval. The coefficients are estimated by 2SLS that are reported in Table 4 .

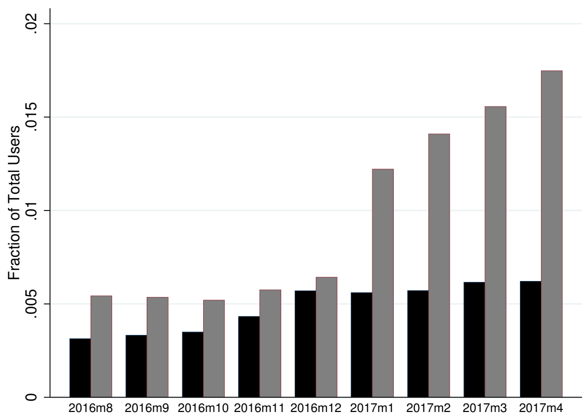
Figure 8: Example of Multihoming I



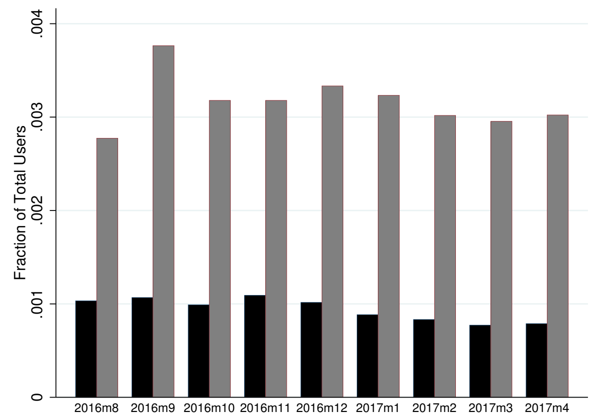
(a) QQMusic and Kugou



(b) QQMusic and Kuwo



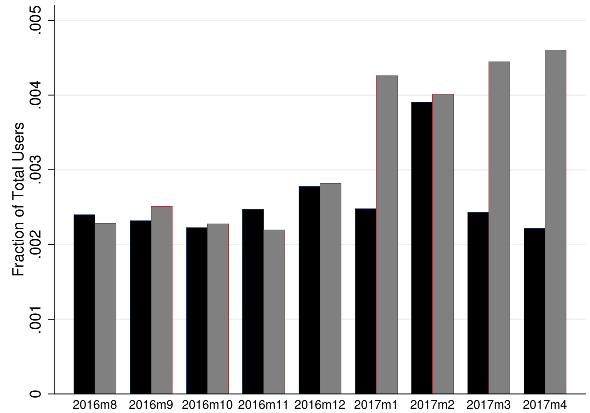
(c) QQMusic and Netease



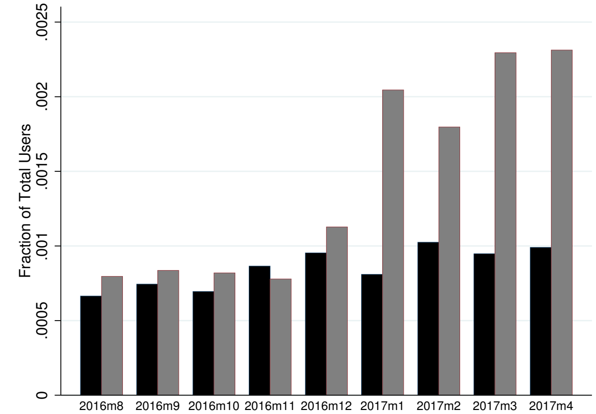
(d) QQMusic and Baidu

Notes: The graphs above plot the share of multihoming 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 multihoming users observed in the data; the gray bar represents the share simulated by independent random choice model.

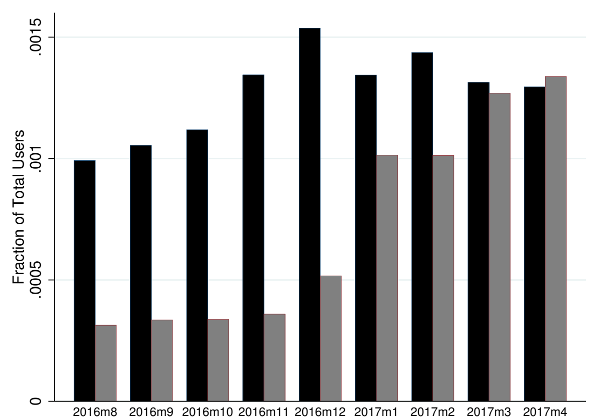
Figure 9: Example of Multihoming II



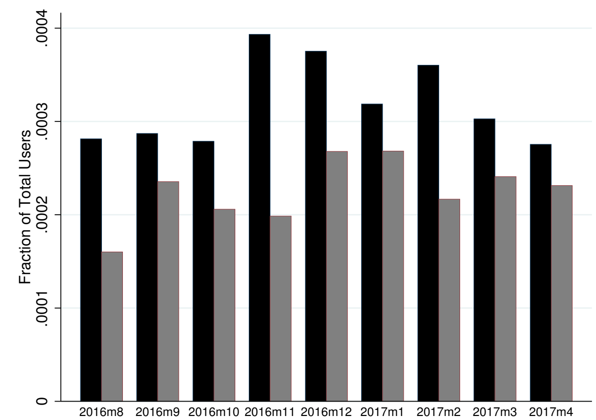
(a) Xiami and QQMusic



(b) Xiami and Kuwo



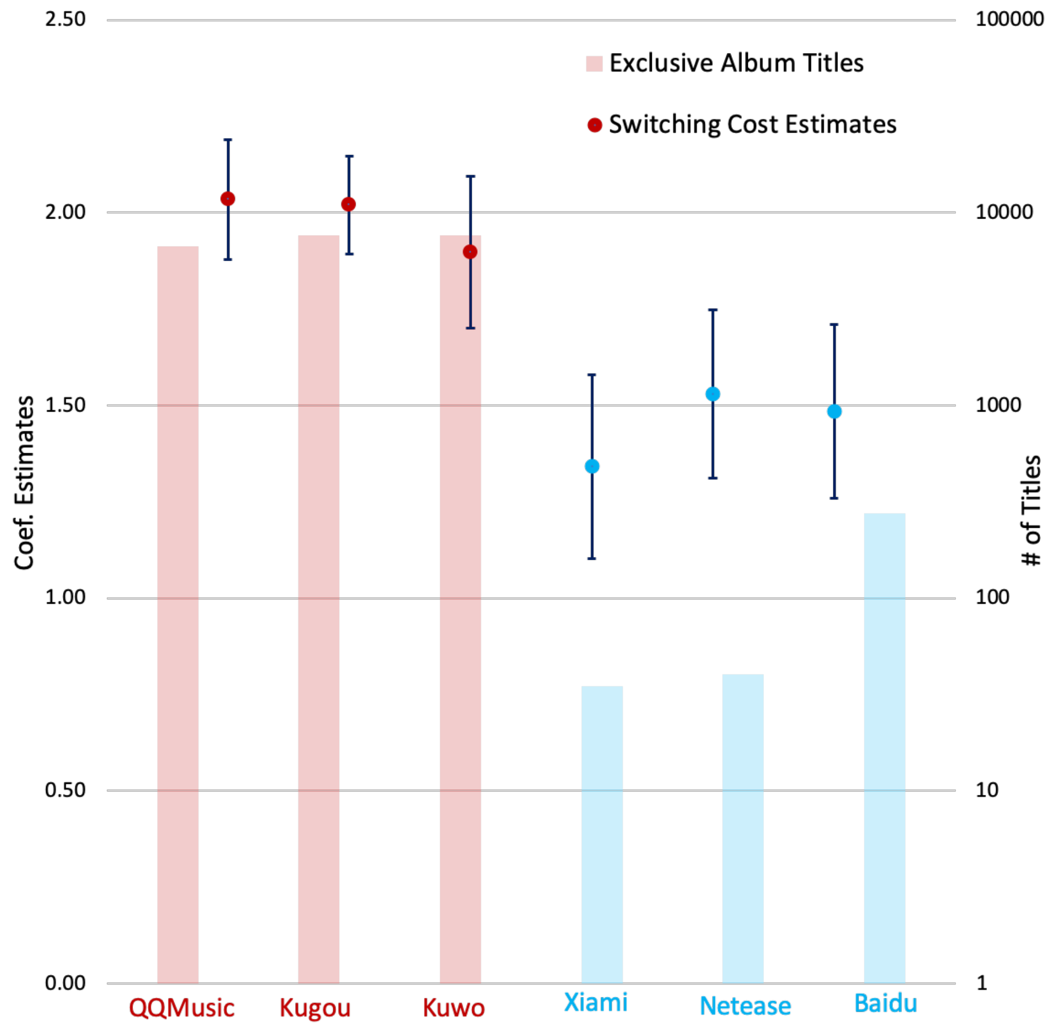
(c) Xiami and Netease



(d) Xiami and Baidu

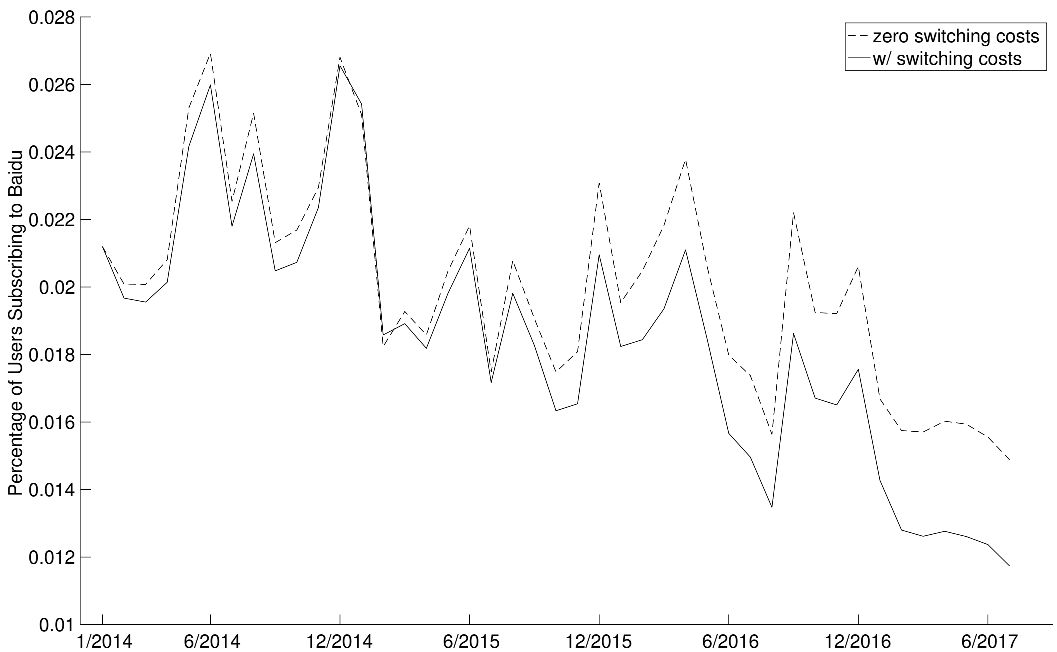
Notes: The graphs above plot the share of multihoming users. The top left graph plots users subscribing to QQMusic and Xiami simultaneously; The top right graph plots users subscribing to Kuwo and Xiami simultaneously; The bottom left graph plots users subscribing to Xiami and Netease; The bottom right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

Figure 10: Plot of Switching Costs



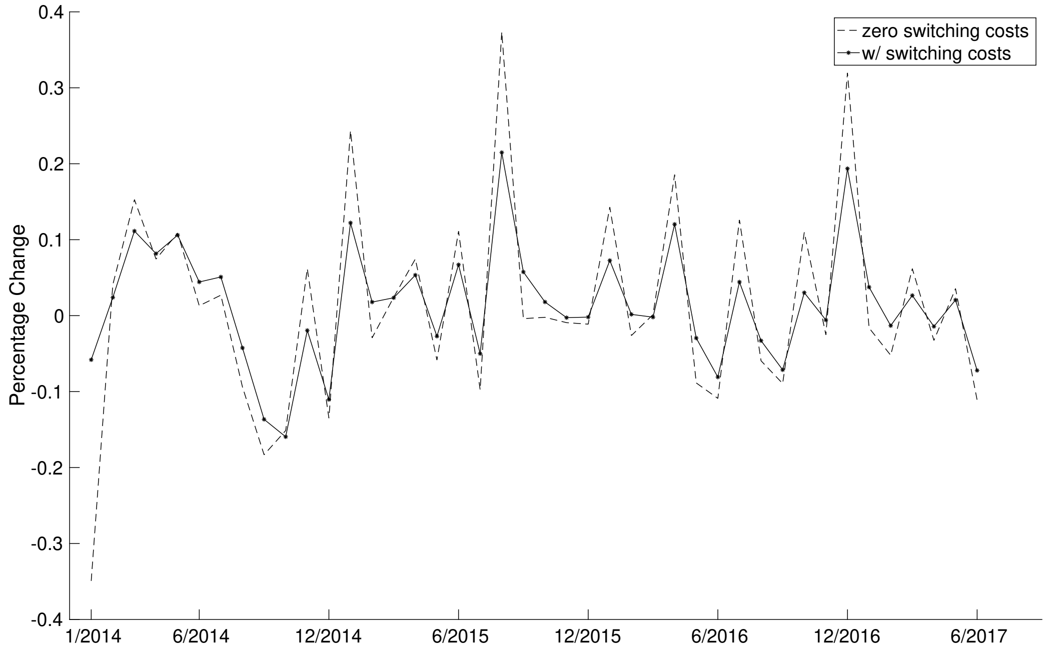
Note: The figure plots a comparison of the switching cost estimates from the dynamic model with their 95% confidence interval. The coefficients are estimated by simulated GMM that are reported in Table 6 . The vertical bar represents exclusive album titles distributed by each service.

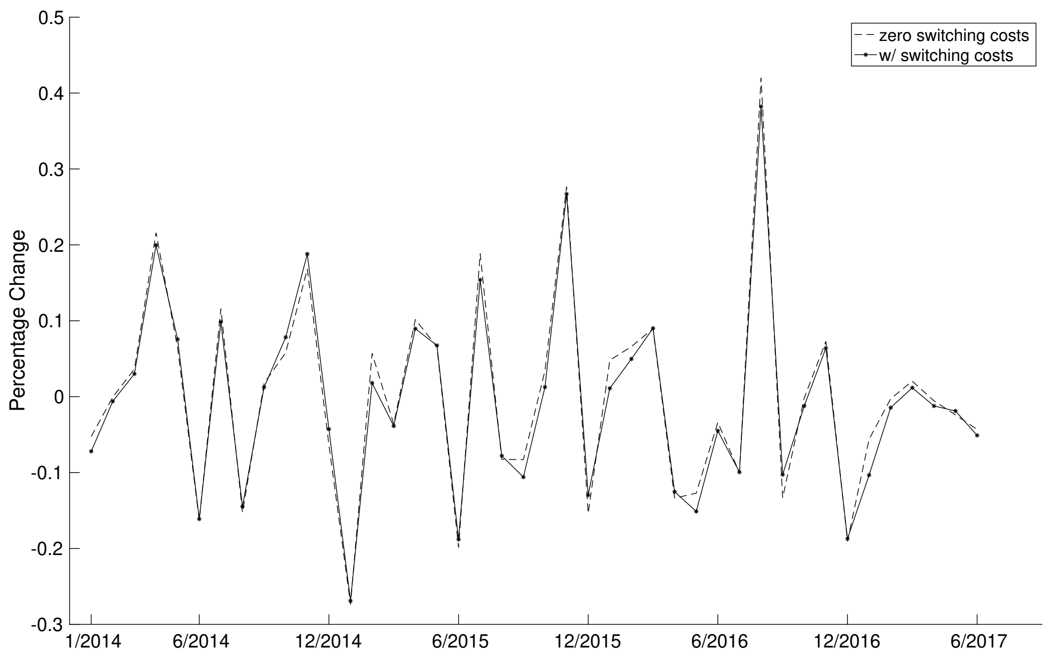
Figure 11: Model Prediction of Service Adoptions



Note: The top graph plots the adoption rates of Kugou and the bottom 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.

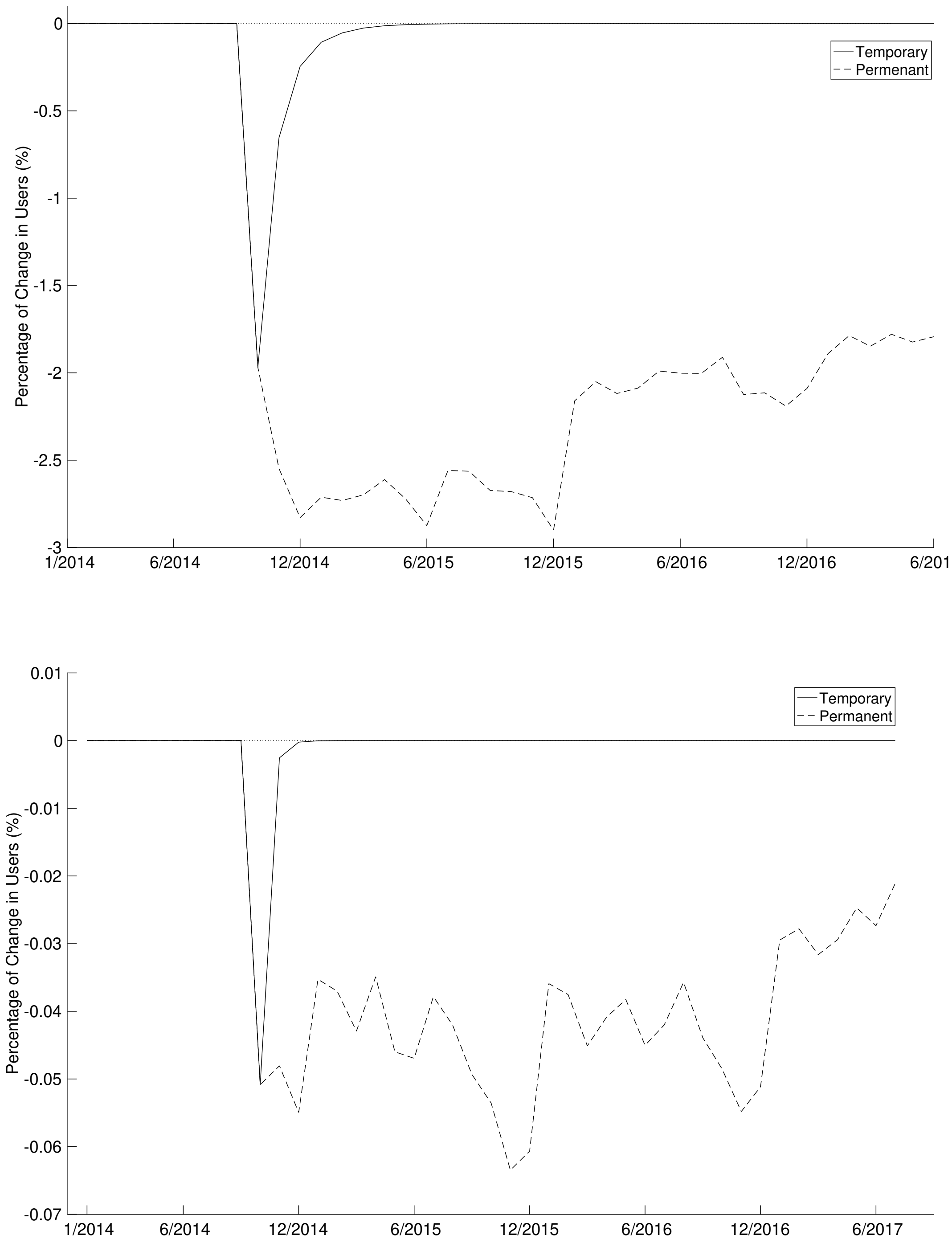
Figure 12: MoM change in Service Adoptions





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 13: Dynamic Elasticities to a Change in Content



Notes: The top graph plots the percentage change in users of Kugou in response to a 10% reduction in its album titles; and the right graph plots the content elasticities of Baidu. Solid line indicates market response to a temporary change; dashed line indicates market response to a permanent change.

Appendix

A Theory Model

In this section, I present the interaction between exclusivity and the switching cost via a stylized theoretical model. I develop a model of competition between two music streaming service providers. Those services are assumed to be horizontally differentiated by their user interface, personalized features (e.g. playlist management, music discovery, and friendship interaction).

Services are differentiated vertically. Except for a common set of music content owned by both services, one of the services has signed an exclusive deal with a monopoly label. From now on, I refer the service as an integrated service because it can choose whether to sublicense the label's content to its rival. An equilibrium outcome is exclusive if the integrated service is the only one distributing the label's content, while the equilibrium outcome is non-exclusive if both services distribute the content. The integrated service can receive sub-licensing revenues paid by the rival in a non-exclusive equilibrium. Both services can generate revenues from users' subscriptions and endogenously set their subscription prices through a Bertrand competition.

A.1 The Model

The market has three agents, services A and B, and a unit mass of consumers. Service A is offering a set of exclusive songs. Following Armstrong (2006), consumers distribute uniformly on a unit-interval market. Each service locates at each end of the interval. By subscribing to services, consumers receive utilities from the music content and other service features.

The competition game takes place in the following four stages:

Stage I: Service A chooses whether or not to stream the content exclusively. If the service choose non-exclusivity, it offers a wholesale contract (by charging the licensing fee) to service B.

Stage II: Service B chooses to accept or reject the contract if A offers to wholesale its proprietary content.

Stage III: Both services simultaneously choose the subscription price r_i.

Stage IV: Consumers make subscription decisions.

The wholesale contract that service A offers to B is in the form of a two-part tariff denoted as $T = (f, c) \in R^2_+$, where f is a lump-sum fee, and c is a per-subscriber fee. [40]. Both services collect revenue from their own subscribers. If the offer is accepted, service A is able to collect

[40] The lump-sum fee is set to be positive in order to rule out the case of collusion. The alternative contract forms can be a per-subscriber fee. The findings of using a lump-sum fee as the form of the contract are still valid if other forms of contract were used.

additional revenue from the rival service. Suppose that Let $q_i \in \{1,0\}$ denote whether service i has the proprietary music content available for streaming. Suppose that the marginal costs of the service are zero, the service's profit can be expressed as follows:

$$\pi_A = p_A N_A + q(f + cN_B), \tag{A.1}$$

$$\pi_B = (p_B - q_B c)N_B - qf, \tag{A.2}$$

where $p_{j\in\{A,B\}}$ is the price charged by each service and $N_{j\in\{A,B\}}$ is the number of subscribers.

A consumer incurs different transportation costs when subscribing to different services. Specifically, the cost is depending on the location that the consumer is at on the unit interval, and a constant marginal transportation cost denoted as t. A consumer locating at x on the unit interval incurs transportation cost tx when subscribing to service A and transportation cost $t(1-x)$ when subscribing to service B. Given this, the utility, which is denoted as u_j, received by a consumer locating at x and subscribing to the service $j \in \{A,B\}$ is defined as follows:

$$u_j = v_j - p_j + (\alpha q_A - tx)\mathbf{1}(j = A) + (\alpha q_B - t(1-x))\mathbf{1}(j = B), j \in \{A,B\}, \tag{A.3}$$

where v_j represents the intrinsic value of subscribing to service j, i.e., utilities received from listening the commonly owned music content and using other service features of service j. Consumer's marginal utility from the distribution of proprietary content, the network effect, is captured by α.

Consumers are also allowed to multihome. That is, a consumer can subscribe to both services at the same time and receive the utility u_{AB} that is defined as follows:

$$u_{AB} = V + \alpha \max\{q_A, q_B\} - p_A - p_B - t. \tag{A.4}$$

Similar to utility v_j received from single-homing utility function, V is the intrinsic value of subscribing to both services.

In the following sections, I will characterize two equilibrium outcomes under different model assumptions by focusing on whether service A would choose to supply the proprietary content to its rival. Before proceeding, I make the following assumptions: consumers always like the proprietary content; services qualities are sufficiently differentiated so that the market always remains competitive.

Assumption 2. *The proprietary content has a positive but finite network effect, i.e.,* $3t > \alpha > 0$.

Assumption 3. v_A *and* v_B *are sufficiently large such that all consumers would choose to subscribe to at least on service in equilibrium.*

Finally I impose assumption on services vertical differentiation. The condition ensures both services will have positive number of subscribers in any equilibrium.

Assumption 4. *Services have limited vertical differentiation on their service qualities other than their music repertoire. That is,* $|v_A - v_B| \leq 3t - \alpha$.

A.2 Benchmark Model

Now assume the game takes place for one period only and consumers can only singlehome. As in Armstrong and Wright (2007) I apply an explicit condition that requires t to be sufficient large that no consumers would subscribe to both services at the same time for all non-negative subscription prices.

Assumption 5. $t \geq \alpha + \delta_A + \delta_B$, *where* $\delta_j = V - v_j, j \in \{A, B\}$.

Lemma 1. *With Assumption 5, no consumer would choose to multihome.*

Whether the service A's supplies the content to its rival is depending on the profits under two scenarios. In the first scenario that the content is distributed exclusively, both services set their own subscription prices simultaneously taking into account the difference in content distribution. Specifically, the prices of both services are:

$$p_A^E = t + \frac{1}{3}(v_A - v_B + \alpha), \tag{A.5}$$

$$p_B^E = t - \frac{1}{3}(v_A - v_B + \alpha). \tag{A.6}$$

Given the prices, the corresponding number of consumers subscribing to service A is:

$$N_A^E = \frac{1}{2} + \frac{v_A - v_B + \alpha}{6t}, \tag{A.7}$$

Intuitively, in the exclusive distribution case, the difference between services' prices is driven by their vertical differences ($v_A - v_B$), and the value of exclusive content to consumers (α). Similarly, the number of subscribers of each service is also driven by these differences between the services. Service A will have more users if its intrinsic value v_A is much greater than service B's intrinsic value v_B, and the exclusive content is attractive.

By Assumption 4 and 5, all the prices are positive and $N_A^E \in (0, 1)$.

The profit that a service gains under the exclusive scenario is:

$$\pi_A^E = p_A^E N_A^E = \frac{(3t + v_A - v_B + \alpha)^2}{18t}, \tag{A.8}$$

$$\pi_B^E = p_B^E (1 - N_A^E) = \frac{(3t + v_B - v_A - \alpha)^2}{18t}. \tag{A.9}$$

If service A chooses non-exclusive distribution, the service will receive a subscription revenue from users, and a sub-licensing revenue from the rival in the form of a two-part tariff, including a lump-sum fee f and per-subscriber fee c. In this case, the prices of both services are:

$$p_A^{NE} = t + c + \frac{1}{3}(v_A - v_B), \tag{A.10}$$

$$p_B^{NE} = t + c - \frac{1}{3}(v_A - v_B). \tag{A.11}$$

Given the prices, total number of consumers subscribing to service A is:

$$N_A^{NE} = \frac{1}{2} + \frac{v_A - v_B}{6t}. \tag{A.12}$$

Note that service B's profit is:

$$\pi_B^{NE} = \frac{(3t + v_B - v_A)^2}{18t} - f, \tag{A.13}$$

which is independent to the per-subscriber fee c. Thus service A can charge the per-subscriber fee as large as possible. The maximum that service A can charge is $c = \frac{v_A+v_B+2\alpha-3t}{2}$ when the surplus of marginal consumers, who are locating at $x = N_A^{NE}$, are fully extracted. [41] Thus the maximum lump-sum licensing fee service B will accept is $f = \frac{\alpha(6t+2v_B-2v_A-\alpha)}{18t}$ when $\pi_B^{NE} = \pi_B^E$. Finally, service A's profit is

$$\pi_A^{NE} = \frac{(3t + v_A - v_B)^2 + \alpha(6t + 2v_B - 2v_A - \alpha)}{18t} + \frac{v_A + v_B + 2\alpha - 3t}{2}. \tag{A.14}$$

Compare with the exclusive distribution, price differences between services depend on their vertical differentiation only. By sharing the common content, service A will have fewer users under the non-exclusive than under the exclusivity distribution. However, the non-exclusivity allows the service A to force the service B's to implement a joint monopoly price through the per-subscriber fee c. Service A can also extract service B's profit up to the alternative profit it would have earned when rejecting the sub-licensing offer. Service A trades off between exclusivity and non-exclusivity by weighing the benefit of more users under exclusivity against benefit of monopoly pricing and profit extraction in the non-exclusive distribution. Specifically, the difference of A's profit between non-exclusivity and exclusivity is:

$$\triangle\pi_A = \pi_A^{NE} - \pi_A^E = \frac{\alpha(4(v_B - v_A) + 18t - 2\alpha)}{18t} + \frac{v_A + v_B - 3t}{2}. \tag{A.15}$$

[41] Note that the per subscriber fee is positive by Assumption 3.

Given Assumptions 3 to 5, the profit difference above is always positive. For that reason service A can always find non-exclusivity is more profitable.[42]

Proposition 1 (Non-exclusivity)**.** *Suppose Assumption 3 to 5 are satisfied, service A always chooses non-exclusivity in the equilibrium .*

The analysis shows that a static framework cannot explain why services will choose an exclusive distribution. In this framework, the benefit of choosing exclusivity is outweighed by the benefits of non-exclusive distribution. In a non-exclusive equilibrium, service A can always find a contract that service B will accept. At the same time, it faces a soft price competition and extra profits from the lump-sum sub-licensing fee.

A.3 Competition with Switching Costs

This section considers the effects of switching costs on the incentive for content exclusivity. I extend the model by adding dynamic elements into consumers' decision problems, which are additional benefits by subscribing to the same service.

The additional benefits occur because the music streaming service can offer enhanced personalized experience to its users that continue their subscriptions. One typical example is that almost all music streaming services offer a suggestive list feature to its users, which comprises a customized list of songs. The recommended playlist is generated based on the user's search history pattern and potential music preference.

Two-period models are often used in the literature in analyzing the effect of switching costs on market competition. And it is shown that firms have an incentive to lower their prices and capture more customers in the first period (Klemperer, 1987).[43] In this study, I use the two-period model to show that with the existence of the switching costs content exclusivity might emerge. This study's analysis is closely related to Weeds (2016) in which the incentives for the exclusive distribution of premium content are studied under the competition with switching costs. However, my model and analysis are different from Weeds (2016) in allowing asymmetric switching costs between services and forward-looking consumers with changing preferences.

A.3.1 Two-period model with switching costs

The competition now takes place in two periods. In the first period, users enter the market and choose a service to subscribe to. Because users are new to the services in this period, no addi-

[42] Here I assume that service A will always use the exclusive content. To justify the non-exclusive equilibrium, one has to check if service A has the incentive to let its rival provide stream the proprietary content exclusively and extract more surplus from the rival by using the two-part tariff. However, a formal analysis shown in the Appendix indicates that service A has no incentive to do so.

[43] see the survey paper by Farrell and Klemperer (2007) for a review of this literature

tional benefits are generated. In the second period, the users who continue the subscription of service $j \in \{A, B\}$ will receive an additional benefit of $\gamma_j > 0$. In contrast, users who switch to a new service will forgo the additional benefits. Consumers are forward-looking. That is, rational consumers can foresee prices and content distributions in the second period. Consumers also have changing preferences, i.e., a user's horizontal preference location, x, is drawn independently across periods from a uniform distribution, $U(0,1)$. Note that allowing consumers to change preferences over periods is not necessary, but it will ease the computation. Besides, allowing changing preference in the model is also close to a logit-style model used in the empirical analysis in which the idiosyncratic errors are drawn independently across time.

In each period, service provider A chooses whether to stream the content exclusively, and the rival service chooses to accept the wholesale offer or not. Both services set subscription prices for their users in each period. It is also allowed that services can price discriminate between its existing and new users.

A.3.2 Analysis

The analysis is focused on the case that services are symmetric in intrinsic values, i.e., $v_A = v_B = v$, while the model allows services to be asymmetric in their switching costs (continuing subscription benefits), i.e., $\gamma_A > \gamma_B$. For tractability it is assumed that $\gamma_B < 3t$ and there is no discounting of future profits and utilities.

In period 2, service provider A will always choose to supply its exclusive content to its rival. The proof (see Appendix A.5) and intuition of this claim follows from the proposition 1 of the static singlehoming case. When the switching costs of service A is relatively high such that $\gamma_A > 3t$,its existing user will never switch to service B in the second period even when subscription price offered by service B is set to zero. In such case, the service acts as monopolist in this submarket and set the price at $p_{AA} = \gamma_A + c_2 - t$, where c_2 is the per-subscriber licensing fee.[44] Note that with the perfect lock-in, service A can extract the entire successive subscription benefits γ_A from locked-in users. By choosing non-exclusivity, provider A can set the proper per-subscriber fee to fully extract the surplus from the marginal users who subscribed to service B in the previous period and is indifferent between subscribing to service A and B in the second period. The second period profit for service provider A is therefore

$$c_2 = v + \alpha - \frac{3t}{2} + \frac{\gamma_B}{2}.$$

at which the marginal users' surplus is fully extracted. Denote N_1 as A's period 1 market share, the

[44] In the second period, each service sets two prices. Here, p_{xy} is denoted as the price of service x charging on users who subscribed to y in the previous period.

profits that service A will gain in the second period is:

$$\pi_{A,2}^{NE} = \begin{cases} N_1 \frac{(3t+\gamma_A)^2}{18t} + (1-N_1)\frac{(3t-\gamma_B)^2}{18t} + c_2 + f_2, & \text{if } \gamma_A < 3t; \\ N_1(\gamma_A - t) + (1-N_1)\frac{(3t-\gamma_B)^2}{18t} + c_2 + f_2, & \text{if } \gamma_A \geq 3t. \end{cases} \tag{A.16}$$

where

$$c_2 = v + \alpha - \frac{3}{2}t + \frac{\gamma_B}{2};$$

and

$$f_2 = \begin{cases} N_1 \frac{\alpha(6t-2\gamma_A-\alpha)}{18t} + (1-N_1)\frac{\alpha(6t+2\gamma_B-\alpha)}{18t}, & \text{if } \gamma_A \leq 3t-\alpha; \\ N_1 \frac{(3t-\gamma_A)^2}{18t} + (1-N_1)\frac{\alpha(6t+2\gamma_B-\alpha)}{18t}, & \text{if } \gamma_A \in (3t-\alpha, 3t) \\ (1-N_1)\frac{\alpha(6t+2\gamma_B-\alpha)}{18t}, & \text{if } \gamma_A \geq 3t. \end{cases}$$

In the first period, however, service A may gain more profit from exclusivity. The following proposition shows, given the optimal strategy in period 2, service A's incentive for content exclusivity mostly depends on how much continue subscription benefits (or switching costs) it can generate for its users in the next period.

Proposition 2 (Exclusivity with switching costs)**.** *Suppose that assumption 2 to 5 and the following condition are satisfied:*

$$t \leq \frac{\alpha^2}{6\alpha + 8v}.$$

Provider A will choose exclusivity in period 1 if γ_A is sufficiently larger than γ_B.

Intuitively, service A will choose exclusivity in the first period because it confers its advantageous position in the second period. The incentive for exclusivity essentially relies on service A's ability to retain users in the second period, driven by the existing switching cost. The opportunity costs that service A forgoes if choosing exclusive distribution include the surplus extraction from service B's profit. For that reason, the result also relies on that service B has a relatively lower ability to retain users. Indeed, suppose service B can generate more profits from its locked-in users. In that case, service A will be more likely to choose a non-exclusive distribution to extract service B's excessive profit via the licensing contract. Figure C.1 illustrates the condition on switching cost by generating equilibrium outcome under each combination of γ_A and γ_B.

The first condition in Proposition 2 requires limited horizontal differentiation, i.e., small t and sufficient large network effect, i.e., large α. The intuition is straight forward: the strategy that using exclusive content to capture consumers in the first period has to be effective.

A.4 Proof of Proposition 1

It has been shown in the paper that service A has no incentive to stream the proprietary content exclusively. Here I show that service A also has no incentive to outsource the content that allows its rival to stream it exclusively.

Proof. Suppose service A outsources the proprietary content to its rival, i.e., let the rival stream the proprietary content exclusively and charges a fixed licensing fee f and per-subscriber fee c. Both services, if service B accepts the offer, will set the subscription prices at:

$$p_A^E = t + c + \frac{1}{3}(v_A - v_B - \alpha), \tag{A.17}$$

$$p_B^E = t + c - \frac{1}{3}(v_A - v_B - \alpha). \tag{A.18}$$

And total consumers subscribing to service A is:

$$N_A^E = \frac{1}{2} + \frac{v_A - v_B - \alpha}{6t}. \tag{A.19}$$

As in the non-exclusive scenario, service B can fully pass the per-subscriber licensing fee to its users. Thus its profit is independent to the per-subscriber fee, which is:

$$\pi_B^E = \frac{(3t + v_B - v_A + \alpha)^2}{18t} - f. \tag{A.20}$$

Provider A can therefore fully extract the surplus of marginal consumers locating at $x = N_A^E$ by setting the per-subscriber fee as large as $\frac{v_A+v_B+\alpha-3t}{2}$. And the fixed licensing fee is set to fully extract service B's additional surplus from the non-exclusive scenario, that is, $f = \frac{2\alpha(3t+v_B-v_A)}{9t}$. The profit that service A gains in this case is:

$$\pi_A^E = \frac{(3t + v_A - v_B - \alpha)^2 + 4\alpha(3t + v_B - v_A)}{18t} + \frac{v_A + v_B + \alpha - 3t}{2}. \tag{A.21}$$

By comparing with the non-exclusivity, the profit difference of service A is:

$$\triangle\pi_A = \pi_A^{NE} - \pi_A^E = \frac{5}{6}\alpha > 0. \tag{A.22}$$

Therefore, service A has no incentive to outsource the proprietary content to its rival service.

□

A.5 Proof of Proposition 2

I prove this proposition by backward induction. Denote the first period market share of service A as N_1. In the second period, because each service can discriminate between its own users and rival's users, the services are competing over two sub-markets separated by each services' user base from the previous period. The following claim shows that service A will always choose non-exclusivity in the second period.

Claim 1. *In period 2, service A will always choose non-exclusivity. If $3t > \gamma_A > \gamma_B$, no service can fully lock-in its users from the previous period. If $\gamma_A \geq 3t > \gamma_B$, service A can fully lock-in its users from the previous period and set the monopolized price in the market with those users, while service B cannot.*

Proof. Proof and intuition of the first argument in the claim follows the proof and intuition of proposition 1. With no further periods ahead, service A will gain a higher profit by choosing non-exclusivity and collecting the licensing fee. The only difference here is that service A can choose exclusivity under which it is easier for locking in its users from the previous period and gain more monopoly profit from this sub-market. Here is the formal proof.

Denote p_{xy} as the price of service y offer to users from service x in period 2, where $x, y \in \{A, B\}$. Suppose that service A choose exclusivity, i.e., $q_A = 1, q_B = 0$. And if no services can monopolize in any sub-market, the prices they offer to its users and rival's users are:

$$
\begin{aligned}
p^E_{AA} &= t + \frac{\alpha + \gamma_A}{3}, \\
p^E_{BA} &= t + \frac{\alpha - \gamma_B}{3}; \\
p^E_{AB} &= t - \frac{\alpha + \gamma_A}{3}, \\
p^E_{BB} &= t - \frac{\alpha - \gamma_B}{3}.
\end{aligned}
$$

Note that if $\gamma_A \geq 3t - \alpha$, $p^E_{AB} \leq 0$ the service B will deviate to offer zero price to users from service A, while the equilibrium price offered by service A to those users will become[45]:

$$
p^E_{AA} = \gamma_A + \alpha - t. \tag{A.23}
$$

[45] If $\alpha > 3t$, service A can easily lock in its existing users by choosing exclusivity.

Overall, services will gain following profits if service A choose exclusivity:

$$\pi_{A,2}^{E} = \begin{cases} N_1\frac{(3t+\alpha+\gamma_A)^2}{18t} + (1-N_1)\frac{(3t+\alpha-\gamma_B)^2}{18t}, & \text{if } \gamma_A < 3t-\alpha; \\ N_1(\gamma_A+\alpha-t) + (1-N_1)\frac{(3t+\alpha-\gamma_B)^2}{18t}, & \text{if } \gamma_A \geq 3t-\alpha. \end{cases} \tag{A.24}$$

(A.25)

$$\pi_{B,2}^{E} = \begin{cases} N_1\frac{(3t-\alpha-\gamma_A)^2}{18t} + (1-N_1)\frac{(3t-\alpha+\gamma_B)^2}{18t}, & \text{if } \gamma_A < 3t-\alpha; \\ (1-N_1)\frac{(3t-\alpha+\gamma_B)^2}{18t} & \text{if } \gamma_A \geq 3t-\alpha. \end{cases} \tag{A.26}$$

Similarly, suppose that service A choose non-exclusivity, given the licensing offer (c_2, f_2) the prices offered by services are:

$$\begin{aligned} p_{AA}^{NE} &= \begin{cases} t+c_2+\frac{\gamma_A}{3}, & \text{if } \gamma_A < 3t; \\ \gamma_A+c_2-t, & \text{if } \gamma_A \geq 3t. \end{cases} \\ p_{BA}^{NE} &= t+c_2-\frac{\gamma_B}{3}. \\ p_{AB}^{NE} &= \begin{cases} t+c_2-\frac{\gamma_A}{3}, & \text{if } \gamma_A < 3t; \\ c_2, & \text{if } \gamma_A \geq 3t. \end{cases} \\ p_{BB}^{NE} &= t+c_2+\frac{\gamma_B}{3}. \end{aligned}$$

where

$$c_2 = v+\alpha-\frac{3t}{2}+\frac{\gamma_B}{2}.$$

at which the marginal users' surplus is fully extracted. And the profits that service A will gain in the non-exclusivity case is:

$$\pi_{A,2}^{NE} = \begin{cases} N_1\frac{(3t+\gamma_A)^2}{18t} + (1-N_1)\frac{(3t-\gamma_B)^2}{18t} + c_2 + f_2, & \text{if } \gamma_A < 3t; \\ N_1(\gamma_A-t) + (1-N_1)\frac{(3t-\gamma_B)^2}{18t} + c_2 + f_2, & \text{if } \gamma_A \geq 3t. \end{cases} \tag{A.27}$$

where

$$f_2 = \begin{cases} N_1\frac{\alpha(6t-2\gamma_A-\alpha)}{18t} + (1-N_1)\frac{\alpha(6t+2\gamma_B-\alpha)}{18t}, & \text{if } \gamma_A \leq 3t-\alpha; \\ N_1\frac{(3t-\gamma_A)^2}{18t} + (1-N_1)\frac{\alpha(6t+2\gamma_B-\alpha)}{18t}, & \text{if } \gamma_A \in (3t-\alpha, 3t) \\ (1-N_1)\frac{\alpha(6t+2\gamma_B-\alpha)}{18t}, & \text{if } \gamma_A \geq 3t. \end{cases}$$

Note that $c_2 > \alpha$ and $f_2 > 0$ give rise to $\pi_A^{NE} > \pi_A^{E}$. □

Note that service A's profit in period 2 depends linearly on the first period user base, N_1, and the derivative of the profit function with respect to N_1 is:

$$\frac{\partial\pi_{A,2}}{\partial N_1} = \begin{cases} \frac{\gamma_A^2-\gamma_B^2+(6t-2\alpha)(\gamma_A+\gamma_B)}{18t}, & \text{if } \gamma_A < 3t-\alpha; \\ \frac{\gamma_A^2-\gamma_B^2+(6t-2\alpha)(\gamma_A+\gamma_B)+(3t-\gamma_A-\alpha)^2}{18t}, & \text{if } \gamma_A \in (3t-\alpha, 3t); \\ \gamma_A - t - \frac{(3t-\gamma_B)^2+\alpha(6t+2\gamma_B-\alpha)}{18t}, & \text{if } \gamma_A \geq 3t. \end{cases}$$

$$\frac{\partial\pi_{B,2}}{\partial N_1} = \begin{cases} -\frac{(\gamma_A+\gamma_B)(6t-2\alpha)-\gamma_A^2+\gamma_B^2}{18t}, & \text{if } \gamma_A < 3t-\alpha; \\ -\frac{(3t-\alpha+\gamma_B)^2}{18t}, & \text{if } \gamma_A \geq 3t-\alpha. \end{cases}$$

Note that $\frac{d\pi_A}{dN_1} > 0$ and $\frac{d\pi_B}{dN_1} < 0$ if assumptions stated in the [proposition 3] are satisfied.

Now consider the first period, consumers are new to the services and they also look forward to the surplus expected to receive in the next period. The difference of the expected surplus by subscribing to different services is:

$$\mathbb{E}(U_{A,2}-U_{B,2}) = \begin{cases} \frac{\gamma_A-\gamma_B}{2} + \frac{\gamma_A^2-\gamma_B^2}{36t}, & \gamma_A < 3t; \\ \frac{7}{4}t - \frac{\gamma_B}{2} - \frac{\gamma_B^2}{36t}, & \gamma_A \geq 3t. \end{cases}$$

Now I check the incentive to choose exclusivity in the first period. Suppose service A choose exclusivity, the equilibrium prices and market share are:

$$\begin{aligned} p_A^E &= t + \frac{\alpha}{3} + \frac{\mathbb{E}(U_{A,2}-U_{B,2})}{3} - \frac{2}{3}\frac{\partial\pi_{A,2}}{\partial N_1} + \frac{1}{3}\frac{\partial\pi_{B,2}}{\partial N_1}; \\ p_B^E &= t - \frac{\alpha}{3} - \frac{\mathbb{E}(U_{A,2}-U_{B,2})}{3} - \frac{1}{3}\frac{\partial\pi_{A,2}}{\partial N_1} + \frac{2}{3}\frac{\partial\pi_{B,2}}{\partial N_1}. \\ N_1^E &= \frac{1}{2} + \frac{\mathbb{E}(U_{A,2}-U_{B,2}) + \alpha + \sum_{j=\{A,B\}} \frac{d\pi_{j,2}}{dN_1}}{6t}. \end{aligned}$$

As γ_A increases, P_A^E increases while p_B^E decreases and eventually goes to negative when γ_A is sufficiently large. Prices are subjected to be non-negative, thus when γ_A is sufficiently large, p_B^E is constrained at zero, which allows the service A to fix the price at

$$\bar{p}_A^E = \frac{t + \alpha + \mathbb{E}(U_{A,2}-U_{B,2}) - \frac{\partial\pi_{A,2}}{\partial N_1}}{2}.$$

And the corresponding market share of service A in this case is

$$\bar{N}_1^E = \frac{\alpha + \mathbb{E}(U_{A,2}-U_{B,2}) + \frac{\partial\pi_{A,2}}{\partial N_1}}{4t}.$$

Now suppose that service A chooses non-exclusivity, the equilibrium prices and market share are:

$$\begin{aligned}
p_A^{NE} &= t+c+\frac{\mathbb{E}(U_{A,2}-U_{B,2})}{3}-\frac{2}{3}\frac{\partial\pi_{A,2}}{\partial N_1}+\frac{1}{3}\frac{\partial\pi_{B,2}}{\partial N_1};\\
p_B^{NE} &= t+c-\frac{\mathbb{E}(U_{A,2}-U_{B,2})}{3}-\frac{1}{3}\frac{\partial\pi_{A,2}}{\partial N_1}+\frac{2}{3}\frac{\partial\pi_{B,2}}{\partial N_1}.\\
N_1^{NE} &= \frac{1}{2}+\frac{\mathbb{E}(U_{A,2}-U_{B,2})+\sum_{j=\{A,B\}}\frac{d\pi_{j,2}}{dN_1}}{6t}.
\end{aligned}$$

where $c=v+\alpha-\frac{3}{2}t+\frac{1}{2}(\frac{\partial\pi_{A,2}}{\partial N_1}-\frac{\partial\pi_{B,2}}{\partial N_1})-\frac{1}{2}\mathbb{E}(U_{A,2}-U_{B,2})$.

Similarly p_B^{NE} decreases as γ_A increases and will eventually be lower than the per-subscriber licensing fee, c, when γ_A is sufficiently large. Suppose that service B will accept the wholesale offer and setting its price at the per-subscriber fee c, which allow the service A to fix the price at

$$\bar{p}_A^{NE}=c+\frac{t+\mathbb{E}(U_{A,2}-U_{B,2})-\frac{\partial\pi_{A,2}}{\partial N_1}}{2}.$$

And the corresponding market share of service A in this case is

$$\bar{N}_1^{NE}=\frac{\mathbb{E}(U_{A,2}-U_{B,2})+\frac{\partial\pi_{A,2}}{\partial N_1}}{4t}.$$

Provider B might be slightly better by accepting the offer because it will lead to a higher profit in the second period by pushing to a lower N_1.

Denote γ_A^{**} as the cut-off of γ_A such that p_B^E and p_B^{NE} becomes negative. The difference between the first period exclusivity profit and non-exclusivity profit of service A when $\gamma_A>\gamma_A^{**}$is:

$$\begin{aligned}
\triangle\pi_{A,1} &\equiv \pi_{A,1}^E-\pi_{A,1}^{NE}\\
&= \frac{\alpha}{2}\frac{\mathbb{E}(U_{A,2}-U_{B,2})+\frac{\partial\pi_{A,2}}{\partial N_1}}{4t}+\frac{\alpha}{4t}\frac{t+\mathbb{E}(U_{A,2}-U_{B,2})-\frac{\partial\pi_{A,2}}{\partial N_1}}{2}+\frac{\alpha^2}{8t}\\
&\quad -c-f,
\end{aligned}$$

where

$$c=v+\alpha-\frac{t}{2}-\frac{3}{4}\mathbb{E}(U_{A,2}-U_{B,2})+\frac{1}{4}\frac{\partial\pi_{A,2}}{\partial N_1},$$

and

$$f=\frac{\alpha}{4t}\frac{\partial\pi_{B,2}}{\partial N_1}.$$

By rearrangement the profit difference is non-negative by assumption:

$$\triangle\pi_{A,1} \quad \geq \quad \frac{\alpha^2}{8t} - \frac{3\alpha}{4} - v \geq 0.$$

A.6 Competition with Multihoming Users

This section extend the previous model by allowing consumers to multihome. To do this, I relax the Assumption 5 that excludes multihoming subscriptions. Moreover, I impose the following necessary condition for multihoming:

Assumption 6. *The intrinsic value received from multihoming subscription is larger than the intrinsic value received from single-homing subscription, i.e.,* $V \geq \max\{v_A, v_B\}$.

Consumer will subscribe to both services if $u_{A,B} > \max\{u_A, u_B\}$ which are consumers locating at x within the following range:

$$x \in \left[1 - \frac{\delta_A + \alpha(1-q_A) - p_B}{t}, \frac{\delta_B + \alpha(1-q_B) - p_A}{t}\right], \tag{A.28}$$

where $\delta_j = V - v_j, j \in \{A, B\}$. Therefore if there are consumers multihome in an equilibrium, the equilibrium prices must set to ensure the above range is well defined. This gives to the following lemma.

Lemma 2 (Multihoming Condition)**.** *If the equilibrium prices,* p_A^* *and* p_B^* *, satisfy the following condition:*

$$p_A^* + p_B^* < \delta_A + \delta_B + \alpha(2 - q_A^* - q_B^*) - t \tag{A.29}$$

then there are consumers subscribing to both services in the equilibrium, i.e., $N_A^* + N_B^* > 1$.

The lemma above also shows that consumers will be more like to multihome in the exclusive case, because the inequality stated above is more likely to be satisfied when $q^*A \neq q^*B$. I first investigate the exclusive case in which service A choose to have the proprietary content streaming on its own service exclusively, i.e., $q_A = 1$ and $q_B = 0$. Suppose that the condition in Lemma 2 is satisfied so that consumers locating in the range of equation A.28 choose to multihome. The subscription prices, total subscribers and profits in the equilibrium are:

$$p_A^E = \frac{\delta_B + \alpha}{2}, N_A^E = \frac{\delta_B + \alpha}{2t}, \pi_A^E = \frac{(\delta_B + \alpha)^2}{4t}; \tag{A.30}$$

$$p_B^E = \frac{\delta_A}{2}, N_B^E = \frac{\delta_A}{2t}, \pi_B^E = \frac{(\delta_A)^2}{4t}. \tag{A.31}$$

The multihoming condition requires $t < \frac{\delta_A+\delta_B+\alpha}{2}$.

Now turn to the non-exclusive case where $q_A = q_B = 1$. Suppose that the contract offer is fixed and the multihoming condition is satisfied, the equilibrium prices, subscriber and profits in the equilibrium are:

$$p_A^{NE} = \frac{\delta_B}{2}, N_A^{NE} = \frac{\delta_B}{2t}, \pi_A^{NE} = \frac{(\delta_B)^2 + 2c(V - v_A - c)}{4t} + f; \tag{A.32}$$

$$p_B^{NE} = \frac{\delta_A + c}{2}, N_B^{NE} = \frac{\delta_A - c}{2t}, \pi_B^{NE} = \frac{(\delta_A - c)^2}{4t} - f. \tag{A.33}$$

Notice that unlike the service B's equilibrium price, as shown in equation A.11, in the non-exclusive case where the multihoming subscription is excluded, service B's price in this case indicates it cannot fully transfer the per-subscriber licensing fee to its users. Thus, service B's profit is not independent to the per-subscriber fee. In fact, service B's profit in the non-exclusive case is always lower than its profit gained in the exclusive case for any contract that charges positive licensing fee. Provider A will also lose profit comparing with the profit in the exclusive case, if the proprietary content were shared to service B free of charge. Intuitively, if sharing the proprietary content cannot fully drive away multihoming subscriptions, service A will always choose to stream the content exclusively in the equilibrium.

It is also worth noting that, if $v_B > v_A$ service A will choose to outsource its proprietary content to service B which allows its rival service to stream the content exclusively. This is shown and proved in the next proposition. Intuitively, if service B's service is more attractive to users, service A tend to outsource the proprietary content to its rival and extract more surplus from the consumers by allowing its rival to stream the content exclusively.

Proposition 3 (Exclusivity with multihoming)**.** *Suppose that Assumption 2 to 4 are satisfied and $t < \frac{\delta_A+\delta_B+\alpha}{2}$. Exclusivity ($q_A \neq q_B$) is chosen in the equilibrium if either of the following conditions is satisfied:*
Condition 1:

$$V \geq v_A + v_B + \alpha, t < \frac{\sqrt{2}}{2}\delta_A.$$

Condition 2:

$$V < v_A + v_B + \alpha, t < \frac{(\alpha + \delta_B)^2 + \delta_A^2}{4\alpha + 2(v_A + v_B)}.$$

Some consumers will multihome in the equilibrium, i.e., $N_A + N_B > 1$. In addition, service A would stream the proprietary content exclusively on its service, i.e., $q_A = 1$ and $q_B = 0$, if $v_A \geq v_B$;

the service would outsource the content to its rival and let the rival service stream the content exclusively, i.e., $q_A = 0$ *and* $q_B = 1$*, if* $v_A < v_B$*,*

The proof consists of three parts. First I show that exclusivity will always be chosen under the conditions stated in the proposition. I then prove that multihoming condition is always satisfied when exclusivity is chosen. Finally, I show that service A will choose different exclusivity schemes depending on the intrinsic utility that consumer will receive from using the services.

If $t < \frac{\delta_A+\delta_B+\alpha}{2}$, some consumers will choose to multihome in the exclusivity case. It has been shown in the paper if multihoming consumers exist in the non-exclusivity case, service B will reject any offer with positive license fee. Thus service A will choose exclusivity.

Note that if services choose the non-exclusivity and set prices as in equation A.10 and A.11 that no consumers would choose to multihome, the equilibrium prices should satisfy:

$$p_A + p_B > \delta_A + \delta_B - t. \tag{A.34}$$

In this case, service B's profit is independent to the per-subscriber licensing fee, so service A can set it as large as $c = \frac{v_A+v_B+2\alpha-3t}{2}$ by which the marginal users' surpluses are fully exploited . Hence the above condition is satisfied if and only if the following condition is hold:

$$v_A + v_B + 2\alpha \geq \delta_A + \delta_B. \tag{A.35}$$

The following claim shows that service A will choose exclusivity even if users do not multihome under non-exclusivity.

Claim 2. *Suppose that all conditions in proposition 3 and the condition as shown in equation A.35 are satisfied, service A will always choose the exclusivity.*

Proof. If the non-exclusivity were chosen, the equilibrium prices and per-subscriber fee would be same as in the static and single-homing only case. However, the lump-sum licensing fee should be different, because service B can reject the offer and consumers would choose to multihome in the exclusivity equilibrium, which led to B's profit of $\frac{(\delta_A)^2}{4t}$. If service B will gain less profit from the non-exclusivity, i.e., $\frac{(3t+v_B-v_A)^2}{18t} < \frac{(\delta_A)^2}{4t}$, it will always reject the wholesaling offer.

This implies

$$t < \frac{\sqrt{2}}{2}\delta_A + \frac{v_A - v_B}{3}.$$

Suppose $\frac{(3t+v_B-v_A)^2}{18t} \geq \frac{(\delta_A)^2}{4t}$, the maximum lump-sum licensing fee service B will accept is $f = \frac{(3t+v_B-v_A)^2}{18t} - \frac{(\delta_A)^2}{4t}$. Provider A would charge at the maximum amount and receives a profit of

$$\pi_A^{NE} = \frac{(3t+v_A-v_B)^2 + (3t+v_B-v_A)^2}{18t} + \frac{v_A+v_B+2\alpha-3t}{2} - \frac{(\delta_A)^2}{4t}. \tag{A.36}$$

By comparing with the non-exclusivity scenario, the profit difference of service A is:

$$\begin{aligned}
\triangle\pi_A &\equiv \pi_A^{NE} - \pi_A^E \\
&= \frac{(3t+v_A-v_B)^2+(3t+v_B-v_A)^2}{18t} + \frac{v_A+v_B+2\alpha-3t}{2} \\
&\quad -\frac{(\delta_A)^2+(\delta_B+\alpha)^2}{4t} \\
&= \frac{(v_B-v_A)^2}{18t} - \frac{t}{2} + \frac{2t(v_A+v_B+2\alpha)-(\delta_A^2+(\delta_B+\alpha)^2)}{4t}.
\end{aligned}$$

By Assumption 4, $(v_B-v_A)^2 < (3t-\alpha)^2$, thus $\frac{(v_B-v_A)^2}{18t} - \frac{t}{2} < \frac{\alpha^2}{18t} - \frac{\alpha}{3}$. And the last term is also negative by the condition that $t < \frac{(\alpha+\delta_B)^2+\delta_A^2}{4\alpha+2(v_A+v_B)}$. Overall the profit difference defined above is negative which implies that service A will choose exclusivity. □

The following claim further shows that the multihoming condition is satisfied if service A outsource the content to its rival and let the rival service stream the content excursively.

Claim 3. *If $q_A = 0$ and $q_B = 1$, the equilibrium prices satisfy the multihoming condition if $t < \frac{\delta_A+\delta_B+\alpha}{2}$. Provider A will outsource the proprietary content to its rival if $v_B > v_A$.*

Proof. Suppose service A outsources the proprietary content to its rival by charging a fixed licensing fee f and per-subscriber fee c. Both services, if the service B accepts the offer and multihoming condition is satisfied, will set the subscription prices at:

$$p_A^E = \frac{\delta_B}{2}, \tag{A.37}$$

$$p_B^E = \frac{\delta_A+\alpha+c}{2}. \tag{A.38}$$

The number of subscribers of both services are:

$$N_A = \frac{\delta_B}{2t}, \tag{A.39}$$

$$N_B = \frac{\delta_A+\alpha-c}{2t}. \tag{A.40}$$

And the profits they gain are:

$$\pi_A = \frac{\delta_B^2}{4t} + \frac{c(\delta_A+\alpha-c)}{2t} + f, \tag{A.41}$$

$$\pi_B = \frac{(\delta_A+\alpha-c)^2}{4t} - f. \tag{A.42}$$

Provider B will reject any licensing fee that gives rise to a lower profit than $\frac{(\delta_A)^2}{4t}$ the profit it will receive if service A choose to steam the content exclusively on its own service. Therefore, service A will charge the lump-sum fee of $f = \frac{(\delta_A+\alpha-c)^2-(\delta_A)^2}{4t}$ and receive the profit of

$$\pi_A = \frac{\delta_B^2 - \delta_A^2 + (\delta_A + \alpha)^2 - c^2}{4t}. \tag{A.43}$$

Note that in this case service A's profit is decreasing as the per-subscriber fee is increasing. Therefore, it will set the fee at zero and subtract service B's surplus through the lump-sum licensing fee. By doing so, service A's profit is

$$\pi_A = \frac{\delta_B^2 - \delta_A^2 + (\delta_A + \alpha)^2}{4t}. \tag{A.44}$$

Comparing with the profit that service A will gain if it chooses to stream the content exclusively on its own service, the profit difference is

$$\pi_A(q_A = 1, q_B = 0) - \pi_A(q_A = 0, q_B = 1) = \frac{\alpha(v_A - v_B)}{2t}. \tag{A.45}$$

It is clear that service A will choose to outsource the content and let the rival service to stream that content exclusively if $v_B > v_A$.

$\square$

B A Supply Model of Music Distribution

To evaluate the effect of switching cost on exclusivity, I develop a simple dynamic supply-side model of music distribution. I then use the model to estimate the marginal costs of distribution exclusive and non-exclusive content separately. The estimates is used to a counterfactual exercise that examines the effect of switching costs on services' choice of exclusive distribution.

The model assumes services make a decision over number of album titles distributed in each period. Each service faces a constant marginal cost that comes from paying for licensing fees and managerial costs. Holding the marginal costs fixed, I assume each service makes a decision on exclusive and non-exclusive decision. The model neither includes the licensing decision of labels, nor include the sub-licensing choices of services. In instead, the model assumes there are enough potential album titles available for distribution exclusively or non-exclusively. A service commits at the beginning of each month the number of alum titles to distribute exclusively and non-exclusively, separately. The decision has an impact not only on the current user base but also future user base via the switching cost. A service's expected discounted profit is specified as follows, given the payoff relevant information set $\Omega_{j,t}$:

$$\mathbb{E}\left[\pi_{jt}|\Omega_{j,t}\right] = \mathbb{E}\left[\sum_{\tau=t}^{T} \mu^{s-t} s_{j\tau} r_j - log(l_{j\tau}) mc_j | \Omega_{j,\tau}\right], \tag{B.46}$$

where μ is the discount rate, r_j is the service j per-subscriber revenue in each period, mc_j is the marginal cost vector of holding exclusive and non-exclusive album titles. Both the per-subscriber revenue r_j and mc_j are assumed to be exogenous and time invariant. The number of album titles, l_{jt}, is transformed by a logarithmic function to capture the non-linear dependence of costs to album titles distributed.

Because the model does not account for the change in per-subscribe revenue or the change in marginal cost in the alternative scenarios, it is fairly stylized and should be treated as a partial equilibrium analysis. However, the model is designed to show important implications of consumer switching costs for the optimal content distribution decisions.

Assuming that number of album titles is a continuous variable, services in each period choose the number of exclusive and non-exclusive titles to maximize its expected profits in each period given rivals' decisions and the information set $\Omega_{j,t}$. Using the one-shot deviation principle, the observed services' decision satisfies following condition:

$$\mathbb{E}\left[\sum_{\tau=t}^{T} \mu^{s-t} s_{j\tau} r_j - log(l^*_{j\tau}) mc_j | \Omega_{j,\tau}\right] \geq \mathbb{E}\left[\sum_{\tau=t}^{T} \mu^{s-t} \tilde{s}_{j\tau} r_j - log(\tilde{l}_{j\tau}) mc_j | \Omega_{j,\tau}\right], \tag{B.47}$$

where $l^*_{j\tau}$ is a vector of observed service j's decision on the number of exclusive and non-exclusive album titles, $\tilde{l}_{j\tau}$ is an alternative decision of service j. The alternative decision is different from the observed decision only in period t that is:

$$\begin{aligned}
\tilde{l}_{jt} &\neq l^*_{jt}; \\
\tilde{l}_{j\tau} &= l^*_{j\tau}, \forall \tau > t.
\end{aligned}$$

Assuming that the variables l_{jt} are continuous and market share s_{jt} is differentiable with respect to l_{jt}. The above condition implies the following first order condition:

$$\mathbb{E}\left[\sum_{\tau=t}^{T} \beta^{s-t} \frac{\partial s_{j\tau}}{\partial l_{jt}} r_j - \frac{mc_j}{l^*_{jt}} | \Omega_{j,\tau}\right] = 0. \tag{B.48}$$

Because without observing a service's revenue it is not jointly identified with the marginal cost, I estimate the marginal cost relative to the per-subscriber revenue. The estimator of the marginal cost mc_j is using a sample analogue of above moment condition:

$$\frac{\hat{mc}_j}{r_j} = \frac{1}{T} \sum_{t=0}^{T} \sum_{\tau=t}^{T} \beta^{s-t} \frac{\partial s_{j\tau}}{\partial l_{jt}} l^*_{jt}. \tag{B.49}$$

The model generates two estimates of marginal costs for each service. One is for the cost of exclusive distribution, and the other is for the non-exclusive distribution. To understand how the model is used to estimate these two marginal costs separately, I look into the change of market share in response to a temporary exclusive and non-exclusive content change. Figure C.2 illustrates the dynamic change in market shares in response to a temporary change in content, i.e., $\frac{\partial s_{j\tau}}{\partial l_{jt}}$. The figure shows that of all services, the change in exclusive content will cause more dramatic change in market share than the change in non-exclusive content. Moreover, the temporary change in content will have longer impact on the market share of the dominant service, Tencent, than other small services. The difference in long-term response to the temporary change is driven by asymmetric switching costs. Therefore, one can use these features to predict that (i) exclusive distribution has a larger marginal cost than non-exclusive distribution; (ii) the dominant service face a larger marginal cost than small services.

The estimation results are reported in Table C.3. As expected, exclusive distribution is more costly than non-exclusive distribution. The marginal cost of exclusive distribution of the dominant service is more than 40% of the per-subscriber revenue, which is more than 14% larger than the corresponding costs of small services. The dominant service also faces a slightly higher cost in non-exclusive distribution than the small services.

With the estimates, I further conduct an analysis focusing on the interaction between the switching cost and exclusive distribution. The counterfactual exercise is straightforward. Specifically, I simulate the counterfactual decision of the dominant service as if its users face zero cost in switching. With zero switching cost, a service's market share will respond more transitorily rather than dynamically to content change. As shown in Figure C.3, when the exclusive content of the dominant service reduces by a small amount, without the switching, the market share changes instantly in a similar magnitude as the change in a scenario with the switching cost, while market share changes in the future periods are less significant. This implies removing the switching cost leads to a reduction in the marginal benefit of music distribution. Therefore, the service will reduce the number of albums that are distributed exclusively (see Figure C.4). Indeed, the counterfactual simulation shows that the dominant service will reduce the number of exclusive distributed titles by more than 80% when the switching cost is absent.

C Additional Figures and Tables

Table C.1: Structural Estimates With Zero Switching Costs

Stage I: Service Adoption:		Stage II: Time Allocation:	
β_{cons}	-8.61	Constant	-3.60
(se)	(0.22)	(se)	(3.82)
β_{trend}	0.07	# of Album	0.20
(se)	(0.03)	(se)	(0.08)
σ_{cons}	0.17	# of Exclusive Album γ^E	0.04
(se)	(0.87)	(se)	(0.16)
$\sigma_{Dominant}$	4.29	Album Depreciation γ^{α}	-1.29
(se)	(0.22)	(se)	(0.79)
β^S	1.88	Diminishing Marginal Utility η	0.84
(se)	(0.47)	(se)	(0.95)
Multihoming Cost Coef.		θ_{mc}	-1.01
		(se)	(1.79)

Note: The estimates are for coefficients of the same dynamic model except the switching costs are assumed to be zeros. Estimation is base on simulated GMM with the same moment conditions as the preferred specification. The standard error (se) is reported in the parenthesis. The random coefficients are the standard deviations of normal distributions, where σ_{cons} is the random coefficient for constant and $\sigma_{Dominant}$ is the random coefficient for the dominant service dummy. The dominant service are QQMusic, Kugou and Kuwo. Service fixed effects are included, but the estimates of those are not reported.

Table C.2: Structural Estimates With Homogeneous Switching Costs

Stage I: Service Adoption:		Stage II: Time Allocation:	
β_{cons}	-6.79	Constant	-5.22
(se)	(0.18)	(se)	(1.99)
β_{trend}	0.06	# of Album	0.59
(se)	(0.03)	(se)	(0.10)
σ_{cons}	1.11	# of Exclusive Album γ^E	1.14
(se)	(0.19)	(se)	(1.25)
$\sigma_{Dominant}$	2.70	Album Depreciation γ^α	-2.41
(se)	(0.12)	(se)	(0.77)
β^S	1.51	Diminishing Marginal Utility η	0.88
(se)	(0.22)	(se)	(0.80)
Multihoming Cost Coef.		θ_{mc}	-1.05
		(se)	(0.37)
Switching Cost Coef.		ψ	1.78
		(se)	(0.04)

Note: The estimates are for coefficients of the same dynamic model except the switching costs are assumed to be homogeneous. Estimation is base on simulated GMM with the same moment conditions as the preferred specification. The standard error (se) is reported in the parenthesis. The random coefficients are the standard deviations of normal distributions, where σ_{cons} is the random coefficient for constant and $\sigma_{Dominant}$ is the random coefficient for the dominant service dummy. The dominant service are QQMusic, Kugou and Kuwo. Service fixed effects are included, but the estimates of those are not reported.

Table C.3: Estimates for Marginal Costs of Music Distribution

Service	Tencent	Xiami	Netease	Baidu
$mc_{exclusive}$	0.401	0.351	0.301	0.211
(std)	(0.032)	(0.058)	(0.038)	(0.028)
$mc_{non-exclusive}$	0.023	0.018	0.013	0.006
(std)	(0.002)	(0.004)	(0.002)	(0.002)

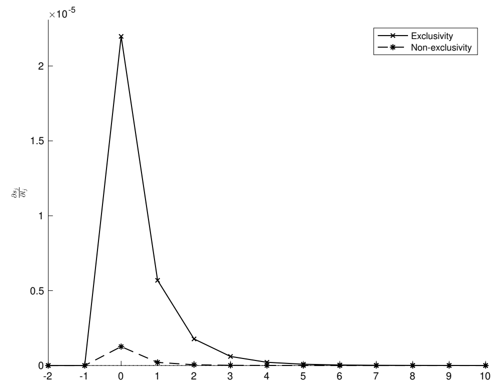
Note: The estimates are for marginal cost of content distribution across services. The first row reports the marginal cost of exclusive distribution. The second reports the marginal cost of non-exclusive distribution. Standard deviation is computed via bootstrap for 1000 times.

Table C.4: Market Shares in Steady State: Baseline, Compulsory Licensing, and Data Portability

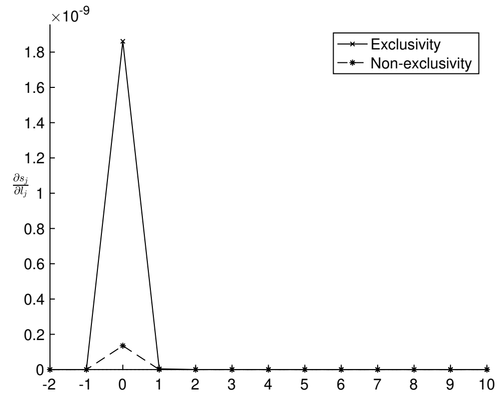
	Baseline	Compulsory Licensing		Data Portability		Data Portability and Compulsory Licensing	
	Market Share	Market Share	% △ to the baseline	Market Share	% △ to the baseline	Market Share	% △ to the baseline
Tencent	0.637	0.727	0.142	0.684	0.073	0.736	0.156
Xiami	0.018	0.015	-0.197	0.055	1.993	0.047	1.556
Netease	0.070	0.064	-0.095	0.158	1.246	0.149	1.123
Baidu	0.013	0.011	-0.168	0.043	2.390	0.038	1.997
Outside Option	0.287	0.206	-0.283	0.083	-0.709	0.049	-0.828

Note: This table shows a comparison in market outcomes between the scenario with exclusive provision and switching costs, the scenario with compulsory licensing and switching costs, the scenario without switching costs under the mandatory data portability, and the scenario with both compulsory licensing and mandatory data portability.

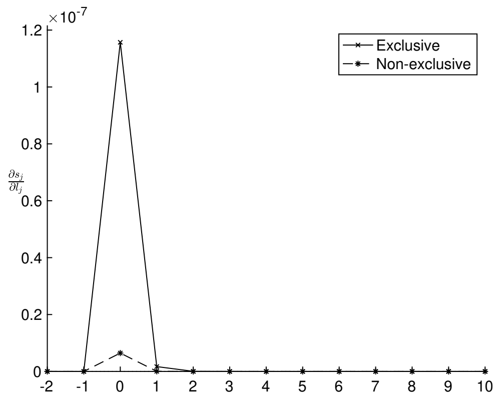
Figure C.2: Dynamic Change in Market Shares



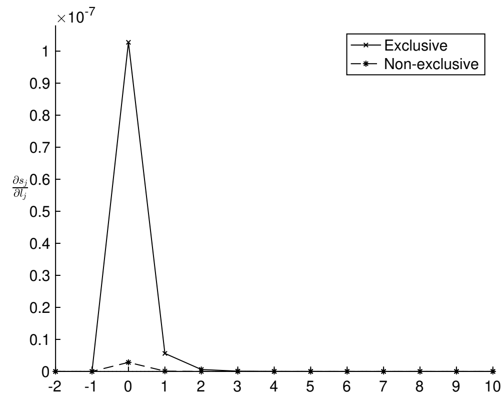
(a) Tencent



(b) Xiami



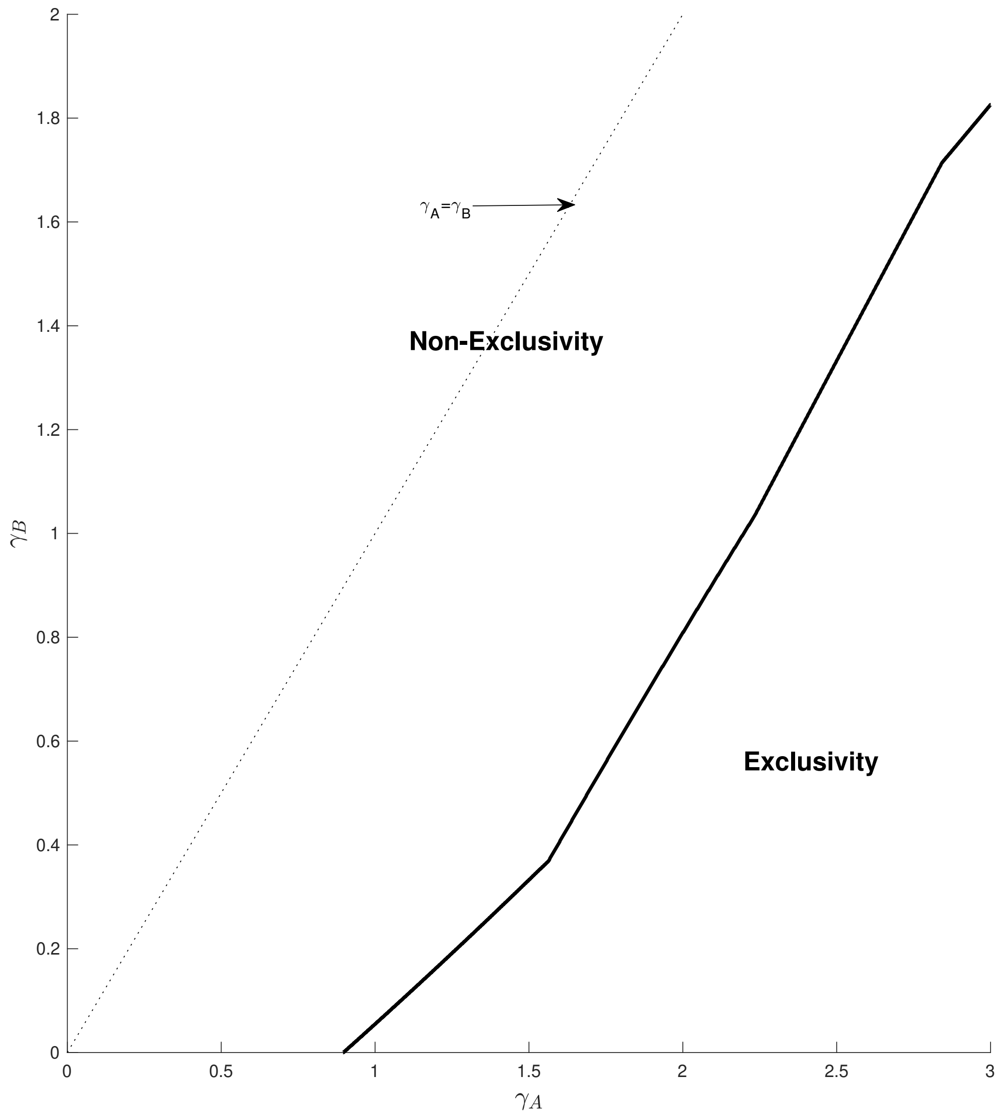
(c) Netease



(d) Baidu

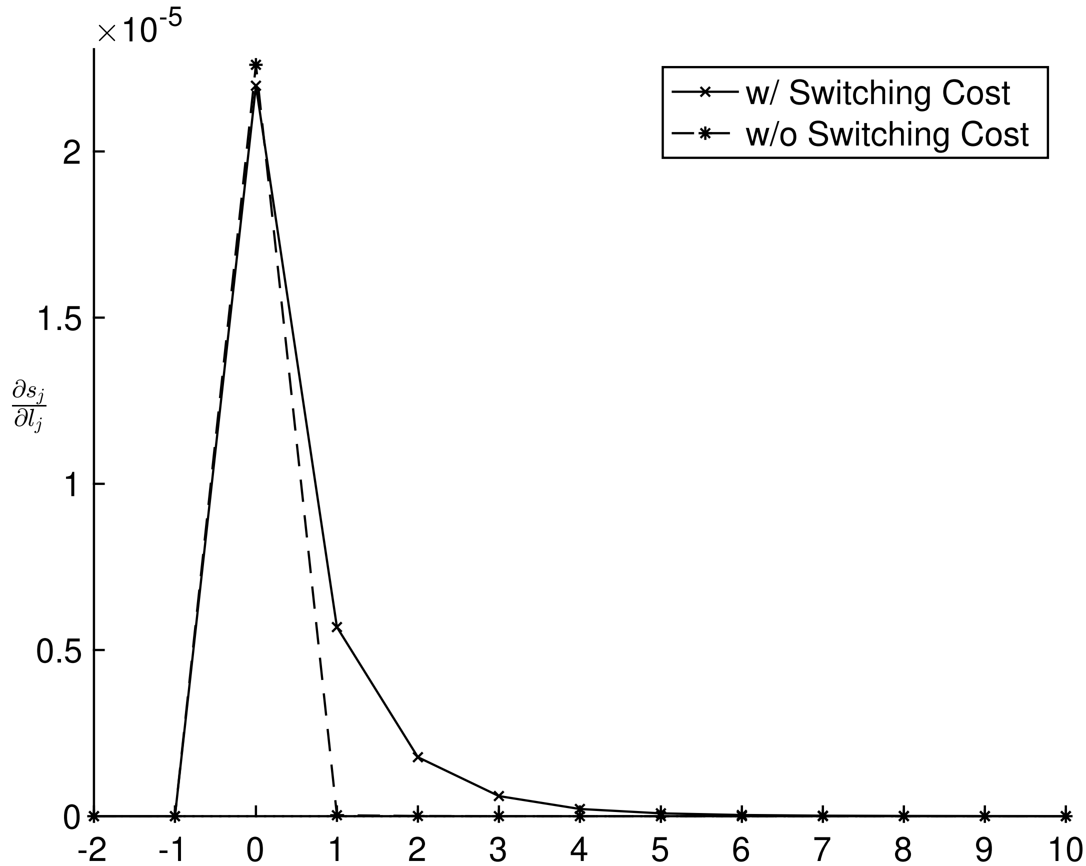
Note: The figure illustrates dynamic change in market shares in response a small increase in exclusive and non-exclusive content. The vertical axis of each figure is the change in market share and the horizontal axis is the time. Period 0 indicates the time of change that is set in November 2014. The negative time is the months before the change, while the positive time is the months after the change.

Figure C.1: Illustration of Switching Cost Asymmetry



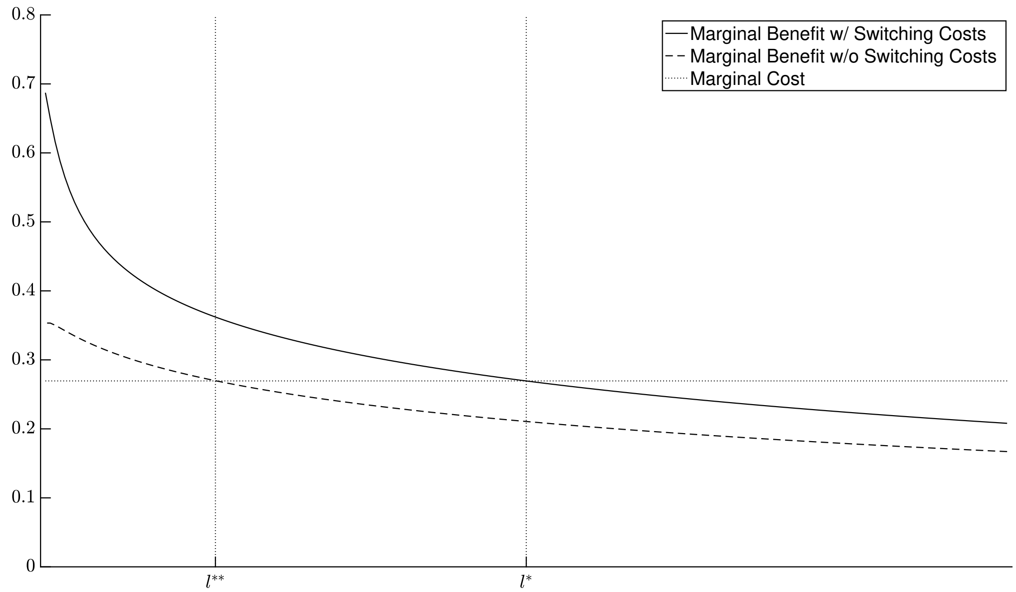
Note: The figure is a illustration of Proposition 2. The solid line is a separation of the equilibrium outcomes under different combination of switching costs. Below the solid line, exclusivity is chosen in an equilibrium. The dash line is a 45 degree line. Parameter value used in the Figure are $v_A = v_B = 0.5$, $t = 1$ and $\alpha = 1.5$.

Figure C.3: Dynamic Change in Market Shares with and without the Switching Cost



Note: The figure illustrates dynamic change in market shares of the dominant service , Tencent, in response a small increase in exclusive. The solid lines corresponds to the case with the switching cost, while the dash line corresponds to the case without the switching cost. The service has a same number of album titles in both cases. The vertical axis of each figure is the change in market share and the horizontal axis is the time. Period 0 indicates the time of change that is set in November 2014. The negative time is the months before the change, while the positive time is the months after the change.

Figure C.4: Optimal Exclusive Distribution Decision



Note: The figure illustrates how a service makes the optimal exclusive distribution decision. The service maximizes its long-run profit when marginal benefit equals the marginal cost. The horizontal axis is the number of exclusive album titles in distribution. l^* is the optimal number of exclusive albums when there exists a switching cost. l^{**} is the optimal number of exclusive albums when the switching cost is absent.

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