Commission Fee Structure and Innovation in Digital Platforms*

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Abstract

This paper quantifies the welfare effects of regulating commission fees in digital platforms, focusing on third-party app developers' innovation and pricing decisions. I employ a comprehensive dataset of music apps within the Apple iOS store in the United States from October 2018 to February 2024 to estimate app users' demand and app developers' cost parameters. The paper reveals key findings with three policy counterfactual simulations where I sequentially solve for optimal innovation and pricing decisions. First, a cap on commission fees promotes innovative efforts by third-party app developers and improves social welfare. Second, when the platform adds a unit fee scheme under the fee cap, developers partly pass unit fees on to app users by increasing in-app purchase prices. Third, a hypothetical buy-out of a streaming app by the platform leads to a significant decrease in the innovative efforts and market share of the acquired app. Notably, welfare analysis without quality adjustment is predicted to underestimate the impact of fee cap on social welfare by 0.91% - 2.06% points compared to the full-stage model estimates. This research highlights the importance of considering quality changes along with price fluctuations when evaluating regulatory intervention in digital platforms.

Keywords: Digital platform, Commission fee, Quality competition, Demand estimation
JEL classification: L13, L40, L50

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1 Introduction

The gatekeeper role of digital platforms has raised antitrust concerns for policymakers, with ongoing legal investigations on major platforms, such as Amazon and Apple. One of the main issues pertains to the legitimacy of the commission fee imposed on third-party firms. Spotify's lawsuit against Apple's excessive fee (up to 30%) highlighted how these fees increase costs for third-party app developers and consumer prices, consequently thwarting innovation. While the European Commission and U.S. Supreme Court upheld Apple's current fee scheme, the Competition Commission of India criticized it as "exorbitant," leaving unresolved debates over the excessive commission fees.[1] Academic literature reflects this debate: some speak to the need of fee regulation to promote innovation (Lu et al., 2023; Tirole and Bisceglia, 2023), while others argue the regulation could only benefit producers at the expense of platform or consumers (Li and Wang, 2024; Sullivan, 2024).

This paper aims to quantify the welfare consequences of capping commission fees in digital platforms, focusing on the innovation and pricing decisions of third-party app developers. To that end, I develop a two-stage structural model of the mobile app marketplace where app developers first choose innovative effort and decide on the in-app purchase price (henceforth IAP) in the second stage. Innovative effort is a proxy for the app quality improvements and continuously increases in the number of app updates and its frequency.

While evaluating policy impact through equilibrium price changes has been standard (e.g., Sullivan (2024)), assessing quality adjustments is becoming equally crucial for welfare analysis, particularly in antitrust cases (Khan, 2016). Leyden (2022) documents that digitization has prompted developers to continuously innovate. For instance, mobile app developers enhance their products by regularly updating their apps to attract and maintain app users. These update decisions are primarily driven by revenue expectations. External factors like platform owner entry (Foerderer et al., 2018; Zhu and Liu, 2018) or commission fee increases (Lu et al., 2023) that potentially decrease developer revenue may lead developers to scale back updates. In light of these observations, relying solely on price fluctuations may not precisely capture market dynamics and lead to biased welfare estimates when evaluating policy impact.

This paper contributes a more comprehensive welfare analysis of regulatory interventions in

[1] https://economictimes.indiatimes.com/tech/technology/cci-reviewing-probe-report-on-apple-app-store-billing-policy/articleshow/101142937.cms?from=mdr

digital platforms by analyzing how app developers adjust both quality and pricing decisions in equilibrium. The model can be extended to evaluate other regulatory interventions in digital platforms, such as speculations on platform integration.

I estimate the model using a comprehensive dataset on individual music apps in Apple's iOS App Store in the United States from October 2018 to February 2024. I observe the app update information, app ratings, in-store revenues (metrics for IAP), and the number of downloads and active users at the app-month level. In a descriptive analysis, I find that app developers' update decisions and past in-store revenues are positively correlated, motivating the hypothesis that an improved revenue potential due to the commission fee cap may bolster app developers' incentive to innovate.

I face endogeneity problems in estimating consumer utility parameters governing sensitivities to IAP and app updates. First, the price coefficient estimate is subject to an upward bias due to the positive correlation between IAP and the unobservable app quality. Second, the innovative effort coefficient is also subject to bias as developers make optimal update decisions to maximize the net returns to improve their app qualities.

These endogeneity concerns are addressed with two types of instrumental variables. The first set, inspired by the BLP approach (Berry et al., 1995), aggregates competitors' observed characteristics from the previous period: 1) app rating, 2) cumulative downloads within the same group, and 3) the differential in the number of app updates within the group. An app's unobserved quality residual is unlikely to correlate with competitors' past observable characteristics. For example, *YouTube Music*'s past app rating is unlikely to be impacted by Spotify's current unobserved quality after controlling for observable attributes. However, an anticipation of a higher market-wide app rating may prompt developers to lower IAP and adjust their innovation strategies. The second and third instruments provide exogenous variations in within-nest market shares to estimate the nesting parameter governing the within-nest correlation of utilities.

The second set of instruments consists of the supply-side factors: 1) the developer's total app count in the App Store and 2) the number of consumer privacy agreements collected. These variables influence developers' cost structures. Multi-app developers may benefit from the economies of scale or learning effects, potentially achieving greater efficiency in app distribution and updates. Additionally, developers can leverage user data obtained through privacy permissions for monetization strategies, such as price discrimination or targeted advertising, and guide update decisions based on post-update user behavior analysis.

With these instrumental variables, I estimate a nested logit demand model where music apps are grouped into streaming, instruments, radio, and social apps. My empirical strategy appears to substantially reduce the bias in price and app update coefficients. These demand parameters allow me to back out app developers' net ancillary benefits using the first-order condition from the supply model. As Tirole and Bisceglia (2023) describe, developers gain ancillary benefits from app usage, such as advertisement revenue or consumer data, while the marginal (app distribution) cost is minimal.[2] I define net ancillary benefits by subtracting marginal costs from ancillary benefits and discover that most developers are estimated to have positive net ancillary benefits. This reflects the prevalence of zero-price strategy in the mobile app marketplace, where app developers rely on ancillary benefits as their main revenue sources.

I then estimate the cost parameters for innovative efforts using the optimality condition. While innovative effort directly affects developer profit, it also has indirect effects by influencing IAP decision in the model's second stage. Consequently, the optimality condition includes cross-price elasticities and cross-effort derivatives, presenting a computational challenge; a marginal change in innovative efforts would shift optimal IAP and market shares for all developers. To address this complexity, I employ the approach developed by Berto Villas-Boas (2007) and Fan (2013).

I simulate three policy counterfactuals. For each scenario, I sequentially solve for the equilibrium innovative effort and IAP. The first counterfactual reflects the regulatory debate on capping digital platform's commission fees. The preliminary results suggest that lowering fees increases both IAPs and app updates, eventually improving developer welfare but reducing platform surplus. Interestingly, capping the fees is predicted to harm consumer welfare while having the fee at 30% improves consumer surplus. This is the result of the prevalence of positive net ancillary benefits in the mobile app marketplace.[3] Nevertheless, the increased levels of innovation appear to partially

[2] Tirole and Bisceglia (2023) define it as a negative opportunity cost of distributing apps and illustrate the prevalence of zero-price strategy in the mobile app marketplace.

[3] The impact of commission fees on IAP is unambiguous in two aspects. Higher fees can increase effective marginal costs for developers, potentially inflating IAP. However, developers with minimal marginal production costs and substantial marginal ancillary benefits may strategically lower IAP, relying more on ancillary revenue sources like advertisements. This is due to the fact that the commission fee is only imposed on in-store purchases. Additionally, reduced innovation resulting from higher fees could also drive down in-app prices (similar to what Zhao et al. (2024) find).

offset the negative effects of fee caps, ultimately improving social welfare.

The second counterfactual resembles Apple's new fee scheme in the EU: it collects 10% on subscription payments with 0.5 Euro per app download.[4] It turns out that the developers would partly pass through unit fees on to consumers by increasing IAP. Though the lower ad-valorem fee promotes innovation, consumers may be worse off due to higher prices. Apple seems to derive a huge benefit from the new fee policy.

The third counterfactual is Apple's hypothetical buy-out of one of the streaming apps in the App Store. Apple is predicted to put less innovative effort into the acquired app compared to the previous owner in the pre-acquisition state, losing market share. This discrepancy between Apple and third-party app developers' innovation incentives is due to the fact that the platform's revenue partly comes from commission fees. The results challenge the allegations of Apple and Google that their market dominance in digital wallets and online search engines primarily results from superior product quality.

In light of these findings, regulating commission fees at lower rates could enhance developer welfare and incentivize their innovation, improving social welfare. From a distributional perspective, a fee cap benefits third-party app developers at the expense of the platform and consumer surplus. Counterfactual studies that treat innovative efforts variable as exogenous indicate that fee caps would harm social welfare. Specifically, they underestimate the impact of fee cap on social welfare by 0.91% - 2.06% points compared to the full-stage model estimates. This suggests that analyzing fee caps solely through price competition could lead to misleading policy implications. The finding emphasizes that quality competition plays a crucial role in evaluating regulatory interventions in digital platform ecosystems.

There are several caveats to my analysis. One could argue that there is a potential risk of platforms increasing core prices to compensate for their welfare loss. For example, the platform could increase access fees for consumers (e.g., iPhone price) as Sullivan (2024) finds in food delivery platforms. Despite the assumption that the platform fully recuperates its surplus loss through consumer surplus extraction, the model demonstrates a net increase in total welfare under commission fee regulation. While this study focuses on unveiling third-party developers' 'short-run' responses to policy intervention, the inclusion of the platform's 'long-run' problem can be a possible exten-

[4] Since this paper uses the number of active users, I set the unit fees as $0.05.

sion. I investigate the music app category that exhibits a subscription-based payment system; thus, it is worth noting that the main findings of this study may be generalizable to other categories with similar payment systems. I will further elaborate on potential criticisms of my model in Section 3.

1.1 Related Literature

This paper is closely related to the literature on platform fee regulation, a topic that originated in debates on credit and debit card interchange fees. From a theoretical perspective, profit-maximizing interchange fees set by card issuers were not considered socially optimal (Wright, 2004; Klein et al., 2005) since merchants would increase consumer prices, though Rochet and Tirole (2003) argued that policy intervention requires robust evidence of market failure and empirical analysis in a two-sided market. Following the implementation of fee caps on debit card platforms in 2010, empirical studies revealed "unintended" policy consequences, such as increases in bank service fees (Evans et al., 2013) and small-ticket transaction fees (Wang, 2016), eventually harming consumers.

The regulatory discourse has recently extended to digital platforms, initially prompted by Spotify's lawsuit against Apple in 2019. While the discussions on interchange fees primarily centered on consumer price impacts, debates on digital platforms also consider the policy's effect on quality (Lu et al., 2023; Zhao et al., 2024). For instance, Lu et al. (2023) investigate the regulatory impact of commission caps on app developers' innovation incentives within the Steam game platform. Using BLP estimation, they demonstrate that lower commission fees increase developers' expected revenue, encouraging more frequent updates while discouraging new app releases, resulting in over-investment in beta testing. This study extends Lu et al. (2023)'s work by incorporating app developers' sequential decisions on innovative effort and price instead of treating price as constant and using an indicator variable for updates. Furthermore, focusing on mobile apps presents a novel approach due to their unique revenue structure, which also depends on ancillary benefits.

The implementation of commission fee caps for food delivery platforms has become prevalent across the United States, prompting various empirical evaluations. Li and Wang (2024) employ a staggered difference-in-differences estimation to explore the impact of commission caps in food delivery platforms (e.g., Doordash, Grubhub) on the third-party stores' revenue and order volumes. Their findings indicate that independent stores, such as local restaurants, experience decreased profits and order volumes in regulated areas due to city-based commission caps that do not apply to nationwide chain restaurants. The platforms are observed to impose higher consumer fees to offset the commission revenue loss from stores. Similarly, Sullivan (2024) assesses the welfare effects associated with commission caps. His findings reveal that while capping commission fees reduces restaurant prices, the platform increases fees for consumers. Although consumers benefit from greater choice variety, higher platform fees reduce overall welfare. My analysis, on the other hand, shows that when accounting for firms' endogenous quality improvement decisions, the welfare consequence of a fee cap becomes positive.

As Leyden (2022) documents, digitization has provided a wider range of monetization options for developers and thus induced a zero-price strategy while increasing the innovation incentive at the same time. This low-price strategy (sometimes called "predatory" pricing for Amazon) has led the antitrust regulators to consider quality aspects when evaluating the regulations on digital platforms, as noted by Khan (2016). With this in mind, my paper provides a novel lens to assess regulatory intervention in digital platforms by constructing a model that incorporates firm decisions on price and quality.

The paper contributes to the growing body of literature on platform regulation that addresses key issues such as platform entry (Hagiu and Wright, 2015; Gutierrez, 2021; Hervas-Drane and Shelegia, 2022), self-preferencing (Zennyo, 2022; Dendorfer, 2024), and its gatekeeper role (Anderson and Bedre-Defolie, 2023; Tirole and Bisceglia, 2023). This paper specifically analyzes the welfare effects of capping commission fees by focusing on its effects on the app developers' innovation and pricing decisions. By examining market outcomes under various commission rates, this study also informs broader discussions on the consequences of platform entry. For instance, the platform can divert consumers toward its own product by increasing commission fees (Etro, 2022).[5]

This paper further contributes to research examining the impact of changing commission fees in various aspects. Prior studies have extensively addressed how higher commission fees increase sellers' costs (Motta, 2023; Sullivan, 2024). Tirole and Bisceglia (2023) propose that regulating commission fees enables third-party app developers to fully benefit from their innovations, thereby fostering a more innovative environment. Gomes and Mantovani (2024) extends the discussion by considering the network externalities of the platform. Their key finding suggests that capping

[5] Such a demand substitution effect can arise since higher fee increases the effective marginal cost for competing firms (Anderson and Bedre-Defolie, 2023).

commission fees reduces platform revenue, potentially leading to decreased investment in market expansion and consumer information enhancement.

This paper also aligns with the stream of empirical papers examining developers' innovation decisions in response to exogenous shocks, such as platform owner's entry (Foerderer et al., 2018; Wen and Zhu, 2019) or platform system change (Leyden, 2024). For example, Leyden (2024) explores how Apple's review system in the App Store influences the innovation incentives for app developers. This paper relates to their works in that I discover how developers' pricing and innovative effort decisions vary when commission fee structures change exogenously.

Finally, this paper extends previous work on estimating demand for mobile applications. While Ghose and Han (2014) find discounts on app price and more updates would increase app downloads, I additionally demonstrate how in-app purchase prices and update decisions affect app usage. To the best of my knowledge, previous studies have not yet shown the intensive margin of demand on mobile apps. For instance, Leyden (2022)'s finding on the positive relationship between innovation and app demand is limited to the extensive margin of demand due to data constraints. He highlights the importance of considering the intensive margin of demand, which this paper reveals by leveraging the number of active users as a quantity variable.[6] In addition, this paper contributes to the research on digital service business models (e.g., for music apps (Lin et al., 2013; Barata and Coelho, 2021) or game apps (Hamari et al., 2017)) by providing strategic guidelines for app developers on in-app price and update frequency decisions.

The remainder of this paper follows: In Section 2, I provide background on the mobile app marketplace with its distinctive features and market definitions. I then show a reduced-form relationship between in-app revenue and developers' decisions on app updates. With this suggestive evidence in mind, I construct a two-stage model in Section 3. Section 4 conducts estimations for demand and supply parameters that will be used to simulate counterfactuals in Section 5. Section 6 provides concluding remarks.

[6]Garg and Telang (2013) also suggest estimating mobile app demand with in-app purchase prices included as a future agenda.

2 Background and Data

2.1 Institutional Background

Apple launched the App Store in 2008, providing iPhone users access to millions of applications. It has since become a major mobile app platform, dominating the United States' mobile app market alongside Google. As of 2023, Apple and Google held market shares of 56.92% and 42.65%, respectively (Statista, 2023). This study focuses on the Apple iOS App Store in the United States, the exclusive app marketplace for iPhone users. The App Store exhibits several distinctive features that differentiate it from other platform markets:

Flat commission rates The App Store enforces fixed commission rates across product categories: 15% for subscriptions and 30% for other transactions.[7] These rates exceed those in other platform markets. For comparison, Amazon typically charges 12% in ad-valorem fees on third-party sellers' revenue, eBay collects up to 12% of sales revenue, and Walmart imposes referral fees ranging from 6% to 15% on fringe sellers' revenue (Borck et al., 2020). The commission fee scheme is considered a long-term optimization problem for Apple, with most major digital platforms (e.g., Google and Steam) implementing a 30% fee as an industry standard (Lu et al., 2023). Consequently, this study introduces the commission fee as an exogenous and constant variable in the model.

Freemium products The mobile app market is characterized by a prevalent zero-price strategy facilitated by minimal marginal costs for app distribution. Tirole and Bisceglia (2023) argue that negative opportunity costs drive this strategy, motivating developers to offer apps with zero prices. App developers have a distinctive revenue structure, that depends on ancillary benefits such as advertisement revenue or collecting consumer data by distributing their free apps. Over 50% of music apps in the dataset are observed to adopt this approach. *Spotify* exemplifies a 'freemium' business model, offering both a free (ad-supported) streaming service and premium (ad-free) subscriptions. This dual-tier strategy expands the user base, with the free version providing ancillary benefits even without direct monetization. Figure 1 demonstrates that the majority of app developers maintain static average IAP, with less than half implementing price adjustments over time.

[7] Apple has a small business program that reduces the commission fee to 15% for developers who earned under $1 million with their total apps in the previous calendar year. However, since this study focuses on the top 200 ranked apps and subscription-based services, Apple's small business program is not considered in this analysis.

Figure 1: Average In-App Purchase Price and Innovative Effort across Months

Note: The values in the figure are based on the panel dataset, which will be discussed in detail in Section 2. This figure illustrates each music streaming app developer's decisions on in-app price (black) and innovative effort (orange) over time. Most apps offer both free (ad-supported) and paid (ad-free) versions, explaining the flat black lines for apps like Spotify and Musi, which indicate a high proportion of free users. In contrast, developers such as AMI Entertainment, Entercom (Audacy), and Mixcloud provide completely free streaming services. This visualization highlights the diverse pricing and innovation strategies in the music streaming app market.

Continuous product improvements On top of the digitization, the mobile app developers' unique revenue model, which derives significant portions from ancillary benefits, results in substantial product differentiation compared to traditional marketplaces like Amazon. Consequently, continuous product enhancement through frequent app updates is a key characteristic of the App Store. Figure 1 underscores the ongoing competition among app developers, exemplifying the dynamic nature of the marketplace beyond price competition. In the same spirit, previous studies on the platform find that app developers primarily respond to platform entry by adjusting update frequency (e.g., Foerderer et al. (2018) and Wen and Zhu (2019)). Therefore, incorporating horizontal and vertical differentiation in the model facilitates a more precise quantification of welfare effects.

2.2 Regulatory Details

Apple and Google have faced ongoing regulatory scrutiny for their 'gatekeeper' roles in the digital platform ecosystem, particularly regarding the imposition of commission fees on third-party developers and vertical integration practices. This study addresses three main antitrust issues surrounding digital platforms. The first case pertains to the legitimacy of Apple's high commission fees on third-party developers, a concern raised by Spotify in 2019.[8] The suitcase highlighted how Apple's excessive commission fee increases costs for developers and consumer prices while ultimately diminishing incentives for quality enhancement. The second issue stems from the antitrust challenge against Google and Apple brought forth by Epic, the developer of the popular mobile game Fortnite, citing an unjust commission fee system. After Epic enabled direct in-app purchases through its own platform, both tech giants removed Fortnite from their stores, citing violations of "anti-steering provisions" and commission fee evasion.

The European Commission and U.S. courts have ruled that while Apple may maintain current commission rates, it must allow third-party developers to offer alternative payment options (Iyengar and Duffy, 2021; Grant, 2023). The European Commission's Digital Markets Act (DMA) further mandates that digital platforms, including Apple, should not restrict developers' payment options and should permit alternative app stores on iPhones. Although these regulations signal a potential upheaval in Apple's current policies, the company's response to the DMA has been

[8] For details, see news article from CNBC (2020).

deemed unsatisfactory. Their proposed terms include a 17% fee on in-app purchase revenue (10% for recurring payments) and a fixed fee of 50 Euro cents per app download, regardless of payment options. Spotify contends that this new structure contravenes the DMA's objectives.[9]

Third, the study addresses antitrust issues on vertical integration of the platform. Whether allowing the digital platform owners, Apple and Google, to have their own products in their marketplace is pro-competitive or anti-competitive has been the topic of heated discussion. Recent legal actions include the U.S. federal attorney and Department of Justice fining Google for dominating the search engine market with Chrome browser (McCabe, 2024) and accusing Apple of foreclosing competing app developers in the digital wallet market. Both companies argue that their dominance stems from superior product quality.

Section 5 of this study explores counterfactual simulations reflecting recent policy issues surrounding Apple's commission fee structure. As an extension, I simulate additional counterfactuals to assess whether acquiring a prominent streaming music app would enhance innovation for the platform.

2.3 Market Description

The unit of analysis in this study is the individual music app developers on the Apple iOS platform in the United States on a monthly basis. The music category was selected for three primary reasons: regulatory relevance, category distinctiveness, and profit function clarity. First, the antitrust debate on excessive commission fees was raised by *Spotify*, and regulators primarily focus on the music app market. Analyzing Music category thus provides more direct policy implications.

Second, the music app category exhibits less overlap with other categories, as users predominantly listen to music via music apps. This contrasts with other app categories that may share similar user bases (e.g., Travel apps and Navigation apps or Health & Fitness, Lifestyle, and Medical apps). Third, the music category contains fewer companion apps, which typically have distinct profit functions. For instance, developers of airline or banking apps primarily compete outside the app platform and may not prioritize app profit maximization. It is worth noting that as most music apps are subscription-based, the main findings of this study may be generalizable to other categories with similar payment systems (e.g., Productivity, TV Streaming).

[9] See their claims on Spotify's website.

Table 1: Sample App List for each Nested Group

Streaming (Online)	**Complementary (+ Headphones)**	**Instrument**
Amazon Music	Airbuds Widget	Audio Editor - editor
AMI BarLink	AmpMe	Audio Editor - Mixer
Apple Music	Bass Booster + Equalizador Pro	Auxy
Audiomack	Bass Booster Volume Boost EQ	BandLab
Bandcamp	Bass Booster Volume Equalizer	Beat Maker
Deezer	Bose Connect	BeatStars
DICE: Tickets for Gigs & Clubs	Bose Music	Chordify
eSound	Clear Wave - Water Eject	DJ it!
Mixcloud	djay	Drum Pad Machine
TIDAL	Songkick Concerts	Mezquite
Trending	SongPal	Moises
YouTube Music	SongShift	MuseScore
Streaming (Offline)	**Radio**	**Socialize**
Cloud Music Offline Downloader	Audacy	Bandsintown Concerts
Evermusic	Calm Radio	Discogs
Melodista Music Offline Player	FM Radio	Guitar Center: Shop for Gear
Music Downloader & Player	iHeartRadio	KaraFun
Trebel	MusiC Play Unlimited Musi.C	K-LOVE
Cloud Music Offline Downloader	myTuner Radio	RA Guide

Note: This table shows the partial list of apps for each sub groups due to limited space.

The iPhone users can download applications only through the App Store due to Apple's privacy policy. Hence, the potential market for app developers consists of iPhone users in the United States, of which the figure increased from 101.9 million in 2018 to 135.97 million in 2023.[10] I define the market size as proportional to the number of iPhone users.[11] Also, I use the number of active users as the quantity variable, which precisely measures an app usage that app developers actually compete for (Dubé et al. (2021) adopt an analogous approach with the number of customer visits per store). This approach allows for identifying the intensive margin of demand for app usage.

2.4 Data

A panel dataset of 200 top-ranked apps in the Music category of the Apple App Store was collected from October 2018 to February 2024 ($T = 65$) using the App Annie website. App Annie, an

[10]https://www.demandsage.com/iphone-user-statistics/

[11]This approach aligns with other empirical studies in Industrial Organization; Miller and Weinberg (2017) set the craft beer market size as 50% greater than the maximum unit sales observed within each region, and Gutierrez (2021) used the average ratio between Amazon's e-commerce share and retail shares to compute market size (approximately 20% of the total population).

AI-powered analytics company, regularly collects app data on a daily, weekly, and monthly basis, providing various app-level data such as the number of app downloads and active users, in-store revenue, app rating, rating counts, and language offerings. Additionally, update dates for individual apps were scraped from the Appfigures website using the Selenium package in Python.

2.4.1 Sub-Groups

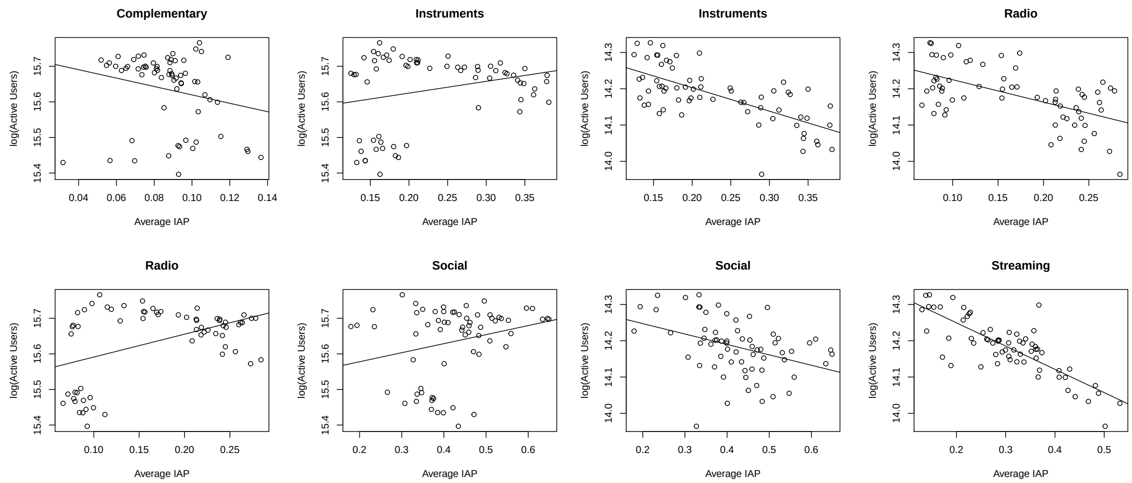
The mobile app platform is characterized as a "short-tail" market rather than a "long-tail" market where the cumulative effect of numerous unpopular niche products constitutes a significant portion of demand (Jiang et al., 2011; Zhong and Michahelles, 2013). Consequently, there was limited information available on the number of active users for some apps, particularly the less renowned ones. Data for 128 individual apps were used from the full sample. The sample was further refined to 73 apps through a two-step process: First, apps launched during the study period were eliminated, thereby being unable to capture the entry or exit behaviors of app developers; however, most of the famous apps were launched before my time period.

Second, I excluded complementary apps from the sample. Considering that the feature of music apps greatly varies from streaming services to music instruments, some would not be in direct competition with each other or even be deemed as a complementary app. Indeed, Headphones & Speaker apps such as *Bose Connect* or music-finding apps (e.g., *Shazam*) would increase the utility of streaming app users. With this in mind, I manually categorized music apps into five groups based on their main feature. Table 1 reports a list of sample apps in different groups.

Figure 2a demonstrates an inverse relationship between the average in-app purchase price (IAP) of complementary apps and streaming app usage, while concurrently showing a positive correlation between other music apps' IAP and streaming app usage. Correspondingly, Figure 2b reveals a negative association between the average IAP of music apps and complementary app usage. These findings suggest a negative cross-price elasticity between complementary apps and both streaming and other music applications. Furthermore, Table D.2 in Appendix D substantiates a positive correlation between streaming app downloads and the innovative efforts of complementary apps. Collectively, these observations indicate that complementary apps may not directly compete with other music apps, but in a complement relation.

Figure 2: Evidence on Cross-Price Elasticities Across Nests

(a) Streaming Apps (b) Complementary Apps



Notes: Figure 2a depicts the correlation between the average in-app purchase price (IAP) changes within each nested group and the number of active users for streaming applications. This visualization elucidates the elasticity of user engagement metrics for streaming apps in response to IAP adjustments across different nests. Figure 2b reports the same for complementary apps.

The complementary apps in a total of 25 were therefore excluded from my dataset. I conducted a regression with a 98-app sample (after the first step, including complementary apps), with results reported in Appendix A. The result differs from my main results, implying that demand for complementary apps moves differently.

2.4.2 In-App Purchase Price (IAP)

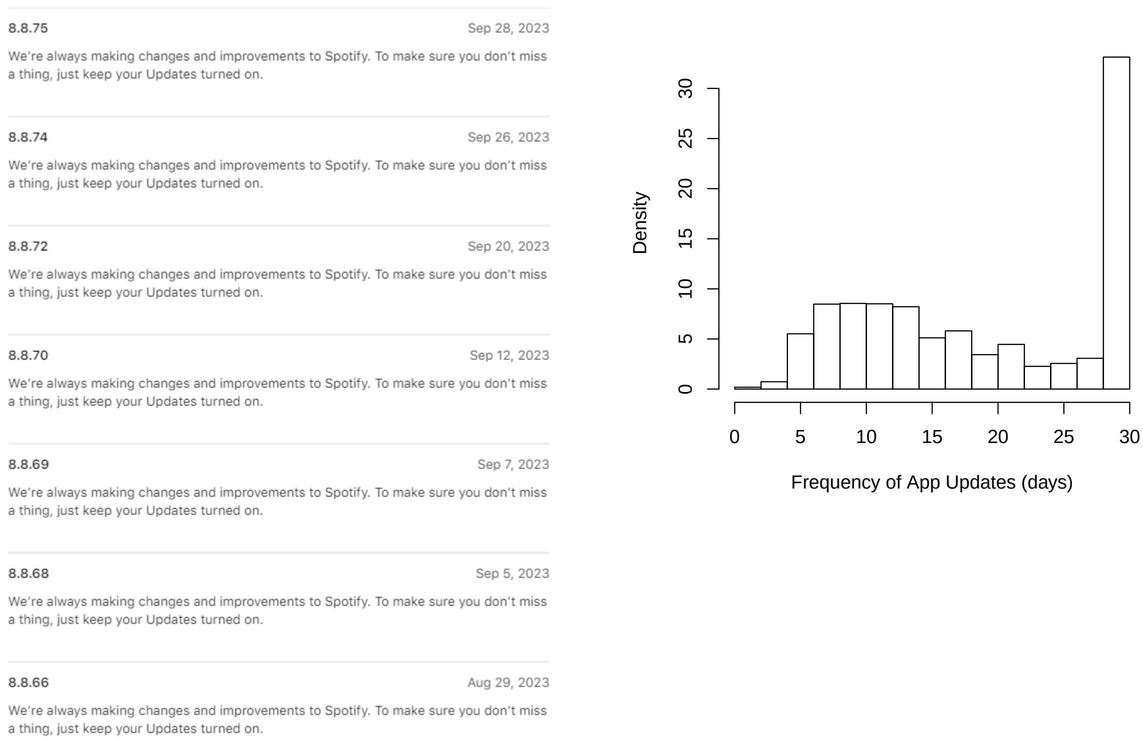
The app developers usually do not charge a price for downloading apps, but users need to pay a subscription fee in order to enjoy the streaming (or premium) service within the music apps. Indeed, most apps offer a 'freemium' service by setting the app price to zero.[12] Hence, it is difficult to find a standardized subscription price variable in the Music app category since the options for a subscription highly vary depending on the length of the subscription period and bundle options (e.g., free trial, family plan).

One way to overcome this difficulty is to use the average transaction price per unit. I divide the total in-store revenue, which aggregates all the revenue made through in-app purchases, by the

[12]The average app price in Appstore is $0.8 in May 2023 (https://www.statista.com/statistics/267346/average-apple-app-store-price-app/).

Figure 3: App Update Information

(a) Spotify (b) Histogram of Update Frequency



Note: Figure 3a shows the version history of the Spotify, captured from the iOS App Store website. The numbers on the left side indicate the version of the app, with descriptions of updates delineated below. The updated date is shown on the right side. Figure 3b depicts the histogram of update frequency for music apps in the dataset, with x-axis representing the days took for a single update. The metric 30 includes apps that have not been updated more than 30 days.

number of active users to compute the average transaction expense. I use this average transaction expense as a proxy for the price, which can be standardized across different music apps. Nevertheless, this measure cannot capture the purchase directly through a developer's website. For example, some *Spotify* users could pay subscriptions on the website and stream music on the mobile apps. This paper abstracts away from such consumer behavior, assuming them as free-version users.

2.4.3 Innovative Effort

Enhancing the quality of an app can be an important strategy for developers to keep active users and attract more users. Compared to other platform marketplaces, firms in mobile platforms can continuously improve their apps through frequent updates. In order to capture this app quality improvement, I introduce the innovative effort variable which continuously increases in the number of app updates and its frequency. In specific, I use the inverse of the time period between two consecutive updates. For example, Figure 3a shows the version history of *Spotify* in the App Store in September. *Spotify* updated its version from 8.8.66 to 8.8.68 within seven days, and after two days, it launched a new version, 8.8.69, and so on. Hence, the innovative effort for *Spotify* in September can be computed as $\frac{1}{7} + \frac{1}{2} + \frac{1}{5} + \frac{1}{8} + \frac{1}{6} + \frac{1}{2} = 1.635$. Note that *Spotify*'s innovative effort increases in the number of app updates and its frequency. Most importantly, this computation makes the variable continuous and enables us to smoothly simulate counterfactual with its optimality condition (11).

2.4.4 Descriptive Statistics

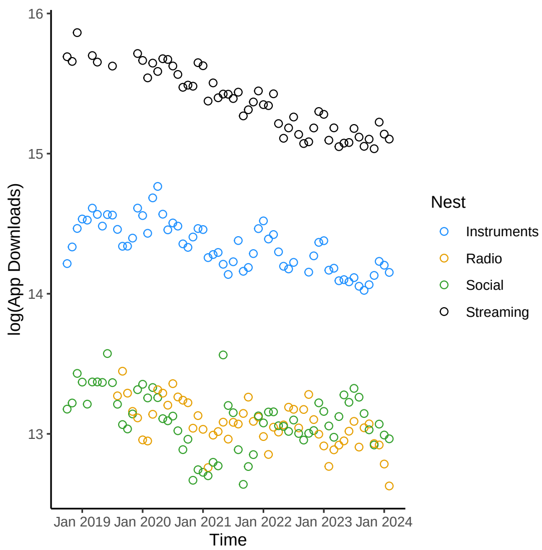
Table D.1 in Appendix D reports the summary statistics of the dataset used in this paper. The market share of each app is computed based on the number of active users each month. Market share highly varies from 0.003% (*UnitedMasters*) to 24.8% (*Spotify*), implying the short-tail feature of the market (Zhong and Michahelles, 2013). The average in-app purchase price (IAP) also shows some variation, while the mean value is close to zero. This indicates the presence of negative opportunity cost in the app marketplace that Tirole and Bisceglia (2023) argue. By offering free service, the app developers gain ancillary benefits, such as advertising revenue or consumer data, that outweigh the marginal cost of app distribution.

Figure 1 further depicts how streaming app developers change their IAP and innovative efforts across time periods. We can witness that innovative decisions greatly vary while pricing decisions remain relatively stable. This suggests that the quality competition is more dynamic than the price competition in the streaming app market. I also introduce a categorical variable, popularity of app, based on the number of 'cumulative downloads' last month: $< 1,000,000$; $< 10,000,000$; $< 50,000,000$; $< 100,000,000$ and the rest.

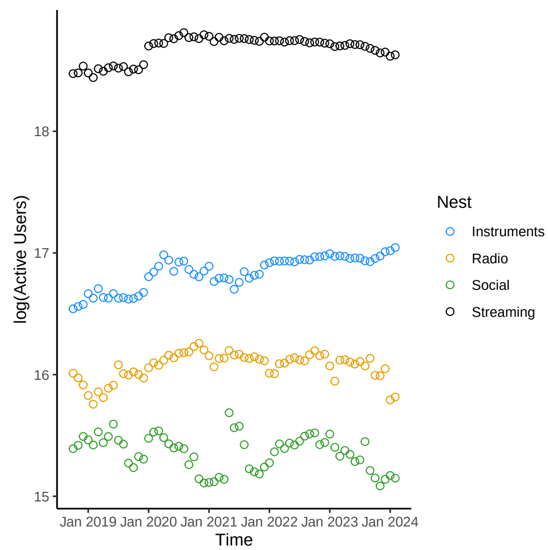
Finally, Figure 4 shows descriptive statistics across the nested groups. On aggregated level, Streaming apps are observed to take the largest share of app downloads and active users while Socialize apps have the least (Figures 4a and 4b). Figure 4c demonstrates the Streaming apps' active updates compared to other groups, while Socialize apps would charge higher IAP, as shown in Figure 4d. A positive correlation between IAP and app updates is also implied in Figure 4d.

Figure 4: Statistics Across the Nest

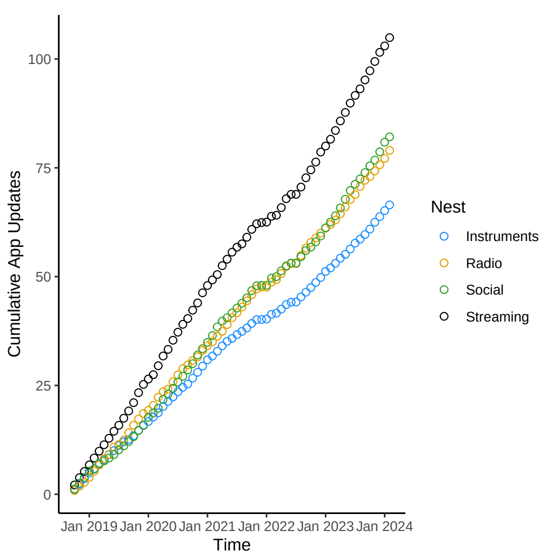
(a) Number of App Downloads



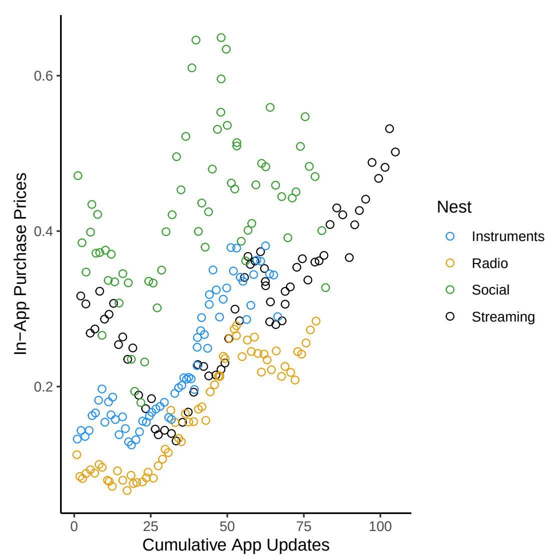
(b) Number of Active Users



(c) Cumulative Number of App Updates



(d) IAP and App Updates



Note: Figures 4a and 4b illustrate the aggregated monthly app downloads and active user counts, respectively, categorized by nested groups denoted by distinct color coding. Figure 4c presents the mean cumulative number of app updates traced within the dataset. Additionally, Figure 4d elucidates the correlation between the average in-app purchase price (IAP) and app updates.

2.4.5 Reduced-Form Evidence

I conduct a reduced-form approach with equation (1), focused on observing the relationship between past in-store revenue and update decisions for app developers. The number of updates or innovative effort (both denoted as ρ_{jt}) for each developer j in month t is regressed on the previous month's in-store revenue (rev_{jt-1}) and a vector of app age, app ratings, the popularity of app in previous month in $\boldsymbol{X_{jt}}$. I also include year-month-fixed effects (μ_t) and app-fixed effects (θ_j). Table 2 reports the OLS regression results.

$$\rho_{jt} = \omega_0 + \omega_1 rev_{jt-1} + \omega_2 s_{jt-1} + \omega_3 b_{jt-1} + \boldsymbol{X_{jt}\Omega} + \mu_t + \theta_j + \varepsilon_{jt} \tag{1}$$

Table 2: Relationship Between In-Store Revenue and Update Decisions

	Dependent variable:			
	Number of update		*Innovative effort*	
	(1)	(2)	(3)	(4)
lagged(In-store revenue)	0.066***	0.016*	0.013***	0.004
	(0.004)	(0.008)	(0.001)	(0.003)
App age	0.006***	−0.010**	0.001***	−0.001
	(0.001)	(0.005)	(0.0002)	(0.002)
App rating	0.245***	0.310**	0.024	0.087*
	(0.084)	(0.134)	(0.026)	(0.046)
Popularity last month	0.146***	0.011	0.026***	−0.010
	(0.027)	(0.063)	(0.008)	(0.022)
Constant	−0.639	1.687**	−0.060	0.054
	(0.408)	(0.702)	(0.126)	(0.242)
Year-Month Fixed Effects	Y	Y	Y	Y
App Fixed Effects	N	Y	N	Y
Observations	4,745	4,745	4,745	4,745
R^2	0.155	0.497	0.090	0.326
Note:				*p<0.1; **p<0.05; ***p<0.01

A notable and positive correlation between the in-store revenue and the innovative effort (and the number of app updates) is evident in all specifications. This persistence suggests that app developers' optimal update decisions are endogenously linked to their in-app revenue. When their in-store revenue decreases due to external factors, a decrease in their innovative effort also would be associated. With this evidence in mind, I develop a structural model that will be used in counterfactual where the platform would choose to raise (or lower) the commission fee that exogenously shifts the revenue for third-party app developers.

3 Model

This paper investigates how developers adjust their innovative efforts and in-app purchase prices against Apple's commission fee structure changes, which is essential for implementing the welfare analysis. In this section, I construct a structural model of consumers and app developers (including Apple's *GarageBand* app) on Apple's iOS App Store to capture the developer behaviors on pricing and innovative effort decisions. The model is a two-stage game with a timeline as follows: i) in the first stage, the app developers simultaneously decide to which extent to put innovative effort, an increasing function of the number of updates and its frequencies, into their apps; ii) then, in the second stage, with the complete information on the optimal innovative effort in the market, developers set the in-app purchase price for the consumers at the same time. The number of updates and its frequency signal to consumers that the developer is putting effort into improving app quality and consumer satisfaction.[13] This two-stage game is solved by backward induction.

3.1 Consumer Side

There are N third-party app developers labeled as $j \in \{1, 2, \cdots, N\}$ in the platform, while Apple also engages in the downstream market by selling its app m. The consumers are assumed to choose developer j's app according to nested logit preferences. The music apps are categorized into five sub-groups: streaming ($g = 1$), radio and podcasts ($g = 2$), socialize ($g = 3$), instruments ($g = 4$), and outside option ($g = 0$). Consumers can choose an "outside good", which is the only member in group $g = 0$, by not using any music apps. For example, some consumers may use streaming services directly from a computer website or not enjoy listening to music. The mean utility of an outside good is defined as zero. Thus, the indirect utility of this outside option is $u_{0jt} = \epsilon_{0jt}$.

[13] Previous research shows common results on the positive effect of updates on consumer demand (e.g., Ghose and Han (2014); Leyden (2022); Lu et al. (2023))

Consumer i gains utility u_{ijt} when using an app from developer $j \in \{1, 2, 3, \cdots, N, m\}$ in group g at month t:

$$u_{ijt} = \delta_{jt} + \zeta_{ig} + (1 - \sigma)\epsilon_{ijt}$$

where $\delta_{jt} = \alpha\rho_{jt} + \beta b_{jt} + \boldsymbol{X_{jt}}\lambda + \xi_{jt}$. The innovative effort is denoted as ρ_{jt} for the developers to improve app quality, and b_{jt} represents the in-app purchase price (IAP). $\boldsymbol{X_{jt}}$ is a K-dimensional vector of observable app characteristics, such as the app age, app rating, and app popularity. The unobserved app quality is captured in a structural term ξ_{jt}. Consumers gain a common utility of ζ_{ig} for the apps in the same group. There is an idiosyncratic shock ϵ_{ijt} to the consumer's preference over developer j's app, which follows Type 1 extreme value distribution with a nesting scale parameter σ.[14] When $\sigma \to 1$, consumer preferences become more correlated across apps in the same nest, while $\sigma \to 0$ indicates a multinomial logit demand.

The probability of purchasing an app from developer j is

$$P_{jt}(\vec{\rho}_t) = \underbrace{\frac{\exp(\delta_{jt}/(1-\sigma))}{\sum_{k\in J_g}\exp(\delta_{kt}/(1-\sigma))}}_{P_{j|gt}} \cdot \underbrace{\frac{[\sum_{k\in J_g}\exp(\delta_{kt}/(1-\sigma))]^{(1-\sigma)}}{1+\sum_{h=1}^{G}[\sum_{k\in J_h}\exp(\delta_{kt}/(1-\sigma))]^{(1-\sigma)}}}_{P_{gt}} \tag{2}$$

where $P_{j|gt}$ is the probability of choosing app j in the nest g and P_{gt} is the probability of choosing the nest g among other nests, given a vector of innovative effort $\vec{\rho}_t = (\rho_{1t}, \rho_{2t}, \cdots, \rho_{Nt}, \rho_{mt})$. I hereafter omit subscript t for ease of exposition and restore it in Section 4.

The model is based on two assumptions that can be criticized. First, using a discrete choice model assumes that consumers will only use a single app in a given period. The quantity in my model is the number of active users in a given month, which does not distinguish single-app and multi-app uses; a consumer can use *Spotify* today and use *SoundCloud* tomorrow, but my data regard him/her as separated users. I leverage the number of minutes spent per app as a dependent variable to conduct a robustness check in Appendix A and find similar results. Since one is unlikely to use multiple apps in one minute, this alternative specification strengthens my main results. Second, app developers are assumed to be single-homing. Put differently, multiple

[14]Following Cardell (1997), for ϵ_{ijt} that is distributed Type 1 extreme value, there exists a unique distribution for ζ_{ig} that allows $\zeta_{ig} + (1-\sigma)\epsilon_{ijt}$ to follow extreme value distribution.

apps of the same developer are treated as owned by separate developers (similar to what Leyden (2022) assumes). This assumption, however, is partially relaxed in my model as there are only two developers who have more than one app in my sample. Hence, a subscript j indicates either a developer or an app hereafter.

3.2 Developer Side

The model assumes single-homing for the app developers; they can distribute their apps only through the platform. The platform is a gatekeeper and charges ad valorem commission fees (f) to developers, while it does not charge access fees to consumers.

3.2.1 Second-stage: Decide IAP (b_j)

In the second stage, I derive the equilibrium in-app purchase price for each app developer. The profit functions for third-party app developers and the platform follow:

$$\pi_j^S = (b_j(1-f) + \phi_j)Ms_j(\vec{\rho}) \tag{3}$$

$$\pi_m^S = M\left(f\sum_{j=1}^{N} s_j(\vec{\rho})b_j + (b_m + \phi_m)s_m(\vec{\rho})\right) \tag{4}$$

where M is the market size and $s_j(\vec{\rho})$ is the market share of app j that depends on effort vector $\vec{\rho}$. The in-store revenues come from two different sources: IAP (b_j) and net ancillary benefits (ϕ_j) that are privately known. The net ancillary benefits is a sum of ancillary benefits (e.g., advertisement revenue) and marginal cost of production. The ad-valorem fee is imposed only on the in-store purchases (b_j). The first-order conditions with respect to b for the developers and the platform are,

$$(b_j + \frac{\phi_j}{1-f})\frac{\partial s_j}{\partial b_j} + s_j = 0 \tag{5}$$

$$f\sum_{j=1}^{N} \frac{\partial s_j}{\partial b_m}b_j + (b_m + \phi_m)\frac{\partial s_m}{\partial b_m} + s_m = 0, \qquad \text{for } j = 1, 2, \cdots, N. \tag{6}$$

I define the implicit best response function $b_j = f^j(\vec{\rho})$ that satisfies the first-order conditions (5) and (6) as follows:

$$b_j = -\frac{\phi_j}{1-f} - \frac{s_j}{\frac{\partial s_j}{\partial b_j}} \tag{7}$$

$$b_m = -\phi_m - \left(\frac{f \sum_{j=1}^{N} \frac{\partial s_j}{\partial b_m} b_j + s_m}{\frac{\partial s_m}{\partial b_m}} \right). \tag{8}$$

It is noteworthy that the marginal effect of commission fee f on the optimal price b_j is negative when the net ancillary benefits is positive ($\phi_j > 0$). Intuitively, when the commission fee gets higher, the best strategy for the developer is to reduce the price (since f is imposed only on b) and depend more on ancillary revenues with higher market share. If a developer has negative ϕ_j, then it would raise its in-app price under a higher commission fee.

3.2.2 First-stage: Decide Innovative Efforts (ρ_j)

In the first stage, the developers simultaneously choose their innovative effort, conditional on their own and competing developers' optimal price functions ($\vec{b}^*(\vec{\rho})$). The first-stage profits for third-party developers and platform are below:

$$\pi_j^F(\vec{\rho}) = \pi_j^S(\vec{b}^*(\vec{\rho}); \vec{\rho}) - C(\rho_j) \tag{9}$$

$$\pi_m^F(\vec{\rho}) = \pi_m^S(\vec{b}^*(\vec{\rho}); \vec{\rho}) - C(\rho_m) \tag{10}$$

where each developer has a convex cost function $C(\rho_j)$ for innovative effort. For this analysis, I specify the slope of the effort cost as $\gamma_0 + \gamma_1 \rho_j + \nu_j$, where ν_j is developer j's unobservable cost shock.

The first-order conditions with respect to ρ_j give us the supply-side estimation equation for the developers and the platform:

$$\frac{\partial \pi_j^S}{\partial \rho_j} + \sum_{k=1}^{m} \frac{\partial \pi_j^S}{\partial b_k} \frac{\partial b_k^*}{\partial \rho_j} \equiv \gamma_0 + \gamma_1 \rho_j + \nu_j. \tag{11}$$

The left-hand side terms $\frac{\partial \pi_j^S}{\partial \rho_j}$ and $\frac{\partial \pi_j^S}{\partial b_k}$ can be derived by taking derivative of equations (3) and (4).

On the other hand, computing $\frac{\partial b_k^*}{\partial \rho_j}$ is a challenge. I follow a similar approach that is used in Berto Villas-Boas (2007) and Fan (2013) by taking the total derivative of the first-order conditions (5) and (6) for all $j = 1, 2, \cdots, N, m$:

$$\sum_{k=1}^{m} \left(\underbrace{\frac{\partial s_j}{\partial b_k}(1-f) + (b_j(1-f) + \phi_j)\frac{\partial^2 s_j}{\partial b_j \partial b_k} + \mathbb{1}(j=k)(1-f)\frac{\partial s_j}{\partial b_j}}_{=f(j,k)} \right) db_k$$
$$+ \left(\underbrace{\frac{\partial s_j}{\partial \rho_j} + (b_j(1-f) + \phi_j)\frac{\partial^2 s_j}{\partial b_j \partial \rho_j}}_{=g(j,1)} \right) d\rho_j = 0$$

where $\mathbb{1}(j = k)$ is an indicator for own-price derivatives. Since equation (11) is an optimality condition for observed innovative efforts, we are only interested in computing $\frac{\partial b_k^*}{\partial \rho_j}$ with assuming $d\rho_j \neq 0$ and $d\rho_k = 0, \forall k \neq j \in \{1, 2, \cdots, N, m\}$ (Fan, 2013). Then if I stack up $f(j,k)$ and $g(j,1)$ for all alternatives $J = 1, 2, \cdots, N, m$, I get a matrix, F, with element $f(j,k)$ and an (N+1)-dimension vector, G, with an element of $g(j,1)$.

Next, taking total derivative on $b_j = f^j(\rho_1, \cdots \rho_N, \rho_m)$ with the assumption $d\rho_j \neq 0$ and $d\rho_k = 0, \forall k \neq j \in \{1, 2, \cdots, N, m\}$,

$$\begin{aligned} db_1 &= \frac{\partial b_1}{\partial \rho_j} d\rho_j \\ &\vdots \\ db_N &= \frac{\partial b_N}{\partial \rho_N} d\rho_j \\ db_m &= \frac{\partial b_m}{\partial \rho_m} d\rho_j. \end{aligned}$$

We can then derive the matrix Δ_b where the general element (i,j) is $\frac{\partial b_i}{\partial \rho_j}$. And the j-th column of Δ_b can be computed as $\frac{d\vec{b}}{d\rho_j} = -F^{-1}G$. With the other values on the left-hand side of equation (11), I can estimate the cost coefficients γ_0 and γ_1 on the right-hand side. I further delineate the details in the Appendix C.

3.2.3 Simulation Study

This section shows a simulation study with selected parameters to demonstrate the model's functionality and derive insights for various scenarios. The simulation setup is as follows: the coefficients for effort and price are set as $\alpha = 1$ and $\beta = -1$, respectively. The number of app developers is denoted as $N = 30$, while the cost coefficients γ_0 and γ_1, along with the net ancillary benefits ϕ, are specified as 0.0001, 0.05, and 0.5 (or -0.5), respectively. These parameters remain constant and symmetric across firms, simplifying the analysis. I posit asymmetries in unobserved quality (ξ_j) in mean utility across 30 developers; ξ_j for $j \in \{1, 2, \cdots, 30\}$ is averaged over 5,000 consumers' ξ_{ij} randomly drawn from the Type I Extreme Value distribution. I investigate various scenarios where the commission fee (f) takes on different values: i) 1%, ii) 15% (baseline), and iii) 30%. The simulation proceeds through fixed-point iterations involving the two first-order conditions. Additionally, I impose lower bounds for each variable: $b_j > 0$ and $\rho_j > 0$. I will discuss more details on the simulation and counterfactual in Section 5.

Table 3: Simulation Results with Selected Parameters

Net Benifits	Scenarios	$\bar{\rho}$	$\bar{b}$	PS	MS	CS	SW
$\phi = 0.5$	f=1%	0.65	0.53	1.01	0.01	4.12	5.14
	f=15% (baseline)	0.55	0.45	0.86	0.07	4.11	5.04
	f=30%	0.46	0.32	0.71	0.09	4.14	4.94
$\phi = -0.5$	f=1%	0.63	1.54	0.98	0.01	3.12	4.11
	f=15% (baseline)	0.53	1.62	0.83	0.23	2.95	4.01
	f=30%	0.43	1.75	0.68	0.49	2.74	3.91

Notes: The table reports the average value for each variable: innovative effort (ρ), IAP (b), app developer surplus (PS), platform surplus (MS), consumer surplus (CS), and social welfare (SW). The first panel shows simulation results when the developers exhibit positive net ancillary benefits ($\phi > 0$) and the second panel shows the opposite case.

Table 3 shows the simulation results with different fee rates, from 1% to 30%. It is notable that reducing the commission fee promotes innovative efforts regardless of the sign of net ancillary benefits. On the other hand, the developers with positive (negative) net ancillary benefits (ϕ) increase (decrease) IAP when the fee is reduced. Such a unique revenue structure of the mobile app platform yields a conclusion that consumer surplus is maximized at $f = 30\%$ when $\phi > 0$. Nonetheless, capping the fee to 1% always improves consumer welfare (and maximizes social welfare) by promoting innovation, and this result highlights the significance of including quality competition in analyzing welfare effects.

Figure 5 further illustrates to which extent incorporating quality competition affects the market outcome. If we treat the innovative effort (ρ) as an exogenous variable, the marginal effect of the fee cap on IAP likely decreases. For example, when the commission fee gets lower to 1% in panel (b), developers reduce the price more with ρ fixed. The reason behind this is intuitive: more innovation under a fee cap drives up the in-app prices at the same time. Hence, excluding the decisions on ρ in the model would overestimate the magnitude of the effects of the fee cap on consumer welfare (conditional on innovation level).

4 Estimation

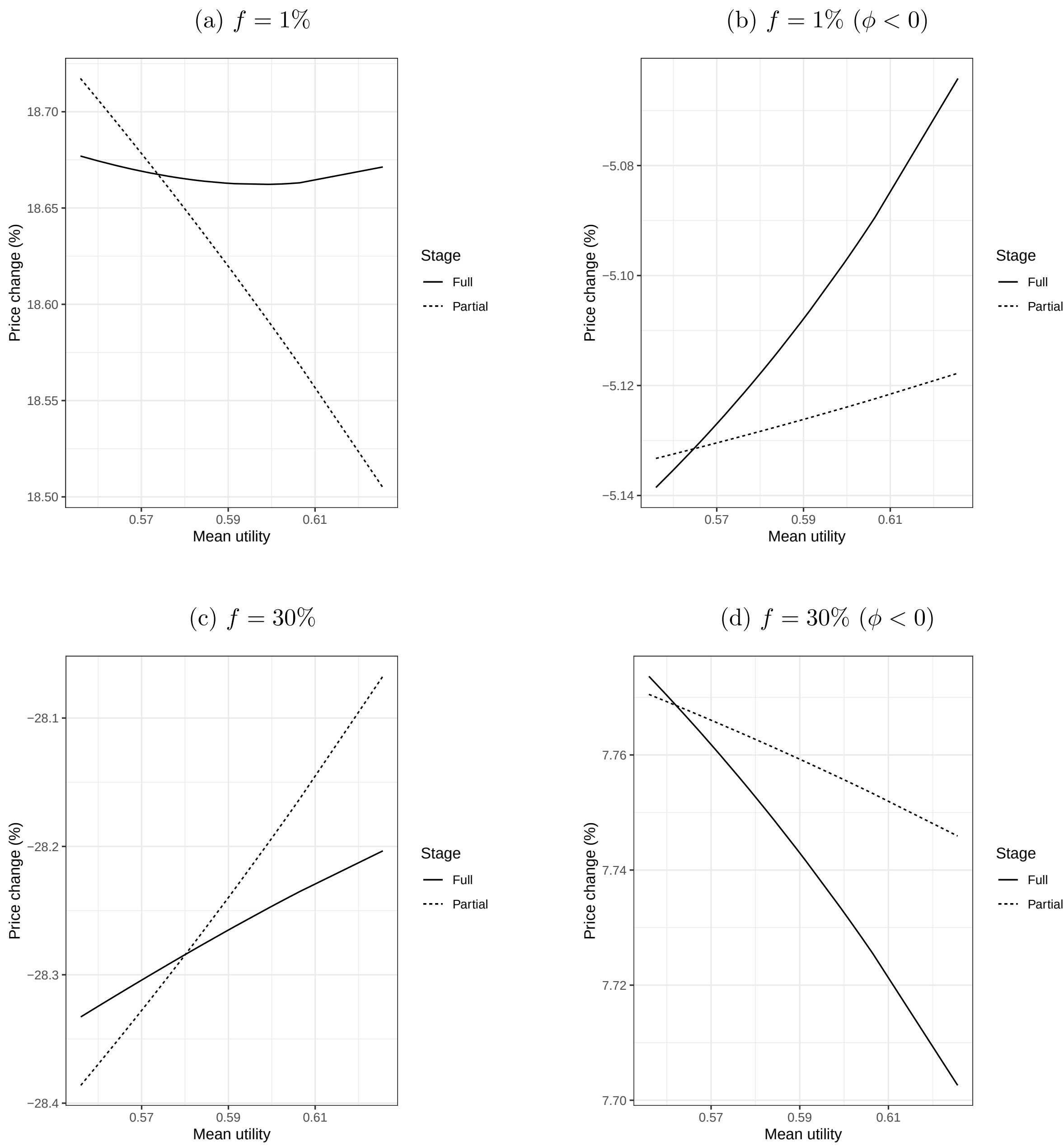
This section derives consistent demand and supply parameters that are needed to conduct counterfactual simulations. I begin with estimating equation (12) below to identify demand parameters (α, β, and σ). Then, the net ancillary benefits (ϕ) can be backed out with FOCs (5) and (6). Finally, I estimate equation (11) to recover cost coefficients. Table 4 explains variables.

$$\ln(s_{jt}) - \ln(s_{0t}) = \alpha\rho_{jt} + \beta b_{jt} + \boldsymbol{\lambda x_{jt}} + \omega \text{pop}_{jt-1} + \sigma \ln(\bar{s}_{j|gt}) + \mu_t + \theta_j + \xi_{jt} \tag{12}$$

Table 4: Variable Descriptions

Variables	**Descriptions**
s_{jt}	Market share of app owned by developer j for the number of active users in month t.
s_{0t}	Outside market share; consumers who do not use music apps or use music service via other methods (e.g., computer).
$\bar{s}_{j\|gt}$	Within market share in group g.
ρ_{jt}	Innovative effort; increases in update frequency and the number of app updates.
b_{jt}	Average in-app purchase price per active user; $\frac{(\text{in-store revenue}_{jt})}{(\#\text{ of active users}_{jt})}$.
$\boldsymbol{x_{jt}}$	Vector of observed app characteristics such as app rating and app age.
$\text{pop}_{j,t-1}$	App specific categorical variables; grouped based on the number of 'cumulative downloads' $< 1,000,000$; $< 10,000,000$; $< 50,000,000$; $< 100,000,000$ and the rest. Consumers likely prefer apps with more cumulative downloads.
μ_t	Year-Month Fixed Effectss; e.g., iOS system update, aggregated shock on music market.
θ_j	App Fixed Effectss; e.g., brand value.
ξ_{jt}	Structural term that captures unobserved app quality.

Figure 5: Optimal In-App Purchase Prices With and Without Quality Competition



Note: This figure shows each developer's simulation results of optimal in-app prices. The x-axis shows the mean utility of each app, and the y-axis shows the percentage change in price compared to the baseline ($f = 15\%$). The dashed line represents the price changes when ρ is fixed. Hence, it shows the outcome when the model is partially simulated only with Stage 2. The black solid line represents price changes when the full model is simulated. Panels 5a and 5c depict when the net marginal benefit is positive, while the net marginal benefit is negative in panels 5b and 5d.

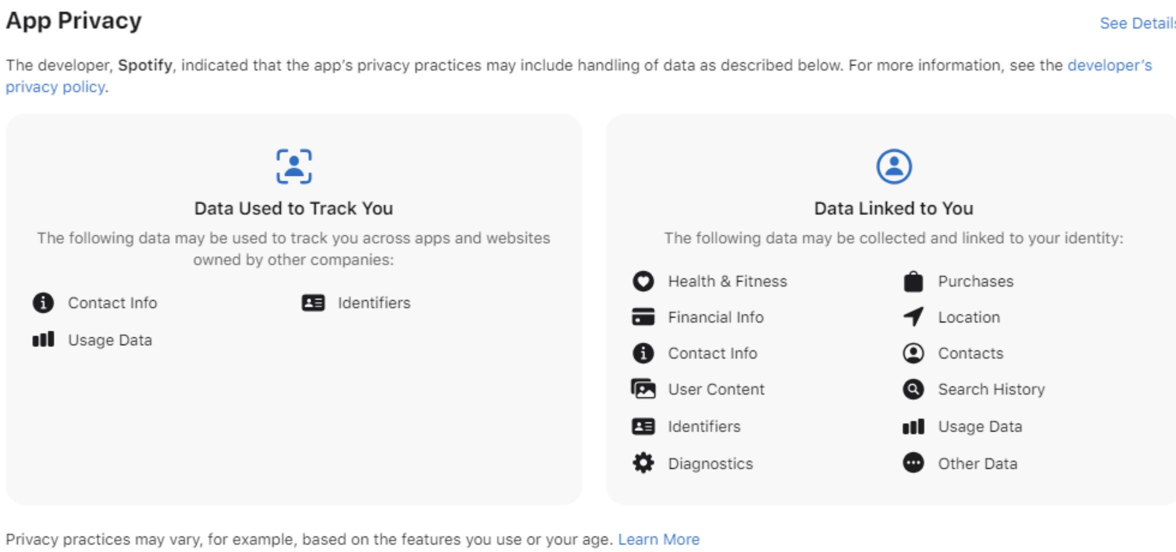
4.1 Identification Strategy

The presence of unobservable quality (ξ_{jt}) in the app developers' optimality conditions poses an identification challenge. On the one hand, the structural term could positively correlate to IAP, introducing a zero toward bias to the price coefficient (Petrin, 2002). For example, the transitory shock on the quality of algorithms in music apps may be observed by app users but not by econometricians. Suppose *Spotify* offers a higher quality of AI-based algorithms than *YouTube Music* has. Ceteris paribus, *Spotify* would likely gain more market share and charge a higher IAP. This positive correlation between IAP and unobserved quality index yields upward bias for β. On the other hand, the relationship between innovative effort and unobserved app quality in the model is more complex, with the former potentially increasing the quality index up until further app updates yield diminishing returns. The innovative effort coefficient (α) is thus also subject to a potential bias.

To deal with the endogeneity, I introduce two types of instruments. The first set is inspired by the 'BLP-instruments' (Berry et al., 1995) by aggregating observed characteristics of competitors in the previous period. Specifically, I use 1) app rating, 2) the cumulative number of app downloads in the same group, and 3) the difference between the number of app updates in the same group: $Z_{jt}^{g} = \sum_{k \in J_g} |x_{kt-1} - x_{jt-1}|$. The unobserved quality of an app is unlikely to be influenced by the predetermined observed characteristics of competing apps. For instance, *YouTube Music* app's rating in previous months can hardly impacted by the current unobserved quality of the *Spotify* app. On the other hand, when the market-wide app rating is observed to increase, the developer will likely reduce the in-app price to attract more consumers and change their innovation decisions (whether to compete or not). The second and third instruments have exogenous variations within-nest market shares to estimate the nesting parameter governing the within-nest correlation of utilities.

The second set of instruments comes from the supply side: 1) app developer's total app count in the App Store and 2) the number of consumer privacy agreements collected by the developer. These variables shift the costs for the app developers. For example, a developer with multiple apps across categories would be more cost-efficient in distributing and updating its apps, possibly by the economies of scale or accumulated learning process. Also, the developer can gather user data by

Figure 6: App Privacy Example



Note: This figure is a screenshot of *Spotify*'s app privacy policy, directly captured from the App Store.

requiring the privacy permissions of its app users, as exemplified in Figure 6. Then, the developers can leverage the collected data in monetization strategy (e.g., price discrimination or advertising) and efficient updates by examining users' behavior after the past updates.[15]

These cost shifters vary across developers and time. *Spotify*, as depicted in Figure 6, collects twelve sorts of privacy data; on the other hand, there are apps that do not collect any privacy data, such as *AMI BarLink* and *Auxy*. The number of apps by the same developer shows more variations as developers launch new apps over time. For example, Amazon had a total of twenty apps in October 2018, including *Amazon Music*, while it launched thirteen more apps during our time period. On the contrary, Auxy distributes only one app *Auxy* for the entire time period. This paper also addresses an identification challenge regarding app heterogeneity. On top of including app-fixed effects, I add the app's popularity in previous months capturing consumers' preferences for music apps with a larger user base.

[15] The determinants of app updates are empirically studied in the previous research. For example, see Ghose and Han (2014) and Leyden (2022).

Table 5: Parameter Estimates

	Dependent variable:			
	$\ln(s_{jt}) - \ln(s_{0t})$			
	Logit		*Nested Logit*	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Innovative effort (α)	0.075***	−0.459	−0.007	0.360**
	(0.029)	(1.070)	(0.007)	(0.120)
IAP ($) ($\beta$)	−0.245***	−1.801***	−0.009	−1.199***
	(0.068)	(0.361)	(0.021)	(0.242)
Nesting parameter (σ)			0.967***	0.287*
			(0.014)	(0.115)
App age (λ_1)	0.006***	−0.011**	0.0004**	−0.006*
	(0.001)	(0.005)	(0.0002)	(0.003)
App rating (λ_2)	0.409*	0.524***	−0.053	0.284***
	(0.225)	(0.135)	(0.041)	(0.081)
Popularity (ω)	0.138	0.096**	0.040**	0.086***
	(0.113)	(0.039)	(0.016)	(0.027)
Constant	−4.020***	−2.473***	0.854***	−1.598***
	(1.059)	(0.563)	(0.197)	(0.532)
Year-Month Fixed Effects	Y	Y	Y	Y
App Fixed Effects	Y	Y	Y	Y
Observations	4,745	4,745	4,745	4,745
R^2	0.951	0.876	0.998	0.941
F-statistics (price)		106.999***		106.999***
F-statistics (effort)		17.049***		17.049***
F-statistics (nesting)				638.640***
Wu-Hausman statistic		29.95***		409.43**
Sargan statistic				0.873
Cost coefficients				
γ_0				$258,689$***
γ_1				$1,329,495$***

Notes: (i) Robust standard errors are clustered by app and month in the parentheses. (ii) The first stage F-statistics are reported at the bottom. The first-stage regression results are reported in Appendix B. (iii) *p<0.1; **p<0.05; ***p<0.01.

4.2 Estimation Results

Table 5 reports the demand and supply parameter estimates from equations (12) and (11), respectively. The first two columns report the estimates under the multinomial logit model, and the next two columns show regression results under the nested logit model. As expected, the coefficients for innovative effort (α) and IAP (β) are significantly negative and positive for most of the specifications. By comparing the coefficients of 2SLS models (second and fourth columns) to the OLS estimators (first and third columns), my empirical strategy appears to substantially reduce the bias in price and update coefficients.[16]

The cost coefficients for innovative effort are shown in the last panel from Table 5. The estimates are \$258,689 and \$1,329,495 for γ_0 and γ_1. Though the figure seems huge, the average in-app revenue is \$814,484, and the average observed ρ is 0.2. The average developer profit is \$612,555 per month. Other papers find that the app update costs even surpass the total revenue. For instance, Leyden (2022) shows a bug fix update costs \$3,355.97 for app developers whose weekly revenue is \$1,436.55 on average.[17] In addition, Figure 7 depicts the net ancillary benefits ϕ for app developers that are recovered from equation (5) with demand parameters α and β. In most cases, developers seem to earn a variable profit of \$1 per active user from IAP and net ancillary benefits.

Table 6: Median Own Elasticities

	Logit		*Nested Logit*	
Nest	IAP	ρ	IAP	ρ
Streaming	-0.0041	0.0030	-0.0156	0.0294
Radio	-0.0242	0.0176	-0.0893	0.0151
Socialize	0.0000	0.0000	0.0000	0.0109
Instruments	-0.0345	0.0250	-0.1290	0.0014

Notes: This table reports median own elasticities for in-app purchase prices (IAP) and innovative efforts (ρ) in each group. The left panel shows elasticities with plain logit estimates, while those of nested logit are used in the right panel.

[16] The instrument variables seem to mitigate the upward bias of β and address a negative correlation between ρ and unobserved quality ξ.

[17] Lu et al. (2023) also derive similar cost estimates for Steam game app developers. Their estimates are relatively small compared to what this paper reports, possibly because they estimate the extensive margin of demand that is based on the number of downloads and app prices on a weekly basis.

Figure 7: Net Ancillary Benefits for App Developers

(a) All Developers (b) Top 4 Apps

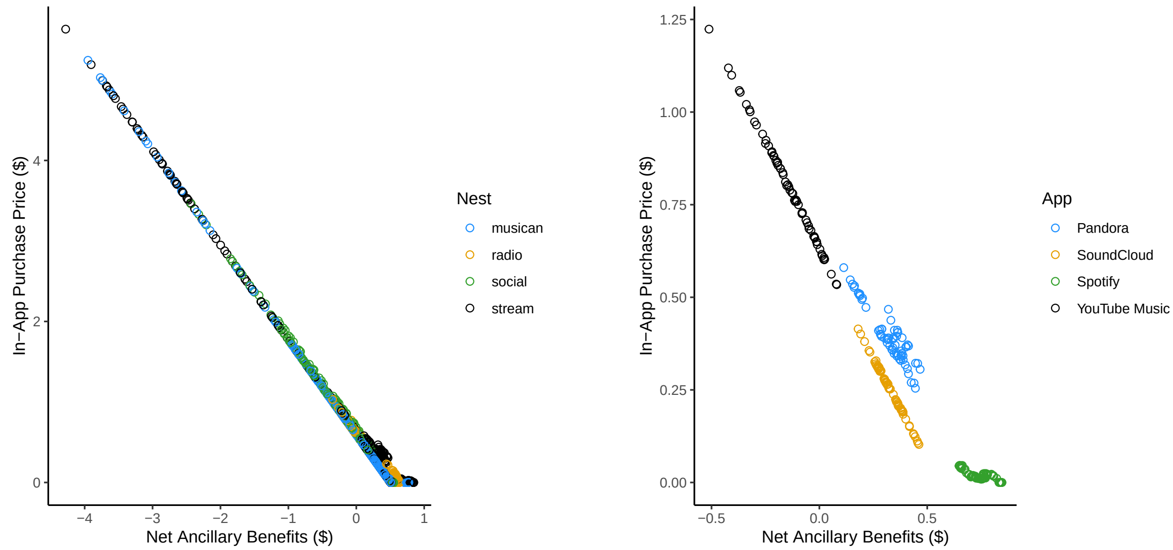


Table 7: Median Diversion Ratio

From	Streaming	Radio	Socialize	Instruments	Outside
Streaming	0.8469	0.0336	0.0712	0.0164	0.1531
Radio	0.4478	0.3179	0.0721	0.0166	0.1543
Social	0.4403	0.0336	0.3729	0.0164	0.1474
Instruments	0.4451	0.0340	0.0723	0.2967	0.1507

Notes: This table shows the median diversion ratio in each nest. For example, when a streaming app marginally increases IAP or decreases innovative efforts, 84% of consumers would switch to another streaming app, while 15% would choose an outside option.

5 Counterfactual Simulation

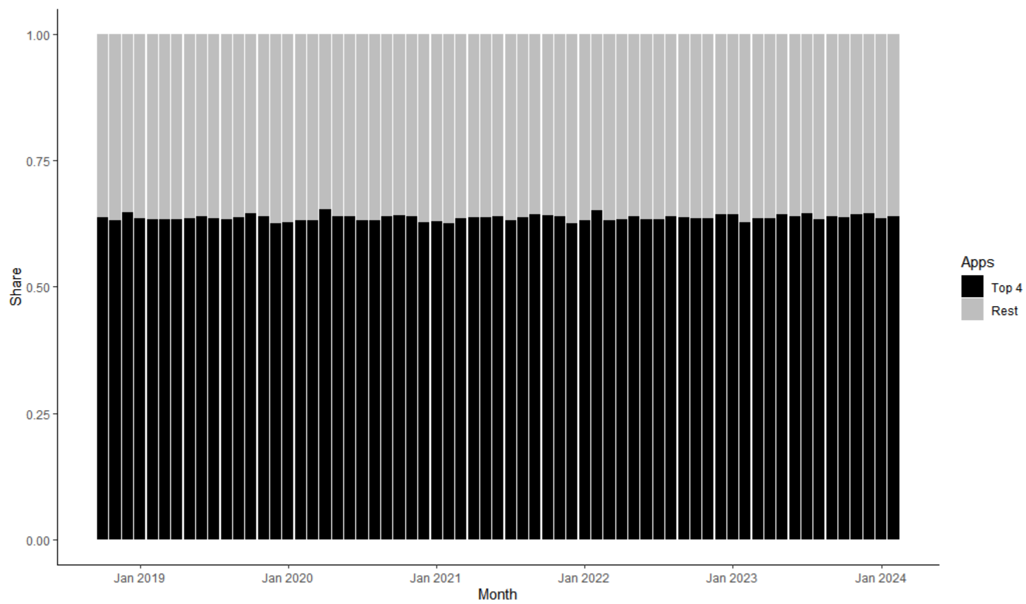
With the demand (α, β, and σ) and supply parameters (ϕ_j, γ_0, and γ_1) from the column (4) in Table 5, I explore various counterfactual scenarios to shed lights on how the market outcome changes upon Apple's different commission fee structure. In the simulation study, I restrict the sample to streaming apps to capture the direct competition between them precisely. Also, since the top 4 apps show dominance in the market, observing their behaviors would be sufficient to draw implications.[18]

The simulation proceeds with the two FOCs. In the first loop, optimal innovative efforts are

[18] The aggregated market share of the top 4 apps in streaming service is around 70% across the whole time period, as depicted in Figure 8.

derived by equation (11) using the Nelder-Mead method. Then $\vec{\rho^*}$ is used to iterate the fixed-point for optimal in-app prices in the second loop, with equations (7) and (8). In the second loop, I follow the work done by Morrow and Skerlos (2011) for convergence efficiency by setting the fixed point equation as $b^j_{n+1} = -\frac{\phi_j}{1-f} + \omega(b_n)$, where $\omega(b_n) = [s_{j|g} - (1-\sigma)(1-s_g)s_{j|g}] \cdot (b^j_n + \frac{\phi_j}{1-f}) - \frac{1-\sigma}{\beta}$.[19] I impose lower bounds for each variables: $b_j > 0$ and $\rho_j > 0$.

Figure 8: Market Share Distributions



Note: This figure illustrates the monthly market share distribution of the top four music streaming apps — Pandora: Music & Podcasts, SoundCloud, Spotify, and YouTube Music— in the music category. Market share is calculated based on the number of active users. The black bar indicates the combined market share of these leading four apps, whereas the grey bar represents the market share of all other music apps.

5.1 Commission Fee Adjustments

In the first counterfactual scenario, I examine the market outcome under different commission fees. I set the commission fee to be 1%, 10%, 15% (baseline), 20%, and 30%. The necessity for capping commission fees has been proposed in academic papers, as exemplified by the work of Tirole and Bisceglia (2023). The validity of such an argument lies in the fact that increasing expected revenue for developers would directly increase their incentive for innovation (e.g., Lu et al. (2023)).

[19] For the platform, $b^m_{n+1} = -\phi_m + \omega^m(b_n)$, with $\omega^m(b_n) = s_m[s_{m|g} - (1-\sigma)(1-s_g)s_{m|g}] \cdot (b^m_n + \phi_m) - \frac{1-\sigma}{\beta}(f\sum_{j=1}^N \frac{\partial s_j}{\partial b^m_n} b^j_n + s_m)$.

5.2 Apple's New Fee Policy

The second counterfactual stems from the antitrust issue raised by Epic, who owns a famous mobile game app Fortnite, against Google and Apple for an unfair commission fee system. Both tech giants banned Fortnite from Playstore and App Store when Epic allowed its app users to make an in-app purchase directly through Epic, violating "anti-steering provisions" and thereby bypassing the commission fee payment to Apple and Google. Epic filed a lawsuit right after the ban on Fortnite, and the United States Court stated that Apple and Google had violated antitrust laws and should allow app developers to freely direct the consumers to alternative payment methods (Iyengar and Duffy, 2021; Grant, 2023). Apple has appealed the court's decision, and Epic also appealed on the statement that Apple has no monopoly over the mobile game app market.

The European Commission also stated Apple should allow various payment options for the app users. As a response, Apple proposed the new price policy, where app developers would be subject to a 17% fee on in-app purchase revenue (10% for recurring payments) and a fixed fee of 50 Euro cents per app download above one million, irrespective of the available payment options.[20]In the U.S. and South Korea, where the same regulation was forced on Apple, the developers need to pay a 27% commission fee with external payment options.[21] In this counterfactual scenario, I assume Apple collects 10% of the commission fee on in-store revenue and \$0.05 unit fees per active user (denoted as κ). The corresponding profit functions for developers and the platform in the second stage are given below:

$$\pi_j^S = ((b_j(1-f) + \phi - \kappa)s_j \tag{13}$$

$$\pi_m^S = \sum_{j=1}^{N} s_j(fb_j + \kappa) + (b_m + \phi_m)s_m. \tag{14}$$

5.3 Acquisitions by Apple

Digital platforms frequently enter their own marketplaces, directly competing with fringe sellers, a practice that has raised significant antitrust concerns. Recently, the Department of Justice has accused Apple of monopolizing the digital wallet and messaging markets through illegal foreclosure

[20]For example, see news article: https://www.nytimes.com/2024/03/04/business/apple-eu-fine-app-store.html
[21]https://developer.apple.com/support/storekit-external-entitlement-us/

of competitors. Also, a federal judge ruled that Google had achieved monopoly status in the online search engine market by anti-competitively suppressing competition.[22] Both Apple and Google have appealed these decisions, asserting that their dominant positions stem from the superior quality of their products rather than anti-competitive practices.

In the last simulation I extend my model to examine the potential effects of vertical integration in the app marketplace. Specifically, I introduce a hypothetical acquisition of a streaming app by Apple and assess whether such an acquisition would promote innovation both for the acquired app and the broader market. In this simulation, the acquired app's profit maximization function is modified to align with equation (4), reflecting its new status as a vertically integrated entity within Apple's ecosystem.

5.4 Counterfactual Results

Fee Adjustments Table 8 presents findings for each counterfactual scenario. I find that the fee caps lead to increased innovative efforts, while developers are less inclined to invest in innovation under higher commission fees (20% or 30%). We can also witness that having lower commission fees leads to a less concentrated market. As Kesler et al. (2017) show, a less concentrated market contributes to fostering quality competition as well.[23] The results overall imply that the current 15% commission rate appears to suppress innovative incentives for app developers, providing supporting evidence for regulatory intervention. The results align with what Lu et al. (2023) show, that Steam game app developers update their apps more frequently under a fee cap.

On the other hand, the average in-app purchase price (IAP) rises under a fee cap, which contradicts previous findings (Li and Wang, 2024; Sullivan, 2024). It is attributed to the unique revenue structure in the mobile app marketplace: the positive net ancillary benefits for app developers causes a negative effect of commission fee on IAP, as illustrated in equation (3). When a developer's ancillary benefits (e.g., advertising revenue) exceed marginal costs, their optimal strategy under high fees is to offer free services. This maximizes market share and leverages non-price revenue streams, offsetting the impact of platform fees. That said, lower fees allow developers to

[22]See details from news articles of The New York Times for lawsuit against Apple and statement on Google.

[23]Zhao et al. (2024) empirically demonstrates that a commission fee increase in a creator platform endows market power to a minor group of creators and lessens the overall productivity. In a similar vein, Khan (2016) warns that firms tend to be reluctant to innovate in less competitive markets.

implement higher mark-ups that were previously unfeasible due to high commission rates. Since the top four app developers all have positive net ancillary benefits (Figure 7b), the IAP would likely hike under a fee cap. In addition, increased innovative effort levels also contribute to higher IAP. Similarly, Zhao et al. (2024) show empirical evidence that the fee cap causes the subscription fees to increase in the creator platform in China. They illustrate that the creators increase the prices to cover additional costs for the enhanced content quality.

From a social welfare perspective, the implementation of a commission fee cap is predicted to enhance the total welfare, primarily through increased innovative effort and developer surplus. Regarding distributional effects, the reduction in commission fees predominantly benefits app developers at the expense of platform and consumer surplus (e.g., Sullivan (2024)). In the second counterfactual, where Apple imposes additional unit fees, developers seem to partially pass these costs to consumers by increasing prices. Apple's new fee policy would decrease consumer and developer surplus while significantly improving platform surplus.

The second panel of Table 8 presents equilibrium outcomes in scenarios excluding innovative effort (ρ) adjustment. When analyzing price competition in isolation, the effects of fee caps on social welfare turn negative. Notably, treating innovative effort as an exogenous variable yields an overestimation of the fee cap's negative impact on social welfare by 0.91% - 2.06% points compared to the full-stage model estimates. This finding emphasizes the critical role of quality competition in evaluating regulatory interventions within digital platform ecosystems.

Simulation results indicate that fee caps generally enhance developer welfare and stimulate innovative efforts, despite marginally diminishing consumer welfare due to elevated in-app purchase prices (IAP). Significantly, platform revenue optimization occurs at a 30% fee rate, highlighting the fundamental tension between platform profitability and user welfare maximization. However, the increased levels of innovation appear to offset the negative effects of fee caps, ultimately improving social welfare.

Table 8: Results for Counterfactual Studies at Market-level (Fee Adjustments)

Scenario	IAP (b_j)	Effort (ρ_j)	Consumer	Developer	Platform	Social Welfare	HHI
Panel A. With ρ adjustments							
Factual (f=15%)	0.41	0.60	234.5M	94.7M	6.9M	336.1M	2198
f=1%	11.84%	16.02%	-1.95%	14.22%	-91.65%	0.78%	2124
f=10%	4.16%	10.50%	-0.06%	3.66%	-27.43%	0.43%	2158
f=20%	-4.77%	-1.01%	1.57%	-5.69%	20.96%	-0.08%	2216
f=30%	-14.71%	-3.00%	5.11%	-15.44%	39.22%	0.02%	2287
f=10% & Unit fees	16.86%	10.50%	-3.26%	0.48%	21.47%	-1.70%	2086
Panel B. Without ρ adjustments							
Factual (f=15%)	0.39	0.48	218.1M	88.7M	5.1M	311.9M	1721
f=1%	11.67%	0.00%	-4.30%	11.38%	-91.57%	-1.28%	1578
f=10%	4.54%	0.00%	-1.69%	4.01%	-26.28%	-0.48%	1665
f=20%	-4.88%	0.00%	1.85%	-3.88%	17.60%	0.48%	1783
f=30%	-14.37%	0.00%	5.45%	-10.71%	30.76%	1.27%	1896
f=10% & Unit fees	18.10%	0.00%	-5.02%	0.86%	26.78%	-2.83%	1600

Note: The first row in each panel presents the average equilibrium outcomes for the in-app purchase price (b) and innovative effort (ρ), along with the corresponding surplus for consumers, developers, the platform, and social welfare under the factual scenario. The change in consumer surplus is computed with the compensating variation $CV_t = \frac{V_t^f - V_t^{cf}}{\beta}$, with $V_t^f = \log(1 + \sum_{j=1}^{J} \exp(\delta_{jt}))$ in the factual ($f = 15\%$) scenario, where $J = \{1, 2, \cdots, N, m\}$ and $\delta_{jt} = \alpha\rho_{jt} + \beta b_{jt} + \boldsymbol{X_{jt}}\lambda + \xi_{jt}$. The counterfactual utility V_t^{cf} is analogous to V_t^f. Then, the total change in consumer surplus is $\sum_t^{65} M_t * CV_t$. The producer surplus and platform surplus each indicate the second stage profits (3) and (4). Subsequent rows report the percentage changes from the factual baseline across various counterfactual scenarios.

Table 9: Individual App's Outcome Before and After Buy-out

App	$\bar{\phi}$	b	ρ	sh	π
Scenario A. Pre-merger					
Spotify	0.74	0.21	1.53	0.38	59.0M
Pandora	0.33	0.44	0.53	0.24	30.5M
SoundCloud	0.33	0.23	0.32	0.03	2.7M
YouTube Music	-0.14	0.77	0.02	0.02	2.6M
Scenario B. Spotify					
Spotify		279.86%	-100.00%	-70.50%	-56.63%
Pandora		24.30%	-29.70%	22.75%	38.75%
SoundCloud		21.86%	373.29%	168.05%	202.12%
YouTube Music		5.29%	4688.88%	188.48%	225.65%
Scenario C. Pandora					
Spotify		8.66%	-5.13%	0.18%	2.23%
Pandora		-13.41%	-100.00%	-15.44%	-22.67%
SoundCloud		5.01%	124.61%	40.32%	44.26%
YouTube Music		0.89%	2277.94%	35.64%	38.98%
Scenario D. SoundCloud					
Spotify		-4.18%	-5.69%	-1.24%	-1.83%
Pandora		2.30%	8.23%	2.60%	4.16%
SoundCloud		45.98%	-47.63%	-25.72%	-12.07%
YouTube Music		0.25%	720.87%	11.07%	11.72%
Scenario E. Google					
Spotify		-18.83%	0.82%	-4.64%	-7.51%
Pandora		-2.15%	32.58%	-2.89%	-4.03%
SoundCloud		-0.43%	22.90%	-5.53%	-5.80%
YouTube Music		-99.16%	-83.29%	211.56%	-180.82%

Note: The first panel presents each app's mean values for key variables: net ancillary benefits (ϕ), IAP (b), innovative effort (ρ), market share (sh), and total profit (π) in the pre-merger state. Subsequent panels display percentage changes from this baseline across various Apple acquisition scenarios.

Acquisitions Table 9 reveals that all acquired apps are predicted to reduce their innovative efforts and increase IAP post-acquisition, ceding market share to competitors. This discrepancy likely stems from the platform's different objective function (4), which incorporates commission fee revenue. These findings cast doubt on Apple and Google's claims that their market dominance in digital wallets and online search engines primarily stems from superior product quality. Possibly, other factors that my model cannot capture may play a significant role in their market positions.

6 Conclusion

This paper quantifies the welfare consequences of capping commission fees in digital platforms, focusing on third-party app developers' innovation and pricing decisions. Based on evidence suggesting a positive relationship between past in-store revenue and app updates, I propose a two-stage structural model of the mobile app marketplace. In this model, app developers first choose innovative efforts and then decide on in-app purchase prices (IAP). Counterfactual simulations yield preliminary results indicating that capping commission fees leads to increased IAP while promoting innovation and improving developer welfare, but reducing platform surplus. The model predicts that consumers will lose surplus under a fee cap due to higher IAP. The negative relationship between fees and IAP results from the prevalence of positive net ancillary benefits in the mobile app marketplace. Put differently, current fees might have forced app developers to take a predatory pricing strategy to gain a larger market share, and then earn ancillary benefits. Nonetheless, the increased levels of innovation appear to offset the negative effects of fee caps, ultimately improving social welfare; app developers benefit from a fee cap at the expense of consumer and platform surplus.

The study also finds that under Apple's proposed unit fee scheme, app developers would partly pass these fees to consumers by increasing IAP. Despite the lower ad-valorem fees promoting innovation, consumers would be worse off due to higher prices, while Apple stands to benefit significantly from this new fee policy. Additionally, the research reveals that in a hypothetical scenario where Apple acquires a streaming app, it would invest less in innovation for the acquired app compared to the previous owner. This finding challenges Apple and Google's assertions that their market dominance in digital wallets and online search engines primarily stems from superior product quality.

In conclusion, this study finds that regulating commission fees at lower rates promotes innovation among app developers with increasing their surplus. However, it also reveals potential drawbacks: consumers may face higher in-app purchase prices, and platform surplus is likely to decrease significantly. As Sullivan (2024) has noted, it is arguable that there is a risk that platforms may increase other fees (e.g., access or hardware prices) to compensate for their losses from lower commission rates. For a possible scenario, platforms would foster vertical integration under a fee cap (Tirole and Bisceglia, 2023), which could be an interesting extension of this paper.

Despite these complexities, I show that treating innovative effort (or quality improvement) as an exogenous variable would lead us to underestimate the welfare effects of fee cap by 0.91% - 2.06% points compared. In light of the findings, this paper emphasizes the critical importance of considering both quality changes and price fluctuations when evaluating regulatory interventions in two-sided digital platform markets like mobile apps.

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Appendices

A Robustness Analysis

Table A.1: Demand Parameter Estimates with Alternative Specifications

	Dependent variable:				
	$\ln(s_{jt}) - \ln(s_{0t})$				
	Full	Time Used	Cumulative	Update	Major
	(1)	(2)	(3)	(4)	(5)
IAP ($)	0.015	-0.041^{***}	-1.187^{***}	-0.528^{***}	-0.447^{***}
	(0.056)	(0.012)	(0.259)	(0.139)	(0.130)
Effort (ρ)	0.095^{***}	0.161^{**}	0.028^{***}	0.129^{***}	0.325^{***}
	(0.031)	(0.063)	(0.006)	(0.028)	(0.084)
Major ($\tilde{\rho}$)					2.149^{***}
					(0.712)
σ	0.980^{***}	0.746^{***}	0.484^{***}	0.481^{***}	0.522^{***}
	(0.032)	(0.042)	(0.082)	(0.065)	(0.059)
Age of app	0.001	-0.005^{***}	-0.008^{***}	0.0001	-0.0003
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
App rating	-0.017	0.093	0.154^{***}	0.145^{***}	0.145^{***}
	(0.032)	(0.059)	(0.046)	(0.043)	(0.043)
Popularity	0.054^{***}	-0.001	0.072^{***}	0.077^{***}	0.080^{***}
	(0.009)	(0.016)	(0.025)	(0.017)	(0.016)
Constant	1.406^{***}	-0.531^{***}	-0.063	-1.424^{***}	-1.089^{***}
	(0.175)	(0.187)	(0.377)	(0.344)	(0.296)
Year-Month Effects	Y	Y	Y	Y	Y
App Effects	Y	N	Y	Y	Y
Observations	5,720	4,615	4,745	4,745	4,745
R^2	0.995	0.993	0.956	0.977	0.981

Notes: (i) This table reports IV regression results by using demand equation (12) with alternative specifications: column (1) uses full dataset including complementary apps sample, column (2) employs the number of minutes used per app as the dependent variable, column (3) uses cumulative innovative effort as a proxy for ρ, column (4) uses the number of app updates as a proxy for ρ, and column (5) includes innovative effort for a major update (version number change). (ii) Robust standard errors are clustered by app and month in the parentheses. (iii) *p<0.1; **p<0.05; ***p<0.01.

B First Stage Regression

Table B.1: First Stage Regression Results

	Dependent variable:		
	b_{jt}	ρ_{jt}	$\bar{s}_{j\|gt}$
	(1)	(2)	(3)
App Age	-0.027^{***}	0.011^{**}	0.074^{***}
	(0.004)	(0.005)	(0.005)
App rating	-0.008	0.370^{**}	0.379^{**}
	(0.136)	(0.172)	(0.183)
Popularity	-0.032^{*}	-0.008	0.132^{***}
	(0.017)	(0.021)	(0.023)
App rating of competing apps	-0.050	0.310^{*}	0.046
	(0.131)	(0.166)	(0.177)
N of downloads in same group	0.322^{**}	-0.369^{*}	-2.674^{***}
	(0.157)	(0.198)	(0.211)
Diff in update in same group	-0.0001	0.004^{***}	0.002^{***}
	(0.0003)	(0.0003)	(0.0003)
Developer's total app	-0.014^{***}	0.004	0.030^{***}
	(0.002)	(0.002)	(0.003)
N of privacy agreements	-0.081^{**}	0.122^{**}	0.578^{***}
	(0.038)	(0.048)	(0.051)
Constant	13.997	-95.244^{*}	14.914
	(42.116)	(53.314)	(56.721)
Year-Month Fixed Effects	Y	Y	Y
App Fixed Effects	Y	Y	Y
Observations	4,745	4,745	4,745
R^2	0.768	0.345	0.952
F Statistic (df = 142; 4602)	106.999^{***}	17.049^{***}	638.640^{***}

Note: *p<0.1; **p<0.05; ***p<0.01

C Derivation

C.1 First derivatives

$$
\begin{aligned}
&\frac{\partial P_{j|g}}{\partial b_j} = \frac{\beta}{1-\sigma} \cdot P_{j|g}(1-P_{j|g}), && \frac{\partial P_{j|g}}{\partial b_r} = -\frac{\beta}{1-\sigma} \cdot P_{r|g} \cdot P_{j|g} \\
&\frac{\partial P_g}{\partial b_j} = \beta \cdot P_j \cdot (1-P_g) \text{ for } j \in J_g, && \frac{\partial P_{j|g}}{\partial b_r^f} = 0 \\
&\frac{\partial P_g}{\partial b_r} = \beta \cdot P_r \cdot (1-P_g) \text{ for } r \in J_g, && \frac{\partial P_g}{\partial b_j} = -\beta \cdot P_{j|f} \cdot P_f \cdot P_g \text{ for } j \in J_f
\end{aligned}
$$

Hence, for $j, r \in J_g$ and $j \neq r$,

$$
\begin{aligned}
\frac{\partial P_j}{\partial b_j} &= \frac{\partial P_{j|g}}{\partial b_j} \cdot P_g + P_{j|g} \cdot \frac{\partial P_g}{\partial b_j} \\
&= \beta \cdot P_j \left(\frac{1}{1-\sigma}(1-P_{j|g}) + (1-P_g)P_{j|g} \right) \\
&= \frac{\beta}{1-\sigma} \cdot P_j \cdot \big(1 - \sigma P_{j|g} - (1-\sigma)P_j\big) \\
\frac{\partial P_j}{\partial b_r} &= \frac{\partial P_{j|g}}{\partial b_r} \cdot P_g + P_{j|g} \cdot \frac{\partial P_g}{\partial b_r} \\
&= \beta \cdot P_j \left(\frac{-1}{1-\sigma} \cdot P_{r|g} + (1-P_g)P_{r|g} \right) \\
&= -\beta \cdot P_r \cdot P_j \left(1 + \frac{\sigma}{1-\sigma}\frac{1}{P_g} \right)
\end{aligned}
$$

For $r \in J_f$ and $r \notin J_g$,

$$
\begin{aligned}
\frac{\partial P_j^g}{\partial b_r^f} &= P_{j|g} \cdot \frac{\partial P_g}{\partial b_r^f} \\
&= -\beta \cdot P_j^g \cdot P_r^f
\end{aligned}
$$

C.2 Second derivatives

Within-Group

$$
\begin{aligned}
\frac{\partial^2 P_j}{\partial^2 b_j} &= \beta^2 P_j \left((\frac{1}{1-\sigma}(1-P_{j|g}) + (1-P_g)P_{j|g})\frac{1}{1-\sigma}(1-P_{j|g}) + (1-P_g)P_{j|g} - P_{j|g}(\frac{1}{(1-\sigma)^2}(1-P_{j|g}) - \frac{1}{1-\sigma}(1-P_g)(1-P_{j|g}) + (1-P_g)) \right) \\
\frac{\partial^2 P_j}{\partial b_j \partial b_r} &= \beta^2 P_j P_{r|g} \left((1 - P_g - \frac{1}{1-\sigma})(\frac{1}{1-\sigma}(1-2P_{j|g}) + (1-P_g)P_{j|g}) - (1-P_g)P_j \right) \\
\frac{\partial^2 P_j}{\partial b_j \partial \rho_r} &= \alpha\beta P_j P_{r|g} \left((1 - P_g - \frac{1}{1-\sigma})(\frac{1}{1-\sigma}(1-2P_{j|g}) + (1-P_g)P_{j|g}) - (1-P_g)P_j \right)
\end{aligned}
$$

Cross-group

$$\frac{\partial^2 P_j^g}{\partial b_j^g \partial b_r^f} = -\beta^2 P_j^g P_r^f \left(\frac{1-\sigma P_{j|g}}{1-\sigma} - 2P_j^g \right)$$
$$\frac{\partial^2 P_j^g}{\partial b_j^g \partial \rho_r^f} = -\alpha\beta P_j^g P_r^f \left(\frac{1-\sigma P_{j|g}}{1-\sigma} - 2P_j^g \right)$$

Cross-Cross derivatives
when $j, m, k \in J_g$,

$$\frac{\partial^2 P_j}{\partial b_m \partial b_k} = 2\beta^2 P_j P_m P_k \left(1 + \frac{\sigma}{1-\sigma}\frac{1}{P_g}\right)^2 + \beta^2 P_j P_m P_k \frac{\sigma}{1-\sigma}\frac{1-P_g}{p_g^2}$$

when $j \in J_g$, $m \in J_f$, $k \in J_h$,

$$\frac{\partial^2 P_j}{\partial b_m \partial b_k} = 2\beta^2 P_j P_m P_k$$

when $j \in J_g$, $m, k \in J_f$,

$$\frac{\partial^2 P_j}{\partial b_m \partial b_k} = \beta^2 P_j P_m P_k (2 + \frac{1}{1-\sigma}\frac{1}{P_f})$$

when $j, m \in J_g$, $k \in J_f$,

$$\frac{\partial^2 P_j}{\partial b_m \partial b_k} = \beta^2 P_j P_m P_k (2 + \frac{1}{1-\sigma}\frac{1}{P_g})$$

when $j, m \in J_g$,

$$\frac{\partial^2 P_j}{\partial^2 b_m} = \beta^2 P_m \left(\frac{-1}{1-\sigma}(1 - \sigma P_{m|g} - (1-\sigma)P_m)(P_j + \frac{\sigma}{1-\sigma}P_{j|g}) + P_m(P_j + \frac{\sigma}{1-\sigma}P_{j|g}) + \frac{\sigma}{(1-\sigma)^2}P_{m|g}P_{j|g} \right)$$

when $j \in J_g$, $m \in J_f$,

$$\frac{\partial^2 P_j}{\partial^2 b_m} = \beta^2 P_j P_m \left(P_m - \frac{1}{1-\sigma}(1 - \sigma P_{m|f} - (1-\sigma)P_m) \right)$$

First-order conditions

$$
\begin{aligned}
\frac{\partial \pi_j^S}{\partial b_k} &= \frac{\partial s_j}{\partial b_k}(b_j(1-f)+\phi_j); \quad \frac{\partial \pi_j^S}{\partial b_j} \equiv 0 \\
\frac{\partial \pi_j^S}{\partial \rho_j} &= \frac{\partial s_j}{\partial \rho_j}(b_j(1-f)+\phi_j) \\
\frac{\partial \pi_m^S}{\partial b_k} &= f \cdot \left(\sum_{j\neq k}^{N} b_j \frac{\partial s_j}{\partial b_k} + s_k + \frac{\partial s_k}{\partial b_k} b_k \right) + (b_m+\phi_m)\frac{\partial s_m}{\partial b_k} \\
\frac{\partial \pi_m^S}{\partial \rho_k} &= f \cdot \sum_{j=1}^{N} b_j \frac{\partial s_j}{\partial \rho_k} + (b_m+\phi_m)\frac{\partial s_m}{\partial \rho_k} \\
\frac{\partial \pi_m^S}{\partial \rho_m} &= f \cdot \sum_{j=1}^{N} b_j \frac{\partial s_j}{\partial \rho_m} + (b_m+\phi_m)\frac{\partial s_m}{\partial \rho_m}
\end{aligned}
$$

C.3 Notes on the supply-side equation

In this section, I delineate the details in deriving $\frac{\partial b_k^*}{\partial \rho_j}$ which will be used in the supply side equation (11):

$$
\frac{\partial \pi_j^S}{\partial \rho_j} + \sum_{k=1}^{N} \frac{\partial \pi_j^S}{\partial b_k}\frac{\partial b_k^*}{\partial \rho_j} \equiv \gamma_0 + \gamma_1 \rho_j + \nu_j .
$$

Let $F^j(\vec{b},\vec{\rho})$ express the first-order conditions (5) and (6), and there also exists $b_j = f^j(\rho_1, \cdots \rho_N, \rho_m)$. Taking total derivative on $F^j(\vec{b},\vec{\rho})$ with respect to $\vec{b}$ and $\vec{\rho}$:

$$
\begin{aligned}
\frac{\partial F^1}{\partial b_1}db_1 + \frac{\partial F^1}{\partial b_2}db_2 + \cdots + \frac{\partial F^1}{\partial b_N}db_N + \frac{\partial F^1}{\partial b_m}db_m &= -(\frac{\partial F^1}{\partial \rho_1}d\rho_1 + \frac{\partial F^1}{\partial \rho_2}d\rho_2 + \cdots + \frac{\partial F^1}{\partial \rho_N}d\rho_N + \frac{\partial F^1}{\partial \rho_m}d\rho_m) \\
\frac{\partial F^2}{\partial b_1}db_1 + \frac{\partial F^2}{\partial b_2}db_2 + \cdots + \frac{\partial F^2}{\partial b_N}db_N + \frac{\partial F^2}{\partial b_m}db_m &= -(\frac{\partial F^2}{\partial \rho_1}d\rho_1 + \frac{\partial F^2}{\partial \rho_2}d\rho_2 + \cdots + \frac{\partial F^2}{\partial \rho_N}d\rho_N + \frac{\partial F^2}{\partial \rho_m}d\rho_m) \\
&\vdots \\
\frac{\partial F^N}{\partial b_1}db_1 + \frac{\partial F^N}{\partial b_2}db_2 + \cdots + \frac{\partial F^N}{\partial b_N}db_N + \frac{\partial F^N}{\partial b_m}db_m &= -(\frac{\partial F^N}{\partial \rho_1}d\rho_1 + \frac{\partial F^N}{\partial \rho_2}d\rho_2 + \cdots + \frac{\partial F^N}{\partial \rho_N}d\rho_N + \frac{\partial F^N}{\partial \rho_m}d\rho_m) \\
\frac{\partial F^m}{\partial b_1}db_1 + \frac{\partial F^m}{\partial b_2}db_2 + \cdots + \frac{\partial F^m}{\partial b_N}db_N + \frac{\partial F^m}{\partial b_m}db_m &= -(\frac{\partial F^m}{\partial \rho_1}d\rho_1 + \frac{\partial F^m}{\partial \rho_2}d\rho_2 + \cdots + \frac{\partial F^m}{\partial \rho_N}d\rho_N + \frac{\partial F^m}{\partial \rho_m}d\rho_m).
\end{aligned}
$$

Then, taking total derivative on $b_j = f^j(\rho_1, \cdots \rho_N, \rho_m)$ with respect to $\vec{\rho}$,

$$db_1 = \frac{\partial b_1}{\partial \rho_1} d\rho_1 + \frac{\partial b_1}{\partial \rho_2} d\rho_2 + \cdots + \frac{\partial b_1}{\partial \rho_N} d\rho_N + \frac{\partial b_1}{\partial \rho_m} d\rho_m$$

$$\vdots$$

$$db_N = \frac{\partial b_N}{\partial \rho_1} d\rho_1 + \frac{\partial b_N}{\partial \rho_2} d\rho_2 + \cdots + \frac{\partial b_N}{\partial \rho_N} d\rho_N + \frac{\partial b_N}{\partial \rho_m} d\rho_m$$

$$db_m = \frac{\partial b_m}{\partial \rho_1} d\rho_1 + \frac{\partial b_m}{\partial \rho_2} d\rho_2 + \cdots + \frac{\partial b_m}{\partial \rho_N} d\rho_N + \frac{\partial b_m}{\partial \rho_m} d\rho_m.$$

Since equation (11) is an optimality condition for observed innovative efforts, we are only interested in computing $\frac{\partial b_k^*}{\partial \rho_j}$ with assuming $d\rho_j \neq 0$ and $d\rho_k = 0, \forall k \neq j \in \{1, 2, \cdots, N, m\}$ (Fan, 2013). Then the above system becomes:

$$db_1 = \frac{\partial b_1}{\partial \rho_j} d\rho_j$$

$$\vdots$$

$$db_N = \frac{\partial b_N}{\partial \rho_j} d\rho_j$$

$$db_m = \frac{\partial b_m}{\partial \rho_j} d\rho_j.$$

Combining the two systems and dividing by $d\rho_j \neq 0$ we can derive the following:

$$\frac{\partial F^1}{\partial b_1}\frac{\partial b_1}{\partial \rho_j} + \frac{\partial F^1}{\partial b_2}\frac{\partial b_2}{\partial \rho_j} + \cdots + \frac{\partial F^1}{\partial b_N}\frac{\partial b_N}{\partial \rho_j} + \frac{\partial F^1}{\partial b_m}\frac{\partial b_m}{\partial \rho_j} = -\frac{\partial F^1}{\partial \rho_j}$$

$$\vdots$$

$$\frac{\partial F^N}{\partial b_1}\frac{\partial b_1}{\partial \rho_j} + \frac{\partial F^N}{\partial b_2}\frac{\partial b_2}{\partial \rho_j} + \cdots + \frac{\partial F^N}{\partial b_N}\frac{\partial b_N}{\partial \rho_j} + \frac{\partial F^N}{\partial b_m}\frac{\partial b_m}{\partial \rho_j} = -\frac{\partial F^N}{\partial \rho_j}$$

$$\frac{\partial F^m}{\partial b_1}\frac{\partial b_1}{\partial \rho_j} + \frac{\partial F^m}{\partial b_2}\frac{\partial b_2}{\partial \rho_j} + \cdots + \frac{\partial F^m}{\partial b_N}\frac{\partial b_N}{\partial \rho_j} + \frac{\partial F^m}{\partial b_m}\frac{\partial b_m}{\partial \rho_j} = -\frac{\partial F^m}{\partial \rho_j}.$$

We can then reformulate it as matrix form,

$$\begin{pmatrix} \frac{\partial F^1}{\partial b_1} & \frac{\partial F^1}{\partial b_2} & \cdots & \frac{\partial F^1}{\partial b_N} & \frac{\partial F^1}{\partial b_m} \\ \frac{\partial F^2}{\partial b_1} & \frac{\partial F^2}{\partial b_2} & \cdots & \frac{\partial F^2}{\partial b_N} & \frac{\partial F^2}{\partial b_m} \\ & & \vdots & & \\ \frac{\partial F^N}{\partial b_1} & \frac{\partial F^N}{\partial b_2} & \cdots & \frac{\partial F^N}{\partial b_N} & \frac{\partial F^N}{\partial b_m} \\ \frac{\partial F^m}{\partial b_1} & \frac{\partial F^m}{\partial b_2} & \cdots & \frac{\partial F^m}{\partial b_N} & \frac{\partial F^m}{\partial b_m} \end{pmatrix} \begin{pmatrix} \frac{\partial b_1}{\partial \rho_j} \\ \frac{\partial b_2}{\partial \rho_j} \\ \vdots \\ \frac{\partial b_N}{\partial \rho_j} \\ \frac{\partial b_m}{\partial \rho_j} \end{pmatrix} = \begin{pmatrix} -\frac{\partial F^1}{\partial \rho_j} \\ -\frac{\partial F^2}{\partial \rho_j} \\ \vdots \\ -\frac{\partial F^N}{\partial \rho_j} \\ -\frac{\partial F^m}{\partial \rho_j} \end{pmatrix}$$

for all $j \in \{1, 2, \cdots, N, m\}$.

Partial derivatives

$$
\begin{aligned}
\frac{\partial F^j}{\partial b_j} &= 2\frac{\partial s_j}{\partial b_j} + (b_j + \frac{\phi_j}{1-f})\frac{\partial^2 s_j}{\partial^2 b_j} \\
\frac{\partial F^j}{\partial b_k} &= (b_j + \frac{\phi_j}{1-f})\frac{\partial^2 s_j}{\partial b_j \partial b_k} + \frac{\partial s_j}{\partial b_k} \\
\frac{\partial F^m}{\partial b_k} &= f\sum_{j=1}^{N}\frac{\partial^2 s_j}{\partial b_m \partial b_k} b_j + f\frac{\partial s_k}{\partial b_m} + (b_m + \phi_m)\frac{\partial^2 s_m}{\partial b_m \partial b_k} + \frac{\partial s_m}{\partial b_k} \\
\frac{\partial F^m}{\partial b_m} &= f\sum_{j=1}^{N}\frac{\partial^2 s_j}{\partial^2 b_m} b_j + 2\frac{\partial s_m}{\partial b_m} + (b_m + \phi_m)\frac{\partial^2 s_m}{\partial^2 b_m} \\
\frac{\partial F^j}{\partial \rho_j} &= (b_j + \frac{\phi_j}{1-f})\frac{\partial^2 s_j}{\partial b_j \partial \rho_j} + \frac{\partial s_j}{\partial \rho_j} \\
\frac{\partial F^j}{\partial \rho_k} &= (b_j + \frac{\phi_j}{1-f})\frac{\partial^2 s_j}{\partial b_j \partial \rho_k} + \frac{\partial s_j}{\partial \rho_k} \\
\frac{\partial F^m}{\partial \rho_k} &= f\sum_{j=1}^{N}\frac{\partial^2 s_j}{\partial b_m \partial \rho_k} b_j + (b_m + \phi_m)\frac{\partial^2 s_m}{\partial b_m \partial \rho_k} + \frac{\partial s_m}{\partial \rho_k} \\
\frac{\partial F^m}{\partial \rho_m} &= f\sum_{j=1}^{N}\frac{\partial^2 s_j}{\partial b_m \partial \rho_m} b_j + (b_m + \phi_m)\frac{\partial^2 s_m}{\partial b_m \partial \rho_m} + \frac{\partial s_m}{\partial \rho_m}.
\end{aligned}
$$

D List of additional Figures and Tables

Table D.1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Market share (%)	4,745	1.1	3.6	0.003	27.5
Market share (time use) (%)	4,745	1.4	5.5	0	55.2
Within share (%)	4,745	5.5	11.1	0.02	74.0
Innovative effort	4,745	0.202	0.455	0.000	8.417
Innovative effort (Major)	4,745	0.0002	0.005	0.000	0.333
Cumulative effort	4,745	6.255	8.855	0.000	74.305
Number of update	4,745	1.244	1.523	0	14
In-app purchase price ($)	4,745	0.270	0.603	0.000	5.631
App rating	4,745	4.536	0.251	2.910	4.860
Number of ratings	4,745	538,371	2,525,580	5	31,044,038
App age (months)	4,745	88.849	34.340	6	184
Popularity	4,745	1.009	0.904	0	4
Number of apps	4,745	6.616	11.541	1	84
Privacy	4,745	3.740	3.057	0	12
In-store revenue ($)	4,745	500,316	1,857,297	0	18,098,777
Cumulative downloads	4,745	12,191,867	28,964,095	630	189,489,028

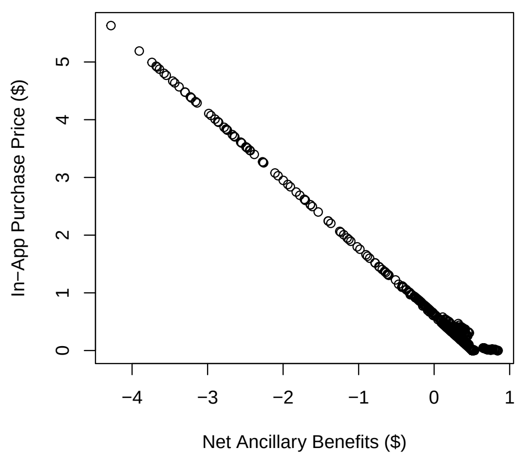
Table D.2: Relationship Between Streaming Apps' Downloads and Innovative Effort of Other Apps across Groups.

	Dependent variable:					
	log(downloads)					
	(1)	(2)	(3)	(4)	(5)	(6)
Non-streaming	-3.027^{**}					
	(1.244)					
Complementary		3.424^{**}				
		(1.407)				
Radio			-1.845^{**}			
			(0.758)			
Instruments				-2.055^{**}		
				(0.845)		
Headphones					6.830^{**}	
					(2.806)	
Socialize						-1.458^{**}
						(0.599)
Constant	13.587^{***}	12.519^{***}	13.309^{***}	13.493^{***}	12.626^{***}	13.242^{***}
	(0.301)	(0.190)	(0.198)	(0.265)	(0.155)	(0.175)
Year-Month Fixed Effects	Y	Y	Y	Y	Y	Y
App Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	1,357	1,357	1,357	1,357	1,357	1,357
R^2	0.898	0.898	0.898	0.898	0.898	0.898

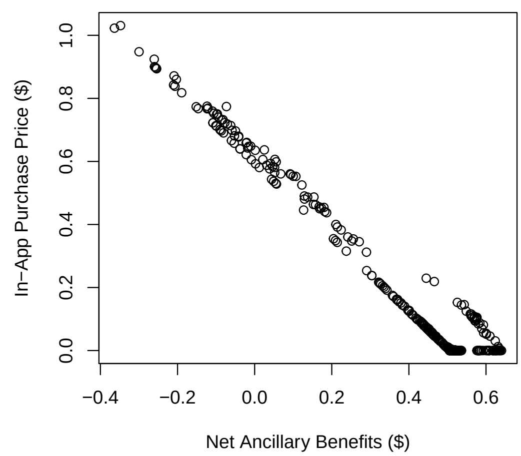
Notes: (i) This table reports the OLS regression results with the equation: $y_{jt} = \boldsymbol{\rho}_{t-1}\beta + \mu_t + \mu_j$, with y_{jt} indicating a logarithm of number of downloads for app j in year-month t in streaming group. $\boldsymbol{\rho}_{t-1}$ represents the average innovative effort of apps in each group. Two-way fixed effects, μ_t and μ_j, are captured. (ii) *p<0.1; **p<0.05; ***p<0.01

Figure D.1: Net Ancillary Benefits by Groups

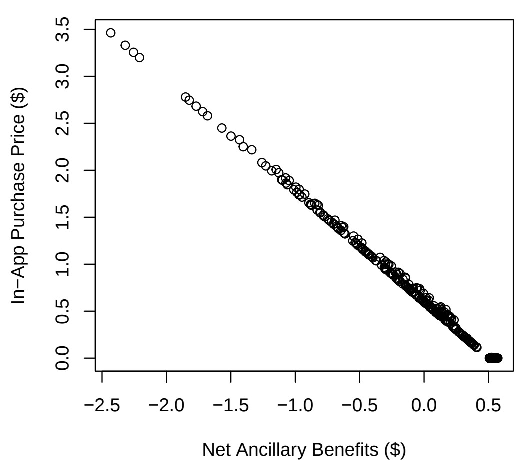
(a) Streaming



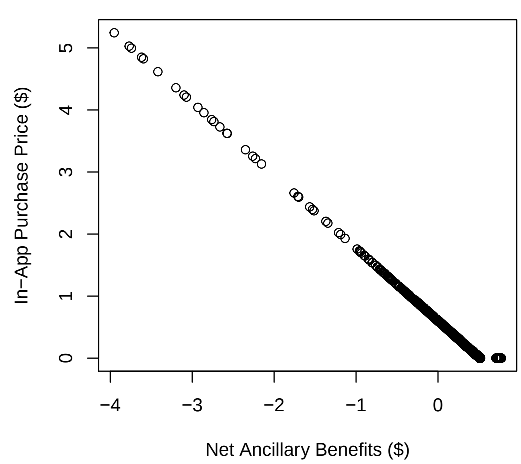
(b) Radio and Podcasts



(c) Socialize

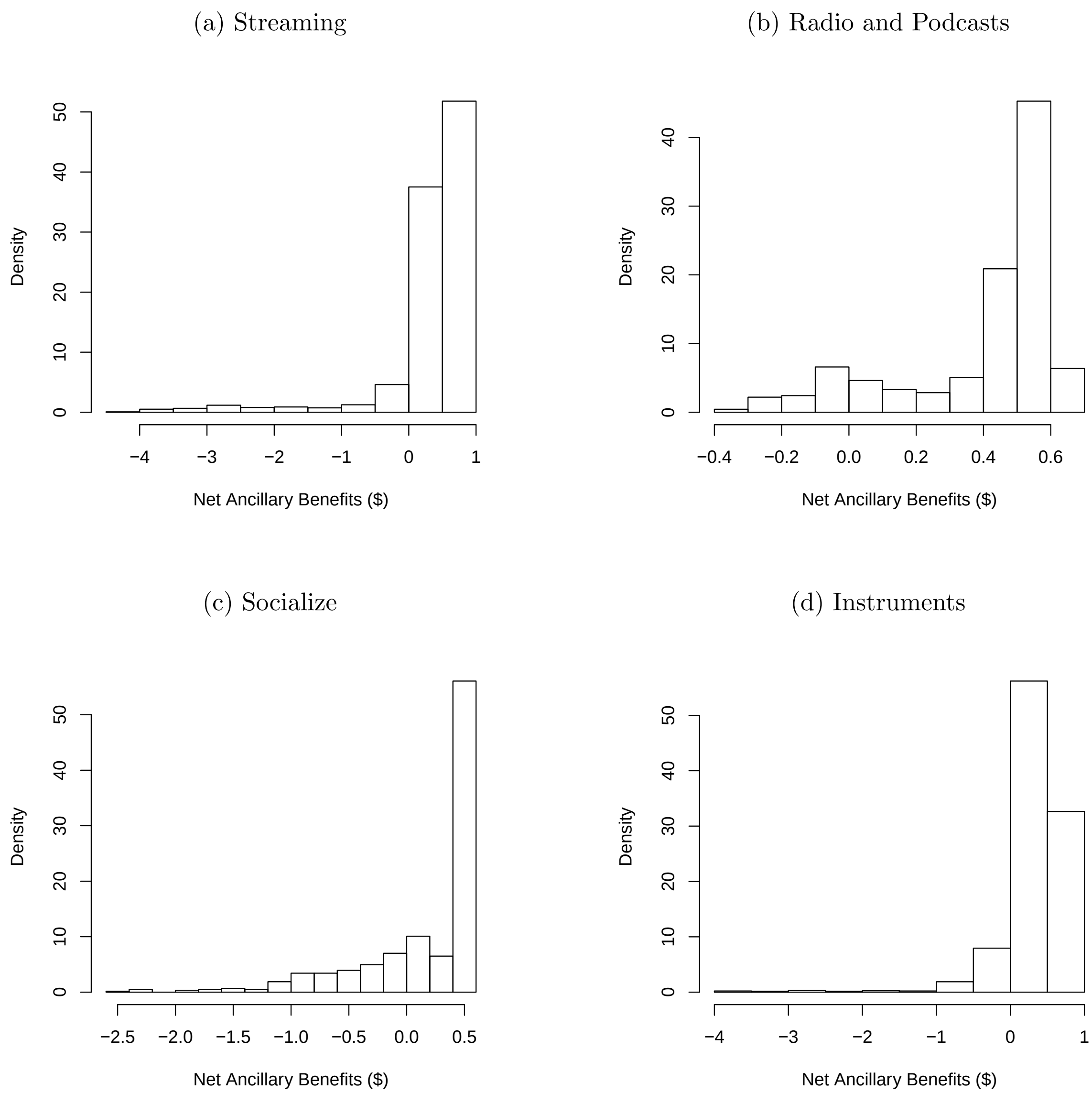


(d) Instruments



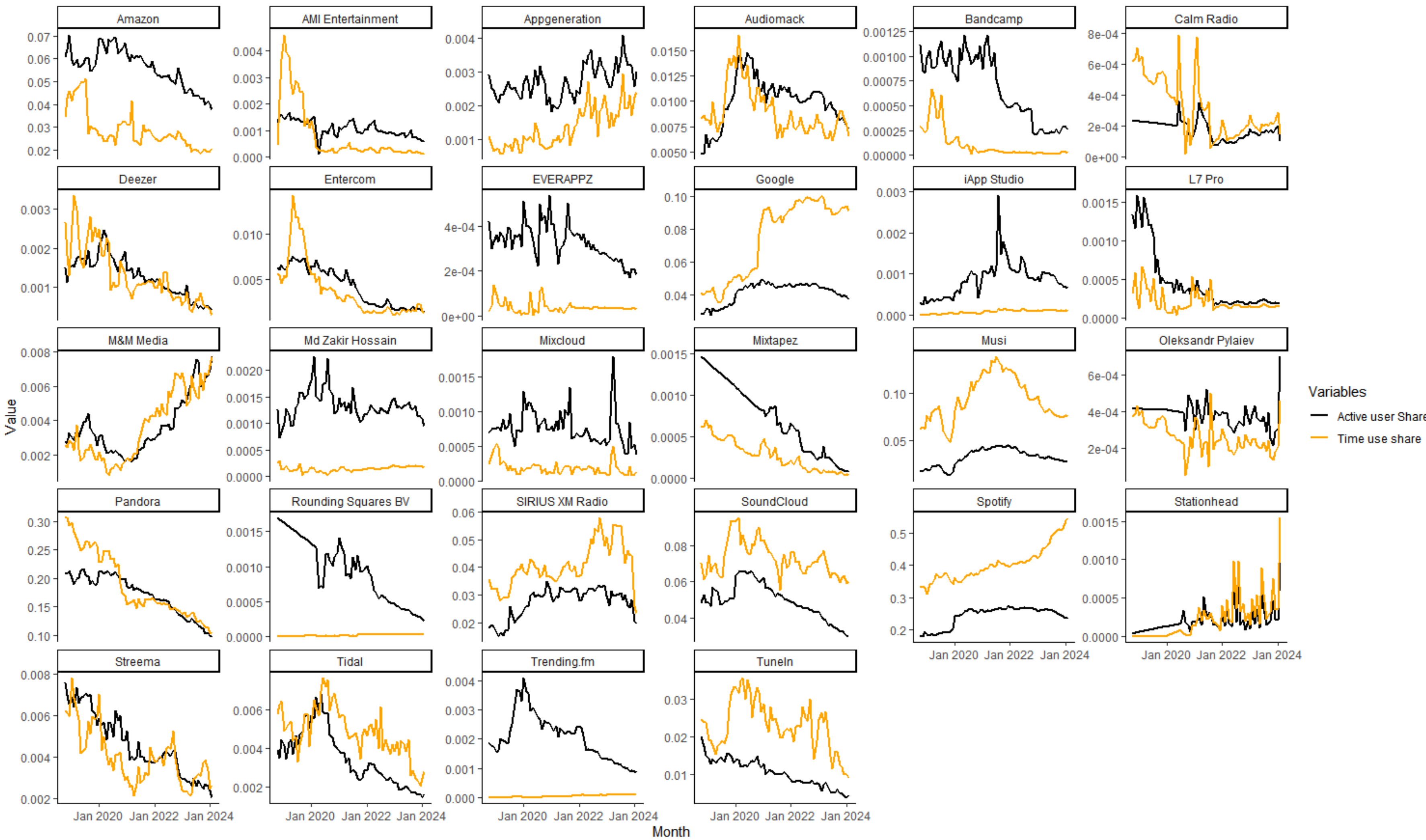
Note: The figures depict net ancillary benefits across the nest groups, with the average in-app purchase price.

Figure D.2: Histogram of Net Ancillary Benefits



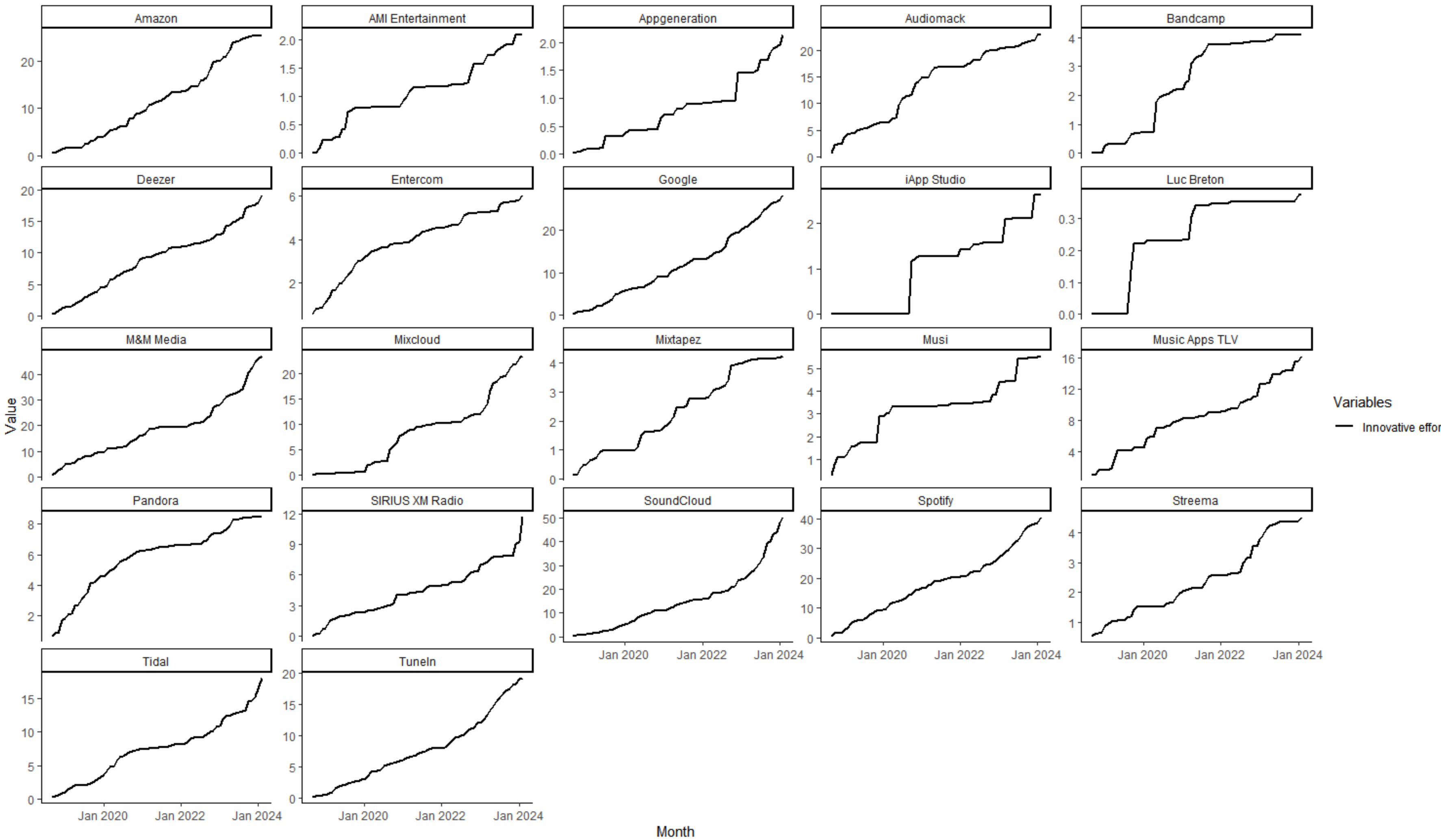
Note: The figures illustrate the distribution of net ancillary benefits across the nest groups. Regardless of their groups, most music apps exhibit positive net ancillary benefits. This reflects the prevalence of freemium products (or zero-price strategy) in the mobile app marketplace.

Figure D.3: Comparison of Market Shares based on The Number of Active Users and Time Used



Note: This figure illustrates market share distribution using two distinct metrics: the number of users (represented by the black line), which serves as the primary measure in this study, and the amount of time used, measured in hours (depicted by the orange line). The former metric quantifies the number of unique users accessing the applications within a specified time frame, while the latter measures these users' cumulative hours of app utilization.

Figure D.4: Cumulative Innovative Effort across Months



Note: This figure illustrates each music streaming app developer's decisions on innovative effort over time.

Table D.3: Equilibrium Outcomes for each App Before and After Buy-out (without Google)

App	$\bar{\phi}$	Δ b	$\Delta\rho$	Δsh	$\Delta\pi$
Scenario A. Pre-merger					
Spotify	0.74	0.22	1.55	0.39	61.2M
Pandora	0.33	0.47	0.71	0.25	33.1M
SoundCloud	0.33	0.23	0.20	0.03	2.9M
Scenario B. Spotify					
Spotify		253.95%	-100.00%	-69.12%	-41.66%
Pandora		30.58%	-12.77%	24.83%	54.74%
SoundCloud		30.63%	795.51%	233.86%	201.60%
Scenario C. Pandora					
Spotify		28.07%	19.80%	7.71%	9.75%
Pandora		-18.15%	-100.00%	-20.85%	-16.63%
SoundCloud		4.37%	288.61%	41.52%	-2.18%
Scenario D. SoundCloud					
Spotify		-1.93%	1.31%	0.32%	-0.94%
Pandora		1.77%	16.64%	2.86%	2.10%
SoundCloud		46.43%	-20.79%	-20.52%	-2.42%

Note: The first panel presents each app's mean values for key variables: net ancillary benefits (ϕ), IAP (b), innovative effort (ρ), market share (sh), and total profit (π) in the pre-merger state. Subsequent panels display percentage changes from this baseline across various Apple acquisition scenarios.