Exclusive Contracts in the Video Streaming Market *

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Abstract

In the video streaming market, streaming services use exclusive contracts to differentiate their content offerings and soften competition, while studios leverage these contracts to negotiate higher licensing fees against streaming services. I investigate who gains and who loses from such contracts. I develop and estimate a structural model that incorporates bilateral negotiations between streaming services and studios, streaming services setting subscription prices, and consumer demand for subscriptions and titles. The findings reveal that the effect of exclusive contracts varies significantly across firms. Streaming services that rely on exclusive third-party content (like Hulu) gain from exclusivity, while those with extensive in-house content (like Netflix) or strong subscriber loyalty (like Amazon Prime) see minimal or negative impacts. For studios, exclusive contracts benefit small studios with weak bargaining power but harm large ones with strong bargaining power. In addition, exclusive contracts reduce consumer surplus by limiting title availability and driving up subscription prices.

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1 Introduction

Exclusive contracts are prevalent in various markets: the iPhone was exclusively available on AT&T's network from 2008 to 2011; Costco exclusively partners with Visa for credit card processing; and Spotify held exclusive rights to the podcast *Joe Rogan Experience* until 2024. These agreements often result from competitive negotiations where firms offer favorable deals to counterparties to secure exclusive rights, consequently shaping both product availability and consumer prices. Despite their prevalence, exclusive contracts have been under regulatory scrutiny due to concerns about potential harm to small firms, new entrants, and consumers. For example, in 1948, the U.S. Supreme Court ruled against large studios' exclusion from distributing to small independent theaters.[1] More recently, exclusive contracts in the credit card, healthcare, and microprocessor markets have also been contested.[2]

In this paper, I examine who gains and who loses from exclusive contracts in the video streaming market, where consumers pay subscriptions to access digital content libraries offered by services like Netflix and Hulu.[3] Using new, highly detailed data from various sources, I conduct an in-depth analysis on this increasingly important market, which now accounts for over a quarter of television viewing time in the U.S. (Nielsen 2022). Exclusive contracts, where studios grant exclusive licensing rights for titles to streaming services, are prevalent here. For example, Netflix has exclusive rights to *Seinfeld* from Warner Bros. (Observer 2019). Consequently, 86.7% of titles from third-party studios are available on only one streaming service as of 2022. While such exclusive distribution can occur without exclusive contracts, these contracts are often used to ensure exclusive distribution.

Exclusive contracts are prevalent in the video streaming market due to two common forces that also apply to many other markets. The first is differentiation: streaming services use them to license exclusive content and differentiate from competitors. This effect softens competition and increases the joint profits to be shared between studios and streaming services, benefiting both parties but hurting consumers who must subscribe to multiple services to access all the content they want. This paper highlights a second force often overlooked by researchers: bargaining. Studios use exclusive

[1] See *United States v. Paramount Pictures, Inc.*, 334 U.S. 131 (1948).

[2] See *United States v. Visa U.S.A., Inc.*, 344 F.3d 229 (2003), *United States v. Dentsply Int'l, Inc.*, 399 F.3d 181 (2005), and *Federal Trade Commission v. Qualcomm, Inc.*, 935 F.3d. 752 (2019).

[3] In this paper, the term "video streaming" specifically refers to Subscription Video on Demand (SVOD), excluding services like YouTube and Amazon Rent or Buy. I discuss market definition in greater detail in Section 2.1.

contracts as a bargaining tool, committing to exclusive distribution to play streaming services off against each other and negotiate favorable deals. This practice results in hefty licensing fees, such as Netflix's \$100 million annual fee for the exclusive rights to *Friends* (Slate 2018).

Exclusive contracts have theoretically ambiguous effects on firms, as it is unclear how the effects of differentiation and bargaining net out. This is further complicated by the equilibrium effects, as a contract between one pair of firms can affect the payoffs of other firms (Segal 1999). The direction and magnitude of these equilibrium effects are unclear and depend on the substitutions between both titles and subscriptions. Consumers lose from exclusive contracts in the short term because they need to subscribe to more services to access desired content, driving up spending. However, in the long term, exclusive contracts may benefit consumers if they stimulate content production or entries of streaming services. While I do not directly model these factors, this paper sheds light on their potential by examining the profitability of studios and small streaming services.

To sort out these various effects, I develop and estimate a structural model that captures both forces of differentiation and bargaining in the formation of exclusive contracts. The model incorporates bilateral negotiations between streaming services and studios, subscription price setting by streaming services, and consumer demand for service subscriptions and titles. I estimate the model combining comprehensive data on viewership, subscription, and title availability.

To reflect the effect of differentiation, I integrate a model of demand for services subscriptions by households and titles by household members, along with a pricing model in which streaming services optimize payoffs. The demand model allows for concurrent subscriptions to multiple services, heterogeneous viewer preferences, and varying influences of household members on subscription decisions. Together with the profit margins recovered from the pricing model, the demand model helps determine the potential profits streaming services can derive from specific titles through incremental subscriptions, which are shared with studios in negotiations.

I estimate the demand model using subscription and viewership data. Subscription data detail market shares for various combinations of service subscriptions at the DMA-month level. The correlation between observed consumer multi-homing and changes in services' content libraries identifies substitutions between service subscriptions (Gentzkow 2007). I observe title viewership at the weekly level, segmented by demographics such as age, gender, and race. Variance in viewership across demographic groups identifies diverse streaming preferences, while its covariance with subscription data helps identify the differential influences of household members. Lastly, I exploit geographical variations in tax rates on service subscriptions to identify price elasticities, which inform the profit margins of subscriptions using the pricing model.

To reflect the effect of bargaining, I develop a bilateral bargaining model in which streaming services negotiate with studios over inclusion in the distribution networks of titles—–defined as the set of streaming services with licensing rights—–and lump-sum licensing fees. During negotiations, a studio can threaten to replace a streaming service with an excluded alternative service to improve its bargaining leverage and demand higher fees (Ho and Lee 2019). This model highlights that studios with weaker bargaining power benefit more from improving their bargaining leverage through such threats of replacement, and therefore, have stronger exclusionary incentives.

Data on title availability support this inverse relationship: the "Big Five" studios (NBCUniversal, Paramount, Warner Bros., Walt Disney, and Sony), generally perceived to have stronger bargaining power, exhibit a 3.7 percentage points lower likelihood of exclusive distribution compared to small studios. Therefore, I estimate bargaining power by searching for parameters that best explain the observed distribution networks. This novel approach requires only readily available data on title availability, bypassing the need for data on privately contracted, lump-sum licensing fees.

The estimation results find that the mean own-price elasticity of service subscriptions is −1.45. Compared to the "Big Five," small studios exhibit much lower bargaining power, leading to stronger exclusionary incentives to improve bargaining leverage.

I apply the model and estimates to evaluate the welfare effects of exclusive contracts by comparing the status quo to a counterfactual scenario where exclusive contracts are prohibited. This policy mirrors similar regulations in other markets, such as the U.K.'s ban on exclusivity clauses in employment contracts that restrict low-paid workers from working with multiple employers.

I find that the impact of exclusive contracts varies significantly across firms. On the streaming service side, small streaming services benefit substantially from exclusive contracts, with Hulu's payoff increasing by 110.7%, while large services see only modest or negative changes, with Netflix and Amazon Prime seeing an increase of 3.0% and a decrease of 9.4%, respectively. This disparity arises because small services lack in-house content and loyal subscribers, making them reliant on exclusive third-party titles for differentiation and competitiveness. In contrast, large services rely less on exclusive third-party titles, so their benefit from differentiation is limited and can be offset by a negative equilibrium effect from increased competition from small services, which use exclusive third-party content to attract previous subscribers from these large services.

On the studio side, the "Big Five" see a 5.4% loss from exclusive contracts, while small studios experience an 8.4% gain. Both groups face a negative equilibrium effect: exclusive contracts differentiate streaming services and reduce their substitution, which lessens their loss of subscribers when losing a title, and therefore, lowers their willingness to pay for titles. However, small studios, with weaker bargaining power, benefit more from using exclusive contracts as a bargaining tool. In addition, small services, with increased profitability, become credible leverage for small studios when negotiating with large services. Both factors improve small studios' bargaining leverage, leading to their gains. In contrast, the "Big Five," with their already strong bargaining power, do not benefit as much from the improved bargaining leverage, resulting in their overall loss.

Finally, exclusive contracts lead to an 9.9% drop in consumer welfare if title production and streaming service participation are held fixed. This loss results from reduced availability of titles and increased subscription prices. However, the positive impacts on small studios and streaming services may stimulate entry in both content production and streaming service sectors in the long run. Analyzing additional counterfactuals, I find that these increased entries may mitigate or even reverse the short-run negative impacts of exclusive contracts on consumers.

Contribution and Related Literature. This paper adds to the growing literature on exclusive contracts. The pro- or anti-competitive nature of exclusive contracts has long been a subject of debate. The Chicago School argues that exclusive contracts cannot be anti-competitive because firms would only adopt them if they are efficient (Bork 1978). Subsequent research has identified both positive and negative impacts of exclusive contracts. On the positive side, they can mitigate contracting externalities (Segal 1999), encourage investment (Segal and Whinston 2000), and stimulate market entry (Lee 2013, Le 2023). Conversely, they can soften competition (Rey and Stiglitz 1995, Nurski and Verboven 2016, Sinkinson 2020), deter or foreclose market entry (Bernheim and Whinston 1998, Asker 2016), and raise competitors' costs (Subramanian, Raju and Zhang 2013). Most of these papers employ offer or bidding games. In contrast, this paper extends the framework to a broader bargaining game, thereby highlighting the pivotal role of bargaining power in prompting exclusive contracts. In this context, this paper aligns with recent theoretical insights from Chambolle and Molina (2023) and Abreu and Manea (2024), who study capacity restriction as bargaining leverage by downstream and upstream firms, respectively. However, this paper goes beyond theoretical analysis by empirically investigating how bargaining power affects the formation of exclusive contracts and evaluating their welfare effects.

This paper contributes to the empirical literature on vertical contracting and bargaining. Observing detailed contractual terms, Mortimer (2007, 2008) and Ho, Ho and Mortimer (2012) study price discrimination restrictions, revenue sharing, and full-line forcing in the video rental market. Most research in this area (e.g., Draganska, Klapper and Villas-Boas 2010, Crawford and Yurukoglu 2012, Gowrisankaran, Nevo and Town 2015, Ho and Lee 2017, Crawford et al. 2018, Zhang and Chung 2020, Jiang 2022) adopts the "Nash-in-Nash" bargaining framework to model price negotiations, which assumes predetermined networks of agreements and requires negotiated prices as inputs. However, these conditions are not suitable for the video streaming market, where exclusive contracts can be strategically employed as a bargaining tool, and licensing fees are negotiated confidentially and paid as lump sums, making them neither observable nor inferable. Ho and Lee (2019) addresses the first limitation with the "Nash-in-Nash with Threat of Replacement" (NNTR) bargaining solution, allowing firms to use excluded counterparties to enhance their bargaining leverage. Hristakeva (2022a,b) adopt a similar approach to study slotting allowances in the retail market. To address both limitations, I extend NNTR to include endogenous network formation. Moreover, I identify bargaining power using only readily available network data, leveraging the relationship that firms with weaker bargaining power have stronger exclusionary incentives. Compared with alternative endogenous network formation models (e.g., Liebman 2018, Jindal and Newberry 2018, Zhang, Manchanda and Chu 2021, Ghili 2022), my approach does not assume fixed costs of bargaining to explain negotiation breakdowns and circumvents the need for negotiated prices, making it more widely applicable for studying contract negotiations in vertical markets.

This paper also adds to the literature on the emerging streaming industry, which has examined aspects such as video streaming's competition with traditional TV (Malone et al. 2021, McManus et al. 2022), consumer binge-watching behaviors (Lu, Karmarkar and Venkatraman 2019, Berbeglia et al. 2021), and content distribution strategies (Berbeglia, Derdenger and Tayur 2023). Research on music streaming has also developed (e.g., Aguiar and Waldfogel 2018, 2021, Datta, Knox and Bronnenberg 2018, Chou and Kumar 2022). Using distinctive data on subscriptions, viewership, and title availability, this study explores the competition and interactions across all major market stakeholders—content providers (studios), distributors (streaming services), and consumers.

Roadmap. The remainder of the paper proceeds as follows. Section 2 introduces industry practices of vertical contracting and develops a stylized model reflecting these practices. Section 3 details the data and descriptive analysis. In Section 4, I outline the framework of the empirical model, followed by its estimation in Sections 5 and 6. Section 7 presents counterfactual exercises along with their implications. Section 8 concludes.

2 Vertical Contracting in the Video Streaming Market

2.1 Industry Practices of Vertical Contracting

In this paper, I focus on the Subscription Video On Demand (SVOD) sector of the video streaming market. SVOD is a type of online video streaming service where users pay a subscription fee to access a digital content library. SVOD is considered a distinct market from transactional video on demand (TVOD) services like Amazon Rent or Buy, and advertising video on demand (AVOD) services such as YouTube, due to their different revenue models and content offerings. In addition, licensing agreements for these titles are negotiated and contracted independently, even for the same titles available on services operated by the same company, such as Amazon Rent or Buy and Prime Video. In the remainder of this paper, I use "video streaming" and "SVOD" interchangeably.

The video streaming market has gained significant traction, rivaling traditional cable TV in viewership (Nielsen 2022). This paper focuses on four leading streaming services—Netflix, Amazon Prime Video, Hulu, and Disney Plus—from March 2021 to February 2022. In this period, these services dominated the market, claiming about 75% of the total SVOD screen time and expenditure in the US (CEPro 2021, Wall Street Journal 2021).[4]

To fuel their growth and differentiate from their competitors, streaming services have sought to offer unique content, including exclusive licensing rights from third-party studios and original productions. Despite a surge in original content provisions, third-party content remains a cornerstone,

[4] During the study period, the fifth largest service, HBO Max, only has a market share about half of the fourth largest service, Disney Plus. The market shares of these top four streaming services have been declining since, due to the entry and growth of smaller competitors such as Apple TV Plus, Peacock, and Paramount Plus.

constituting nearly 60% of the top 2000 titles on these services, according to my data.[5] 86.7% of these third-party titles are exclusively available on a single service. Together with in-house titles, they lead consumers to multi-home across streaming services to access content they are interested in, with my data showing that the average US household subscribed to 1.7 of the four leading services during the study period.

In the video streaming market, vertical contracting typically operates as follows. Licensing negotiations these third-party titles typically occur on a per-title basis, with most contracts outlining exclusive rights and *lump-sum* fees. There is typically no revenue-sharing provision between studios and streaming services, even for advertising revenues.[6] Contracts usually last for a year, though sometimes can span to three years, with rare opportunities for renegotiation.

The widespread adoption of exclusive contracts also has significant effects on the bargaining and contracting dynamics between streaming services and production studios. During negotiations, studios strategically use threats of exclusion and replacement to negotiate more favorable licensing deals. By restricting contracts to exclusive licensing, studios often go back and forth between streaming services, compelling them to make competitive offers to outbid their rivals. This practice often results in substantial licensing agreements. Notable examples include Netflix's $100 million annual exclusive agreement for *Friends* in 2019 and *Seinfeld* from 2021 onwards (Slate 2018, Observer 2019). Amazon, in 2023, made a substantial $90 million offer for exclusive rights to *Crime 101* and a multi-million dollar bid for *Sound of Freedom* (Screen Rant 2023, Vulture 2023).

In this paper, I do not address the impact of exclusive contracts on title production, primarily due to significant capacity constraints during the research period. Because of the surge in title production induced by exploding demand following COVID-19, no studio had the capacity to produce additional shows within a 2-3 year time frame from the study period. This widespread capacity restriction justifies the assumption of a fixed set of titles in the market for the duration of this study.

[5]Titles whose intellectual properties are completely owned by the streaming services, but are produced by third-party studios are not counted as third-party titles. For example, *The Sandman* is produced by Warner Bros., but its intellectual property is controlled by Netflix. Such titles involve the streaming services bearing all production costs plus a 20-30% premium. However, no recurring licensing contracts are needed.

[6]Additional references on licensing payments can be found in the investor question section on Netflix's website: `https://ir.netflix.net/ir-overview/top-investor-questions/default.aspx`. While Amazon pays some independent titles based on viewership via Prime Direct, it primarily offers lump-sum payments for licensing more popular titles, which account for the majority of licensing fees and are the main focus of this paper.

2.2 A Stylized Model of Vertical Contracting

In this subsection, I present a stylized model of vertical contracting to illustrate the formation of exclusive agreements and their market efficiency implications. Consider a market with one studio, j, and two streaming services, k_1 and k_2, playing a two-stage game as follows:

- **Stage 1** (Bilateral Contracting): Studio j chooses a set of streaming services to reach licensing agreements with. Each contract is negotiated bilaterally, includes a *lump-sum* licensing fee τ, and specifies whether the licensing right is exclusive.
- **Stage 2** (Downstream Competition): k_1 and k_2 compete downstream and realize sales profits. These profits are denoted as Π_1^e and Π_2^e when the title is only on each of the services, and as Π_1^{ne} and Π_2^{ne} when on both services.

Figure 1 illustrates the game. I use pure-strategy weak perfect Bayesian equilibrium as the equilibrium concept. Players are assumed to hold "passive beliefs," meaning that even when acting off the equilibrium path, a player maintains the belief that other players will continue to reach the equilibrium contracts.[7] In addition, to refine equilibrium outcomes, I assume that either party may terminate a bilateral contract at will, following Ho and Lee (2019).

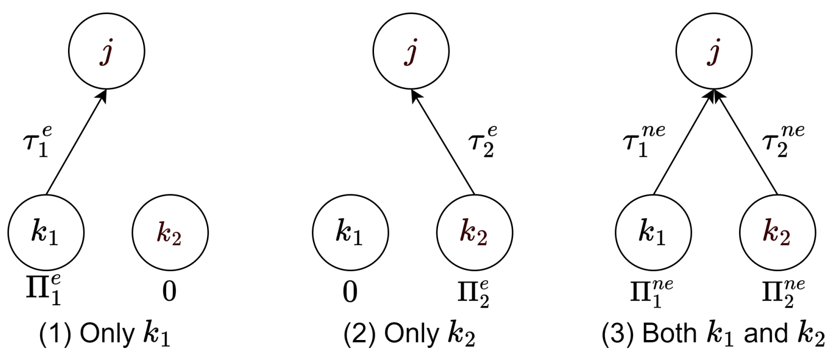


Figure 1: Market Outcomes Under Various Distribution Networks

Bilateral Contracting Outcome in Equilibrium. As highlighted in the industry background, studios leverage exclusive contracts as a bargaining tool, playing streaming services off against each other to negotiate more favorable licensing deals. To capture this market feature, I adopt the

[7]This assumption of passive belief limits changes in beliefs following actions that deviate from the equilibrium path, as noted in Collard-Wexler, Gowrisankaran and Lee (2019). It is a widely adopted assumption in both theoretical (e.g., McAfee and Schwartz 1994, Segal 1999) and empirical literature (e.g., Draganska, Klapper and Villas-Boas 2010, Gowrisankaran, Nevo and Town 2015, Ho and Lee 2017, 2019) on vertical contracting.

Nash-in-Nash with Threat of Replacement (NNTR) bargaining solution from Ho and Lee (2019) to determine the negotiations of licensing fees.

When studio j intends to only license to k_1, the NNTR solution of the licensing fee is

$$\tau_1^e = \arg\max_{\tau} (\tau)^b (\Pi_1^e - \tau)^{(1-b)} \text{ s.t. } \tau \geq \Pi_2^e, \tag{1}$$

where $b \in [0, 1]$ represents studio j's bargaining power against streaming services. The bargaining outcome maximizes the Nash product of gains-from-trade received by j and k_1, which are τ and $\Pi_1^e - \tau$, respectively, subject to a constraint. This constraint $\tau \geq \Pi_2^e$ highlights the studio's ability to improve bargaining leverage through exclusive distribution. By committing to only license to one streaming service, the studio can go back and forth between k_1 and k_2, using the offer from k_2 as leverage when bargaining with k_1. This approach ensures that the payment from k_1 matches or exceeds the highest possible offer of Π_2^e from k_2, under which k_2 would break even.

I assume, without loss of generality, that $\Pi_1^e > \Pi_2^e$, indicating that k_1 can generate more profit than k_2 when the title is solely available on each respective service. Therefore, studio j must not enter into an agreement with k_2 alone. This is because k_1, being more efficient, is always willing to offer slightly more than Π_2^e, outbidding k_2's maximum offer of Π_2^e while maintaining positive payoff.

When studio j negotiates non-exclusive contracts with both k_1 and k_2, it lacks an outside option to use as leverage. Therefore, the NNTR solution default to the "Nash-in-Nash" bargaining solution, specified as

$$\tau_k^{ne} = \arg\max_{\tau} (\tau)^b (\Pi_k^{ne} - \tau)^{(1-b)}, k \in \{1, 2\}. \tag{2}$$

Building upon Ho and Lee (2019), I then analyze the conditions that give rise to the formation of exclusive contracts. The total licensing fees for studio j is:

$$\Pi_j(\mathcal{K}_j) = \begin{cases} \max\{b\Pi_1^e, \Pi_2^e\}, & \mathcal{K}_j = \{k_1\} \\ b \cdot \Pi_1^{ne} + b \cdot \Pi_2^{ne}, & \mathcal{K}_j = \{k_1, k_2\} \end{cases}, \tag{3}$$

where $\mathcal{K}_j$ refers to the *distribution network*, the set of streaming services licensing the title.

Exclusionary Incentives of Studios. As the owner of the title, the studio has the discretion to choose a distribution network. Therefore, it will opt for the exclusive distribution network, which may be facilitated through an exclusive contract, if and only if it generates a higher payoff than the non-exclusive network: $\max\{b\Pi_1^e, \Pi_2^e\} \geq b \cdot \Pi_1^{ne} + b \cdot \Pi_2^{ne}$.

This condition breaks down into two scenarios. The first scenario is when the joint profit for the bargaining parties is higher if the title is distributed exclusively to k_1,

$$\Pi_1^e \geq \Pi_1^{ne} + \Pi_2^{ne}. \tag{4}$$

This condition implies that exclusive contracts can improve contracting efficiency by allowing the studio to commit to a distribution network that maximizes joint profits to be divided between itself and the contracting streaming services. Similar insights are also discussed by Bernheim and Whinston (1998), Segal (1999), among others.

The other scenario is when the studio has weak bargaining power so that it finds profitable to exclude k_2 and use it as bargaining leverage to acquire more surplus from k_1,

$$\underbrace{\Pi_2^e - b \cdot \Pi_1^{ne}}_{\substack{\text{Gain from Improved} \\ \text{Bargaining Position}}} \geq \underbrace{b \cdot \Pi_2^{ne}}_{\substack{\text{Loss from} \\ \text{Exclusion}}} \implies b \leq \frac{\Pi_2^e}{\Pi_1^{ne} + \Pi_2^{ne}}. \tag{5}$$

This condition illustrates the role of bargaining in the formation of exclusive contracts. By excluding k_2 from its distribution network $\mathcal{K}_j$, the studio can use k_2 as leverage to strengthen its bargaining position against k_1. This allows the studio to charge a licensing fee of at least Π_2^e from k_1, instead of $b \cdot \Pi_1^{ne}$ when the title is distributed to both services. Using this tactic, the studio effectively shifts the surplus division with k_1 in its favor, even when the exclusive network is less jointly profitable.

Moreover, condition (5) suggests a negative correlation between bargaining power and exclusionary incentive. A studio with strong bargaining power does not rely on exclusion to improve its bargaining position, as indicated by the decreasing gain from exclusion in (5), $\Pi_2^e - b \cdot \Pi_1^{ne}$. In addition, the studio's loss from excluding k_2, $b \cdot \Pi_2^{ne}$, increases with its bargaining power.[8]

[8] I extend this model to allow streaming services to have heterogeneous bargaining parameters in Appendix B.1. Similar intuitions still hold.

3 Data and Descriptive Evidence

3.1 Data

This study utilizes a wide variety data with three main categories: (a) title viewership and characteristics, (b) title production and availability, and (c) prices and quantities of service subscriptions. The data include the top four streaming services—Netflix, Amazon Prime Video, Hulu, and Disney Plus—covering the period from March 2021 to February 2022. I briefly discuss each in turn.

Title Viewership and Characteristics. I draw on two data sources for viewership statistic and characteristics. The primary source is Nielsen's title rating data. This dataset provides weekly figures on time spent by U.S. individuals aged two years and above for each title on the top four streaming services, with demographic breakdowns by age, gender, and race.[9] I supplement it with title characteristics data from Reelgood, which offer information on title characteristics such as release dates and the most related genre. Genres are aggregated into six major categories: action, comedy, horror and thriller, kids, drama, and others.

The final sample includes 2,028 of the most popular titles across the top four streaming services. Inclusion criteria are based on a title's maximum or average weekly rating falling within the top quintile on at least one service. This sample, which accounts for 91% of total viewership on these platforms, includes 1,399 titles from Netflix, 280 from Amazon, 310 from Hulu, and 229 from Disney Plus, highlighting its comprehensiveness for the study.

Title Availability and Production. Reelgood provides data on both title migration history and production. The first include daily updates on title availability on the top four streaming services, while the latter detail information on production studios and distributors.[10] Titles produced by a streaming service or solely distributed through streaming on a single service worldwide are considered in-house, with intellectual properties typically fully controlled by the streaming service. All other 1,145 titles (59.0%) are defined as third-party titles. Licensing negotiations between streaming services and studios only involve these third-party titles.[11]

[9]Industry experts widely regard Nielsen's ratings as the most accurate market data, aligning well with streaming services' internal data. For a more detailed introduction to Nielsen data, see Appendix C.1.

[10]I scraped production studio information from IMDB for titles lacking this information from Reelgood. However, 88 titles in the final sample still have missing production company information.

[11]The summary statistics of the characteristics, viewership, and availability of titles are reported in Table A.1.

Data highlight the prevalence of exclusive distribution: among the 1,145 third-party titles, 993 (86.7%) of them are on only one streaming service.[12] In contrast, only 125 (10.9%) and 27 (2.4%) of them are available on two and three services, respectively.

Quantities and Prices of Service Subscriptions. Data on service subscriptions come from two sources. The Nielsen Household Universe Estimates dataset provides aggregated monthly figures on household subscriptions in the 30 most populous DMAs. Figure A.5 presents a map of these DMAs, which cover 55% of U.S. households in total.

A distinctive advantage of this dataset is the detailing of household subscriptions to service bundles, defined as unique combinations of the top four streaming services. For example, it reports how many households in the Atlanta DMA subscribed to Netflix and Hulu but not to Amazon Prime and Disney Plus in June 2021.[13] This unique feature enables an analysis of the prevalent consumer multi-homing behavior in the video streaming market.

Subscription prices are collected through online price increase announcements. During the study period, Netflix, Hulu, and Disney Plus raised their subscription prices by \$1 to \$2, whereas Amazon Prime Video's subscription price remained at \$8.99.

3.2 Descriptive Evidence on Title Availability

Bargaining as an Exclusionary Incentive. The stylized model highlights that studios with weaker bargaining power have a stronger exclusionary incentive to improve its bargaining leverage. This leads to the question: "Do studios' distribution network choices depend on their bargaining power in practice?" Affirmative evidence would support the model's applicability.

To answer this question, I compare the likelihood of exclusive distribution for titles produced by the "Big Five" versus small studios. The "Big Five," which produce almost half of the sampled third-party titles (46.1%) and are known for extensive bargaining experiences, are expected to possess stronger bargaining power.[14] I find that 15.2% titles produced by the "Big Five" are available on

[12] 222 titles (10.9%) in the final sample migrated across streaming services at least once during the study period. To simplify the analysis, a title's distribution network is defined by the unique combination of streaming services where it has the longest period of availability during the study period.

[13] To validate the data's accuracy, I matched Nielsen's national subscriber counts for each streaming service with those reported by the services themselves. Further details on this alignment are discussed in Appendix C.2.

[14] This assumption is supported by Crawford and Yurukoglu (2012), who find that large channels (content providers) have stronger bargaining power than the small ones in the cable TV market, using Nash-in-Nash bargaining model.

multiple streaming service, compared to only 11.5% for small studios. This difference implies a substantial distinction in the contracting strategies of the "Big Five" and small studios.

This difference remains consistent after controlling for title characteristics, estimated using the following regression:

$$E_j = \beta_0 + \beta_1 \cdot \text{BigFive}_j + \beta_2 \mathbf{X}_j + \varepsilon_j, \tag{6}$$

where E_j and BigFive_j are binary indicators of whether titles are available on only one streaming service and whether they are produced by one of the "Big Five" studios, respectively. $\mathbf{X}_j$ includes title characteristics including release years, type (movie or TV show), and genres. The regression results are presented in Column (1) of Table 1. This regression is used as an indirect inference moment when estimating the structural model.

Table 1: Distribution Networks of Titles

	(1) Exclusive Distribution			(2) Contract between Service-Title Pairs		
	Estimate	SE		Estimate	SE	
Big Five	−0.038	0.019	**			
Disney's Studio				−0.236	0.034	***
Disney's Studio × Hulu				0.709	0.056	***
Other Controls	Title Chars			Streaming Service FE		
Observations	1145			3435		

Notes. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Differential Reliance on Third-Party Titles by Streaming Services. Third-party titles are crucial to Netflix, Amazon, and Hulu, contributing 66.3% of the titles in their content libraries and 69.0% of their total viewership. Notably, Disney Plus primarily collaborates with Walt Disney-operated studios like Pixar and Marvel, and rarely engages in licensing third-party titles.

However, streaming services' reliance on third-party titles varies. In Figure 2, I show the share of titles licensed from third-party studios for each streaming service, as well as the share of viewership they contribute. Hulu relies most heavily on third-party content, with such titles accounting for more than 90% of its content library and viewership. Thanks to its substantial in-house content, Netflix is the least dependent on third-party titles.

Interestingly, Figure 2 shows that nearly all third-party titles on Netflix are exclusively dis-

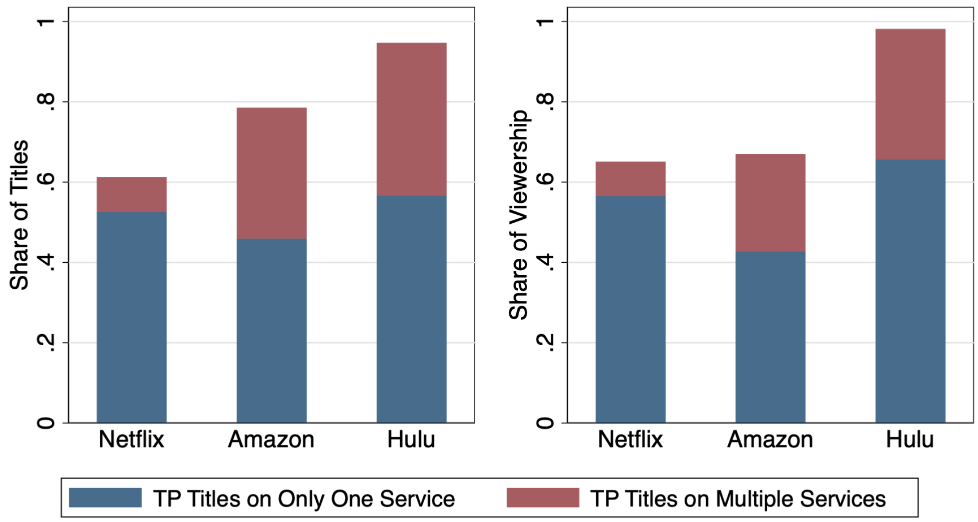


Figure 2: Reliance on Third-Party Titles Across Streaming Services

Notes. This figure displays the share of third-party titles that are exclusively distributed versus those that are not, as well as their respective contributions to the total viewership on each streaming service.

tributed, while many on Amazon Prime and Hulu are available on multiple services. This aligns with studios' motives to maximize joint profits when choosing distribution networks, as discussed in the stylized model. The joint profits primarily come from attracting new subscribers who do not already subscribe to any licensed services. Since only 26.3% of households have no subscriptions to both Netflix and Amazon Prime, licensing a title to both services would attract few new subscribers to either of them, rendering such arrangements unprofitable. The same logic applies to Netflix and Hulu. However, 41.6% of households do not subscribe to both Hulu and Amazon Prime, making distribution to both services potentially profitable due to the higher number of potential new subscribers.

Effect of Vertical Integration. Data reveal that studios often foreclose competing streaming services of their vertically integrated services when licensing titles.[15] During the study period, Hulu—under Disney's control—was the only top streaming service vertically integrated with non-in-house studios.[16]

Figure 3 shows that Disney-affiliated studios are more likely to license titles to Hulu compared to

[15]Vertically integrated streaming services must negotiate and pay for titles from studios they control but do not operate directly. For instance, Hulu must negotiate and pay for titles from ABC, even though both are owned by The Walt Disney Company.

[16]Amazon's acquisition of MGM was completed in March 2022, one month after the conclusion of the study period.

its competitors, Netflix and Amazon Prime, compared with other studios. This finding is confirmed by the following regression:

$$L_{jk} = \beta_0 + \beta_1 \cdot \text{WaltDisney}_j + \beta_2 \cdot \text{WaltDisney}_j \cdot \mathbf{1}(k = \text{Hulu}) + \delta_k + \varepsilon_{jk}, \tag{7}$$

where L_{jk} and WaltDisney_j are binary indicators of whether title j is licensed to service k, and if it is produced by Walt Disney, respectively. δ_k refers to service fixed effects. I present the estimation results in Column (2) of Table 1, and use this regression as an indirect inference moment in structural estimation. The finding implies that Disney-affiliated studios consider Hulu's benefit when selecting distribution networks, highlighting the impact of vertical integration on bargaining outcomes.

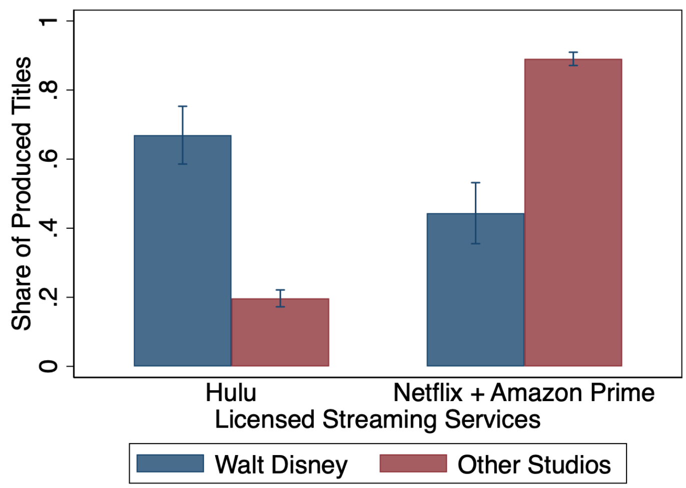


Figure 3: Choices of Licensees: Walt Disney vs. the Others

Notes. This figure displays the likelihood of distributing to Hulu and its competitors, Netflix and Amazon Prime, by Walt Disney and all other studios. The vertical segments delimit the 95% confidence intervals.

3.3 Descriptive Evidence on Consumer Demand

The Effects of Taxes and Household Sizes. Households face tax rates on their subscriptions, which vary significantly across the nation. Most states impose a sales tax on streaming subscriptions, but states like California, New York, and Utah, do not levy taxes.[17] States and cities may impose unique taxes. Florida, for example, charges a communication services tax of up to 15% in some

[17]New York State started taxing Netflix subscriptions from December 2021 due to Netflix's introduction of games, though other streaming services remained tax-exempt.

counties.[18] I collect tax rates combining data from Bloomberg tax, Thomson Reuters' Tax Data Systems, and government websites.[19] Figure A.7 displays average tax rates across the top 30 DMAs.

High tax rates make subscriptions more expensive for consumers, suppressing their demand. However, larger households often show stronger preferences for service subscriptions because the subscription can be shared among all household members, making it more valuable for them.

Therefore, I investigate the correlation between service subscription demand and two factors: tax rates and household sizes, in Figure 4, where each dot represents a unique DMA. The analysis reveals substantial geographical variation in demand: the average number of service subscriptions per household varies from 1.39 in Miami to 1.91 in Salt Lake City. In addition, there is a negative association with tax rates and a positive one with household size, highlighting their significant impacts on subscription choices.[20]

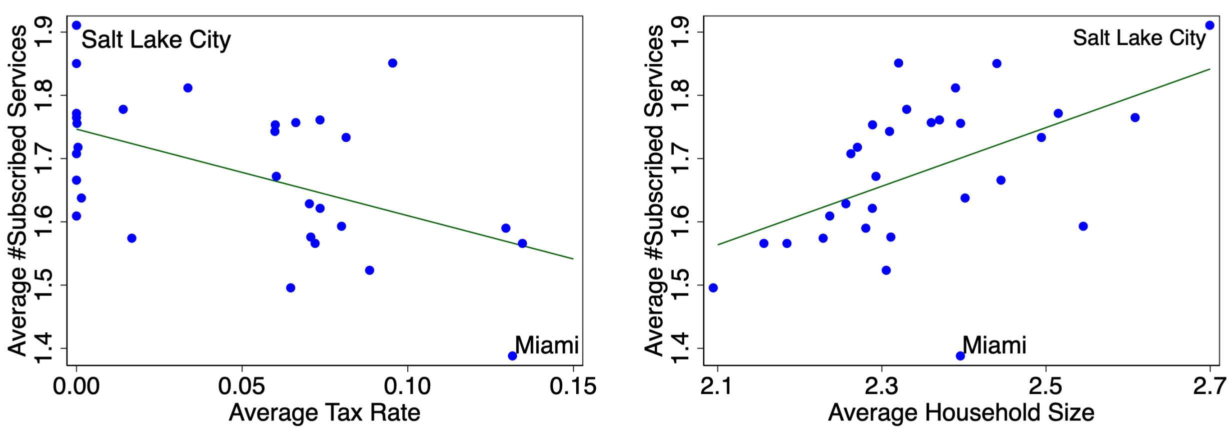


Figure 4: Demand for Streaming Service Subscriptions

Notes. This figure reports the correlation between the average numbers of subscribed services per household and two factors: tax rates and household sizes. The tax rate for a DMA is computed as the average of ZIP-code-level tax rates, weighted by their populations. Each dot corresponds to the average values of the variables in each of the top 30 DMAs during the study period. The green lines depict the first-order polynomial fits between the variables.

[18] Other notable examples include Chicago, which imposes a 9% amusement tax on streaming subscriptions, though Illinois does not apply a sales tax on streaming service subscriptions.

[19] To gather data on tax rates, I first use Bloomberg tax to determine the tax categories applied in each state and major city. Then, I collect ZIP-code and month-level tax rates from Thomson Reuters' Tax Data Systems for states that impose sales taxes on streaming subscriptions. The Thomson Reuters data are also used by Houde, Newberry and Seim (2023) to analyze the effect of nexus tax laws on the expansion of Amazon's fulfillment center network. For special cases like Florida, relevant information was gathered from respective state or local government websites.

[20] A regression analysis on service subscription demand with additional dependent variables is presented in Table A.2. It shows the the correlations between consumer demand and both tax rates and household sizes are significant at 5% level.

Heterogeneous Streaming Preferences and Decision-Making Power. Viewership patterns vary significantly across demographic groups, reflecting diverse streaming preferences. Figure 5 shows the average weekly streaming time by genre for three demographic cohorts: male adults, female adults, and children. Female adults and children are more engaged in streaming than male adults, spending at least 20% more time. In addition, they exhibit distinctive genre preferences: Kids prefer kid shows and dramas over comedies, while male adults favor horror and thriller titles more than female adults. This preference heterogeneity extends across age and racial groups, as shown in Figures A.3 and A.4.

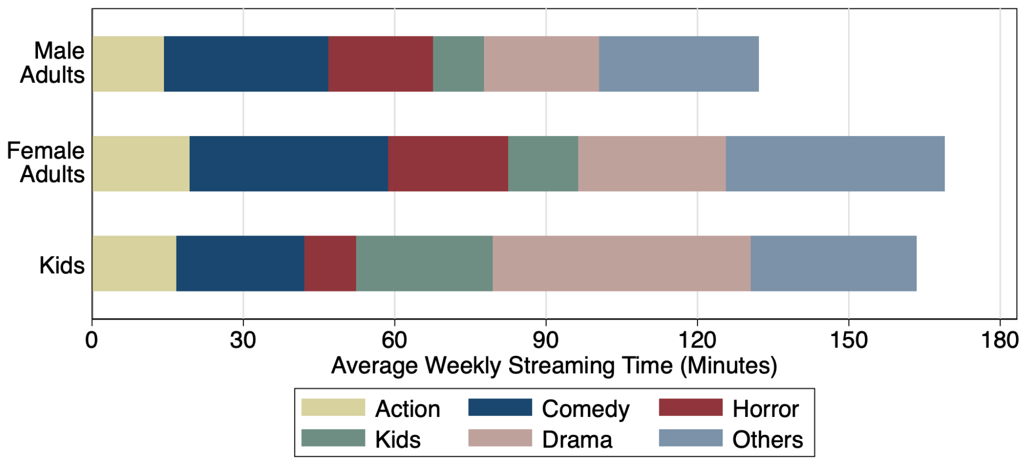


Figure 5: Average Weekly Streaming Time by Genre and Demographic Group

Notes. This figure displays the average weekly streaming time across six different genres for U.S. individuals, categorized into three demographic groups: male adults, female adults, and kids (age 2–17).

In addition, the observation of kids' strong preferences for streaming challenges the likelihood of equal decision-making power among household members on subscription choices, which implies that they may have stronger influence than their parents. To rectify this, I incorporate differential decision-making power within the household in the structural model.

4 Model

This section introduces a model that consists of both demand and supply, where studios, streaming services, and consumers make decisions according to the following timing. On the supply side, in stage 1, streaming services bilaterally bargain with studios over inclusion in distribution networks of titles and licensing fees, while setting subscription prices simultaneously. On the demand side, in stage 2, households make monthly subscriptions to bundles of streaming services. Finally, in stage 3, each household member selects titles available on the subscribed services to watch. I present the model in reverse order of timing and discuss the key assumptions at the end of this section.

4.1 Demand

A key output from the demand model is the impact of title availability change on demand for service subscriptions. This in turn defines the incentives of forming a contract and the profits to be divided in negotiations between studios and streaming services. The estimation of this output necessites the modeling of demand for both service subscriptions and titles.

The demand model employs the following key notations: households and their members are indexed by h and i, respectively; titles by j; streaming services by k; and weeks by w. A bundle, representing a unique combination of the top four streaming services, is denoted as c. A market, defined as a DMA-month combination, is denoted by m. The content library of streaming service k at week w, comprising the set of available titles, is denoted by $\mathcal{J}_{kw}$.

4.1.1 Stage 3: Title Viewership

In each 30-minute period t during week w, each individual i considers which title to watch. Her utility from watching title j is specified as

$$u_{ijt}^{T} = \beta_i^0 + \boldsymbol{g}_j \boldsymbol{\beta}_i^g + smr_{w(t)} \beta_i^{smr} + \mathbf{w}_{jw(t)} \boldsymbol{\beta}^{\mathrm{w}} + \zeta_{jw(t)} + \epsilon_{ijt}, \tag{8}$$

where β_i^0, $\boldsymbol{\beta}_i^g$, and β_i^{smr} represent individual preferences for streaming in general, different genres $\boldsymbol{g}_j$, and streaming during summer seasons $smr_{w(t)}$, respectively. $\mathbf{w}_{jw}$ denotes title j's characteristics at week t, including time since release and title fixed effects. For shows, it also includes a dummy for binge release. The preferences for $\mathbf{w}_{jw}$, denoted as β^{w}, can vary between shows and movies. ζ_{jw} represents characteristics observed by consumers but not econometricians. ϵ_{ijt} are individual preference shocks that are i.i.d. T1EV distributed. The utility of choosing the outside option is normalized as $u^T_{i0t} = \epsilon_{i0t}$. I specify random coefficients that vary across individuals as

$$\begin{gathered}\beta_i^0 = \beta^0 + \boldsymbol{\pi}^0 d_i + \sigma^0 v_i^0, \;\; v_i^0 \sim N(0,1), \\ \boldsymbol{\beta}_i^g = \boldsymbol{\beta}^g + \boldsymbol{\pi}^g d_i, \text{ and } \beta_i^{smr} = \beta^{smr} + \pi^{smr} d_i,\end{gathered} \tag{9}$$

where d_i denotes demographic variables, including age (2–17, 18–44, and 45+ years old), gender (male and female), and race (white, African American, and others). v_i represents unobserved demographics that follow a standard normal distribution.

I assume that individuals can stream up to 50 hours a week. A viewer chooses the title that maximizes her utility among all the titles available on the streaming services to which she subscribes in every 30-minute interval.[21] Assuming individual preference shocks ϵ_{ijt} are i.i.d. T1EV distributed, the market share of title j at week w among subscribers to service bundle c is

$$s^T_{jw|c} = \int s^T_{ijw|c} dF(\boldsymbol{\beta}_i^g, \beta_i^0) = \int \frac{\exp\left(\beta_i^0 + \mathbf{g}_j \boldsymbol{\beta}_i^g + \mathbf{w}_{jw}\boldsymbol{\beta}^{\mathrm{w}} + \zeta_{jw}\right)}{1 + \sum_{j' \in \mathcal{J}_{cw}} \exp\left(\beta_i^0 + \mathbf{g}_{j'} \boldsymbol{\beta}_i^g + \mathbf{w}_{j'w}\boldsymbol{\beta}^{\mathrm{w}} + \zeta_{j'w}\right)} dF(v_i^0, d_i), \tag{10}$$

where $\mathcal{J}_{cw} = \cup_{k\in c}\mathcal{J}_{kw}$ represents the collection of titles available on all streaming services within bundle c, and $F(\cdot)$ is the probability density function.

4.1.2 Stage 2: Streaming Service Subscriptions

At the beginning of each month, household h decide which bundle of streaming services to subscribe to. I specify household h's utility conditional on subscribing to bundle c as

$$u^S_{hcm} = V_{hcm}\alpha^V - p_{hcm}\alpha^p_h + \mathbf{x}_{cm}\boldsymbol{\alpha}^{\mathrm{x}} + \xi_{cm} + \varepsilon_{hcm}. \tag{11}$$

The first component, $V_{hcm}\alpha^V$, corresponds to utility derived from content offered by services in bundle c. V_{hcm} represents the household's utility from viewing these content, and α^V represents its marginal impact perceived by the household when making subscription choice. V_{hcm} is defined as

$$V_{hcm} = \sum_{i\in h} \kappa_i \sum_{t\in m} \mathbf{E}_\epsilon \left[\max\nolimits_{j\in\{0,\mathcal{J}_{ct}\}} u^T_{ijt}\right], \tag{12}$$

where the expression is a weighted sum of the expected value derived by each household member

[21] A viewer derives the same utility from viewing a title, regardless of the service she streams on.

from the outside option and viewing content on their subscribed streaming services, $\mathcal{J}_{cw}$, during all time periods t within the month. This expected value, $\sum_{t \in m} \mathbf{E}_{\epsilon}[\max_{j \in \{0, \mathcal{J}_{ct}\}} u^T_{ijt}]$, is scaled by predetermined weights κ_i, which represent the decision-making power of i within the household. I assume κ_i varies across three age-gender groups: male adults, female adults, and children.

The second element in the utility function, denoted as $p_{hcm}\alpha^p_h$, corresponds to the disutility derived from paying price p_{hcm}. The prices paid by households include taxes imposed on service subscriptions, and therefore, vary by households based on their residential locations. The price coefficient α^p_h is formulated as $\alpha^p_h = \alpha^p + \pi^p_{inc} \cdot inc_h$, where inc_h represents household income.

Other elements of the subscription utility function (11) are as follows. $\mathbf{x}_{cm}$ includes three dummies. The first two, for Amazon Prime Video and Hulu, control for additional utilities from add-on channels, with the Amazon dummy also accounting for broader Prime benefits. The last dummy is for bundles that include both Hulu and Disney Plus, controling for the impact of Walt Disney's promotional strategy that markets these two services as a combined package.[22] ξ_{cm} represents bundle-market deviations that are observed by households but not by econometricians. ε_{hcm} represents household preference shocks. The value of the outside option is normalized to $u_{h0m} = \varepsilon_{h0m}$.

Under the assumption that ε_{hcm} is i.i.d. T1EV, the probability that household h subscribes to streaming service bundle c in market m is

$$s^S_{hcm} = \frac{\exp\left(V_{hcm}\alpha^V - p_{cm}(1+\tau_h)\alpha^p_h + \mathbf{x}_{cm}\boldsymbol{\alpha}^{\mathrm{x}} + \xi_{cm}\right)}{1 + \sum_{g \in \mathbf{C}} \exp\left(V_{hgm}\alpha^V - p_{gm}(1+\tau_h)\alpha^p_h + \mathbf{x}_{gm}\boldsymbol{\alpha}^{\mathrm{x}} + \xi_{gm}\right)}, \tag{13}$$

where $\mathbf{C}$ is the set of all bundles that households can choose from. The market share for bundle c is then $s^S_{cm} = \int s^S_{hcm} dF(\{V_{hgm}, \forall g \in \mathbf{C}\}, inc_h)$. Combining it with the conditional title share (10), the unconditional market share of title j is

$$s^T_{jw} = \int \sum_{c \in \mathbf{C}} \mathbf{1}(j \in \mathcal{J}_{ct}) \cdot s^S_{h(i)cm(w)} \cdot s^T_{ijw|c} dF(s^S_{hcm}, v^0_i, d_i), \tag{14}$$

Substitution between Service Subscriptions. The degree of substitutability or complementarity between the four streaming services is determined by the added utility of consuming all services $k \in c$ together, compared to each individually: $u_{hcm} - \sum_{k \in c} u_{hkm}$ (Gentzkow 2007). A positive added

[22] Notably, households can also gain access to ESPN Plus when subscribing to the bundle of Hulu and Disney Plus.

utility implies that these service subscriptions are complements, otherwise, they are substitutes.

Three components of the model determine this added utility. The first is the decreasing marginal utility perceived by individual viewers from accessing more content, which is determined by the substitution between titles. This substitution is captured by the random coefficients in the viewership utility model (8). The second component is the parameters of bundle-specific dummies. For example, a positive parameter of the Hulu and Disney Plus bundle implies additional utility from subscribing to both services, such as free access to ESPN Plus. Finally, the added utility also depends on the value of unobserved demand shocks, ξ_{cm} and $\{\xi_{km}, \forall k \in c\}$.

4.2 Supply

In stage 1, studios and streaming services engage in bilateral contract negotiations, while streaming services set subscription prices simultaneously. I assume that bilateral contracts and subscription prices are optimal with respect to each other in equilibrium. I now discuss the optimality conditions for subscription price setting (given bilateral contracts) and bilateral contracting (given subscription prices), respectively.

4.2.1 Stage 1b: Subscription Price Setting

In the first stage, the owners of the four streaming services simultaneously set monthly prices to maximize their payoff functions, which are defined as

$$\Pi_K = \sum_{k \in O_k} \sum_{m} M_m \cdot (p_{km} + a_k - mc_k + \lambda_k) \cdot \mathbf{E}_{\zeta,\xi}[s^S_{km}(p_{km}, \mathcal{J}_k)] - \sum_{k \in O_k} \sum_{j \in \mathcal{J}_k} \tau_{jk}, \tag{15}$$

where the first component accounts for the expected benefits from consumer subscriptions, and the second for lump-sum licensing fees, τ_{jk}, paid for all licensed titles $j \in \mathcal{K}_k$. O_k represents the three owners of the top four streaming services, including the Walt Disney Company that owns both Hulu and Disney.[23] M_m represents the number of household. p_{km} and a_k represent k's price and advertising revenue per subscriber, respectively. The marginal cost mc_k includes data transfer costs and, for Amazon and Walt Disney Company, lost revenue from DVD sales and

[23] Though Comcast owned 33% stake in Hulu during the study period, it relinquished its control in Hulu to Disney effectively on May 14, 2019.

rentals.[24] The parameter $\lambda_k > 0$ reflects the importance of market share in k's decision-making, as investors and managers often prioritize market shares and growth of streaming services over short-term profitability.[25] a_k, mc_k, and λ_k are assumed to be constant across all markets for each service.

I assume that streaming services consider the expected market shares $\mathbf{E}_{\zeta,\xi}[s^S_{km}(p_{km}, \mathcal{J}_k)]$, when setting prices. This approach contrasts with the common assumption in the literature, where firms consider realized market shares. The rationale for this assumption is that price changes are usually determined and pre-announced long before implementation. Consequently, at the time of pricing, streaming services do not know the exact values of the unobserved demand shocks, ζ and ξ, but only their distributions, F_ζ and F_ξ.

In practice, subscription prices are uniform nationwide and rarely adjusted over time.[26] To capture this feature, I utilize the necessary conditions on the optimality of pricing: no streaming service can improve its payoff by changing its subscription prices uniformly across all months and markets. This results in the following pricing first-order conditions:

$$\sum_m M_m \cdot \mathbf{E}_{\zeta,\xi} s^S_{km} + \sum_m \sum_{k' \in O_k} M_m \cdot (p_{k'm} + a_{k'} - mc_{k'} + \lambda_{k'}) \frac{\partial \mathbf{E}_{\zeta,\xi} s^S_{k'm}}{\partial p_{km}} = 0. \tag{16}$$

4.2.2 Stage 1a: Bilateral Contracting

In the bilateral contracting stage, for each title j, its production studio decides the set of streaming services it intends to reach agreement with, denoted as distribution network $\mathcal{K}_j$. The studio then engages in bilateral negotiations with the services in the distribution network to determine both the inclusion in the network and a corresponding *lump-sum* licensing fee τ_{jk}. In this model, all third-party titles licensed by Walt Disney are distributed to Hulu, as Disney Plus seldom licenses titles from third-party studios.[27]

[24] Chapter 3 in Smith and Telang (2016) describes the dynamics about the release windows of movies. It illustrates that the time windows for DVD sales and rentals often overlaps with those of subscription streaming services.

[25] Similar deviations from optimal pricing assumptions are adopted in studies of the ride-hailing industry (Castillo 2022, Rosaia 2020) and the online retail sector (Gutierrez 2021). They argue it captures platforms' long-term incentives in a reduced-form way.

[26] Notable, vertical contracts with studios never impose restrictions in streaming services' prices. The rare price adjustment are possibly due to the significant costs associated with notifying existing subscribers, along with the need for personalized retention offers.

[27] Data indicates that fewer than 2% of the titles on Disney Plus are produced by studios not affiliated with Walt Disney. This is supported by insights from interviews with a Disney Plus representative, who indicated that their content acquisition team primarily works with studios affiliated with Walt Disney. However, Walt Disney still takes

When licensing its title j, a studio contemplates the payoff Π_j , specified as

$$\Pi_j = \underbrace{\sum\nolimits_{k\in\mathcal{K}_j} \tau_{jk}}_{\text{Licensing Fees}} + \underbrace{\gamma \cdot \log\left(r_j(\mathcal{K}_j)\right)}_{\text{Logged Viewership}} + \underbrace{\sum\nolimits_{k\in\mathcal{K}_j} \nu_k(\mathcal{K}_j)}_{\text{Unobserved Preferences}} + \underbrace{\mu \cdot \sum\nolimits_{k\in O_j} \Pi_k}_{\text{Effects of VI}} . \tag{17}$$

In addition to the licensing fees collected from streaming services, as represented by the first term above, studios consider three other factors. The first is the expected viewership of the title, denoted as $r_j(\mathcal{K}_j)$. Studios value high viewership because it generates buzz and supports the production of sequels.[28] This advantage diminishes for highly popular titles that are already well funded. Therefore, I use the logarithms of viewership to capture the decreasing marginal return.[29]

In addition, studios can have preferences for contracting with specific services based on their long-term relationships. For example, Sony licenses its titles more often to Netflix than to other services due to their long-time cooperation history. The term $\nu_{jk}(\mathcal{K}_j)$ reflects these preferences, which vary at the network-streaming service level. These preferences, though observable to players, are not observed by econometricians. They are assumed to be i.i.d. and follow a normal distribution $N(0, \sigma_\nu^2)$.

Finally, as represented by the last component, studios also factor in the payoffs of their vertically integrated streaming services, O_j. This explains the tendency for studios to license to their vertically integrated services, as shown in Figure 3. The internalization parameter, μ, measures the extent to which studios incorporate these payoffs. A value of $\mu = 1$ implies complete internalization (Crawford et al. 2018). However, conglomerates like Walt Disney may experience intra-firm frictions, where affiliated studios and streaming services operate independently with limited conversations between each other. This suggests that μ may be less than 1. Therefore, I estimate μ to understand the extent of internalization in the market.

Bargaining of Licensing Fees. To model the bargaining of licensing fees, I adopt the Nash-in-Nash with the threat of replacement (NNTR) bargaining solution from Ho and Lee (2019). This

into account the payoff of Disney Plus when it negotiates licensing third-party titles for Hulu.

[28] Interviews with personnel from Netflix support the relevance of considering title ratings in studios' payoff functions. Netflix considers its large subscriber base as an advantage compared to its competitors in contract negotiations with studios, as it increases the potential audience for their titles.

[29] I construct r by taking the logarithm of one plus the expected viewership, measured in millions of hours viewed by U.S. individuals. This approach ensures that the variable is defined even when a title is not licensed to any streaming services and thus has no viewership.

approach aligns with industry practices, where studios can strategically use streaming services excluded from bargaining as "threat of replacement" when bargaining with their included counterparts, thereby strengthening their bargaining leverage. Building on the industry norms from section 2.1, I make two additional assumptions: first, studios, rather than streaming services, possess the ability to employ outside options as threats of replacement to improve bargaining leverage; and second, licensing fees are negotiated on a per-title basis and paid as lump-sums.

The licensing fee paid by service k for title j under the NNTR solution is determined as

$$\tau_{jk} = \arg\max_{\tau} \underbrace{[\Delta_{jk}\Pi_j(\mathcal{K}_j, \{\tau, \boldsymbol{\tau}_{-jk}\})]}_{\text{Studio's Gain-from-Trade}}^{b_{jk}} \underbrace{[\Delta_{jk}\Pi_k(\mathcal{J}_k, \{\tau, \boldsymbol{\tau}_{-jk}\})]}_{\text{Service's Gain-from-Trade}}^{1-b_{jk}}, \tag{18}$$

$$\text{s.t.} \quad \underbrace{\Pi_j(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\})}_{\text{Studio's payoff under } \mathcal{K}_j} \geq \max_{k' \notin \mathcal{K}_j} \underbrace{\left[\Pi_j(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \{\tau_{jk'}^{res}, \boldsymbol{\tau}_{-jk}\})\right]}_{\text{Studio's payoff when replacing } k \text{ with } k'}. \tag{19}$$

Equation (18) represents the Nash bargaining solution, where $b_{jk} \in [0,1]$ is a studio-service specific bargaining parameter. A higher b_{jk} indicates greater bargaining power for the studio to command higher fees. The gains-from-trade for title j's studio and service k from reaching a licensing agreement are

$$\begin{aligned} \Delta_{jk}\Pi_j(\mathcal{K}_j, \{\tau, \boldsymbol{\tau}_{-jk}\}) &= \Pi_j(\mathcal{K}_j, \{\tau, \boldsymbol{\tau}_{-jk}\}) - \Pi_j(\mathcal{K}_j \backslash \{k\}, \boldsymbol{\tau}_{-jk}), \\ \Delta_{jk}\Pi_k(\mathcal{K}_j, \{\tau, \boldsymbol{\tau}_{-jk}\}) &= \Pi_k(\mathcal{K}_j, \{\tau, \boldsymbol{\tau}_{-jk}\}) - \Pi_k(\mathcal{K}_j \backslash \{k\}, \boldsymbol{\tau}_{-jk}), \end{aligned} \tag{20}$$

where $\mathcal{K}_j \backslash \{k\}$ represents the scenario when the bargaining breaks down so that service k is excluded from title j's distribution network. $\boldsymbol{\tau}_{-jk}$ represents the vector of negotiated licensing fees among all other pairs of streaming services and studios. I adopt the "passive belief" assumption as in the stylized model and the literature (e.g., McAfee and Schwartz 1994, Segal 1999, Collard-Wexler, Gowrisankaran and Lee 2019), that in each bilateral negotiation, firms hold constant beliefs about $\boldsymbol{\tau}_{-jk}$, regardless of the outcome of their own negotiation.

The constraint (19) illustrates the strategic use of exclusivity as a bargaining tool. A studio can enhance its bargaining position by committing to exclude specific streaming services from its distribution network $\mathcal{K}_j$. It can then exploit these excluded services as leverage in negotiations with the included services. Consequently, the negotiated fee, τ_{jk}, must ensure that the studio's profit is at least equivalent to the profit it would obtain by replacing service k with an alternate service k', which is not included in the distribution network, at the latter's reservation fee. This reservation fee, denoted as $\tau^{res}_{jk'}$, represents the amount that k' would accept, making it indifferent between replacing k in $\mathcal{K}_j$, and remaining outside of $\mathcal{K}_j$ along with k:

$$\Pi_{k'}\left(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \{\tau^{res}_{jk'}, \boldsymbol{\tau}_{-jk}\}\right) = \Pi_{k'}\left(\mathcal{K}_j \backslash \{k\}, \boldsymbol{\tau}_{-jk}\right). \tag{21}$$

Implications of the Bargaining Solution. To illustrate the NNTR solution, I focus on the scenario where the studio of title j and service k are not vertically integrated. In Appendix B.2, I show that the studio's gain-from-trade is

$$\Delta_{jk}\Pi_j(\mathcal{K}_j, \{\tau, \boldsymbol{\tau}_{-jk}\}) = \max\left\{ \underbrace{b_{jk} \cdot \Delta_{jk}\Pi_{jk}(\mathcal{K}_j, \cdot)}_{\text{Nash Bargaining Outcome}}, \underbrace{\max_{k' \notin \mathcal{K}_j}\left[\Delta_{jk'}\Pi_{jk'}(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot)\right]}_{\text{Outcome with Threat of Replacement}} \right\}, \tag{22}$$

where $\Delta_{jk}\Pi_{jk}(\mathcal{K}_j, \cdot) = \Delta_{jk}\Pi_j(\mathcal{K}_j, \cdot) + \Delta_{jk}\Pi_k(\mathcal{K}_j, \cdot)$ denotes the bilateral surplus generated from the two firms reaching a licensing agreement. It is also the total surplus to be divided by the studio and the streaming service k in the bargaining. Notably, the bilateral surplus is not a function of licensing fees because they are lump sum transfers and therefore cancel out.

Equation (22) reflects the two options the studio has when negotiating with service k: it can either secure b_{jk} share of the bilateral surplus through Nash bargaining, or leverage the threat of exclusion to negotiate a licensing fee so high that its gain-from-trade is at least equivalent to the bilateral surplus generated from reaching a licensing agreement with an excluded service $k' \notin \mathcal{K}_j$. The studio will choose the more favorable outcome. The bargaining scenario involving vertically integrated firms has similar economic meaning and is further discussed in Appendix B.2.

This equation also highlights the trade-offs faced by the studios when selecting distribution networks, as illustrated in the stylized model. A studio may opt for a joint profit-maximizing network to improve its Nash bargaining outcome, or choose a narrower network to enhance its outside option. The latter strategy improves its bargaining outcome with the threat of replacement but can potentially lower the joint profits to be divided in the negotiation. The condition for which network will arise in equilibrium is specified in the distribution network formation model below.

Comparison with Nash-in-Nash Bargaining Solution. The more commonly used Nash-in-Nash bargaining solution, which is derived using only (18), assumes that networks are formed exogenously, and that each pair of firms bargain independently without communicating with its counterparts (Horn and Wolinsky 1988, Collard-Wexler, Gowrisankaran and Lee 2019). Consequently, it predicts that the streaming services excluded from distribution networks have no direct effect on the bargaining outcome. In contrast, the NNTR solution allows a studio to go back and forth between included and excluded services, thereby enabling the studio to leverage excluded services as outside options in bargaining with included services and affecting the bargaining outcomes. Therefore, the NNTR solution can better predict the outcomes arised in the market, for example, streaming services generally pay more for exclusive than for non-exclusive licensing rights.

Distribution Network Formation. As the intellectual property owner of a title, its studio has the discretion to select a set of streaming services, denoted as a distribution network $\mathcal{K}_j$, to reach agreements with. At equilibrium, a distribution network $\mathcal{K}_j$ must satisfy two necessary conditions: the stability condition and the optimality condition. I detail each in turn.

The stability condition stipulates that no streaming service within the network would benefit from unilaterally rejecting its contract with the studio at the NNTR licensing fees $\boldsymbol{\tau}$: $\Delta_{jk}\Pi_k(\mathcal{K}_j, \boldsymbol{\tau}) \geq 0$.[30] For non-vertically integrated studios, this condition can be expressed as:

$$\Delta_{jk}\Pi_{jk}\left(\mathcal{K}_j, \cdot\right) \geq \Delta_{jk'}\Pi_{jk'}\left(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot\right), \forall j, \forall k \in \mathcal{K}_j, k' \notin \mathcal{K}_j \tag{23}$$

where $\Delta_{jk}\Pi_{jk}\left(\mathcal{K}_j, \cdot\right)$ represents the bilateral surplus generated by the studio and service k that is previously defined.[31] This implies that an included service must generate a higher bilateral surplus with the studio compared to any excluded service. Otherwise, as indicated by (22), the included service would incur a negative payoff to outbid a more efficient excluded service, making it profitable for the included service to reject the contract. The implications of this condition when the studio is vertically integrated are further discussed in Proposition 2 from Appendix B.3.

The optimality condition requires that no alternative, stable distribution network is more prof-

[30] The stability condition is analogous to the no commitment condition from Ghili (2022), although he adopts a distinct network formation model from Ho and Lee (2019).

[31] This condition resembles Proposition 2 from Ho and Lee (2019). A detailed proof can be found in Proposition 2 from Appendix B.3.

itable for the studio of any title in equilibrium:

$$\Pi_j\left(\mathcal{K}_j, \boldsymbol{\tau}(\mathcal{K}_j, \boldsymbol{b}_j)\right) \geq \Pi_j(\mathcal{K}_j', \boldsymbol{\tau}(\mathcal{K}_j', \boldsymbol{b}_j)), \forall j, \forall \mathcal{K}_j' \text{ that is stable,} \tag{24}$$

where $\boldsymbol{\tau}(\mathcal{K}_j, \boldsymbol{b}_j)$ denotes the vector of negotiated licensing fees under distribution network $\mathcal{K}_j$ and the bargaining parameters vector $\boldsymbol{b}_j = \{b_{jk}, \forall k\}$. Bargaining power plays an important role in determining the optimality of the distribution networks: a studio with weaker bargaining power is more inclined to opt for a narrower distribution network to strengthen its bargaining leverage, thereby acquiring a larger share of a potentially smaller pie.

4.3 Discussion of Modeling Assumptions

Static Demand. I assume the demand for service subscriptions to be static. However, consumers may be inert, as highlighted in recent studies on demand for subscriptions (Miller, Sahni and Strulov-Shlain 2023, Einav, Klopack and Mahoney 2023). Not accounting for inertia can bias the estimation of price coefficient α^p. However, the extent of inertia may be small. Streaming services are often concerned about the lack of demand stickiness, noting it as a major challenge (e.g., Wall Street Journal 2022, 2024). Furthermore, as will be detailed in the next section, the identification of α^p primarily relies on cross-market rather than cross-time variation. This approach is expected to be robust, even with potential consumer inertia.

Simultaneous Pricing and Bilateral Contracting. I assume that subscription prices and bilateral contracts between studios and streaming services are determined simultaneously. This assumption is more realistic than the alternative that subscription prices are determined after bilateral contracting. In practice, streaming services often set their subscription prices well in advance and do not regularly adjust them in response to changes in content catalog, even including the acquisition or loss of major titles. In addition, this timing assumption greatly simplifies model estimation and counterfactual simulations by allowing for keeping subscription prices fixed while evaluating contracting outcomes, and vice versa. Similar assumptions are also adopted by Draganska, Klapper and Villas-Boas (2010), Ho and Lee (2017), and Crawford et al. (2018), among others.

Effectiveness of Exclusion in Bargaining. In negotiations, I assume exclusion to be an effective bargaining tool: as a threat to included services, each excluded service is willing to accept an offer from a studio, in which it surrenders entire bilateral surplus to the studio. This assumption might be violated if a streaming service gains little from licensing a title and faces substantial fixed costs of bargaining, leading it to opt out of licensing altogether. However, this concern should be alleviated by the focus of this study on the 1,145 most popular third-party titles in the market. According to both my estimation and discussion with industry experts, the licensing fee for any of these titles should exceed $1 million annually. Given the high popularity of these titles, even if the fixed costs of bargaining exist, they are unlikely to be of first-order importance and should minimally impact the outcomes.

No Threat of Replacement by Streaming Services. I assume that streaming services do not have the ability to use the threat of replacement to enhance their bargaining leverage. This assumption is supported by the absence of evidence of streaming services making contractual commitments to not license specific titles. In contrast, studios often implement these strategies by specifying exclusivity clauses or limiting the set of services to which they license in the contracts. Moreover, unlike grocery stores that are constrained by limited assortment spaces and can thus play manufacturers off against each other to compete for them (Hristakeva 2022a,b), streaming services have unlimited "shelf space" for titles. This factor makes the threat of replacement by streaming services, even if it exists, less credible.

Unobserved Demand Shocks Under Counterfactual Distribution Networks. The bilateral contracting model requires assumptions about the distributions of unobserved demand shocks under hypothetical networks, F_ζ and F_ξ, to understand streaming services' profit responses to title availability changes. However, these shocks are not directly observable. Following the literature (e.g. Wollmann 2018, Hristakeva 2022a), I assume that the distributions of these unobserved shocks are independent from distribution networks and thus remain consistent with those observed under the counterfactual scenarios. A potential concern is that streaming services might bias search results against non-exclusive titles so that they receive lower demand shocks ζ. However, this concern is largely alleviated by insights from my interviews with streaming service representatives, who are not aware of any of such discrimination. The search algorithms, they suggest, primarily focus on the relevance of titles to searched keywords and viewing histories of the users.

Exogenous Production of Titles. The model does not endogenize the production of titles. While exclusive contracts can stimulate investment and content production in the long term (Segal and Whinston 2000), this aspect is less relevant within the study period, when the studios were faced with significant capacity constraint (further discussed in section 2.1). In addition, the unpredictable nature of content quality at the time of production further complicates the modeling of this factor (Aguiar and Waldfogel 2018). Although I do not directly model title production, I explore the impact of exclusivity on studio profits and how consumer welfare responds to changes in the level of title production. This analysis provides insights into the long-term influence of exclusive contracts on content production and consumer welfare. I study relevant counterfactuals in section 7.2.

5 Demand Estimation and Results

5.1 Estimation and Identification

I jointly estimate consumer demand for service subscriptions and titles because the two demand systems are interdependent: viewers choose titles from the content libraries offered by their subscribed services, while households decide subscriptions based on streaming preferences. In addition, joint estimation addresses the selection problem that subscribers to streaming services are more likely to have a strong preference for streaming.

The parameters to estimate are $\theta_1 = \{\boldsymbol{\alpha}^{\mathrm{x}}, \boldsymbol{\beta}^{\mathrm{w}}\}$ and $\theta_2 = \{\alpha^V, \alpha^p, \pi^p, \boldsymbol{\pi}^0, \boldsymbol{\pi}^g, \pi^{smr}, \sigma^p, \sigma^0, \kappa_d\}$. θ_1 includes coefficients of service bundle and title characteristics, which are homogeneous for all households and individuals. θ_2 includes all nonlinear parameters in the utility functions, as well as α^V that associates subscription decisions with title streaming choices.[32]

Identification of Title Demand. The variance in streaming preferences related to observed demographics, represented by π_d^0, $\boldsymbol{\pi}_d^g$, and π_d^{smr}, is identified through the covariance between observed demographics and viewership of titles in different genres at different times. These covariances are observed in the title viewership data, which provide segmentation by age, gender, and race.

[32]Mean price coefficient α^p is also a nonlinear parameter because it is interacted with tax rates ω, which varies across households.

The substitution between titles helps identify streaming preferences related to unobserved demographics, σ^0. A large σ^0 indicates that titles are close substitutes for each other, so the addition of a title to a content library results in little substitution from the outside option. In addition, the correlation between average household viewership and the number of service subscribers also identifies σ^0. If there is significant preference heterogeneity for streaming, services that expand their content libraries over time will likely see later subscribers exhibit lower streaming preferences compared to earlier subscribers.

Identification of Subscription Demand. The geographical variation in tax rates identifies the mean price coefficient α^p, as shown in Figure 4. In addition, the covariance between market shares and bundle sizes helps with its identification because subscription prices for a given service do not vary with the bundle. The heterogeneity in price coefficient, governed by parameter π^p_{inc}, is identified by the correlation between household income and subscription demand across DMAs.

The identification of the viewership utility coefficient, α^V, relies on subscription responses to variations in content libraries and characteristics. The identification of differential decision-making powers of household members, represented by κ, relies on two sources of variation. The first is the covariance between demographics and subscription demand across markets. A large, positive covariance implies strong decision-making power of the corresponding demographic group. The second is the covariance between service subscriptions and demographic group-specific viewership. For example, if kids' viewership increases over summer while the market shares of streaming services remain unchanged, it implies that kids may have limited decision-making power within their households.

Moment Conditions. I estimate θ_1 and θ_2 using GMM with four sets of moment conditions. The first two sets are instrumental variable moments applied on unobserved title and subscription demand shocks, ζ_{jw} and ξ_{cm}:

$$\mathbf{G}^1 = \mathbf{E}[\mathbf{Z}^T_{jw}\zeta_{jw}] = 0, \text{ and } \mathbf{G}^2 = \mathbf{E}[\mathbf{Z}^S_{cm}\xi_{cm}] = 0, \tag{25}$$

where $\mathbf{Z}^T_{jw}$ and $\mathbf{Z}^S_{cm}$ are vectors of instrumental variables uncorrelated with ζ_{jw} and ξ_{cm}, respectively. I detail the selected instrumental variables subsequently.

The third and fourth sets are micro moments. The third set compares simulated and observed title viewership across demographic groups:

$$\mathbf{G}_D^3 = \sum_{j \in \mathbf{J}} \sum_w \hat{s}_{Djw}^T - \sum_{j \in \mathbf{J}} \sum_w s_{Djw}^T = 0, \tag{26}$$

where $\hat{s}_{Djw}^T$ and s_{Djw}^T are the simulated and observed market share of title j in week w among a demographic group D, defined by age, gender, and race. Title groups, denoted as $\mathbf{J}$, are categorized by genre and seasonality. These moments help identify demographic-specific viewership preferences, governed by π_d^0, $\boldsymbol{\pi}_d^g$, and π_d^{smr} (Petrin 2002).

The last set matches simulated and observed covariances between subscriptions and demographic group-specific viewership to identify differential decision-making power among household members, governed by κ:

$$\mathbf{G}_D^4 = \sum_{\tilde{m}} \hat{n}_{\tilde{m}} \hat{R}_{D\tilde{m}} - \sum_{\tilde{m}} n_{\tilde{m}} R_{D\tilde{m}} = 0, \tag{27}$$

where $\hat{n}_{\tilde{m}}$ and $\hat{R}_{D\tilde{m}}$ represent the simulated average number of streaming services a household subscribes to and the simulated total viewership for demographic group D across all titles in month $\tilde{m}$, respectively. $n_{\tilde{m}}$ and $R_{D\tilde{m}}$ are the observed values. I construct additional moments using the share of households without any subscription, replacing $\hat{n}_{\tilde{m}}$ and $n_{\tilde{m}}$ in $\mathbf{G}^4$.

Instrumental Variables. In $\mathbf{Z}_{jw}^T$, I include the so-called "BLP instruments" to identify unobserved streaming preference heterogeneity, σ^0. They are constructed using the number of titles available on each service bundle, interacted with a dummy variable indicating the availability of each title on the bundle. They reflect the level of competition for viewership faced by titles and are exogenous, under the assumption that timing of title release and contracting precedes the realization of unobserved demand shocks ζ_{jw}.

I include five instrumental variables in $\mathbf{Z}_{cm}^S$ to identify subscription demand. The first is z^p, the interaction between the number of services in a bundle and DMA-level mean tax rates, calculated as the weighted average of ZIP code-level tax rates, with household numbers as weights. This instrumental variable is powerful by capturing price variations due to both bundle sizes and tax rates. It is exogenous to unobserved subscription demand shocks ξ_{cm}, since streaming services set uniform national prices and are generally not responsive to local tax variations or consumers' bundle choices.[33] Furthermore, tax rates are exogenous because they apply to various businesses and are unlikely to respond to local demand shocks for streaming services.[34] I further interact z_p with average household income in each DMA as another instrumental variable to identify heterogeneity in price sensitivity (Miller and Weinberg 2017).

The remaining three instrumental variables are as follows. The third is the average content portfolio value V_{hcm} of each bundle across all households in each market, which identifies coefficient of viewership utility α^V. To identify decision-making power parameters κ, I include the average shares of female adults and kids among total population within each DMA as the last two instrumental variables.[35]

Implementation of the Estimation. The estimation of (θ_1, θ_2) follows the nested fixed point approach from Berry, Levinsohn and Pakes (1995). The outer loop searches for θ_2 that minimizes the GMM objective function, constructed from the moments $\mathbf{G}_1$ to $\mathbf{G}_4$. The inner loop solves for θ_1 and evaluates the objective function at a given θ_2. This process uses an iterative contraction mapping method adapted from Lee (2013), which equates simulated and observed demand for both service subscriptions and titles. To balance computational precision and efficiency, I use the sparse grid method from Heiss and Winschel (2008) for numerical integration. Appendix D details the computational procedure.

5.2 Estimation Results

Title Demand. I report the parameter estimates of demand for title viewership in Table 2. For computational feasibility, I set some coefficients of demographic-genre interactions, $\boldsymbol{\pi}^g$, to zero. The estimates imply substantial heterogeneity in streaming preferences. On average, males, individuals over 45 years old, and non-white non-African Americans show less interest in streaming compared to their respective counterparts. Kids show strong preferences for kids and drama genres. In addition, the scale of σ^0 implies considerable preference heterogeneity in streaming that cannot be explained

[33]The only exception is the Hulu and Disney Plus bundle, which offers a bundled discount. However, the control variable for bundles including both Hulu and Disney Plus maintains the instrumental variable's validity.

[34]Whether state sales tax can be applied to streaming service subscriptions is typically decided by state courts. While there are special cases like Florida's communication services tax and Chicago's amusement tax, they are not tailored to the streaming service industry but are also imposed on a range of businesses, such as broadband and tickets for sporting events.

[35]The share of male adults is not used as an instrumental variable because it is collinear with the shares of female adults and kids.

by observed demographics.

Table 2: Demand Estimates: Titles

	Estimates	SE	
Nonlinear Parameters ($\sigma^0, \boldsymbol{\pi}^0, \boldsymbol{\pi}^g, \pi^{sum}$)			
Intercept: Standard Deviation	0.820	0.048	***
Intercept × Age: 2-17	−0.405	0.350	
Intercept × Age: 45 and Above	−0.382	0.057	***
Intercept × Gender: Female	0.259	0.068	***
Intercept × Race: African American	0.054	0.019	***
Intercept × Race: Others	−0.197	0.005	***
Genre: Action × Race: African American	0.045	0.237	
Genre: Comedy × Age: 45 and Above	0.349	0.764	
Genre: Horror/Thriller × Age: 45 and Above	0.346	0.306	
Genre: Horror/Thriller × Gender: Female	−0.073	0.019	***
Genre: Kids × Age: 2-17	1.017	0.236	***
Genre: Kids × Gender: Female	0.058	0.054	
Genre: Drama × Age: 2-17	0.793	0.258	***
Genre: Drama × Age: 45 and Above	−0.197	0.037	***
Genre: Drama × Race: African American	−0.080	0.068	
Time: Summer × Age: 2-17	0.206	0.160	
Linear Parameters ($\boldsymbol{\beta}^{\mathrm{w}}$)			
TV Shows: Weeks Since Release	−0.116	0.006	***
TV Shows: Weeks Since Release^2	0.002	0.000	***
TV Shows: Old (≥51 weeks)	−2.168	0.038	***
TV Shows: Binge Release	0.573	0.144	***
Movies: Weeks Since Release	−0.190	0.020	***
Movies: Weeks Since Release^2	0.002	0.000	***
Movies: Old (≥51 weeks)	−3.937	0.117	***
Holiday (Christmas and Thanksgiving)	0.253	0.094	***

Notes. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Title fixed effects are controlled. Reference group is Age: 18-44, Gender: Male, and Race: White. Standard errors are computed analytically.

The analysis also reveals that the age of a title, measured in weeks since its most recent update or release, negatively affects viewers' utility, indicating a decay effect (Einav 2007). However, the positive coefficients for squared age variables imply that this decay effect diminishes over time. Moreover, the model indicates a preference for streaming during holidays and binge-released shows, the latter of which defined as simultaneous releases of at least four episodes.

Subscription Demand. The parameter estimates of demand for service subscriptions, reported in Table 3, aligns with expectation: demand is downward sloping, and price sensitivity decreases with household income. Amazon has a significant loyal subscriber base stemming from its diverse range of businesses, implied by the large positive coefficient for the Amazon dummy.

Table 3: Demand Estimates: Service Subscriptions

	Estimates	SE	
Nonlinear Parameters			
Price Coefficients			
Mean (α^p)	0.455	0.013	***
$\times$ HH income (π^p_{inc})	−0.061	0.005	***
Title Value (α^V)	0.846	0.286	***
Decision-Making Weights (κ)			
Male Adults	1.000	N.A.	
Female Adults	1.064	0.475	**
Kids	0.160	0.180	
Linear Parameters ($\boldsymbol{\alpha}^{\mathrm{x}}$)			
Amazon	1.970	0.070	***
Hulu	0.655	0.093	***
Hulu Disney Plus Bundle	0.448	0.056	***
Intercept	0.817	0.117	***

Notes. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Household income is measured in $100,000 dollars. κ for male adults is standardized to one. Standard errors are calculated analytically.

I report own- and cross-price elasticities for service subscriptions in Table 4, as well as diversion ratios in Table A.3. The demand estimates imply an average own-price elasticity of −1.45. Notably, Netflix's price elasticity, at −0.94, is significantly lower compared to the other three services. This lower elasticity for Netflix can be partly attributed to its higher subscription prices, which tend to attract less price-sensitive households.

Table 4: Demand Elasticities for Service Subscriptions

	Netflix	Amazon	Hulu	Disney
Netflix	−0.945	0.218	0.286	0.349
Amazon	0.117	−1.705	0.110	0.144
Hulu	0.111	0.080	−1.601	−0.178
Disney	0.107	0.083	−0.140	−1.568

Notes. The table presents elasticity of the demand for the column with respect to the price of the row.

Table 4 shows that most pairs of streaming services are substitutes. This is largely due to the substitutions between titles, leading to diminishing marginal utility for viewers from accessing additional titles. However, Hulu and Disney Plus are complements. This is because households derive greater utility from subscribing to both as a bundle, due to the Walt Disney Company's active promotion of these services as a bundle. This demand synergy results in the complementarity between Hulu and Disney Plus (Gentzkow 2007).

The estimates for decision-making weights, κ_i, reveal significant heterogeneity among household members. Because the average value of κ is not separately identifiable from α^V, the coefficient of content library value, I standardize κ to 1 for male adults. While the decision-making weight of female adults is not significantly different from that of male adults, the weight assigned to kids is substantially lower and not significantly different from zero. This implies that children's preferences have little impact on the household's subscription decisions compared to their parents' preferences.

Willingness-to-Pay (WTP) for Titles. The key output of the demand model and its estimation is the demand response to the addition or removal of each title from a service's content library, which depends on households' WTP for that title. To compute the WTP for each title, I firstly evaluate its contribution to the utility of the content library (as defined in (12)) for each household, holding the availability of other titles constant. This value is then multiplied by the estimate of α^V/α_h^p to convert it into a dollar amount.

Figure 6 presents histograms of the WTPs for four selected titles. There is significant heterogeneity in the average WTP across titles. For example, *False Positive*, a title with median rating in the sample, has an average WTP of \$0.08 during the study period. In contrast, *Grey's Anatomy*, a highly popular title, has an average WTP of \$3.73.

The demand model's flexibility is key to the precision of these WTP estimates. For example, while the average viewer is estimated to derive similar utilities from *The Simpsons* (a kids' show) and *Ozark* (a thriller), the average WTP for *Ozark* is 27% higher than for *The Simpsons*. This discrepancy is mainly because most of *The Simpsons*'s viewers are kids, who, despite their strong preference for kids shows, have limited decision-making power within their households. By accounting for heterogeneity in both streaming preferences and household decision-making power, the flexibility of the model enables more precise estimations of household WTPs.

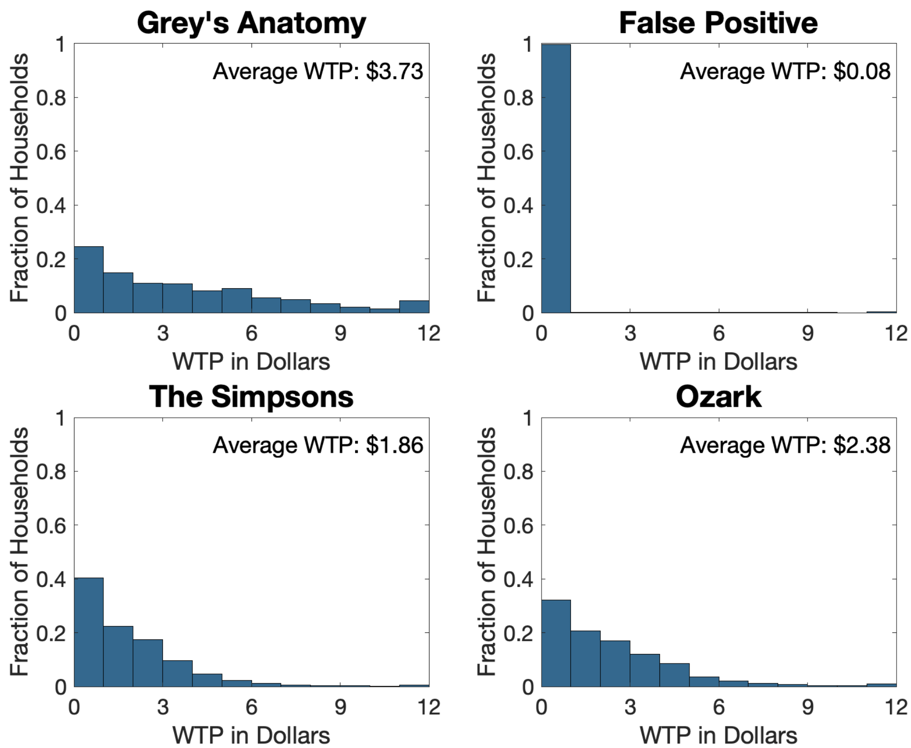


Figure 6: Willingness-to-Pay for Titles

Notes. This figure displays distribution of households' WTP for four selected titles over March 2021 to February 2022, conditional on their access to all other titles. The width of each bin is $1. Data are right-censored at $12.

6 Supply Estimation and Results

6.1 Estimation and Identification

The estimation of the supply model involves three sets of parameters: (a) the marginal variable payoff streaming services earn per subscriber, excluding subscription prices, $a_k - mc_k + \lambda_k$, (b) the bargaining parameters, $\boldsymbol{b}$, and (c) the parameters that govern studios' payoffs, $(\gamma, \sigma_\nu, \mu)$. I identify the first set of parameters using streaming services' first-order conditions (16), and the other parameters by exploiting the variation in distribution networks of titles. I discuss their identification and estimation in greater detail below.

Identification of Service Payoff Parameters. I identify the marginal variable payoffs of streaming services, excluding subscription prices, $a_k - mc_k + \lambda_k$, from the first-order condition of optimal pricing (16). Here, a_k, mc_k, and λ_k represent the advertising revenue, marginal cost, and perceived heuristic benefit from market expansion per subscriber, respectively. These parameters are assumed to be constant across all markets over the observation period for each service. However, I do not separately identify these parameters because only their combined value, $a_k - mc_k + \lambda_k$, affects the streaming services' subscription pricing decisions.

Identification of Bargaining Parameters. The identification of the bargaining parameters depends on studios' likelihood of opting for exclusive distribution. Studios with strong bargaining power will choose distribution networks that maximize the bilateral surplus in negotiations, as they can extract most of this surplus. Conversely, studios with weaker bargaining power may opt for exclusivity as a bargaining tool. In the main specification, the "Big Five" studios share a common bargaining parameter against all streaming services, while the other small studios have a distinct parameter.[36] Differences in the distribution networks of titles produced by the "Big Five" and small studios help identify the difference in their bargaining power.

Identification of Studio Payoff Parameters. Studios' preferences for title viewership, governed by γ, are identified by the extent to which studios tend to license to streaming services with larger subscriber bases, such as Netflix. These services are more likely to deliver substantial viewership for titles compared to those with smaller subscriber bases.

The standard deviation of unobserved preferences, σ_ν, is primarily identified by the stability condition (23). As σ_ν increases, whether a streaming service can satisfy the stability condition mainly depends on unobserved preferences ν, implying that the predicted probability of each streaming service being licensed any title will approach equality. Instead, a low σ_ν implies that a streaming service's inclusion in a title's distribution network depends largely on its ability to generate high incremental variable payoff through licensing the title, compared to its competitors.

The identification of the internalization parameter μ relies on the tendency for Disney-affiliated studios to favor reaching agreements with Hulu: as μ increases, these studios are more motivated to license to Hulu while foreclosing Hulu's competitors, thereby protecting Hulu's benefits.

[36] In Section E.3, I conduct robustness checks with different specifications of bargaining parameters. The estimation results align closely with the main specification.

Estimation and Implementation. The estimation proceeds in two steps, with demand parameters taken as primitives. In the first step, I use the first-order condition (16) to recover the value of $a_k - mc_k + \lambda_k$ for each streaming service k. In this step, I use random draws to compute the expected market shares of streaming services, along with their derivatives with respect to subscription prices, as streaming services do not know the exact values of demand shocks, ζ and ξ, when setting subscription prices.

In the second step, I estimate bargaining and studio payoff-related parameters using simulated methods of moments. I use two sets of moment conditions. The first set is instrumental variable moments applied on the discrepancy between simulated likelihoods and observed choices of distribution networks for each title, following Pakes and Pollard (1989):

$$\mathbf{E}[(\hat{P}_{j\mathcal{K}} - D_{j\mathcal{K}})\mathbf{Z}_{j\mathcal{K}}] = 0, \forall j, \mathcal{K}, \tag{28}$$

where $\hat{P}_{j\mathcal{K}}$ and $D_{j\mathcal{K}}$ are the simulated probability and observed binary indicator, respectively, for title j to be available on distribution network $\mathcal{K}$. $\mathbf{Z}_{j\mathcal{K}}$ is a vector of instrumental variables. It includes distribution network-specific dummies and logged title viewership under different networks. They capture the variation in title availabilities to identify bargaining parameters $\boldsymbol{b}$ and studios' viewership preferences γ, respectively. The last instrumental variable in $\mathbf{Z}_{j\mathcal{K}}$ captures the difference in bilateral surpluses to be divided with studios between all pairs of included services k and excluded services k', excluding the unobserved preferences ν:

$$\sum_{k \in \mathcal{K}} \sum_{k' \notin \mathcal{K}} \left(\mathbf{E}_\nu \left[\Delta_{jk} \Pi_k(\mathcal{K}_j) \right] - \mathbf{E}_\nu \left[\Delta_{jk} \Pi_{jk'}(\mathcal{K}_j \backslash \{k\} \cup \{k'\}) \right] \right). \tag{29}$$

This instrumental variable identifies σ_ν. A small σ_ν indicates that factors like incremental variable profits generated from licensing a title, rather than ν, primarily determines the likelihood of a distribution network becoming an equilibrium outcome. Therefore, it implies a strong correlation between the instrumental variable and the observed distribution networks.

The second set includes indirect inference moments that match regression results using simulated and observed data (Gourieroux, Monfort and Renault 1993). I consider two linear probability regressions: (a) a regression on whether a title is exclusively distributed based on whether a production studio belongs to the "Big Five" or small studios, and (b) a regression comparing the probabilities of licensing to Hulu, rather than Netflix and Amazon Prime, for Disney-affiliated studios versus other studios. These moments help identify the discrepancy in bargaining power between the "Big Five" and small studios, as well as the degree of internalization by vertically integrated studios that is governed by μ. The regression results using observed data are presented in Table 1.

6.2 Estimation Results

In Table 5, I present the estimation results of the supply model. Title viewership is found to have a significant effect on studios' payoffs: doubling a title's viewership is valued at 0.77 million by its production studio. This emphasis on viewership offers Netflix a distinct advantage in competing for title licensing rights due to its larger subscriber base and higher engagement levels. Comparatively, the variance of studios' unobserved contracting preferences (σ_ν) is not economically significant.

Table 5: Estimation Results: Supply

	Estimates	SE	
Bargaining Parameters $\boldsymbol{b}$			
"Big Five"	0.819	0.035	***
Small studios	0.534	0.192	***
Studio Payoff Parameters			
Viewership preference γ	0.775	0.184	***
STD of unobserved preferences σ_ν	0.147	0.025	***
Internalization μ	0.627	0.137	***

Notes. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Studios' payoffs are measured in millions of dollars. Standard errors are computed using 100 bootstrap samples.

The internalization parameter μ is estimated to be 0.63, significantly lower than 1. It suggests that studios do not fully internalize their vertically integrated streaming services: for every dollar earned by a streaming service, it is perceived as only 0.63 dollars by its vertically integrated studios. This lack of full internalization may be attributed to the internal frictions between the content production and streaming service arms within the conglomerates.[37]

The estimation results show that studios generally have stronger bargaining power than streaming services, as suggested by their bargaining parameters being above 0.5. Together with the studios'

[37] The existence of internal frictions are not unique to the video streaming industry: Crawford et al. (2018), Cuesta, Noton and Vatter (2019), and Chen, Yi and Yu (2023) find internal frictions in vertically integrated conglomerates in the cable TV, healthcare, and movie theater industries, respectively. Hortaçsu et al. (2024) find that different arms of a large U.S. airline do not operate as a unitary decision maker.

ability to use excluded streaming services as bargaining leverage, it suggests that studios are effective in extracting a significant share of the surplus in their negotiations with streaming services. On average, studios are estimated to receive a licensing fee of \$9.22 million per title, which amounts to 90.3% of the incremental profits generated by streaming services that have entered into licensing contracts for these titles, upon adding the titles to their content libraries.

Furthermore, the estimation highlights a notable disparity in bargaining power between the "Big Five" and small studios. The stronger power of the "Big Five" is likely due to their ownership of about half of the titles in the sample and their extensive experience in negotiating with streaming services. This bargaining power disparity implies significant difference in contracting strategies: the model predicts that the "Big Five" are 9.0% less likely to opt for exclusive distribution networks compared to small studios, when controlling for title characteristics.[38]

6.3 Model Fit

Equilibrium Computation. To investigate in-sample model fit, I simulate the equilibrium outcomes using the model and estimates, and compare them with the observed data. This involves finding subscription prices, title distribution networks, and negotiated licensing fees that are optimal against each other, alongside consumers' subsequent subscription and viewing choices. Due to the interdependent nature of these decisions, the action space for firms is extensive, making the direct enumeration of all possible equilibria unfeasible.

To address this computational challenge, I apply the algorithm from Lee and Pakes (2009). In this algorithm, studios sequentially select the payoff-maximizing distribution network for each of the 1,145 third-party titles, conditional on the choices for all other titles. Simultaneously, streaming services adjust their subscription prices in response to updated distribution networks. I iterate this procedure until there are no further adjustments in title networks or subscription prices, achieving a simultaneous-move Nash equilibrium for a given draw of unobserved contracting preferences. I perform this algorithm for 30 random draws of these unobserved preferences, simulating the market outcome for each and averaging the results. Wollmann (2018), Fan and Yang (2020), and Hristakeva (2022a), among others, adopt similar algorithms to compute counterfactual market outcomes such

[38]This is computed by comparing the proportion of titles that are exclusively available on only one streaming service when all studios' bargaining parameters are set at 0.53, versus when they are set at 0.82, across all 1145 sampled third-party titles in the analysis.

as product offerings in various markets.

In-sample Model Fit. In Table 6, I present the results of the in-sample fit comparison. It demonstrates a close alignment between the model's predictions and actual data on subscription prices, consumer demand, and distribution networks, though it overestimates Amazon's shares in both content licensing and consumer demand while underestimating Hulu's.

Table 6: In-Sample Model Fit

	Observed	Simulation
Monthly Avg. Prices		
Netflix	13.532	14.678
Amazon Prime	8.990	9.546
Hulu	8.407	8.204
Disney Plus	7.907	7.829
Distribution Networks		
Shares of Third-Party Titles on		
Netflix	0.712	0.755
Amazon Prime	0.185	0.229
Hulu	0.248	0.222
Only One Service	0.867	0.829
Consumer Demand		
Market Shares		
Netflix	0.570	0.556
Amazon Prime	0.461	0.443
Hulu	0.358	0.289
Disney Plus	0.300	0.299
Multi-Homing	0.526	0.500
Multi-Homing (Excl. Disney)	0.447	0.414
Avg. Weekly Streaming Hours	2.500	2.537

Notes. Subscription prices and market shares are monthly averages from March 2021 to February 2022.

Out-of-sample Model Fit. To evaluate out-of-sample model fit, I compare the estimated annual licensing fees paid by Hulu, the only streaming service that solely operates in the U.S., with its reported expenses. The model's prediction of \$3.05 billion closely aligns with Hulu's reported spending of approximately \$3.3 billion in 2020, indicating a good model fit.[39]

[39] Hulu has not disclosed its spending on third-party content after 2021. Therefore, 2020 data is the latest benchmark for comparison. During this year, Hulu's total content expenditure was roughly \$3.5 billion, as per data from Bloomberg, including an approximately \$200 million spending on in-house productions.

7 Counterfactuals: The Impact of Exclusive Contracts

In this section, I apply the model to evaluate the impact of exclusive contracts on the welfare of three major industry stakeholders: studios, streaming services, and consumers.[40] I begin by simulating outcomes under counterfactual scenarios where exclusive contracts are prohibited, maintaining constant the sets of competing streaming services and produced titles as observed. Compared with the status quo, these counterfactual studies reveal the short-term effects of exclusive contracts. In addition, I explore how they affect market outcomes in a long run by reshaping competition in streaming service and content production markets.

7.1 The Short-Term Impact of Exclusive Contracts

I examine two counterfactual scenarios. In the first scenario, studios are required to license their titles to all of Netflix, Amazon Prime, and Hulu, ensuring a complete distribution network for each title. In the second scenario, exclusive contracts are prohibited, preventing studios from committing to specific distribution networks in their contracts. Instead, a network can be an equilibrium outcome only if it is unprofitable for the studio to contract with additional services. Under both scenarios, I assume the current array of streaming services and titles remains unchanged. I report the results of these simulations in Column (1) and (2) of Table 7.

Complete Network. I conduct this counterfactual as a benchmark to investigate the effects of removing all exclusive distribution networks, including those not facilitated by exclusive contracts. The results are presented in Column (1) of Table 7. Compared to the status quo, the downstream competition intensifies significantly under the complete network scenario. This is because streaming services can only rely on their in-house content for differentiation, as no third-party content remains exclusive. This reduced differentiation also decreases consumer multi-homing: the share of households subscribing to multiple services among Netflix, Amazon Prime, and Hulu drops by 12.0 percentage points. The intensified competition leads to a significant price drop across these services. Hulu loses the most, with a 95.2% decrease in its payoff due to its limited in-house content library (unlike Netflix) and a less loyal subscriber base (unlike Amazon Prime).

[40]The surplus for streaming services accounts for their preference for larger market shares, while studio surplus considers ratings and unobserved contracting preferences. Fixed title production costs are excluded.

Table 7: Counterfactual Results

	Simulated Status Quo	(1) Complete Network	(2) No Exclusive Contracts	(3) Hulu Exit	(4) Title Cut
Avg. Monthly Prices					
Netflix	14.678	7.416	15.540	19.894	14.418
Amazon Prime	9.546	8.359	9.630	9.945	9.285
Hulu	8.204	6.116	6.178		6.137
Disney Plus	7.829	8.064	7.867	8.341	7.867
Distribution Networks					
Shares of Third-Party Titles on					
Netflix	0.755	1.000	0.853	0.811	0.757
Amazon Prime	0.229	1.000	0.451	0.299	0.362
Hulu	0.222	1.000	0.437		0.467
Only One Service	0.829	0.000	0.566	0.890	0.529
Consumer Demand					
Market Shares					
Netflix	0.556	0.613	0.557	0.502	0.583
Amazon Prime	0.443	0.442	0.456	0.454	0.430
Hulu	0.289	0.231	0.209		0.232
Disney Plus	0.299	0.301	0.301	0.252	0.308
Multi-Homing	0.500	0.477	0.492	0.376	0.504
Multi-Homing (Excl. Disney)	0.414	0.294	0.370	0.279	0.332
Avg. Weekly Streaming Hours	2.537	3.008	2.719	2.387	2.671
Service Surplus					
Netflix	5.940	2.084	5.768	6.709	3.967
Amazon Prime	2.416	0.570	2.668	2.575	2.435
Hulu	0.331	0.016	0.157		−0.323
Disney Plus	2.056	2.174	2.090	1.926	2.139
Total Service Surplus	10.744	4.844	10.684	11.210	8.218
Studio Surplus					
"Big Five"	8.470	8.203	8.956	8.254	9.684
Small Studios	4.361	3.201	4.022	4.240	2.986
Total Studio Surplus	12.831	11.405	12.978	12.495	12.670
Consumer Surplus	26.920	41.879	29.894	24.349	29.837
Total Surplus	50.495	58.128	53.556	48.054	50.725

Notes. Prices are measured in dollars and surpluses are measured in billion dollars per year. Counterfactual (1) licenses all third-pary titles across Netflix, Amazon Prime, and Hulu; (2) prohibits exclusive contracts; (3) assumes the exit of Hulu; and (4) assumes a content production cut of 25% by small studios. Subscription prices and market shares are monthly averages from March 2021 to February 2022.

In addition, the decreased content differentiation further intensifies competition among streaming services for title licensing, as the risk of losing subscribers to competitors increases if a service fails to license a title. Therefore, despite the significant decrease in streaming services' profits, studios' payoffs decrease to a much lesser extent, with their total payoff decreasing by only 11.1% compared to the streaming services' 54.9% drop. The joint surplus for studios and streaming services decreases by 31.1%, illustrating that exclusive contracts can increase the joint profits to be shared between firms. In contrast, consumer welfare rises by 55.6% due to improved title availability and reduced subscription prices.

Banning Exclusive Contracts. The complete network counterfactual may be overly restrictive, as it is rare even in markets where exclusive contracts is not commonly adopted, such as healthcare and retailing. Therefore, I investigate an alternative counterfactual that prohibits exclusive contracts between studios and streaming services. This policy retains studios' ability to choose distribution networks for their titles but prevents them from committing to any distribution network arrangements through exclusivity clauses. This results in scenarios where, for example, Warner Bros. would not be able to commit to the exclusivity of *Seinfeld*'s licensing right it currently grants to Netflix, thereby permitting additional services like Hulu to license the title.

Without commitment from exclusive contracts, studios can negotiate additional agreements with previously excluded services. To reflect these changes, I apply the following equilibrium refinement condition to the counterfactual. This condition requires that under an equilibrium distribution network $\mathcal{K}_j$, there are no mutually beneficial bilateral contracts between the studio and any set of services outside of $\mathcal{K}_j$, thereby ruling out any profitable deviations for studios and excluded streaming services.[41] Specifically, for any set of exclusive services, denoted as K'_j with $K'_j \cap \mathcal{K}_j = \varnothing$, and any set of bilateral contracts between the studio and K'_j with licensing fees τ', at least one of the following must hold: the studio does not benefit from deviating to accept these contracts:

$$\Pi_j(\mathcal{K}_j, \tau) \geq \Pi_j(\mathcal{F}(\mathcal{K}_j \cup K'_j), \{\tau, \tau'\}), \tag{30}$$

[41] This refinement condition is weaker than the "pairwise stability" condition from Jackson and Wolinsky (1996) and adopted in Ghili (2022), which only allows a studio to deviate to contract with one additional streaming service. This condition is also better aligned with the supply model, where a studio can reach agreement with any set of streaming services.

or at least one streaming service in K'_j does not benefit:

$$\exists k' \in K'_j, \text{s.t. } \Pi_{k'}(\mathcal{K}_j, \tau) \geq \Pi_{k'}(\mathcal{F}(\mathcal{K}_j \cup K'_j), \{\tau, \tau'\}). \tag{31}$$

Here, the function $\mathcal{F}$ adjusts the distribution network after the studio's deviation to capture a service's ability to unilaterally terminate its existing contract, a refinement condition used in the main model, as well as Ho and Lee (2019) and Ghili (2022). A service within the distribution network $k \in \mathcal{K}_j$ will decide to terminate its contract if its profitability falls below zero after deviation by the studio: $\Pi_k(\mathcal{K}_j \cup K', \{\tau, \tau'\}) < 0$. Any service opting for termination will not be part of the adjusted network, $\mathcal{F}(\mathcal{K}_j \cup K')$, after the deviation.

This counterfactual highlights the trade-off associated with exclusive contracts. Compared to the status quo, these refinement conditions underscore the efficiency benefits exclusive contracts can offer by enabling parties to commit to joint profit-maximizing distribution networks (Bernheim and Whinston 1998, Segal 1999). Concurrently, this counterfactual policy makes equilibriums with exclusive networks less stable, thereby mitigating inefficient exclusions.[42] The search for equilibrium distribution networks follows the algorithm described in section 6.3. I present the counterfactual outcomes in Column (2) of Table 7.

Impacts on Firms. Comparing the counterfactual scenario to the status quo, exclusive contracts increase the share of titles that are available on only one service by 26.3 percentage points, indicating many current distribution networks rely heavily on contractual commitment for sustainability.

The results imply that the impact of exclusive contracts varies significantly among firms. On the streaming service side, small services like Hulu, which typically lack extensive in-house content and do not have a substantial loyal subscriber base, derive significant benefits from such contracts. In particular, Hulu incurs a substantial increase of 110.7%. This benefit is largely due to their reliance on exclusive third-party content to differentiate from competitors, which attracts new subscribers and enhances their pricing power. In addition, this increase in profitability strengthens Hulu's

[42] Notably, studios can still use excluded streaming services as threat when bargaining with included services. The existing literature often assumes firms can use excluded bargaining counterparties as leverage, even in the absence of commitment to exclusive distribution. This assumption is adopted in studies like Liebman (2018), Ho and Lee (2019), and Ghili (2022), which explore insurers' use of exclusion against hospitals in healthcare, and Hristakeva (2022a,b), which examine retailers' use of similar strategies to negotiate better terms with manufacturers.

position in licensing negotiations, particularly when competing for exclusive licensing rights. This is exemplified by the stability condition (23), which mandates that included services must generate higher bilateral surpluses than any excluded services.

In contrast, larger services see minimal gains or even negative impacts. Netflix gains a modest 3.0%, while Amazon Prime sees a 9.4% loss. Specifically, both services see reductions in their variable payoffs excluding licensing fees, with drops of 4.0% for Netflix and 4.9% for Amazon Prime. These outcomes arise due to their substantial in-house content catalogues or loyal subscriber bases from other businesses, which already provide differentiation from competitors without needing exclusive third-party content. While exclusive contracts do enhance content differentiation and reduce substitution among services, the incremental benefit to these larger platforms is limited. However, such contracts also lead to increased competition from small services like Hulu, which leverage exclusive third-party content and lower prices to attract previous subscribers to larger services. The adverse effects of this heightened competition often outweigh the modest gains from reduced substitution, resulting in an overall decline in their variable payoffs.

On the studio side, the "Big Five" experience a 5.4% decrease in their payoffs. This is due to a negative equilibrium effect: when exclusive contracts are allowed, streaming services' willingness-to-pay for titles becomes lower. This is because exclusive contracts increase differentiation among content libraries, reducing substitution across services and making their demand less responsive to changes in content libraries. Therefore, the bilateral surplus generated from two firms reaching a licensing agreement decreases, as a streaming service suffers subscriber losses after losing a title. Given their strong bargaining power, the "Big Five" studios can extract most of these bilateral surpluses during negotiations, regardless if exclusive contracts can be used as a bargaining tool or not. Consequently, the overall decrease in bilateral surpluses lowers the licensing fees that the "Big Five" can demand, reducing their profitability.

However, small studios see an 8.4% increase in payoffs. This differential impact is due to their lower bargaining power (0.53 compared to 0.81 for the "Big Five"), which makes them more reliant on exclusive contracts to improve bargaining leverage. Exclusive contracts can facilitate exclusive distribution networks, allowing studios to use excluded streaming services as bargaining threats. In addition, the improved profitability of small services makes them credible threats in negotiations against Netflix and Amazon Prime. Both factors improve the bargaining leverage of small studios.

Although the bilateral surpluses to be divided in negotiations are smaller, as with the "Big Five," the enhanced bargaining leverage enables small studios to overcome these adverse effects, thereby securing higher licensing fees and improving their profitability.

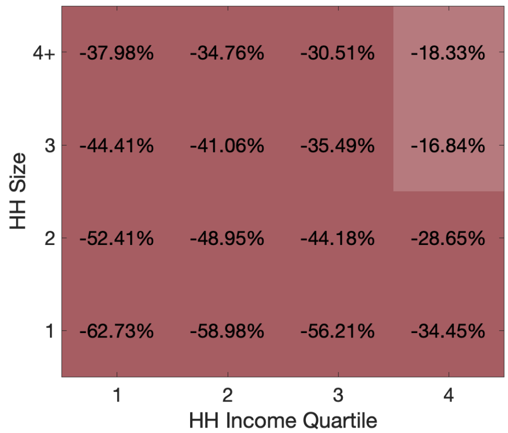
Impacts on Consumers. Exclusive contracts result in a 9.9% decrease in overall consumer welfare, due to not only the limited availability of titles but also the softened competition among streaming services: when distribution networks are fixed at the status quo, the adjustment in subscription prices alone accounts for a 4.5% decrease in consumer welfare. This finding implies that exclusive contracts can significantly soften competition among the streaming services, enabling them to extract higher profits from consumers.

The analysis in Figure 7b reveals that the exclusive contracts' harm to households varies by size and income. Smaller households, who typically have lower streaming preferences, and as a result, subscribe to fewer services, see more substantial losses due to more restrictive access to titles under the status quo. Conversely, larger households, already subscribing to multiple services for a broader range of content, experience lesser losses. Moreover, the increase in Hulu's subscription cost disproportionately harms low-income households, who are more likely to choose Hulu due to its lower price compared to Netflix and Amazon Prime.

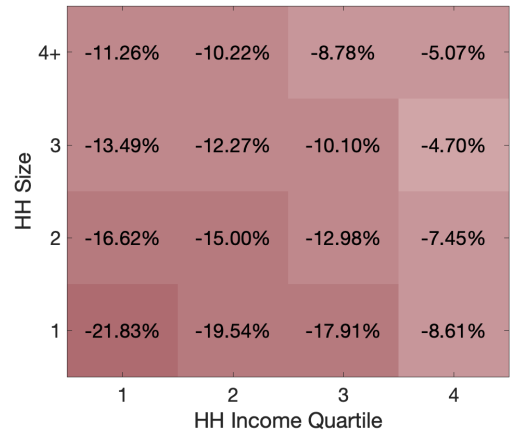
7.2 The Potential Long-Term Impact of Exclusive Contracts

The analyses above suggest that exclusive contracts may benefit consumers in the long run by improving the profitability of small studios and streaming services, potentially stimulating streaming service entrants and content production. To explore this, I analyze counterfactual scenarios that include Hulu's market exit and reduced content production by small studios. Comparing them with the status quo, these scenarios help illustrate the potential long-term effects of exclusive contracts as markets become more competitive. I maintain the equilibrium refinement conditions (30) and (31) across these simulations, which results from the ban of exclusive contracts.

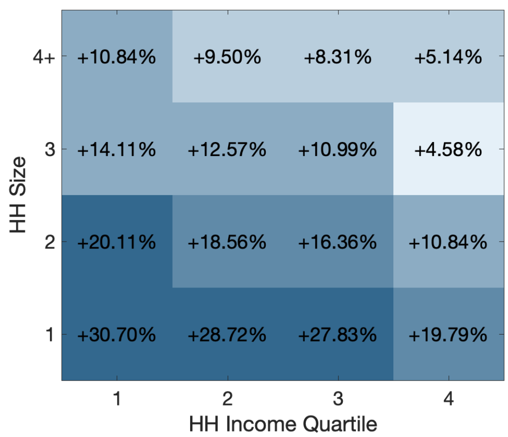
Increased Service Entry. In Column (3) of Table 7, I present the counterfactual outcomes of banning exclusive contracts alongside Hulu's market exit. Surprisingly, comparing them with the status quo, exclusive contracts facilitate broader distribution networks by stimulating the entry



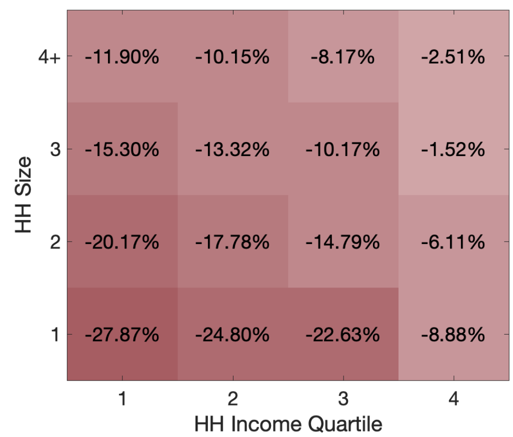
(a) Short-Term: Change from Complete Network



(b) Short-Term: Change from Exclusive Contract Ban



(c) Long-Term: Increased Service Entry



(d) Long-Term: Increased Title Production

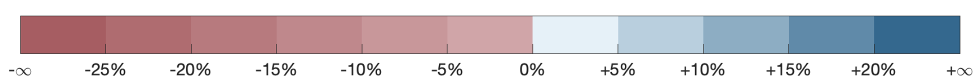


Figure 7: The Effects of Exclusive Contracts on Household Surplus by Income and Size

Notes. This figure displays the percentage points change in household surplus across income levels and household sizes from each of the four counterfactual scenarios to the status quo. Households are grouped by their income levels (quartile 1: less than \$52,000; 2: \$52,000–\$89,599; 3: \$89,600–\$150,259; 4: \$150,260 and above) and sizes (1, 2, 3, and 4 and more).

of small streaming services like Hulu. This is because a studio's loss from excluding all but one streaming service increases with the number of services in the market. This larger loss of potential revenue motivates studios to license non-exclusively. Consequently, the share of titles available exclusively on one streaming service drops by 6.1 percentage points.

The entrance of small services results in more intensive competition for larger services like Netflix and Amazon Prime, compelling them to reduce their subscription prices and resulting in market share losses. As a result, Netflix and Amazon Prime see their payoffs decrease by 11.5% and 6.2%, respectively. In contrast, studios experience a 2.7% increase in payoffs due to increased competition among streaming services vying for licensing rights.

The increased competition among streaming services, coupled with less restrictive title availability, results in a 10.6% increase in consumer surplus. Specifically, Figure 7c shows that households with low income and small sizes, who were most adversely affected by exclusive contracts if the arrays of streaming services and produced titles are held constant, benefit the most. This is because new entrants, such as Hulu, offer content libraries that are small but can satisfy their streaming needs, along with lower subscription prices compared to larger services. These shifts in consumer surplus underscore how exclusive contracts may benefit consumers in a long term by intensifying downstream market competition.

Increased Title Production. In the final counterfactual study, I assume that small studios will cut their title production by 25% under the ban on exclusive contracts.[43] For each of the 30 simulation draws, I randomly select 25% of the titles produced by small studios, assuming these titles are not produced under the counterfactual.[44] Comparing it to the status quo, this counterfactual can highlight the long-term impact of exclusive contracts if it stimulates content production by small studios.

In column (4) of Table 7, the counterfactual outcomes show that exclusive contracts lead to a 46.1% increase in payoffs of small studios due to increased title production. However, the "Big Five" experience a significant 12.5% decrease, larger than the 5.4% drop in the short-term exclusive contract ban scenario. The decline for the "Big Five" arises because an increased number of titles on the market leads to reduced marginal value of each title, as consumers view them as substitutes, resulting in lower licensing fees that streaming services are willing to offer.

With increased title production, exclusive contracts increase the payoffs for all streaming services,

[43] The 25% reduction is based on studios' profit margins of 25-30%. Given that the total payoff (excluding fixed production costs) of small studios is about 8% lower without exclusive contracts, a 25% production cut is reasonable.

[44] An alternative counterfactual scenario is that small studios would cut their 25% least popular titles. However, studios may not have sufficient foresight about title popularity during productions. Therefore, I assume that production cuts by small studios are random. If studios have good predictions about title popularity, this counterfactual may underestimate the magnitude of small studios' surpluses and consumer welfare.

except for Amazon Prime.[45] The overall increase in service payoffs can be attributed to reduced downstream competition, as a greater variety of titles allows services to differentiate themselves and charge higher subscription prices. However, Amazon Prime experiences a small loss of -3.5% because it already differentiates itself effectively with its loyal subscriber base, even without much exclusive content under the counterfactual scenario. Nevertheless, exclusive contracts enhance the competitiveness of other services by enabling them to offer more unique content, which has an adverse effect on Amazon Prime's profitability.

Consumer surplus is 9.8% lower than under the status quo. Surprisingly, this adverse effect is only 0.2% smaller without the newly produced titles (discussed in Section 7.1). This is because the benefits from an increased variety of titles available are largely offset by the higher subscription prices. Comparing Figure 7d to Figure 7b, households with lower income and streaming preferences even get worse off, since they gain minimally from improved title variety but are more sensitive to price increases. Compared to the significant consumer welfare gains from streaming service entry observed in the previous counterfactual, the minimal improvement from increased title production suggests that downstream competition may have a more pivotal effect on consumers than entry and competition in the upstream market, aligning with insights from Rey and Tirole (2007).

8 Conclusions

In this paper, I develop a framework to analyze the welfare implications of exclusive contracts in the video streaming market. This framework incorporates a demand model that accounts for household subscription decisions and individual title viewership, and a supply model where streaming services set subscription prices and negotiate bilateral contracts with studios. In particular, the negotiations determine both licensing fees and distribution networks of titles. This model reveals that studios with weaker bargaining power are more inclined to opt for exclusive distribution to improve their bargaining leverage. This inverse relationship helps with the identification of firms' bargaining power without data on negotiated licensing fees.

I apply the model to study a counterfactual where exclusive contracts are banned. Comparing it to the status quo, I find that the effects of exclusive contracts vary significantly among firms.

[45] Notably, Hulu's payoff is negative under the counterfactual scenario, as it pays licensing fees that exceed its variable profit due to considering the benefits of Disney Plus when licensing titles.

Smaller streaming services without much in-house content, such as Hulu, benefits substantially due to their reliance on exclusive third-party titles for differentiation, whereas Netflix and Amazon Prime see minimal or negative impacts. Though the "Big Five" studios see decreased profitability, smaller studios gain from exclusive contracts. This is due to the increased bargaining leverage provided by exclusive distribution and the enhanced profitability of smaller services, both facilitated by exclusive contracts. Exclusive contracts harm consumers in a short run, but this harm may get mitigated or reversed on a long run due to stimulated content production and streaming service entries.

This paper can be extended in a number of directions. One of them is the explicit modeling of title production, which is not addressed in this paper due to significant capacity constraints during the research period. With more comprehensive data, future research could explore the impacts of exclusive contracts on content production of both studios and streaming services, which may further affect firms' strategies in bilateral contracting games and consumer welfare. In addition, the operations of the video streaming market relies on various sectors, including cloud computing services for data storage, Internet Service Providers (ISPs) for data transmission, and digital media players for content distribution (Cho 2020). The prevalence of vertical integration within these sectors, such as Amazon's ownership of Amazon Cloud in cloud computing and Fire TV in digital media players, is a notable feature of the market. Research into these vertical relationships and their interplay with the studio-streaming service relationship could offer valuable insights for both academic researchers and business managers by enhancing the understanding of the broader impacts of vertical relationships in the video streaming market.

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Appendix A Additional Figures and Tables

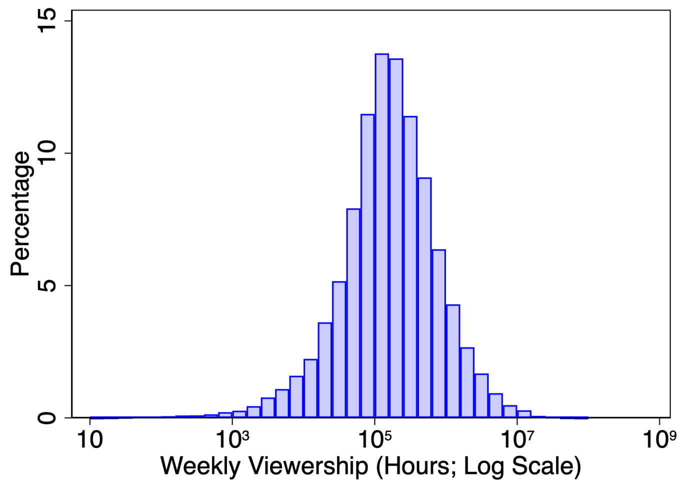

Figure A.1: Distribution of Title Viewership

Notes. This figure displays title-week level viewership from March 2021 to February 2022, measured in hours spent by U.S. individuals aged over two years.

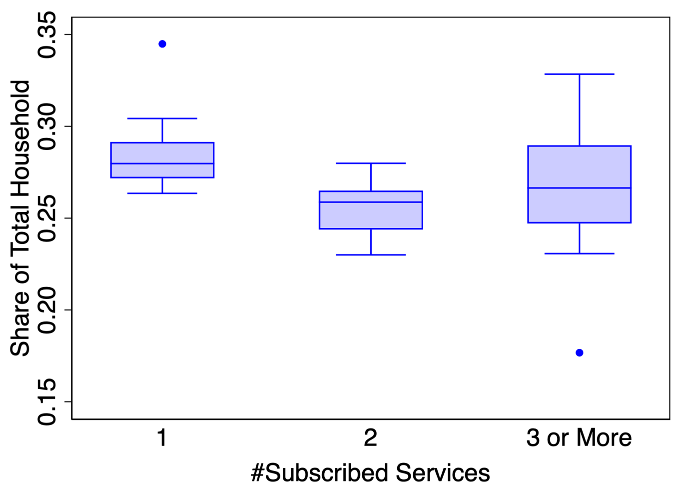

Figure A.2: Distribution of the Number of Subscribed Services

Notes. This figure presents the average proportion of households in each DMA that subscribe to varying numbers of the top four streaming services during March 2021 to February 2022. Dots represent DMAs whose values exceed 1.5 times the interquartile range from the nearest quartile.

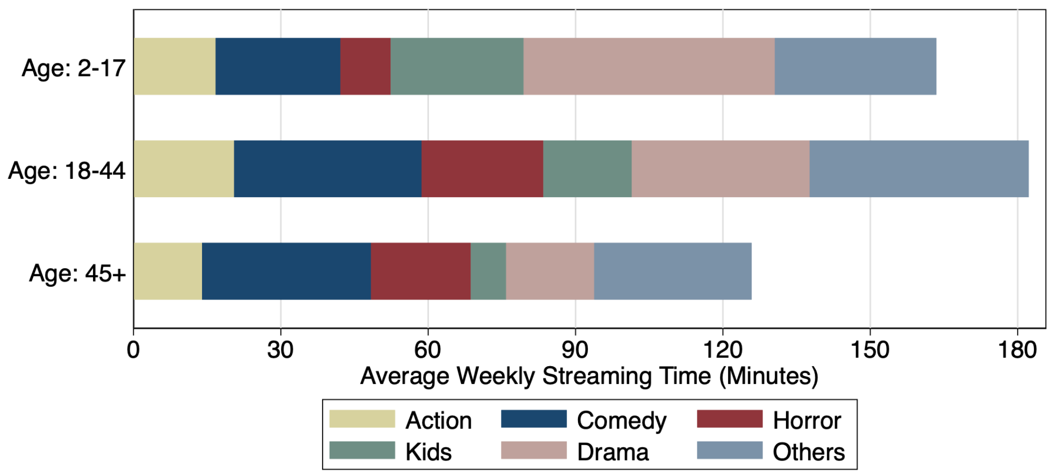

Figure A.3: Average Weekly Streaming Time by Genre and Age Group

Notes. This figure displays the average weekly streaming time across six different genres for U.S. individuals, categorized into three age groups: 2-17, 18-44, and 45 and above.

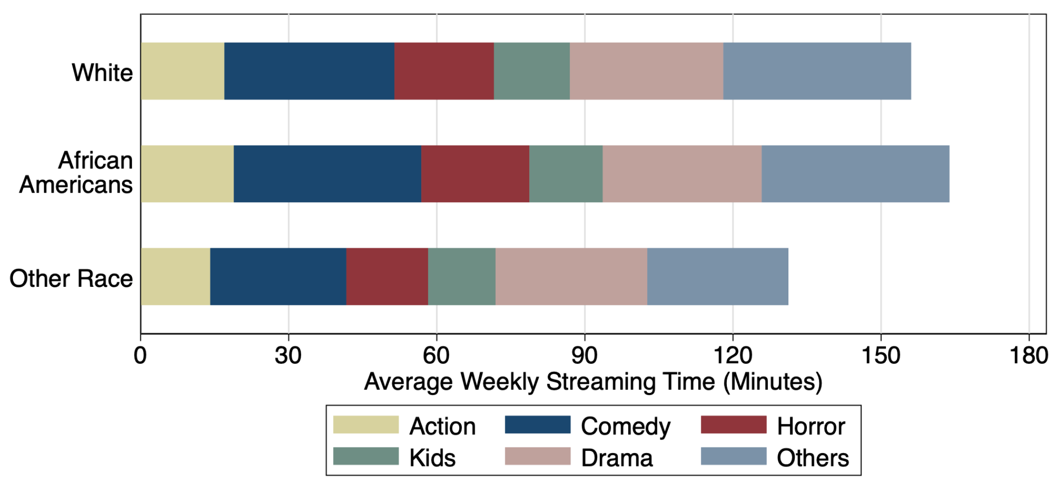

Figure A.4: Average Weekly Streaming Time by Genre and Race Group

Notes. This figure displays the average weekly streaming time across six different genres for U.S. individuals, categorized into three race groups: white, African Americans, and others.

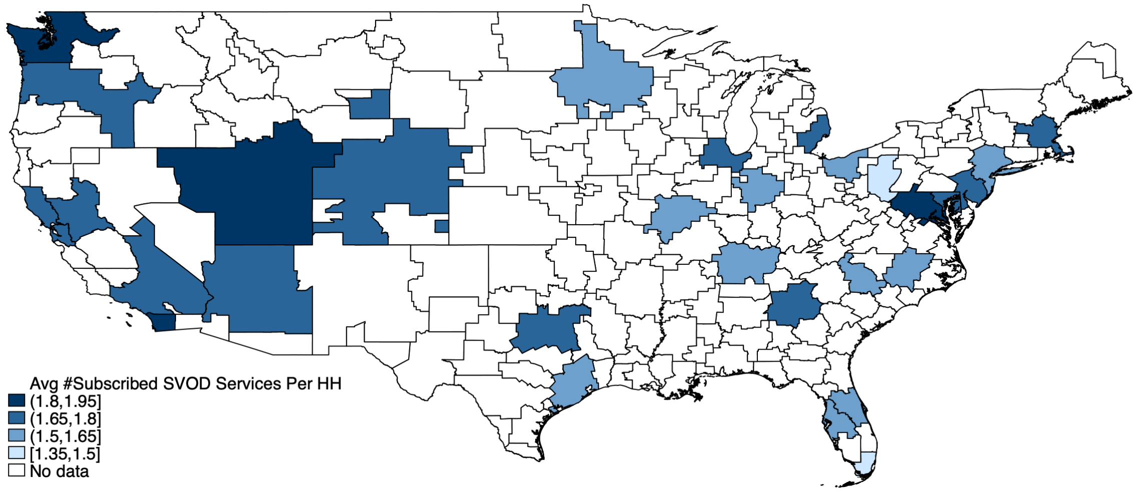

Figure A.5: Average Numbers of Subscribed Streaming Services per Household in Top 30 DMAs

Notes. This map displays the average number of top four streaming services subscribed by households from March 2021 to February 2022 in the 30 most populous DMAs.

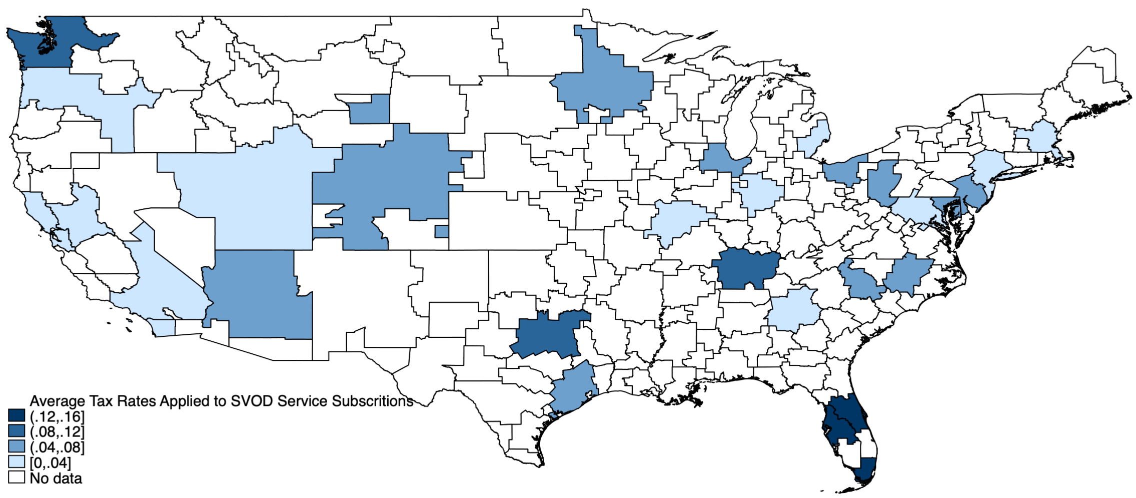

Figure A.6: Average Tax Rates Applied to Streaming Service Subscriptions in Top 30 DMAs

Notes. This map displays the average tax rates paid by households for streaming service subscriptions from March 2021 to February 2022 in the 30 most populous DMAs, calculated as the population-weighted average of tax rates across each ZIP code within every DMA.

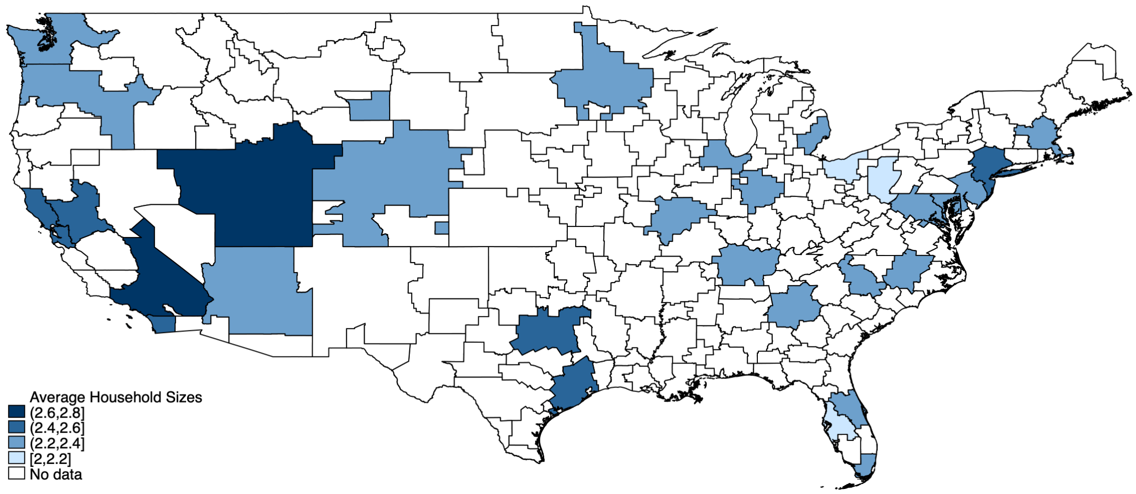

Figure A.7: Average Household Sizes in Top 30 DMAs

Notes. This map displays the average household sizes in the 30 most populous DMAs, calculated using 2020 census data.

Table A.1: Summary Statistics: Titles

	N. Obs.	Mean	Std. Dev.	Median	5th Pctile.	95th Pctile.
Among All Titles						
Viewership (million hours)	2,028	20.356	40.569	8.086	1.642	77.136
Third-Party	1,940	0.590	0.492	1.000	0.000	1.000
Genre: Action	2,028	0.169	0.375	0.000	0.000	1.000
Genre: Comedy	2,028	0.176	0.381	0.000	0.000	1.000
Genre: Horror/Thriller	2,028	0.148	0.356	0.000	0.000	1.000
Genre: Kids	2,028	0.078	0.269	0.000	0.000	1.000
Genre: Drama	2,028	0.223	0.417	0.000	0.000	1.000
Genre: Others	2,028	0.206	0.404	0.000	0.000	1.000
Among Third-Party Titles						
Viewership (million hours)	1,145	21.684	45.238	7.970	1.863	83.580
"Big Five"	1,145	0.470	0.499	0.000	0.000	1.000
Available on One Service	1,145	0.867	0.339	1.000	0.000	1.000
Available on Two Services	1,145	0.109	0.312	0.000	0.000	1.000
Title-Week Level Statistics						
Viewership (million hours)	82,693	0.499	1.426	0.162	0.009	1.875
Viewership: Netflix Titles	54,267	0.496	1.506	0.151	0.008	1.867
Viewership: Amazon Titles	12,024	0.503	1.253	0.156	0.008	2.133
Viewership: Hulu Titles	14,146	0.579	1.365	0.202	0.014	2.310
Viewership: Disney Plus Titles	9,883	0.583	1.417	0.263	0.022	1.904
TV Shows: Binge Release	48,504	0.428	0.495	0.000	0.000	1.000

Notes. The table reports summary statistics for the period between March 2021 and February 2022. It covers 2,028 titles, including 1,145 third-party titles. 88 titles are missing production data to determine if they are third-party titles. Binge release is defined as simultaneous releases of at least four episodes.

Table A.2: Descriptive Evidence: Demand for Streaming Service Subscriptions

	#Subscribed Services		Spending: Pre-Tax	
	(1)	(2)	(1)	(2)
Tax rate	-1.417***	-1.069**	-13.067***	-9.486**
	(0.447)	(0.522)	(3.934)	(4.526)
Household size		0.345**		3.552**
		(0.124)		(1.101)
Constant	1.749***	0.923***	17.782***	9.258***
	(0.026)	(0.304)	(0.240)	(2.703)
#Observations	360	360	360	360

Notes. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Observations are at DMA-month level. Standard errors are clustered at DMA level and reported in the parentheses. The two dependent variables are the average number of subscribed services and the total pre-tax spending on SVOD subscriptions per household.

Table A.3: Diversion Ratios for Streaming Service Subscriptions

	Netflix	Amazon	Hulu	Disney
Netflix		0.186	0.189	0.193
Amazon	0.085		0.050	0.055
Hulu	0.111	0.064		−0.094
Disney	0.130	0.082	−0.108	

Notes. This table displays diversion ratios from the column to the row. However, caution is needed when interpreting these results because households often subscribe to multiple services simultaneously. For instance, subscribers who leave Netflix may already have subscriptions to Hulu; subscribers to both Amazon Prime and Hulu may cancel both subscriptions and switch to Netflix after a price increase of Hulu.

Appendix B Details on Model

B.1 Stylized Model Extension: Heterogeneous Bargaining Power

In the stylized model discussed in Section 2.2, I implicitly assume the same bargaining power across all streaming services when negotiating with studios. In this subsection, I extend the model to accommodate differential bargaining strengths among streaming services. This analysis illustrates that the core insights from the stylized model persist. Moreover, it demonstrates how variations in distribution networks can identify differences in streaming services' bargaining power.

Consider a scenario involving one studio, j, and two streaming services, k_1 and k_2, as depicted in Figure 1. Denote the sales profits for k_1 and k_2 under non-exclusive (ne) and exclusive (e) distribution scenarios as Π_1^{ne}, Π_2^{ne} and Π_1^e, Π_2^e, respectively. Without loss generality, assume $\Pi_1^e > \Pi_2^e$. The respective bargaining powers of the studio with each streaming service are represented by b_1 and b_2. The analysis follows the game timeline and equilibrium concept outlined in Section 2.2.

The NNTR bargaining solution implies the payoffs for the studio under exclusive ($\mathcal{K}_j = \{k_1\}$)

and non-exclusive ($\mathcal{K}_j = \{k_1, k_2\}$) networks as follows:

$$\Pi_j(\mathcal{K}_j) = \sum_{k \in \mathcal{K}_j} \tau_{jk}(\mathcal{K}_j) = \begin{cases} \max\{b_1 \Pi_1^e, \Pi_2^e\}, & \mathcal{K}_j = \{k_1\} \\ b_1 \Pi_1^{ne} + b_2 \Pi_2^{ne}, & \mathcal{K}_j = \{k_1, k_2\} \end{cases}. \tag{B.1}$$

The studio will opt for a non-exclusive distribution strategy if and only if it yields a higher payoff, which requires the satisfaction of the following conditions:

$$b_2 \Pi_2^{ne} \geq \Pi_2^e - b_1 \Pi_1^{ne}, \tag{B.2}$$

$$(\Pi_1^{ne} + \Pi_2^{ne}) + \left(\frac{b_2}{b_1} - 1\right) \Pi_2^{ne} \geq \Pi_1^e. \tag{B.3}$$

Condition (B.2) mirrors (5), reflecting the studio's preference for using exclusive contracts as leverage. If the extra surplus from k_2 when including it in a non-exclusive network (left-hand side of the inequality), exceeds the reduction in surplus from k_1 (right-hand side), the studio will choose a non-exclusive distribution network.

Condition (B.3) is different from (4) due to varying bargaining powers of the streaming services, encapsulated in the term $\left(\frac{b_2}{b_1} - 1\right) \Pi_2^{ne}$. This term reflects how differential bargaining powers influence the studio's preferences: a higher b_2 compared to b_1 suggests that the studio is able to extract more surplus from k_2, thereby valuing k_2's sales profit more. Conversely, when b_1 surpasses b_2, the studio prioritizes k_1's sales profit. Thus, this term reflect the studio's steering incentive based on the relative bargaining power of the streaming services.

In addition, condition (B.3) affirms the significance of network efficiency, which is also suggested by (4). The efficiency of a non-exclusive network (measured by $\Pi_1^{ne} + \Pi_2^{ne}$) over an exclusive one (Π_1^e) increases the likelihood of the studio choosing the former. In sum, (B.2) and (B.3) highlight the balance between leveraging bargaining power and optimizing network efficiency in the studio's distribution strategy.

Identification of Differential Bargaining Powers of Streaming Services. The necessary and sufficient condition for the studio to opt for a non-exclusive network, $\Pi_j(\{k_1\}) \leq \Pi_j(\{k_1, k_2\})$, can be rewritten as

$$b_2 \leq \frac{\max\{b_1 \Pi_1^e, \Pi_2^e\} - b_1 \Pi_1^{ne}}{\Pi_2^{ne}}. \tag{B.4}$$

This condition illustrates that, all else being equal, a studio is more inclined to exclude service k_2 from the network when k_2 has stronger bargaining power (indicated by a smaller b_2). Intuitively, the studio prefers to integrate k_2 into the network when it can extract substantial surplus from it.

The interaction between exclusivity and k_1's bargaining power (governed by b_1) is more nuanced. There are two countervailing forces. Higher b_1 value means the studio can extract more surplus from k_1, potentially motivating the studio to enhance k_1's profitability by providing exclusive rights to the title. Conversely, a larger b_1 also implies the studio has a strong bargaining position against k_1, reducing the need to exclude k_2 for as a leverage in negotiations with k_1. Regardless of the nuanced relationship, the value of b_1 can still be identified through the observed relationships between exclusivity and the services' sales profits under various distribution networks: Π_1^e, Π_2^e, Π_1^{ne}, and Π_2^{ne}. For instance, if data show studios often exclude k_2 despite a high Π_1^{ne}, this could indicate a relatively weak bargaining position of the studio against k_1, compelling it to resort to exclusivity for negotiation leverage.

Above all, this analysis reveals that differential bargaining powers among streaming services can be idenfied solely through network configuration data. While the main paper assumes uniform bargaining power for simplicity, Appendix E.1 uses Monte Carlo simulations to demonstrate the identifiability of differential bargaining powers among streaming services.

B.2 NNTR Solution with Lump-sum Licensing Fees

Non-Integrated Bargaining. When the "threat of replacement" constraint is not binding, the first-order condition of Nash-in-Nash bargaining implies that

$$(1 - b_{jk}) \cdot \Delta_{jk}\Pi_j(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\}) = b_{jk} \cdot \Delta_{jk}\Pi_k(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\}). \tag{B.5}$$

Given that licensing fees are lump-sum payments and do not impact consumer demand or streaming service pricing conditional on distribution networks, the gains-from-trade can be expressed as

$$\begin{aligned} \Delta_{jk}\Pi_j(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\}) &= \Delta_{jk}\Pi_j(\mathcal{K}_j, \{0, \boldsymbol{\tau}_{-jk}\}) + \tau_{jk}, \\ \Delta_{jk}\Pi_k(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\}) &= \Delta_{jk}\Pi_k(\mathcal{K}_j, \{0, \boldsymbol{\tau}_{-jk}\}) - \tau_{jk}. \end{aligned} \tag{B.6}$$

Consequently, the first-order condition above can be reconstructed as

$$(1 - b_{jk}) \left[\Delta_{jk}\Pi_j(\mathcal{K}_j, \{0, \boldsymbol{\tau}_{-jk}\}) + \tau_{jk}\right] = b_{jk} \cdot \left[\Delta_{jk}\Pi_k(\mathcal{K}_j, \{0, \boldsymbol{\tau}_{-jk}\}) - \tau_{jk}\right] \tag{B.7}$$

which leads to the derivation of the Nash-in-Nash bargaining solution:

$$\tau_{jk} = b_{jk} \cdot \Delta_{jk}\Pi_k(\mathcal{K}_j, \{0, \boldsymbol{\tau}_{-jk}\}) - (1 - b_{jk}) \cdot \Delta_{jk}\Pi_j(\mathcal{K}_j, \{0, \boldsymbol{\tau}_{-jk}\}). \tag{B.8}$$

Under this solution, the studio's gain-from-trade with service k is:

$$\Delta_{jk}\Pi_j(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\}) = b_{jk} \cdot \Delta_{jk}\Pi_{jk}(\mathcal{K}_j, \cdot), \tag{B.9}$$

where $\Delta_{jk}\Pi_{jk}(\mathcal{K}_j, \cdot) = \Delta_{jk}\Pi_j(\mathcal{K}_j, \cdot) + \Delta_{jk}\Pi_k(\mathcal{K}_j, \cdot)$ represents the bilateral surplus from the licensing agreement between the two firms. Notably, this surplus is unaffected by the negotiated licensing fees because they are lump sums.

When the "threat of replacement" constraint (19) is binding, the reservation licensing fee of excluded service k' is

$$\tau_{jk'}^{res} = \Delta_{jk'}\Pi_{k'}(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \{0, \boldsymbol{\tau}_{-jk}\}), \tag{B.10}$$

which implies that k' is willing to forgo all bilateral gains-from-trade, allowing the studio to capitalize fully if it chooses to switch from k to k'. Under this reservation price definition, the "threat of replacement" constraint implies that the negotiated licensing fee must satisfy the following condition:

$$\Delta_{jk}\Pi_j(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\}) = \max_{k' \notin \mathcal{K}_j} \left\{\Delta_{jk'}\Pi_{jk'}(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \{0, \boldsymbol{\tau}_{-jk}\})\right\}. \tag{B.11}$$

Combining (B.9) and (B.11), the NNTR solution suggests that the studio's gain-from-trade with a contracting partner $k \in \mathcal{K}_j$ is

$$\Delta_{jk}\Pi_j(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\}) = \max\left\{b_{jk} \cdot \Delta_{jk}\Pi_{jk}(\mathcal{K}_j, \cdot), \max_{k' \notin \mathcal{K}_j} \left[\Delta_{jk'}\Pi_{jk'}(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot)\right]\right\}, \tag{B.12}$$

which corresponds to equation (22). Consequently, the studio's payoff from licensing title j to a distribution network $\mathcal{K}_j$ is calculated as:

$$\begin{aligned}
\Pi_j(\mathcal{K}_j, \boldsymbol{\tau}) &= \sum_{k \in \mathcal{K}_j} \left[\tau_{jk}(\mathcal{K}_j) + \nu_{jk}(\mathcal{K}_j)\right] + \gamma \cdot r_j(\mathcal{K}_j) \\
&= \sum_{k \in \mathcal{K}_j} [\tau_{jk}(\mathcal{K}_j) + \underbrace{\nu_{jk}(\mathcal{K}_j) + \gamma \cdot (r_j(\mathcal{K}_j) - r_j(\mathcal{K}_j \backslash \{k\}))}_{\Delta_{jk}\Pi_j(\mathcal{K}_j, \{0, \boldsymbol{\tau}_{-jk}\})}] + R \\
&= \max\left\{b_{jk} \cdot \Delta_{jk}\Pi_{jk}(\mathcal{K}_j, \cdot), \max_{k' \notin \mathcal{K}_j} \left[\Delta_{jk'}\Pi_{jk'}(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot)\right]\right\} + R,
\end{aligned} \tag{B.13}$$

where $R = \gamma \cdot \left[r_j(\mathcal{K}_j) - \sum_{k \in \mathcal{K}_j} \left(r_j(\mathcal{K}_j) - V_j(\mathcal{K}_j \backslash \{k\})\right)\right]$. The second equality is achieved by replacing the studio's gains-from-trade, represented within the brackets, with (B.12).

Bargaining Between Vertically Integrated Firms. For simplicity in our discussion, this analysis assumes $\mu < 1$, indicating incomplete vertical integration. The validity of the assumption is further explored at the end of this section.

When the "threat of replacement" constraint is not binding, the first-order condition of Nash-in-Nash bargaining leads to

$$\begin{aligned}
&(1 - b_{jk}) \cdot \left[\Delta_{jk}\pi_j(\mathcal{K}_j, \{0, \boldsymbol{\tau}_{-jk}\}) + \tau_{jk} + \mu \cdot (\Delta_{jk}\Pi_k(\mathcal{K}_j, \{0, \boldsymbol{\tau}_{-jk}\}) - \tau_{jk})\right] \\
=&b_{jk} \cdot \left[\Delta_{jk}\Pi_k(\mathcal{K}_j, \{0, \boldsymbol{\tau}_{-jk}\}) - \tau_{jk}\right],
\end{aligned} \tag{B.14}$$

where π_j represents the studio's payoff, excluding effects from its vertically integrated counterparts, and is defined as $\pi_j = \sum_{k \in \mathcal{K}_j} [\tau_{jk} + \nu_{jk}(\mathcal{K}_j)] + \gamma \cdot r_j(\mathcal{K}_j)$. This equation determines the licensing fee under non-binding constraints as

$$\tau_{jk}^{NN} = -\frac{(1 - b) \cdot \Delta_{jk}\tilde{\Pi}_{jk}(\mathcal{K}_j, \cdot)}{1 - \mu(1 - b)} + \Delta_{jk}\Pi_k(\mathcal{K}_j, \{0, \boldsymbol{\tau}_{-jk}\}), \tag{B.15}$$

where $\Delta_{jk}\tilde{\Pi}_{jk}(\mathcal{K}_j, \cdot) = \Delta_{jk}\pi_j(\mathcal{K}_j, \{\tau, \boldsymbol{\tau}_{-jk}\}) + \Delta_{jk}\Pi_k(\mathcal{K}_j, \{\tau, \boldsymbol{\tau}_{-jk}\}), \forall \tau$ is the maximum gain-from-trade the studio could secure when licensing to its vertically integrated streaming service, given that the service surrenders all its surplus to the studio under $\mu < 1$.

When the "threat of replacement" constraint is binding, the studio's gain-from-trade with service $k \in \mathcal{K}_j$ must equal or surpass the bilateral surplus from licensing to any excluded service $k' \notin \mathcal{K}_j$:

$$\begin{aligned}
&\Delta_{jk}\pi_j(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\}) + \mu \cdot \Delta_{jk}\Pi_k(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\}) \\
=& \max_{k' \notin \mathcal{K}_j} \left[\Delta_{jk'}\tilde{\Pi}_{jk'}(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot) + \mu \cdot \Delta_{jk'}\Pi_k(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot\}) \right].
\end{aligned} \tag{B.16}$$

Notably, $\Pi_k(\mathcal{K}_j \backslash k \cup k', \cdot)$ remains constant irrespective of lump-sum transfers between service k' and the studio because any lump-sum transfer between competing service k' and the studio does not affect the pricing nor consumer demand of k, conditional on the distribution network. The negotiated licensing fee under a binding constraint becomes:

$$\begin{aligned}
\tau_{jk}^{TR} =& \frac{1}{1-\mu} \left(\max_{k' \notin \mathcal{K}_j} \left[\Delta_{jk'}\tilde{\Pi}_{jk'}(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot) + \mu \cdot \Delta_{jk'}\Pi_k(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot) \right] - \Delta_{jk}\tilde{\Pi}_{jk}(\mathcal{K}_j, \cdot) \right) \\
&+ \Delta_{jk}\Pi_k(\mathcal{K}_j, \{0, \boldsymbol{\tau}_{-jk}\}).
\end{aligned} \tag{B.17}$$

The term in the first line must be non-positive following the stability condition from the distribution network formation model. This follows the stability condition dictated by the distribution network formation model. This condition mandates that the bilateral surplus between the studio and any excluded service k' (denoted within the brackets) must not exceed the maximum possible gain-from-trade that the studio can obtain from service k, denoted as $\Delta_{jk}\tilde{\Pi}_{jk}(\mathcal{K}_j, \cdot)$.

In summary, the negotiated licensing fee between two vertically integrated firms can be represented as:

$$\tau_{jk} = \max\left\{\tau_{jk}^{NN}, \tau_{jk}^{TR}\right\}. \tag{B.18}$$

Notably, τ_{jk} decreases with μ when $\mu < 1$, as both τ_{jk}^{NN} and τ_{jk}^{TR} do. This property is consistent with what I learned from interviewees from Hulu, who admitted that they may get more favorable licensing deals from Disney-affiliated studios than their competitors can do. Subsequently, the gain-from-trade perceived by the studio from contracting with its vertically-integrated service k is:

$$\begin{aligned}
&\Delta_{jk}\pi_j(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\}) + \mu \cdot \Delta_{jk}\Pi_k(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\}) \\
=& \max\left\{ \frac{b}{1-(1-b)\mu} \cdot \Delta_{jk}\tilde{\Pi}_{jk}(\mathcal{K}_j, \{0, \boldsymbol{\tau}_{-jk}\}), \right. \\
&\left. \max_{k' \notin \mathcal{K}_j} \left[\Delta_{jk'}\tilde{\Pi}_{jk'}(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot) + \mu \cdot \Delta_{jk'}\Pi_k(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot) \right] \right\}
\end{aligned} \tag{B.19}$$

Discussion: Assumption of $\mu < 1$. The above analysis adopts the assumption that $\mu < 1$. In contrast, $\mu \geq 1$ implies that the studio prioritizes the payoff to its vertically integrated service over its own, to the extent that it would accept a licensing fee approaching negative infinity. This scenario is not consistent with actual market behaviors, where streaming services pay licensing fees to the studio.

The assumption of $\mu < 1$ suggests incomplete integration between the studio and the streaming service, possibly due to internal frictions within the conglomerate. This assumption is not only in line with literature documenting such frictions within conglomerates (e.g., Crawford et al. 2018, Hortaçsu et al. 2024), but also corroborated by Disney representatives. They noted that the content acquisition team does not always coordinate with affiliated studios within the conglomerate. Furthermore, the estimation results also imply that μ is indeed less than 1, lending additional support to this assumption.

B.3 Distribution Network Formation: The Stability Condition

In this section, I derive the sufficient and necessary condition of the stability condition, denoed as $\Delta_{jk}\Pi_k(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\}) \geq 0$, for non-integrated and vertically integrated firms in Proposition 1 and 2, respectively.

Proposition 1. *The stability condition for two non-integrated firms, j and k, is equivalent to*

$$\Delta_{jk}\Pi_{jk}(\mathcal{K}_j, \cdot) \geq \Delta_{jk'}\Pi_{jk'}(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot), \forall k' \notin \mathcal{K}_j, \tag{23}$$

where $\Delta_{jk}\Pi_{jk}(\mathcal{K}_j, \cdot)$ represents the bilateral surplus generated by j and k reaching an agreement with each other.

Proof. This proposition resembles Proposition 2 from Ho and Lee (2019). Under distribution network $\mathcal{K}_j$, the gain-from-trade for non-integrated service k from licensing title j is

$$\begin{aligned} &\Delta_{jk}\Pi_k(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\}) = \Delta_{jk}\Pi_{jk}(\mathcal{K}_j, \cdot) - \Delta_{jk}\Pi_j(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\}) \\ &= \min\left\{(1-b_{jk}) \cdot \Delta_{jk}\Pi_{jk}(\mathcal{K}_j, \cdot), \Delta_{jk}\Pi_{jk}(\mathcal{K}_j, \cdot) - \max_{k' \notin \mathcal{K}_j}\left[\Delta_{jk'}\Pi_{jk'}(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot)\right]\right\} \end{aligned} \tag{B.20}$$

Here, the first equality is derived from the definition of bilateral surplus and its independence from negotiated lump-sum licensing fees, while the second equality is obtained by substituting the studio's gain-from-trade $\Delta_{jk}\Pi_j(\mathcal{K}_j, \tau_{jk}, \boldsymbol{\tau}_{-jk})$ with equation (B.12). Considering that the bilateral surplus is always positive in this study, the stability condition can be reformulated as:

$$\Delta_{jk}\Pi_{jk}(\mathcal{K}_j, \cdot) - \max_{k' \notin \mathcal{K}_j}\left[\Delta_{jk'}\Pi_{jk'}(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot)\right] \geq 0, \tag{B.21}$$

which is equivalent to condition (23). □

Proposition 2. *Assuming the internalization parameter $\mu < 1$, the stability condition for two vertically integrated firms, j and k, is equivalent to*

$$\Delta_{jk}\tilde{\Pi}_{jk}(\mathcal{K}_j, \cdot) \geq \Delta_{jk'}\tilde{\Pi}_{jk'}(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot) + \mu \cdot \Delta_{jk'}\Pi_k(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot), \forall k' \notin \mathcal{K}_j, \tag{B.22}$$

where $\Delta_{jk}\tilde{\Pi}_{jk}(\mathcal{K}_j, \cdot) = \Delta_{jk}\pi_j(\mathcal{K}_j, \cdot) + \Delta_{jk}\Pi_k(\mathcal{K}_j, \cdot)$.

Proof. For service k licensing title j from its vertically integrated studio, its gain-from-trade, denoted as $\Delta_{jk}\Pi_k(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\})$, has the following property:

$$
\begin{aligned}
&(1-\mu) \cdot \Delta_{jk}\Pi_k(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\}) \\
&= \Delta_{jk}\tilde{\Pi}_{jk}(\mathcal{K}_j, \cdot) - [\Delta_{jk}\pi_j(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\}) + \mu \cdot \Delta_{jk}\Pi_k(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\})] \\
&= \min \left\{ \frac{(1-b)(1-\mu)}{1-(1-b)\mu} \cdot \Delta_{jk}\tilde{\Pi}_{jk}(\mathcal{K}_j, \{0, \boldsymbol{\tau}_{-jk}\}), \right. \\
&\qquad \left. \Delta_{jk}\tilde{\Pi}_{jk}(\mathcal{K}_j, \cdot) - \max_{k' \notin \mathcal{K}_j} \left[\Delta_{jk'}\tilde{\Pi}_{jk'}(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot) + \mu \cdot \Delta_{jk'}\Pi_k(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot) \right] \right\},
\end{aligned}
\tag{B.23}
$$

where the first equality is derived from the definition of $\tilde{\Pi}_{jk}(\mathcal{K}_j, \cdot)$, while the second is derived from substituting the term in the within the bracket with its equivalence from (B.19).

Because $\mu < 1$ and $\Delta_{jk}\tilde{\Pi}_{jk}(\mathcal{K}_j, \{0, \boldsymbol{\tau}_{-jk}\}) > 0$, $\frac{(1-b)(1-\mu)}{1-(1-b)\mu} \cdot \Delta_{jk}\tilde{\Pi}_{jk}(\mathcal{K}_j, \{0, \boldsymbol{\tau}_{-jk}\}) > 0$ always holds. Consequently, the stability condition $\Delta_{jk}\Pi_k(\mathcal{K}_j, \{\tau_{jk}, \boldsymbol{\tau}_{-jk}\}) \geq 0$ can be translated to

$$
\Delta_{jk}\tilde{\Pi}_{jk}(\mathcal{K}_j, \cdot) - \max_{k' \notin \mathcal{K}_j} \left[\Delta_{jk'}\tilde{\Pi}_{jk'}(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot) + \mu \cdot \Delta_{jk'}\Pi_k(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot) \right] \geq 0. \tag{B.24}
$$

which is effectively equivalent to condition (B.22). □

These propositions indicate that under the stability condition, a service included in a distribution network must generate a higher bilateral surplus for division with the studio compared to any excluded service, irrespective of whether the firms are vertically integrated. The impact of vertical integration on this condition might not be immediately evident but is clarified when analyzing the term $\Delta\tilde{\Pi}_{jk}(\mathcal{K}_j, \cdot)$. It represents the maximum gain-from-trade for studio j, which effectively equates to the bilateral surplus from an agreement with service k, minus any impact from vertical integration. Furthermore, in negotiations with non-vertically integrated services k', the studio considers benefits to its integrated partners, captured by $\mu \cdot \Delta_{jk'}\Pi_k(\mathcal{K}_j \backslash \{k\} \cup \{k'\}, \cdot)$. Hence, according to condition (B.22), a service's inclusion in its vertically integrated studio's network hinges on its ability to create more surplus than any excluded service, with the effects of vertical integration not considered when determining the bilateral surplus between the integrated firms.

Appendix C Details on Data

C.1 Details on Nielsen Ratings Data

I use Nielsen ratings data from March 2021 to February 2022 in this paper. The data are at the weekly level and also offer ratings by demographic breakdowns, including age groups (2–17, 18–44, and 45+ years old), gender (male and female), and race (white, African American, and others).

Nielsen measures title viewership by monitoring and surveying households within their panel. Two types of information are collected. The first type concerns which titles are watched by each household on any of their screens. This information is collected using Automatic Content Recognition (ACR), a pattern-matching technology. ACR collects short audio and visual clips of media played on screens, which are then cross-referenced with a library of signals from shows and movies to identify the watched content. Viewerships are only considered for ratings if they meet specific criteria, such as a minimum continuous viewing duration of fifteen minutes.

The second type of data is the demographics of the viewers. Nielsen conducts in-house surveys to collect demographic information and validate the subscription choices of surveyed households simultaneously. These surveys are conducted regularly, typically every six months. In addition, Nielsen installs meters in the households within their survey panel to identify the viewer every time a screen is on. Household members are required to report their unique survey ID upon turning on a screen to confirm their identity.

C.2 Sample and Variable Construction

In this section, I outline the methodology used for constructing variables on the prices and market shares of streaming service bundles, and the process of constructing the title data. This includes a detailed explanation of the criteria used for selecting titles into the final sample.

Prices. Subscription prices were primarily gathered from online announcements on price increases. During the study period, from March 2021 to February 2022, Amazon Prime Video and Disney Plus each offered only one subscription tier. Amazon Prime Video maintained a consistent monthly subscription price of \$8.99, while Disney Plus increased its price from \$5.99 to \$6.99. These numbers are used as the subscription prices in the data.

In contrast, Netflix and Hulu provide multiple subscription tiers. To calculate the average prices paid by consumers, I interviewed experts from these companies and data analysts from YipitData, a data vendor that collects SVOD subscription receipts from millions of U.S. users' mailboxes. Both sources provided tier-wise subscriber distributions, and their data closely matched. The average prices for Netflix and Hulu were then computed by averaging the prices across different tiers, weighted according to the proportion of subscribers in each tier. To validate these calculations, I compared the derived average prices for Netflix with those reported in Netflix's financial statements. The difference between these two sources was minimal, with discrepancies consistently under \$0.5 for each quarter within the study period.

Market Shares. Market shares for each "bundle" of streaming services, defined as a unique combination of the top four services, are determined by dividing the number of households with access to each bundle by the total number of households in each DMA. Both variables are sourced from Nielsen Household Universe Estimates.

However, there is a potential for overestimation in the Nielsen data. For example, Nielsen reports 77 million subscribers in the U.S. for Netflix in March 2021, while Netflix's fiscal report has only 74 million subscribers across both the U.S. and Canada. This discrepancy can be attributed to two primary factors. The first is that some households may receive shared subscriptions at no cost. Nielsen usually identifies a household's subscription by checking if any member can browse titles on each streaming service through installed meters. In addition, Nielsen conducts in-house surveys to detect account sharing and to ensure the precision of their subscriber numbers. However, undetected password sharing could still occur, potentially leading to an overcount of subscribers. The second reason is differing definitions of subscriptions. Fiscal reports from streaming services typically count subscribers as of a specific date, whereas Nielsen considers a household a subscriber if they have had access to a service at any point within a month.

To rectify this, I first calculate the ratio of national subscribers according to Nielsen versus those reported in fiscal documents for each of the top four streaming services over 12 months. Since Netflix combines its U.S. and Canadian subscriber numbers, I assume that both countries have an equal market share when calculating this ratio. I then apply this ratio to adjust the number of subscribers for all streaming service *bundles* that include these services across all DMAs and months. As a result, the final sample's total household subscription numbers for each of the top four services should more accurately reflect the figures reported in fiscal documents.

Title Sample Selection. The original dataset from Nielsen ratings consists of 8,835 titles with "significant viewership" across the top four streaming services. For our analysis, the final sample is narrowed down to the top 2,028 titles. These are selected based on their maximum or average weekly rating, which must fall within the top 20% for each respective streaming service.

A limitation of this selection criterion is its potential bias towards including non-exclusive titles in the final sample. This problem arises because Nielsen ratings do not provide separate viewership data for non-exclusive titles across different services. Consequently, non-exclusive titles are more likely to have higher ratings than exclusive ones. This discrepancy leads to a challenge to the identification of the supply model, where the identification of bargaining parameters relies on the likelihood of studios opting for exclusivity in their contracts with streaming services.

While I cannot entirely eliminate this concern, the composition of the final sample offers reassurance. Exclusive third-party titles constitute 86.7% of our final sample, closely aligning with their 86.1% representation among all titles available on the top four services, according to Reelgood data. This similarity supports the representativeness of the selected sample.

Merging Nielsen and Reelgood Data. A major challenge in constructing the title dataset was to merge the Nielsen ratings data with Reelgood data, as they use different title identifiers: Nielsen ratings data provided only the names of titles, while Reelgood data included the more universally recognized IMDB IDs. To integrate these datasets, I adopted the following approach. For each title in Nielsen's data, an IMDB search was conducted using the provided title name. If a unique IMDB title matched the Nielsen name, its IMDB ID was scraped. In cases where multiple matches or no clear match were found, the IMDB IDs and titles of the top five search results were scraped. The title that best matched the release date indicated by the Nielsen data—determined by its first week of appearance in the Nielsen ratings—was then selected through a brute-force matching process. This manual matching approach was used for 467 (23.03%) of the 2,028 titles in the final sample.

Title Characteristics Variables. The age of a title is constructed based on the number of weeks elapsed since its most recent release or update. This means that the age of a title resets to one week whenever a new episode is released. Titles that have not been released or updated in the last 50 weeks are categorized as "old," and their age is marked as zero in the dataset. In addition, a show is classified as binge-released if, during its latest release or update, it debuts at least four episodes.

The production of most titles involves more than one studio. However, in these cases, the distribution of a title generally relies on the studio with strongest power in the market. Therefore, if any "Big Five" studio is involved in the production of a title, I assume it is responsible for the negotiation of the licensing fee with streaming service, and as a result, the title is assigned as a "Big Five" title.

The production of the majority of titles often involves collaborations between multiple studios. For any title that is produced by multiple studios, the studio holding the most market power is often in charge of its distribution. Therefore, whenever a title's production includes any of the "Big Five" studios, I assume that this studio leads the negotiation for licensing fees with the streaming service.

Appendix D Details on Demand Estimation

D.1 Computational Algorithm

To calculate the GMM objective, I first estimate ζ_{jt} and ξ_{cm}, which are then utilized in moments $\mathbf{G}_1$ and $\mathbf{G}_2$. The approach for recovering $\zeta_{jw(t)}$ and ξ_{cm} is similar to the methods used in Lee (2013) and Derdenger (2014), though I do not consider dynamics in demand. The approach employs a nested fixed-point method, as outlined in Figure D.1. The process can be described as follows: for each guess of θ_2, I obtain an initial estimate of the content value (V_{hcm}) for each service bundle and market by assuming homogeneous preferences for all households and individuals. Next, using the contraction mapping introduced by Berry, Levinsohn and Pakes (1995), I recover the mean service bundle utility in each market ($\delta^S_{cm} = \mathbf{x}_{cm}\boldsymbol{\alpha}^x + \xi_{cm}$). The recovered δ^S_{cm} must correspond to the predicted service bundle shares under the given guess of θ_2 and V_{hcm}. I then calculate the probabilities for each household to select a bundle using the recovered δ^S_{cm}, which are used to estimate the title viewing decisions for each individual. The contraction mapping process for mean title utilities ($\delta^T_{jt} = \mathbf{w}_{jt}\boldsymbol{\beta}^w + \zeta_{jt}$) is similar to that for service bundle subscription choices. After δ^T_{jt} converges, the content value variables (denoted as V^+_{hcm}) are updated using definition (12).

The procedure iterates between contraction mapping of δ^S_{cm} and δ^T_{jt} until V_{hcm} converges, indicated by $|V^+_{hcm} - V_{hcm}| < 1e^{-12}, \forall h, c, m$. Once convergence is achieved, I project δ^S_{cm} and δ^T_{jt} on $\mathbf{x}_{cm}$ and $\mathbf{w}_{jt}$, respectively, to compute the unobserved service bundle and title demand shocks, ξ_{km} and ζ_{jt}. Once recovering ξ_{km} and ζ_{jt}, I compute the GMM objective. Using multiple starting values, I find the vector that minimizes the objective function, which serves as the estimate of θ_2.

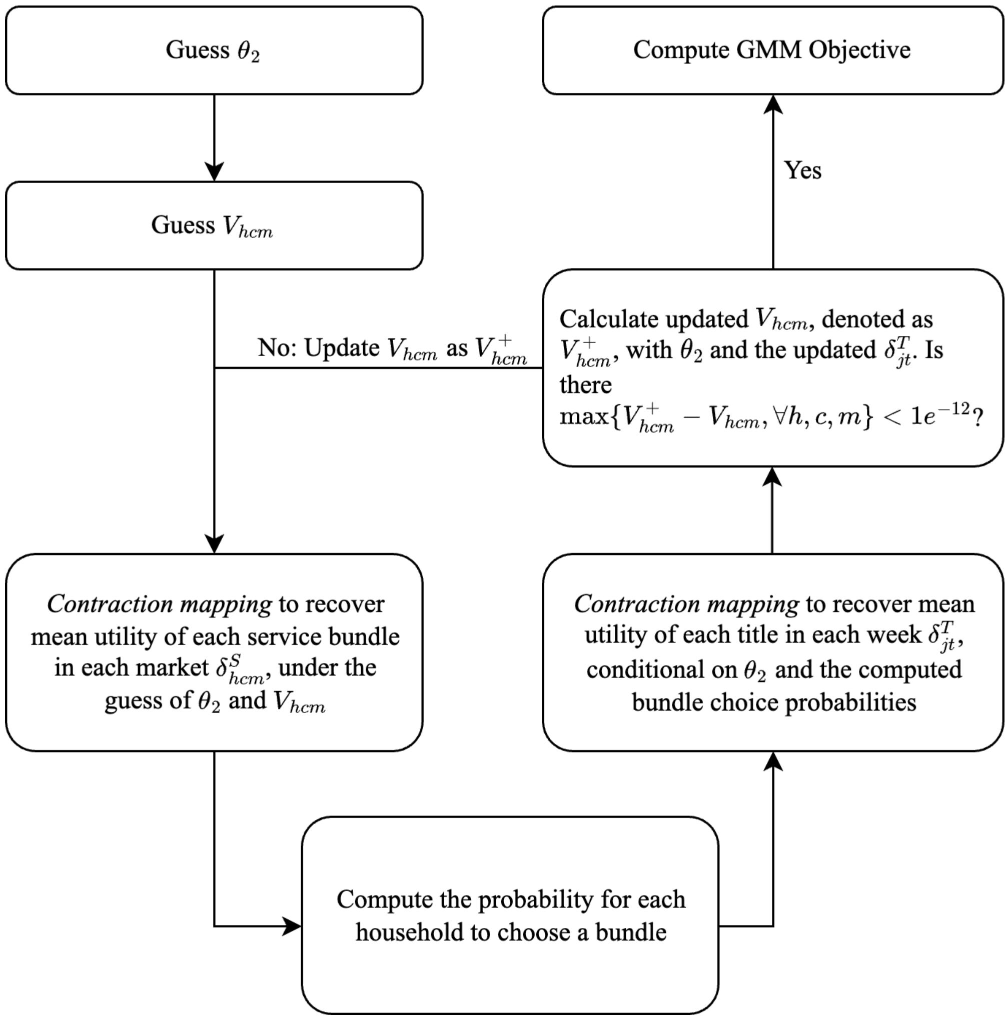

Figure D.1: Nested Fixed Point Algorithm

D.2 Sampling Errors in Integration

The contraction mapping procedure described in D.1 involves simulating market shares of bundle services and titles. Therefore, it requires integration of choice probabilities over different household and individual types, including random coefficients $\{\alpha^p_h, \beta^0_i, \boldsymbol{\beta}^g_i\}$, and household compositions.

Typically, the Monte Carlo method and Gaussian quadrature are used for such integrations. However, both present challenges for this project. First, the Monte Carlo method is prone to significant sampling errors with "heavy tails." This issue is significant in this project, as over 8% of households in the top 30 DMAs consist of five or more members, who are more likely to subscribe to service bundles and stream titles. Furthermore, both methods are computationally inefficient: Monte Carlo requires calculating the probability of each title choice for every sampled individual in simulating title market shares (as shown in Figure D.1), a process hindered by the variation in unobserved demographics v_i from equation (12). Though Gaussian quadrature is somewhat more efficient for simulating title market shares, its use in simulating bundle service market shares becomes prohibitively time-consuming: a household of seven members needs $5^7 > 7e^4$ nodes for an accuracy level of three.

To address these challenges, I employ the sparse grid method from Heiss and Winschel (2008) for integrating over unobserved demographics, including v_h^p and $v_i^0, \forall i \in h$. This method extends the Gaussian quadrature approach but avoids the curse of dimensionality. The key idea is that, to achieve a certain level of accuracy k, researchers only need quadrature rules that are exact for polynomials of order $2k-1$ or lower. It outperforms the Monte Carlo method in accuracy and is significantly more computationally efficient than Gaussian quadrature for the purposes of this project.

Simulation-Based Numerical Integration with Sparse Grid Method. The integration process begins with randomly selecting households from each of the 30 DMAs, based on 2020 census data, with a upper limit of seven members per household. Any household larger than seven is replaced with a randomly selected seven-member household. For these 3000 sampled households, I apply a sparse grid with an accuracy level of four. This results in 116,514 households, which consist of 470,489 individuals. The individuals can be categorized 126 demographic groups defined by both observed and unobserved demographics. When compared to the Monte Carlo and Gaussian quadrature methods, this approach reduces computational time by approximately 87% and by more than 99%, respectively.

Appendix E Details on Supply Estimation

E.1 Monte Carlo Simulations

In this section, I conduct a Monte Carlo study using simulated data to verify the identifiability of the supply model. This involves testing whether variations in bargaining power parameters are identifiable not just among studios, as outlined in the stylized model, but also across different streaming services.

The simulation involves 1,000 titles and three distinct streaming services. For simplicity, I assume that no studios are vertically integrated with any streaming service. Studios have a constant bargaining power parameter, b_k when negotiated with streaming service k. The incremental sales profit for service k from obtaining exclusive rights to a title is denoted as $\pi_k + \epsilon$, where $\epsilon \sim U[-5, 5]$. When a title is licensed to two or three streaming services, service k's incremental sales profit reduces to $\delta_2 \cdot (\pi_k + \epsilon)$ and $\delta_3 \cdot (\pi_k + \epsilon)$, respectively, with $\delta_2 \sim U[0.35, 0.85]$ and $\delta_3 \sim U[0.3, 0.8]$. In addition, studios have unobserved preferences $\nu \sim N(0, \sigma_\nu)$ for contracting with each streaming service under various distribution networks.

The simulated data contain distribution network of each title, as well as the values of $\pi_k + \epsilon$ for each pair of title and streaming service under each distribution network. Using the data, the program is aimed to estimate bargaining parameters $\{b_k, \forall k\}$ and standard deviation of the unobserved preferences σ_ν.

Identification of Bargaining Parameters. A streaming service with a lower π_k or a higher b_k is more likely to be excluded from a studio's distribution network. Service with lower π_k tend to be excluded as they less efficiently contribute to bilateral surplus, failing to meet the stability condition (23). Furthermore, services with a higher b_k are also likely to be excluded as studios with weaker bargaining power (indicated by higher b_k values) are more likely to employ exclusivity as a strategic bargaining tool. In addition, studios find little disadvantage in excluding a service with strong bargaining power; they would struggle to secure favorable licensing terms with these powerful services regardless of their inclusion in the distribution network.

Moment Conditions. In the Monte Carlo study, I estimate the parameters $b_1, b_2, b_3, \sigma_\nu$ using simulated data samples. This approach resembles the estimation methodology outlined in Section 6, where I employ the same two sets of instrumental variables. These variables are designed to be independent of the deviations between observed licensing outcomes and the simulated probabilities of these outcomes, formalized as:

$$\mathbf{E}[(\hat{P}_{j\mathcal{K}} - D_{j\mathcal{K}})\mathbf{Z}_{j\mathcal{K}}] = 0, \text{ for all } j, \mathcal{K}, \tag{28}$$

where $\mathbf{Z}_{j\mathcal{K}}$ comprises network-specific indicators and an instrumental variable that quantifies the aggregated pairwise differences in expected profits, $\pi_k + \epsilon$. This is described by:

$$\sum_{k \in \mathcal{K}} \sum_{k' \notin \mathcal{K}} \left(\mathbf{E}_\nu[\Delta_{jk}\Pi_k(\mathcal{K}_j)] - \mathbf{E}_\nu[\Delta_{jk}\Pi_{jk'}(\mathcal{K}_j \backslash k \cup k')] \right). \tag{29}$$

I do not apply the indirect inference moment conditions in this study because they are pivotal for identifying the internalization parameter μ and delineating the bargaining power disparities between the "Major Five" studios and others, while these elements are abstracted away in this study.

Results. Table E.1 displays the results. The discrepancy between any estimate and its true value is always well below one standard error. This observation means that all parameters are well-identified, including the variation of bargaining parameters across the streaming services. It demonstrates the identification power of the moment conditions adopted in the analysis.

E.2 Computational Details

The supply estimation involves two steps: the recovery of "benefits" per consumer using the first-order condition of optimal pricing, and the estimation of bargaining parameters and those governing studios' payoff function using simulated method of moments. The computational details of both steps are provided below.

Step 1: Recovery of "Benefit" Per Consumer. The process of recovering the benefit per consumer for each streaming service, represented as $p_k + a_k - mc_k + \lambda_k$, relies on the first-order condition of optimal pricing as outlined in (16). This step involves calculating the expected sales

Table E.1: Monte Carlo Simulations: Results

	(1)	(2)	(3)	(4)
Specified Parameters				
Incremental Profits $\{\pi_1, \pi_2, \pi_3\}$	10, 10, 10	10, 8, 5	10, 10, 10	10, 8, 5
Bargaining Parameters $\{b_1, b_2, b_3\}$	0.9, 0.6, 0.3	0.9, 0.6, 0.3	0.6, 0.5, 0.3	0.6, 0.5, 0.3
STD of Unobserved Shocks σ_ν	3	3	3	3
Estimation Results				
b_1	0.903	0.904	0.582	0.591
	(0.030)	(0.051)	(0.083)	(0.088)
b_2	0.587	0.617	0.473	0.511
	(0.081)	(0.064)	(0.089)	(0.064)
b_3	0.314	0.287	0.337	0.295
	(0.079)	(0.082)	(0.103)	(0.069)
σ_ν	3.033	3.003	3.077	3.057
	(0.269)	(0.459)	(0.282)	(0.320)

Notes. Results are based on 100 simulations of 1145 titles and three streaming services. Standard errors are reported in the parentheses. The data generating process varies in the incremental sales profits generated by the streaming services, the bargaining parameters, and the standard deviation of unobserved preference shocks, specified in the first panel of the table above.

profits of streaming services and their derivatives with respect to subscription prices. This necessity arises because the values of demand shocks for title viewership and service subscriptions, ζ and ξ, are unknown by the services at the time of pricing decisions. Instead, They are only aware of the distributions of these shocks.

To accurately assess the expected profits and their derivatives, I employ 25 random draws of (ζ, ξ) from the empirical distribution obtained from demand estimation. Specifically, the demand shocks for titles, ζ, are drawn based on the age and type (movie or TV show) of the titles. This approach is informed by the observation that the variation in ζ tends to decrease as a title ages and that the variation in ζ for TV shows is generally larger. This pattern could be attributed to the increasing knowledge of viewers with the quality of titles over time and a better understanding of movies compared to TV shows. The mean values of these simulated sales profits and the derivatives of subscription prices across all 25 draws are then employed to recover the "benefit" per consumer.

Step 2: Simulated Method of Moments. In this step, under each guess of bargaining parameters and studio-related payoff parameters, I simulate the probability of each distribution network emerging as the equilibrium outcome for every title, $\hat{P}$. This requires evaluating the expected market shares of streaming services and title ratings for each network. I start with 25 random draws of the demand shocks (ζ, ξ) to calculate the expected market shares of streaming services and the ratings of titles under each distribution network. In this process, I keep other titles' distribution networks and SVOD subscription prices constant due to the simultaneity assumption, where all titles' bilateral contracting and SVOD subscription pricing occur at the same time.

Following this, For each of draw, I find out the equilibrium distribution network for each title that satisfies both the stability condition (23) and the optimality condition (24), while holding subscription prices and the distribution networks of all other titles fixed as observed. Among these, the network yielding the highest studio payoff is selected as the equilibrium distribution network.The simulated probability for each distribution network to be an equilibrium outcome among all random draws is used as $\hat{P}$.

To ensure robust optimization and avoid local minima, I use the Matlab command fminsearchOS, an improved version of the Nelde-Meade search algorithm. It is more effective in getting over the kinks and identifying the global minimum. The optimization process is further strengthened by using 1000 random draw of ν and 10 different starting points, ensuring the convergence to the global minimum.

E.3 Robustness Checks

In the main specification, I categorize titles into two groups: those produced by the "Big Five" studios and those by smaller studios. Since most titles involve more than one production company, I classify a title as being produced by the "Big Five" if at least one of its production companies is among the "Big Five." According to my interviewees, the "Big Five" typically handle contract negotiations in these cases due to their strong bargaining power.

Alternative Studio Categorization. To ensure the robustness of the estimation results to different title categorizations, I re-estimate the model using an alternative categorization approach. Specifically, I divide titles involving at least one "Big Five" studio into two categories: those where at least 50% of the production companies are "Big Five," and those where less than 50% are "Big Five." This results in 216 titles in the first category, named "Big Five: Major," and 327 titles in the second category, named "Big Five: Minor."

I re-estimate the supply model, allowing for different bargaining powers for these two categories. The regression results, reported in Column (1) of Table E.2, show that the parameters change only marginally from the main specification in Table 5. Specifically, the bargaining powers of studios for these two categories are indifferent, supporting the validity of my interviewees' insights and the main specification.

Differential Bargaining Powers of Streaming Services. In the main specification, I assume that all streaming services have the same bargaining powers against studios. As a robustness check, I relax this assumption by allowing Netflix, the largest streaming service worldwide, to have a different bargaining power from its competitors, Amazon Prime and Hulu. I parameterize the bargaining power as follows:

$$b_{jk} = \mathbf{1}(j \in \{\text{Smaller Studios}\})b_{small} + \mathbf{1}(j \in \{\text{Big Five}\})b_{big} - \mathbf{1}(k = \text{Netflix})b_{Netflix}. \tag{E.1}$$

The parameter $b_{Netflix}$ captures the difference in bargaining power between Netflix and its competitors. A larger $b_{Netflix}$ implies stronger bargaining power for Netflix.

Table E.2: Robustness Check: Supply Estimation

	(1) Studio Categorization			(2) Differential $\boldsymbol{b}$ for Studios		
	Estimates	SE		Estimates	SE	
Bargaining Parameters						
Big Five: Major	0.817	0.155	***			
Big Five: Minor	0.820	0.117	***			
Big Five: All				0.866	0.158	***
Smaller Studios	0.576	0.152	***	0.559	0.154	***
Against Netflix				−0.063	0.169	
Studio Payoff Parameters						
Logged Viewership	0.869	0.207	***	0.780	0.187	***
STD of Unobserved Preferences	0.164	0.030	***	0.146	0.026	***
Internalization	0.657	0.134	***	0.626	0.124	***

Notes. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Studios' payoffs are measured in millions of dollars. Standard errors are computed using 100 bootstrap samples.

The identification of $b_{Netflix}$ relies on the variation in distribution networks. As shown in Section B.1, all else equal, a streaming service with stronger bargaining power is more likely to be excluded, as the studio suffers smaller losses from excluding it.

I present the estimation results in Column (2) of Table E.2. I find that the difference in bargaining powers between Netflix and its competitors is statistically insignificant and small in magnitude. This robustness check suggests that the main specification has captured most of the variation in bargaining powers across pairs of firms.

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