Pricing and Foreclosure on Integrated Platforms: Evidence from Internet Service Providers*

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PRELIMINARY

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Abstract

This paper studies the joint pricing decisions of internet service providers (ISPs), who sell internet access and pay-TV subscriptions. I estimate a model of consumer choice over ISP and third-party online video subscriptions (such as Netflix) using novel household-level data containing online video usage information at the hourly level. I find that the elasticity of demand for internet access is -0.99, and that TV elasticities are between -6.45 and -3.13, implying much higher margins for internet than TV. The average internet subscriber is willing to pay $19 for Netflix and $32 for Streaming TV. When access to online video is removed from the average household's preferred bundle, willingness-to-pay falls by 20%, or $38. Next, I use a model of bundle pricing to study the implications of alternative ISP strategies for pricing internet content. I find that foreclosure of online video is not profitable due to a combination of the large contribution of online video access to internet valuations and low TV profit margins. When the ISP adopts an add-on pricing strategy for online video, the price changes cause most consumers to purchase both internet and TV, and new consumer surplus is unlocked through additional TV subscriptions.

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1 Introduction

In many industries, consumers rely on platforms to access goods or services. When platform firms vertically integrate, they face a trade-off between maintaining the standalone value of the access network and promoting integrated products. Integrated platforms possess a variety of tools to influence consumer behavior; they not only set prices for their own goods, but also control the assortment of third-party goods that consumers can access. Altering the assortment of available substitute goods allows the platform to gain market share by foreclosing third-parties. This paper studies the joint pricing and assortment decisions faced by platforms and the impact of new selling strategies on the distribution of industry surplus.

There are many examples of integrated platforms across different industries: Amazon offers private-label goods through AmazonBasics; Netflix produces original content; Apple owns applications on its App Store. Despite the growing use of platforms, several empirical questions remain unanswered: What is the optimal tariff structure in these settings? Are product assortment decisions by platforms anticompetitive? Are these industry structures harmful to consumers?

This paper contributes to the literature by studying the impact of internet service provider (ISP) decisions over the pricing and assortment of third-party video streaming applications available on their broadband networks. ISPs are platforms: they sell access to a network that connects consumers to a content providers such as Netflix or Sling TV. They are also content providers, selling bundles of TV channels and dedicating a share of network resources towards the delivery of TV content. Third-party video streaming applications increase the value of internet access, but also compete with TV, with many applications offering the same content as the traditional TV product delivered by ISPs. An ISP's decision regarding which applications to make available over the internet thus evokes a trade-off between inducing substitution from online video to TV subscriptions and damaging the value of internet access.

Internet access and video content differ from other platform contexts because they are information goods, which are distinct from other commodities in two important ways. First, the value of access to content is not immediately realized, but rather depends on the amount of time spent consuming it. Attention is a scarce resource for consumers, making time-intensive goods inherent substitutes. Second, because the value of information content decays over time, these goods are sold using a subscription-based pricing model. In contrast to other platforms, ISPs charge a subscription fee for access to the internet in addition to a subscription fee for TV, resulting in multiple mechanisms by which they can extract surplus.

The treatment of third-party content by ISPs is a contentious policy issue. In 2017, the Federal Communications Commission voted to repeal rules established by an earlier 2015 decision which prohibited ISPs from blocking, throttling, or prioritizing individual websites or applications. The repeal of net neutrality protections broadens the scope of ISP control over the pricing of internet content, but the implications of newly permissible pricing strategies are not well-understood. Studying these pricing incentives is of particular interest given the recent wave of consolidation in the telecommunications industry involving both service providers and content providers, such as the 2018 merger between AT&T and Time Warner. Though the competitive implications of TV network ownership by TV distributors have been studied (Chipty, 2001; Suzuki, 2009; Crawford et al., 2018), the effect of AT&T's stake in Time Warner's online content on its internet pricing incentives is less-understood. For example, AT&T may stand to benefit post-merger from blocking or otherwise degrading Netflix, so that more subscribers switch to HBO Now.

At the time of this writing, limiting the assortment of content on their networks is within the purview of ISP decision-making. However, ISPs have not yet modified the set of content available on their networks. As such, the ideal natural experiment needed to study the implications of this type of strategy, one in which the researcher observes the decisions of consumers who are offered alternative assortments, does not exist. I proceed instead by simulating counterfactual settings using a model of ISP pricing and a continuous-discrete choice model of demand for internet and video content in the spirit of Crawford and Yurukoglu (2012), in which the utility derived from access to content depends on the time allocated to it.

At the core of this effort is a novel dataset on household-level purchases and usage obtained from an anonymous North American ISP. The micro-data contain over 130 million household-day-hour observations of subscription information for both internet and television tiers, and utilization data collected from internet modems and TV set-top boxes. The average internet subscriber in the sample consumes 7.75 gigabytes per day, 62% of which is online video. The average Internet household watches nearly 4.75 hours of online video per day, while the average TV household watches 4.84 hours of TV per day. Households with internet and TV subscriptions consume 30% fewer hours of online video than internet-only households and 13% fewer hours of TV than TV-only households. A key feature of this dataset is visibility into streaming consumption at the application level. I infer streaming application subscriptions based on the timing and intensity of usage. The two most-used applications in the data are Netflix and YouTube, which respectively make up 15% and 12% of total internet traffic, and have penetration rates of 63% and 94% among internet subscribers.

I estimate the model using a two-step mixture estimator related to the methodology described in Fox et al. (2011) and Fox et al. (2016), where the objective is to find mixture weights for a set of basis densities describing model heterogeneity. The model estimates imply a much less elastic demand for internet than TV subscriptions, with an internet own-price elasticity of -0.99 and TV tier elasticities ranging from -6.45 to -3.13, leading to much higher margins on internet than TV. I find that the average internet household is willing to pay \$19 for Netflix and \$32 for Streaming TV, and when access to streaming applications is removed, willingness-to-pay for the average household's preferred bundle falls by \$38, or 20%.

The first finding of this paper concerning ISP strategies is that foreclosing on streaming is not profitable. The results of this counterfactual, a study of the implications of the FCC's "no blocking" rule repeal, suggest that foreclosure concerns may be somewhat mitigated given current ISP pricing practices. When access to third-party video applications is removed, the ISP's TV service benefits from less competition, and prices rise by 32%. However, this additional surplus capture from consumers with a taste for TV is offset by a loss in the profitability of internet subscriptions. The optimal internet price falls by 21% and ISP profits fall by $3 per subscriber-month. In blocking access to internet content, ISPs damage the value of internet access as a whole, and consumer surplus falls by $3.50 per subscriber-month.

Next, I explore the implications of more flexible pricing strategies in which the ISP is able to set not only a baseline price for internet access, but also add-on prices for access to specific third-party applications. Intuitively, this type of strategy aligns internet pricing more closely with TV pricing, with add-ons for premium online video subscriptions serving a similar role to higher-tier TV subscriptions that allow access to more channels. Though an add-on internet pricing model has not yet been implemented in practice, its implications are analogous to zero-rating practices employed by mobile and residential broadband providers that employ usage-based pricing. Just as zero-rating creates differences in the marginal price of consumption of certain content by not counting consumption against usage allowances, the add-on pricing strategy creates differences in the relative prices of subscriptions by charging additional fees.

I find that under add-on pricing, the ISP sets a dramatically higher price for standalone internet access, increasing the price by 50%, but a combination of lower TV prices (40% reduction) and lower internet and TV bundle prices (27% decrease) cause nearly every internet household to switch to a bundle containing both internet access and TV. The optimal add-on prices for Netflix and Streaming TV are $6 and $40, respectively. Not surprisingly as it nests the ISP's baseline strategy, add-on pricing is profitable for ISPs, and leads to a $24 increase in profit per subscriber-month for ISPs. This profit increase comes from increased TV subscriptions as over 90% of previously internet-only households add TV, and increased revenue from previous online video users that retain their third-party subscriptions under the new pricing policy. Consumer surplus increases overall by 14$ per month, with 75% of the welfare gains captured by two groups—previously internet-only households that switched from online video to TV, and households that already purchased both TV and online video at baseline prices.

These findings are subject to several noted limitations. First, the pricing counterfactuals explored with the estimated model are "partial" in the sense that they do not account for the possible actions of competing ISPs, and do not allow online video prices to adjust. Price discrimination is possible under imperfect competition, but the implications of new strategies such as blocking or add-on pricing will change if the outside purchase option includes a competing ISP. Second, counterfactuals assume that the channel composition of the ISP's TV tiers does not adjust. Individual channels vary in their availability online from third-parties, so removing outside sources for some channels may increase the value of moving them into higher-revenue tiers. Third, due to a lack of ISP cost data, the results do not account for long-term investment savings from reduced internet consumption that may result from reducing online video use.

Contributions and Related Literature.—Previous work studying the television and broadband industries has primarily focused on one or the other industry in isolation, whereas this paper seeks to understand joint pricing across internet and TV. In the cable industry, Chipty (2001), Suzuki (2009), and Crawford et al. (2018) study foreclosure incentives when programmers and distributors vertically integrate. In this paper, TV distributors also sell broadband, which gives them vertical leverage over online video competitors. Other papers study the demand for broadband and ISP pricing strategies (Rosston et al., 2010; Greenstein and McDevitt, 2011; Nevo et al., 2016), as well as ISP relationships with content providers (Goetz (2019), Tudon (2019)). McManus et al. (2018) study ISP incentives to steer consumers from third-party online video to TV subscriptions. I extend their largely reduced-form results using a structural approach which allows me to make welfare statements and consider counterfactual pricing and assortment scenarios.

This paper takes a similar approach to previous studies that learn about valuations from time-allocation and usage decisions. Goolsbee and Klenow (2006) combine earnings information with time spent on the internet to learn about consumer benefits from broadband. Crawford and Yurukoglu (2012) use ratings data to learn about relative valuations of TV channels. Many other papers have studied TV viewing behavior, in particular with respect to advertising. (Wilbur, 2008; Deng and Mela, 2018).

Finally, this paper complements a literature pertaining to the economic analysis of net neutrality, the bulk of which is theoretical, dating back to Wu (2003). Definitions of net neutrality vary based on whether restrictions are placed on interactions between ISPs and content providers or ISPs and consumers (Economides and Hermalin, 2012; Armstrong, 2006; Bourreau et al., 2015; Choi et al., 2015; Choi and Kim, 2010; Economides and Tag, 2012; Gans, 2015; Economides and Tag, 2016; Reggiani and Valletti, 2016). This paper considers the relationship between ISPs and consumers. The literature is reviewed in Lee and Wu (2009) and Greenstein et al. (2016).

Road Map.—In Section II, I describe the data sources used in the analysis and highlight key empirical facts. Section III contains a model of consumer demand for internet and video subscriptions and viewership, as well as a model of ISP pricing. Section IV is a discussion of the identification and estimation of the structural model, the results of which are presented in Section V. I analyze counterfactual pricing and demand responses to varied product assortment in Section VI. Finally, I offer my conclusions in Section VII.

2 Data

In this section, I describe the data used in the empirical analysis and highlight the role of substitution from traditional TV to video streaming applications in driving internet traffic growth.

Data Sources and Description.—The data used in this analysis come from an anonymous North American internet service provider (ISP), which provides information on subscriptions and utilization of internet and TV services.

The sample is collected from a market of approximately 20,000 addresses passed, i.e., addresses that are connected to the ISP's network and thus capable of receiving service. The panel spans a 15-month period between May 2017 and July 2018, and contains approximately 130 million household-day-hour observations.

The ISP sells broadband internet access, TV, and landline voice services. Information on household take-up of the ISP's offerings is provided at a daily frequency and includes characteristics of the chosen package, e.g., internet download speed and set of TV channels. Approximately 13,000 of the addresses passed purchase internet or TV from the ISP. Of these served households, 64% choose a bundle of internet and TV service, 35% choose internet without TV, and fewer than 1% choose TV alone.

For each household with an internet subscription, I observe aggregated information from a deep packet inspection (DPI) analysis that reports byte counts passed downstream and upstream, as well as a breakdown of total bytes passed into several traffic categories. The scope of the data include traffic on all devices, including mobile devices, as long as it is directed over the home broadband network (i.e., via Ethernet or WiFi). Cellular data plans and internet consumption outside of the home are both unobserved. These data, aggregated from the household-day-hour to household-day level of observation, are summarized in Table 1.

The average sampled internet household consumes 7.75 gigabytes per day of bandwidth. The majority of internet traffic, nearly two thirds of the total, comes from the "Streaming/Video" category, which consists primarily of traffic consumed by online video applications such as Netflix, as well as some embedded video content on other websites.[1] The next-largest category is "Web Browsing", accounting for 11% of the average household's daily usage, with similar consumption also captured in the "Email" and "Social Networking" groups. The distributions of total usage and usage by traffic type are very heterogeneous, with the right-skewed 95th percentiles of total usage and streaming usage accounting for three and four times the respective mean levels.

[1]The majority of encrypted traffic is observable and sorted into the appropriate application type, though some encrypted video traffic for which a content provider is not identified is counted in the Bulk Transfer category.

Application-level usage information is available for all traffic falling under the video category. Each video byte can be matched to a specific application, e.g., Netflix, as well as information about the streaming session, such as the total time duration, the resolution, and the device used. Table 2 summarizes take-up and conditional usage of the most-used online video applications in the data. The largest application in terms of traffic is Netflix, with the average subscriber consuming nearly 2 gigabytes per day on the application. Its market share among internet subscribers in the sample is 66%. The application reaching the most households is YouTube, with nearly 100% penetration and over a gigabyte per day of consumption per household.

For each household with a TV subscription, I also observe tuning information from the household's set-top box. These tuning data are aggregated to the household-day-hour level. The average TV household watches 4.5 hours per day.

The rise in popularity of online video affects ISPs in two ways. As a potential substitute to TV, it may impact ISP subscription revenue, and as a driver of traffic growth, it influences costs by increasing the burden on bandwidth-constrained network infrastructure.

Industry reports document annual growth rates of approximately 30% in residential broadband traffic (Cisco, 2017). Figure 1 shows the growth in internet traffic over the course of the sample. During the 15-month sample period, average daily consumption increased by over 50%.

Cord-cutting.—Since the emergence of online video, the number of households with traditional TV has plateaued. Fewer new consumers purchase TV subscriptions, while an increasing number of previously "bundled" households, those with TV and internet access, opt to "cut the cord," or cancel their TV subscription in favor of an internet subscription alone. The decline in number of TV subscriptions observed in the sample is approximately 2.7%, consistent with Nielsen's (2019) estimate of an annual rate of 2-3%.

The fact that consumers are now switching from the bundle of TV and internet to internet-only subscriptions suggests that internet itself or specific internet applications may be substitutes for TV. Figure 2 shows the internet consumption habits of observed households that cut the cord. In particular, the two panels demonstrate how cross-household averages of total consumption as well as consumption of video streaming applications change in the 60 days preceding and following the cord-cut date. The horizontal lines indicate pre- and post-transition averages. From the left panel, we see that total consumption immediately increases by nearly 4 gigabytes per day, or 54%, and that this increase is driven by a 2.8 gigabyte, or 68%, increase in online video consumption. For this group of households, video's share of total consumption increases from 57% to 63% after cutting the cord.

The right panel shows that the change in total online video consumption is heterogeneous across applications. Daily consumption of Netflix increases modestly, by 12%, while use of Streaming TV, defined as applications that offer the same content as the ISP's TV service—in this sample, Hulu, Sling TV, DirecTV Now, and PlayStation Vue—increases four-fold to 1.75 gigabytes per day. The difference in engagement between these two application types is suggestive of variation across online video applications in the degree of substitutability with TV. While cord-cutters may already be close to saturation levels with Netflix's original content before dropping TV, streaming TV's overlap in content with traditional TV makes it a natural substitution destination after a cancelled TV subscription.

In addition to the content itself, another reason online video and traditional TV may be substitutes is that they are both time-intensive activities that require attention. Table 3 shows how the distribution of time spent on media across internet and TV varies depending on the video subscription the household purchases from the ISP. In general, households that purchase a TV subscription which includes a greater number of channels watch more TV and relatively less streaming video. Although the increase in TV consumption moving into higher tiers is somewhat offset by a decline in streaming consumption, the total time allocated to media is increasing, suggesting that the two mediums are not fully substitutes.

Choice Set and Selection of Content Types.—The ISP sells TV and internet access, offering a menu of differentiated tiers. TV tiers are nested packages of channels, with higher-revenue tiers containing tier-specific channels in addition to all channels offered by lower tiers. Internet tiers are differentiated by download speed. I group all internet tiers together and abstract from modeling a preference for speed for two reasons. First, internet tiers are not associated with bandwidth allowances in this market and thus do not restrict the level of internet consumption. Second, the ISP's network is modern and congestion-free, and without such capacity constraints the download speeds realized on even the slowest tier are well in excess of the speeds recommended by video streaming providers.[2]

I dis-aggregate total time spent on media into several content types. In addition to the three sets of channels in the ISP's TV tiers, I focus on four types of internet content. Netflix is the most-used application in the data, accounting for 15% of total internet traffic, and makes up its own consumption type. I also distinguish streaming TV viewership (usage of Sling TV, DirecTV Now, Hulu, and PlayStation Vue) from other streaming for two reasons. First, it is marketed as a direct substitute to the ISP's TV product, and as such is intuitively a close competitor for which exclusion may be optimal for the ISP. Second, despite having a smaller reach than applications like Netflix, streaming TV subscribers engage with the service far more than subscribers of any other streaming application, viewing content on the application in excess of three hours per day. Since each consumption type requires additional model parameters, for feasibility of estimation, consumption of the remaining video applications is grouped into a single category. Time spent on non-video internet activities (web browsing, social networking, email, etc.) is grouped into a final category.[3]

In total there are eight consumption types including the outside option. The three sets of channels making up the ISP's TV tiers contribute three, while the remaining

[2]Netflix recommends a 25 Mbps download speed for streaming Ultra HD/4K content, its highest available video quality.

[3]Consumption of non-video activities is observed in bytes rather than hours. I use conversion rates published by Cable One at https://www.cableone.net/data-calculator to obtain time allocated to this consumption type.

four require an internet subscription. These include Netflix and Streaming TV, each of which requires an additional third-party subscription to view, in addition to "Other Streaming" and "Other Web", both of which are available to any household with an internet subscription. Appendix Table 12 lists the full set of subscription combinations from the ISP and third parties, and the consumption types that are available to households that choose each bundle.

3 Model

In this section I describe a model of household decision-making and ISP pricing. First, households make choices over bundles of subscriptions, each of which includes internet access and TV tiers sold by the ISP in addition to third-party online video applications. Each subscription bundle grants access to a set of content types, which households allocate their time to in a second stage. The utility derived from a bundle is expressed in terms of the optimal allocation of time to the content it provides, as in Crawford and Yurukoglu (2012). Finally, ISPs set prices for internet access, three TV tiers, and a bundle discount given the population distribution of the preference parameters that guide household decision-making.

Subscription Choice and Content Usage.—Each household chooses a product bundle b from a menu of available subscriptions. The available subscriptions include both products sold by the ISP (internet access and tiers of the ISP's TV service) and third-party video streaming applications, e.g., Netflix. For any bundle of subscriptions b, let $s(b)$ denote the assortment of content provided by the subscriptions in b.

Households compare the indirect utility $v(b;\boldsymbol{\theta})$ they would receive from viewing each set of content $s(b)$ with the posted price for the bundle b, p_b. The optimal bundle choice satisfies

$$\max_b u(b;\boldsymbol{\theta}) = v(b,\boldsymbol{\theta}) - p_b.$$

A household with access to content $s(b)$ allocates time $h_c(b)$ to each content type $c \in s(b)$ and its remaining time $h_0(b)$ to outside activities. A vector $\mathbf{h}(b)$ is a time-allocation decision, specifying the time allocated to each content type provided by b. For any time-allocation decision $\mathbf{h}(b)$, let the utility from viewing content be given by $w(\mathbf{h}(b); \boldsymbol{\theta})$, where $\boldsymbol{\theta}$ is a vector of parameters governing the shape of utility, henceforth referred to as a household type. The indirect viewing utility from set $s(b)$, attained from the optimal time allocation decision $\mathbf{h}(b)$, is given by

$$v(b; \boldsymbol{\theta}) = \max_{\mathbf{h}} w(\mathbf{h}(b); \boldsymbol{\theta})$$
$$\text{s.t.} \sum_{c \in s(b)} h_c + h_0 = T$$

where T is the total amount of time available to the household. The utility of the outside bundle option $b = 0$ is given by the viewing utility associated with the time allocation $h_0 = T$ in which all time is allocated to the outside consumption option.

For the remainder of this section, I discuss the parameterization of viewing utility and its ability to capture key empirical features of consumption. Viewing utility takes a nested constant elasticity of substitution (CES)-type form in the time allocated across content:

$$w(\mathbf{h}; \boldsymbol{\theta}) = \left[\delta_1 \left(\sum_{c \in s(b)} \delta_c h_c^{-\rho_2} \right)^{\rho_1/\rho_2} + \delta_0 h_0^{-\rho_1} \right]^{-1/\rho_1}$$

The δ_c parameters set the marginal utility of consuming content. The relative value of platform and outside option utility is controlled by δ_1 and δ_0, the latter of which is normalized to 1 for the estimation. The ρ_1 and ρ_2 parameters control the curvature of utility and affect willingness to substitute time between different activities. The ρ_2 parameter controls the flexibility of time spent on TV or internet activities, while the ρ_1 parameter governs willingness to substitute between platform content and the outside option.

The substitution parameters have two important implications for the shape of utility. First, they control the decay of the marginal utility of content. For small ρ_2, an individual will spend most of his time on the consumption type with the highest marginal utility. However, as ρ_2 increases, utility for a given consumption type decays more rapidly, and the model predicts that time is spread more evenly across consumption types. The second implication follows from the first, but concerns subscription utility. When ρ_2 is large, the value of choosing larger bundles with more content types increases. A larger set $s(b)$ means there are more content types to choose from, and the marginal instant of attention allocated to each type is subject to less decay. As such, for a pair of bundles b and b' for which $s(b) \subset s(b')$, i.e., bundles for which b' offers at least as much content as b, the difference $v(b';\boldsymbol{\theta}) - v(b;\boldsymbol{\theta})$ is increasing in ρ_2.

The model provides an optimal time allocation $h_j^*(b,\boldsymbol{\theta})$ for each consumption type $j \in s(b)$. The Lagrangian for the time allocation problem is:

$$\mathcal{L} = w(\mathbf{h};\boldsymbol{\theta}) + \Lambda\left(T - \sum_{c\in s(b)} h_c + h_0\right)$$

The solution is defined by the following system of first-order conditions:

$$\partial u/\partial h_c : \left[\left(\sum_{c\in s(b)} \delta_c h_c^{-\rho_2}\right)^{\rho_1/\rho_2} + \delta_0 h_0^{-\rho_1}\right]^{\frac{-1-\rho_1}{\rho_1}} \left(\sum_{c\in s(b)} \delta_c h_c^{-\rho_2}\right)^{\frac{\rho_1-\rho_2}{\rho_2}} \delta_1 h_1^{-\rho_2-1} = \Lambda \quad (1)$$

$$\partial u/\partial h_0 : \left[\left(\sum_{c\in s(b)} \delta_c h_c^{-\rho_2}\right)^{\rho_1/\rho_2} + \delta_0 h_0^{-\rho_1}\right]^{\frac{-1-\rho_1}{\rho_1}} \delta_0 h_0^{-\rho_1-1} = \Lambda \quad (2)$$

$$\partial u/\partial \Lambda : \sum_{c\in s(b)} h_c + h_0 = T \quad (3)$$

The optimal viewing of type j is related to the size of δ_j relative to the marginal utility parameters of other available consumption types. To see this, consider the case when $\rho_2 = \rho_1$ and $\delta_1 = 1$ so that there is no nest. The first-order conditions are all of the form given by equation (2) and optimal consumption has a simple closed form:

$$h_j^*(b;\boldsymbol{\theta}) = \frac{\delta_j^\sigma}{\sum\limits_{c\in s(b)} \delta_c^\sigma + \delta_0^\sigma} \cdot T$$

where $\sigma \equiv 1/(1+\rho_1)$. Here it is easy to see the effect of the substitution parameters on time allocations. When ρ_1 and ρ_2 approach -1, viewing utility is linear and the optimal time allocation is a corner solution in which all time is allocated to the content type with the highest marginal utility parameter. As ρ_1 and ρ_2 approach 0, the utility function approaches the Cobb-Douglas utility function, and time is allocated exactly proportionally to the relative size of the δ parameters.

ISP Bundling Problem—The ISP offers internet access and three TV service tiers, differentiated by the number of channels they contain. It sets a price for standalone internet and each TV tier in addition to a fixed bundling discount p_δ that applies when consumers purchase both internet and TV together. Prices are as shown in the following table.

Mixed Bundle Prices

	TV Tier			
Internet	None	Tier 1	Tier 2	Tier 3
Yes	0	$p_{0,1}$	$p_{0,2}$	$p_{0,3}$
No	$p_{1,0}$	$p_{1,0} + p_{0,1} - p_\delta$	$p_{1,0} + p_{0,2} - p_\delta$	$p_{1,0} + p_{0,3} - p_\delta$

The primary costs associated with TV are network affiliate fees paid by the ISP to the producer of each channel it broadcasts. These affiliate fees are a per-subscriber payment. The constant marginal cost of selling TV tier j is the sum of the affiliate fees associated with each channel in tier j, referred to henceforth as c_j. The bulk of the costs associated with supplying internet access are in the form of investments in internet infrastructure, which are infrequent and not observed in this sample. Without the data needed to inform a model of investment, I model only the short-run marginal cost of supplying internet access.[4] The profit function is

$$\pi(\mathbf{p}; F(\theta)) = \sum_b \left(p_b - \sum_{j \in b} c_j \right) s_b(\mathbf{p}; F(\theta)),$$

where the share of bundle b is determined by integrating across the distribution of types, $F(\theta)$, i.e.,

$$s_b(\mathbf{p}) = \int_\theta \mathbb{1} \left[b = \arg\max_{b'} \left(v(b', \theta) - p_b \right) \right] dF(\theta),$$

where p_b is the price of bundle b, i.e., the sum of the price indicated in the above table and any third-party subscriptions, and the sum over j adds up the individual marginal costs of each component in bundle b.

4 Estimation and Identification

In this section, I outline the estimation procedure and discuss the identification of model parameters. It is well-known from the price discrimination literature that optimal pricing solutions are highly sensitive to parametric demand assumptions. For this reason, I take a flexible approach to estimating the distribution of random coefficients describing preference heterogeneity related to the methodology described in Fox et al. (2011) and Fox et al. (2016). The approach expresses the joint distribution of parameters as a mixture of normal densities. The estimation objective is to find mixing weights for each of these densities.

Recall that a household's decisions are fully described by its type, a $K = 10$-dimensional vector of parameters $\theta = (\rho_1, \rho_2, \delta_1, \boldsymbol{\delta})$. The object of interest for estimation is the joint distribution of types $F(\theta)$.

I assume that $F(\theta)$ can be expressed as a mixture of $R = 1,024$ normal basis densities, which are chosen to cover the parameter space. Let $\phi(\theta \mid \mu^r, \sigma^r)$ denote the

[4] The marginal costs associated with providing internet access consist of the electricity costs of delivering traffic, customer service, and exchange costs as traffic is routed from the access network to upstream sources outside of the ISP's network.

Estimation Notation

θ	vector of model parameters
Θ	parameter space
K (index k)	dimension of parameter space (10)
S (index s)	number of simulated types (1,048,576)
I (index i)	number of moments
R (index r)	number of basis densities (1,024)
J (index j)	number of bundle choices (20)
β^r	mixture weight attached to basis r
$z_{i,j}$	ith model moment for bundle choice j
$y_{i,j}$	ith empirical moment for bundle choice j

joint normal density corresponding to the rth basis. Each joint density is the product of K independent marginal distributions, i.e.,

$$\phi(\theta \mid \mu^r, \sigma^r) = \prod_{k=1}^{K} \phi(\theta_k \mid \mu_k^r, \sigma_k^r).$$

The μ^r and σ^r parameters describing density r are fixed pre-estimation. Given a vector of probability weights $\boldsymbol{\beta}$, the resulting density function is

$$f(\theta) = \sum_{r=1}^{R} \beta^r \phi(\theta \mid \mu^r, \sigma^r).$$

The goal of estimation is to recover $\boldsymbol{\beta}$.

Estimation proceeds by "matching" a collection of I model moments, $m_{i,j}(\theta)$, for each of J bundle choices, with their empirical counterparts $y_{i,j}$. Each model moment is evaluated using each of the R basis densities to form "regressors" $z_{i,j}^r$:

$$z_{i,j}^r \equiv \int_{\Theta} m_{i,j}(\theta)\phi(\theta \mid \mu^r, \sigma^r) d\theta. \tag{4}$$

To simulate this integral, I use the importance sampling methodology of Ackerberg (2009), which is often employed when simulation is computationally intensive (Goettler and Clay, 2011; Roberts and Sweeting, 2013). Although solving my model for a single type is not computationally burdensome, the dimensionality of the parameter space requires a very large number of simulation draws. The benefit of importance sampling in this context is that each simulation draw can contribute to the evaluation of moment integrals with respect to multiple basis densities.

To this end, I pre-solve the model for a fixed grid of $S = 1,048,576$ (4^{10}) types, or all combinations of a uniform fixed grid of four values for each of the 10 parameters describing preference heterogeneity. When presented with a bundle j, each type θ^s has a unique time allocation solution specified by the model. These usage decisions, along with the optimal bundle choice, are saved.

To proceed, I rewrite Equation 4 as

$$z_{i,j}^r = \int_\Theta m_{i,j}(\theta) \frac{\phi(\theta \mid \mu^r, \sigma^r)}{h(\theta)} h(\theta) d\theta,$$

where $h(\theta)$ is the known (uniform) probability density from which the S simulation types were drawn in the first step. Finally, I approximate the integral as

$$z_{i,j}^r \approx \frac{1}{S} \sum_{s=1}^{S} m_{i,j}(\theta^s) \frac{\phi(\theta^s \mid \mu^r, \sigma^r)}{h(\theta^s)}.$$

I estimate the vector of weights β using inequality-constrained least squares. The estimator is

$$\hat{\boldsymbol{\beta}} = \arg\min_{\boldsymbol{\beta}} \frac{1}{NJ} \sum_{i=1}^{I} \sum_{j=1}^{J} \left(y_{i,j} - \sum_{r=1}^{R} \beta^r z_{i,j}^r \right)^2,$$

where the objective function is minimized subject to the constraint that $\boldsymbol{\beta}$ lies within the R-dimensional unit simplex.

The moments are chosen to capture the rich heterogeneity of empirical usage while maintaining computational ease. To this end, the selected moments are all linear in the type weights. Three types of moments are used in the estimation. First, to capture the marginal distribution of usage of each content type, I include percentiles from the population distribution of viewership of each type. Second, I include percentiles from the joint distribution of pairs of content types to capture correlation in tastes. Finally, bundle market shares are included to adjust the weights attached to the set of types that choose each bundle to match those in the data. Standard errors are obtained by resampling the dataset and repeating the estimation procedure (Lahiri, 2003). I sample the data with replacement 500 times, re-calculate the empirical moments for each sample, and then re-estimate the weights. I calculate standard errors for subsequent results and counterfactuals by repeating each calculation using each weight estimate.

Identification.—The identification discussion is split into two parts. First, I discuss the identification of type weights. Second, I discuss the data variation that isolates the contribution of each model parameter to predicted behavior.

Type weights are recovered by finding the mixture of candidate types whose decisions best match the bundle shares and usage choices observed in the data. It is useful to think about the estimation as a process by which we update a prior about how the types are distributed across the population using layers of information from the data.

Empirical bundle market shares provide the first piece of information about the type distribution. Each type corresponds to an optimal bundle choice; types that choose bundles with larger market share receive more weight.

Next, usage moments provide additional information that allows the market share weights to be distributed across the set of types that choose each bundle. The "larger" a bundle, i.e., the larger the set of content it contains, the more information is provided by its usage moments. Smaller bundles provide less information on usage and will thus have more observationally equivalent types. For example, consider a household that purchases a bundle comprised of internet access and Netflix. Two bundle types containing the same substitution (ρ_1, ρ_2) and internet utility parameters, but with different TV utility parameters, are equivalent with respect to the observable usage moments (provided the TV utility parameters are both in the region that justify the observed choice).

Variation in usage comes from variation in quantiles of usage across choices. Each parameter affects behavior in a different way. The δ parameters, those governing the distribution of marginal utility, are determined by the relative amount of time a household spends on each content type. Those content types c that are viewed for longer durations will have higher values of δ_c. The substitution parameters are driven by the relative market shares of larger bundles and differences in time allocation between similar households with access to different content. When all other parameters of the model are held fixed, as the willingness to substitute between activities increases, the predicted share of smaller bundles increases. For example, if the only bundle options are TV, Internet, and "both services," when ρ_2 decreases, households are more willing to substitute Internet use for TV use, and the market share of "both services" will fall relative to the shares of TV and Internet alone.

5 Results

Out of a total of 1,024 basis functions, I estimate mixture weights greater than 0.01% for 80. 90% of weight is given to the 33 highest-weighted basis densities and 99% of weight is given to the top 66. The type with the most weight chooses the bundle "Internet, Expanded TV 1".

The set of weights attached to these basis functions translates to a 10-dimensional joint distribution of the model's parameters across the sample population. Table 4 reports the mean and standard deviation summarizing the marginal distribution of each parameter. These marginal distributions are plotted in Figure 3. From these plots, we see that the distribution of substitution parameters ρ_1 and ρ_2 implies less elastic substitution between the content nest and the outside option. In addition, the content types c that are consumed at higher frequency in the data tend to have larger estimated marginal utility parameters δ_c. Figure 4 shows selected joint distributions of estimated parameters. These irregular distributions show the value of the flexible estimation strategy; allowing empirical patterns to determine the joint distribution of parameters yields patterns that could not be captured by typical parametric approaches.

To show how the model fits the empirical distributions, figure 5 shows the empirical and predicted distributions of viewing for each content type. Most distributions are matched quite well. In some cases, the model slightly over-estimates the use of consumption types that require a higher subscription fee in order to rationalize the purchase decision.

Another way to interpret the parameter results is to translate them into willingness-to-pay. Figure 6 shows the distribution of willingness-to-pay for online video applications among internet subscribers. I find that mean willingness-to-pay for Netflix is \$19, the standard deviation is \$22, and the median \$13. For Streaming TV, mean willingness-to-pay is \$32, the standard deviation is \$36, and the median is \$23.

Removing access to online video will be a large part of the counterfactual exercises discussed in the next section, so it is useful to first determine the contribution of access to online video to the willingness to pay for internet. Figure 7 quantifies this distribution. First, the willingness-to-pay is calculated for each type's preferred bundle. Next, third-party streaming applications are removed from the bundle and the willingness-to-pay is re-calculated. The two panels show both the share of willingness-to-pay that is retained when streaming is removed, and the decrease in the level of willingness-to-pay when streaming is removed. I find that, for the average household, willingness-to-pay decreases by 20%, or \$38, when streaming is removed from their preferred bundle.

I evaluate the substitution patterns implied by the model results by computing elasticities. Elasticities are computed by calculating the effect of raising the price of a product by 1% on subscription choices, with all other prices and model parameters held fixed. Table 5 shows these elasticities at the product level. Comparing own-price elasticities, we see that the most price-elastic good is Network Tier 1, with an own-price elasticity of -6.45. Network Tier 2 and Basic TV are also elastic relative to the other goods, with own-price elasticities of -4.70 and -3.13, respectively. Benchmarking against previous estimates, these elasticities are largely in line with other studies.[5]. In

[5]Crawford and Yurukoglu (2012) find average own-price elasticities of -4.1 and -6.3 for basic and

contrast, Internet, and both streaming services each have relatively lower own-price elasticities. The average internet elasticity is slightly inelastic at -0.99.[6]

The average TV profit margins implied by these elasticities and the observed prices are 6% for Basic TV, 7% for Expanded TV 1, and 20% for Expanded TV 2, with an average TV margin of 11%. The internet margin is 88%. These lopsided margins are consistent with industry estimates. FCC (2017) cites video margins of "just over 10 percent" at the end of 2015, with continued year-over-year decreases in the profit margin on TV. The estimated internet margin is high, but not surprising as the majority of the costs faced by ISPs in providing data are large fixed investment costs. In contrast, the ISP pays a per-subscriber programming cost for every network it includes in its TV tiers.

Turning to cross-price elasticities to understand which products are the best substitutes, we see that the closest product substitutes for TV services are other tiers of TV service. There is also a larger cross-price elasticity of demand for Streaming TV with respect to the price of higher-tier TV subscriptions. The presence of bundle discounts and the fact that internet access is needed for online video lead to some non-standard results for cross-price elasticities involving online applications, as some elasticities imply that goods are actually slight complements. There are two challenges in interpreting these elasticities at the product level. First, the option value of access to third-party applications contributes to the value of internet access as a whole. When the value of these applications falls, as when their prices are increased for the elasticity calculations, so too does the value of internet access. Second, the ISP's strategy of discounting bundles of TV and internet access makes the two goods complements for some consumer types, meaning that a change in the price of one good may lead a

expanded cable. Goolsbee and Petrin (2004) find elasticities ranging from -1.5 to -3.2. Studies using older data tend to find less elastic estimates. This pattern is consistent with FCC reports of increased competition from online video distributors and rising TV input costs (FCC 2017)

[6] One useful benchmark is the elasticities reported in the FCC's modification of the merger analysis submitted by Berry and Haile in support of the AT&T-DirecTV merger case in 2015. This simulation is the only other study that structurally models TV and internet access in the same demand system, although the results were not peer-reviewed. The elasticities reported are -8.07 for cable TV and -0.66 for internet access. Although the difference is more extreme in the Berry and Haile results, my findings agree that demand for TV is much more elastic than internet access.

bundled subscriber to drop all services.

An alternative way to understand substitution patterns is to compute elasticities with quantity responses calculated at the bundle level (Table 6). At the bundle level, negative elasticities are seen only for bundles containing the product for which the price increases. Elasticities with respect to the price of the ISP's TV products suggest that streaming applications are substitutes to higher TV tiers on their own, as well as when they are purchased in conjunction with basic TV. Netflix is best substituted by bundles containing Streaming TV, while the elasticities suggest that Streaming TV does not have a close substitute bundle.

6 Counterfactuals

In this section, I use the model's estimates to study the effect of counterfactual internet pricing strategies on consumer choices and the distribution of industry surplus.

First, I consider the profitability of two alternative product assortments, one in which all subscription streaming services are removed from the ISP's network ("no streaming"), and one in which only Streaming TV, the closest substitute to traditional TV, is blocked ("no Streaming TV"). Both of these actions were previously prohibited under the FCCs "no blocking" rules. In simulating these alternate assortments, the marginal utility attained from viewing each out-of-assortment product is set to zero. The ISP is allowed to adjust the prices it sets for each of its services and then consumers modify their subscription and usage decisions. Table 7 summarizes the results for both scenarios.

These policy changes have three effects on prices. First, the price of internet access falls by 21%, responding in kind to a lower willingness-to-pay for internet without streaming. Second, the removal of online video alleviates downward pressure on the price of TV, which rises by 32% in the "no streaming" case. Third, the average bundle price increases by 9%. Intuitively, removing online video reduces the degree of overlap between internet and TV valuations. This increases the value of having both products together relative to either component alone, meaning the ISP can offer a smaller discount on the purchase of the bundle.

Next, I describe the effect of the price change on consumer choices. Table 8 depicts the frequencies of bundle transitions between the baseline pricing strategy and the "no streaming" strategy. The two bundle groups that include streaming subscriptions become infeasible under the streaming ban. Before discussing surplus changes, I ask whether subscribers who chose streaming services in the baseline case moved to the ISPs TV service under the streaming ban. While 90% of former TV and streaming subscribers retained both internet and TV, only 2% of former streaming subscribers without TV added a new TV subscription, 84% added no new service, and 13% moved to the outside option.

I find that the streaming ban strategy is not profitable for ISPs, with profits falling \$3.15 per household-month; nor is it good for consumers, with consumer surplus falling \$3.51 per household-month. Table 9 decomposes the surplus change by bundle transition group. Most of the surplus decline comes from former streamers; the most-impacted group consists of former streamers who do not adopt TV after streaming is banned, whose surplus decline makes up 46% of the total loss. These results indicate that the surplus that is destroyed by banning streaming is not redistributed via new TV subscriptions.

In a final counterfactual, ISPs are allowed to set "add-on" prices for Netflix and Streaming TV. In this counterfactual, the ISP sets three prices for internet access: one price for internet without access to streaming, a second price for access to Netflix, and a third price for access to Streaming TV. This policy allows ISPs to increase the relative attractiveness of a TV subscription without fully banning access to streaming. Though an add-on internet pricing model has not yet been implemented in practice, its implications are analogous to zero-rating practices employed by mobile and residential broadband providers that employ usage-based pricing. Just as zero-rating creates differences in the marginal price of consumption of certain content by not counting consumption against usage allowances, the add-on pricing strategy creates differences in the relative prices of subscriptions by charging additional fees.

Under add-on pricing, the ISP sets prices so that the joint purchase of internet access and TV is preferred by nearly every household to the purchase of internet access alone. The price for internet access increases 50%, the average TV subscription price falls by 40%, and the average price of TV and internet bundles falls by 27%. The ISP selects add-on prices of $6 per month for Netflix and $40 per month for Streaming TV. Table 10 shows subscriber transition frequencies under add-on pricing and Table 11 breaks down the surplus change by transition group.

In contrast to the streaming ban case, where the majority of subscribers who choose streaming without TV in the baseline did not take-up TV after the ban, nearly all (97%) former streamers take up TV under add-on pricing. In addition, 88% pay the add-on price to retain their subscriptions, while 9% transition from streaming to TV alone. Fewer than 7% of baseline internet-only and internet and streaming subscribers transition to the outside option. The add-on pricing strategy increases ISP profits by $24 per subscriber-month, driven by new TV subscriptions and increased revenue from add-on fees. Consumer surplus increases by $15 per subscriber-month. 58% of the increase in consumer surplus is captured by subscribers who originally purchased internet and TV, and an additional 19% of surplus is enjoyed by former streamers who add a new TV subscription.

7 Conclusion

This paper studies the joint pricing decisions of platform firms and their incentives to foreclose competitors. I develop a framework for studying these trade-offs in the telecommunications industry that accounts for household time-allocation and subscription decisions as well as ISP pricing and online content assortment decisions.

My main results are as follows: (i) access to online video contributes substantially to the willingness-to-pay for internet access; (ii) foreclosure of online video applications is not profitable for ISPs, as increased TV revenue is offset by damage to internet valuations; (iii) more flexible strategies for pricing access to online content can be welfare-enhancing.

These results suggest that the repeal of net neutrality protections may not be as harmful to consumers as has been predicted. Looking to other industries in which firms provide access to third-party competitors, foreclosure concerns may be alleviated if firms earn greater profits as access providers than as sellers. In the telecommunications industry, these results may change as firms continue to consolidate and integrate into content production, and improving mobile quality leads to more competition for broadband provision. Each of these issues are fruitful areas for future research.

8 Tables and Figures

Table 1: Daily Internet Usage by Traffic Type

	Mean	SD	p25	p50	p75	p95	p99
Traffic Types							
Bulk Transfer	0.89	2.38	0.13	0.32	0.75	3.68	9.14
Email	0.02	0.16	0.00	0.01	0.02	0.07	0.21
Gaming	0.18	0.89	0.00	0.00	0.04	0.85	3.60
Miscellaneous	0.23	1.08	0.04	0.10	0.22	0.65	1.66
Network Storage	0.27	5.32	0.02	0.06	0.16	0.69	2.44
Peer-to-peer	0.08	1.83	0.00	0.00	0.00	0.00	0.88
Communication/Voice	0.13	0.39	0.00	0.02	0.11	0.59	1.41
Social Networking	0.12	0.18	0.03	0.08	0.16	0.36	0.77
Tunnel	0.05	0.95	0.00	0.00	0.00	0.06	0.62
Web Browsing	0.93	4.80	0.27	0.56	1.05	2.57	5.63
Streaming/Video	4.81	6.45	0.44	2.38	6.75	17.35	29.95
Total (All Types)	7.75	11.94	1.52	4.49	10.58	24.72	42.26
Household-months	45741						

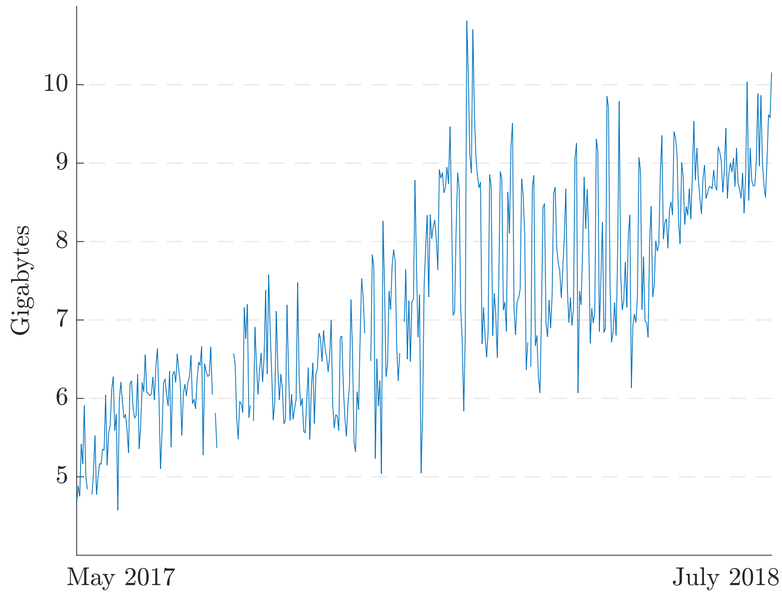
Note: This table shows the distribution of daily household internet usage by traffic type measured in gigabytes. Observations are household-months. A description of traffic types with example applications and protocols in parentheses follows. Bulk Transfer is comprised of large file transfers (FTP). E-mail captures the use of service-provider and webmail e-mail services (Gmail, SMTP, POP3). Gaming consists of console and PC gaming (PlayStation, Xbox). Network Storage is primarily comprised of file-hosting and backup services (Dropbox, MegaUpload). Peer-to-peer consists of file-sharing applications (BitTorrent). Communication/Voice captures the use of interactive video and voice communications (Skype). Streaming/Video consists of applications involving "on-demand" entertainment that is consumed as it arrives (applications like Netflix, YouTube, protocols like RTSP, Flash). Social Networking comprises of the use of social networking websites (Facebook, Twitter). Tunnel traffic consists of encrypted channels used for VPN and secure web transactions (SSL, SSH). Web Browsing consists of the use of specific websites (HTTP).

Table 2: Consumption of Online Video Applications

	Daily Usage	Penetration	Conditional Usage
Netflix	1.13	0.63	1.81
YouTube	0.90	0.94	0.95
Amazon Video	0.27	0.36	0.74
Hulu	0.09	0.10	0.89
Sling TV	0.08	0.03	2.66
Twitch	0.07	0.19	0.35
DirecTV Now	0.05	0.01	3.35
Facebook	0.04	0.89	0.04
HBO	0.03	0.04	0.59
Vudu	0.02	0.03	0.77
Household-months	45741	45741	43914

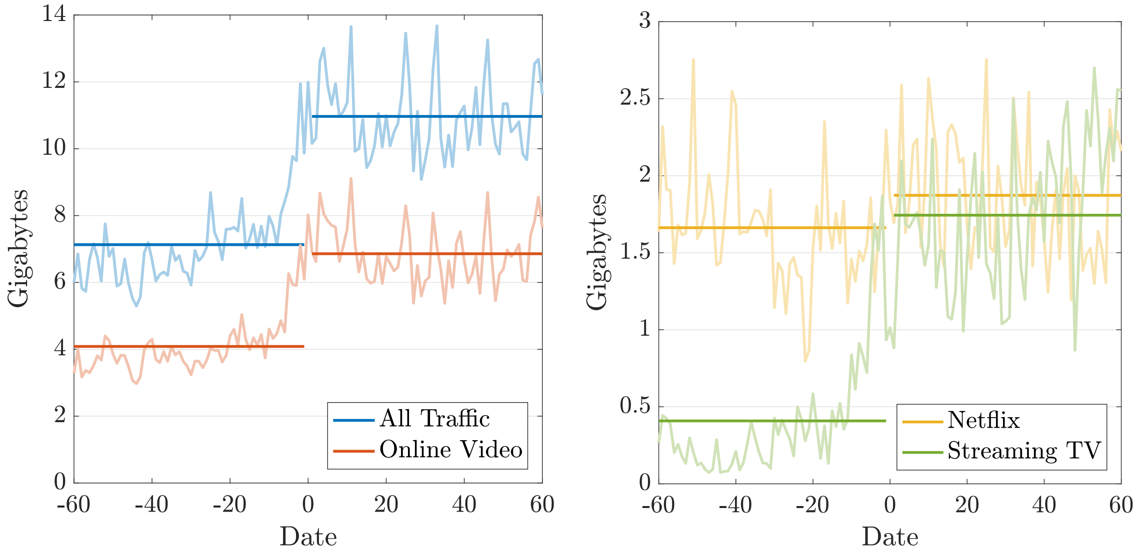
Note: The applications listed are the top 10 ranked applications by total traffic volume. Observations are household-months. Usage is average daily consumption measured in gigabytes. Penetration is the share of internet households with positive usage. Conditional usage is daily consumption among households with positive usage.

Figure 1: Growth in Average Internet Usage per Household



Note: This plot depicts average daily internet usage for a 15 month period beginning in May 2017.

Figure 2: Effect of Cord-cutting on Internet Consumption



Note: These figures show the average daily consumption of cord-cutters in the 60 days before and after they cancel their TV subscription. The left panel is a plot of total consumption and online video consumption. The right panel shows consumption of Netflix and streaming TV, defined as traffic consumed on Hulu, Sling TV, DirecTV Now, and Playstation Vue.

Table 3: Cross-platform Media Consumption by TV Subscription

	Internet-only	Basic TV	Network Tier 1	Network Tier 2
TV	0.00	1.79	4.49	5.48
Streaming/Video	5.71	6.44	4.11	4.14
Netflix	0.84	0.92	0.59	0.50
YouTube	3.83	4.54	3.08	3.08
Amazon Video	0.23	0.32	0.17	0.16
Streaming TV	0.43	0.37	0.06	0.05
Other	0.38	0.28	0.20	0.35
Total	5.71	8.27	8.58	9.62
Household-months	13305	4571	18308	9557

Note: This table shows average daily hours spent viewing media on the internet and TV for households with different ISP subscriptions. All households in the table have internet access and vary based on their TV subscription. Observations are household-months.

Table 4: Parameter Estimates

Parameter	Mean	(100 × SE_{Mean})	SD	(1000 × SE_{SD})
ρ_1	-0.36	(0.15)	0.08	(0.25)
ρ_2	-0.52	(0.23)	0.12	(0.46)
δ_1	0.33	(0.16)	0.21	(0.36)
$\delta_{\text{Basic TV}}$	0.39	(0.27)	0.24	(0.76)
$\delta_{\text{Expanded TV 1}}$	0.37	(0.19)	0.24	(0.63)
$\delta_{\text{Expanded TV 2}}$	0.34	(0.19)	0.23	(0.59)
δ_{Netflix}	0.41	(0.16)	0.25	(0.26)
$\delta_{\text{Streaming TV}}$	0.39	(0.26)	0.24	(0.45)
$\delta_{\text{Other Streaming}}$	0.49	(0.28)	0.25	(0.29)
$\delta_{\text{Other Web}}$	0.32	(0.22)	0.22	(0.98)

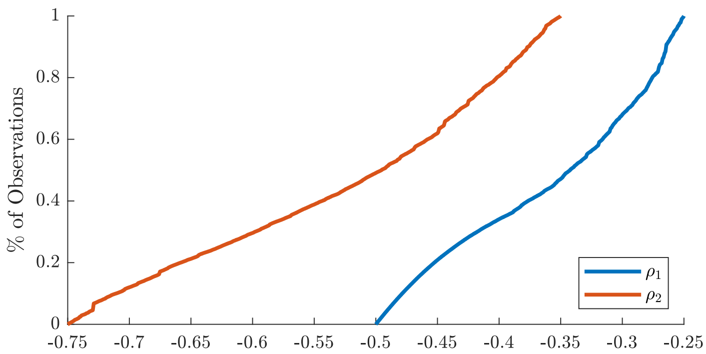
Note: This table shows the mean and standard deviation of the marginal distribution of each model parameter.

Table 5: Product Elasticities

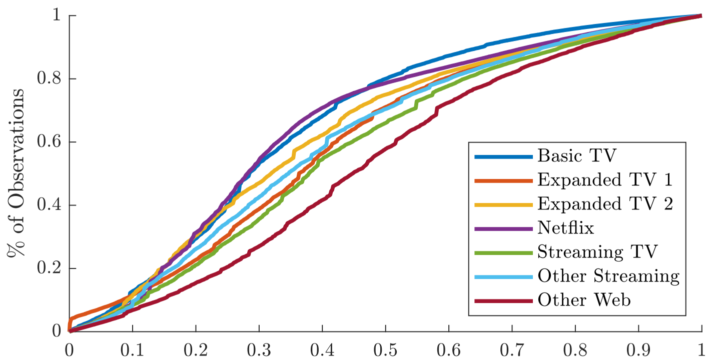
	With respect to the price of:					
Price elasticity of:	Basic	ETV1	ETV2	Int.	Netflix	Str. TV
Basic TV	-3.13	7.53	1.46	5.28	0.45	0.00
Expanded TV 1	0.12	-6.45	0.73	0.11	0.00	-0.04
Expanded TV 2	0.16	7.10	-4.70	0.11	0.02	0.00
Internet	0.00	-0.02	-0.02	-0.99	-0.06	-0.01
Netflix	-0.01	-0.48	0.01	-0.48	-1.09	-0.05
Streaming TV	0.03	0.08	2.36	-0.09	-0.01	-0.79

Note: This table shows own- and cross-price elasticities for the four products offered by the ISP and the two online video subscriptions. The estimate in row i and column j refers to the response in purchases of bundle i following a 1% increase in the price of product j.

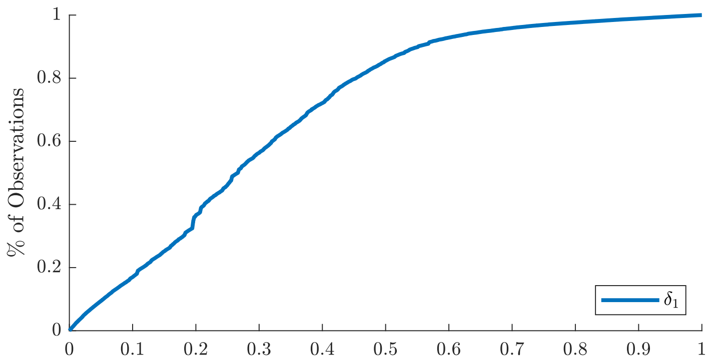
Figure 3: Marginal Distributions of Estimated Parameters



(a) Substitution Parameters



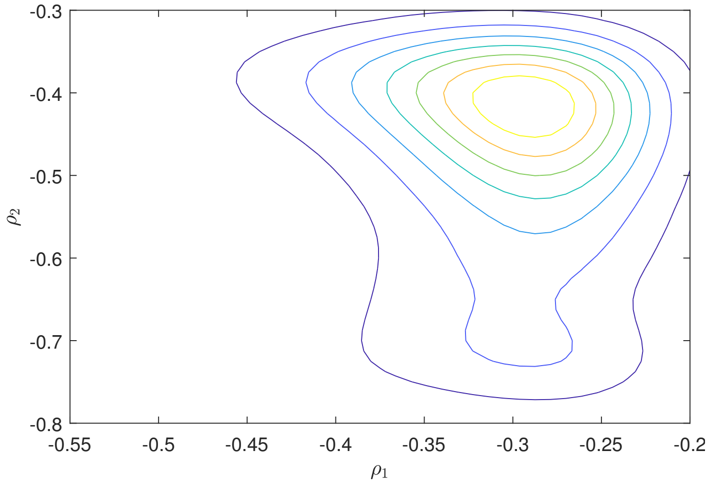
(b) Marginal Utility of Consumption Types (δ_c)



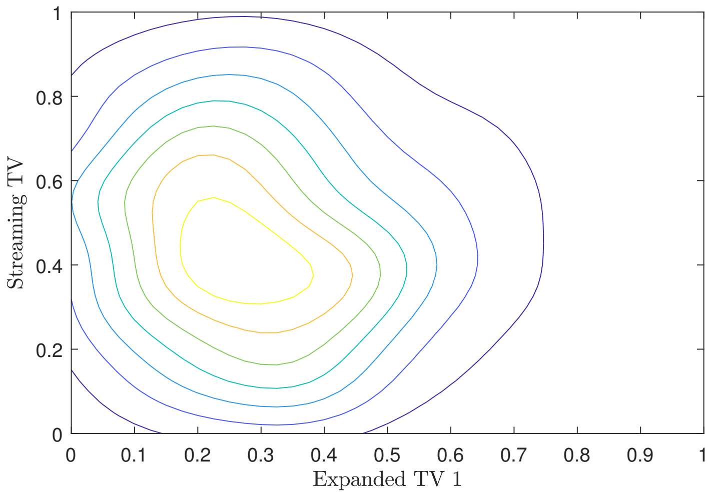
(c) Nest Utility

Note: This figure shows the marginal CDFs of estimated parameters.

Figure 4: Selected Joint Distributions of Estimated Parameters



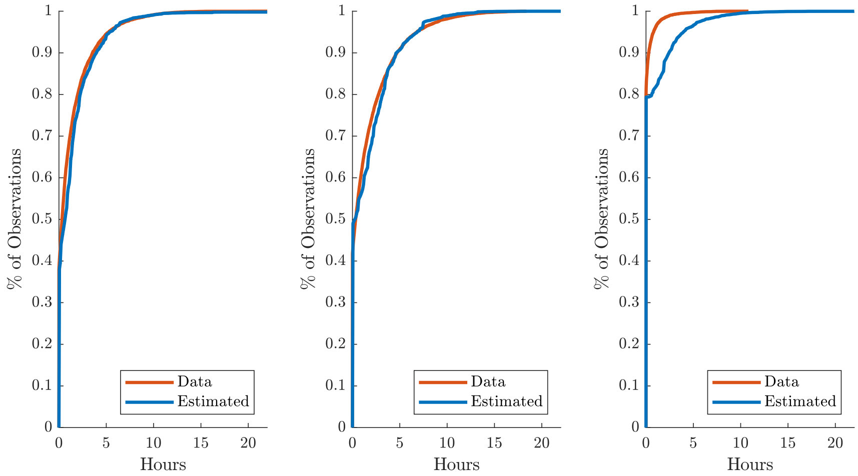
(a) Substitution Parameters (ρ_1, ρ_2)



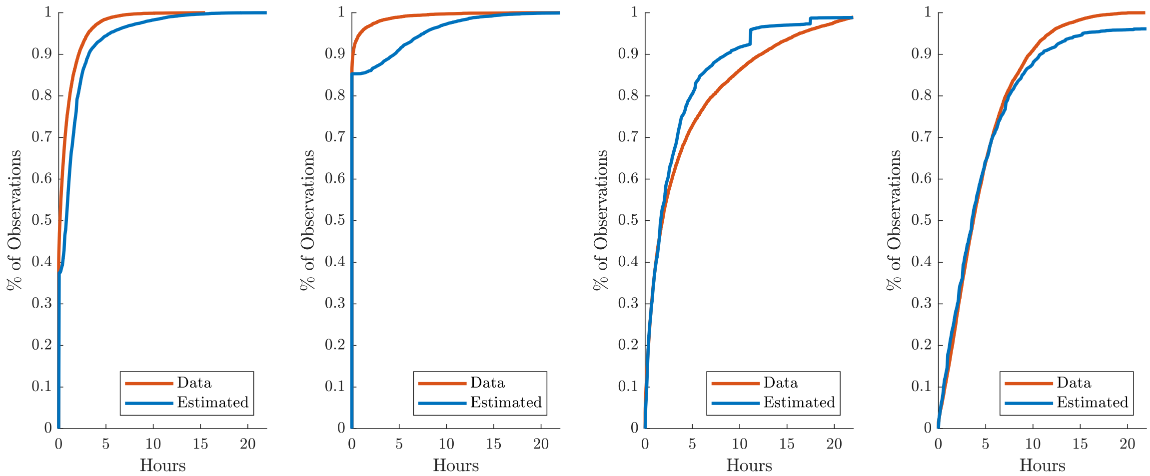
(b) Expanded TV 1 & Streaming TV Marginal Utilities (δ_c)

Note: This figure shows selected joint CDFs of pairs of estimated parameters.

Figure 5: Model Fit of Usage Distributions



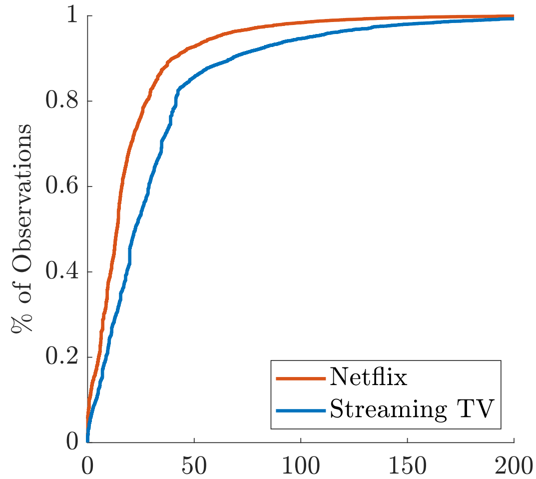
(a) Basic TV (b) Expanded TV 1 (c) Expanded TV 2



(d) Netflix (e) Streaming TV (f) Other Streaming (g) Web Browsing

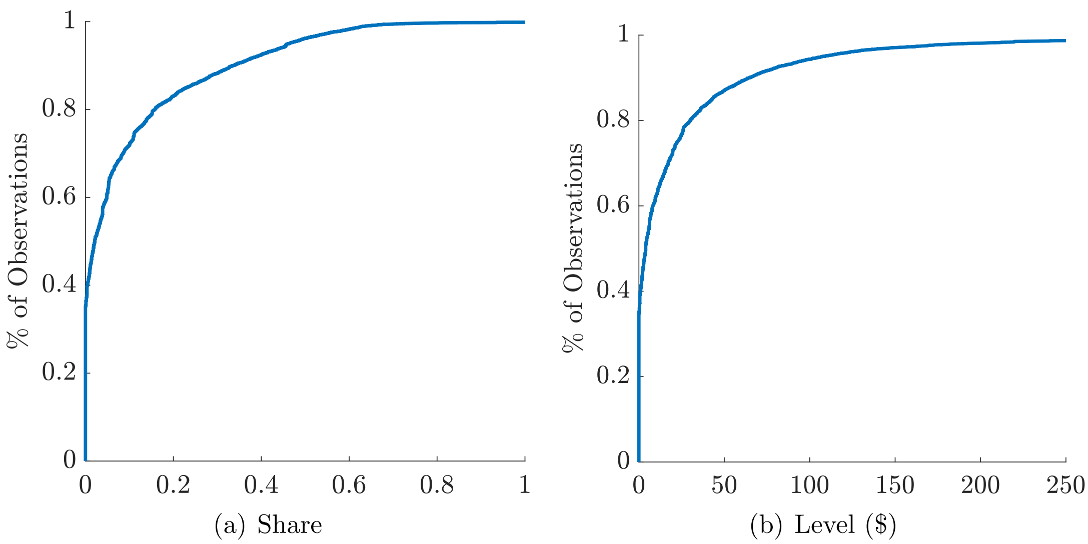
Note: This figure shows the empirical and predicted distributions of hours spent viewing each consumption type.

Figure 6: Estimated Willingness-to-Pay



Note: This figure shows the distribution of estimated willingness-to-pay for access to Netflix and Streaming TV content among internet subscribers.

Figure 7: Reduction in WTP for Preferred Bundle without Streaming



Note: This figure shows the contribution of streaming access to willingness-to-pay (WTP) for ISP subscriptions. To construct the figure, first the WTP is calculated for each type's preferred bundle. Next, third-party streaming applications are removed from the preferred bundle and the WTP is re-calculated. The two panels show (a) the share of WTP that is retained when streaming is removed, and (b) the level decrease in WTP when streaming is removed.

Table 6: Bundle Elasticities

	With respect to the price of:					
Price elasticity of:	Basic	ETV1	ETV2	Int.	Netflix	Str. TV
Internet	0.33	3.15	0.79	-4.00	1.34	0.20
Internet, Netflix	0.19	0.42	0.88	-1.26	-1.19	0.27
Internet, Streaming TV	0.99	3.99	64.71	-0.44	12.96	-1.24
Internet, Netflix, Str. TV	0.33	0.91	0.11	-0.09	-0.90	-0.75
Internet, Basic TV	-4.92	17.37	0.72	-1.71	1.56	0.02
Internet, Basic TV, Netflix	-2.03	4.88	2.15	-0.54	-0.80	0.14
Internet, Basic TV, Str. TV	-3.47	6.72	1.40	-0.12	5.33	-0.82
Internet, Basic TV, Netflix, Str. TV	-3.27	0.64	0.16	-0.18	-0.41	-0.27
Internet, Expanded TV 1	0.27	-6.22	0.47	-0.12	1.86	0.04
Internet, Expanded TV 1, Netflix	0.01	-6.37	0.94	-0.24	-1.37	0.10
Internet, Expanded TV 1, Str. TV	0.27	-7.87	0.45	-0.21	10.18	-0.30
Internet, Exp. TV 1, Netflix, Str. TV	0.18	-7.73	0.58	-0.03	-0.93	-1.15
Internet, Expanded TV 2	0.06	6.28	-6.67	-2.29	1.10	0.00
Internet, Expanded TV 2, Netflix	0.13	6.96	-3.59	-0.20	-0.86	0.08
Internet, Expanded TV 2, Str. TV	0.54	9.76	-3.26	-0.11	8.01	-0.38
Internet, Exp. TV 2, Netflix, Str. TV	0.88	11.76	-1.96	-0.04	-0.53	-0.55

Note: This table shows price elasticities at the bundle level. The estimate in row i and column j refers to the response in purchases of bundle i following a 1% increase in the price of product j.

Table 7: Summary of Pricing Counterfactuals

	No Streaming	No Streaming TV	Add-on Streaming
Surplus ($/HH-month)			
Δ ISP Profit	-3.27	-0.07	+24.11
Δ Consumer Surplus	-3.51	-2.76	+14.52
Δ Streaming Revenue	-4.27	-1.47	-2.34
ISP Price Changes			
Internet	−21%	−17%	+50%
TV	+32%	+13%	−40%
Internet + TV	+9%	+5%	−27%

Note: This table summarizes the change in surplus and prices under three counterfactual ISP pricing strategies. No Streaming blocks all access to both Netflix and Streaming TV. No Streaming TV blocks access to Streaming TV. Add-on Streaming lets the ISP choose an add-on price for access to Netflix and Streaming TV.

Table 8: Transition Frequencies from Baseline to Streaming Ban

	Streaming Ban Choice					
Baseline Choice	(0)	(1)	(2)	(3)	(4)	(5)
(0) Outside Option	0.9447	0	0.0509	0.0044	0	0
(1) TV-only	0.1581	0.0174	0.2882	0.5363	0	0
(2) Internet-only	0	0	1.0000	0	0	0
(3) Internet, TV	0.0020	0	0.0838	0.9142	0	0
(4) Internet, Streaming	0.1329	0.0062	0.8389	0.0219	0	0
(5) Internet, TV, Streaming	0.0324	0.0003	0.0610	0.9063	0	0

This table shows the frequencies of bundle transitions between the baseline pricing strategy and the "no streaming" case. Each row indicates a baseline choice and each column indicates a choice under the new strategy. The entries in each row sum to 1. All TV tiers are aggregated into "TV" and all online video subscriptions are aggregated into "Streaming".

Table 9: Consumer Surplus Change by Transition Group Under Streaming Ban

	Streaming Ban Choice					
Baseline Choice	(0)	(1)	(2)	(3)	(4)	(5)
(0) Outside Option	0	0	0.1910	0.0266	0	0
(1) TV-only	-0.1118	-0.0490	0.0133	-0.2445	0	0
(2) Internet-only	0	0	0.5175	0	0	0
(3) Internet, TV	-0.0000	0	0.0190	0.5288	0	0
(4) Internet, Streaming	-0.7579	-0.0910	-1.6339	-0.2045	0	0
(5) Internet, TV, Streaming	-0.1907	-0.0031	-0.3668	-1.1561	0	0

This table decomposes the change in consumer surplus between the baseline and "no streaming" cases according to subscription transition groups. Each row indicates a baseline choice and each column indicates a choice under the new strategy. The entries in each row sum to 1. All TV tiers are aggregated into "TV" and all online video subscriptions are aggregated into "Streaming".

Table 10: Transition Frequencies from Baseline to Add-on Pricing

	Add-on Pricing Choice					
Baseline Choice	(0)	(1)	(2)	(3)	(4)	(5)
(0) Outside Option	0.8705	0.0004	0	0.0643	0	0.0648
(1) TV-only	0.0788	0.0523	0	0.6724	0	0.1966
(2) Internet-only	0.0605	0.0069	0	0.8140	0	0.1186
(3) Internet, TV	0	0.0014	0	0.9421	0	0.0565
(4) Internet, Streaming	0.0306	0.0032	0	0.0902	0.0000	0.8760
(5) Internet, TV, Streaming	0	0.0001	0	0.0191	0	0.9807

Note: This table shows the frequencies of bundle transitions between the baseline pricing strategy and the "add-on pricing" case. Each row indicates a baseline choice and each column indicates a choice under the new strategy. The entries in each row sum to 1. All TV tiers are aggregated into "TV" and all online video subscriptions are aggregated into "Streaming".

Table 11: Consumer Surplus Change by Transition Group Under Add-on Pricing

	Add-on Pricing Choice					
Baseline Choice	(0)	(1)	(2)	(3)	(4)	(5)
(0) Outside Option	0	0.0053	0	0.8643	0	1.0358
(1) TV-only	-0.0179	-0.0151	0	0.6713	0	0.1747
(2) Internet-only	-0.0168	0.0001	0	0.7121	0	0.1240
(3) Internet, TV	0	0.0042	0	2.0311	0	0.1076
(4) Internet, Streaming	-0.0502	0.0041	0	0.2626	-0.0003	2.6919
(5) Internet, TV, Streaming	0	0.0009	0	0.1044	0	6.1012

This table decomposes the change in consumer surplus between the baseline and "add-on pricing" cases according to subscription transition groups. Each row indicates a baseline choice and each column indicates a choice under the new strategy. The entries in each row sum to 1. All TV tiers are aggregated into "TV" and all online video subscriptions are aggregated into "Streaming".

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A Appendix

A.1 Non-nested utility time-allocation solution

Setting $\rho_2 = \rho_1$ in the full utility function yields the following simplified non-nested maximization problem, the solution to which has a simple closed form.

$$\max_{\mathbf{h}} \tilde{u}(\mathbf{h};\boldsymbol{\theta}) = \left[\left(\sum_{c \in s(b)} \delta_c h_c^{-\rho_1} \right) + \delta_0 h_0^{-\rho_1} \right]^{-1/\rho_1}$$
$$\text{s.t.} \sum_{c \in s(b)} h_c + h_0 = T$$

The first-order conditions reduce to (for Lagrange multiplier Λ_1):

$$\partial u / \partial h_c : -\rho_1 \delta_c h_c^{-\rho_1 - 1} = \Lambda_1 \tag{5}$$
$$\partial u / \partial h_0 : -\rho_1 \delta_0 h_0^{-\rho_1 - 1} = \Lambda_1 \tag{6}$$
$$\partial u / \partial \Lambda_2 : \sum_{c \in s(b)} h_c + h_0 = T \tag{7}$$

Equating (1) and (2), then substituting into (3) gives, for any $j \in s(b) \cup 0$,

$$h_j^* = \frac{\delta_j^\sigma}{\sum_c \delta_c^\sigma + \delta_0^\sigma} \cdot T$$

where $\sigma \equiv 1/(1 + \rho_1)$.

A.2 Nested utility time-allocation optimality conditions

The maximization problem with the full utility function is:

$$\max_{\mathbf{h}} \tilde{u}(\mathbf{h};\boldsymbol{\theta}) = \left[\left(\sum_{c \in s(b)} \delta_c h_c^{-\rho_2} \right)^{\rho_1/\rho_2} + \delta_0 h_0^{-\rho_1} \right]^{-1/\rho_1}$$
$$\text{s.t.} \sum_{c \in s(b)} h_c + h_0 = T$$

The first-order conditions are (for Lagrange multiplier Λ_2):

$$\partial u/\partial h_c : \left[\left(\sum_{c\in s(b)} \delta_c h_c^{-\rho_2}\right)^{\rho_1/\rho_2} + \delta_0 h_0^{-\rho_1}\right]^{\frac{-1-\rho_1}{\rho_1}} \left(\sum_{c\in s(b)} \delta_c h_c^{-\rho_2}\right)^{\frac{\rho_1-\rho_2}{\rho_2}} \delta_1 h_1^{-\rho_2-1} = \Lambda_2 \tag{8}$$

$$\partial u/\partial h_0 : \left[\left(\sum_{c\in s(b)} \delta_c h_c^{-\rho_2}\right)^{\rho_1/\rho_2} + \delta_0 h_0^{-\rho_1}\right]^{\frac{-1-\rho_1}{\rho_1}} \delta_0 h_0^{-\rho_1-1} = \Lambda_2 \tag{9}$$

$$\partial u/\partial \Lambda_1 : \sum_{c\in s(b)} h_c + h_0 = T \tag{10}$$

A.3 Subscription Bundles and Consumption Types

Table 12: Subscription Bundles and Consumption Types

Bundle	Basic TV	ETV1	ETV2	Netflix	Streaming TV	Other Streaming	Other Web	O.O.
No Subscription	No	No	No	No	No	No	No	Yes
Basic TV	Yes	No	No	No	No	No	No	Yes
Expanded TV 1	Yes	Yes	No	No	No	No	No	Yes
Expanded TV 2	Yes	Yes	Yes	No	No	No	No	Yes
Internet	No	No	No	No	No	Yes	Yes	Yes
Internet, Netflix	No	No	No	Yes	No	Yes	Yes	Yes
Internet, Streaming TV	No	No	No	No	Yes	Yes	Yes	Yes
Internet, Netflix, Streaming TV	No	No	No	Yes	Yes	Yes	Yes	Yes
Internet ,Basic TV	Yes	No	No	No	No	Yes	Yes	Yes
Internet ,Basic TV ,Netflix	Yes	No	No	Yes	No	Yes	Yes	Yes
Internet ,Basic TV ,Streaming TV	Yes	No	No	No	Yes	Yes	Yes	Yes
Internet, Basic TV, Netflix, Streaming TV	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Internet, Expanded TV 1	Yes	Yes	No	No	No	Yes	Yes	Yes
Internet, Expanded TV 1, Netflix	Yes	Yes	No	Yes	No	Yes	Yes	Yes
Internet, Expanded TV 1, Streaming TV	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Internet, Expanded TV 1, Netflix, Streaming TV	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Internet, Expanded TV 2	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Internet, Expanded TV 2, Netflix	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Internet, Expanded TV 2, Streaming TV	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Internet, Expanded TV 2, Netflix, Streaming TV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N								

Notes: This table lists the twenty subscription bundles that make up each household's choice set (left column) and shows which of the eight consumption types are provided by each bundle.