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Optimal Assortment on an Integrated Platform

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Optimal Assortment on an Integrated Platform*

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Abstract

Consumers rely on platforms to access goods and services in many industries. Platform firms are often integrated, including their own goods in the menu of products offered to consumers. With the ability to impact both pricing and product assortment, these integrated firms face a trade-off between foreclosing third-party competitors to promote their integrated products and maintaining the value of the platform as a whole. This paper studies the pricing and assortment decisions of internet service providers (ISPs), which sell broadband internet access and TV packages. The ISP's network connects consumers to third-party online video, which increases the value of internet access, but also competes with the ISP's TV packages. I develop a model of consumer choice over ISP and third-party subscriptions and estimate the model using a novel household-level dataset of ISP subscriptions and usage. Next, I use a model of bundle pricing to study alternative pricing strategies in which internet prices vary with access to online video. I find that a strategy of blocking access to online video is not profitable due to the imbalance in the profit margins of TV and internet access. For low-margin TV firms, restricting online video usage leads to increased TV market share, but is offset by lower willingness-to-pay for internet access. When the ISP sets an additional access charge for online video, profits rise, and a decrease in the price charged for non-streaming internet access leads to previously unserved consumers gaining access to the internet.

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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 platform and promoting the integrated product. 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. When products are substitutes, altering the assortment of available goods allows the platform to gain market share by foreclosing third-party competitors. This paper studies product assortment on digital platforms and its impact on competition, pricing, and welfare.

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 increasingly prevalence of digital platforms, several empirical questions remain unanswered: What is the optimal tariff structure in these settings? Are product assortment decisions by integrated 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 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 variety of content providers such as Netflix or Sling TV. They are also content providers, selling bundles of TV channels and dedicating network bandwidth towards delivering TV content. Third-party video streaming applications increase the value of internet access, but they 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 the value of internet access and the profitability of selling TV.

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 derived utility of a purchased information good is not immediately realized, but rather depends on the amount of time spent consuming content. Attention is a scarce resource for consumers, making time-intensive information 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. At the time of this writing, product assortment 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 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 environments using a model of ISP pricing and a continuous-discrete choice model of demand for internet and video content, 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 from an anonymous North American ISP. The micro-data include subscription information for both internet and television tiers, and utilization data collected from internet modems and set-top boxes. The key feature of this dataset is visibility into the intensive margin of TV viewership and video streaming consumption at the application level. I infer streaming application subscriptions based on the timing and intensity of usage.

The main finding of this paper is that limiting the assortment of content available on their networks is not generally a profitable strategy for ISPs. When access to third-party video applications is limited, ISPs benefit from consumer substitution to their integrated TV products. However, this additional surplus capture from consumers with a taste for TV is offset by a loss in the profitability of the platform itself. In reducing the assortment of internet content, ISPs degrade the value of internet access, and consumer willingness to pay falls relative to the full assortment baseline. When ISPs are able to set prices more flexibly, charging an additional fee for access to online video, I find that ISP profits rise at the expense of online video providers. Consumer surplus falls slightly, but the additional mechanism for extracting online video surplus allows the standalone internet price to fall, providing previously unserved consumers without a strong taste for online video the opportunity to gain internet access.

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. Second, 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 assortment modifications. Finally and more broadly, the implications of substitution between residential and mobile internet, and the role of advertising revenues in guiding

ISP decision-making are both left for future work.

Contributions and Related Literature.—Previous empirical work on assortment has focused primarily on retail environments such as grocery stores. A large literature beginning with van Ryzin and Mahajan (1999) uses standard discrete choice demand models to characterize the assortment of potential products that optimizes a retailer’s profits. The context discussed in this paper concerns information goods, which differ from durable goods purchases in several ways. Although a subscription purchase is a discrete choice, the utility derived from internet applications depends on the intensive margin of time a purchaser allocates to using them. Estimating consumer valuations and substitution patterns thus requires developing an alternative to traditional discrete choice approaches.

Vertical integration in platform industries has also been studied in retail environments, with several papers exploring retailer strategies in the face of competition between private or store brands and national labels (Chen et al., 2010; Nasser et al., 2013; Dawes and Nenycz-Thiel, 2013; ter Braak et al., 2013)

This paper also contributes to an empirical literature studying telecommunications demand and internet pricing (Nevo et al. (2016); Malone et al. (2016); McManus et al. (2018)). In particular, McManus et al. (2018) study ISP incentives to steer consumers towards integrated products. I extend their largely reduced-form results using a structural approach which allows me to solve for optimal prices and to consider counterfactual pricing and assortment scenarios.

Other papers have considered demand models in which utility depends on time allocation (Goolsbee and Klenow, 2006; Crawford and Yurukoglu, 2012; Crawford et al., 2017; Deng and Mela, 2018). My model relies on the same assumption that time spent is informative of value, and it extends previous approaches by adding a nesting structure to make substitution patterns more flexible. In particular, my data allow me to infer household size and thus capture how time allocated to online content differentially impacts time spent on other video content and outside activities.

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 end-users (Economides and Hermlin, 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 end-users. 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 two primary sources. The principle source is an anonymous North American internet service provider (ISP), which provides information on subscriptions and utilization of internet and TV services. These ISP micro-data are complemented with the product offerings and market footprint of a competing ISP and third-party video applications, obtained from competitors’ websites.

The ISP subscription and usage 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 mid-2017 and mid-2018. The level of observation is household-day-hour.

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, 63% choose a bundle of internet and TV service, 36% choose internet without TV, and fewer than 1% choose TV alone.

For each household with an internet subscription, I observe aggregated information from a packet 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 3.

The average sampled internet household consumes 7.5 gigabytes per day of band-

width. 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.

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 4 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.

Substitution between Streaming and Traditional TV.—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%.

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%.

¹The 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.

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—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 have already been close to saturation levels with Netflix’s original content, streaming TV’s overlapping content was a natural destination for time to move 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 5 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. Despite significant differences in how time is allocated across content providers, the total amount of time allocated does not vary as substantially with subscription choice. This fact further supports that a change in the assortment of video applications may affect the time allocated across content types in a heterogeneous manner.

3 Model

This section describes a model of household subscriptions and content engagement. Household decisions are modeled using a discrete-continuous demand system in which the value of access to a subscription depends on how time is allocated across the set of content it provides.

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 .

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 $\tilde{u}(\mathbf{h}(b); \boldsymbol{\theta})$, where $\boldsymbol{\theta}$ is a set of parameters governing the shape of utility. The indirect viewing utility from set $s(b)$, attained from the optimal time allocation decision $\mathbf{h}(b)$, is given by

$$v(b; \boldsymbol{\theta}) = \max_{\mathbf{h}} \tilde{u}(\mathbf{h}(b); \boldsymbol{\theta})$$

$$\text{s.t. } \sum_{c \in s(b)} h_c + h_0 = T$$

where T is the total amount of time available to the household.

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

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

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:

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

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 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 util-

ity. 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 $u(b'; \boldsymbol{\theta}) - u(b; \boldsymbol{\theta})$ 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 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 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:

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

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

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 and thus do not restrict the level of internet consumption. Second, the ISP's network is not

capacity-constrained, and as such the download speeds realized on even the slowest tier are in excess of the speeds recommended by video streaming providers.²

In addition to the ISP’s three TV tiers, I focus on several types of internet content. Netflix is the most-used application in the data, accounting for 17% of total internet traffic and 30% of video streaming, and is given 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 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. Table 6 shows 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.

ISP Bundling Problem—The ISP offers internet access and N_T 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. In the empirical example, $N_T = 3$, and prices are as shown in the following table.

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

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

³Consumption 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.

Table 1: Mixed Bundle Prices

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

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. The profit function before fixed costs is

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

where p_b is the price of bundle b , 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. Model parameters are estimated using a two-step mixtures estimator related to the methodology described in Fox et al. (2011) and Fox et al. (2016). First, I solve for the plan choices and time allocation decisions of a large number of simulated household types. Second, weights for a set of mixture densities describing model heterogeneity are found by “matching” a weighted average of behavioral moments calculated from the simulated types to their empirical counterparts. The result is a population distribution of types.

Table 2: 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)
N (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
$z_{i,j}$	i th model moment for bundle choice j
$y_{i,j}$	i th empirical moment for bundle choice j

In the first step, I solve the model for $S = 1,048,576$ (4^{10}) types, or all combinations of a fixed grid of four values for each of the $K = 10$ parameters describing household

heterogeneity. Each type θ^s is a unique combination of parameters $(\rho_{1s}, \rho_{2s}, \delta_{1s}, \delta_s)$. When presented with a bundle j , each type s has a unique time allocation solution specified by the model. These usage decisions, along with the optimal bundle choice, are saved for use in the next step.

Next, type weights are chosen to describe the distribution of heterogeneity. I assume that the distribution of heterogeneity can be expressed as a mixture of R normal basis densities. Let $\phi(\theta \mid \mu^r, \sigma^r)$ denote the joint normal density corresponding to the r th basis. This 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. The goal of estimation is to ascertain each β^r , the probability weight attached to the r th basis density.

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

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

To simulate this integral, I use the importance sampling methodology of Akerberg (2009) to correct the sampling frequencies of the types simulated in the first stage so that it is as if they were drawn from $\phi(\theta \mid \mu^r, \sigma^r)$. Although solving the model for each 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 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 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

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

where the objective function is minimized subject to the constraint that β lies within the R -dimensional unit simplex.

The resulting estimated density function is

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

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 set of types that choose each bundle to match those in the data.

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 that best matches 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. Selecting a grid amounts to placing a uniform prior on the distribution of types across the grid and zero probability on all points outside of the grid.

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. After adjusting weights using market share information, each type has a weight equal to the empirical market share of its chosen bundle divided by the total number of candidate types with the same optimal bundle.

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).

Since each moment is linear in the weights, identification follows the intuition of a standard OLS regression: the weights are identified provided there is sufficient variation across the moments used in the regression so that the predicted behavior of individual types is not collinear.

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

I estimate mixture weights greater than 0.01% for 80 basis densities. 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 estimated distributions of each individual parameter are shown 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 that are consumed at higher frequency in the data tend to have larger estimated marginal utility parameters δ_c .

To show how the model fits the empirical distributions, figure 4 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.

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 7 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.⁴ In contrast, Internet, and both streaming services each have relatively lower own-price elasticities.

The average TV 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 implied 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, while TV costs are predominantly per-subscriber fees paid to individual networks.

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 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 8). At the bundle level, negative elasticities are seen only for bundles containing the product for which the

⁴Crawford and Yurukoglu (2012) find average own-price elasticities of -4.1 and -6.3 for basic and expanded cable. Goolsbee and Petrin (2004) find elasticities ranging from -1.5 to -3.2. Older studies 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).

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.

The results also provide information on willingness-to-pay. Figure 5 shows the density of willingness-to-pay for some of the available subscriptions. I find that median willingness-to-pay for Netflix and Streaming TV among subscriber types that take up service from the ISP is \$13 and \$23, respectively.

6 Counterfactuals

In this section, I return to the main goal of the paper, which is to ascertain the implications of ISP strategies that both set prices and control the assortment of third-party video providers available online.

First, I consider the profitability of two alternative product assortments, one in which all subscription streaming services are removed from the ISP’s network, and one in which only Streaming TV, the closest substitute to the traditional TV, is blocked. In simulating these alternate assortments, the marginal utility attained from viewing each out-of-assortment product is set to zero. The ISP is then allowed to adjust the prices it sets for each product. Table 9 summarizes the results for both scenarios. There are two main effects. First, the removal of online video options induces some substitution to the ISP’s TV service, which sees an increase in market share. Second, more subscribers purchase internet access as the ISP lowers its subscription price in response to preferences for internet access without streaming. On net, the gains from increased TV market share and additional internet sales do not offset the loss of surplus extracted from online video subscribers in either case, and profit falls. Intuitively, the ISP has less to gain by increasing its TV market share when margins are lower, and the value of retaining a high internet market share is elevated when internet subscriptions are more profitable.

Next, I give the ISP the option to set “add-on” prices for Netflix and Streaming TV. In this counterfactual, the ISP sets three prices for internet: one price for internet access without streaming, a second fee for access to Netflix, and a third fee for access to Streaming TV. Under this counterfactual, profits increase by approximately 5% over the empirical levels, while consumer surplus falls by half a percent. The flexibility of the add-on prices allows the ISP to lower the standalone internet price, increasing its total internet market share by attracting consumers without a strong taste for online video while extracting surplus from higher taste subscribers through the additional

fees. The market share of TV falls, with the main benefit of the pricing strategy coming from increasing the market share of the high-margin internet service rather than the low-margin TV service. Implications for third-party online video providers are significant, with the market shares of Netflix and Streaming TV decreasing by 43% and 36%, respectively.

The results suggest that online video is an integral part of the value of internet access, with willingness to pay falling significantly when the option to view it is removed. ISPs lack the incentive to foreclose access to online video outright, as the revenue gained from substitution to TV does not offset the harm caused to the platform itself by altering assortment. More flexible pricing strategies allow the ISP to extract surplus associated with online video in a way that lowers the prices paid by non-streamers, but at large cost to third-party providers.

7 Conclusion

This paper studies a trade-off faced by integrated platforms when choosing product assortment. Limiting the assortment of alternatives available to consumers increases the platform's integrated product market share, but decreases consumer willingness to pay for the platform as a whole.

I examine the ISP decision over what assortment of online video providers to connect their internet consumers to. The results suggest that streaming TV and Netflix, when purchased in conjunction with internet access, are both substitutes for the ISP's TV service. Nevertheless, I find that online video of all types is a core part of the value of internet access. When access to Netflix and Streaming TV is removed in counterfactual simulations, firm profitability falls, as substitution to the integrated TV service does not offset the loss in internet profitability caused by a reduction in consumer willingness to pay for internet access. When the ISP is able to set separate prices for access to internet with and without streaming services, it enjoys higher profits at the expense of online video providers. Consumer surplus falls slightly, but lower internet prices lead to an overall increase in internet access.

The results are dependent on the relative profitability of the ISP's two products. If TV margins were higher, the ISP would have a stronger incentive to increase its market share, and online video assortments that resulted in higher TV uptake would be more profitable.

More broadly, the results are relevant to current and ongoing debates over net neutrality, as they suggest that some forms of content discrimination such as outright foreclosure of competitors are not optimal for ISPs. These results may change, however, 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.

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8 Tables and Figures

Table 3: 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
N	45741						

Note: This table shows the distribution of daily household internet usage by traffic type measured in gigabytes. Observations are subscriber-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 4: 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
N	45741	45741	43914

Note: The applications listed are the top 10 ranked applications by total traffic volume. Observations are subscriber-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 5: 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
N	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 subscriber-months.

Table 6: 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.

Figure 3: Distributions of Estimated Parameters

(a) Substitution Parameters

(b) Marginal Utility of Consumption Types (δ_c)

(c) Nest Utility

Note: This figure shows the CDFs of estimated parameters.

Figure 4: Model Fit of Usage Distributions

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

Table 7: Product Elasticities

Price elasticity of:	With respect to the price 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 5: Estimated Willingness-to-Pay

Note: This figure shows the density of estimated willingness-to-pay for access to selected subscriptions.

Table 8: Bundle Elasticities

Price elasticity of:	With respect to the price 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 9: Summary of Pricing Counterfactuals

% Change in:	No Streaming	No Streaming TV	Add-on Streaming
Surplus			
Profit	-8.33	-2.65	5.08
Consumer Surplus	-3.91	-0.37	-0.50
Internet Price	-14.15	-12.16	-9.58
Market Shares			
Internet	5.10	12.06	8.17
TV	3.58	0.00	-9.95
Netflix	-100	3.23	-42.54
Streaming TV	-100	-100	-35.57

Note: This table summarizes the percent change in surplus, internet price, and market shares 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.

9 Appendix

9.1 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.

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

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

$$\partial u / \partial h_c : -\rho_1 \delta_c h_c^{-\rho_1-1} = \Lambda_1 \quad (5)$$

$$\partial u / \partial h_0 : -\rho_1 \delta_0 h_0^{-\rho_1-1} = \Lambda_1 \quad (6)$$

$$\partial u / \partial \Lambda_2 : \sum_{c \in s(b)} h_c + h_0 = T \quad (7)$$

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

9.2 Nested utility time-allocation optimality conditions

The maximization problem with the full utility function is:

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

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

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

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

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