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# THE STEERING INCENTIVES OF GATEKEEPERS IN THE TELECOMMUNICATIONS INDUSTRY

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**ABSTRACT**

We study trade-offs faced by multiple-system operators (MSOs), the gatekeepers in the provision of internet service, when setting prices and quality for internet access and TV service. In response to improvements in over-the-top video (OTT), MSOs choose between accommodating OTT to share in the surplus it provides consumers, or steering consumers towards TV. We augment the standard mixed bundling model to show that in some cases MSOs have incentives to steer consumers towards TV, but that these incentives vary with the available pricing tools. We then estimate the distribution of model parameters using household panel data on subscription choices and internet usage. Our estimates imply that if MSOs can set different prices for different internet content, under many cost circumstances MSOs discount the OTT usage price. Furthermore, we find that the ability to charge prices based on internet usage strengthens the MSOs' incentive to improve OTT quality.

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# 1 Introduction

Firms that sell internet access serve as gatekeepers to online content, including over-the-top video (OTT) content. Internet access providers typically also sell traditional TV service, to which OTT may be a direct substitute. This potentially raises the concern that these multiple system operators (MSOs) have an incentive to steer consumers toward their TV service by either raising the price of internet service or by degrading the access to and quality of OTT content. If MSOs were to take these actions, OTT providers and the consumers that use these increasingly popular services could be harmed. Concerns over harm to consumers and OTT providers are at the heart of the net neutrality debate, and they have been considered in public actions such as the FCC order issued after Charter's acquisition of Time Warner Cable.[1]

We study these issues by analyzing the steering incentives of an MSO. As OTT streaming services improve in quality, the MSO benefits through increased demand for its internet service. However, these benefits may be offset if consumers respond to OTT's improvement by substituting away from TV service.[2] The MSO therefore faces a trade-off between encouraging the growth of OTT so it may increase profit from an improved internet offering, versus steering consumers away from OTT and towards its own video service. We empirically study how an MSO manages this trade-off.

The optimal trade-off depends on the demand the MSO faces and the pricing tools available to it. We therefore develop and estimate a model that captures unique features of the industry. We start with a standard bundling model (Adams and Yellen, 1976; McAfee et al., 1989) to capture the fact that internet and TV are typically sold both as standalone options and together as a bundle. We add to the standard bundling model by allowing consumers to make usage decisions in addition to the subscription decision. Also, consumers may access video content via a TV subscription or and a subset of TV content via the internet with a streaming service. Finally, the MSO

[1]For example, the order restricts Charter's ability to offer usage-based pricing out of concern that it will harm OTT. See https://docs.fcc.gov/public/attachments/FCC-16-59A1.pdf.

[2]Internet usage has grown steadily during recent years, largely driven by an increase in streaming video. About 60M U.S. households (46%) used a streaming video service in 2018, up from 44M in 2016 (comScore, 2018). Cisco, a major telecommunications and IT firm, estimates that 81% of North American internet usage was video during 2017, and this share will grow to 85% by 2022 (Cisco, 2018). The emergence and popularity of OTT services coincides with a trend in consumers dropping their TV service ("cord cutting") and instead consuming video through the internet. Between 2014 and 2017 in the U.S., the number of consumers who cut the cord grew from 3.1M to 14.1M (MarketWatch, 2018).

offers a menu of plans that include standalone and bundled options, and it can charge usage-based prices (UBP) for internet in addition to a simple subscription fee for each plan.

Before structurally estimating the model, we describe the MSO's incentives in a simplified setting. We use the model to describe the challenges that the MSO would face if it were not to respond to increased OTT availability, and then we assign specific values to the model parameters to illustrate potential MSO pricing responses to these challenges. We show that an opportunity to meter usage, i.e, charge consumers different prices based on their usage level, can moderate the MSO's incentive to steer customers away from OTT. For example, the MSO may meter usage with tiered internet service, where higher-priced tiers include a higher usage allowance. The intuition is simple: when the MSO adds internet tiers that associate greater usage with higher prices, it can generate more revenue from high-demand consumers. Contrary to concerns that usage-related prices or constraints are necessarily at odds with net neutrality's goal of uninhibited access to third-party content, we find that MSOs may have an incentive to improve OTT quality when these pricing tools are available. Our analysis also demonstrates that steering and foreclosure incentives, which are often discussed in terms of upstream relationships between MSOs and content providers, can appear in downstream interventions through the prices consumers pay the MSO.

To study the MSO's trade-off beyond the setting of the simplified model, we structurally estimate the model using rich household-level panel data from a North American MSO. The behavior we observe in the data is highly heterogeneous and therefore we allow for heterogeneity in consumers' demand for overall internet usage, streaming video content, internet speed, and price sensitivity. We use a a flexible fixed grid approach (Ackerberg, 2009; Fox et al., 2011, 2016; Malone et al., 2017) to estimate the distribution of heterogeneity. A unique feature of the data is the introduction of usage-based pricing during the sample period. The UBP takes the form of a menu of three-part tariffs, each of which includes an access fee, an internet usage allowance, and an overage charge. The policy's introduction helps us identify the parameters of our demand model.

The estimates allow us to quantify the MSO's incentives to steer consumers toward the bundle versus generating more profits from improved internet service. We do this by using the empirical estimates to compute the profit maximizing usage prices for general internet usage and (separately) streaming video usage, as a function of the cost of providing internet and TV services. This allows us to separate the MSO's incentive to meter overall internet usage from its incentive to steer usage away from OTT by using a OTT-specific price. We find that the OTT price can be positive or negative—meaning that the MSO in some cases prefers to charge a premium for OTT use, and in other cases prefers a lower price for OTT use—depending on the relative profit margins of TV and internet service. In scenarios that resemble current industry conditions in the US, with low TV margins and higher internet margins, given our estimates the MSO prefers to set a lower price for OTT use compared to other internet usage. Therefore, an analysis of the concerns about usage-related prices needs to separate the MSO's metering and steering incentives, or otherwise it can miss the strength and even the direction of the firm's steering incentive.

Our findings are directly relevant to the debate on MSOs' incentives under net neutrality. The OTT-specific price is analogous to a policy that increases or diminishes the quality of streaming video. We study this directly by looking at the MSO's incentive to set the quality of OTT, which is directly linked to the degree of substitution between TV and OTT. We show that the MSO may have an incentive to increase or decrease OTT quality, again depending on relative profit margins. Furthermore, when using UBP, the MSO wants to improve OTT quality under a larger set of circumstances. The result is quite intuitive: the MSO's incentive to encourage new content and expand their networks is generally stronger when it shares in more of the surplus generated by OTT content.

In a variety of industries where consumers access products or services through a gatekeeper platform, the gatekeeper faces a trade-off between steering consumers' choices within the platform towards more profitable products, versus allowing consumers free choice among the platform's products and hoping to capture the surplus this generates. Examples of industries where gatekeepers are important and might have incentives to steer include health care markets and online search.[3] Our results

[3] In health care markets, consumers enroll in an insurance plan and then access health care providers mostly through the insurer's network. The network's structure and the plan's prices will reflect the insurance company's incentive to steer consumers towards certain providers while also providing a broad set of care options so that enrollment is attractive for a variety of individuals. In online search, consumers might reach online shopping sites through a search platform that could have incentives to steer consumers to its own sites or sites that pay a higher fee. Steering activity, however, might turn off some consumers who prefer different products, and therefore reduce total visits to the platform. Indeed, such steering activity is the basis for the fine imposed on Google in June 2017 by the European Commission.

do not directly speak to these markets, but our framework provides intuition on the nature of their trade-offs.

**Related literature** At a high level, our paper relates both to papers that study the market for cable TV (Crawford and Shum, 2007; Crawford and Yurukoglu, 2012; Crawford et al., 2018, 2019), and those that study the market for internet services using high-frequency data (Nevo et al., 2016; Malone et al., 2016, 2014).[4] Our contribution relative to these papers is that we model both TV subscriptions and internet use, the interaction between them, and how the availability of OTT impacts the pricing and quality-provision incentives of MSOs.

Our work is closely related to two of our other papers that study similar questions but use different data and methods. Malone et al. (Forthcoming) use a different data set to study consumer behavior on the internet after cutting the cord, namely dropping TV service. The motivation is somewhat similar between the two papers, but the analysis they provide is purely descriptive and they do not estimate consumer preferences or conduct counterfactual analysis as we do here. McManus et al. (2022) use a difference-in-differences design to measure the effect of UBP's introduction on households' subscription and usage decisions. They are also interested in separating steering and metering incentives, but the empirical analysis in that paper documents consumers' responses, and it does not involve estimation of preferences or conduct a counterfactual. As such, the analysis is complementary to the estimation and analysis in this paper.

Relationships between MSOs and internet content providers are an active area for public policy, especially concerning merger approval and net neutrality.[5] These policy issues converge in vertical mergers between MSOs and media companies, which can affect MSOs' profits from various content sources and therefore induce steering activity. The literature on these issues largely began with Wu (2003), who introduced the term "net neutrality" and provides a summary of the issues. Lee and Wu (2009) and Greenstein et al. (2016) discuss and review the literature on the topic. However,

[4]Other studies of demand for broadband services include Prince and Greenstein (2017), Goolsbee and Klenow (2006), Dutz et al. (2009), Rosston et al. (2013), Greenstein and McDevitt (2011), Edell and Varaiya (2002), Varian (2002), and Hitte and Tambe (2007).

[5]The FCC's 2015 Open Internet Order prevented MSOs from discriminating among various online applications. This order limited MSOs' ability to reduce usage of video services from some third-party providers. The FCC voted in 2017 to roll back the order, and future policy in this area continues to be debated.

most of the existing economic analysis of the topic is theoretical (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; Sidak, 2006). Our empirical analysis on steering incentives complements these theoretical studies by providing insight into relevant trade-offs for the debate. Goetz (2019) and Tudon (2021) also make recent related empirical contributions. Goetz (2019) studies the how bargaining between internet service providers and Netflix affects mergers. Tudon (2021) examines the trade-off between content providers' entry and congestion on Amazon's Twitch, and he finds that a Pigouvian tax on traffic improves consumer welfare.

As we noted earlier, our model and empirical analysis provide insights into firms' strategic efforts to steer and sort heterogeneous consumers across product menus in other industries. Ho and Lee (2019), Liebman (2017), and Raval and Rosenbaum (2017) study how insurers influence patients' choices across medical providers. Barwick et al. (2017) examine conflicts of interest and steering by residential real-estate brokers. Crawford et al. (2018) consider similar incentives in cable TV markets and estimate the value to cable distributors of including vertically integrated versus non-integrated sports networks in their channel bundles. Lee and Musolff (2021) examine Amazon's influence on market structure and welfare, as it seeks to balance sales of its own goods against entry of sellers that increase the platform's attractiveness to consumers. Raval (2022) studies Amazon's ability to steer consumers to its own products and services through the Buy Box default purchase option.

The incentive to degrade product quality for discriminatory or steering purposes, as is present in our model, is related to the classic work of Mussa and Rosen (1978), which Crawford and Shum (2007) apply in the context of the telecommunications industry. Contrary to the incentive to degrade, Crawford et al. (2019) find quality to be 23% to 55% higher than is socially optimal in the provision of cable TV. In the bundling literature, Armstrong (2013) and Gentzkow (2007) study how the consumption of one product in a bundle affects utility from other products, which is similar to the relationship between OTT and TV that we study. Chu et al. (2011) and Crawford and Yurukoglu (2012) empirically explore how variations on bundling and other pricing strategies can affect firm profit and consumer welfare. Nonlinear pricing strategies similar to those we examine have been studied in broadband markets (Economides and Hermalin, 2015; Lambrecht et al., 2007), phone service contracts (Miravete, 2003; Grubb, 2015; Grubb and Osborne, 2015), and other markets (Hagemann, 2017; McManus, 2007).

# 2 The Model

In this section we introduce a model that allows us to illustrate and quantify the trade-offs faced by the MSO in pricing internet and TV services. The model captures some of the unique features of the problem. Since internet and TV are typically offered both as standalone options and together as a bundle, we start with a standard bundling model and augment it in several ways. First, we allow consumers to make usage and subscription decisions, so that we capture both the intensive and extensive margin choices that are relevant to pricing. Second, we allow consumers with internet subscriptions to access some video content using online streaming services. Third, the MSO can offer a variety of plans that include both standalone and bundled options, and vary by both speed and price. Finally, we allow the MSO to utilize usage-based pricing in addition to a simple subscription fee for each plan.

These extensions allow us to explore a range of pricing strategies for the MSO, from uniform bundle prices for subscriptions, which do not vary with usage and to which we refer to as "bundle pricing", to more sophisticated nonlinear prices that vary with usage. With bundle pricing, the MSO may find it profitable to steer consumers away from OTT usage because the MSO is hurt by improvements in streaming video. By contrast, when the MSO can offer a variety of internet usage tiers or cap internet usage, the MSO can benefit from OTT's availability. Depending on the impact OTT has on the MSO's profits, the MSO has incentives to either expand or restrict use of third-party firms' video content. We demonstrate these incentives via numerical simulations later in this section using a simplified version of our model. In the following sections we estimate the more general model, allowing for flexible distributions of consumer heterogeneity needed to match the data, and we use the estimates to empirically quantify the MSO's incentives.

## 2.1 Setup

Consider a market in which an MSO offers consumers two products indexed by $j$. Product 1 is internet service, which gives access to content available on the internet, and product 2 is TV service, which grants access to video entertainment available through TV. To access the services, the MSO offers consumers a set of subscription plans. Consumers choose one of these plans or the outside option (denoted by 0), which provides utility normalized to zero. We denote the options available to the consumer by $\mathcal{K}$. A subscription plan $k \in \mathcal{K}$ is either a standalone internet-only plan, a TV-only plan, or a bundle that includes both TV and internet services. Plans can vary in their prices and other attributes. For example, plan $k$ has subscription price $f_k$, and if it includes internet service it does so at speed $s_k$. A bundle pricing plan charges the fee $f_k$ only. If the household is subject to UBP in plan $k$, it faces the price schedule $\mathcal{P}_k$ on top of its subscription price, where $\mathcal{P}_k$ captures all details related to incremental charges for internet usage.

## 2.2 Demand

When a consumer of type $r$ chooses to consume $q_{r,j}$ units (e.g. hours) of $j$, he receives utility of $q_{r,j}/\mu$ up to utility satiation levels $v_r = (v_{r,1}, v_{r,2})$. In other words, the consumer gets a constant marginal utility, captured by $1/\mu$, from consumption up to a quantity of $q_{r,j} = \mu * v_{r,j}$ and then gets zero marginal benefit for any additional consumption. The parameter $\mu$, which applies to both internet and video consumption, can be interpreted as capturing (the inverse of) the consumer's per-unit value of time for the MSO's services.[6] Consumers decide on consumption based on their tastes, $v_r$ and $\mu$, and the subscription plan's characteristics.

To capture the presence of OTT, we assume that consumers can receive some fraction, $\delta_r \in [0, 1]$, of TV video content through the internet. The parameter $\delta_r$ is consumer-specific and captures a combination of OTT availability and the consumer's net benefit from the available OTT content. The quantity consumed of product 2, the video service, $q_{r,2}$, includes content consumed through traditional TV, $q_{r,t,2}$, and OTT content, $q_{r,i,2}$, with $q_{r,2} = q_{r,t,2} + q_{r,i,2}$.

Given this setup, a consumer with taste $v_2$ and a TV-only subscription consumes $q_{t,2} = \mu v_2$ units of video entertainment through his TV and receives surplus of $v_2$ from this activity. When the consumer uses OTT, his marginal utility from video hours remains equal to $1/\mu$ up to $\delta \mu v_2$, where it falls to zero. This can be viewed

[6] A more general model would assign a different parameter value for TV and internet usage. However, since we only observe internet usage, in gigabytes, we cannot identify a separate parameter for TV usage.

as a scenario where a consumer enjoys $v_2$ distinct shows available on TV, but only the fraction $\delta$ of the shows are available through OTT.[7] To simplify the consumption choices of bundle subscribers, we assume that TV subscribers receive all video content through TV, with $q_{t,2} = \mu v_2$ and $q_{i,2} = 0$.[8]

Consumers make monthly plan and usage decisions. When a consumer chooses a plan he does not know the realization of $\mu$, only $dF_\mu$, the density of potential $\mu$ values. We assume that $\mu$ is a realization of a random variable drawn from an exponential distribution with a parameter that is specific to type $r$, $F_\mu(\mu; \lambda_r)$. After committing to plan $k$, the consumer observes $\mu$ and makes usage decisions optimally given $\mu$ and the other taste parameters. Our timing assumption for $\mu$ allows a consumer's usage to vary substantially across months while the consumer (rationally) remains with a fixed plan $k$.

For a type-$r$ consumer, the expected utility from choosing plan $k$ is given by

$$u_{rk} = v_r^*(\mathcal{P}_k) - \phi_r/s_k - \alpha_r \left[f_k + \mathcal{O}^*(\mathcal{P}_k)\right] + \epsilon_{rk}. \tag{1}$$

where $\phi_r$ is preference for internet speed, $v_r^*(\mathcal{P}_k)$ is the expected utility from consumption, $\alpha_r$ is the marginal utility from income, $\mathcal{O}^*(\mathcal{P}_k)$ are overage charges associated with the optimal consumption if the consumer is subject to UBP, and $\epsilon_{rk}$ is a taste shock distributed i.i.d type-I extreme value.[9] The expected utility from consumption is:

$$v_r^*(\mathcal{P}_k) = \int_0^\infty v_r^*(\mathcal{P}_k|\mu) dF_\mu(\mu; \lambda_r),$$

where $v_r^*(\mathcal{P}_k|\mu)$ is utility conditional on a realization of $\mu$ for a household $r$ with tastes $v_r$. This expression is equal to the satiation utility level of $v_{r,1} + \delta_r v_{r,2}$ if the consumer can choose $q_{r,1}^*$ and $q_{r,2}^*$ without concern about overage fees. More generally, $\mathcal{P}_k$ and the consumer's $\mu$ may generate $q_{r,1}^*(\mu) < \mu v_{r,1}$ or $q_{r,2}^*(\mu) < \mu \delta_r v_{r,2}$. In that case,

[7] We do not model consumers' choices across third-party OTT subscription services. We effectively hold these services' characteristics fixed throughout our analysis, while assuming that consumers do not subscribe to these services when the same content is available to them on TV.

[8] When internet usage is costly, this assumption represents the best-case/least-cost outcome for the MSO and strengthens incentives to steer consumers to the bundle.

[9] Speed's role in $u_{rk}$ is consistent with $v_{r,1}$ and $v_{r,2}$ capturing the benefits of instantaneous internet service. In $u_{rk}$, the consumer's benefit from speed is increasing in $s_k$ at a decreasing rate.

realized utility is:

$$v_r^*(\mathcal{P}_k|\mu) = \min\left(\frac{q_1^*(\mu)}{\mu}, v_{r,1}\right) + \min\left(\frac{q_2^*(\mu)}{\mu}, \delta_r v_{r,2}\right).$$

For bundled subscribers, $q_{r,2}^*$ always equals the satiation value of video content, $v_{r,2}$, and therefore

$$v_r^*(\mathcal{P}_k|\mu) = \min\left(\frac{q_1^*(\mu)}{\mu}, v_{r,1}\right) + v_{r,2}.$$

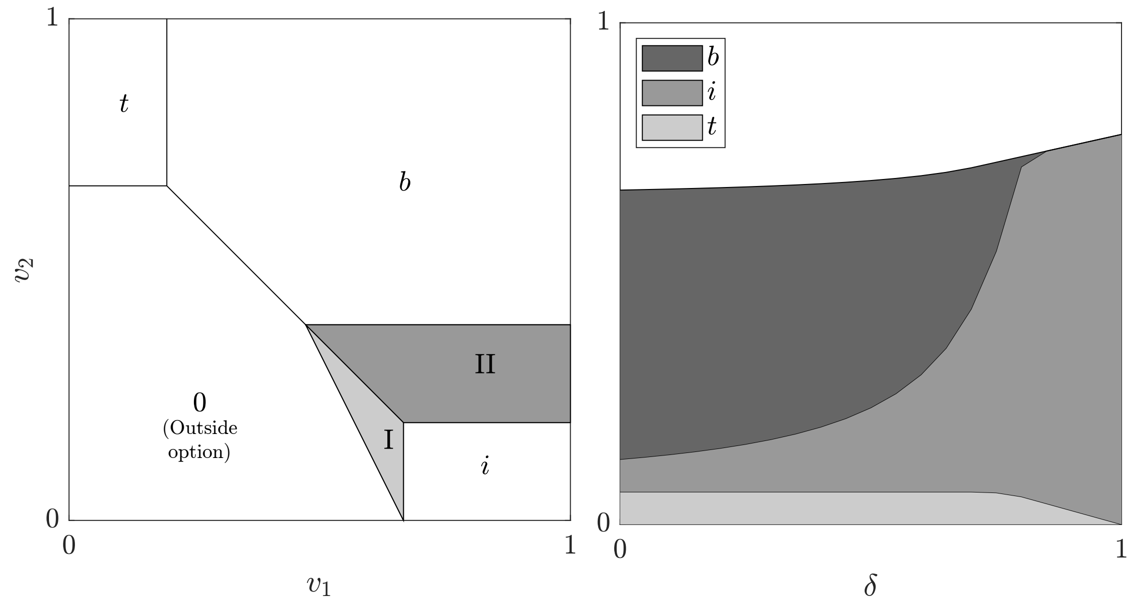
If the consumer faces UBP, the price schedule for plan $k$, $\mathcal{P}_k$, determines optimal usage, $q_1^*(\mu)$ and $q_2^*(\mu)$. In our data, this schedule consists of a usage allowance $\kappa_k$ and a "top-up" fee $\overline{p}_k$ for each discrete increase of the allowance of size $\overline{q}_k$ gigabytes (GBs). Therefore, the consumer's usage either equals the satiation level or the usage allowance plus a fixed number of top-ups. In Online Appendix A.1 we show how the optimal consumption is determined. In sum, for each household of type $r$, given by $(v_{r,1}, v_{r,2}, \phi_r, \lambda_r, \delta_r, \alpha_r)$, the model predicts plan choice and usage for each period (i.e., a month) given the realizations of $\epsilon$ and $\mu$.

#### 2.2.1 Choices in a Simplified Environment

We now illustrate consumer choices in a simplified version of the model that is closer to the standard mixed bundling model used in the literature (Adams and Yellen, 1976; McAfee et al., 1989). We simplify the model in several ways. First, we assume that the MSO offers three plans: broadband internet access ($i$), TV ($t$), and a bundle ($b$) that includes both $i$ and $t$. The MSO's mixed bundling pricing strategy includes prices for the stand-alone plans ($f_i$ and $f_t$) and a price for the bundle ($f_b$). Second, we assume that the shock to utility, $\epsilon_{rk}$ in equation (1) has no variance. Therefore, it and the term involving speed are absorbed in other terms. Third, we assume that $\mu = 1$ for all consumers in all periods. Fourth, we assume $\delta_r = \delta$ for all consumers. Finally, we normalize the consumer population to one and assume that consumers' tastes are distributed independently and uniformly on $[0, 1] \times [0, 1]$.

Putting this all together, consumers who choose internet-only plans receive utility of $U_i = v_1 + \delta v_2 - \alpha f_i$, where the first and second terms capture utility (and quantities) from consuming internet content and OTT content, respectively. A subscription to the TV service, $t$, results in consumption of $q_{t,2} = v_2$, zero internet usage given the lack of access, and net utility equal to $U_t = v_2 - \alpha f_t$. Bundle subscribers consume $q_1$

Figure 1: Consumer Response to Changes in $\delta$




(a) Consumer Types (b) Market Shares

Notes: In panel (a) we present consumer choices for $\delta = 0$ and $\delta = 0.5$ holding prices fixed at $(p_i, p_t, p_b) = (0.667, 0.667, 0.862)$, which are the profit-maximizing levels when $\delta = 0$ and both internet and TV are supplied at zero marginal cost. In panel (b), we present market shares when $\delta$ increases from 0 to 1 and prices are fixed at the same baseline levels.

and $q_2$ equal to their satiation levels and receive utility equal to $U_b = v_1 + v_2 - \alpha f_b$.

We now turn to the choices consumers make in this setup. In panel (a) of Figure 1 we present choices different consumers make for a fixed set of prices. When no OTT is available (i.e., $\delta = 0$), consumers in the areas labeled '0' and 'I' select the outside option, and those in areas '$b$' and 'II' select the bundle. Consumers in areas $i$ and $t$ select the stand-alone internet and TV subscription plans. The split is intuitive and resembles outcomes from standard bundling models. Consumers with low valuations of both services choose the outside option, consumers with high valuations for both services choose the bundle, and consumers with high valuation for one service and not the other choose the plan with just one service. The boundaries between the different choices depend on the prices of the various options.

We also demonstrate in panel (a) the effect of OTT becoming more attractive, namely, $\delta$ increasing, holding prices fixed. Two types of consumers change their choices. First, some consumers (in area I) who did not purchase will now purchase $i$ because it became more attractive than no purchase. These new consumers are one reason the MSO has an incentive to promote improvements in OTT. Second, some consumers (in area II) decide to "cut the cord." These consumers initially choose a bundle but have relatively low TV entertainment tastes among bundle subscribers. As $\delta$ increases, they prefer stand-alone internet service because they can consume OTT using the internet service. In addition to changes in subscription choices, an increase in $\delta$ affects the level and composition of internet usage. Consumers who would have purchased $i$ subscriptions without an improvement in $\delta$ (i.e. those in area $i$) increase their internet consumption in proportion to the $\delta$ increase. Consumers who move from $b$ to $i$ subscriptions, however, generate a discrete jump in internet usage, and streaming video viewing among this group is above the average of $i$ subscribers.

In panel (b) of Figure 1 we present the market shares of the 3 products, holding prices fixed, as $\delta$ increases from 0 to 1. We see that as $\delta$ increases and there is more OTT content, which means that internet service becomes a closer substitute to the bundle, more consumers cut the cord and purchase the internet-only product. There is also a slight increase in the the number of consumers who choose to purchase a product. As we discuss next, this is what generates the trade-off for the MSO.

## 2.3 Supply

We now turn to discussing the MSO's incentives. The MSO offers both TV and internet service and therefore will internalize externalities between these products. When $\delta > 0$, i.e., OTT content is a (partial) substitute for TV content, the MSO will have an incentive to increase the price of the internet product or to degrade its quality, relative to the case where internet and TV are offered by separate firms. On the other hand, $\delta > 0$ may allow the MSO to expand the consumer population who receive (some) video service, perhaps under favorable cost conditions, which can create countervailing incentives for the MSO to favor OTT.

As we saw in Figure 1, an improvement in OTT can lead to cord cutting and potentially a loss in MSO profits, holding prices fixed. Of course, in equilibrium as $\delta$ increases the MSO will respond to the changing circumstances by updating its pricing. The MSO's incentive to respond depends on the relative profitability of TV and internet services, as well as the pricing tools available to the MSO. In Online Appendix A.2 we provide numerical analysis of our simple theoretical model to illustrate the factors that can lead to qualitatively different outcomes under optimal pricing by the MSO. We describe the key findings here, and in the sections below we present similar results using the estimates from the more general empirical model.

In the numerical analysis we focus on two factors that influence MSO incentives: the relative costs of TV and internet service, and the opportunity to charge usage-based prices for internet consumption. The interaction between these two factors determines whether the MSO's incentives are dominated by an incentive to steer consumers away from or toward internet service for a fixed $\delta > 0$, as well as whether the MSO benefits from altering $\delta$ directly.

When the MSO's pricing strategy is restricted to subscription fees that do not vary with usage (i.e., bundle pricing), we show that cost conditions determine whether the MSO has an incentive to steer consumers away from internet service. In particular, when delivering video via the internet is sufficiently costly relative to TV, we show that the MSO raises internet subscription prices to steer consumers into the bundle. As $\delta$ grows, the MSO's steering incentive becomes stronger, and for sufficiently high $\delta$ the MSO can cut off stand-alone internet entirely. By contrast, when internet costs are low relative to TV costs, an increase in $\delta$ leads the MSO to adjust prices so that consumers move from the bundle into internet-only service. In these cases, the MSO's profit in $\delta$ moves in parallel with its incentive to steer toward or away from the bundle. While the MSO's profit may fall in $\delta$ when internet service is sufficiently costly, the increase in $\delta$ can be profit-enhancing for the MSO when cost conditions favor internet content delivery relative to TV.

When we allow for UBP, a different picture emerges. In the analysis described in Online Appendix A.2, we allow the MSO to offer (and optimally price) low-usage and high-usage internet tiers, which mirror the effect of UBP, and this facilitates discrimination of consumers by their intended internet usage, including video. The price premium for the higher-usage tier strikes a balance between steering internet-only consumers to the bundle versus increasing profit through metering the usage of high-demand internet subscribers. We find that even when relative costs would lead a bundle-pricing MSO to steer consumers away from internet service as $\delta$ grows, an MSO with UBP may actually steer consumers toward internet service. Intuitively, what has changed is that, as $\delta$ increases, UBP allows the MSO to share in more of the gains generated by the greater demand for internet usage. These additional gains may be sufficient to overcome the cost disadvantages of delivering video via the internet and the profit lost from TV service.

In the other cost case, when TV is costly relative to the internet, the MSO's incentive to steer consumers toward internet service further increases, and cord-cutting is even more strongly encouraged through relative prices. In the cost cases we consider, UBP allows the MSO's profit to increase in $\delta$ at optimal pricing, with the profit slope increasing as costs favor internet service over TV.

Up to this point we took the change in $\delta$ as exogenously given. However, the MSO may have the ability and incentive to alter $\delta$ directly. The MSO can increase or decrease $\delta$ by choice of technology or by adding surcharges for OTT access. For example, the MSO could reduce $\delta$ with lower-quality video transmission over the internet or blocking some video sites. Alternatively, the MSO could invest in transmission infrastructure, software and device design choices that facilitate streaming video access, or create its own streaming video content to increase $\delta$. In our numerical analysis, cases with a positive relationship between $\delta$ and profit are associated with MSO incentives to improve streaming video. A similar intuition can apply to discriminatory usage prices for OTT content. A targeted usage price for video content has the same effect as reducing $\delta$ in consumers' utility, plus the usage price would bring additional revenue to the MSO. While an OTT-specific fee captures some benefit for the MSO from improvements in $\delta$, it lacks the general UBP's ability to collect revenue on internet usage of all varieties. In our simple model, this appears through willingness-to-pay for non-video usage, which varies among $i$ subscribers. More generally, the MSO may face a complex variety of services that compete with TV for consumers' attention, and substitution away from individual activities subject to discriminatory UBPs toward other unmetered forms of usage may represent a lost opportunity for the MSO.

# 3 Data

Our data come from one MSO and describe activity for approximately 9 months in a large North American city.[10] We observe 34,752 consumers' billing information, subscriptions, and internet usage. To preserve customer anonymity, we do not observe demographic information for individual households.

Like most North American MSOs, the firm we observe offers internet and TV

[10]Our agreement with the MSO prevents us from identifying the firm or any details that could be used to infer its identity. This includes the specific market served, the exact dates and details of the implementation of UBP, as well as detailed characteristics of the MSO's product offerings.

services via mixed bundling, giving discounts off stand-alone prices when consumers subscribe to both services.[11] Across internet tiers, the average price difference between the bundle and internet-only subscriptions is about \$100. 23% of the MSO customers have internet-only subscriptions, and the remaining 77% subscribe to an internet-TV bundle; no MSO customers in our data subscribe to TV alone. The MSO offers tiers of internet service differentiated by speed and, as we discuss below, usage allowance during part of our sample period. The typical price difference between adjacent internet tiers is about \$15. In the first row of Table 1 we present the share of households who choose different plans, aggregated by plan speed.

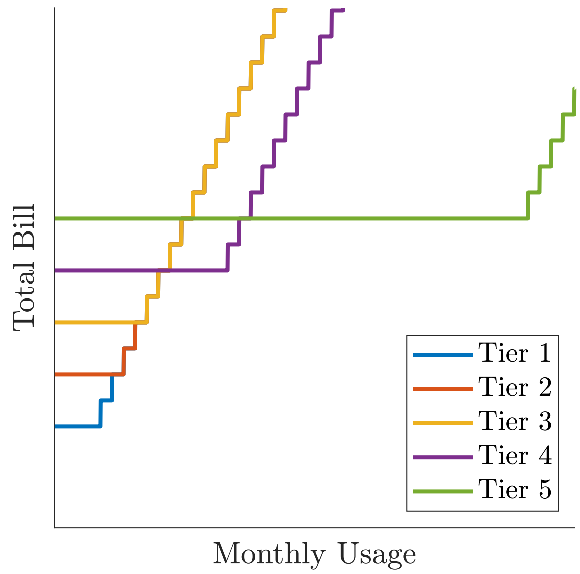
For each household in the sample, we observe download and upload volume each month, which we aggregate into total household monthly usage (in gigabytes). In Table 1 we show descriptive statistics on monthly usage by subscription type. The mean (median) monthly usage level across all households in the sample is 105 (49) gigabytes, equivalent to about 3.5 (1.6) gigabytes per day. Internet usage differs substantially across households. Average usage in the highest-priced (and highest-speed) tier is nearly seven times that in the lowest-priced tier. Within-tier usage dispersion is also substantial; coefficients of variation range from 1.67 to 2.05 across tiers. Across combinations of TV and internet service, internet-only subscribers have mean (median) internet usage 61% (137%) greater than bundle subscribers. There is also substantial variation in usage across months within a household. Decomposing the variance in usage across all subscriber-months, 83% of variation is explained by heterogeneity across/between households, while the remaining 17% is explained by within-household variation. Our model captures both the within household variation, by allowing the realization of $\mu$ to vary across months, and the between household variation by allowing the distribution from which $\mu$ is drawn to vary across households, in addition to variation in $v$.

UBP was introduced in this market in the middle of our sample period. To our knowledge, the market was chosen for the introduction of UBP due to the network characteristics that permitted billing on usage. The timing of UBP's introduction was based on engineering considerations, not local demand conditions that would impact the return from UBP.[12] The MSO implemented UBP through a menu of service tiers

[11] The MSO also offers telephone service, which about 40% of its customers subscribe to. We do not use the telephone service information in this paper.

[12] Competitors' subscription offerings did not change meaningfully during the sample period, in response to the UBP policy's introduction. Satellite TV was available in the market, as was a

Figure 2: Cost of Usage by Tier Under UBP




Notes: We do not provide numerical labels on the axes to preserve the MSO's anonymity.

that consumers could choose from, where each tier is a three-part tariff. Tiers vary in their monthly usage allowance in GBs. Usage up to this allowance is included in the monthly subscription charge, but if a household exceeds its allowance, it is charged for an extra top-up of data, which the consumer may use fully or partially. In Figure 2 we illustrate the total price consumers pay for different monthly usage depending on their plan.

The MSO's introduction of UBP came in two phases. The MSO announced that it would implement UBP starting on a specified date, and it provided households with information about how their monthly usage compared to the data allowance of their current internet tier. During this phase, which we call the "announcement period," households were not billed if their usage exceeded their tier's allowance. In the next phase, which we call the "treatment period," the MSO assessed overage charges on households that exceeded their allowances. We observe several months of activity (a "pre-policy period"), immediately prior to the announcement and treatment periods, which each last several months. For the analysis below, we use data from the pre-policy period and the treatment period, but not the announcement period.

The third panel of Table 1 shows that some internet-only consumers added TV

substantially slower alternative internet service via DSL.

Table 1: Descriptive Statistics

| | Internet-only | | | Internet & TV | | |
|---|---|---|---|---|---|---|
| Speed Tier | Low | Median | High | Low | Median | High |
| Choice Share | 0.07 | 0.12 | 0.04 | 0.18 | 0.50 | 0.09 |
| Monthly Usage | | | | | | |
| Mean | 98.90 | 171.23 | 307.56 | 43.18 | 84.54 | 171.20 |
| Standard Deviation | 106.48 | 151.90 | 266.07 | 71.46 | 116.83 | 208.23 |
| 5th Percentile | 2.86 | 13.55 | 30.95 | 0.42 | 1.49 | 3.98 |
| 25th Percentile | 22.91 | 62.53 | 119.16 | 4.38 | 12.09 | 28.77 |
| Median | 65.83 | 132.87 | 244.07 | 15.04 | 39.18 | 94.94 |
| 75th Percentile | 138.78 | 236.95 | 424.70 | 49.52 | 112.63 | 247.01 |
| 95th Percentile | 305.11 | 452.08 | 759.40 | 185.88 | 313.12 | 569.83 |
| Subscription Changes | | | | | | |
| Upgrade Tier | 0.06 | 0.08 | 0.21 | 0.07 | 0.06 | 0.22 |
| Add Video | 0.03 | 0.03 | 0.03 | – | – | – |
| Price Change Impact | | | | | | |
| Share w/ Overages | 0.04 | 0.08 | 0.05 | 0.02 | 0.02 | 0.01 |
| Mean Overage ($) | 23.44 | 31.93 | 33.60 | 24.88 | 34.03 | 43.69 |
| Median Overage ($) | 20.00 | 20.00 | 30.00 | 20.00 | 20.00 | 30.00 |
| Observations | 22,773 | 36,994 | 12,550 | 57,026 | 156,171 | 27,252 |

Notes: Summary statistics at a subscriber-month level of observation using 312,678 observations across 34,752 households and 9 months. The first two panels contain shares and usage levels by subscription type. The third panel contains the fraction of households who changed their pre-policy period subscriptions during the announcement or treatment periods. The final panel describes overages that would have resulted from applying the treatment period billing schedule to pre-policy period usage levels, with the means and medians conditional on positive overage charges.

service after the introduction of UBP. However, upgrades of internet service tiers were much more common, especially for the high speed consumers who upgraded to the highest available allowance. The bottom panel of Table 1 shows that 3% of household-month usage levels during the pre-policy period would have resulted in overages after the price change, with an average bill of $32 conditional on exceeding the usage allowance. Consistent with the expectation of overages, 9% of households upgraded their initial internet tier to a tier with a higher usage allowance.

# 4 Econometrics

We now discuss how we estimate the model presented in Section 2 using the data described in Section 3. The model describes the preferences and choices of a household of type $r$, with the vector of parameters $\theta_r = (v_{r,1}, v_{r,2}, \phi_r, \lambda_r, \delta_r, \alpha_r)$. Our goal is to estimate the distribution of $\theta$ in the population. One way to approach this problem is to specify a parametric distribution for $\theta$, say a normal distribution, and then estimate the parameters of this distribution, possibly by maximum likelihood. We take a different approach. As we saw in Table 1, there is significant heterogeneity in consumer usage and therefore we want to estimate the distribution of parameters flexibly. To do so, we use a fixed grid approach similar to Ackerberg (2009), Fox et al. (2011), and Fox et al. (2016). Our application of these methods most closely follows the likelihood-based approach of Malone et al. (2017) that exploits the parametric specification of utility but limits assumptions on the distribution of parameters across households.

The estimation approach proceeds in two steps. In the first step, we choose $R$ candidate types, where each type, $r$ is characterized by a value of $\theta_r$. We effectively begin with a uniform prior over the discrete distribution of $R$ types and zero mass elsewhere. For this reason it is important that we choose a large number of types with wide enough support and dense enough distribution within this support. Next, we use the data to update the prior. To do so, for each type, we apply our empirical model to compute the probability of choosing each plan $k$ and the optimal usage conditional on $k$. For each household in the data we compute the likelihood of the actual choices made by the household if it were of type $r = 1, \ldots, R$. We apply Bayes rule to update the initial prior and calculate the probability distribution of types for each household. We then aggregate the distribution across households to obtain the (posterior) distribution of $\theta$.

## 4.1 Identification

Our goal is to identify the distribution of $\theta$. In the estimation approach described above, identification is equivalent to asking: How informative are the observed choices in the data in updating the prior assumption of a uniform type distribution? In this section, we discuss the issues conceptually. The information we use includes the plan subscription choices, both before and after the introduction of UBP, as well as the variation in internet usage, between and within households.

To start, consider the subscription decision of a household that chooses among internet-only service plans that have only a subscription fee (i.e., pre-UBP.) Since there are no usage allowances, the only reason to choose a more expensive plan is greater speed. To build intuition, assume there is no $\epsilon_{rk}$, the "logit" shock to plan specific utility, shown in equation (1). With this abstraction, plan choice is deterministic. Therefore, any household that chooses plan $k$ must come from a type that satisfies

$$\frac{p_k - p_k^-}{1/s_k^- - 1/s_k} < \frac{\phi_r}{\alpha_r} < \frac{p_k^+ - p_k}{1/s_k - 1/s_k^+},$$

where $^-$ and $^+$ denote "adjacent" plans. In other words, for a household that chooses plan $k$ the distribution of types changes from the prior of $1/R$ over all types, to zero for all types that do not satisfy the above condition and uniform for those types that do. Aggregated across all households, this yields a step-wise distribution over types. With the addition of the the logit error in equation (1), the plan selection is not deterministic but the basic idea remains: different types will have different likelihoods of choosing each plan and therefore plan choices are informative about the distribution of types.

As we add more plans, or as their characteristics and prices change, then plan choices become even more informative. For example, once UBP is implemented and the effective price of each tier changes due to expected overages, the plan choice informs us about price sensitivity. Similarly, abstracting away from the logit error, a household's choice of an internet-only plan over a bundle option in the pre-UBP period implies that the utility from internet-only option, $i$, is greater than the utility from the bundle option, $b$, i.e., $v_{r,1} + \delta_r v_{r,2} - \alpha_r f_i > v_{r,1} + v_{r,2} - \alpha_r f_b$. This implies $\frac{v_{r,2}(1-\delta_r)}{\alpha_r} < (f_b - f_i)$, and therefore places further restrictions on the likelihood an observed choice was generated by different types. UBP adds additional restrictions by affecting the endogenous choices made by different types with respect to usage allowances and top-up prices.

In addition to the information from subscription choices, described above, a household's usage data provides complementary information about the likelihood the household is of a specific type. To see how usage data is informative, we note that before UBP is implemented, given a realization $\mu$ of the disturbance from the type-specific exponential distribution $F_\mu(\lambda_r)$, usage for an internet-only household equals $\mu(v_{r,1}+\delta v_{r,2})$. Over time for a given household, this usage varies only because of variation in the realization of $\mu$. Thus, within-household variation in usage across billing periods in the pre-UBP period carries information about which values of $\lambda_r$ are most consistent with the data. Similarly, the average usage over time (and the knowledge of $\lambda_r$) place restrictions on $(v_{r,1}+\delta_r v_{r,2})$, limiting 3-tuples of $v_{r,1}$, $v_{r,2}$, and $\delta_r$ to a known hyperplane. This provides a substantial refinement to the household's posterior when combined with the restrictions on these parameters from the household's subscription choices.

The set of candidate types able to rationalize a sequence of decisions is further refined for those households who make changes to subscriptions once UBP is introduced. Consider a household that switches from internet-only to the bundle after the implementation of UBP. For these households, the distribution of usage changes proportionally to $\delta v_{r,2}$, and therefore is informative about the determinants of usage (i.e., $v_{r,1}$, $v_{r,2}$, and $\delta_r$). For those households that upgrade tiers, the choice provides additional information about the preference for speed ($\phi_r$). Conversely, the absence of subscription changes by a household provides restrictions on price sensitivity and preference for speed.

In section 5, we present the degree of refinement of household-specific posteriors to demonstrate the identifying power of different sources of variation in our data.

## 4.2 Estimation

We flexibly estimate the distribution of $\theta$ using a two-step approach similar to Malone et al. (2017). In the first step, we choose $\theta_r$, $r = 1, \ldots, R$ using a six-dimensional Halton point set over a fixed support; we set $R$ = 1,000,000. We then calculate expected internet-only usage under the observed bundle pricing, i.e., $\lambda\left(v_1+\delta v_2\right)$, and remove those types with expected usage greater than the largest value in our data (about 4 Terabytes in a single month). For the remaining 67,753 candidate types, $\theta_r = (v_{r,1}, v_{r,2}, \delta_r, \phi_r, \lambda_r, \alpha_r)$, we compute plan choice probabilities ($P_d$) and the density of usage ($P_q$) for the pricing schedules observed in the data.

Working backwards through the choices for type $\theta_r$, we first describe the density of internet usage conditional on plan $k$. The exponential assumption for $dF_\mu$ results in a cumulative distribution function for internet usage given by

$$P_q(q^* < q|d = k; \theta_r, \mathcal{P}_k)) = \int_0^\infty \mathbb{1}[q^*(\mu, \mathcal{P}_k; \theta_r) < q] dF_\mu(\lambda_r),$$

where $q^*(\mu, \mathcal{P}_k; \theta_r)$ is the optimal usage of the type $r$ facing pricing schedule $\mathcal{P}_k$ given a realization of $\mu$. The density of usage, $P_q(q^* = q|d = k; \theta_r, \mathcal{P}_k)$, can then be calculated from the cumulative distribution function of usage with appropriate consideration of the discontinuities that arise due to the non-linearity of the pricing schedule. We numerically recover this distribution by calculating optimal usage (i.e., $q^*(\mu, \mathcal{P}_k; \theta_r)$) with 50,000 draws from the type-specific exponential distribution for each $r$. We use this distribution to calculate expected utility from usage and overages, $v^*(\mathcal{P}_k)$ and $\mathcal{O}_r^*(P_k)$, respectively. Given these values, we compute type $_r$'s expected utility from each plan $k$. The type-I extreme value distribution assumption on plan-specific utility shocks implies that the probability that type $r$ chooses plan $k$ equals

$$P_d(d^* = k; \theta_r, \mathcal{P}) = \frac{\exp\Big(-\frac{\phi_r}{s_k} + v_r^*(\mathcal{P}_k) - \alpha_r\left(f_k + \mathcal{O}_r^*(\mathcal{P}_k)\right)\Big)}{1 + \sum_m \exp\Big(-\frac{\phi_r}{s_m} + v_r^*(\mathcal{P}_m) - \alpha_r\left(f_m + \mathcal{O}_r^*(\mathcal{P}_m)\right)\Big)}.$$

In the second step, we use the decisions of households in our data and the optimal actions of the candidate types to compute the relative likelihood that a household is each type. Specifically, for each household ($h = 1, \ldots, N$) in our sample, we observe a sequence ($t = 1, \ldots, T$) of monthly subscription ($d_{ht}$) and usage ($q_{ht}$) decisions. The likelihood of any sequence of decisions by a household in our sample with preferences given by $\theta_r$ equals

$$\mathcal{L}_h(\theta_r) = \prod_{t=1}^{T} P_d(d_{ht}; \theta_r, \boldsymbol{\mathcal{P}}_t) \times P_q(q_{ht}|d_{ht}; \theta_r, \boldsymbol{\mathcal{P}}_t),$$

where $\boldsymbol{\mathcal{P}}_t$ is the the set of plan-specific price schedules $\mathcal{P}_k$ available at time $t$. Assuming a uniform prior across candidate types for households, the relative likelihoods correspond to weights in a discrete posterior distribution. Specifically, the probability that household $h$ is of type $r$ equals

$$\omega_{hr} = \frac{\mathcal{L}_h(\theta_r)}{\sum\limits_{m=1}^{R} \mathcal{L}_h(\theta_m)}$$

where $\mathcal{L}_h(\theta_m)$ is set to zero for any type $m$ that was eliminated in the initial screening described above. To obtain our estimate of the distribution of types in the population, we aggregate the households' posterior weights across types so that $\omega_r = \frac{1}{N}\sum_{h=1}^{N}\omega_{hr}$ for $r = 1, \ldots, R$.

To calculate standard errors for the weights, $\omega_r$, and associated statistics of the weights, we use block re-sampling at the household level. Specifically, we re-sample the population of households with replacement (500 draws) and re-compute each candidate type's weight (or function of those weights). This is computationally advantageous because it does not require re-solving the model or re-computing likelihoods, rather just re-weighting each household's contribution in the calculation of each $\omega_r$.

# 5 Results

We now turn to the results. First, we describe the estimates of the distribution of model parameters. We show that our flexible approach is able to capture the wide range of behaviors observed in the data. Next, we use the estimates to characterize willingness-to-pay for access to OTT and service attributes like internet connection speeds. Finally, we use the estimates to study an MSO's incentives to steer consumers, which can occur through technological means that alter $\delta$ directly, or through pricing via UBP schedules that discriminate against OTT traffic.

## 5.1 Model Estimates and Fit

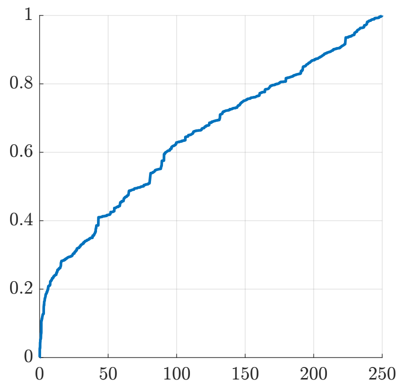
The estimation approach described in Section 4 yields weights that characterize a discrete distribution of the parameters. As previously noted, we aggregate the household-specific weights, $\omega_{hr}$, for each candidate type across households, $\omega_r = \sum_h^N \omega_{hr}$, to obtain a distribution of $\theta = (v_1, v_2, \delta, \phi, \lambda, \alpha)$.

In Figure 3, we present a marginal cumulative distribution function for each parameter. The wide range of $\phi$ captures the heterogeneity in preference for speed, which drives selection of consumers across tiers in the absence of UBP, along with $\alpha$ which determines willingness-to-pay for such features. Similarly, the long tail of $\lambda$'s distribution helps the model match the substantially higher usage of some households. There is also substantial heterogeneity in $v_1$, $v_2$, and $\delta$, which collectively play an important role in valuations of services and plan selection.

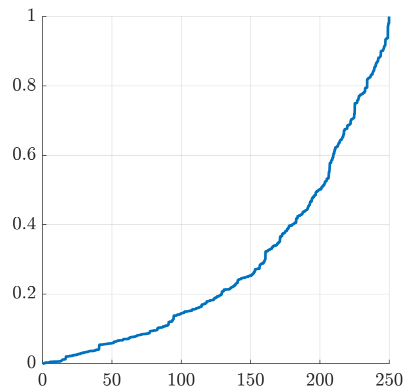
In the top panel of Table 2, we present the means, standard deviations, medians, and $25^{th}$ and $75^{th}$ percentiles for each parameter. In the bottom panel, we present the correlations between pairs of parameters. There are some intuitive patterns in these correlations. For example, $v_1$, $v_2$, $\delta$, and $\lambda$, which collectively determine usage, are positively correlated with $\phi$. Thus, higher usage households have a greater preference for speed. This pattern is reflected in the pre-UBP period, when households with greater usage selected tiers with greater speed. Given the complexity of the relationships between the parameters and implied behaviors, other correlations are more difficult to interpret. The value of our flexible estimation approach is also clear in the parameters' joint distribution. For example, in Figure 4 we present the joint distribution of $\delta$ and $\phi$, which is non-normal and has multiple modes.

As we discussed in Section 4.1, we use the information in the data to update the posterior distribution of parameters. Indeed, the posterior distributions make clear that the data substantially refine the uniform prior across the $R$ candidate types for each household. One measure of the amount of refinement is to consider the posterior weights' concentration across candidate types for a household. Specifically, for each household, we sort the posterior weights ($\omega_{hm}$) from largest to smallest and calculate the cumulative weight up to each value. We can then ask how many types are needed to capture a given amount of cumulative posterior weight for a household, or how much cumulative posterior weight is associated with a given number of types for the household. In Figure 5, we plot the average relationship between number of types and cumulative weight for three categories of household: those that make no plan changes, those that upgrade tiers, and those that add video. For an average household that adds video, the 10 types with the greatest weight have a cumulative value that is close to 100%. Households that upgrade their internet tier have an average of 80% of weight on 10 types, and households with no subscription change have an average

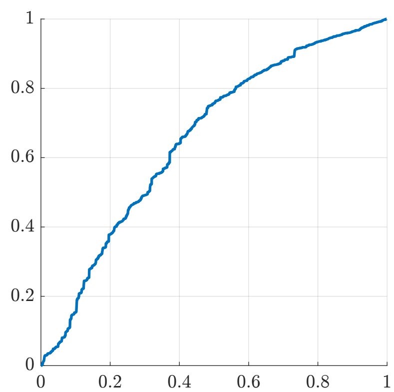
Figure 3: Marginal Distributions of Structural Parameters



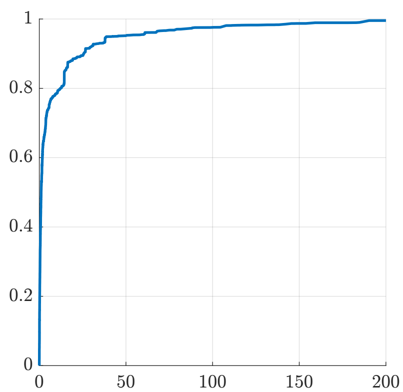

(a) $v_1$



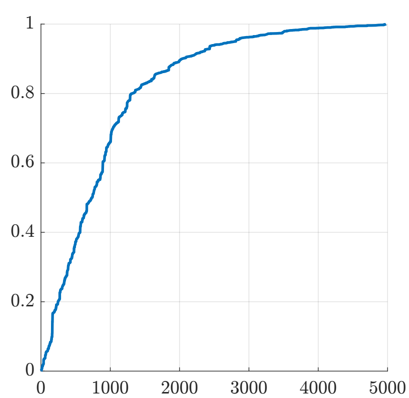

(b) $v_2$



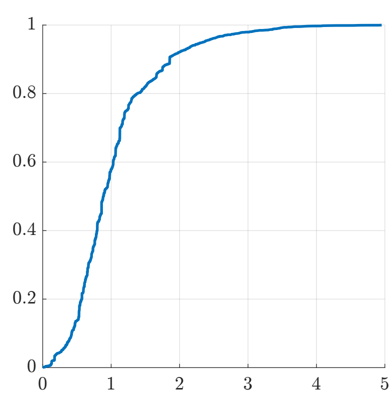

(c) $\delta$




(d) $\lambda$




(e) $\phi$




(f) $\alpha$

Notes: Estimates of the marginal distributions of the six structural parameters in the empirical model.

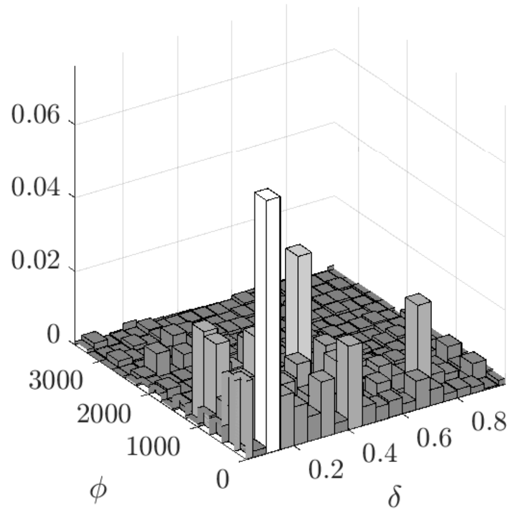
Table 2: Summary Statistics of Type Distribution

| Marginals | $v_1$ | $v_2$ | $\delta$ | $\phi$ | $\lambda$ | $\alpha$ |
|---|---|---|---|---|---|---|
| Mean | 88.27 | 178.73 | 0.35 | 950.30 | 1.04 | 10.63 |
| | (0.01) | (0.01) | (0.00) | (0.19) | (0.00) | (0.00) |
| SD | 78.09 | 62.50 | 0.25 | 884.96 | 0.65 | 31.49 |
| | (0.01) | (0.01) | (0.00) | (0.19) | (0.00) | (0.01) |
| 25th Pct. | 12.74 | 145.13 | 0.13 | 331.85 | 0.61 | 0.35 |
| | (0.01) | (0.06) | (0.00) | (0.17) | (0.00) | (0.00) |
| 50th Pct. | 74.68 | 198.47 | 0.31 | 745.74 | 0.88 | 1.10 |
| | (0.06) | (0.02) | (0.00) | (0.13) | (0.00) | (0.00) |
| 75th Pct. | 149.15 | 225.41 | 0.49 | 1226.34 | 1.21 | 5.74 |
| | (0.04) | (0.02) | (0.00) | (0.37) | (0.00) | (0.01) |

| Correlations | $v_1$ | $v_2$ | $\delta$ | $\phi$ | $\lambda$ | $\alpha$ |
|---|---|---|---|---|---|---|
| $v_1$ | 1.00 | -0.26 | 0.22 | 0.30 | 0.54 | -0.34 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| $v_2$ | | 1.00 | -0.20 | 0.05 | 0.08 | -0.04 |
| | | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| $\delta$ | | | 1.00 | 0.16 | 0.28 | -0.23 |
| | | | (0.00) | (0.00) | (0.00) | (0.00) |
| $\phi$ | | | | 1.00 | 0.36 | -0.11 |
| | | | | (0.00) | (0.00) | (0.00) |
| $\lambda$ | | | | | 1.00 | -0.19 |
| | | | | | (0.00) | (0.00) |
| $\alpha$ | | | | | | 1.00 |
| | | | | | | (0.00) |

Notes: Summary statistics of the estimated type distribution. Standard errors for each statistic are shown in parentheses and are bootstrapped using 500 samples with replacement of the full set of households used in estimation.

Figure 4: Joint Distribution of $\delta$ and $\phi$

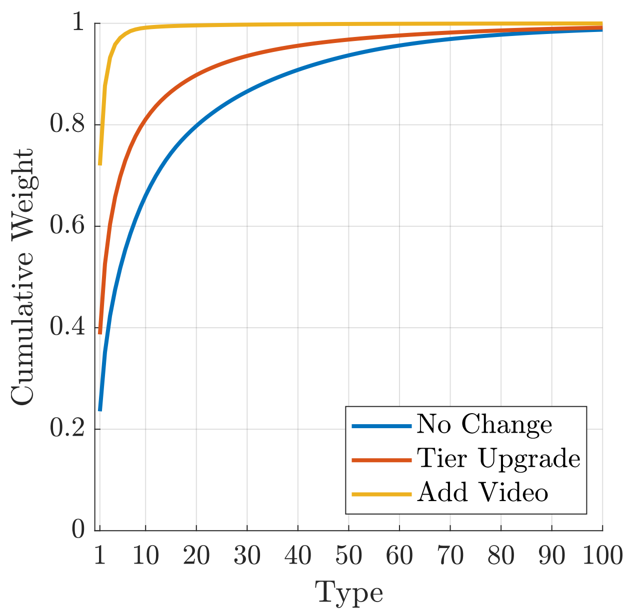



Notes: This figure shows the joint distribution of $\delta$ and $\phi$.

cumulative posterior weight of 65% on 10 types. Thus, the complexity of the plan and usage choices allow for substantial refinement of the uniform prior even for households that do not switch plans. This implies that the substantial variation in parameter distributions displayed in Figure 3 is due to heterogeneity across households rather than diffuse posteriors for individual households.

Next, we assess model fit. In Table 3 we compare the empirical and model-predicted market shares and usage levels by plan, where we distinguish six plan categories by speed (Low, Median, High) and internet-only versus bundle ($i$, $b$). We compute each value under the baseline (bundle) pricing model and with usage-based pricing. Overall, the predicted market shares and usage are comparable to the empirical levels. One difference that emerges is a slight under-prediction of subscriptions to higher speed tiers during the bundle pricing period, and a slight over-prediction of subscriptions to these speed tiers during usage-based pricing, when higher speeds are associated with higher allowances. In terms of usage predictions, the model generally matches key empirical usage differences by plan type, including the large difference in levels between internet-only and bundle households, and the increasing average usage across tiers by speed, both before and during usage-based pricing. As one might expect, the model matches the empirical usage levels most accurately for the

Figure 5: Household Posterior Refinement




Notes: For each household, we calculate the smallest number of types ($T$) needed to account for a given cumulative posterior weight. We divide households into three groups based on observed subscription choices, and we graph the average cumulative weight for each $T$ from 1 to 100.

Table 3: Model Fit

| | Bundle pricing | | Usage-based pricing | |
|---|---|---|---|---|
| Shares | Model | Data | Model | Data |
| $i$ Low Speed | 7.8 | 7.3 | 7.0 | 7.2 |
| $i$ Median Speed | 13.1 | 11.6 | 11.2 | 12.0 |
| $i$ High Speed | 3.0 | 4.6 | 4.5 | 3.5 |
| $b$ Low Speed | 18.7 | 17.9 | 18.1 | 18.6 |
| $b$ Median Speed | 49.6 | 48.8 | 48.6 | 51.1 |
| $b$ High Speed | 7.9 | 9.8 | 10.5 | 7.6 |
| | Bundle pricing | | Usage-based pricing | |
| Mean Usage | Model | Data | Model | Data |
| $i$ Low Speed | 144.9 | 102.8 | 83.4 | 95.0 |
| $i$ Median Speed | 169.4 | 173.0 | 125.5 | 169.5 |
| $i$ High Speed | 204.4 | 334.2 | 212.2 | 272.5 |
| $b$ Low Speed | 60.3 | 45.0 | 43.9 | 41.4 |
| $b$ Median Speed | 98.0 | 85.4 | 75.0 | 83.7 |
| $b$ High Speed | 141.9 | 188.3 | 167.7 | 149.2 |

Notes: Empirical and model-predicted market shares and average monthly usage levels by plan. Plans are grouped by bundle status ($i$ for internet-only and $b$ for bundle) and internet download speed (Low, Median, High). "Bundle pricing" applies to the pre-UBP empirical lump-sum prices. "Usage-based pricing" adds the MSO's empirical UBP schedule.

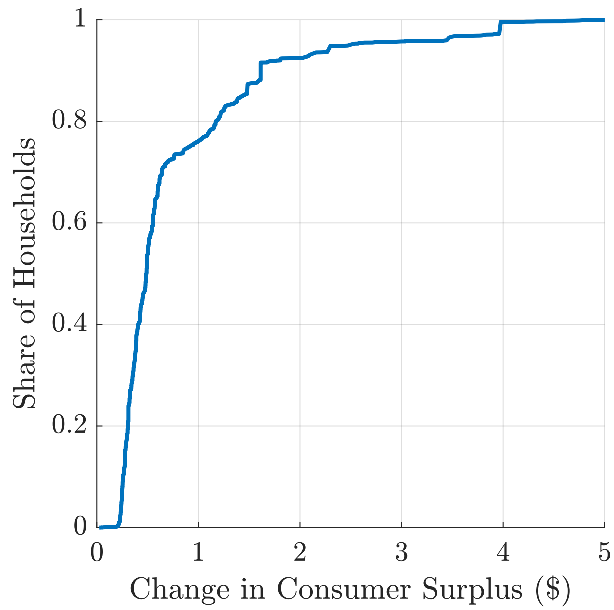
highest-share tiers where we have more information (e.g., $b$ Median Speed, which is chosen by nearly half of the households in the data). The model is less accurate for plans with very low take-up, but these contribute relatively little to the overall type distribution (e.g., $i$ high speed, which has less than 5% market share).

## 5.2 Consumers willingness-to-pay

We use our estimates to compute consumers' willingness-to-pay (WTP) for various aspects of the internet service. The first measure we present is the WTP for greater connection speeds. We compute this WTP as the difference in consumer surplus for households facing the observed menu of internet plans versus a menu with the same prices but internet speeds one megabit per second faster for all tiers.[13] For a given

[13]Across plans, the average observed speed is about 48Mbps.

Figure 6: Distribution of Willingness to pay for Speed Increase



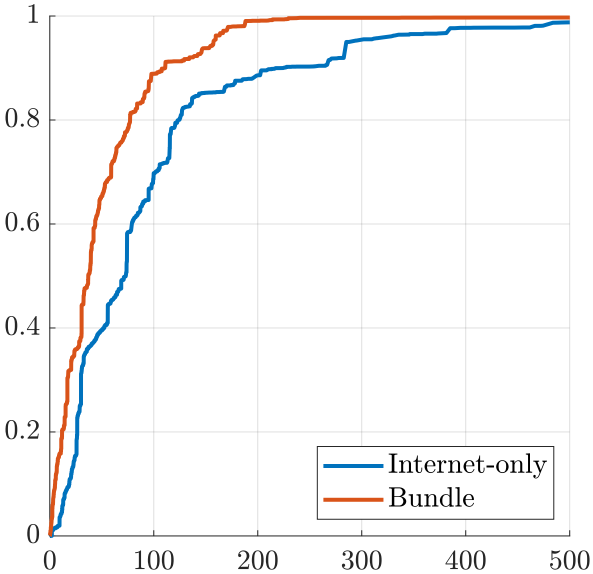

Notes: The change in consumer surplus (measured in dollars) resulting from a 1 Mbps increase in the download speed associated with all internet tiers.

menu of internet plans, each indexed by $k$ with price schedule $\mathcal{P}_k$ and speed $s_k$, the consumer surplus is

$$CS_r(\mathcal{P}, s) = \frac{1}{\alpha_r} \log \left( \sum_k \exp \left( -\frac{\phi_r}{s_k} + v_r^*(\mathcal{P}_k) - \alpha_r \left( f_k + \mathcal{O}_r^*(\mathcal{P}_k) \right) \right) \right).$$

For a household of type $r$, the WTP for internet speed is the difference in $CS_r$ values for the observed and augmented speed values. We use the estimated distribution of types, $w_r$, to compute the distribution of $CS_r$ values in the population, and we repeat this exercise for both bundle and usage-based pricing. In Figure 6 we present the willingness-to-pay for the speed increase for one complete billing cycle under bundle pricing. The distribution of $\phi$, together with the functional form of $s_k$ in utility, generate marginal valuations that are large but decline rapidly for tiers with greater speeds. The average consumer surplus change is \$0.81 under bundle pricing and \$0.73 with UBP. For either price schedule, within a given plan usage does not change with $s_k$, so the difference in surplus changes must follow from how the consumers view the utility differences across menu options.

Figure 7: Willingness to pay for OTT Video

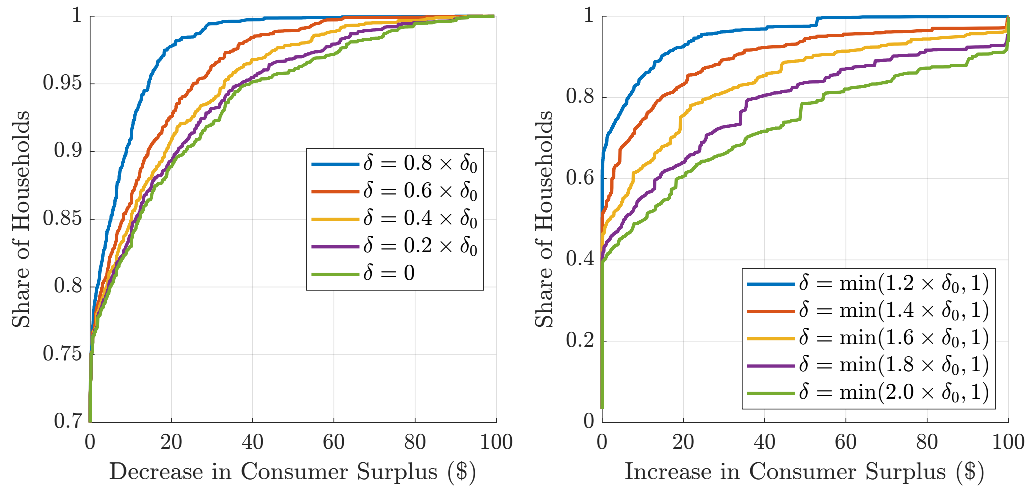



Notes: Marginal distribution of $\delta v_2/\alpha$. The Internet-only distribution weights type-specific values using both the estimated type weights and the probability that the type chooses an internet-only plan, while the Bundle distribution weights type values using the probability that the type chooses an internet and TV bundle plan.

The next consumer welfare measure we consider is the dollar value households place on access to OTT. For type $r$, this value is equal to $(\delta_r v_{r,2}/\alpha_r)$, and we compute its distribution using the posterior weights across candidate types. In Figure 7 we present the cumulative distribution function of this dollar value, both for types that prefer internet-only plans and for types that prefer bundle plans. Both distributions are right-skewed, with substantial variation. Types that prefer internet-only plans have a 25th percentile valuation of \$29 per month, median of \$73, and 75th percentile of \$115. Types that prefer a bundled internet and TV plan intuitively have lower OTT valuations, with a 25th percentile of \$15, median of \$37, and 75th percentile of \$66.

The final welfare measure we consider is the impact of changing $\delta$ on consumer surplus. We follow the same approach as above with internet speed: we calculate the difference in consumer welfare between the status quo and proportional changes to $\delta$'s value. In our model, when households prefer the bundle, a change in $\delta$ has no effect on welfare, holding subscription choice constant. A change in $\delta$ affects utility conditional on an internet-only subscription, and therefore can affect the relative util-

Figure 8: Consumer Surplus Implications of $\delta$ Changes (Bundle Pricing)




(a) $\delta$ Decreases

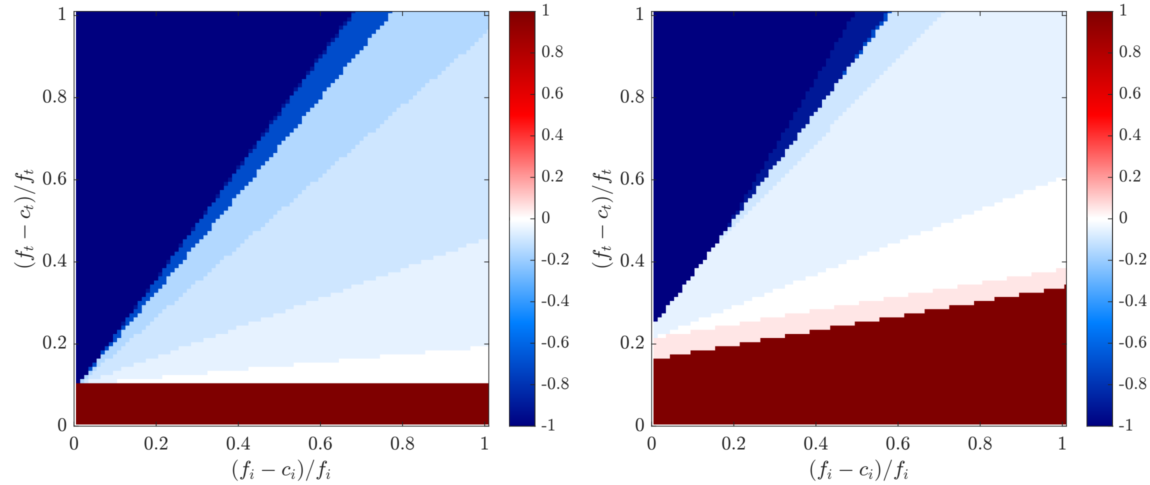
(b) $\delta$ Increases

Notes: We show the dollar change in consumer surplus from changes in $\delta$. Each consumer's estimated value, $\delta_0$, is scaled by a proportional factor.

ity of internet-only versus the bundle. In Figure 8 panels (a) and (b), we present the distribution of consumer welfare changes for decreases and increases in $\delta$, respectively, when the MSO uses bundle pricing. When $\delta$ is reduced, roughly 70% of households are not impacted meaningfully because they would have selected the bundle. Others minimize their losses by choosing the bundle rather than internet-only. If $\delta$ is set to zero (i.e., OTT access is completely eliminated), about 15% of households lose $20 or more in welfare, and 5% lose more than $40.

If $\delta$ improves, on the other hand, a larger proportion of households can benefit because consumers become more likely to subscribe to an internet-only plan. If each household's $\delta$ improves by 40% (capped at 1), the mean consumer welfare increase is $17, with 15% of households gaining more than $20 and 10% gaining more than $40. In Figure 15 (Online Appendix B) we present analogous results for when the MSO uses UBP. The results are qualitatively very similar with only slight changes in the magntitudes of the welfare implications. For example, the benefits from an increase in $\delta$ in panel (b) are smaller because some of the gains are captured by the MSO through UBP overages.

Figure 9: Profit-maximizing $\delta$ as a function of costs




(a) Bundle Pricing (b) Usage-Based Pricing

Notes: The level of the heat map corresponds to a percent change in all households' $\delta$ levels, e.g., at 1, $\delta$ is increased by 100% (capped at $\delta = 1$), at 0, $\delta$ remains at the baseline level, and at -1, all $\delta$ values are reduced by 100% down to zero for different levels of costs ($c_i$ and $c_t$), holding subscription prices ($f_i$ and $f_t$) at the empirical levels.

## 5.3 The MSO's Steering Incentives

As we discussed in Section 2.3 , the MSO might have an incentive to steer consumers by altering $\delta$ or by setting prices. We explore both of these strategies using our estimates.

First, we consider the MSO's incentive to directly impact $\delta$, which the MSO might accomplish through a variety of channels. For instance, in its interactions with customers, the MSO could increase $\delta$ by providing subsidized or free streaming hardware, or decrease $\delta$ by customizing the hardware to limit access to particular OTT content providers. Upstream from consumers, the MSO could alter its network investment, which could either facilitate or impede access to high-quality streaming video. In the absence of net neutrality regulation, an MSO may simply throttle certain sources of traffic like OTT.

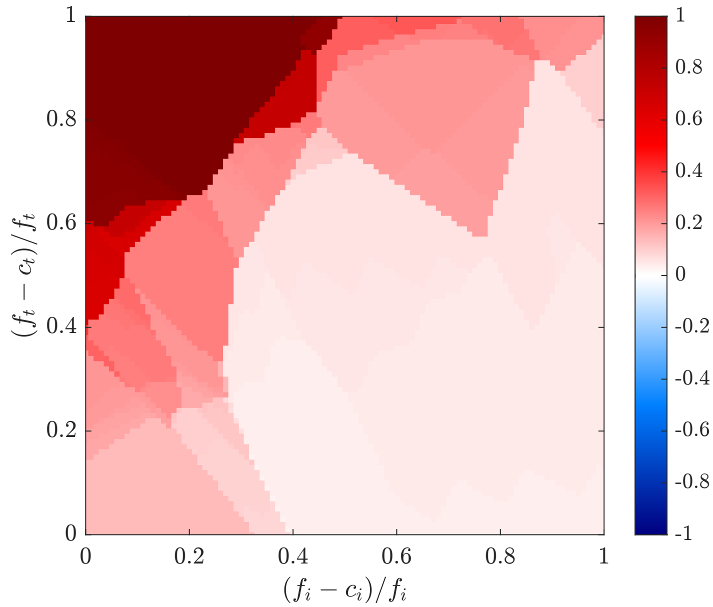
We explore the MSO's incentives to alter $\delta$ under different assumptions about the relative profitability of internet and video. Specifically, we assume that the MSO's subscription fees for internet and TV, $f_i$ and $f_t$, are held constant at their empirical pre-UBP levels, while we consider different values for the firm's internet and TV costs, $c_i$ and $c_t$. We construct bundle fees and costs by combining the component values, including accounting for the bundle discount we observe in the data. Given the fees and costs, we calculate the (single) proportional change to all households' $\delta$ values to maximize the MSO's profit. We present the results in Figure 9 panels (a) and (b) for the observed prices with bundle pricing and UBP, respectively. Along the axes we display different cost conditions. Since fees are held constant, it is convenient to express the cost changes as a change in the proportion of the fees, $\frac{f_i - c_i}{f_i} = 1 - \frac{c_i}{f_i}$ and $\frac{f_t - c_t}{f_t} = 1 - \frac{c_t}{f_t}$. Thus, movement outward along either axis implies lower costs or greater relative profitability. When the MSO uses bundle pricing, for given internet costs ($c_i$) the firm benefits from greater $\delta$ when TV costs ($c_t$) are high, but it prefers a lower $\delta$ when $c_t$ is smaller. Lower internet costs decrease the incentive to degrade $\delta$. When the MSO charges usage-based prices, there are fewer cost circumstances when the firm wants to reduce $\delta$, and in more situations the firm would benefit from larger $\delta$.[14] The difference in $\delta$ incentives between panels is intuitive: with UBP, the MSO can capture rents associated with $\delta$ for households that prefer OTT alternatives to the bundle.

Next, we investigate the MSO's steering incentives using pricing tools and how these incentives vary with the relative profitability of internet and TV. We explore these incentives by studying the impact of differential pricing of OTT and non-OTT internet usage. As we describe in Section 2.3, when studying the pricing incentives of OTT content, one needs to avoid confounding steering and metering incentives. To study the pricing incentives, therefore, we take as given the bundle pricing menu (without UBP), and we let the MSO choose two new prices: $\tau$, which applies uniformly to every unit of internet usage, and $\tau_\delta$, which applies to OTT usage only. This fee structure allows the ISP to act on two pricing incentives. First, it can increase the price of internet overall by increasing $\tau$. Second, it can exercise a discriminatory incentive by changing $\tau_\delta$ to raise or lower the effective price of OTT consumption ($\tau + \tau_\delta$).

In Figure 10, we show how the profit-maximizing OTT usage price, $\tau + \tau_\delta$, varies with the relative profitability of internet and TV. The price is positive for all cost levels, and it is larger as the TV costs decrease. This might be read as suggesting that an MSO will always want to impose a surcharge for OTT. However, that conclusion is premature since it is important to decompose the forces that contribute to $\tau + \tau_\delta$. In

[14]We assume that there is no cost to adjust $\delta$, so when the MSO benefits from a higher $\delta$ the firm generally wants the maximum increase that we allow.

Figure 10: Profit-maximizing usage fees as a function of costs

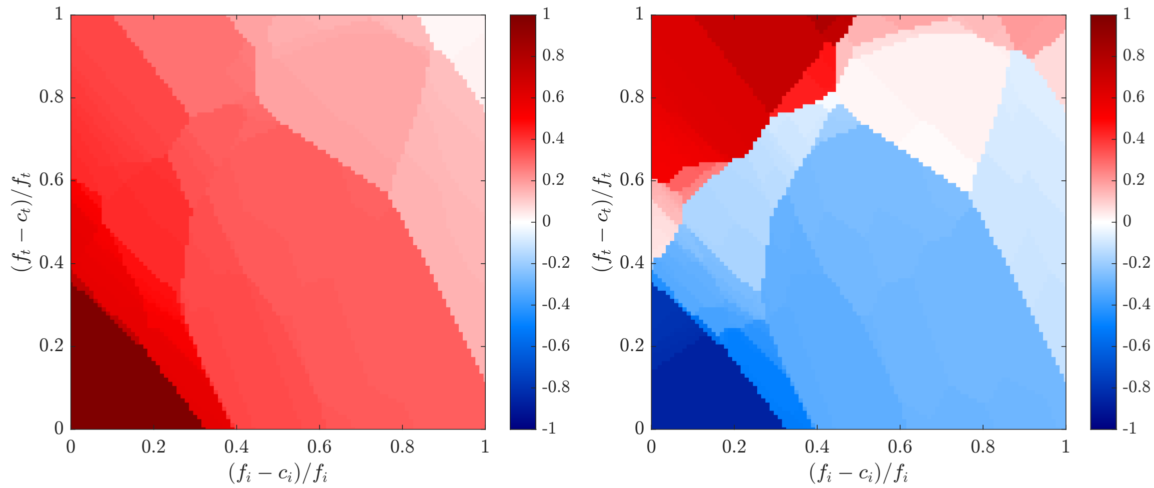



Notes: Profit-maximizing $(\tau + \tau_\delta)$ for different levels of costs ($c_i$ and $c_t$), holding subscription prices ($f_i$ and $f_t$) at the empirical levels.

a setting with consumers who are heterogeneous in their WTP for a given quantity, a firm charging a lump-sum price can generally increase profit by adding an additional per-unit price that meters the usage of high-demand individuals. In the setting we study, we see this effect through the MSO always benefiting from an all-purpose usage fee $\tau$.

In Figure 11, we show both the profit-maximizing $\tau$ and $\tau_\delta$ levels for each combination of costs. In panel (a), the optimal $\tau$ decreases as costs decrease because lost subscriptions are not worth the additional revenue from usage. If subscriptions are less profitable, i.e., near the origin, the MSO prefers a greater value of $\tau$. The MSO's isolated steering incentive is apparent in panel (b), which provides optimal values of $\tau_\delta$. For a fixed value of internet costs, as TV profitability increases the MSO is more likely to set $\tau_\delta > 0$, steering consumers toward the bundle. Across the full range of TV and internet costs that we consider, charging a positive fee for online video usage (net of the MSO's general incentive to meter internet usage) is only profitable for low TV costs. The preferred pricing policy for relatively high internet and low TV profitability, which is likely more relevant empirically, is to discount OTT relative to non-video internet usage. Reducing $\tau_\delta$ helps induce bundle subscribers to

Figure 11: Profit-maximizing usage fees as a function of costs




(a) $\tau$ (b) $\tau_\delta$

Notes: Optimal $\tau$ and $\tau_\delta$ for different levels of costs ($c_i$ and $c_t$), holding subscription prices ($f_i$ and $f_t$) at the empirical levels.

cut the cord, and the MSO trades a (low) TV margin for metered OTT use at the price $\tau + \tau_\delta$. In Figure 16 of Online Appendix B, we present the consumer welfare implications of the profit-maximizing usage fees. Given the price increases, consumer welfare decreases everywhere, with the largest harm occurring when internet and TV costs are greatest.

In Table 4, we present details on the implications of optimal linear usage fees for sources of MSO revenue and changes in household subscriptions and welfare relative to the bundle-pricing baseline. Each column of Table 4 presents these values for different combinations of the relative profitability of TV and internet, $\left(\frac{f_i - c_i}{f_i}, \frac{f_t - c_t}{f_t}\right)$. For example, when $\frac{f_i - c_i}{f_i} = 0.5$ and $\frac{f_t - c_t}{f_t} = 0.3$, the MSO sets $\tau^* = 0.325$ and offers a discount of \$0.05 to OTTV traffic. Relative to the bundle-pricing baseline, total revenue increases marginally by about \$1 per household, but is now comprised of both fixed fee subscription revenue and usage fees. Revenue from usage fees equals \$21.76 and \$14.66 for internet-only and bundle subscribers, respectively. This implies a decrease in consumer welfare of \$18.96, mostly driven by substitution to the outside option. We find little substitution into the bundle for any combination of costs, reinforcing our finding that UBP has limited impact as a steering instrument for the MSO. Most of the substitution resulting from optimal linear usage fees is to the outside good.

Table 4: Summary of Pricing Results

| $\left(\frac{f_i-c_i}{f_i}, \frac{f_t-c_t}{f_t}\right) =$ | (0.5,0.1) | (0.5,0.3) | (0.7,0.1) | (0.7,0.3) | (0.9,0.1) | (0.9,0.3) |
|---|---|---|---|---|---|---|
| $\tau^*$ | 0.355 | 0.325 | 0.325 | 0.320 | 0.320 | 0.315 |
| $\tau_\delta^*$ | -0.320 | -0.275 | -0.285 | -0.280 | -0.285 | -0.275 |
| $\tau + \tau_\delta^*$ | 0.035 | 0.050 | 0.040 | 0.040 | 0.035 | 0.040 |
| Revenue | 150.190 | 150.607 | 150.631 | 150.686 | 150.668 | 150.726 |
| $I$ Usage Fees | 21.287 | 21.761 | 21.095 | 20.990 | 20.593 | 20.883 |
| $B$ Usage Fees | 15.253 | 14.664 | 14.664 | 14.559 | 14.559 | 14.452 |
| Consumer Harm | -20.032 | -19.024 | -18.958 | -18.767 | -18.732 | -18.574 |
| $s_I$ | 0.147 | 0.150 | 0.152 | 0.153 | 0.154 | 0.154 |
| $s_B$ | 0.717 | 0.719 | 0.719 | 0.719 | 0.719 | 0.720 |
| $s_O$ | 0.136 | 0.131 | 0.129 | 0.128 | 0.127 | 0.127 |

Notes: Firm and consumer choices under linear usage fee pricing for a range of assumed internet and TV marginal costs. $\tau^*$ and $\tau_\delta^*$ are the optimal linear usage fees holding subscription fees fixed at the empirical levels. Revenue is the sum of subscription fees and usage fees. $I$ and $B$ usage fees are the average fees collected from internet-only and bundle plan subscribers. Consumer harm is the difference between consumer surplus with linear usage fees and consumer surplus with bundle pricing. $s_I, s_B, s_O$ are the choice shares of internet-only plans, bundle plans, and the outside option, respectively.

# 6 Conclusions

We study the pricing and quality provision incentives of MSOs, which serve as gatekeepers in providing internet access. OTT increases the demand for an MSO's internet subscription services, but this may come at the expense of reduced subscriptions to the MSO's TV service or with increased internet network costs. In confronting these challenges, the MSO may use its prices or direct intervention in OTT quality to shift consumers out of or into streaming video.

We provide a model that describes some of the central incentives behind MSOs' policies. We show that indeed the MSO might have an incentive to steer consumers away from OTT, but these incentives decline as the MSO has richer pricing tools that allow it to share in the gains generated by OTT. We demonstrate these results first in a simple numerical model and with the demand model estimated using household-level panel data. We show that the direction of steering incentives is affected by the MSO's relative costs of internet and TV service, and in some scenarios the MSO would be willing to stimulate improvements in and increased consumption of OTT.

Understanding the incentives to steer is relevant for antitrust policy in the telecommunications industry. In particular, the evaluation of mergers, whether between distribution firms or between content and distribution firms, presents a number of challenges. First, market boundaries may be difficult for regulators and antitrust authorities to identify because little evidence exists on consumers' willingness to substitute across conventional TV, streaming video, and other non-video internet applications. Our results show that consumers are willing to substitute across the types of entertainment. Thus, telecommunications antitrust analysis might need to consider broad market definitions that encompass many forms of digital entertainment, as well as the central role of MSOs in shaping how content is distributed and surplus is allocated.[15] Second, antitrust authorities need to assess how existing or new vertical relationships may affect an MSO's incentives to introduce restrictive cross-licensing agreements or use price instruments to favor its own content over competitors'. The impact of these strategies depends on consumers' sensitivity to steering strategies. An MSO that is vertically integrated with a content-producing firm may foreclose some content from availability to consumers via a competing MSO.[16] Our estimates show that even blunt mechanisms like usage-based pricing can have important allocative consequences among consumers and various firms.

More broadly, our results are also relevant for the net neutrality debate, in which empirical evidence is rare. Net neutrality's 2017 repeal provides MSOs more latitude to discriminate across types of internet traffic. While we do not observe source-specific discrimination in our data, our results are informative about MSOs' incentives to discriminate when they have the opportunity. For example, MSOs may respond to increased popularity of individual applications by introducing application-specific prices or barriers, or they may prefer to use general usage-based tiers to extract some of the surplus from OTT innovations.

There are several issues our model and empirical results do not address, and we leave for future research. While our model provides a useful framework for studying the steering incentives of MSOs, a richer specification is required to quantify how steering affects the welfare distribution between MSOs and consumers. Similarly, the

[15]To construct market definitions in specific contexts, it would be necessary to perform additional, case-specific analysis beyond our paper's data and results.

[16]A price-based steering strategy with similar effects is "zero rating," which favors certain content by not counting its usage against a monthly allowance. Zero rating has been used by telecommunications providers including T-Mobile and Comcast (https://www.vice.com/en/article/nz7nyx/comcast-hit-with-fcc-zero-rating-complaint-over-stream-tv).

model makes simplifying assumptions on the interaction between firms, for example by holding fixed OTT supply. Given the differences in OTT content across applications and the potential pricing power of third-party firms, modeling and evaluating the relationships between these firms and MSOs is a fruitful area for future research.

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# Online Appendix

## A Additional Model Discussion

### A.1 Calculating usage choices and overage charges under UBP

In this subsection we illustrate consumer usage decisions when consumers face UBP. To build intuition on households' optimal choices, in Figure 12 we illustrate the optimal usage decision of a household that chooses the bundle and the implied values of $v^*(\mathcal{P}_k|\mu)$ and $\mathcal{O}^*(\mathcal{P}_k|\mu)$. In panel (a) of Figure 12, consumer utility increases with $q_1$ until it reaches the satiation level equal to $\mu v_1$. We indicate on the horizontal axis the plan allowance $\kappa_k$ and the allowance plus one top-up (i.e., $\kappa_k + \bar{q}_k$). The household's decision is whether to use just the allowance, or purchase one or two top-ups to the allowance, each with price $\bar{p}_k$. The household only realizes the full $v_1$ if it chose the satiation level of usage (i.e., where utility plateaus). The optimal level of usage is easiest to see in panel (b) of Figure 12, which shows the marginal utility of usage, which equals $\frac{1}{\mu}$ up to $\mu v_1$ and zero after. Purchasing one top-up is optimal if

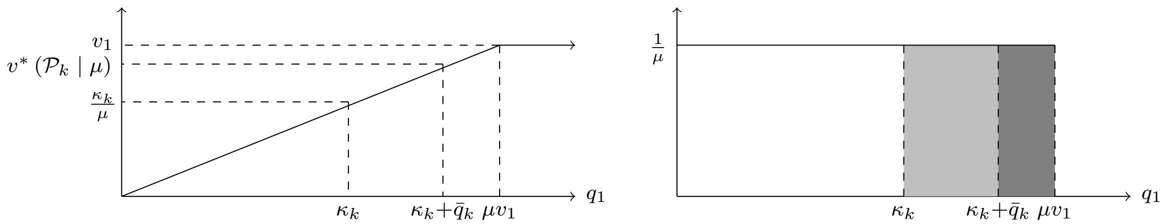
$$\frac{\bar{q}}{\mu} \geq \alpha \bar{p}_k \quad \text{and} \quad \frac{\mu v_1 - \kappa_k - \bar{q}}{\mu} < \alpha \bar{p}_k.$$

In panel (b), these conditions hold when the lighter shaded region is greater than $\alpha \bar{p}_k$, and the darker region is smaller than $\alpha \bar{p}_k$. For this realization of $\mu$, $v^*(\mathcal{P}_k|\mu)$ and $\mathcal{O}^*(\mathcal{P}_k|\mu)$ equal $\frac{\kappa_k + \bar{q}}{\mu}$ and $\bar{p}_k$, respectively. We capture in the possibility of an arbitrary number of top-ups in a more general expression for optimal internet usage by bundle subscribers:

$$q^*(\mu) = \begin{cases} \mu v_1 & \text{if} \quad v_1 > \kappa_k \quad \& \quad v_1 - \frac{1}{\mu}\left(\kappa_k - \overline{q}_k \lfloor \frac{v_1 - \kappa_k}{\overline{q}_k} \rfloor\right) > \alpha \overline{p}_k \\ & \quad \text{or} \quad \mu v_1 \leq \kappa_k \\ \kappa_k - \overline{q}_k \lfloor \frac{v_1 - \kappa_k}{\overline{q}_k} \rfloor & \text{if} \quad v_1 > \kappa_k \quad \& \quad v_1 - \frac{1}{\mu}\left(\kappa_k - \overline{q}_k \lfloor \frac{v_1 - \kappa_k}{\overline{q}_k} \rfloor\right) \leq \alpha \overline{p}_k, \end{cases} \tag{2}$$

where $\lfloor \cdot \rfloor$ is the floor function, i.e. the largest integer less than or equal to the function's argument. For internet-only plans, the household determines its optimal *total*

Figure 12: Utility from Usage




(a) Utility

(b) Marginal Utility

Notes: Utility (left) and marginal utility (right) from internet consumption for a household that chooses the bundle.

internet usage given a realization of $\mu$ (i.e., $q^*(\mu) = q_1^*(\mu) + q_2^*(\mu)$). The structure of the internet-only household's choice follows the same logic as in the bundled household, but with $v_1 + \delta v_2$ replacing all instances of $v_1$ in equation (2).

Overage charges associated with optimal consumption of internet and video content equal

$$\mathcal{O}^*(\mathcal{P}_k|\mu) = \begin{cases} \overline{p}_k \lceil \frac{q_1^*(\mu)+q_2^*(\mu)-\kappa_k}{\bar{q}_k} \rceil & \text{if plan } k \text{ is internet-only} \\ \overline{p}_k \lceil \frac{q_1^*(\mu)-\kappa_k}{\bar{q}_k} \rceil & \text{otherwise.} \end{cases}$$

where $\lceil \cdot \rceil$ refers to the ceiling function applied to internet usage in excess of the allowance, i.e., the smallest integer greater than or equal to $q$. Integrating over realizations of $\mu$ gives expected overages on plan $k$ of

$$\mathcal{O}^*(\mathcal{P}_k) = \int_0^\infty \mathcal{O}^*(\mathcal{P}_k|\mu) dF_\mu(\mu).$$

## A.2 The MSO's steering incentives and optimal pricing

In this subsection, we provide details of simulation exercises, summarized in Section 2.3, in which we solve for an MSO's optimal prices. The simulations are based on the simplified model discussed in Section 2.2.1, to which we add assumptions on the MSO's costs of providing internet and TV service. We assume that the MSO's internet-related costs increase with the bytes transmitted through its network and therefore are increasing in total usage. Specifically, we assume that the MSO's internet transmission costs are $c_i \geq 0$ for each unit of content due to $q_1$ and $q_{i,2}$. On the TV side, we assume that the firm has a constant per-subscriber cost of $c_t \geq 0$, which captures affiliate or re-transmission fees.

In this setting, without usage prices or restrictions, an internet-only subscriber uses $q^i(v) = v_1 + \delta v_2$ internet units, while a bundle subscriber uses $q^b(v) = v_1$. Combining consumers' choices with the firm's cost structure, the MSO's profit function is:

$$\pi = \int\limits_{v \in S_i} \left[p_i - c_i q^i(v)\right] dv + \int\limits_{v \in S_t} [p_t - c_t] dv + \int\limits_{v \in S_b} \left[p_b - c_i q^b(v) - c_t\right] dv.$$

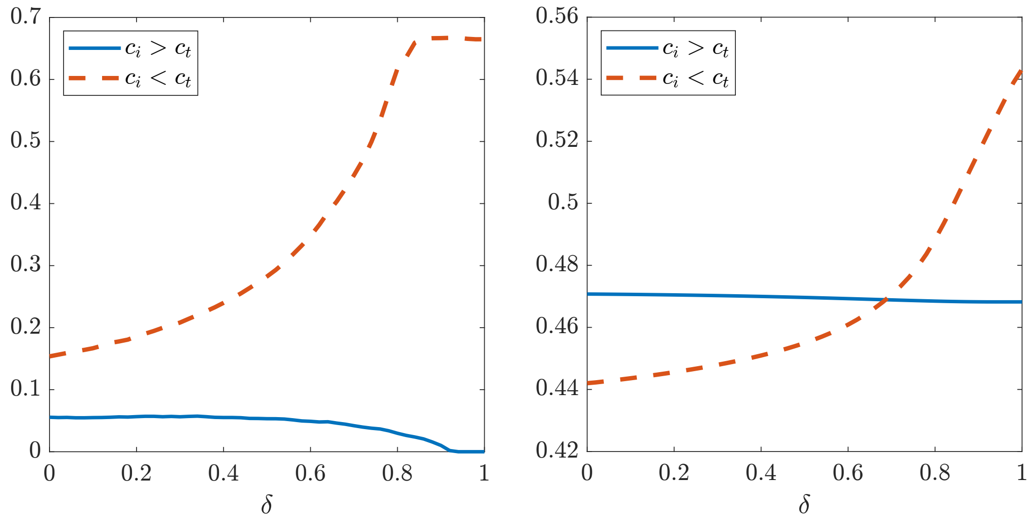
The terms $S_i$, $S_t$, and $S_b$ are the sets of consumers who choose internet, TV, and the bundle, respectively.

In Section 2.2.1, we showed that an improvement in OTT content can lead to cord cutting and a loss in MSO profits, holding prices fixed. Of course, in equilibrium the ISP can and will respond. Here we discuss some possible responses, including changing subscription prices and adding usage-based tiers. We consider the MSO's strategy over a range of $\delta$ values for two cost cases. In one scenario, the MSO has greater costs of providing internet service than TV ($c_i > c_t$), and in the other scenario the opposite cost condition holds. We first discuss optimal prices under the assumption that $\delta$ is determined exogenously, and we conclude by considering the MSO's incentive to directly affect $\delta$.

**Optimal Bundle Pricing.** We begin by considering the MSO's pricing incentives when it sets only subscription prices for internet, TV, and the bundle, i.e. $f_i$, $f_t$, and $f_b$. We solve for profit-maximizing $f_k$ values for each $\delta \in \{0.0, 0.02, ..., 1\}$. To represent a situation where TV service is more profitable than internet, we set $c_i = 0.2$ and $c_t = 0.0$. To represent the case of internet service as being more profitable than TV, we set $c_i = 0.0$ and $c_t = 0.2$.

In Figure 13 panel (a) we display the internet-only market shares implied by optimal pricing given the assumed MSO costs, as $\delta$ varies from 0 to 1. At $\delta = 0$, the MSO sets $f_i$ and $f_b$ so that the internet market share is greater when cost conditions favor internet service. As $\delta$ grows, the MSO adjusts prices and the internet market shares diverge in the two cost scenarios. When internet service is relatively costly, the MSO raises $f_i$, allowing it to converge to $f_b$, so that internet service is reduced and even eliminated from the market for sufficiently large $\delta$. In this situation, the cost-increasing nature of OTT video overtakes any benefits of increased willingness-

Figure 13: Internet Shares and MSO Profit with Bundle Pricing




(a) Internet Market Share (b) Profit

Notes: Panel (a) displays the MSO's internet market share associated with optimal subscription prices as $\delta$ varies from 0 to 1. Panel (b) provides the profit values associated with varying $\delta$.

to-pay (WTP) for internet subscriptions, and the MSO prefers to steer all potential internet customers into the bundle. The MSO's pricing incentives have the opposite impact on internet market shares when TV service is more costly: the MSO allows the internet-only market share to grow in $\delta$, eventually replacing the bundle completely.

In Figure 13 panel (b) we display the impact of $\delta$ on MSO profit in the two cost scenarios. When internet service is relatively costly, the MSO's profit declines gradually in $\delta$. This outcome follows from pricing that eliminates the stand-alone internet option. Without internet subscriptions, the firm is unexposed to $\delta$ but also gives up the opportunity to segment the market, as when $\delta = 0$. When TV is more costly than internet, by contrast, the MSO's profit increases in $\delta$ at the MSO's optimal prices. This outcome mirrors the MSO's implicit choice of internet market share with growing $\delta$.[17]

**Optimal Usage-Based Prices.** The MSO's response to improvement in OTT content may be different when it is able to implement UBP or other tools that allow

[17]The intersection of the profit curves is due to internet cost increasing in usage. When $\delta = 0$, an individual with $v_1 = 1$ generates cost equal to $c_i$, while consumers with values $v_1 < 1$ generate $c_i v_1$. When TV is costly for the firm, all TV customers generate $c_t$ regardless of their $v_2$ values.

it to better capture the benefit of $\delta > 0$. One possible strategy is to offer tiered internet service in which consumers must pay a premium for greater usage. We illustrate this strategy with a simple menu of two internet plans, with the low-usage plan ($i_L$) available for price $f_{i,L}$ and usage cap $\kappa_L$, plus a high-usage plan ($i_H$) with price $f_{i,H}$ and usage limit $\kappa_H$. This is a simplified version of the menu of three-part tariffs we see in our data under UBP, where the consumer pays an overage charge when he exceeds the allowance.[18]

The usage caps and tiers serve two purposes in an internet subscription. First, the high-usage tier extracts a premium from high-demand individuals who are willing to pay a premium ($f_{i,H} - f_{i,L}$) for extra usage ($\kappa_H - \kappa_L$). Second, the usage cap prevents additional internet usage by inframarginal consumers whose tastes would lead them to consume in excess of the cap. In a setting with $\delta > 0$, the caps and tiers limit OTTV usage in some cases while charging a premium for it in others. Both effects can also steer consumers toward the bundle.

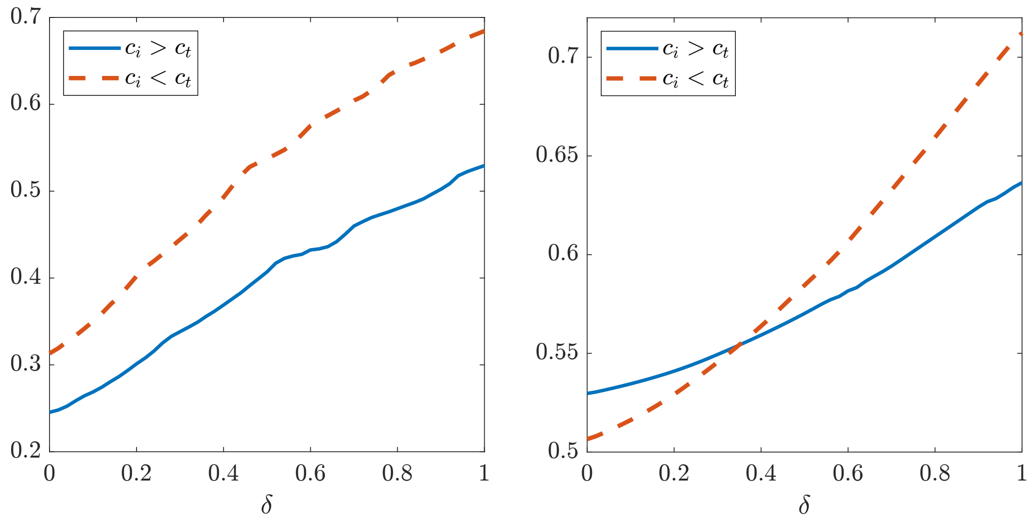
To solve this model, we make a few additional simplifying assumptions. First, we assume that consumers can combine either internet tier with TV service in a bundle, and the MSO does not alter the internet caps or prices depending on whether a consumer has a TV subscription. Second, the MSO offers the same bundle discount regardless of which tier is selected. Third, internet-only consumers facing a cap select quantities of services 1 and 2 in proportion to their total value from the services. That is, a consumer with $(v_1, v_2)$ and usage cap $\kappa$ chooses the share $v_1/(v_1 + \delta v_2)$ of service 1, and the remainder is used on service 2. Fourth, we set the usage caps just above the internet tier prices (e.g. $\kappa_L \approx p_{i,L}$) to simplify the numerical optimization.[19]

As above, we solve for optimal prices for varying $\delta$ and different assumptions on relative costs. In Figure 14 panel (a), we display the sum of internet tier shares under each cost assumption. In contrast to Figure 13, the MSO sets prices so that total internet subscriptions grow with $\delta$, even when internet has greater cost than TV. Bundle and TV subscriptions all fall in $\delta$. These shifts in markets shares occur despite the internet subscription prices, $f_{i,H}$ and $f_{i,L}$, remaining relatively flat in $\delta$

[18]With our assumption of marginal utility equal to either one or zero, depending on the quantity consumed, an optimally-set overage charge is equal to one, and ISP's only interesting strategic choice is the usage allowance.

[19]In versions of the numerical model where we have solved for caps separately from prices, for most parameter values each tier's cap is equal to its price. In our simplification, we impose appropriate small differences between caps and prices so that higher-demand consumers find it incentive compatible to select the high-usage tier.

Figure 14: Internet Shares and MSO Profit with Tiered Pricing




(a) Internet Market Share (b) Profit

Notes: Panel (a) displays the MSO's internet market share associated with optimal subscription prices as $\delta$ varies from 0 to 1. Panel (b) provides the profit values associated with varying $\delta$.

while bundle prices rise. The increase in $\delta$ has no impact on consumers' value from the bundle or TV-only subscriptions, so to take advantage of the change in $\delta$ the MSO must do it through internet-only subscriptions. Contrary to the case where the MSO can only set simple subscription prices, the MSO steers consumers toward the services that are growing in value, i.e. internet subscriptions.[20] In Figure 14 panel (b) we display firm profits in $\delta$ when the MSO implements internet usage tiers. Regardless of the cost ordering, profit increases in $\delta$.

**OTT video quality and discriminatory prices.** The differences in profit functions in Figures 13 and 14 suggest that an MSO's incentive to improve or diminish OTT video quality depends on both its cost conditions and the pricing strategies it may execute. The greater profit's slope in $\delta$, the greater the MSO's incentive to improve consumers' OTT video experiences. Lower-cost internet service is associated with an MSO's incentive to increase $\delta$, as is its opportunity to use tiered or usage-based internet pricing.

The profit slope in $\delta$ also reflects the MSO's incentive to set internet usage prices

[20] Across cost conditions, the difference in market share levels follows from the cost difference, which is also present when $\delta = 0$.

targeted toward OTT video. A surcharge on streaming video has the effect of reducing a consumer's net utility from OTT, which reduces the WTP for internet subscriptions in general. If profit falls in $\delta$, as in Figure 13 when internet service is relatively costly, the MSO will have a greater incentive to charge OTT-specific premia to push consumers back toward the bundle. On the other hand, if the MSO's cost conditions or pricing strategies favor internet services and OTT video, it will have less incentive to place discriminatory fees on streaming video.

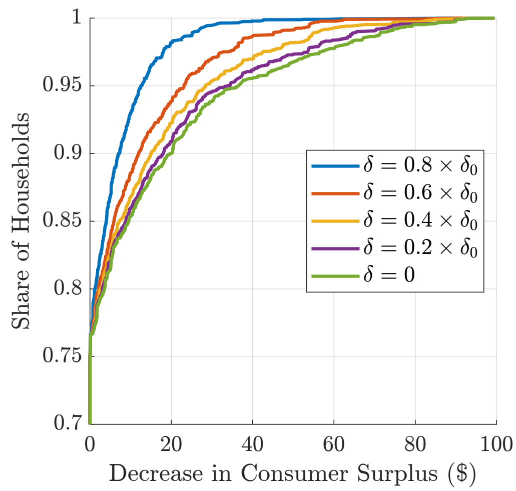
# B Additional Empirical Results

In this section, we provide additional detail on the empirical results.

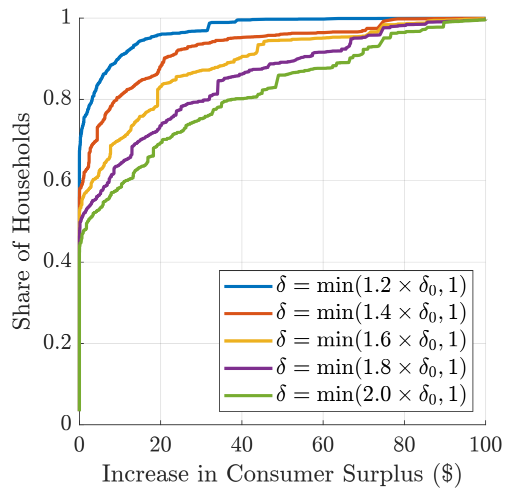
Figure 15 presents the analogous results to Figure 9 in Section 5, but with a baseline of UBP as implemented by the MSO rather than bundle pricing.

Figure 16 depicts the consumer welfare implications from the profit-maximizing linear usage fees presented in Figures 10 and 11.

Figure 15: Consumer Surplus Implications of $\delta$ Changes (UBP)



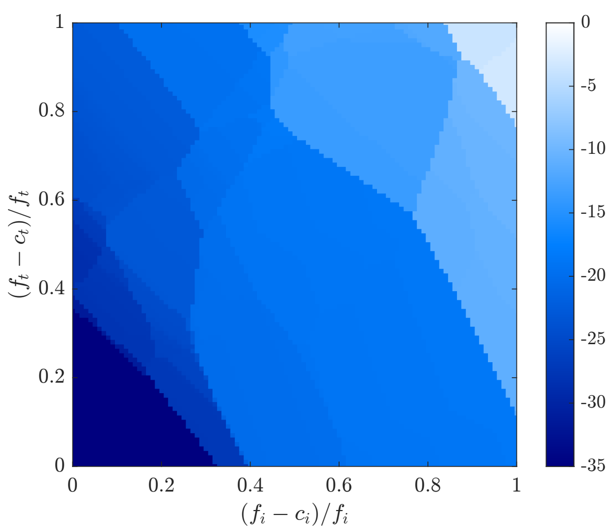

(a) $\delta$ Decreases




(b) $\delta$ Increases

Notes: This figure depicts the change in consumer surplus (measured in dollars) resulting from changes in $\delta$. To perform the calculation, each consumer's estimated delta level ($\delta_0$) is scaled by a proportional factor, ranging from 2 down to 0.

Figure 16: Consumer surplus at optimal usage fees




Notes: Consumer surplus at optimal $\tau$ and $\tau_\delta$ for different levels of costs ($c_i$ and $c_t$), holding subscription prices ($f_i$ and $f_t$) at the empirical levels.