

Is OTT Video a Substitute for TV? Policy Insights from Cord-Cutting*

Jacob B. Malone[†] Aviv Nevo[‡] Zachary Nolan[§]
Jonathan W. Williams[¶]

April 2, 2021

Abstract

The video entertainment industry has experienced increases in over-the-top (OTT) video usage and cord-cutting behavior in recent years. Using unique data, we document characteristics of the 2.4% of households who cut the cord annually. We show that after cutting the cord, households increase internet usage by 22%, mostly from OTT video usage. In addition to reducing payments to multiple-system operators by 50%, 16% of cord-cutting households increase the number of OTT video subscriptions. We discuss the implications this substitution has for competition policy in the video industry and Net Neutrality debate.

Keywords: Cord-cutting, Net Neutrality, Over-the-top Video, Residential Broadband, Competition Policy

JEL Codes: L11, L13, L96.

*We thank Greg Crawford, Shane Greenstein, Tommaso Valletti, and Ali Yurukoglu for comments, and the National Science Foundation (Grant SES-1324717), the NET Institute, and Cable Television Laboratories, Inc., and its member organizations, for their support of this work. We are grateful for the generosity of the North American MSO that provided the data. All remaining errors are our own.

[†]CableLabs, j.malone@cablelabs.com

[‡]Department of Economics and Wharton School, University of Pennsylvania, nevo@upenn.edu.

[§]Department of Business Administration, University of Delaware, znolan@udel.edu.

[¶]Department of Economics, University of North Carolina at Chapel Hill, jonwms@unc.edu.

1 Introduction

One of the most important recent developments in the video entertainment industry is the emergence of over-the-top (OTT) video. While companies like Netflix and Hulu are household names, tech giants continue to enter this space with Amazon Prime, Apple TV+, and YouTube (owned by Google) all competing for production of original content. Additionally, offerings are expanding to include live broadcasts such as sporting events. To access this rich content, consumers must connect to the internet through an internet service provider. Most internet service providers, such as cable companies (e.g., Comcast) or telecoms (e.g., AT&T), are multiple-system operators (MSOs), offering both internet and TV service.¹

In this paper, we provide insight into whether OTT video is a meaningful substitute to the MSO's TV service by empirically studying the behavior of households who drop TV service, i.e., "cut the cord". Specifically, we rely on a unique household-level panel that includes detailed information on internet usage, TV viewership, and subscriptions to provide empirical facts that add to a discussion that has been mostly theoretical. We document the characteristics of households who cut the cord, their behavior after they cut the cord, the implications of cord-cutting for MSO revenue and costs, and its impact on the revenues of OTT video providers.

Whether OTT video is a substitute for TV is relevant for competition policy in video markets. For example, if OTT video is a substitute for TV service it should be considered when defining markets in merger and antitrust conduct investigations. Knowing whether OTT video is a substitute to the MSO's TV service is also important when evaluating the MSO's incentives to embrace or impede the rise of OTT video. On one hand, the popularity of OTT video increases the value of internet access, which is now the primary service MSOs provide. This suggests the MSO should do what it can to promote these services, if it can capture a share of the surplus and the additional network costs are not too great. On the other hand, if OTT video is a substitute for the MSO's TV service, improvements to OTT video will pull consumers away from the MSO's TV service. This is consistent with the industry trend of cord-cutting, where households cancel their TV subscriptions but retain internet access. The loss of profits from the TV service, which includes lost sales for a product with a positive margin, as well as potential loss of TV advertising, suggests the MSO might try to limit the expansion of OTT video. Concerns over this latter effect have led to calls for Net Neutrality, i.e., internet service providers must treat all types of internet traffic equally and not block, or slow down, specific services.²

¹Hereafter, we will use "MSO's TV service" to refer to the managed video products sold by MSOs, e.g. Comcast's XFINITY Digital Cable TV.

²The Net Neutrality debate has been an active and lively debate for most of the previous decade

Our data is a household-level panel obtained from a North American MSO. The data include two separate panels, one from 2012 and the other from 2015-2016. The 2012 sample includes household-level subscription and payment information from billing records, usage of the MSO’s TV service, and the volume (bytes) of internet usage. We also have detailed demographic information (e.g., income bracket, age, etc.) from credit-report records for each of the 28,884 households. The 2015-2016 sample, which is comprised of the same set of households, contains billing records and the volume of internet usage by application or protocol (e.g. Netflix). Using these data, we provide previously undocumented descriptive statistics such as the relationship between household demographics and volume of internet usage.

During the course of our sample, 2,710 households cut the cord, yielding an annualized rate of approximately 2.4%. We find that households who cut the cord tend to be smaller, younger, lower-income, and heavier internet users. Households who prefer content for which there is a lack of close substitutes in OTT video subscriptions (e.g., sports and premium channels) are less likely to cut the cord. Conversely, households who spend their time viewing general interest and broadcast channels, which are readily available in OTT video bundles, are more likely to cut the cord.

After cutting the cord, we find households increase overall internet traffic by 22%. This increase in usage is driven by OTT video, which accounts for over 60% of traffic in our sample and increases by 24% when a household cuts the cord. Sling TV, a streaming service comprised of bundles of linear television channels and arguably the closest substitute to the MSO’s TV service, sees a ten-fold increase in usage. We also observe increases in active use of Netflix, Hulu, Sling TV and other streaming services: at least 16% of cord-cutters take up additional OTT video subscriptions after dropping the MSO’s TV service. These findings suggest that OTT video is, to some degree, a substitute for TV service.

Cancelled TV subscriptions reduce the MSO’s revenue by \$69 per household-month, approximately half of the average cord-cutting household’s monthly bill.³ Additionally, the MSO also faces the costs of upgrading their network to accommodate increased internet usage. At the same time, OTT video operators see an increase in revenues of \$4.11 per household-month, which accounts for only 6% of lost MSO revenue.

Our findings demonstrate that the loss of revenue for the MSO from cord-cutting is not trivial. We therefore provide empirical support to the theoretical concern that MSOs may have the incentive to impede access to OTT video and try to steer con-

and likely will continue into the future. For discussions of Net Neutrality see [Wu \(2003\)](#), which introduced the term, as well as [Lee and Wu \(2009\)](#) and [Greenstein et al. \(2016\)](#).

³The MSO saves fees it pays to TV content providers, since these are typically paid per subscriber, but since margins on the TV service are positive, even more so once advertising revenues are considered, the cancelled subscriptions reduce the MSOs profits.

sumers back to its TV service. For example, by degrading network performance or introducing pricing policies that increase the cost of video streaming. However, as we discuss below, the MSO’s problem is complex and there are several tools at its disposal that might be more profitable than impeding OTT video access. Several of our empirical findings indeed suggest that this might be the case. As such, our analysis also provides suggestive evidence that concerns over this particular aspect of Net Neutrality might be exaggerated. We do not speak to other aspects of the debate, such as the division of surplus between MSOs and content providers, content entry, network management, or investment trade-offs associated with alternative Net Neutrality policies.

Our analysis allows us to demonstrate there is meaningful substitution between TV service and OTT video, but it does not allow us to measure a price elasticity that determines the optimal MSO response to OTT video. For example, we find here and elsewhere (Nevo et al. (2016) and Malone et al. (2020)) that usage and willingness to pay are heterogeneous across consumers. Therefore, permitting the MSO to price discriminate between users who are likely to cut the cord and more heavily use the network can help reduce the incentive to take other actions to prevent cord-cutting by capturing surplus associated with OTT video. In a related paper, McManus et al. (2020) offer a theoretical model to further study these MSO incentives. They use a different data set than used here, with variation in prices created by the introduction of usage-based pricing, to estimate consumers’ price responsiveness along several dimensions and quantify some of the incentives discussed in this paper. Both papers study the MSO incentives but differ in methods and key variation in the data (here the time series of cord-cutting and in McManus et al. (2020) the introduction of usage-based pricing). As such the two papers complement each other.

Related to the point that the MSO might want to degrade its internet service by impeding OTT video access, Mussa and Rosen (1978) theoretically show how firms may seek to degrade product quality to impact consumer’s choices, while Crawford and Shum (2007) empirically study bundling of channels in TV packages to demonstrate this effect. More broadly, there are a number of theoretical and empirical studies of discriminatory nonlinear pricing and its impact on consumer choices in telecommunications: Economides and Hermalin (2015), Lambrecht et al. (2007), Miravete (2003), Grubb (2015), and Grubb and Osborne (2015). Our work also relates to the recent literature focusing on the distribution of live TV and the relationships between telecommunications and media firms. For example, see Crawford and Yurukoglu (2012) and Crawford et al. (2017).

Our results complement an extensive, but largely theoretical, literature on Net Neutrality: 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), and Sidak (2006). One notable and recent empirical contribution on the neutrality of platforms, but not MSOs specifically, is Tudon (2018) that studies the implications of neutrality on Amazon’s Twitch platform.

Our study also contributes to the literature on demand for broadband services: Prince and Greenstein (2017), Goetz (2016), Goolsbee and Klenow (2006), Dutz et al. (2009), Rosston et al. (2013), Greenstein and McDevitt (2011), Goolsbee and Klenow (2006), Edell and Varaiya (2002), and Hitte and Tambe (2007). In terms of the data used, the research closest to ours include Malone et al. (2014), Nevo et al. (2016), Malone et al. (2020), and McManus et al. (2020). Like these papers, we analyze high-frequency data on usage of telecommunications services, but the data used in this paper is unique in several ways. First, it includes information on both TV and Internet subscriptions and usage. Second, it includes two distinct panels that span a period of rapid change for the industry, allowing for comparison of trends over a longer time horizon. Third, it contains demographics for each included household.

The remainder of the paper is organized as follows. Section 2 describes our data sources and provides descriptive statistics from the two panels. Section 3 analyzes the characteristics and behavioral changes of households who cut the cord. Section 4 discusses re-distributive effects for market participants and the implications of our results for MSO incentives. Section 5 concludes and discusses topics for future research.

2 Data and Descriptive Analysis

Our data set contains a sample of 28,884 households served by a North American MSO,⁴ which we observe during two periods: 2012 and 2015-2016. We define the sample as households who are observed throughout the whole period and had TV services in 2012. The 2015-2016 data, which is our primary source for most of what follows, contain nine months of detailed information on the composition of internet traffic, including the identities of specific applications and websites (e.g., Netflix) accessed by each household. The 2012 data contain seven months of somewhat less-detailed household-level information on internet and TV engagement, in addition to household demographic characteristics. In both periods, we observe the MSO services chosen by each household. Therefore, using the account identifier, which did not change across the two periods, we are able to observe service plan and usage choices over a span of almost five years. The longer panel is helpful in analyzing cord-cutting, which occurs

⁴In this market, like many other markets in the U.S., the MSO is the primary option for high-speed broadband access.

at a fairly low annual rate. The data sources are described in greater detail in the data appendix [A1](#).

2.1 Plan choice and usage statistics

In Table 1 we present descriptive statistics of plan choice and usage for the households in the sample. In both periods, the MSO offered multiple internet service tiers that varied by speed. In 2012, the most popular internet tier, which offered the median speed, was chosen by 65% of households. An additional 25% of households chose tiers with slower speeds, and 10% chose tiers with faster speeds. In the 2015-16 sample, more households (14% of the sample) switched to the above median speed tier, even though all tiers improved in speed relative to 2012 (as can be seen in the average speed presented in the first row).

By construction, in 2012 all households in the sample subscribed to a plan that gave them access to a TV service, which included both re-transmitted broadcast channels (e.g., NBC, CBS, etc.) and network channels (e.g., ESPN, USA, etc.). In addition to these core channels, approximately half of the households in our sample chose a supplemental package offered by the MSO, which included a sports and news channel package, a movie channel package, and premium channel upgrades (e.g., HBO, Showtime, etc.).

By the end of the 2015-16 period in our data, 2,710 households, or just under 10% of the sample, “cut the cord”, namely, dropped their TV service while retaining only internet service.⁵ Of those who kept the bundle, a higher percentage subscribed to the above median internet speed tier (13% compared to 10%). This was even more true for those households who dropped TV service: 16% subscribed to the above median tier. The households who eventually cut the cord ended up with speeds that were on average about 20% higher, despite having similar speeds in 2012.

Internet usage increased significantly from 2012 to 2015-2016. In 2012, the median household used about 0.85 gigabytes (GBs) per day, while the mean household used twice as much at 1.70 GBs per month. In 2015-16, both numbers increased significantly: the median household used 2.56 GBs per day, while the mean household used 3.93 GBs per day. The households who eventually cut the cord started at a higher level in 2012, but also saw a slightly larger percentage increase in usage between the two periods.

A common feature of both sample periods is that the distribution of internet usage

⁵We define a household as a “cord cutter” if we see them with TV service at the start of the sample, but without one at the end of the sample. Our sample is balanced and therefore does not include consumers who moved out of town or dropped the MSO’s services all together during the sample period.

is very heterogeneous and heavily skewed. For example, in 2012 the 95th percentile of usage was 5.98 GBs daily and the 99th percentile was 11.86 GBs daily. In 2015, the 95th percentile household used 12.21 GBs daily and the 99th percentile household used 19.98 GBs daily.

The key addition to the 2015-2016 sample, relative to the 2012 sample, is information on the composition of internet usage. Streaming and OTT video account for 54% of all internet usage, and another 33% of traffic comes from web browsing. While web browsing makes up the majority of internet usage for households in the lower tail of the total usage distribution (60% for the 10th percentile household vs. 15% for the 90th percentile household), online video usage is highly correlated with the total usage level (20% for the 10th percentile household vs. 55% for the 90th percentile household). We illustrate these composition changes graphically in Figure A1 in the Appendix.

2.2 Household heterogeneity

The demographic information for our sample is representative of a typical U.S. market. The median household has 3 members, adults with an average age of 47, an income of \$62,500, and has lived at its current address for 10 years. We find all sample statistics fall within one standard deviation of the average demographic values across U.S. MSAs (reported in the 2012 American Community Survey).

In Table 2 we report the results of regressions relating internet usage levels to household characteristics. In particular, we regress the log of total usage and log streaming usage, measured in GBs, on plan choices and demographic information. We find that internet usage varies with demographic characteristics. Larger households and those with more children tend to engage more with the internet, while older or longer tenure households use the internet less overall. These differences are significant both in terms of total traffic and specifically for streaming traffic, although in both cases these variables explain a relatively small fraction of the overall variation. Internet usage decisions also vary meaningfully with internet-tier and TV plan subscriptions. Households with a TV subscription have less overall and streaming usage and those on more expensive internet tiers have greater overall and streaming usage. The effect of demographic characteristics on internet usage and streaming does change slightly once we include plan selection, which should not be surprising since plan selection varies with household demographics. In Table A2 we present more detail on the relationship between plan selection and demographics.

3 Empirical Analysis

We now use the data described in Section 2 for two purposes. First, we document household-usage patterns that are predictive of cord-cutting. Second, we document how a household’s usage behavior changes after cutting the cord.

3.1 Household attributes that predict cord-cutting

To provide insight on the attributes of who is likely to cut the cord, we create an indicator equal to one if the household is a “cord-cutter” (i.e., a household that drops the MSO’s TV service by the end of the 2015-2016 period.) We then run a series of Probit regressions of the cord-cutting indicator on household characteristics, including demographics, plan selection, and usage decisions. Average marginal effects from these regressions are reported in Table 3. While specifications (1) and (2) employ the full sample, specifications (3) and (4) focus only on cord-cutting that occurs during the 2015-2016 period in order to leverage the internet usage decomposition that we only observe during that period. We observe 2,710 cord-cuts over the course of the sample, of which 605 occur during the 2015-2016 nine month period.

From specifications (1) and (2) in Table 3, we see certain demographic characteristics are important predictors: younger, smaller, and less affluent households are more likely to cut the cord. These demographic results are intuitive for several reasons. First, preferences for television are known to vary with age. Nielsen, for example, reports that older adults watch much more traditional TV than younger individuals. Second, larger households may have more diverse content preferences, making it harder to find substitutes to TV. In addition, larger households likely watch more TV than smaller households, making substitution to online video more bandwidth-intensive and thus more costly as a substitute to the MSO’s TV service. Third, since cord-cutting leads to a significant reduction in monthly payments, we would expect these savings to be more attractive to lower-income households, all else equal.

The variables that have the most predictive power are related to internet usage. For example, an increase in 2012 usage from the median level to the 95th percentile increases the predicted probability of cord-cutting by 3.4 percentage points, about 35% of the observed rate. TV subscription choices also have a strong impact. Intuitively, households who prefer content that is not attainable through online video might be less likely to drop the MSO’s TV service in favor of an OTT video substitute. Indeed, households who subscribed to the Sports and Premium channel packages, which during our sample contained content with few online substitutes, were much less likely to drop the MSO’s TV service.

Specifications (3) and (4) in Table 3 focus on cord-cutting instances that occur

during the 2015-2016 sample period in order to incorporate additional predictors from the 2015-2016 sample. This allows us to check the robustness of the 2012 results and include information on which applications each household engages with online. We limit our sample to those households who had not yet cut the cord by the start of the 2015-2016 sample period. After this reduction in the sample, we are left with 605 cord-cuts out of the remaining 26,779 households. To study the effect of OTT video engagement on cord-cutting, we create indicators for active use of the three largest OTT video applications in our data based on the first two months of the 2015-2016 sample and then ask which of the remaining bundled households drop the MSO’s TV service during the sample period.

We find that engaging with Sling TV in the first two months of the 2015-2016 sample increases the probability of cord-cutting by 4.2 percentage points, approximately 185% of the base rate in the sample. Engaging with Hulu and Netflix increase the probability of a cord-cut by 26% and 29%, respectively. The magnitude of the Sling TV effect is intuitive, as it was the primary OTT video application to offer a live TV experience similar to the MSO’s TV service during the sample period. The results on demographics and internet use are similar to those from the full sample.⁶

3.2 Usage and streaming behavior after the cord is cut

We previously showed that internet usage, streaming behavior, and the likelihood of cutting the cord all vary with household attributes. In this section, we demonstrate how internet behaviors change when households cut the cord. We focus on the 2015-2016 panel because it allows us to observe internet activity by category and by application, both before and after cord-cutting occurs. We show that behavioral changes around the time of cord-cutting reflect direct substitution of viewing habits from TV to OTT video alternatives.

In Figure 1 we report changes in average total usage, streaming usage, and web browsing usage in the weeks surrounding the cord-cut date. Our sample allows us to identify the exact date each household drops the MSO’s TV service, which we use as a reference point for these behavioral changes. The other households are included to emphasize that the changes we observe are attributable to the subscription change and not a result of aggregate usage growth over time.⁷ The first takeaway from Fig-

⁶When comparing the results across samples, it is important to note that the sample period used in the 2015-2016 regressions is approximately one fifth the length of the period in the first two specifications. As such, when comparing the magnitude of coefficients between specifications (1) and (2) and specifications (3) and (4), multiply the coefficients in the latter column by five to adjust for period length.

⁷We construct the time series of daily usage for other households by calculating average usage by households who do not cut the cord on each day in the sample, centering the date range according

ure 1 is that cord-cutters have greater total usage than other subscribers, and greater streaming usage specifically, even before cutting the cord. In general, the difference between the two groups grows after the MSO’s TV service is dropped. Specifically, we observe a 22% increase (4.9 to 6 GB/day) in average daily usage between the eight weeks prior and eight weeks following a cord-cut. There is also an increase in daily streaming usage from 2.9 to 3.6 GB/day, a 24% increase, consistent with cord-cutters using OTT video to substitute for the MSO’s TV service.

Just as the total usage and streaming usage levels immediately increase with cord-cutting, we also observe shifts in usage across other categories of traffic. Comparing average usage for the eight weeks before and after households drop the MSO’s TV service, 63% of the increase in total daily usage is due to streaming usage and another 27% is from web browsing. Overall, 90% of the increase is explained by these two categories alone.⁸

Figure 2 reports the change in usage of specific OTT video applications among households who drop the MSO’s TV service. In panel (a), we report the average change in daily GBs used of each application. We observe the largest increases in OTT video usage in Netflix, Hulu, and Sling TV. Netflix usage increases by 0.25 GB/day, a 17% increase that explains nearly half of the total increase in OTT video usage. Hulu and Sling TV together account for another 0.3 GB increase in usage, and both applications are used substantially more after households drop the MSO’s TV service, with increases of 198% and 1,083% respectively. The case of Sling TV is particularly interesting because of its linear video format, which sets it apart from the other OTT video applications we observe.

In panel (b) of Figure 2, we use information published by the four most-used OTT video applications to convert bytes of traffic into time spent and assess changes in viewing duration for each application among active users.⁹ Netflix is the most-watched application by its users both before and after households drop the MSO’s TV service, with average viewing increasing 15% to just over an hour and a half per day after its subscribers cut the cord. Viewing of Sling TV increases 628%, over an hour per day, after households drop the MSO’s TV service, while Hulu viewing increases by nearly 30 minutes/day, and YouTube usage remains constant. Sling TV’s increase stands out again with a daily increase of over 90 minutes per day among households who are active users of the application. In fact, Sling TV is the only

to each cord-cut reference date, and then averaging across cord-cutters.

⁸These estimates might be conservative if we think that households start ramping up their usage prior to cutting the cord.

⁹We determine which households are “active” users by tracking positive usage of each application, since we do not have data on actual subscriptions. This method of identifying active users of the services cannot take into account the prevalence of password sharing.

OTT video service aside from Netflix that we estimate over an hour of daily viewing. The similarity in content to the MSO’s TV service and the substantial increase in time allocation together suggest that after cutting the cord, households are directly substituting viewing from the MSO’s TV service to the OTT video platform.

Besides an increase in usage and time spent on the services, we find that 16% of cord cutters increase the number of OTT video services they actively use. This increase comes from increases in the 3 largest services: 1.66% of the cord-cutter sample begins actively watching Hulu, 7.35% begins actively watching Netflix, and 6.30% begins actively watching Sling TV.

4 Policy Insights

4.1 Insights for Competition Policy

Historically, U.S. competition agencies have not included OTT video services as part of the relevant market when investigating competition in video markets, either on the viewer or advertising side. Our results demonstrate that consumers substitute to OTT video services when cutting the cord. Although further work is needed to quantify this substitution, this result suggests this definition warrants closer examination. We note that including OTT video services might mean that in some cases, say a merger between two TV stations, the market is more competitive than previously thought. On the other hand, as we show below, substitution between TV service and OTT video service can potentially raise concerns of anti-competitive conduct by firms with market power.

More recently, MSOs have merged with producers of media content, which introduces further challenges for competition policy. In the past, mergers like Comcast - NBC Universal and AT&T - Time Warner could reasonably be viewed as a vertical merger with the MSO acquiring an input into their video-distribution service. Concerns like the foreclosure of the input to competing video distributors would still exist, but so would pro-consumer aspects like the elimination of double marginalization. The innovation of OTT video introduces additional trade-offs for MSOs that complicate evaluation of these mergers. For example, the introduction of OTT video offerings like HBO Max and Peacock allow an MSO to capture a share of the surplus from cord cutters, but also introduces an incentive for the MSO to prioritize their own OTT video over competing sources (e.g., “zero rating” of certain content against usage allowances). These concerns have led to strong merger preconditions over prioritization and increased pressure on the FCC to pursue complementary regulatory policy like

4.2 Insights for Net Neutrality

Cord-cutting has implications for MSO revenue and therefore its incentives. We find that average monthly revenue to the MSO from cord-cutters falls by 50%, from \$138 to \$69, after TV service is dropped. This is a significant loss for MSOs. A cord-cutting rate of 2.4% per year shrinks operator revenue at a rate exceeding 1% per year. In addition to a lower mean, the distribution of revenue per household following a cord-cut also has less variance, due to households paying for fewer services with fewer add-on options.¹¹ Some households also change internet tiers at the time they drop the MSO’s TV service, meaning the overall revenue change consists of both a decline in TV revenue and a change in revenue due to contemporaneous internet tier transitions. Approximately 12% of households also make a change to their internet tier at the same time that they drop the MSO’s TV service. Overall, the number of households on below-median speed tiers remains the same, while upgrades from the median speed tier to higher-speed tiers results in a 27% increase in the take-up of premium speed tiers among cord-cutters. In Figure A6 we depict the distribution of internet tier selection among cord-cutters as well as a transition matrix. The impact of these upgrades does little to offset the loss in TV revenues.

The increase in OTT video services revenue is much smaller. Using the increase in subscriptions reported in the previous section and the monthly cost of these subscriptions,¹² we estimate the per-household increase in monthly OTT video spending after cutting the cord to be \$4.11.¹³ Comparing our estimates, OTT video providers capture approximately 6% of the lost MSO TV revenue due to cord-cutting, while the rest remains as consumer savings.¹⁴

These numbers confirm the theoretical predictions discussed in the Introduction:

¹⁰AT&T recently began counting HBO Max usage against wireless data limits, nationwide, after passage of California’s Net Neutrality standards. <https://www.cnbc.com/2021/03/17/att-will-count-hbo-max-toward-data-caps-blames-net-neutrality-law.html>

¹¹We provide a visualization of the effect of a cord-cut on monthly operator revenue in Figure A5.

¹²We use the prices of a standard subscription to each service: a Hulu Plus subscription is \$7.99, a standard Netflix streaming subscription is \$9.99, and the cost of a Sling TV subscription with two add-ons is \$30.

¹³We may be underestimating this number for two reasons. First, we do not observe subscriptions directly, but rely on observing active usage of a service to infer whether each household is a subscriber. Some households may pay for more OTT subscriptions than we observe them use during the sample period. Second, as shown in Figures A4 and A7, we find evidence that households experiment with online video alternatives to the MSO’s TV service in advance of cutting the cord. As such we maybe under-counting new subscription changes that occurred before households drop the MSO’s TV service.

¹⁴It is possible that some households reallocate their TV savings to television bundles from other operators, e.g., competing local cable/telco firms or satellite TV. We believe these instances would be rare due to the loss of the bundling discount associated with purchasing TV and broadband subscriptions from different MSOs.

the increase in popularity of OTT video is indeed both a dilemma and an opportunity for MSOs. We find that after cutting the cord consumers increase usage of and subscriptions to OTT video services. Therefore, as the quality of OTT video increases, consumers are more likely to cut the cord and subsequently increase internet usage. This reduces the MSO’s revenue from cord cutters by 50% and reduces profits since the MSO loses the positive margin on TV services and potentially advertising revenues. The MSO’s costs are also higher because of higher internet usage. The reductions in revenues are non-trivial and therefore suggest concerns regarding the MSO’s incentive to impede access to OTT video have some empirical support.

On the other hand, there are several factors that suggest concerns over the MSO’s incentives to extract rent from OTT video providers, one of the motivations for Net Neutrality, might be exaggerated. If interaction in the video market was a “zero sum game,” namely, a loss to the MSO is a gain to the OTT video providers, then these concerns might be better founded. However, our evidence shows that this is far from being true. Cord-cutting reduces the revenues of MSOs, but the gain to OTT video providers is small, only 6% of the MSO lost revenue. It does not seem that impeding OTT video service is an efficient way to recover some of the lost surplus.¹⁵ Furthermore, the MSO could try to combat cord-cutting by simply raising the price of its internet service, which is neutral with respect to content.

Instead of impeding access the MSO might find it optimal to improve the quality of its internet offerings by encouraging high quality OTT video services. Our results show the heaviest users of internet service also use OTT video and therefore an improvement of internet service would likely increase their willingness-to-pay for it. There are many strategies that MSOs may use to slow cord-cutting and benefit from improved OTT video, especially if valuations are heterogeneous as our results here and elsewhere suggest (Nevo et al. (2016) and Malone et al. (2020)). For example, McManus et al. (2020) show that flexible usage-based pricing strategies can be effective at splitting the surplus generated by OTT video innovations in a way that leads MSOs to embrace their presence. This is consistent with industry trends. During this time period, MSOs were worried, as our numbers suggest they should be, about the cord-cutting trend that arose due to the rapid introduction and innovations associated with OTT video. However, the few MSOs that acted, took strategies that were focused on trying to benefit from the improved OTT offerings.

¹⁵One could imagine a world where the MSO would try to extract rent from the OTT video providers by auctioning exclusivity to one OTT video service, who would then significantly increase prices. This seems somewhat unlikely to be optimal since many households seem to be multi-homing.

5 Future Directions

We use consumer behavior post cord-cutting to provide evidence that consumers view TV service and OTT video services as substitutes. More empirical work is needed to quantify the magnitude of the substitution and provide insight into strategies that MSOs may use to deal with increasing numbers of competing OTT video services. For example, numerous services that increasingly pressure traditional TV bundles have been introduced (e.g., Disney+, Peacock) and more are soon to be released. It is unclear how MSOs will respond to these new offerings, perhaps through usage-based pricing as some already have, more aggressively discounting bundles and personalized à la carte offerings, or even moving away from the managed video business entirely and focusing on data services. Compounding these issues, there is an increasingly complicated web of relationships between media companies and MSOs, established by vertical integration (e.g., AT&T-Time Warner or Comcast-NBC) and partnerships that integrate only selected OTT video services into hardware platforms distributed by the MSO (e.g., Comcast’s Flex streaming box).

To study these topics prospectively and offer insights to guide policy, rather than retrospectively after the introduction of new policies by MSOs, more economic modeling is necessary to offer counterfactual predictions about their impacts on welfare. These types of welfare calculations can offer insight into the distribution of surplus in the industry, which determines long run investments in networks and media content.

References

- Armstrong, Mark (2006). “Competition in Two-Sided Markets.” *RAND Journal of Economics*, 37(3): 668–691.
- Bourreau, Marc, Frago Kourandi and Tommaso Valletti (2015). “Net Neutrality with Competing Internet Platforms.” *Journal of Industrial Economics*, 63(1): 30–73.
- Choi, Jay Pil, Doh-Shin Jeon and Byung-Cheol Kim (2015). “Network Neutrality, Business Models, and Internet Interconnection.” *American Economic Journal: Microeconomics*, 7(3): 104–141.
- Choi, Jay Pil and Byung-Cheol Kim (2010). “Net Neutrality and Investment Incentives.” *RAND Journal of Economics*, 41(3): 446–471.
- Crawford, Gregory, Robin Lee, Michael Whinston and Ali Yurukoglu (2017). “The Welfare Effects of Vertical Integration in Multichannel Television Markets.” *Econometrica*, 86.
- Crawford, Gregory and Matthew Shum (2007). “Monopoly Quality Degradation and Regulation in Cable Television.” *Journal of Law and Economics*, 50(1): 181–219.
- Crawford, Gregory and Ali Yurukoglu (2012). “The Welfare Effects of Bundling in Multichannel Television Markets.” *American Economic Review*, 102(2): 643–685.
- Dutz, Mark, Jonathan Orszag and Robert Willig (2009). “The Substantial Consumer Benefits of Broadband Connectivity for US Households.” *Internet Intervention Alliance Working Paper*.
- Economides, Nicholas and Benjamin Hermalin (2012). “The Economics of Network Neutrality.” *The RAND Journal of Economics*, 43(4): 602–629.
- Economides, Nicholas and Benjamin Hermalin (2015). “The Strategic Use of Download Limits by a Monopoly Platform.” *The RAND Journal of Economics*, 46(2): 297–327.
- Economides, Nicholas and Joacim Tag (2012). “Network Neutrality on the Internet: A Two-Sided Market Analysis.” *Information Economics and Policy*, 24(2): 91–104.
- Economides, Nicholas and Joacim Tag (2016). “Internet Regulation, Two-Sided Pricing, and Sponsored Data.” *Working Paper*.
- Edell, Richard and Pravin Varaiya (2002). *Providing Internet Access: What We Learn from INDEX*, volume Broadband: Should We Regulate High-Speed Internet Access? Brookings Institution.

- Gans, Joshua (2015). “Weak Versus Strong Net Neutrality.” *Journal of Regulatory Economics*, 47(2): 183–200.
- Goetz, Daniel (2016). “Competition and Dynamic Bargaining in the Broadband Industry.” *Princeton University Working Paper*.
- Goolsbee, Austan and Peter Klenow (2006). “Valuing Products by the Time Spent Using Them: An Application to the Internet.” *American Economic Review P&P*, 96(2): 108–113.
- Greenstein, Shane and Ryan McDevitt (2011). “The Broadband Bonus: Estimating Broadband Internet’s Economic Value.” *Telecommunications Policy*, 35(7): 617–632.
- Greenstein, Shane, Martin Peitz and Tommaso Valletti (2016). “Net Neutrality: A Fast Lane to Understanding the Tradeoffs.” *Journal of Economic Perspectives*, 30(2): 127–150.
- Grubb, Michael (2015). “Consumer Inattention and Bill-Shock Regulation.” *Review of Economic Studies*, 82(1): 219–257.
- Grubb, Michael and Matthew Osborne (2015). “Cellular Service Demand: Biased Beliefs, Learning, and Bill Shock.” *American Economic Review*, 105(1): 234–271.
- Hitte, Loran and Prasanna Tambe (2007). “Broadband Adoption and Content Consumption.” *Information Economics and Policy*, 74(6): 1637–1673.
- Lambrecht, Anja, Katja Seim and Bernd Skiera (2007). “Does Uncertainty Matter? Consumer Behavior Under Three-Part Tariffs.” *Marketing Science*, 26(5): 698–710.
- Lee, Robin and Tim Wu (2009). “Subsidizing Creativity through Network Design: Zero-Pricing and Net Neutrality.” *Journal of Economics Perspectives*, 23(3): 61–76.
- Malone, Jacob, Aviv Nevo and Jonathan Williams (2020). “The Tragedy of the Last Mile: Congestion Externalities in Broadband Networks.” *Working Paper*.
- Malone, Jacob, John Turner and Jonathan Williams (2014). “Do Three-Part Tariffs Improve Efficiency in Residential Broadband Networks?” *Telecommunications Policy*, 38(11): 1035–1045.
- McManus, Brian, Aviv Nevo, Zachary Nolan and Jonathan Williams (2020). “Steering Incentives of Platforms: Evidence from the Telecommunications Industry.” *Working Paper*.
- Miravete, Eugenio (2003). “Choosing the Wrong Calling Plan? Ignorance and Learning.” *American Economic Review*, 93(1): 297–310.

- Mussa, Michael and Sherwin Rosen (1978). “Monopoly and Product Quality.” *Journal of Economic Theory*, 18(2): 301–317.
- Nevo, Aviv, John Turner and Jonathan Williams (2016). “Usage-Based Pricing and Demand for Residential Broadband.” *Econometrica*, 84(2): 411–443.
- Prince, Jeffrey and Shane Greenstein (2017). “Measuring Consumer Preferences for Video Content Provision via Cord-Cutting Behavior.” *Journal of Economics & Management Strategy*, 26(2): 293–317.
- Reggiani, Carlo and Tommaso Valletti (2016). “Net Neutrality and Innovation at the Core and at the Edge.” *International Journal of Industrial Organization*, 45(1): 16–27.
- Rosston, Gregory, Scott Savage and Bradley Wimmer (2013). “Effect of Network Unbundling on Retail Price: Evidence from the Telecommunications Act of 1996.” *Journal of Law and Economics*, 56(2): 487–519.
- Sidak, Gregory (2006). “A Consumer-Welfare Approach to Network Neutrality Regulation of the Internet.” *Journal of Competition Law & Economics*, 2(3): 349–474.
- Tudon, Jose (2018). “Congestion v. Content Provision in Net Neutrality: The Case of Amazon’s Twitch.tv.” *Working Paper*.
- Wu, Tim (2003). “Network Neutrality, Broadband Discrimination.” *Journal of Telecommunications and High Technology Law*, 1(2): 141–178.

6 Exhibits

Table 1: Broadband Plans and Usage

	All HHs		Cord-Cutters		Non-Cord Cutters	
	2012	2015-16	2012	2015-16	2012	2015-16
<i>Plan Selection</i>						
Speed (Mbps)	22.50	49.32	23.41	51.76	22.41	49.07
Below Median Tier	0.25	0.25	0.24	0.27	0.25	0.25
Median Tier	0.65	0.61	0.66	0.57	0.65	0.62
Above Median Tier	0.10	0.14	0.10	0.16	0.10	0.13
<i>Internet Usage</i>						
Mean	1.70	3.93	2.27	5.65	1.64	3.76
Standard Deviation	2.66	4.76	3.32	6.39	2.58	4.53
25th Percentile	0.29	0.96	0.47	2.04	0.28	0.85
Median	0.85	2.56	1.28	4.13	0.82	2.40
75th Percentile	2.08	5.37	2.73	7.52	2.01	5.14
95th Percentile	5.98	12.21	7.52	15.30	5.84	11.79
99th Percentile	11.86	19.98	16.83	23.61	11.32	19.28
<i>Number of Households</i>	28,884		2,710		26,174	

Notes: This table summarizes broadband plan choice and internet usage for households in the 2012 and 2015-2016 samples. Observations are at the household level, with usage aggregated to the average daily level for each household. Below (above) median speed tier refers to broadband plans with download speeds lower (higher) than the plan selected by the median household in the sample.

Table 2: Internet Usage Descriptive Regressions

	Log Total GB		Log Streaming GB	
	(1)	(2)	(3)	(4)
Household Size	0.009 (0.006)	0.010* (0.005)	0.017** (0.009)	0.018** (0.008)
Average Adult Age	-0.294*** (0.008)	-0.260*** (0.008)	-0.432*** (0.012)	-0.391*** (0.012)
Number of Children	0.276*** (0.011)	0.273*** (0.011)	0.446*** (0.017)	0.443*** (0.016)
Tenure at Address	-0.138*** (0.009)	-0.122*** (0.008)	-0.210*** (0.013)	-0.192*** (0.013)
Income	0.057*** (0.013)	-0.008 (0.012)	0.017 (0.019)	-0.057*** (0.019)
TV Subscriber		-0.548*** (0.030)		-0.714*** (0.046)
Phone Subscriber		-0.075*** (0.016)		-0.072*** (0.026)
Below Median Internet Tier		-0.677*** (0.019)		-0.809*** (0.029)
Above Median Internet Tier		0.427*** (0.023)		0.437*** (0.036)
Constant	1.994*** (0.042)	2.535*** (0.047)	1.354*** (0.064)	2.050*** (0.073)
Observations	28,884	28,884	28,762	28,762

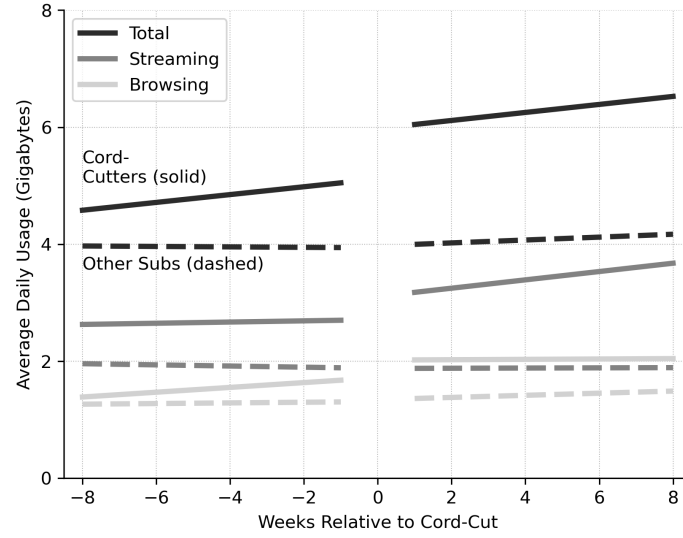
Notes: OLS regression coefficients with standard errors in parentheses. Column headings indicate the dependent variable. Average adult age and tenure at address are measured in tens of years. Income is measured in hundreds of thousands of dollars. 122 households never use streaming, and are omitted from regressions (3) and (4). * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table 3: Predictors of Cord-cutting

	(1)	(2)	(3)	(4)
Household Size	-0.005*** (0.001)	-0.005*** (0.001)	-0.000 (0.001)	-0.000 (0.001)
Average Adult Age	-0.018*** (0.002)	-0.017*** (0.002)	-0.003*** (0.001)	-0.002** (0.001)
Tenure at Address	-0.017*** (0.002)	-0.016*** (0.002)	-0.004*** (0.001)	-0.004*** (0.001)
Income	-0.171*** (0.027)	-0.167*** (0.027)	-0.035** (0.015)	-0.039*** (0.015)
Phone Subscriber		-0.009*** (0.003)		
Premium Channels Subscriber		-0.017*** (0.004)		
Sports Package Subscriber		-0.010*** (0.003)		
Daily Internet Use		0.052*** (0.005)		0.008*** (0.002)
Active Sling TV				0.042*** (0.007)
Active Hulu				0.006*** (0.002)
Active Netflix				0.006*** (0.002)
Time Period	2012-2016	2012-2016	2015-2016	2015-2016
Observations	28,884	28,884	26,779	26,779

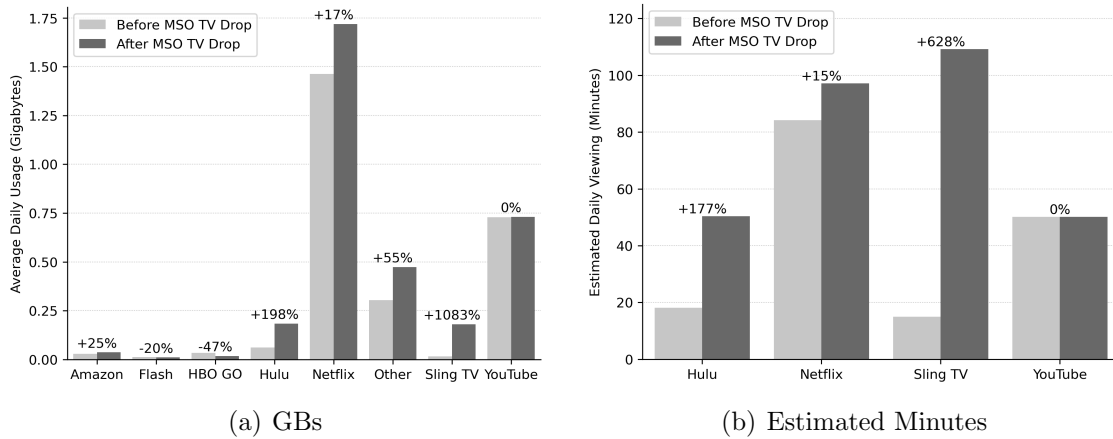
Notes: Probit regression average marginal effects with standard errors in parentheses. The dependent variable in the first two columns is an indicator for cord-cutting between the end of the 2012 sample and the end of the 2015-2016 sample. The dependent variable in the second two columns is an indicator for cord-cutting during the 2015-2016 sample. Households who cut the cord prior to the third month of the 2015-2016 sample are excluded. Active Sling TV, Active Hulu, and Active Netflix are indicators of positive use of each service during the first two months of the 2015-2016 sample. Daily Internet Use is in tens of gigabytes. Average adult age and tenure at address are measured in tens of years. Income is measured in hundreds of thousands of dollars. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Figure 1: Average Daily Usage Before and After Cord-Cutting



Notes: This figure presents OLS lines of fit for average daily usage of Total, Streaming, and Browsing traffic for the eight weeks before and after cord-cutting. The solid lines are the estimates of cord-cutter usage and the dashed lines are for all other subscribers.

Figure 2: OTT video Usage Before and After Cord-cutting



Notes: This figure depicts the change in daily usage of OTT video applications in the eight weeks before and after households drop the MSO's TV service. Panel (a) shows the average change in GBs used of each application among all households that cut the cord. Panel (b) shows the estimated change in daily minutes engaged with the most-used applications among households that actively use them. Minutes are calculated by comparing the byte counts observed in the data with average bit-rates published by the application. A household is considered an active user if it ever engages with the application in either the eight weeks before or after dropping the MSO's TV service.

Appendix

A1 Additional Description of Data Sources

The two sample periods contain data from four unique data sources: Internet Protocol Detail Records (IPDR), Deep-Packet Inspection (DPI) data, billing records, and household demographic information. Each of these sources are described in more detail below.

Internet Protocol Detail Records (IPDR).—IPDR data are commonly used to track network usage over a period of time. Households are identified by the Media Access Control (MAC) address of their cable modem, which is de-identified for our purposes. These data are produced in 15-minute intervals, and in our sample are aggregated to an hourly frequency. We observe, for each day-hour, the number of downstream and upstream bytes and packets recorded for each cable modem. IPDR are considered by MSOs to be an authoritative source of usage information, as they are frequently employed to measure network demand during peak periods and calculate usage over a billing cycle by operators that implement usage-based pricing. IPDR data are part of both the 2012 and 2015-2016 samples.

Deep-Packet Inspection (DPI).—Similar to IPDR, DPI data record a count of bytes sent and received by an individual cable modem over a specified period of time. However, while IPDR include only an overall byte count, DPI data uses information in packet headers to determine which application (e.g., Netflix) or protocol (e.g., File Transfer Protocol (FTP)) is responsible for the data.¹⁶ Given the vast number of applications indexed by the DPI vendor (over 1,000 individual applications and protocols), we use a standard taxonomy within the industry to group applications together by function (e.g., Web Browsing, Gaming, etc.). Similar to IPDR, the DPI data in this sample are aggregated to an hourly level of observation. DPI data are available in the 2015-2016 sample.

Billing Records.—Billing records provide information on a household’s monthly bill amount, active products and services, basic product information such as downstream and upstream speeds, and hardware identifiers that can be used to merge together

¹⁶Both the IPDR and DPI data contain byte counts for each household at an hourly frequency, but the aggregation process results in small discrepancies between the two sources. To resolve the differences, we treat IPDR as the authoritative source of total traffic, which is consistent with its standing as the industry’s gold-standard for usage-based billing. We then use the hourly DPI data to calculate the proportion of traffic within each hour that is generated by different applications or protocols. These proportions multiplied by the hourly IPDR byte counts yield hourly byte counts for each application.

IPDR, DPI, and STB data. Each household is given an account identifier that is not attached to specific hardware and that is constant across product changes and hardware upgrades. This account identifier enables us to link each of the data sources for a single household. Billing information are part of both the 2012 and 2015-2016 samples.

Household Demographic Information.—Demographic information on households is derived from the U.S. Census and credit reporting data available to the MSO. These data contain details including the number of people in the household, income, age, and home value. Demographic information is available in the 2012 sample.

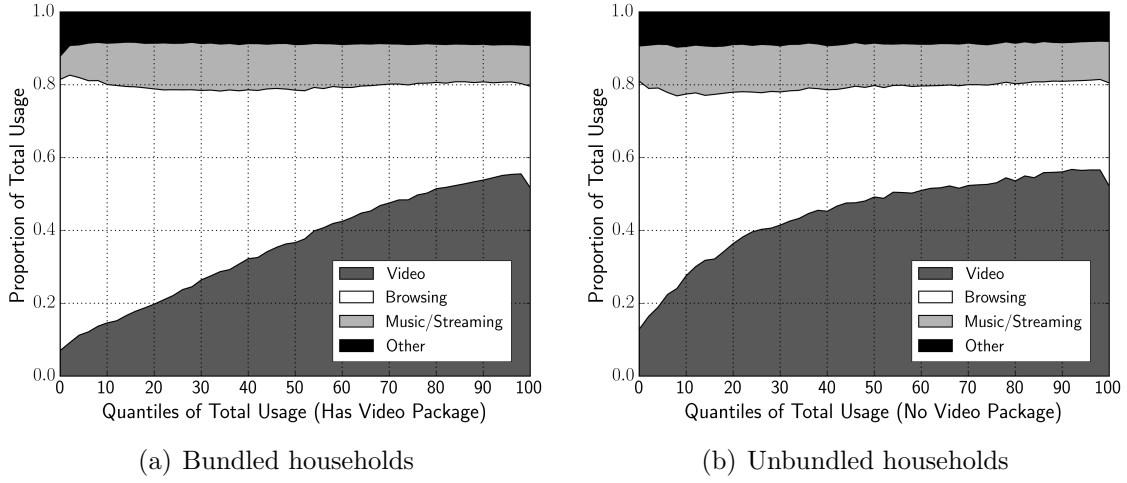
A2 Additional Descriptive Statistics

Table A1: Average Usage by Demographic Group

	Total	Web Browsing	Online Video	Netflix	YouTube
Income Quartile					
0-42,500	3.820	1.248	1.870	1.057	0.651
42,501-62,500	3.865	1.261	1.895	1.085	0.660
62,501-112,500	3.999	1.289	1.952	1.105	0.698
112,500+	4.143	1.433	1.870	1.081	0.613
Age Quartile					
18-40	4.845	1.529	2.416	1.386	0.845
41-45	4.189	1.389	2.008	1.157	0.692
46-53	3.826	1.294	1.793	1.013	0.627
54+	2.560	0.915	1.160	0.659	0.374
Number of Children					
0	3.397	1.184	1.555	0.903	0.490
1	4.466	1.427	2.227	1.274	0.803
2	5.433	1.614	2.837	1.581	1.087
3+	6.646	1.855	3.584	1.899	1.544
Observations	28,884				

Notes: This table describes average daily internet usage in gigabytes by household income quartile, average adult age quartile, and number of children.

Figure A1: Composition of Broadband Traffic



Notes: These figures depict a decomposition of total usage into four types of traffic: video, browsing, music/streaming, and all other traffic. In panel (a), observations are of bundled households only, while in panel (b), observations are of unbundled households only. Moving from left to right across the figure, the sampled households have higher total usage; each vertical slice of the figure is the distribution of usage for a particular usage quantile.

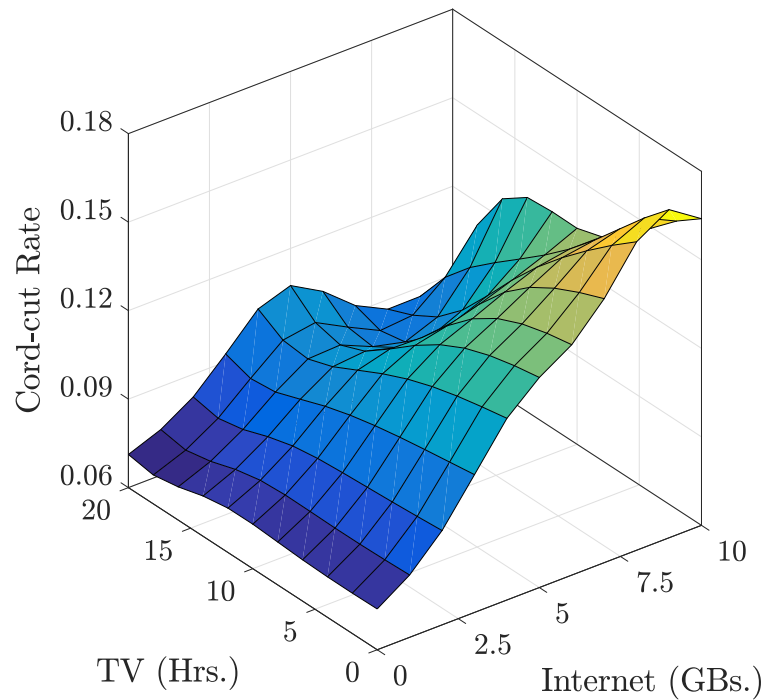
Table A2: Plan Selection Descriptive Regressions

	Internet			TV
	Below Median	Median	Above Median	
Household Size	-0.004*** (0.001)	0.001*** (0.000)	0.003*** (0.001)	0.015*** (0.002)
Average Adult Age	0.023*** (0.002)	-0.007*** (0.001)	-0.016*** (0.001)	0.018*** (0.003)
Number of Children	-0.003 (0.003)	0.001 (0.001)	0.002 (0.002)	0.032*** (0.004)
Tenure at Address	0.009*** (0.002)	-0.003*** (0.001)	-0.006*** (0.002)	0.011*** (0.003)
Income	-0.074*** (0.003)	0.024*** (0.001)	0.050*** (0.002)	0.010** (0.005)
Home Value				-0.009*** (0.002)
Observations	28884	28884	28884	28884

Notes: The first 3 columns are average marginal effects from an ordered probit regression of internet tier choice. Tiers with lower and higher speeds than the median tier are grouped into the “Below Median” and “Above Median” outcomes. The final column provides average marginal effects from a probit regression of whether each household has home phone service. Average adult age and tenure at address are measured in tens of years. Income and home value are measured in hundreds of thousands of dollars. Standard errors in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

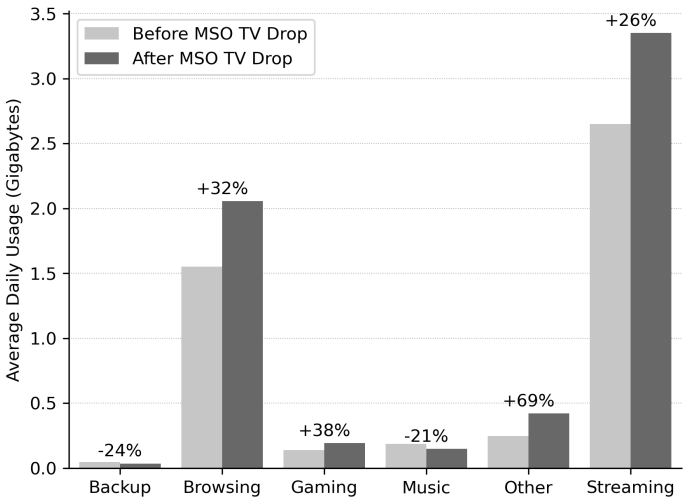
A3 Additional Cord-cutting Analysis

Figure A2: Observed Cord-cut Rate by Internet and TV Usage



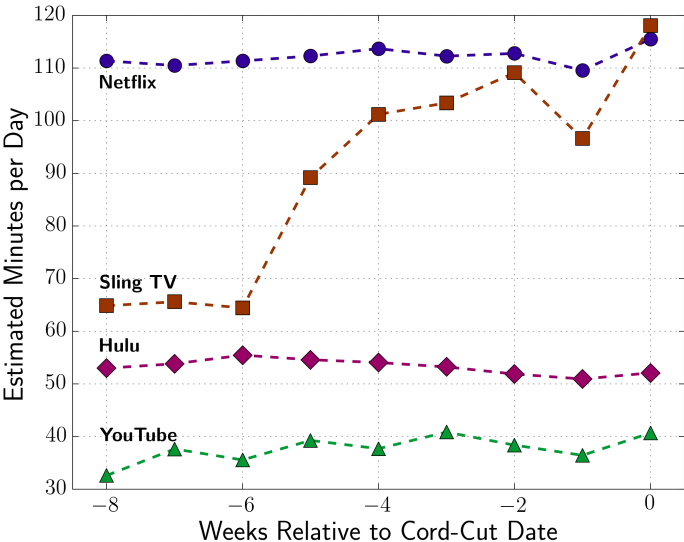
Notes: This figure depicts a local linear regression of the cord-cut indicator, depicted on the vertical axis, on average daily internet usage (GBs) and average daily television usage (hours). Usage data are taken from the 2012 sample and are at the household level. Cord-cutters are households that were bundled in the 2012 sample and transitioned to an internet-only subscription by the end of the 2015-2016 sample.

Figure A3: Average Daily Usage by Type Before and After Cord-Cutting



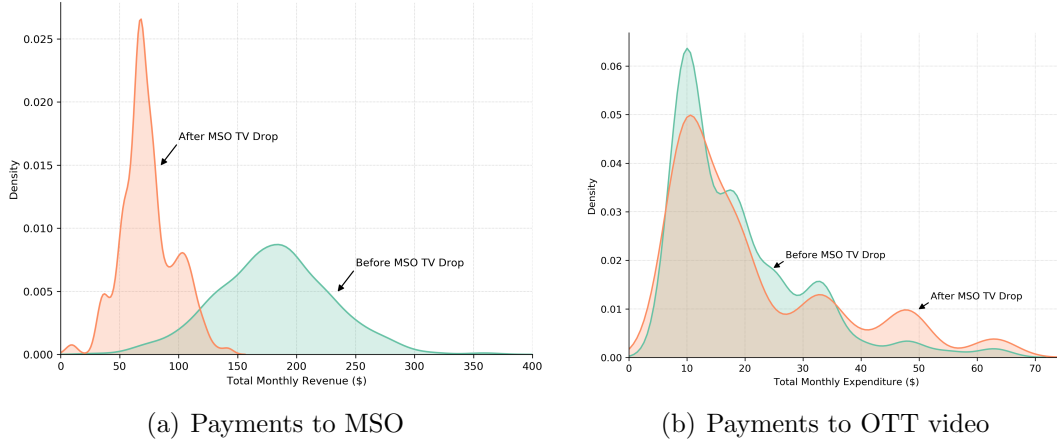
Notes: This figure presents average daily usage in GBs for each type of traffic in the eight weeks before and after households cut the cord.

Figure A4: OTT Video Engagement Prior to Cord-cutting



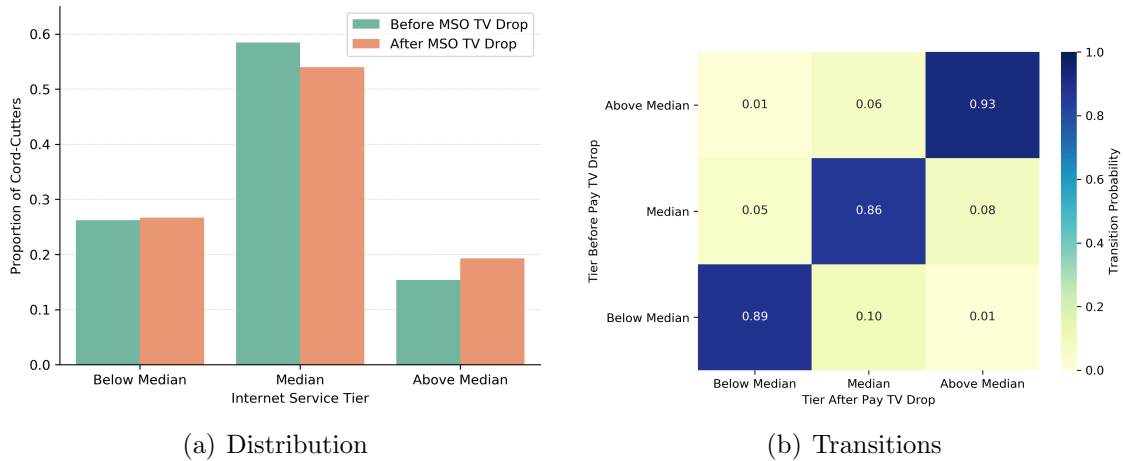
Notes: This figure presents the change in daily minutes viewed of each OTT video service in the eight weeks leading up to the date a household drops the MSO's TV service.

Figure A5: Household Monthly Payments



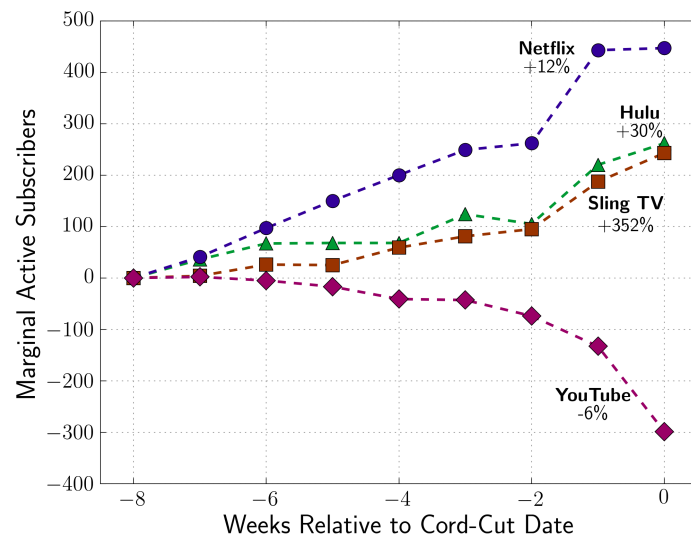
Notes: This figure presents kernel density estimates of the distribution of monthly payments across households. Panel (a) presents the pdf of household payments to the MSO for internet and TV, before and after cutting the cord. Panel (b) presents the pdf of estimated expenditures on OTT video subscriptions, before and after cutting the cord.

Figure A6: Broadband Plan Selection



Notes: This figure presents the change in internet tier by households that cut the cord. Tiers are ranked by download speed and grouped by proximity to the tier with the median speed. Panel (a) provides the frequency of each tier across households before and after cutting the cord. Panel (b) provides a matrix of the probabilities of different transitions made by households beginning on a particular tier.

Figure A7: Change in Active OTT Video Users Prior to Cord-cutting



Notes: This figure plots the change in active users of each OTT video service in the weeks leading up to the date a household cuts the cord.