# Implications of Cord-Cutting for Net Neutrality*

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**Abstract**

The video entertainment industry has seen an increase in over-the-top (OTT) video and "cord-cutting" behavior. Using unique data, we identify characteristics of households likely to cut the cord and document subsequent usage and subscription changes. These households reduce payments to the multiple-system operator (MSO) by 50% and increase internet usage by 22%. This creates incentives for MSOs to impede access to OTT video. However, we find that OTT providers gain only 6% of the revenue lost by MSOs, and that internet usage is heterogeneous; thus, MSOs might prefer to introduce pricing strategies that embrace OTT video.

**Keywords**: Bundling, Cord-cutting, Net Neutrality, Over-the-top Video, Residential Broadband

**JEL Codes**: L11, L13, L96.

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# 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 have become 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. In addition, offerings are expanding and now 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., ATT), are multiple-system operators (MSOs) and offer both internet and TV service.[1]

The rise of OTT video creates a complex trade-off for MSOs. On one hand, improved OTT video increases the value of internet access. This suggests that the MSO should do what it can to promote OTT offerings. On the other hand, OTT video is a substitute to the MSO's TV service. This is highlighted by an industry trend of cord-cutting, where households cancel their TV subscriptions but retain internet access. This loss of profits 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]

In this paper, we empirically study the behavior of households who drop TV service, i.e., "cut the cord", to gain insight into MSO incentives to impede the growth of OTT video. The data used in our analysis spans a five year period and includes detailed household-level information on internet usage, TV viewership and subscriptions, and demographics. We document the characteristics of households who cut the cord, the implications of cord-cutting for MSO revenue and costs, and its impact on the revenues of OTT video providers. We use these estimates to understand the trade-off facing MSOs, and the potential need for policy intervention.

Our data is a household-level panel spanning 2012 to 2016 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, information on usage of the MSO's TV service, and information on 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

[1] Hereafter, 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.

[2] Discussions of the Net Neutrality debate include Wu (2003), which introduced the term, as well as Lee and Wu (2009) and Greenstein et al. (2016).

of households, contains billing records, information on the volume of internet usage, as well as information on the identity of applications used (e.g. Netflix). Using these data, we provide descriptive statistics that have not been previously documented, including the relationship between household demographics and the composition and volume of internet usage.

The first step of our analysis is to document the types of households who cut the cord. During the course of our sample, 2,710 households cut the cord, yielding an annualized rate of approximately 2.4%. We identify several characteristics observable to the MSO that predict cord-cutting behavior. In particular, households who cut the cord tend to be smaller, younger, lower-income, and heavy internet users. Television preferences are also important predictors of cord-cutting; households who prefer content for which there is a lack of close substitutes in OTT video subscriptions (e.g., sports and premium channels) are far less likely to cut the cord. On the other hand, households who spend their time viewing general interest and broadcast channels, which are readily available in OTT video bundles, are more likely to drop the MSO's TV service. These predictive characteristics may be useful for MSOs to proactively target households with (bundle) discounts or personalized "skinny" bundles with select TV programming at lower cost to prevent cord-cutting.[3]

The second step of our analysis describes the behavioral changes that occur for households who 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. We also observe an increase in new subscriptions to Netflix, Hulu, and Sling TV. The OTT video services that see the greatest increase are the closest substitutes to the MSO's TV service. In particular, Sling TV, a streaming service comprised of a bundle of linear television channels similar to the MSO's offerings, sees a ten-fold increase in usage.

Next, we estimate the implications of these behavioral changes for the division of industry surplus and the MSO's strategic incentives. Cancelled TV subscriptions reduce the MSO's revenue by $69 per household-month, approximately half of the average cord-cutting household's monthly bill. In addition, the MSO also faces the costs of upgrading their network to accommodate increased internet usage. OTT video operators see an increase in revenues of $4.11 per household-month, which accounts for only 6% of lost MSO revenue.

One of the most important policy discussions of the previous decade, and likely

[3]For example, Comcast will soon sell TV packages with fewer channels: https://www.cordcuttersnews.com/comcast-will-start-selling-smaller-10-tv-packages-to-fight-cord-cutting-in-2020/.

the next decade, for the telecommunications industry is centered on Net Neutrality, the principle that internet service providers must treat all forms of internet traffic equally. The FCC's 2015 Open Internet Order established conduct rules consistent with net neutrality, but its repeal in 2017 has led to regulatory uncertainty that is likely to persist in the absence of a legislative solution. Our findings inform this debate by providing empirical insights into MSO incentives to discriminate amongst internet traffic. The loss of revenue and increased costs from cord-cutting potentially create an incentive for MSOs to try to steer consumers back to its TV service. For example, MSOs might degrade network performance to lower the quality of OTT video. Alternatively, they could introduce usage-based pricing or non-neutral pricing policies aimed at increasing the cost of video streaming. Our results suggest there is indeed empirical support to the theoretical concern that MSOs might have the incentive to impede access to OTT video.

However, our analysis also provides evidence that concerns over Net Neutrality might be exaggerated. If substitution to OTT video is the driving force behind cord-cutting, we would expect the gain to OTT video providers to be similar in magnitude to the losses incurred by MSOs. In this case, MSOs should be more likely to take action to impede access to OTT video. Instead, we find that the revenue gained by OTT video providers due to cord-cutting is only 6% of the revenue lost by the MSO. This suggests the loss to the MSO is from consumers looking to reduce their expenditure, which had increased significantly leading up to and during our sample period.[4] While this does not rule out actions by MSOs against OTT video providers, it does suggest MSOs might want to introduce pricing strategies that embrace OTT video and allow it to share in the gains, especially from consumers who value these gains the most.

Our findings here and elsewhere (Nevo et al. (2016) and Malone et al. (2020)) are 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 incentives to take other actions to prevent cord-cutting. McManus et al. (2020) formalize this idea and augment the standard mixed-bundling model by introducing an intensive margin for usage of TV and internet access, and allowing for substitution between the two. Their theoretical predictions and empirical findings complement ours. Using different data that exploits price variation created by the introduction of usage-based pricing, McManus et al. (2020) estimate consumers' price responsiveness along several dimensions and quantify some of the incentives we discuss in this paper.

[4] An FCC report on cable industry prices reports a compound ten-year average rate of increase from 2005-2015 of 4.8 percent in the price of expanded basic TV compared to a 1.5 percent increase in the CPI (FCC, 2012).

Related to this point, 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 and 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).[5]

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 rich literature on demand for broadband services. These include 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 at least two ways. First, it includes two distinct panels that span a period of rapid change for the industry and allow for comparison of trends over a longer time horizon. Second, it contains demographics for each household and information on usage of both TV and internet services.

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 are comprised of a nationally representative sample of 28,884 households served by a North American MSO, which we observe during two periods: 2012 and

[5]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).

2015-2016.[6] 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 particularly helpful in analyzing cord-cutting, which occurs at a fairly low annual rate.[7]

## 2.1 Plan choice and usage statistics

In Table 1 we present descriptive statistics of plan choice and usage. In both periods, the MSO offered multiple internet service tiers which varied by speed. In 2012, the most popular internet tier, which offered the medium speed, was chosen by 65% of households while 25% 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).

At the start of the sample all households subscribed to a plan that gave them access to a TV service that 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 one of the MSO's TV upgrade packages, which included a sports and news channel package, a movie channel package, and several 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, dropped their TV service while retaining only internet service. 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

[6] All household-specific information was de-identified by the MSO before we obtained the data so we are unable to identify the households or link the data with any external data sources.

[7] Each of these data sources is described in greater detail in the data appendix (Section A1).

twice as much at 1.70 GBs per month. In 2015-16 both these numbers increase significantly: the median household used 2.56 GBs per day, while the average 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 slighty larger percentage increase in usage between the two periods.

A common feature of both sample periods is that the distribution of internet usage is very heterogeneous and heavily skewed. For example, in 2012 the 95th percentile of usage was 5.98 GBs per day, and the 99th percentile of usage was 11.86 GBs per day. In 2015, the 95th percentile household used 12.21 GBs per day and the 99th percentile household used 19.98 GBs per day.

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 is comprised of web browsing. While web browsing tends to make up the majority of internet usage for households in the lower tail of 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).[8]

## 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. Benchmarking against the distribution of these statistics across U.S. MSAs (reported in the 2012 American Community Survey), we find that all sample statistics fall within one standard deviation of the average MSA. As such we believe our sample is nationally representative.

In Table 2 we report the results of OLS 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

[8] Figure A1 in the Appendix illustrates these composition changes graphically.

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.[9]

# 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 a household-specific cord-cutting indicator that equals one for every household in our sample 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 is only available 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 that 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

[9] See Table A2 for greater detail on the relationship between plan selection and demographics.

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 to 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.[10]

## 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.

[10]When 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.

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.[11] The first takeaway from Figure 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.

Figure 2 reports the change in usage of specific OTT video applications among households that 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 which 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 among active users.[12] Netflix is the most-watched application by its users both before and after households drop the MSO's

[11]We construct the time series of daily usage for other households by calculating average usage by households that do not cut the cord on each day in the sample, centering the date range according to each cord-cut reference date, and then averaging across cord-cutters.

[12]We 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.

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 that are active users of the application. In fact, Sling TV is the only 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.

# 4 Implications

In this section we compute the impact of cord-cutting on industry surplus. We then use this split to discuss the implications for MSO incentives.

## 4.1 Impact on Industry Surplus

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; with a cord-cutting rate of 2.4% per year, operator revenue shrinks at a rate exceeding 1% per year due to cord-cutting. 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.[13] 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.[14] The impact of these upgrades is minimal and does little to offset the loss in TV revenues.

We find that increases in monthly OTT video expenditure are much smaller than the decrease in MSO payments; 75% of cord-cutters keep the same number of OTT video services, 16% increase the number after dropping the MSO's TV service, while the remaining households are active on fewer services. We observe usage of three

[13] Figure A5 provides a visualization of the effect of a cord-cut on monthly operator revenue.

[14] Figure A6 depicts the distribution of internet tier selection among cord-cutters as well as a transition matrix.

subscription-based OTT video services: Hulu, Netflix, and Sling TV. We see a net increase in the number of active households in each service following the cord-cut event: 1.66% of the cord-cutter sample begin actively watching Hulu, while 7.35% and 6.30% of the sample begin watching Netflix and Sling TV, respectively. Using the monthly cost of these subscriptions,[15] we estimate the per-household increase in monthly OTT video spending after cutting the cord to be $4.11.[16] This result, taken together with the increase in OTT video usage in the weeks leading up to cord-cutting, suggests cord-cutter OTT video behavior is well-established before dropping the MSO's TV service (i.e., few new services are added after the MSO's TV service is dropped). As such, cord-cutters experience a large decrease in monthly expenditure even after accounting for OTT video subscriptions, as any marginal increase in OTT video expenditure is outweighed by the large decrease in the MSO payment. 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.[17]

## 4.2 Implications for MSO incentives

The above numbers confirm the theoretical predictions discussed in the Introduction: the increase in popularity of OTT video is indeed both a dilemma and an opportunity for MSOs.

Theoretically, OTT video is a substitute for the MSO's TV service. Therefore, as the quality of OTT video increases, consumers are more likely to cut the cord and subsequently increase internet usage. Our empirical analysis shows this is not a purely theoretical concern. The cumulative effect of cord-cutting is increasing over time, as OTT video offerings improve. We find that after cutting the cord, the MSO loses nearly 50% of revenues from the household and traffic increases by 22%, much of the increase coming from third-party OTT video sources. This reduces the MSO's revenue and increases its cost through higher internet usage. The reductions in revenues are non-trivial and therefore suggest concerns regarding the MSO's incentive to impede

[15] We 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.

[16] We 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 well in advance of cutting the cord. As such we may be under-counting new subscription changes that occurred before households drop the MSO's TV service.

[17] It 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.

access to OTT video have some empirical support. In other words, concerns over Net Neutrality might be empirically relevant.

On the other hand, there are several factors that suggest concerns over Net Neutrality might be exaggerated. Net Neutrality is primarily concerned with limiting the ability of MSOs to extract surplus from content providers. 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 concerns over Net Neutrality would be better founded. However, our evidence shows that this is far from being true. As we show in the previous subsection, cord-cutting reduces the revenues of MSOs, but the gain to OTT video providers is small, only 6% of the MSO lost revenue. This seems to suggest cord-cutting behavior is driven by households' desire to reduce expenses and therefore the MSO might be better off trying to modify its offerings to consumers rather than impeding the success of OTT video.

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. This is consistent with other findings (e.g., Nevo et al. (2016) and Malone et al. (2020)) that usage and willingness to pay are very heterogeneous across consumers. Our results show that 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. For example, McManus et al. (2020) provide a theoretical framework that shows 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. They also use the introduction of usage-based pricing in one market to demonstrate the effects empirically.

# 5 Concluding Comments

Our study reveals the types of households who are more likely to cut the cord and the implications for the distribution of industry surplus. We find lower-income households with fewer and younger members who watch limited TV or particular OTT video services are most likely to cut the cord. Cutting the cord decreases MSO revenues by nearly 50% and increases internet traffic by 22%. Yet, only a small proportion (about 6%) of these consumer savings are redistributed to third-party OTT video sources. As we discuss, this redistribution has important implications for MSO incentives in the short run to slow cord-cutting, as well as investment in networks and content in the longer term.

More empirical research is needed to provide insight into other 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 many more are soon to be released. It is not clear 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.

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# 6 Exhibits

Table 1: Broadband Plans and Usage

| | All HHs | | Cord-Cutters | | Non–Cord Cutters | |
|---|---|---|---|---|---|---|
| | 2012 | 2015-16 | 2012 | 2015-16 | 2012 | 2015-16 |
| *Plan Selection* | | | | | | |
| 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 |
| *Internet Usage* | | | | | | |
| 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 |
| *Number of Households* | 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 | 0.010* | 0.017** | 0.018** |
| | (0.006) | (0.005) | (0.009) | (0.008) |
| Average Adult Age | -0.294*** | -0.260*** | -0.432*** | -0.391*** |
| | (0.008) | (0.008) | (0.012) | (0.012) |
| Number of Children | 0.276*** | 0.273*** | 0.446*** | 0.443*** |
| | (0.011) | (0.011) | (0.017) | (0.016) |
| Tenure at Address | -0.138*** | -0.122*** | -0.210*** | -0.192*** |
| | (0.009) | (0.008) | (0.013) | (0.013) |
| Income | 0.057*** | -0.008 | 0.017 | -0.057*** |
| | (0.013) | (0.012) | (0.019) | (0.019) |
| TV Subscriber | | -0.548*** | | -0.714*** |
| | | (0.030) | | (0.046) |
| Phone Subscriber | | -0.075*** | | -0.072*** |
| | | (0.016) | | (0.026) |
| Below Median Internet Tier | | -0.677*** | | -0.809*** |
| | | (0.019) | | (0.029) |
| Above Median Internet Tier | | 0.427*** | | 0.437*** |
| | | (0.023) | | (0.036) |
| Constant | 1.994*** | 2.535*** | 1.354*** | 2.050*** |
| | (0.042) | (0.047) | (0.064) | (0.073) |
| Observations | 28,884 | 28,884 | 28,762 | 28,762 |
| $R^2$ | 0.124 | 0.192 | 0.123 | 0.163 |

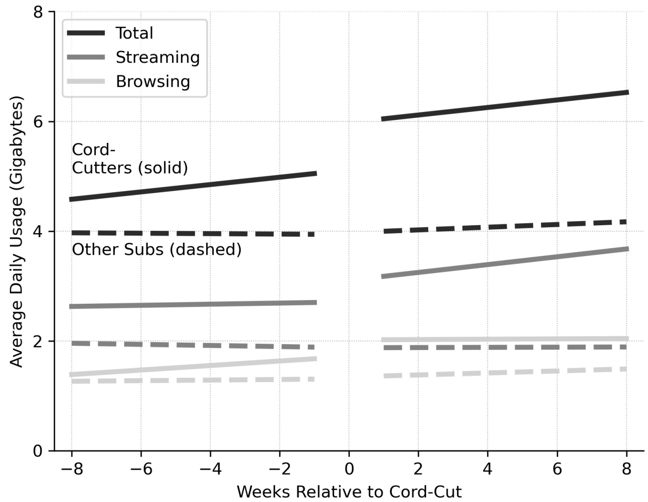
Notes: OLS regression coefficients with standard errors in parentheses. Column headings indicate the dependent variable. Average adult age and tenure at address are measured in tens of years. Income is measured in hundreds of thousands of dollars. 122 households never use streaming, and are omitted from 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*** | -0.005*** | -0.000 | -0.000 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Average Adult Age | -0.018*** | -0.017*** | -0.003*** | -0.002** |
| | (0.002) | (0.002) | (0.001) | (0.001) |
| Tenure at Address | -0.017*** | -0.016*** | -0.004*** | -0.004*** |
| | (0.002) | (0.002) | (0.001) | (0.001) |
| Income | -0.171*** | -0.167*** | -0.035** | -0.039*** |
| | (0.027) | (0.027) | (0.015) | (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*** | | 0.008*** |
| | | (0.005) | | (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 |
| Pseudo $R^2$ | 0.025 | 0.033 | 0.010 | 0.028 |

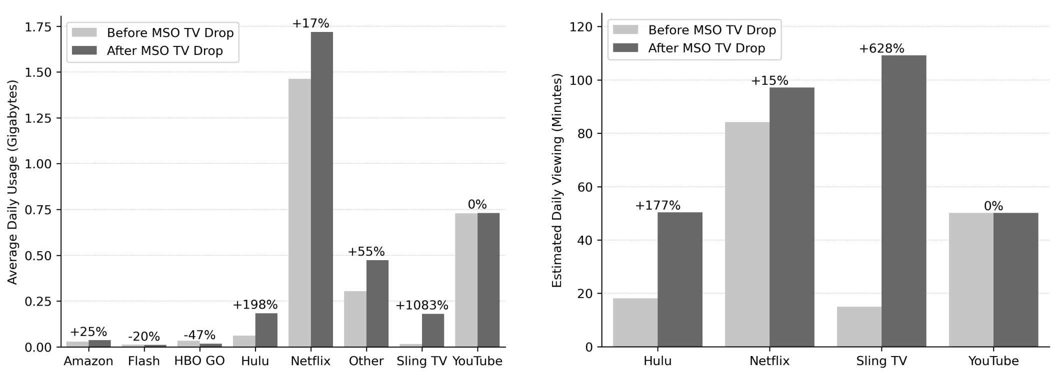
Notes: Probit regression average marginal effects with standard errors in parentheses. The dependent variable in the first two columns is an indicator for cord-cutting between the end of the 2012 sample and the end of the 2015-2016 sample. The dependent variable in the second two columns is an indicator 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




(a) GBs

(b) Estimated Minutes

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.[18] 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

[18]Both 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.

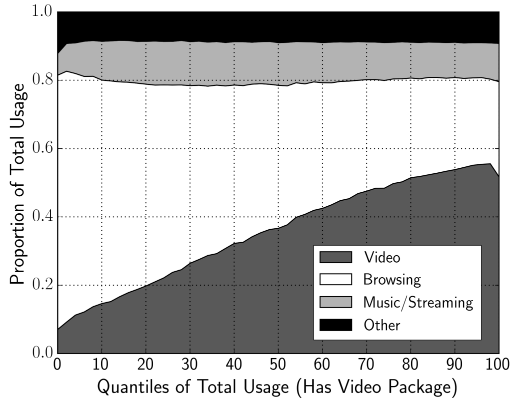
## A2 Additional Descriptive Statistics

Table A1: Average Usage by Demographic Group

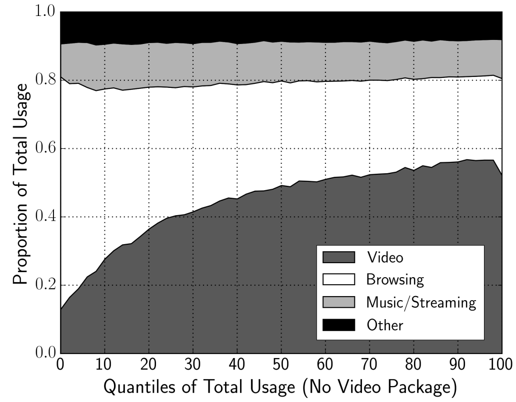
| | Total | Web Browsing | Online Video | Netflix | YouTube |
|---|---|---|---|---|---|
| Income Quartile | | | | | |
| 0-42,500 | 3.820 | 1.248 | 1.870 | 1.057 | 0.651 |
| 42,501-62,500 | 3.865 | 1.261 | 1.895 | 1.085 | 0.660 |
| 62,501-112,500 | 3.999 | 1.289 | 1.952 | 1.105 | 0.698 |
| 112,500+ | 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




(a) Bundled households




(b) Unbundled households

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.

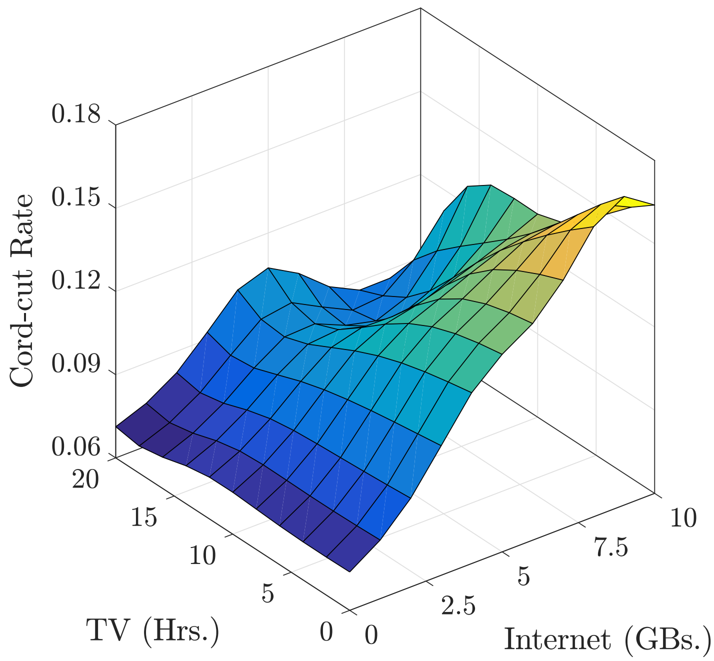
Table A2: Plan Selection Descriptive Regressions

| | Internet | | | TV |
|---|---|---|---|---|
| | Below Median | Median | Above Median | |
| Household Size | -0.004*** | 0.001*** | 0.003*** | 0.015*** |
| | (0.001) | (0.000) | (0.001) | (0.002) |
| Average Adult Age | 0.023*** | -0.007*** | -0.016*** | 0.018*** |
| | (0.002) | (0.001) | (0.001) | (0.003) |
| Number of Children | -0.003 | 0.001 | 0.002 | 0.032*** |
| | (0.003) | (0.001) | (0.002) | (0.004) |
| Tenure at Address | 0.009*** | -0.003*** | -0.006*** | 0.011*** |
| | (0.002) | (0.001) | (0.002) | (0.003) |
| Income | -0.074*** | 0.024*** | 0.050*** | 0.010** |
| | (0.003) | (0.001) | (0.002) | (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. $^{*}(p < 0.10)$, $^{**}(p < 0.05)$, $^{***}(p < 0.01)$.

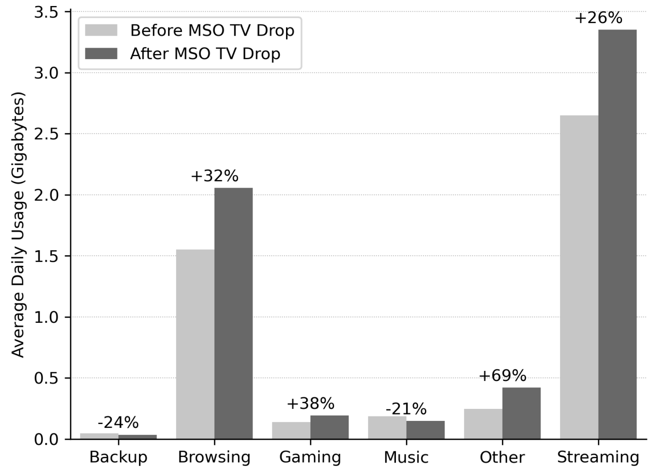
# A3 Additional Cord-cutting Analysis

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



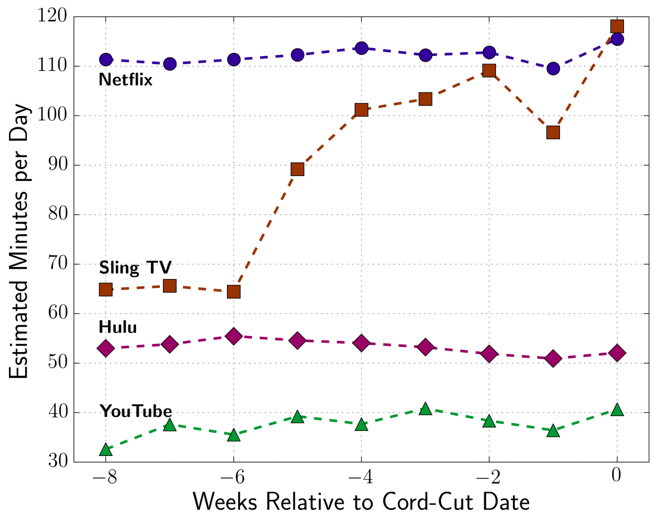

Notes: This figure depicts a local linear regression of the cord-cut indicator, depicted on the vertical axis, on average daily internet usage (GBs) and average daily television usage (hours). Usage data are taken from the 2012 sample and are at the household level. Cord-cutters are households that were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



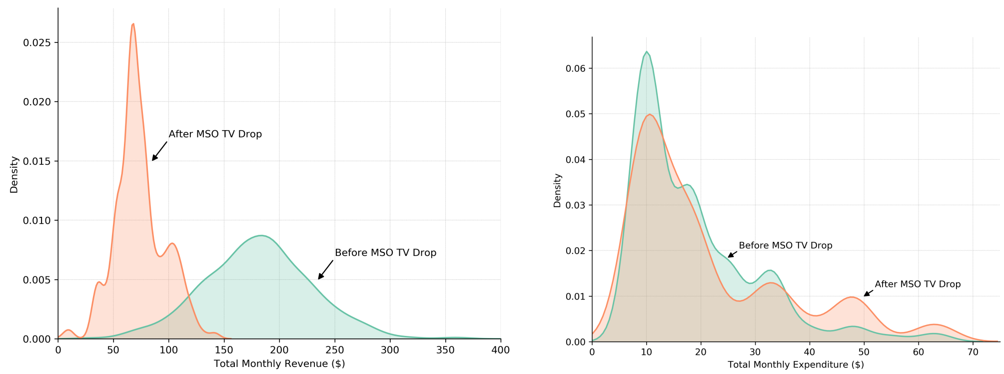

Notes: This figure presents average daily usage in GBs for each type of traffic in the eight weeks before and after households cut the cord.

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

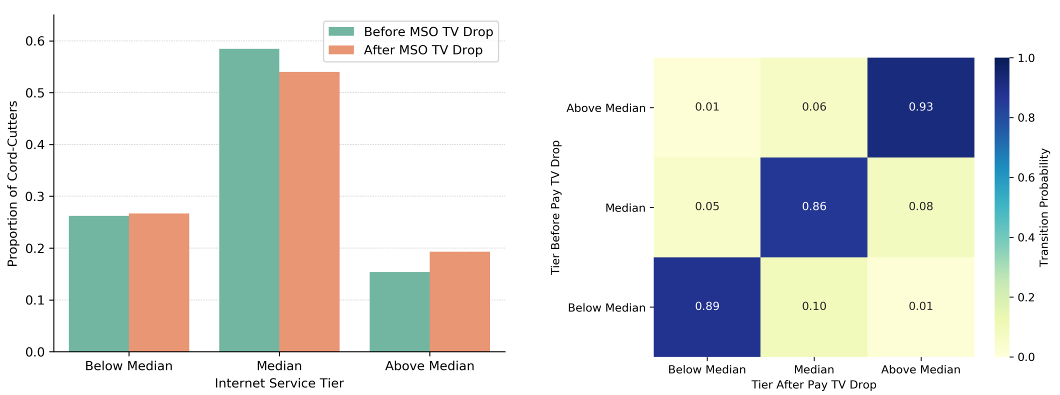



(a) Payments to MSO

(b) Payments to OTT video

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

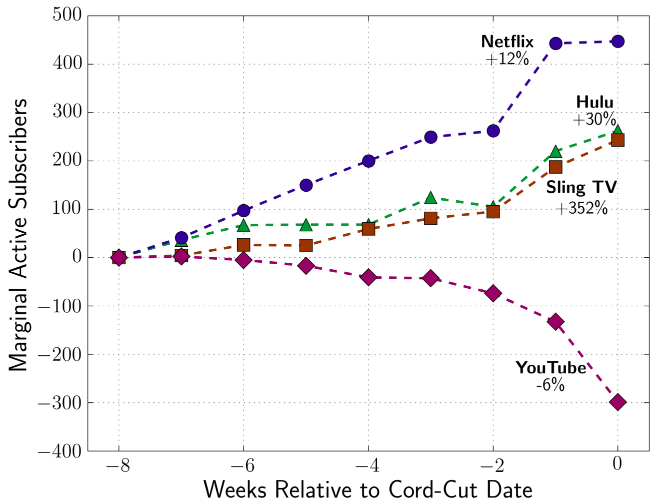



(a) Distribution

(b) Transitions

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.