Net Neutrality and Consumer Demand in the Video On-demand Market*

Andrea Szabó
Department of Economics
University of Houston
aszabo2@uh.edu

Vinh Pham
Ernst & Young
Vinh.Pham@ey.com

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Abstract

Proponents of Net Neutrality rules argue that these regulations prevent internet service providers (ISP) from slowing down content that competes with some of their own services (vertical foreclosure). To study these incentives, we measure consumers' willingness to pay for speed on the video on-demand market. We use a survey experiment to estimate a differentiated-product demand system for choosing how to view specific content. We establish a necessary condition for ISP's to have an incentive for vertical foreclosure: consumers respond to reduced speeds by substituting to a service offered by the ISP. We also show that by eliminating vertical foreclosure, Net Neutrality could provide incentives for ISPs to compete on prices.

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1 Introduction

In February 2015, the Federal Communications Commission (FCC) adopted the Open Internet Order, commonly known as "Net Neutrality." These rules prohibited internet service providers (ISP) from discriminating among customers based on how they use the internet, specifically preventing ISPs from intentionally blocking or slowing down specific content. In a sharp policy reversal that received much attention, the FCC voted to repeal this regulation in June 2018. In September 2018, California passed its own Net Neutrality law, and was immediately sued by the Department of Justice. As of early 2019, more than 30 states had introduced bills to create their own Net Neutrality protections.[1]

One of the arguments made by proponents of Net Neutrality is that, without the rules, ISPs have an incentive to block or slow down content that competes with some of their own services (vertical foreclosure). Opponents of Net Neutrality claim that these incentives, to the extent that they exist, would simply result in ISPs charging content providers for speed, and this would lead to efficient price discrimination. To support the policy repeal, the FCC argued that removing the Net Neutrality rules will reduce internet congestion and help future technology investment, which in turn will help consumers.

A first step towards measuring ISPs incentive for vertical foreclosure (or for charging content providers for speed) is to measure the magnitude of consumers' response to changes in speed. Consumers having a nontrivial willingness to pay (WTP) for speed is a necessary condition for ISP's to have an incentive to foreclose, and may be suggestive of the magnitude of fees ISPs could charge content providers. This paper provides an estimate of such willingness to pay in the context of the transactional video on-demand (TVOD) market,[2] and uses these estimates to simulate consumer response to some of the changes in speed and prices that may happen as a result of Net Neutrality rules.

TVOD is an important market, with an estimated revenue of \$1.15 billion in 2017.[3] Between 2017-2022, the revenue on this market has doubled, and this trend is expected to continue due to the continuing effects of the Covid-19 pandemic on consumer habits and industry practices (such as the release of feature films on TVOD simultaneously with, or instead of, movie theaters).[4] TVOD is vertically integrated with the ISP market, and it is a major revenue source for several ISPs such as Comcast.[5]

[1] "Net Neutrality Repeal at Stake as Key Court Case Starts," *The New York Times*, 2/1/2019.

[2] In TVOD, the consumer pays to view individual content. This is different from subscription based services, where the consumer has unlimited access to a menu of content for a flat fee.

[3] https://www.statista.com/forecasts/1285478/pay-per-view-video-revenue-united-states

[4] https://nscreenmedia.com/2020-tvod-growth-c-19-pvod/

[5] https://www.cmcsa.com/news-releases/news-release-details/comcast-reports-4th-quarter-and-year-end-2017-results?linkId=47304539

On this market, ISPs offering cable TVOD have faced increasing competition from online TVOD services. To offset this increased competition, an ISP who also provides cable TVOD could reduce the download speed of online providers that offer similar movies or TV shows. However, the ISP only has an incentive to do this if consumers are sensitive enough to download speeds that they would substitute to cable TVOD instead. In this paper, we measure this substitution by estimating the demand for different platforms, such as online TVOD or the ISP's cable TVOD platform, for viewing *specific media content*, such as a TV show or a movie. Holding the content fixed allows us to isolate consumers' trade-off between price and speed.

Estimating the differentiated-products demand system for various platforms has nontrivial data requirements. To collect a dataset with the necessary information, we use a conjoint survey experiment (Ben-Akiva, McFadden, and Train, 2019). In the survey, consumers are presented with different options for viewing specific media content (in one version of the experiment, a TV show, in another version, a movie). Consumers can view the content on cable TVOD, online TVOD, or buy a physical DVD (or decide not to view the content). Each option is described by different combinations of price and "wait time" (in the case of downloaded content, this is the buffer time before the content begins to play;[6] in the case of a DVD, it is the time it takes to buy the physical product). Based on the observed choices, we estimate consumer preferences using a random utility discrete choice model.

Our estimates imply that the median consumer's WTP for 1 minute less buffer time is 3.6 cents for the TV show and 3.1 cents for the movie. With a typical internet connection, we estimate that the average consumer would be willing to pay 10 percent more for completely eliminating online TVOD buffer time for the 140 minute long high-definition movie used in our experiment. In this setting, consumers appear to attach high value to download time when choosing how to view specific content. We also find that demand for the various viewing platforms is price elastic, particularly for online TVOD and cable.

We use the estimated model to simulate some of the ways Net Neutrality rules could impact the demand for viewing platforms. Relative to a baseline with positive buffer time for online TVOD, we simulate the impact of eliminating the buffer. This might correspond to a situation where the ISP is prohibited from creating extra buffer time for online TVOD compared to cable on-demand. In this counterfactual experiment, we find that eliminating the buffer time for online TVOD increases this platform's market share by 1.1 (4.5) percentage points for the TV show (movie). Cable loses the most from this change, with a decline

[6] When viewing movies or TV shows online, some of the content needs to be downloaded in advance in order for the video to run uninterrupted. The amount of time elapsing while this is taking place, i.e., the wait time before the video starts, is referred to as buffer time.

in its market share of 0.4 (2.2) percentage points for the TV show (movie). This finding highlights the incentive that an ISP who also offers cable TVOD may have for limiting the speed of competing online TVOD providers in the absence of Net Neutrality.

We also study a scenario where the ISP/cable provider adjusts its price to match the (lower) online TVOD price in order to limit the adverse impact of the regulation on its market share. This experiment quantifies one way in which Net Neutrality could lead to *more* competition by giving cable providers an incentive to lower prices on their TVOD content. When the elimination of buffer time is followed by cable lowering its price, this wipes out the gain of online TVOD from the reduction in buffer time in the case of the TV show. For the movie, the gains from the buffer time reduction for online TVOD are large enough that its market share increases even after cable's price reduction. Here both online TVOD and cable gain a market share of around 2.7 percentage points, while the DVD market share declines. These findings suggest that if Net Neutrality eliminates competition in download speed, the nature of competition in the remaining attribute, price, is likely to be a crucial determinant of the impact of the regulation on the market shares of different content providers.

The literature on Net Neutrality, which is primarily theoretical, is discussed in the next section. In terms of methodology, the paper closest to ours is Leung (2013), who studies the impact of government response to software piracy. While that paper addresses a different topic, it also features estimates of consumer response to increased download speeds for a specific product (a pirated copy of Microsoft Office). Other than this study, we are not aware of WTP estimates for download speeds of fixed content in the existing literature.

Our paper is also related to a growing literature estimating consumer demand for internet service (Nevo et al., 2016; Grzybowski et al., 2018; Liu et al., 2018; Malone et al., 2019; Tudon, 2021). This literature uses different sources of variation to estimate consumers' WTP for internet speed in order to study ISP incentives related to issues such as congestion and bundling. While these papers focus on different ISP incentives, WTP for speed is a key parameter to those incentives as well. An important challenge is that consumer choices between internet plans are affected by what a consumer uses the internet for, i.e., the content that (s)he wants to access. Our experimental approach allows us to estimate WTP for internet speed holding the content constant, thus isolating consumer responses from other potential incentives that would affect the interpretation of the results.

Three key limitations of our study should be kept in mind. First, online TVOD is only part of the large market for online entertainment. Another important part is subscription-based video on-demand (SVOD), which involves several considerations that our experiment was not designed to study. Second, we focus exclusively on the demand side, and cannot directly address questions that would also require modeling provider behavior (including the full welfare effects of Net Neutrality rules). Third, although our sample is representative of the US population in several relevant dimensions, it excludes older customers (see Section 6.4 for details).

In the remainder of the paper, section 2 gives some background, section 3 presents our experiment and the data, section 4 describes the demand model and the estimation method, section 5 contains the estimation results, section 6 presents the counterfactual experiments, and section 7 concludes.

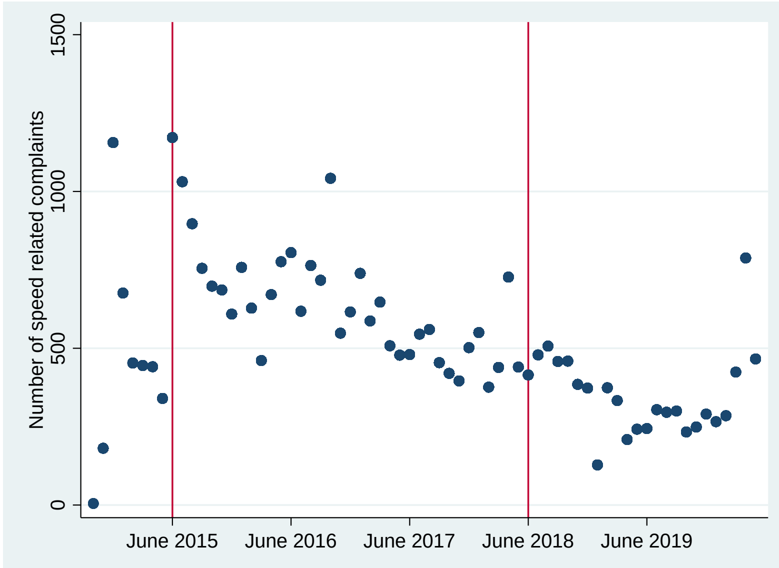
2 Background

Net neutrality rules have been a contentious issue generating much debate. As Economides and Hermalin (2012) note, "there are many advocacy papers written on the subject, but significantly less economic research." Most academic discussion on the subject has focused on theoretical questions.[7] For example, is Net Neutrality desirable when it prevents ISPs from price discriminating between providers? (Economides and Hermalin, 2012; Choi et al., 2015; Bourreau and Lestage, 2019). Standard theory says that price discrimination is efficient. Yet, there are theoretical reasons why price discrimination may not be efficient in the present context - for example, when internet providers operate on a two-sided market (Lee and Wu, 2009), or when internet traffic is subject to congestion (Economides and Hermalin, 2012, 2015). Another theoretical question focuses on whether ISPs have an incentive to foreclose content providers (Broos and Gautier, 2017). Some of an ISP's products (such as its TVOD service) compete with content providers, while others (such as the broadband service itself) do not. If an ISP views content providers mostly as complements, rather than substitutes, for its own products, then vertical foreclosure would not be profitable. If there are no incentives to foreclose, then Net Neutrality rules may be unnecessary.

Clearly, some of these questions (e.g., whether an ISP's products complement or substitute a content provider's service) are inherently empirical. Yet, little systematic data exists. Early reports of ISPs selectively slowing down content were based on anecdotes and consumer complaints. Figure 1 shows the number of consumer complaints filed with the FCC from 2014 to 2020 regarding internet speed. The period of Net Neutrality (June 2015 to June 2018) is indicated with the red vertical lines. Naturally, there were more complaints while the rules were in effect. More importantly, the number of complaints declined throughout

[7] See Lee and Wu (2009), Becker et al. (2010), and Greenstein et al. (2016) for summaries of the policy arguments and the existing economics research on this topic. All these papers highlight the lack of empirical estimates to guide policy. For example, Becker et al. (2010) write: "We are unaware of any evidence on the magnitude of various spillover effects." (517)

Figure 1: Consumer complaints regarding internet speed filed with the FCC



Notes: Monthly counts of complaints about internet speed. Total over the period: 35,304. The red lines indicate the period of Net Neutrality rules. Source: Authors' calculations based on data from https://opendata.fcc.gov/Consumer/CGB-Consumer-Complaints-Data/3xyp-aqkj

this period, but flattened out after the rules were repealed, with some increases in the last 3 months of the data. In total, 42,916 complaints were filed specifically regarding internet providers' alleged violation of Net Neutrality rules (while the rules were in effect).

There are also documented cases of ISPs slowing down (throttling) some services. In a recent (post-repeal) example that received much attention, Sprint was accused of regularly slowing down Skype, supposedly to reduce competition for its own calling service.[8] A recent study that directly measured throttling confirmed that Sprint throttled Skype (Li et al., 2019). That study also found that nearly every US cellular ISP throttled at least one streaming video provider, but did so selectively. For example, AT&T throttled Netflix and YouTube, but not Amazon Prime. Greenstein et al. (2016) provide a summary of many cases before the original policy was introduced.

What seems to be missing both from the academic literature and the policy debates is systematic data that would help us understand ISPs incentives for throttling behavior. Since it is difficult to imagine that such incentives could ever be directly observed in real data, we propose an approach to measure one ingredient to these incentives: consumers' willingness to pay for download speeds of specific content.

[8]https://www.latimes.com/business/technology/la-fi-tn-sprint-skype-20181108-story.html)

3 Study design and data collection

3.1 Experiment design

3.1.1 Motivating the design

Concerns about vertical foreclosure in the context of Net Neutrality arise for specific online content or services. The concern is not that an ISP would slow down a consumer's monthly internet service - it is that it may slow down the streaming of specific content at a specific time. Thus, to evaluate these incentives, one needs to estimate consumers' response and willingness to pay for download speed in the context of specific media content.

The data requirements for estimating this kind of response are nontrivial. Ideally, one would identify individual consumers of a specific product (online content), and collect information on the platform used to access that content, prices paid, and internet speeds / buffer times, across multiple choice situations for each consumer. One would then repeat this data collection for different products. It is difficult to imagine a non-experimental (real world) dataset that would contain this information. Moreover, even if real-world data was available, studying the impact of characteristics such as price on consumer choices would require (i) sufficient variation in the price of specific content to identify the corresponding parameters, and (ii) exogenous variation (or an instrument akin to the exogenous variation created in our experiment).

Our survey experiment provides an arguably second-best solution to this data problem. As usual, the experimental method is subject to a trade-off between internal and external validity. We had to choose a limited number of products to study, and we explain the considerations that guided our choice below. We also conducted our experiment using a specific subject pool, and we investigate the extent to which our subjects are representative of the overall population.

3.1.2 Description of the experiment

We pick a product that is homogenous across platforms except in terms of price and download (buffer) time, and study how consumers choose between viewing platforms *for this product* as a function of these two characteristics. We do this using a survey experiment known as "conjoint survey," where subjects face hypothetical choices described by different characteristics. The setup of our experiment closely follows the design of Leung (2013), who also studies tradeoffs between prices and internet speed (in the context of software piracy). A monograph by Ben-Akiva, McFadden and Train (2019), BMT from now on, provides a thorough introduction to choice-based conjoint analysis, reviews its long history in marketing and policy analysis, explains how it differs from other methods of stated preference elicitation such as contingent valuation, and discusses both its advantages and limitations. Our design follows many of their recommendations regarding both experimental design (see their Table 2.1) and estimation method.[9] We discuss specific features after presenting the details of the experiment.

In picking the product, we aimed to make the hypothetical choice scenarios for the consumers as close to real choices as possible. Before the experiment, we identified two products, a TV show and a movie, which at the time of the survey could not be rented either through cable or online TVOD, nor could be streamed with a subscription service such as Hulu, Netflix, or Amazon Prime. Thus, a consumer who wanted to consume these products would have to purchase either a digital copy or a physical DVD.

In the survey, consumers faced hypothetical choice scenarios about either season 1 of the TV series "Modern Family" in standard definition (SD), or about the movie "Star Wars Episode III – Revenge of the Sith" in high definition (HD). Both of these products satisfy the above criteria (Table 12 in the Appendix shows the actual availability and prices of these products in March 2016).

For both of the products we chose, there is substantial price variation across viewing platforms: the same product is about 20 percent cheaper on any online TVOD service compared to cable TVOD, and buying the physical disc provides the cheapest option in both cases (see Table 12). There is also substantial variation in buffer time. To compute this, we used the speed of specific internet providers in the area where our experiments were conducted - see Table 13 and 14 in the Appendix for more details. Naturally, the buffer time is substantially different for a short TV show compared to a long HD movie.[10]

The choice experiment presented hypothetical scenarios in which subjects chose between different viewing platforms to watch the same product (either the movie or the TV show). About half of the subjects were presented with the movie version of the experiment, and half with the TV show version. For example, in the movie experiment, we started with the statement: "Imagine you would like to watch the popular movie "Star Wars Episode III – Revenge of the Sith" (2005) in High Definition. You currently don't own this movie. This movie is not available on Netflix, Amazon Prime or Hulu, and it is also not available for rent anywhere. This movie is only available for purchase. Imagine the four options below are your only choices. Which one would you choose?"

Respondents could choose to purchase a physical DVD, use a cable provider's TVOD

[9] See also Sawtooth Software (2008) for a practitioner's guide to conjoint surveys.

[10] For the TV show, even if the consumer watches several episodes of the season back-to-back, buffering occurs before each episode. The viewer only has to wait until the specific episode can play uninterruptedly.

service, or use an online TVOD service. In addition, they could choose the option "I do not buy or watch this movie." Each viewing option was described by two characteristics: (1) price and (2) buffer time (or, in the case of DVD, the time it took to obtain the physical disc). We varied these two characteristics and asked the respondents the same hypothetical choice question. The values of the characteristics used in the experiment are shown in Table 1. We chose the values to include both a set of realistic values (based on Tables 12, 13 and 14 in the Appendix), and some outliers. Figure 3 in the Appendix shows how the survey was presented to respondents.[11]

Table 1: Values of the choice attributes used in the experiment

	Option 1 Buying a DVD	Option 2 Cable TVOD	Option 3 Online TVOD	Option 4 Do not buy
TV show				
Price	5, 8, 12, 20, 30	21, 25, 30, 35, 40	10, 20, 24, 28, 36	-
Buffer time (minutes)	5, 10, 20, 30, 60	0	0, 3, 15, 30, 120	-
Movie				
Price	6, 12, 20, 24, 29	21, 25, 29, 35, 38	8, 14, 20, 25, 30	-
Buffer time (minutes)	5, 10, 20, 30, 60	0	0, 15, 45, 120, 540	-

Each subject was asked to make choices in 10 scenarios, creating a panel dataset. We created a total of 50 choice scenarios for both the TV and the movie version. We then created 10 versions of the survey for the movie and 10 for the TV show (20 in total), with each version containing 10 of the corresponding 50 scenarios. Each participant was randomly given one of the 20 survey versions to complete. The Online Appendix shows all possible versions of the survey.

The experiment was administered in person at the University of Houston among students and some staff and faculty. We randomly selected 12 classes from the course catalog and surveyed all students in these classes in Summer 2016. The data was collected through self-administered questionnaires. Subjects did not receive any compensation for participating in the experiment. Before beginning the choice experiment, subjects were also asked some basic demographic information, and questions on how they typically viewed TV shows / movies.

3.1.3 Discussion

Subscriptions and rentals. Streaming providers offer three types of products that compete with an ISP's on-demand service: TVOD for purchase, TVOD for rent, and subscriptions

[11] All versions of the full survey questionnaire are available at https://uh.edu/~aszabo2/net_survey_all.pdf.

that allow consumers to watch a variety of content (SVOD). To measure consumer substitution as a function of speed and price, we focus on the first of these.

The tradeoffs faced by consumers when buying or renting specific content are similar. We chose to focus on purchase rather than rental behavior because the rental market tends to have considerably less price variation, with only a subset of the content available to rent.[12] Rentals and purchases account for similar shares of consumers' home entertainment spending, with purchases increasing slightly relative to rentals in recent years.[13]

Subscriptions offer different types of content, sometimes including content that is not available anywhere else (as in the case of TV series produced by Amazon). Consumer choices between cable and these subscriptions are likely to be driven in part by the content offered, so changes in buffer time are less likely to cause consumers to switch. Moreover, WTP for a bundle of movies and TV shows is likely to depend on whether those shows complement or substitute each-other. Thus, our results cannot directly be used to study consumer demand for SVOD and how Net Neutrality may affect that market.

The DVD option. Our experiment includes a DVD option because, as of 2016, viewing a DVD was a realistic choice for many consumers.[14] In our view, it is meaningful to compare the time it takes to acquire a DVD to the time it takes to download online content, and in our experiment we explicitly highlighted this comparison along with the comparison of prices (see Figure 3 in the Appendix). However, one could also argue that the time spent acquiring the DVD (travel) is qualitatively different from the time spent waiting for a download to finish. In Appendix 8.9 we therefore re-estimate our results excluding the DVD option. This is possible because our experiment also collected respondents' second choice in each scenario (similar to Leung (2013)). Thus, we directly observe what a respondent who chose the DVD option would have chosen if this option had not been offered.

Choice complexity. Our experiment presents subjects with 10 scenarios, each involving 3 options (plus the outside option) that differ on 2 attributes (price and time). We focus on these two attributes because it is this tradeoff, consumers' willingness to pay for speed, that is directly relevant for understanding the demand impacts of Net Neutrality. Sometimes subjects' ability to understand complex choices is a concern in conjoint survey experiments

[12]For example, as of February 2020, of the 10 most popular movies released in 2018, only 5 are available to rent on Amazon, DirecTV or Xfinity, but all 10 are available for purchase. Across the 3 platforms and 5 movies available for rent, 14 of the 15 rental prices are identical ($3.99). By contrast, there are 10 different purchase prices, varying between $7.99 and $21.99.

[13]In 2017, the share of individual video rentals and purchases were both at 11%, in 2018 rentals accounted for 9.7% and sales for 11%. https://nscreenmedia.com/home-entertainment-spending-up-due-to-svod/

[14]In spite of the increase in streaming, as of 2017, a third of Americans still bought or rented DVDs, and the revenue from DVD sales was twice as large as the revenue from digital video sales, https://qz.com/1136150/even-with-streaming-video-a-third-of-americans-still-buy-and-rent/ https://nscreenmedia.com/home-entertainment-spending-up-due-to-svod/

that feature many products and a detailed list of attributes. BMT describe the "widespread folklore" that "subjects have trouble processing more than six attributes and more than four or five products, and begin to exhibit fatigue when making choices from more than 20 menus" (p21). Note that our surveys are well below these thresholds on all dimensions.

Our experiment presents a choice problem (how to watch a movie / TV show) that all subjects are familiar with. If subjects are not interested in seeing the particular movie or TV show in the experiment (for any reason), they can choose a well-defined outside option (do not watch). This is a straightforward design compared to many others used in the literature, where researchers have to consider whether subjects are familiar with the type of choice being studied (e.g., when choosing between cars, whether the subject ever purchased a car), and how the outside option of not buying will be interpreted (e.g., keep my current car, or buy a car later, etc.). Our design avoids these common issues encountered in conjoint survey experiments (see BMT (p17-18) for a discussion).

Values of characteristics. When choosing values for each characteristic, one must balance realism with a need to create sufficient variation in the characteristics (BMT, p19-20). As described above, the values we chose were based on published product prices and download speeds. In contrast to typical conjoint surveys where there is very little real-world price variation, so that most scenarios presented to subjects are "unrealistic" by design, our setting features large actual price variation for the same product (see Table 12). In general, the ability to include more variation in characteristics than might be observed in real-market data is one of the advantages of the conjoint survey, and helps map out a larger portion of consumers' demand curve than would be possible using observational data. By considering two products, a TV show and the movie, we further extend the range of the realistic choice situations included in the experiment.

Price variation and identification of the demand function. The conjoint survey provides clean identification of consumers' WTP for speed through several features of our experiment. First, we create exogenous variation in prices and buffer times through the randomized bundles presented to respondents. Second, an important advantage of the experiment is the ability to hold fixed the content being consumed: this allows us to isolate the response to variation in speed from other incentives that consumers might face when content is also a choice.[15] Third, our estimates use information from repeated observations of the same respondent choosing between the same products under different price/speed combinations. (This is again a feature that is unlikely to be available in real-world data: most consumers will not watch a specific show more than once or a few times.) Finally, our data makes it

[15] For example, real-world data on consumer choices between internet subscriptions is likely to be affected by how the consumer uses internet.

possible to include in the estimation heterogeneity across consumers *both* through observed consumer characteristics and through random coefficients.

3.2 Data description

In total, we collected responses from 416 subjects. Of these, 93 subjects always marked the "Do not buy" option, and 11 always marked one of the other options (e.g., always option 1). Because these respondents' behavior may reflect unobserved factors that are outside our model, we drop them from the estimation.[16] We also drop 17 respondents who had missing data on one or more relevant demographic variables. In the analysis below, we use surveys of the remaining 295 respondents. These surveys contain choices in a total of 2890 scenarios (1488 for the TV show and 1402 for the movie).

Table 2 presents the characteristics of the respondents, as well as the average product characteristics (price and buffer time) across all choice options. The respondent samples do not differ significantly between the TV show and the movie version of the experiment.

About 28% of the respondents had household incomes less than $40,000 per year, and 48% had more than $70,000. The mean age of the respondents is 22 with a range of 18 to 50. Twenty percent of the students were aged 25 or older, and 8 percent were 30 or older. More than 80 percent of the respondents have high speed internet connection at home, but less than 60% have a Blu-ray player, likely showing the changing trends in the industry.

There could be a concern that this younger population may have different preferences and hence make different choices than the US population. This could lead to non-representative counterfactuals and potentially misleading interpretations of the overall results. We address this issue in two ways. First, since we estimate individual-specific parameters and include demographic variables in the estimation, we are able to assess the impact of age and other demographics on our results. Second, we also reestimate the model using weights based on age, family income, access to high-speed internet and ownership of Blu-ray player for the US population (see section 6.4). Of course, the fact that we have no respondents over the age of 50 remains a potentially important limitation.

[16] These responses are not due to a lack of the necessary equipment. All 5 respondents who always selected the DVD option also reported having high-speed internet connection at home as well as owning a computer. All 6 respondents who either always selected online TVOD or always selected cable also reported owning a DVD/Blu-ray player.

Table 2: Summary statistics of respondent demographics and product characteristics

	TV sample	Movie sample	Difference	p-value	N
Demographics					
Age	21.896	21.894	0.002	0.996	295
	(4.189)	(4.928)			
Low income	0.357	0.312	0.045	0.414	295
	(0.481)	(0.465)			
Medium income	0.377	0.333	0.043	0.440	295
	(0.486)	(0.473)			
High income	0.266	0.355	-0.088	0.101	295
	(0.443)	(0.480)			
Owns a dvd player	0.766	0.801	-0.035	0.466	295
	(0.425)	(0.400)			
Owns a bluray player	0.552	0.560	-0.008	0.886	295
	(0.499)	(0.498)			
Owns high speed internet	0.818	0.830	-0.012	0.795	295
	(0.387)	(0.385)			
Product characteristics					
TV Price	17.203				5952
	(13.360)				
TV buffer time	19.754				5952
	(34.769)				
Movie price		16.779			5608
		(12.470)			
Movie buffer time		48.724			5608
		(123.016)			

Notes: Average respondent characteristics (with standard deviations in parentheses) for the 295 respondents used in the analysis. Product characteristics are for all choice options in all all scenarios. The third and fourth columns show the difference in means and the p-value for the equality of means t-test. The min/max values are 18/50 for age and 0/1 for all other demographics. See Table 1 for product characteristics values. Variable definitions are in the Appendix.

4 Demand model

We describe decision makers using a mixed logit model (Train, 2009). Facing a choice scenario t, the utility that decision maker n obtains from choosing alternative j is given by

$$U_{njt} = \alpha_n p_{njt} + \beta_n b_{njt} + z_n' \gamma_j + \varepsilon_{njt}, \qquad (1)$$

where p_{njt} is price, b_{njt} is buffer time, z_n is a vector of decision maker characteristics that may affect the utility of different choices differently (as captured by the choice-specific parameters γ_j), and ε_{njt} is a random term drawn from a Type I extreme value distribution. The individual-specific coefficients (α_n, β_n) are drawn i.i.d. from a distribution $f(.|\theta)$, where

θ are parameters of the distribution. In addition to the different viewing platforms, the decision maker can also choose not to view the given product, and we normalize the utility of this to 0. The probability that the decision maker chooses alternative j is

$$P_{nj} = \int \frac{\exp(\alpha_n p_{njt} + \beta_n b_{njt} + z_n' \gamma_j)}{\sum_{i=1}^{J} \exp(\alpha_n p_{nit} + \beta_n b_{nit} + z_n' \gamma_i)} f(\alpha, \beta | \theta) d(\alpha, \beta).$$

Since we observe an individual making several choices, this can be taken into account in the analysis. The probability of a particular sequence of choices is given by

$$P_n = \int \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{\exp(\alpha_n p_{njt} + \beta_n b_{njt} + z_n' \gamma_j)}{\sum_{i=1}^{J} \exp(\alpha_n p_{nit} + \beta_n b_{nit} + z_n' \gamma_i)} \right]^{I_{njt}} f(\alpha, \beta | \theta) d(\alpha, \beta) \tag{2}$$

where I_{njt} is equal to 1 if the individual chose alternative j in choice scenario t, and 0 otherwise. We estimate the parameters θ and γ by maximizing the simulated log-likelihood corresponding to (2), simulating the integral in (2) using 1000 Halton draws.[17]

The estimation procedure described above allows us to estimate *individual* choice probabilities for the consumers. Heterogeneity between consumers comes from two sources: unobserved heterogeneity in the marginal utility of price and buffer time, and observed consumer characteristics. Observed consumer characteristics include demographic variables (age and income) and the ownership of high-speed internet and DVD/Blu-ray player. These variables are interacted in each likelihood specification with the choice specific constants to account for their potentially differential effect on the valuation of different choices.[18] As we show below, using corresponding data on the US population, these characteristics also make it possible for us to obtain suggestive results on how our estimates would extend to a broader population.

A potential alternative to this estimation approach would be a Hierarchical Bayesian approach, as in Leung (2013). As Train (2001) points out, one advantage of the classical approach to estimating mixed logit models is that it is more straightforward and computationally easier to include a large number of fixed parameters. Since our survey contains rich consumer characteristics, we follow this route to account for observed demographic differ-

[17] See Hole (2007) for a practical guide to implementing this estimator.

[18] We did not collect information on whether respondents have a TV set since that is unlikely to be a constraint on choices: accessing an ISP's video on-demand service does not require a TV set (content can be watched on a computer).

ences in platform choice. Huber and Train (2001) find that the two methods provide very similar results on their typical sample.

Parameter estimates are in Tables 15 and 16 in the Appendix. In both tables, column (1) allows for individual heterogeneity in the price coefficients by assuming a normal distribution on this parameter. Column (2) adds heterogeneity in the buffer time parameter as well, using a normal distribution independent from the price parameter. Column (3) and (4) repeat these specifications replacing the normal distributions with log-normal. As shown in the table, the model produces the lowest log likelihood value in column (4) specifications, where both parameters have a log-normal distribution. In column (5) we allow for correlation between the buffer time and price coefficients and estimate the covariance matrix of these two variables. For the movie, we find that the covariance parameters are not statistically significant. In addition, the model's fit is virtually unchanged compared to the specification in column (4), indicating that the specification using independent random coefficients is adequate. In what follows, we use column (4) as our preferred specification for the movie. For the TV show, the covariance parameters are significant. Although the change in overall fit is small, we use column (5) as our preferred specification for the TV show. For our preferred specifications, the lognormal distribution ensures that the price coefficients are always negative, and that the willingness-to-pay values calculated below have finite moments (Daly, Hess, and Train, 2012). Demographic characteristics are not significant once choice specific constants are included, but in all cases their inclusion improves the model's fit.

We also investigated specifications allowing for a quadratic effect of buffer time (also with a random coefficient). For the movie, we found both the mean and the standard deviation of the quadratic coefficient to be small and statistically insignificant. For the TV show, although the coefficient was statistically significant, its magnitude was small. As a result, the distribution of the implied willingness to pay estimates was very similar to those obtained from the linear specification for the relevant range of buffer times (see Appendix 8.8 for details).

Our estimates yield individual-specific buffer time and price coefficients. To display these, we compute summary statistics of the distribution of each coefficient. These are reported in Table 3. The full distribution of the coefficients across individuals is shown in Figures 4 and 5 in the Appendix. We find substantial variation in the coefficients across individuals for both buffer time and price.

Table 3: Summary statistics of individual coefficients and WTP buffer time

	Mean	Median	St.dev.	10%	90%	N
TV show						
Price	-0.209	-0.156	0.144	-0.420	-0.081	154
Buffer time	-0.076	-0.007	0.412	-0.078	-0.002	154
WTP for buffer time	0.417	0.036	2.473	0.015	0.463	154
Movie						
Price	-0.220	-0.169	0.123	-0.376	-0.106	141
Buffer time	-0.021	-0.005	0.073	-0.046	-0.002	141
WTP for buffer time	0.098	0.031	0.222	0.008	0.246	141

Notes: Summary statistics of the estimated individual-level price and buffer time coefficients based on column (4) of Table 15 (movie) and column (5) of Table 16 (TV show) in the Appendix, and implied willingness to pay for buffer time.

5 Estimation results

5.1 Willingness to pay estimates

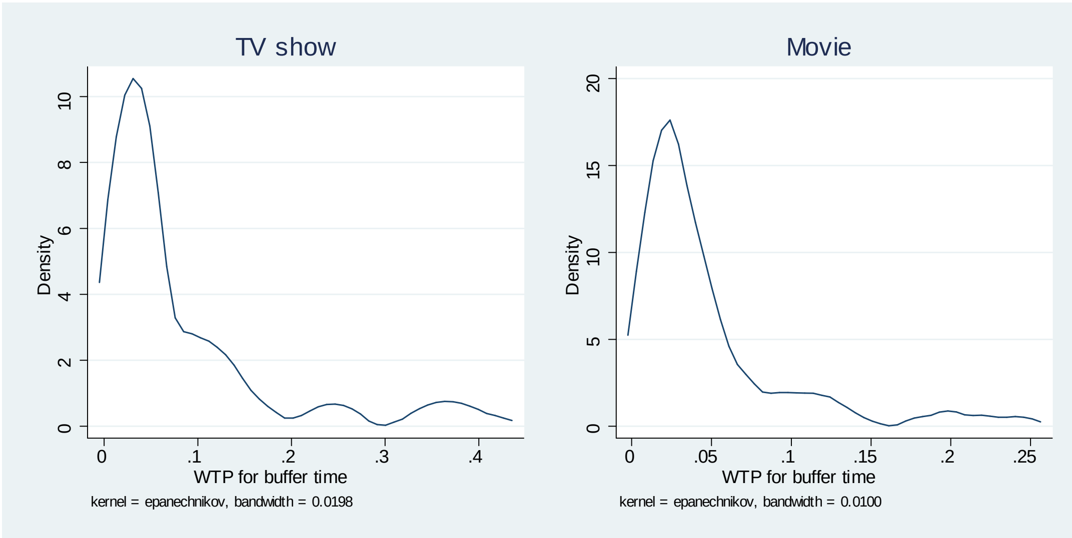
To describe the heterogeneity across individuals, we compute the marginal rate of substitution between price and buffer time (i.e., the willingness to pay for buffer time) for each individual based on the parameter estimates. Since utility is linear in the choice attributes, willingness to pay (WTP) for the non-price attribute (buffer time) is the negative of the ratio of the estimated individual coefficients for this attribute and for price.

The distribution of the individual WTP values implied by the parameter estimates is shown in Table 3 and Figure 2. The median willingness to pay for 1 minute less buffer time is 3.6 cents for the TV show and 3.1 cents for the movie. WTP values tend to be larger for the TV show: the $10 - 90$ percentile range is $1.5 - 46.3$ cents for the TV show compared to $0.8 - 24.6$ cents for the movie. This is plausible: since the TV show is shorter than the movie, an extra minute of buffer time is a larger fraction of the total viewing period for the former. Perhaps for the same reason, the standard deviation of WTP for buffer time is also larger in the case of the TV show: five times the mean, compared to twice the mean for the movie.

In our counterfactual experiment below we investigate the impact of eliminating a typical buffer time of 23 minutes for the movie or 3 minutes for the TV show.[19] To put those results in context, note that the WTP estimates shown in Table 3 imply that the median (average) consumer is willing to pay 71.3 cents ($2.12) more for eliminating a 23 minute buffer time for the movie. This corresponds to 3.6% (10.6%) of the movie's price of $19.99. Interestingly,

[19] See the Appendix for the computation of these values.

Figure 2: Distribution of individual WTP for time



Notes: Individual WTP for buffer time computed using the parameter estimates in column (4) of Table 15 and column (5) of Table 16 in the Appendix. Values are for the 10-90 percentile range.

the average WTP corresponds almost exactly to the price difference between streaming the movie, or watching it on cable TVOD with no buffer time (which costs $21.99). For the TV show, the median (average) consumer's WTP for eliminating the 3 minutes buffer time is 10.8 cents ($1.25).

As noted by Train and Weeks (2005), in some cases WTP values computed using the parameter estimates of mixed logit models produce implausibly large values for a large fraction of consumers. In such cases, they suggest estimating the model "in WTP space," assuming a normal or log-normal distribution for the individual WTP values rather than the coefficients themselves. In our case, the WTP estimates obtained using the parameters do not seem implausibly large. Still, to assess the robustness of the patterns above, in the Appendix we re-estimate the model in WTP space. The results are qualitatively similar to those reported above.

We are not aware of directly comparable willingness to pay estimates for download speeds in the existing literature. Nevo et al. (2016) estimate that consumers are willing to pay between 0 and 5 dollars per month for increasing their internet speed by 1 megabyte per second (Mbps), with an average of 2.02 dollars and a median of 2.48. This is based on a dataset of internet subscribers and the internet plans they purchased. Liu et al. (2018) study a choice experiment where subjects choose between different hypothetical internet plans, and estimate that consumers are willing to pay $14/month to increase download speeds from 4

Mbps to 10 Mbps (or around 2 dollars a month for one extra Mbps in this range). They also show that, compared to the average consumer, users who stream video are typically willing to pay significantly more for increased download speeds.

Our setting differs from both of these studies since we are studying willingness to pay for internet speed when consuming a specific product, rather than when choosing monthly internet subscriptions. Still, to translate our findings into WTP for internet speed we can do a back-of-the-envelope calculation. To do this, we need to assume the internet speed offered by the provider as well as the streaming bit rate, since both of these affect the buffer time. Suppose the internet speed is 6 Mbps, which is the mean speed among unlimited internet plans in the Nevo et al. (2016) data (see their Table II). To calculate a consumer's willingness to pay for 1 Mpbs faster internet, consider a bit rate of 7 Mpbs (this is in the middle of the range of the bit rate of various providers listed in Appendix Tables 13-14).

Based on Table 3, the median WTP for 1 minute less buffer time is 3.6 cents in the TV sample and 3.1 cents in the movie sample. If a consumer's connection speed is 6 Mbps, streaming a 20-minute episode of the TV show on a 7 Mbps streaming service involves a buffer time of 3.33 minutes. Based on the median WTP, this consumer would be willing to pay 12 cents to eliminate this buffer time.

To achieve the same experience, the consumer could upgrade his internet speed to a bandwidth of 7 Mbps that would allow streaming the TV show without buffer time. In this sense, the consumer would be willing to pay 12 cents for the 1 Mbps faster connection. As an alternative way to frame this comparison, based on the Nevo et al. (2016) estimates, the \$2.48 that a median consumer is willing to pay for a 1 Mbps faster internet *for the month* is worth it for a consumer who wishes to eliminate the buffer time for 21 or more TV shows over the month ($2.48/0.12 = 20.67$).

For the movie, the median WTP for 1 minute less buffer time is 3.1 cents, and the buffer time for the 140 minute long movie at 6 Mbps connection speed is 23 minutes. Assuming that WTP increases linearly, the customer would be willing to pay 71.3 cents to download the movie immediately. Based on the Nevo et al. (2016) estimates, paying \$2.48 for a 1Mbps faster monthly internet is thus worth it for a consumer who wishes to eliminate the buffer time for 4 or more movies over the month ($2.48/0.713 = 3.48$). Based on these figures, consumers in our experiments appear to attach high value to internet speed when choosing how to view a specific type of content.[20]

[20] That consumers are willing to pay more to reduce wait times for a specific movie they are about to watch than to increase their overall internet speed is consistent with present bias and other psychological phenomena documented in economics and marketing. It is also consistent with Krishnan and Sitaraman (2013), who find that consumers start abandoning online videos after as little as 1 second extra buffer time.

5.2 Substitution patterns

In order to study the substitution patterns implied by our model estimates, we first use the estimates to compute price elasticities. To do this, for each viewing platform, we first predict demand (choice probabilities) at the actual prices of that platform. We then raise this price by 1 percent, and predict demand for all viewing platforms at this new price. (Throughout, prices of the other platforms are held fixed at the values given in the choice experiment.) We compute individual price elasticities as the percentage change in demand following this price change. In each case, demand predictions are based on 1000 simulations for each consumer from the estimated distribution of individual coefficients. Note that, because the mixed logit model relaxes the Independence of Irrelevant Alternatives (IIA) assumption of the simple logit model, the cross-price elasticities of the different alternatives are not restricted to be equal. Indeed, this is an important advantage of using mixed logit, which therefore allows for more realistic substitution patterns.

Summary statistics of the individual price elasticities for each platform and each program (TV show or movie) are given in Table 4. Each column shows the change in the market share of the different options when the price of the given platform changes by 1 percent. For example, in the case of the TV show and a 1 percent change in the price of the DVD, the median price elasticity of the DVD is -1.092 percent, while the (cross-)price elasticities of cable and online TVOD are, respectively, 0.547 and 0.635. The cross-price elasticity of the outside good is 0.751, indicating that some consumers prefer not to watch the TV show when the price of the DVD increases. In general, Table 4 shows that consumer demand is price elastic for each platform. Median own-price elasticity for cable and online TVOD is between -2.1 and -2.3. The own-price elasticity is lower in absolute value for the DVD: -1.1 for the TV show and -1.6 for the movie.

Table 5 presents the impact of varying buffer time. To make buffer time changes meaningful, we consider the impact of increasing buffer time of online TVOD from 0 to, respectively, 3, 5, and 10 minutes (holding everything else constant). We present the resulting changes in demand (i.e., choice probabilities) in percentage points. These can be interpreted as the changes in market shares resulting from the increase in buffer time. We find that, naturally, the impact is largest on online TVOD, resulting in a decline in market shares between 0.8 and 2.6 percentage points. The decline is always larger for the TV show, presumably because the buffer time is a larger fraction of the viewing experience in that case. Table 5 also shows that cable TVOD is the closest substitute of online TVOD for these changes in buffer time, followed by the outside good (not watching the program), and finally DVD. Based on these results, cable benefits most from slower online TVOD speeds. More generally, these findings highlight that consumers in the sample care about buffer time in addition to the prices of different platforms.

In the Appendix, Tables 19 and 18 present more details on the distribution of these elasticities. We also show that the findings are qualitatively similar if we consider relative changes in demand (percent instead of percentage points, Table 20).

Table 4: Median own and cross-price elasticities

Panel A: TV show			
	DVD	Cable TVOD	Online TVOD
DVD	-1.092	0.292	0.374
Cable TVOD	0.547	-2.317	0.449
Online TVOD	0.635	0.420	-2.097
Outside	0.751	0.215	0.179
Panel B: Movie			
	DVD	Cable TVOD	Online TVOD
DVD	-1.648	0.654	0.622
Cable TVOD	0.880	-2.153	0.573
Online TVOD	0.995	0.542	-2.207
Outside	0.901	0.440	0.399

Notes: Cell entires i,j where i indexes row and j column, give the percentage change in demand (choice probabilities) of option i following a 1 percent change in the price of platform j. Each entry represents the median of the elasticities across individuals. Changes are computed relative to the actual price of using the platform (TV show: 12.99 for DVD, 29.99 for cable TVOD, and 24.99 for online TVOD; movie: 16.96 for DVD, 21.99 for cable TVOD, 19.99 for online TVOD.)

6 Policy experiment

Net Neutrality rules would prohibit internet service providers (ISP) from discriminating between different content providers by slowing down some providers and speeding up others. In order to gain some insight into the possible effect of Net Neutrality rules through this channel, we consider the effect of changing the buffer times of online TVOD. As our baseline, we consider a world without Net Neutrality. We then model the impact of Net Neutrality by lowering the buffer time of online TVOD to 0 (i.e., equal to the buffer time for cable TVOD). We study two versions of this experiment, one where prices are held constant, and one where either the cable TVOD or the online TVOD change their price to match their competitor's (so that *both* buffer time and price are equalized between these two platforms). In line with the rest of our analysis, we focus on shedding light on the possible demand-side effects of

Table 5: Demand impacts of changes in the buffer time for online TVOD

Panel A: TV show			
	Buffer time change		
	0 to 3 min	0 to 5 min	0 to 10 min
DVD	0.140	0.231	0.451
Cable TVOD	0.356	0.527	0.841
Online TVOD	-1.099	-1.612	-2.593
Outside	0.401	0.565	0.829
Panel B: Movie			
	Buffer time change		
	0 to 3 min	0 to 5 min	0 to 10 min
DVD	0.155	0.253	0.498
Cable TVOD	0.246	0.386	0.690
Online TVOD	-0.806	-1.308	-2.465
Outside	0.296	0.475	0.881

Notes: Changes in demand (choice probabilities) in percentage point following an indicated change in the buffer time of online TVOD, holding everything else constant at the values used in the experiment. Each entry represents the median change across individuals.

these changes. To study either different industry equilibria or social welfare impacts would require a supply side model.

6.1 Baseline

To model the no-Net Neutrality baseline, we first need to choose reasonable prices and buffer times. Appendix Table 12 lists the actual prices of the movie and TV show used in our experiment around the time of the experiment. These show remarkable homogeneity within platform type (in particular, each of these products had the same price across all TVOD providers we could find). Based on this table, we set the no-Net Neutrality baseline price of the TV show for DVD, cable, and online TVOD to 12.99, 29.99, and 24.99, respectively. We set the price of the movie to 16.99, 21.99, and 19.99 for these three platforms.

We also need to decide what a reasonable nonzero buffer time is. To do this, we computed actual buffer times under different internet packages around the time of our experiment (Tables 14 and 13) and we chose the lowest nonzero buffer time for both the movie and for the TV show. This was, respectively, 23 minutes and 3 minutes. We think these values should provide a conservative estimate of the impact of Net Neutrality. In the Appendix, we also repeat the exercise using baseline buffer times that are either twice as large or half of these (i.e., using 1.5 or 6 minutes for the TV show and 11.5 or 46 minutes for the movie). We find that the patterns using these values are qualitatively similar to those we obtain with the original values.

Since cable TVOD involves no buffering, its buffer time is set to 0. For the DVD option, time depends on many unobserved factors (like transportation options, traffic, etc.). Here we set the times equal to the actual times given in the choice experiment scenarios (between 5 and 60 minutes): predicted demand will reflect each consumer's average choices across these values. These baseline attribute values are summarized in Table 6, and Table 7 shows predicted demand in the baseline.

Table 6: Baseline attribute values for the counterfactual experiments

	DVD / Blu-Ray	Cable TVOD	Online TVOD
TV show			
Actual prices	12.99	29.99	24.99
Actual buffer time (minutes)	Between 5 and 60	0	3
Movie			
Actual prices	16.99	21.99	19.99
Actual buffer time (minutes)	Between 5 and 60	0	23

In the baseline, DVD has the largest market share, which can be explained by the lowest price of this option. The market share of DVD is relatively larger in the case of the TV show, where the price difference relative to cable or online TVOD is particularly large. For the movie, the price advantage of DVD is smaller, and consequently the market shares are more balanced.

Note that here "market shares" reflect consumers' choices on how to watch a particular TV show or movie, rather than all the choices made for all the content they might consume over a period of time using different platforms. Note also that, by design, the content we chose for the experiment was not available on subscription streaming services (e.g., Netflix). For these reasons, we may not expect the market shares in Table 7 to correspond to more broadly interpreted observed market shares. Still, the market shares in Table 7 are not unrealistic. According to 2017 industry data, consumers spent twice as much on DVDs as they did on buying electronic video content.[21] In the same year, 56% of consumers who bought or rented video content reported exclusively using physical copies (DVD or Blu-ray).[22]

Table 31 in the Appendix shows the same baseline market shares when the model is

[21] https://nscreenmedia.com/home-entertainment-spending-up-due-to-svod/

[22] For other years, the corresponding figure was 60% (2015), 59% (2016), and 49% (2018). https://www.npd.com/wps/portal/npd/us/news/press-releases/2018/more-than-half-of-video-buyers-and-renters-in-the-us-purchased-digital-content-in-2017/

estimated without the DVD option (using the 2nd choices indicated in the survey). When this option is excluded, we obtain relatively larger market shares for online TVOD in the case of the TV show, while the market shares remain more balanced for the movie.

Table 7: Predicted market shares at baseline

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
DVD	0.424	0.424	0.063	0.343	0.508
Cable TVOD	0.108	0.108	0.011	0.094	0.122
Online TVOD	0.166	0.165	0.025	0.136	0.202
Outside	0.302	0.299	0.050	0.239	0.369
Panel B: Movie					
DVD	0.308	0.295	0.071	0.228	0.405
Cable TVOD	0.210	0.217	0.071	0.113	0.310
Online TVOD	0.210	0.201	0.049	0.155	0.271
Outside	0.272	0.270	0.024	0.242	0.305

Notes: Predicted market shares (choice probabilities) under the baseline attribute values (see Table 6).

6.2 Experiment 1: equal buffer time for online and cable TVOD

Table 8 shows the impact on market shares of a counterfactual policy experiment where the buffer time for online TVOD is set to 0, i.e., equated to cable's buffer time, while holding prices fixed at their baseline values. Values are percentage point changes in market shares relative to the baseline values in Table 7. The lower buffer time results in an increase of online TVOD's market share of around 1.12 percentage points for the TV show and 4.54 percentage points for the movie. The change is particularly disadvantageous for cable, which loses 0.45 percentage points in market share for the TV show and 2.19 percentage points for the movie.

These findings help further quantify why an ISP may have an incentive to limit the speed of competing online TVOD providers (or to charge them for higher speeds).

It is interesting to note that, based on Table 8, lowering the buffer time of online TVOD also has a market expansion effect. For example, in the case of the movie, the share of consumers choosing the outside option decreases by just over 1 percentage point. The presence of these consumers, who would leave the market rather than switch to cable if the ISP throttled online TVOD, suggest that in some cases the ISP could gain by allowing online TVOD a higher speed in exchange for a fee. Theoretically, the fee could be set high enough

Table 8: Experiment 1: equal buffer time for online and cable TVOD

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
DVD	-0.226	-0.211	0.095	-0.385	-0.120
Cable TVOD	-0.449	-0.457	0.106	-0.585	-0.302
OnlineTVOD	1.120	1.143	0.127	0.941	1.267
Outside	-0.446	-0.463	0.093	-0.549	-0.304
Panel B: Movie					
DVD	-1.288	-1.192	0.501	-1.988	-0.707
Cable TVOD	-2.193	-2.234	0.656	-2.988	-1.183
Online TVOD	4.538	4.586	0.686	3.654	5.396
Outside	-1.057	-1.022	0.367	-1.556	-0.619

Notes: Changes in market shares when the buffer time for online TVOD is set to 0. Changes are in percentage points relative to the baseline.

to extract online TVOD's increased revenue from *both* the consumers who switch to it from cable *and* the consumers who switch to it from the outside option. In this case, charging a lump-sum fee could make the ISP better off than simply throttling. This highlights another potential implication of the finding that consumers' willingness to pay for download speed is nonzero in this context. Table 21 and 22 in the Appendix shows qualitatively similar effects for alternative values of baseline buffer times.

Table 23 in the Appendix shows price elasticities when buffer time for online TVOD is set to 0. Intuitively, when the speed advantage of cable is removed, cable and online TVOD become closer substitutes, resulting in larger elasticities. Consequently, small changes in prices can be expected to induce larger changes in market shares in the presence of Net Neutrality. This may create incentives for increased price competition, as well as a number of other actions by ISPs (such as bundling their services or charging access fees, etc.). Of course, modeling these explicitly would require information on marginal costs and the nature of strategic interactions in this market. Our setting allows us to explore the demand impacts of specific changes to prices, and we investigate one such change in our second counterfactual.

6.3 Experiment 2: equal buffer time and price for online and cable TVOD

We consider a second experiment, where in addition to reducing online TVOD buffer time to 0, we also set the price of cable equal to that of online TVOD. This may be interpreted as simulating the introduction of Net Neutrality, followed by a price reduction by the cable provider in an attempt to stay competitive with online TVOD. Since for a given content these providers only compete in two dimensions, download time and price, it is interesting to study the impact of competition in price alone if competition in download time is shut down by Net Neutrality rules. Of course, we can only simulate the effect of these changes on the demand side. A full analysis of these issues would require comparing pricing equilibria using a supply side model.

As shown in Table 9, lowering the price of cable to that of online TVOD has an important mediating effect on the simulated impact of Net Neutrality.[23] For the TV show, the price reduction wipes out the gains of online TVOD from the reduction in buffer time, and the market share of cable increases by 5.46 percentage points relative to the baseline. For the movie, price equalization still benefits cable, but the gains from the buffer time reduction for online TVOD were large enough that the net effect is an increase in market shares for both cable and online TVOD by approximately equal amounts (around 2.7 percentage points). Eliminating buffer time and equalizing the price of cable and online TVOD lowers the market share of DVD by about 3.3 percentage points for both the TV show and the movie.

Table 9: Experiment 2: equal buffer time and price for online and cable TVOD

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
DVD	-3.305	-3.342	0.453	-3.897	-2.708
Cable TVOD	5.462	5.425	0.483	4.846	6.091
Online TVOD	-0.649	-0.608	0.302	-1.061	-0.294
Outside	-1.508	-1.532	0.350	-1.964	-1.007
Panel B: Movie					
DVD	-3.268	-3.306	0.617	-4.087	-2.356
Cable TVOD	2.767	2.794	1.128	1.187	4.287
Online TVOD	2.686	2.660	0.797	1.618	3.846
Outside	-2.184	-2.256	0.375	-2.621	-1.664

Notes: Changes in market shares when the buffer time for online TVOD is set to 0, and simultaneously the price of cable is set equal to the price of online TVOD. Changes are in percentage points relative to the baseline.

These results indicate that Net Neutrality has the potential to increase price competition on the video on-demand market by creating an incentive for cable to lower its price in order to offset any reduction in the buffer time of online TVOD. An alternative scenario is that

[23] Here, since both attributes of cable and online TVOD are equalized, differences in the demand for the two platforms reflect consumer preferences captured by the choice-specific constants and their interactions with demographics.

instead of cable lowering prices, the online TVOD provider could find it profitable to increase its price.[24] To investigate this possibility, Table 24 in Appendix 8.6 considers an experiment where after its buffer time is set to 0, as above, the online TVOD provider raises its price to match the baseline price of cable. We find that this would result in *reductions* in demand for online TVOD both for the TV show and the movie relative to the baseline. Based on this simple experiment, it is not clear that online TVOD would find it worthwhile to raise its price.

6.4 Representativeness of the results

The sample consists of students, whose decisions may be different from the US population. To gauge the extent to which our sample differs from the population, we look at all the factors entering our estimation (high-speed internet availability at home, DVD/Blu-ray ownership, age and household income) and compare them to the US population. We collected data on internet access from the FCC's Internet Access Services Status Report, and DVD/Blu-ray ownership data from Nielsen's Total Audience Report. Information about age and income for the US population was taken from the Census.

Table 10 shows the distribution of these four variables both in the sample and the population. Measures of DVD/Blu-ray ownership and high-speed internet access closely match those of the US population. The distribution of household income is also very close.[25] As expected, the biggest difference is in the age distribution.[26] In particular, we have no respondents over the age of 50, which is an important limitation of our study.

In an attempt to assess the validity of our conclusions for the (under-50) population as a whole, we compute weighted estimates. Specifically, we create weights based on household income and age (because of limited data, we assume that these attributes are independent). We create nine weights separately for both the TV and the movie sample, capping the highest age at 50.

Section 8.7 in the Appendix contains the distribution of willingness to pay (corresponding to Table 3) and the results from the policy experiments using the weighted data. We find that the results are very similar to those reported above. This is likely due to the fact that

[24] Whether this is realistic depends on the timing of the different players' responses. Since the immediate impact of Net Neutrality is to lower cable's revenue, cable would likely have an incentive to offset these losses by moving quickly to reduce prices, rather than wait for the online TVOD provider to increase its price.

[25] The University of Houston is one of the largest public universities in the country and ranks at or near the top of diversity rankings. A large share of the undergraduate population is non-traditional (older students, who work, have dependents, and commute to school). These features help explain the representativeness of our sample.

[26] Note that all estimates presented above control for age, and we do not find a significant correlation with choice probabilities.

Table 10: Characteristics of the sample vs the US population

Characteristic	US Census	Survey sample
Household income		
Under 39,999	0.43	0.34
40,000 to 69,999	0.29	0.36
70,000 and over	0.28	0.31
Age		
18-24	0.22	0.82
25-29	0.17	0.16
30-49	0.61	0.02
Internet		
Broadband internet at home based on survey		0.82
Subscribership ratio from FCC (Texas)	0.78	
Subscribership ratio from FCC (US)	0.82	
Dvd/Blu-ray		
Owns a dvd / blu-ray player based on survey		0.78
Nielsen technology penetration (dvd/blu-ray)	0.77	

Sources: U.S. Census Bureau, Current Population Survey, 2017 (Annual Social and Economic Supplement, Table 2). FCC: Internet Access Services: Status as of December 31, 2016 (Figure 32 and 34), https://www.fcc.gov/general/iatd-data-statistical-reports. The Nielsen Total Audience Report, Q1, 2016. The Nielsen Company (p9, 13).

the only characteristic significantly correlated with choices was household income, and the sample turns out to be highly representative of the US population along this dimension.

7 Conclusion

In this paper, we estimate consumer substitution between cable on-demand and competing viewing platforms for fixed content. Given that approximately 100 million US households have cable service and 80% of these households also have broadband internet, the substitution between cable and online TVOD is an important ingredient in understanding an ISP's incentive to engage in vertical foreclosure or to price discriminate between content providers through speed-based access fees.

We designed and analyzed a hypothetical choice experiment where consumers decide between various viewing platforms for a specific media content, either a movie or a TV show. Estimating a random utility demand model shows that consumers in this setting are highly sensitive to both price and download time. The latter means that a necessary condition for ISP's incentive for vertical foreclosure (or access fees) is satisfied. This sets the stage for an analysis of the impact of Net Neutrality on the market for on-demand media content. When the buffer time of the online TVOD service is eliminated, cable on-demand loses a significant share of the market. By prohibiting this, Net Neutrality hurts the cable provider. If the cable provider reacts to the policy by lowering its price, it can offset these losses, particularly for the product where the price difference is currently larger. This suggests that Net Neutrality may create incentives for increased price competition on the video on-demand market.

By focusing on consumers' choice between platforms for a given content, we have analyzed one important aspect of the impact of Net Neutrality on the market for on-demand media content. Understanding how consumers trade off internet speed and price is a crucial first step in studying many other aspects of Net Neutrality rules, including pricing of internet plans, bundling, or even market integration. Of course, a full policy analysis would also need to carefully model considerations that our experiment was not designed to answer. For example, it is unknown how many consumers would switch away from an ISP in protest if they learned that it practiced foreclosure. Similarly, by modeling the supply side, future research might quantify how the nature of price competition mediates the impact of Net Neutrality, as well as broader impacts of the policy on firm profits or product innovation.

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8 Appendix

8.1 Definitions of the variables

Table 11: Variable definitions

Price	Price of the tv show / movie.
Buffer time	Measured in minutes. This is the wait time until a purchased TV show / movie can be viewed after purchase without interruption. For the physical dvd, the buffer time attribute is travel time to a store.
Age	Age of the respondent
Low income	1 if the respondent's household income is below 40,000 USD, 0 otherwise.
Medium income	1 if the respondent's household income is between 40,001 and 70,000 USD, 0 otherwise
High income	1 if the respondent's household income is above 70,001 USD, 0 otherwise
Owns a DVD player	1 if the respondent owns a dvd-player or a Blu-ray player, 0 otherwise. The TV show scenarios are about an SD version, this can be viewed using either a DVD or a Blu-ray player
Owns a Blu-ray player	1 if the respondent owns a Blu-ray player, 0 otherwise. The movie scenarios are about an HD version which can only be viewed using a Blu-ray player.
Owns high speed internet	1 if the respondent has a DSL, Cable or Fiber internet connection at home. 0 if the responent has a satellite connection or no internet connection at home.

8.2 Product availability, prices, and buffer times

Table 12: Availability and price of the products used in the choice experiment

	Movie	TV show
Subscription based services		
Netflix	Not available	Not available
Hulu	Not available	Not available
Amazon Prime	Not available	Not available
Pay per movie		
Google Play - rent	Not available	Not available
Google Play - buy	SD: not available, HD: 19.99	SD: 24.99, HD: not available
Amazon on Demand - rent	Not available	Not available
Amazon on Demand - purchase	SD: 19.99, HD: 19.99	SD: 24.99 or 1.99 per episode, HD: only per episode, 24*2.99=73
Comcast Xfinity on Demand - rent	Not available	Not available
Comcast Xfinity on Demand - purchase	SD: 21.99, HD: 21.99	SD: 29.99, HD:39.99
Dierct TV on Demand - purchase	Not available	Not available
Direct TV on Demand - rent	Not available	Not available
PlayStation - purchase	SD: 19.99, HD: 19.99	SD: 24.99 or 1.99 per episode, HD: not available
PlayStation - rent	Not available	Not available
VUDU - rent	Not available	Not available
VUDU - buy	SD: not available, HD: 19.99	SD: 24.99, HD: 29.99
Redbox	Not available	Not available
YouTube - rent	Not available	Not available
YouTube - purchase	SD: not available, HD: 19.99	SD: 24.99, HD: 29.99
Buy DVD	10.46	12.99
Buy Blu-ray	16.96	15.83
Itunes - rent	Not available	Not available
Itunes - purchase	SD: 19.99, HD: 19.99	SD:24.99, HD: 29.99

Notes: Availability and price of the products for common providers as of 3/16/2016. The movie is "Star Wars Episode III - Revenge of the Sith," the TV show is "Modern Family - Season 1."

This section describes how we selected the buffer time values used in the choice experiment based on actual buffer times available on the market around the time of our study (March-June 2016). The two most important factors that determine buffer time are the speed of the internet connection and the bit rates of the streaming service. In order to stream a movie without buffering, one's connection must be able to download its content at least as fast as the bit rate of the streaming service. The lower the internet speed and the higher the video bit rate, the longer is the buffer time.

Denote x the streaming bit rate in megabytes per second (Mbps), y the speed of the internet connection in Mbps and b the length of the content in minutes (140 for the movie, 20 for the TV show). Since the connection can keep downloading while viewers watch, if the connection speed is greater than the video bit rate ($y > x$), streaming can start immediately without interruption. On the other hand if $x > y$, there will be a buffer time. Since viewers can watch while downloading, they do not have to wait for the whole content to be downloaded to be able to watch uninterruptedly. This requires only that the whole content finishes downloading at the same time as the length of the movie plus the buffer time:

$$\text{buffer time} = \text{download time} - \text{video length}$$

In general,

$$\text{Buffer time} = b\frac{x-y}{y},$$

where bx is size of the content, thus $\frac{bx}{y}$ is the time needed to download the full content. Based on the formula, we computed the buffer time for different types of streaming service with different internet providers These values are shown in Table 13 and 14 for the movie and the TV show, respectively. Internet connection speed is based on the most popular advertised download tiers for various providers according to the FCC. For completeness, the tables also include computed buffer times for services that were not available in the survey area, such as Fiber.

Table 13: Buffer time in minutes for movie for different combinations of internet and streaming service

Internet provider (download speed, Mbps)	*Streaming service* (video bit rate, Mbps) Comcast on demand HD (15)	Netflix HD (7)	Vudu (4.5)	Amazon HD (3.5)	Amazon SD (0.9)
ATT-DSL (3)	560	187	70	23	0
ATT-DSL (6)	210	23	0	0	0
ATT-Uverse (12)	35	0	0	0	0
ATT-Uverse (18)	0	0	0	0	0
CenturyLink (10)	70	0	0	0	0
Frontier DSL (3)	560	187	70	23	0
Verizon (1.5)	1260	513	280	187	78
Windstream (6)	210	23	0	0	0
Cablevision (50)	0	0	0	0	0
Charter (30)	0	0	0	0	0
Charter (60)	0	0	0	0	0
Comcast (25)	0	0	0	0	0
Comcast (50)	0	0	0	0	0
Cox (25)	0	0	0	0	0
Cox (50)	0	0	0	0	0
Mediacom (15)	0	0	0	0	0
Mediacom (50)	0	0	0	0	0
TWC (30)	0	0	0	0	0
Frontier Fiber (25)	0	0	0	0	0
Verizon Fiber (35)	0	0	0	0	0
Hughes (5)	280	56	0	0	0
Hughes (10)	70	0	0	0	0
Viasat/Exede (12)	35	0	0	0	0

Notes: Download speed values for different internet providers are from Table 1 of "Measuring Broadband America Fixed Broadband Report, A Report on Consumer Fixed Broadband Performance in the United States" by FCC's Office of Engineering and Technology and Consumer and Governmental Affairs Bureau, 2015. (https://www.fcc.gov/reports-research/reports/measuring-broadband-america). When more than two tiers are listed, we use the middle tier(s); otherwise, we use each listed tier. Video bit rates refer to the amount of data stored for each second of media that is played. Videos that are encoded with higher bit rates usually have higher quality, and therefore need a higher internet speed to download without buffer. Video bit rates are collected from the provider's websites.

Table 14: Buffer time in minutes for TV show for different combinations of internet and streaming service

Internet provider (download speed, Mbps)	*Streaming service* (video bit rate, Mbps) Comcast on demand HD (15)	Netflix HD (7)	Vudu (4.5)	Amazon HD (3.5)	Amazon SD (0.9)
ATT-DSL (3)	80	27	10	3	0
ATT-DSL (6)	30	3	0	0	0
ATT-Uverse (12)	5	0	0	0	0
ATT-Uverse (18)	0	0	0	0	0
CenturyLink (10)	10	0	0	0	0
Frontier DSL (3)	80	27	10	3	0
Verizon (1.5)	180	73	40	27	13
Windstream (6)	30	3	0	0	0
Cablevision (50)	0	0	0	0	0
Charter (30)	0	0	0	0	0
Charter (60)	0	0	0	0	0
Comcast (25)	0	0	0	0	0
Comcast (50)	0	0	0	0	0
Cox (25)	0	0	0	0	0
Cox (50)	0	0	0	0	0
Mediacom (15)	0	0	0	0	0
Mediacom (50)	0	0	0	0	0
TWC (30)	0	0	0	0	0
Frontier Fiber (25)	0	0	0	0	0
Verizon Fiber (35)	0	0	0	0	0
Hughes (5)	40	8	0	0	0
Hughes (10)	10	0	0	0	0
Viasat/Exede (12)	5	0	0	0	0

Notes: Download speed values for different internet providers are from Table 1 of "Measuring Broadband America Fixed Broadband Report, A Report on Consumer Fixed Broadband Performance in the United States" by FCC's Office of Engineering and Technology and Consumer and Governmental Affairs Bureau, 2015. (https://www.fcc.gov/reports-research/reports/measuring-broadband-america). When more than two tiers are listed, we use the middle tier(s); otherwise, we use each listed tier. Video bit rates refer to the amount of data stored for each second of media that is played. Videos that are encoded with higher bit rates usually have higher quality, and therefore need a higher internet speed to download without buffer. Video bit rates are collected from the provider's websites.

8.3 Survey design

Figure 3: Sample scenario from the choice experiment

Imagine you would like to watch the popular movie "Star Wars Episode III – Revenge of the Sith" (2005) in High Definition. You currently don't own this movie. This movie is not available on Netflix, Amazon Prime or Hulu, and it is also not available for rent anywhere. This movie is only available for purchase.
Imagine the four options below are your only choices. Which one would you choose? (Please indicate your first choice and your second choice)

First choice: ❍1 ❍2 ❍3 ❍4 **Second choice**: ❍1 ❍2 ❍3 ❍4

Option 1: Buy the movie on Blu-Ray.	Option 2: Buy the movie on Cable on Demand (such as Xfinity on Demand)	Option 3: Buy the movie on a streaming service (such as Amazon, VUDU or Google Play)	Option 4: I do not buy or watch this movie.
$12	**$21**	**$30**	
Going to the store and back will take **30 minutes.**	You can start watching the movie **IMMEDIATELY.**	You need to wait **9 hours** before you can start watching the movie.	

8.4 Parameter estimates

Table 15: Parameter estimates, movie

Mean parameters	(1)	(2)	(3)	(4)	(5)
Mean parameters					
owns dvd player x dvd	0.332	0.278	0.336	0.285	0.297
	(0.504)	(0.516)	(0.540)	(0.554)	(0.553)
owns dvd player x cable	0.288	0.229	0.354	0.317	0.333
	(0.599)	(0.615)	(0.619)	(0.647)	(0.644)
owns dvd player x online	-0.037	-0.153	-0.078	-0.168	-0.157
	(0.497)	(0.512)	(0.536)	(0.548)	(0.548)
age x dvd	-0.025	-0.025	-0.013	-0.016	-0.016
	(0.038)	(0.039)	(0.047)	(0.046)	(0.047)
age x cable	-0.043	-0.046	-0.033	-0.037	-0.037
	(0.055)	(0.057)	(0.066)	(0.069)	(0.068)
age x online	-0.006	-0.005	0.007	0.003	0.003
	(0.032)	(0.034)	(0.042)	(0.041)	(0.042)
owns high-speed x dvd	-0.397	-0.333	-0.205	-0.002	-0.004
	(0.679)	(0.686)	(0.716)	(0.739)	(0.741)
owns high-speed x cable	0.143	0.224	0.260	0.573	0.567
	(0.729)	(0.737)	(0.779)	(0.740)	(0.737)
owns high-speed x online	0.354	0.441	0.541	0.763	0.760
	(0.602)	(0.618)	(0.647)	(0.665)	(0.667)
low income x dvd	-0.144	-0.217	-0.165	0.125	0.124
	(0.573)	(0.600)	(0.626)	(0.622)	(0.622)
low income x cable	-1.218*	-1.297*	-1.331*	-1.155	-1.156
	(0.674)	(0.703)	(0.705)	(0.713)	(0.715)
low income x online	-0.582	-0.710	-0.646	-0.410	-0.412
	(0.575)	(0.630)	(0.652)	(0.650)	(0.651)
med income x dvd	-0.395	-0.413	-0.251	-0.092	-0.103
	(0.587)	(0.600)	(0.632)	(0.684)	(0.695)
med income x cable	-0.723	-0.737	-0.627	-0.440	-0.455
	(0.702)	(0.716)	(0.735)	(0.778)	(0.792)
med income x online	-0.355	-0.405	-0.234	-0.079	-0.093
	(0.593)	(0.618)	(0.648)	(0.689)	(0.702)
dvd	5.012***	5.139***	4.669***	4.884***	4.886***
	(1.074)	(1.090)	(1.286)	(1.271)	(1.271)
cable	5.598***	5.740***	5.389***	5.411***	5.427***
	(1.430)	(1.470)	(1.689)	(1.727)	(1.717)
online	4.398***	4.560***	4.091***	4.338***	4.339***
	(0.946)	(0.988)	(1.167)	(1.144)	(1.149)
download time	-0.004***	-0.005***	-0.005***	-5.619***	-5.614***
	(0.000)	(0.002)	(0.002)	(0.289)	(0.292)
price	-0.196***	-0.199***	-1.737***	-1.674***	-1.673***
	(0.016)	(0.016)	(0.082)	(0.082)	(0.082)
SD parameters					
download time		0.004**	0.004*	1.793***	1.811***
		(0.002)	(0.002)	(0.217)	(0.233)
price	0.110***	0.111***	0.608***	0.575***	0.572***
	(0.012)	(0.012)	(0.051)	(0.052)	(0.052)
Covariance (price - time)					-0.028
					(0.098)
N	5,608	5,608	5,608	5,608	5,608
Log likelihood at convergence	-1308.78	-1305.59	-1298.30	-1269.97	-1269.92

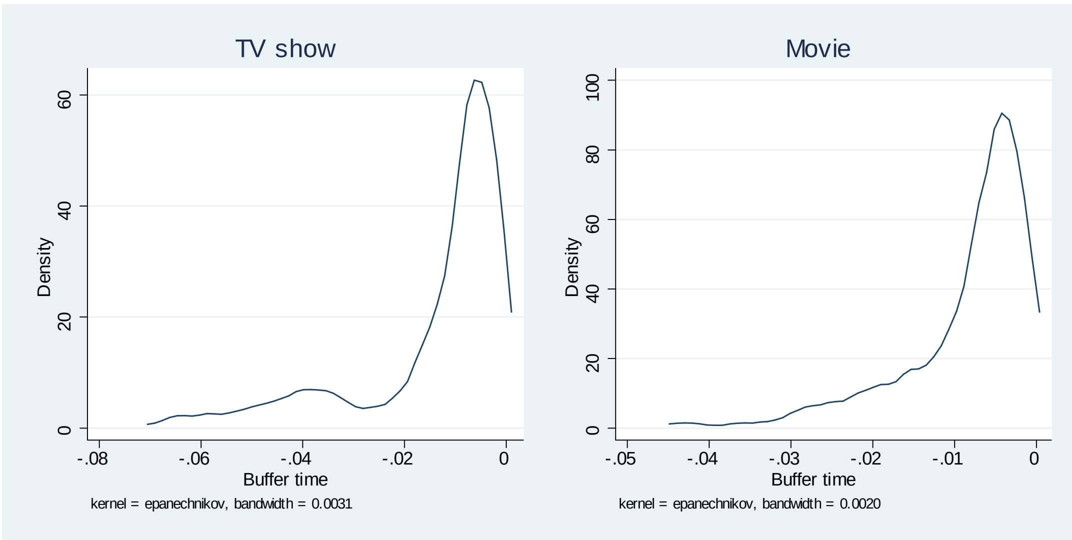
Notes: Parameter estimates from the mixed logit model for the movie scenarios. The specification of the random coefficients is as follows. Column 1: normal distribution for price; column 2: normal distribution for both price and time, independent; column 3: log-normal distribution for price; column 4: log-normal distribution for both price and time, independent; column 5: log-normal distribution for both price and time, correlated. Robust standard errors in parentheses. ***, **, * denote significance at the 1, 5, and 10 percent level, respectively.

Table 16: Parameter estimates, TV show

	(1)	(2)	(3)	(4)	(5)
Mean parameters					
owns dvd player x dvd	0.536	0.650	0.858	0.726	0.737
	(0.499)	(0.516)	(0.547)	(0.586)	(0.589)
owns dvd player x cable	0.470	0.537	0.822	0.792	0.760
	(0.564)	(0.567)	(0.609)	(0.606)	(0.599)
owns dvd player x online	0.576	0.715	0.975	0.810	0.804
	(0.543)	(0.584)	(0.603)	(0.590)	(0.588)
age x dvd	0.004	0.002	-0.023	-0.025	-0.027
	(0.062)	(0.066)	(0.070)	(0.073)	(0.074)
age x cable	0.028	0.037	0.020	0.007	0.004
	(0.073)	(0.074)	(0.075)	(0.075)	(0.075)
age x online	0.042	0.048	0.020	0.017	0.015
	(0.073)	(0.083)	(0.086)	(0.084)	(0.085)
owns high-speed x dvd	-0.636	-0.968*	-0.636	-0.366	-0.382
	(0.584)	(0.580)	(0.609)	(0.628)	(0.642)
owns high-speed x cable	-0.377	-0.760	-0.344	-0.163	-0.182
	(0.722)	(0.676)	(0.672)	(0.674)	(0.674)
owns high-speed x online	-0.426	-0.836	-0.453	-0.189	-0.219
	(0.667)	(0.639)	(0.652)	(0.649)	(0.657)
low income x dvd	0.846	0.709	0.724	0.778	0.792
	(0.570)	(0.603)	(0.659)	(0.684)	(0.704)
low income x cable	0.690	0.432	0.537	0.605	0.656
	(0.731)	(0.730)	(0.762)	(0.778)	(0.788)
low income x online	0.472	0.251	0.293	0.375	0.409
	(0.682)	(0.725)	(0.763)	(0.756)	(0.774)
med income x dvd	0.186	0.196	0.239	0.297	0.309
	(0.511)	(0.547)	(0.594)	(0.622)	(0.632)
med income x cable	0.092	0.021	0.147	0.143	0.157
	(0.648)	(0.652)	(0.668)	(0.675)	(0.676)
med income x online	-0.160	-0.207	-0.125	-0.054	-0.038
	(0.620)	(0.666)	(0.704)	(0.693)	(0.699)
dvd	2.970**	3.457**	3.646**	3.787**	3.860**
	(1.492)	(1.573)	(1.691)	(1.710)	(1.720)
cable	2.932*	3.232*	3.095*	3.415**	3.566**
	(1.704)	(1.753)	(1.811)	(1.719)	(1.708)
online	2.684	2.993	3.145	3.369*	3.466*
	(1.765)	(1.966)	(2.057)	(1.963)	(1.969)
download time	-0.005***	-0.012***	-0.010***	-5.612***	-5.452***
	(0.002)	(0.003)	(0.003)	(0.475)	(0.486)
price	-0.181***	-0.179***	-1.845***	-1.813***	-1.796***
	(0.016)	(0.016)	(0.091)	(0.090)	(0.090)
SD parameters					
download time		0.018***	0.016***	2.188***	2.225***
		(0.003)	(0.003)	(0.393)	(0.608)
price	0.116***	0.109***	0.730***	0.701***	0.659***
	(0.015)	(0.013)	(0.066)	(0.066)	(0.062)
Covariance (price - time)					-0.185***
					(0.053)
N	5,952	5,952	5,952	5,952	5,952
Log likelihood at convergence	-1467.15	-1437.71	-1421.53	-1409.86	-1409.02

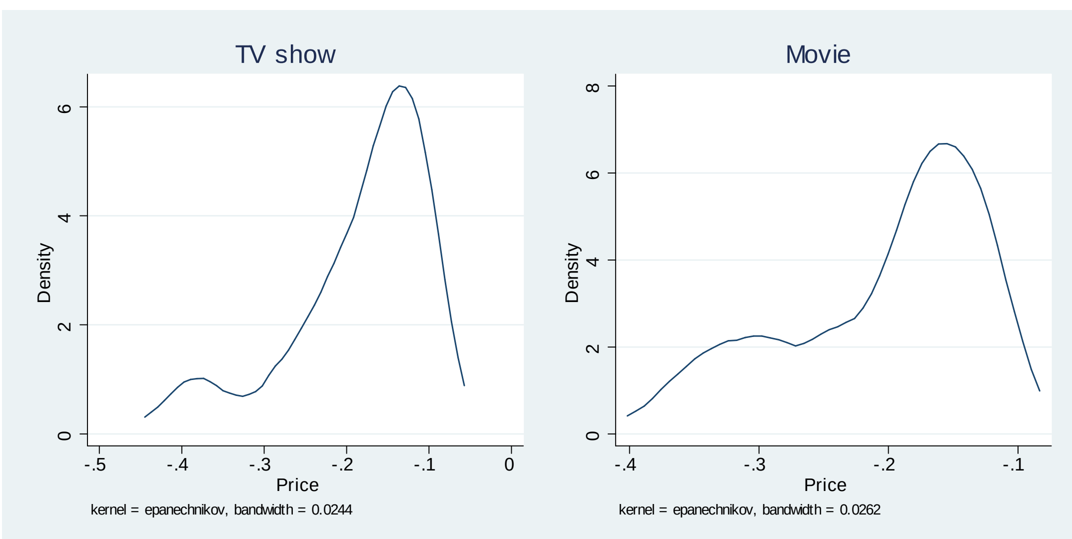
Notes: Parameter estimates from the mixed logit model for the movie scenarios. The specification of the random coefficients is as follows. Column 1: normal distribution for price; column 2: normal distribution for both price and time, independent; column 3: log-normal distribution for price; column 4: log-normal distribution for both price and time, independent; column 5: log-normal distribution for both price and time, correlated. Robust standard errors in parentheses. ***, **, * denote significance at the 1, 5, and 10 percent level, respectively.

Figure 4: Distribution of individual buffer time coefficients



Notes: Buffer time coefficients from the specification in column (4) in Table 15 and column (5) in Table 16 for the 154 (141) individuals faced with the TV show (movie) scenario. Graphed values are for the 10-90 percentile range.

Figure 5: Distribution of individual price coefficients



Notes: Price coefficients from the specification in column (4) in Table 15 and column (5) in Table 16 for the 154 (141) individuals faced with the TV show (movie) scenario. Graphed values are for the 10-90 percentile range.

8.5 Alternative WTP estimates

Following Train and Weeks (2005), we also estimate the model in "WTP space." Here, equation (1) is rewritten as

$$U_{njt} = \alpha_n p_{njt} + \alpha_n w_n b_{njt} + z_n' \gamma_j + \varepsilon_{njt},$$

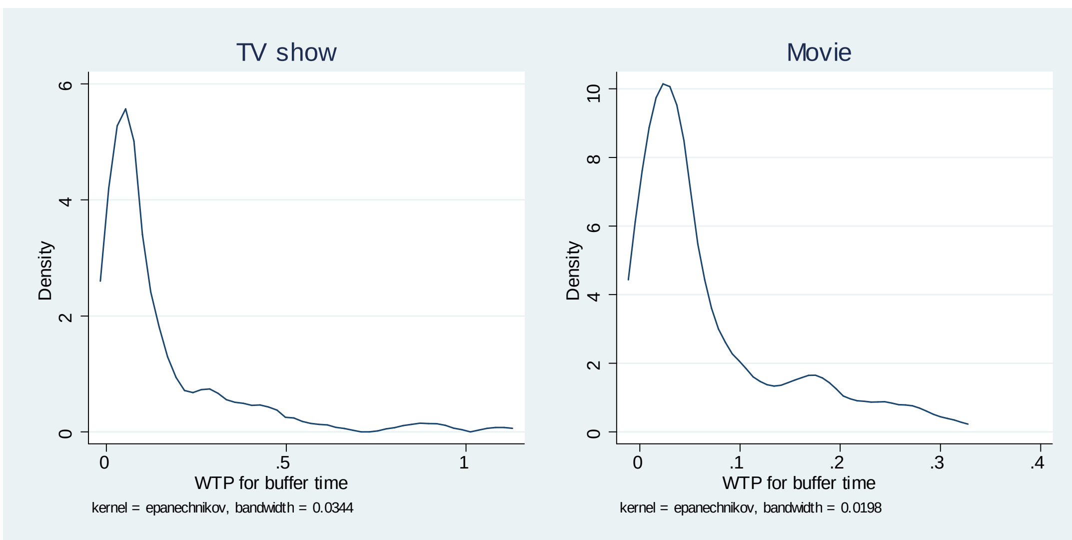
where $w_n = \beta_n / \alpha_n$ is the decision maker's willingness to pay for buffer time. A log-normal distribution is assumed for the price coefficient α_n and the *willingness to pay* coefficient w_n, and estimation proceeds using Simulated Maximum Likelihood as above. Resulting estimates are summarized in Table 17 and Figure 6.

Table 17: WTP for buffer time using model estimates in WTP space

	Mean	Median	St.dev.	10%	90%	N
TV show	0.975	0.065	4.141	0.018	1.095	154
Movie	0.168	0.034	0.412	0.008	0.311	141

Notes: WTP estimates from a model estimated in WTP space, assuming lognormally distributed WTP coefficients for both price and buffer time (see Train and Weeks, 2005). Estimation was performed using the mixlogitwtp command in Stata. The model also controls for demographic variables as described in the text.

Figure 6: WTP for buffer time using model estimates in WTP space



Notes: Distribution of WTP estimates from a model estimated in WTP space, assuming lognormally distributed WTP coefficients for both price and buffer time (see Train and Weeks, 2005). Values shown are for the 10-90 percentile range. Estimation was performed using the mixlogitwtp command in Stata. The model also controls for demographic variables as described in the text.

8.6 Additional tables

Table 18: Price elasticities

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
Price change for DVD					
DVD	-1.108	-1.092	0.255	-1.503	-0.782
Cable TVOD	0.539	0.547	0.165	0.301	0.743
Online TVOD	0.647	0.635	0.16	0.438	0.868
Outside	0.743	0.751	0.262	0.311	1.072
Price change for cable					
DVD	0.427	0.292	0.300	0.151	0.910
Cable TVOD	-2.309	-2.317	0.153	-2.510	-2.114
Online TVOD	0.484	0.420	0.265	0.175	0.872
Outside	0.237	0.215	0.121	0.096	0.416
Price change for online TVOD					
DVD	0.486	0.374	0.322	0.142	0.962
Cable TVOD	0.517	0.449	0.280	0.197	0.924
Online TVOD	-2.104	-2.097	0.170	-2.319	-1.916
Outside	0.236	0.179	0.186	0.038	0.494
Panel B: Movie					
Price change for DVD					
DVD	-1.665	-1.648	0.374	-2.175	-1.175
Cable TVOD	0.837	0.880	0.335	0.318	1.253
Online TVOD	0.969	0.995	0.388	0.419	1.463
Outside	0.833	0.901	0.356	0.259	1.257
Price change for cable					
DVD	0.760	0.654	0.508	0.180	1.537
Cable TVOD	-2.143	-2.153	0.288	-2.516	-1.753
Online TVOD	0.705	0.542	0.478	0.191	1.470
Outside	0.514	0.440	0.317	0.154	0.997
Price change for online TVOD					
DVD	0.699	0.622	0.473	0.114	1.442
Cable TVOD	0.608	0.573	0.397	0.111	1.178
Online TVOD	-2.148	-2.207	0.319	-2.539	-1.680
Outside	0.468	0.399	0.337	0.041	0.988

Notes: Percentage change in demand (choice probabilities) following a 1 percent change in the price of the indicated platform. Changes are computed relative to the actual price of using the platform (TV show: 12.99 for DVD, 29.99 for cable, and 24.99 for online TVOD; movie: 16.96 for DVD, 21.99 for cable, 19.99 for online TVOD.

Table 19: Demand impacts of changes in the buffer time for online TVOD

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
Buffer time changes: 0 to 3 min					
DVD	0.192	0.140	0.157	0.040	0.398
Cable TVOD	0.412	0.356	0.201	0.198	0.725
Online TVOD	-1.182	-1.099	0.566	-2.040	-0.452
Outside	0.578	0.401	0.427	0.100	1.242
Buffer time changes: 0 to 5 min					
DVD	0.315	0.231	0.261	0.066	0.648
Cable TVOD	0.611	0.527	0.306	0.292	1.075
Online TVOD	-1.764	-1.612	0.892	-3.126	-0.658
Outside	0.837	0.565	0.647	0.139	1.857
Buffer time changes: 0 to 10 min					
DVD	0.605	0.451	0.509	0.129	1.257
Cable TVOD	0.991	0.841	0.524	0.432	1.762
Online TVOD	-2.910	-2.593	1.593	-5.449	-1.032
Outside	1.314	0.829	1.084	0.193	3.114
Panel B: Movie					
Buffer time changes: 0 to 3 min					
DVD	0.194	0.155	0.142	0.050	0.402
Cable TVOD	0.279	0.246	0.147	0.115	0.513
Online TVOD	-0.770	-0.806	0.217	-1.024	-0.467
Outside	0.297	0.296	0.151	0.081	0.518
Buffer time changes: 0 to 5 min					
DVD	0.323	0.253	0.236	0.084	0.663
Cable TVOD	0.444	0.386	0.234	0.187	0.814
Online TVOD	-1.241	-1.308	0.368	-1.655	-0.714
Outside	0.474	0.475	0.251	0.111	0.837
Buffer time changes: 0 to 10 min					
DVD	0.634	0.498	0.467	0.163	1.260
Cable TVOD	0.799	0.690	0.430	0.313	1.462
Online TVOD	-2.297	-2.465	0.754	-3.162	-1.194
Outside	0.863	0.881	0.493	0.177	1.548

Notes: Changes in demand (choice probabilities) in percentage point following an indicated change in the buffer time of online TVOD, holding everything else constant at the values used in the experiment.

Table 20: Relative demand impacts of changes in buffer time

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
Buffer time changes: 0 to 3 min					
DVD	0.724	0.525	0.676	0.144	1.378
Cable TVOD	4.713	4.532	2.559	1.502	8.184
Online TVOD	-5.670	-5.429	1.920	-8.371	-3.451
Outside	3.483	1.866	3.823	0.339	9.625
Buffer time changes: 0 to 5 min					
DVD	1.209	0.849	1.172	0.232	2.287
Cable TVOD	7.089	6.662	4.112	2.066	12.776
Online TVOD	-8.272	-7.929	2.609	-12.011	-5.313
Outside	5.061	2.593	5.785	0.450	14.336
Buffer time changes: 0 to 10 min					
DVD	2.400	1.604	2.458	0.442	4.746
Cable TVOD	11.694	10.354	7.502	3.134	22.380
Online TVOD	-13.188	-12.562	3.685	-18.472	-9.100
Outside	7.964	3.856	9.641	0.613	23.485
Panel B: Movie					
Buffer time changes: 0 to 3 min					
DVD	0.890	0.758	0.647	0.216	1.900
Cable TVOD	4.481	4.460	2.302	1.541	7.478
Online TVOD	-3.365	-3.112	2.015	-6.401	-0.998
Outside	2.243	1.578	1.847	0.374	5.056
Buffer time changes: 0 to 5 min					
DVD	1.495	1.265	1.115	0.354	3.214
Cable TVOD	7.308	7.103	3.942	2.252	12.721
Online TVOD	-5.258	-4.921	2.963	-9.718	-1.700
Outside	3.652	2.417	3.173	0.559	8.504
Buffer time changes: 0 to 10 min					
DVD	3.020	2.509	2.381	0.675	6.549
Cable TVOD	13.609	12.647	8.217	3.668	25.254
Online TVOD	-9.242	-8.844	4.648	-16.228	-3.435
Outside	6.844	4.183	6.495	0.882	16.820

Notes: Percentage changes in demand (choice probabilities) following an indicated change in buffer time.

Table 21: Experiment 1: equal buffer time for online and cable TVOD, lower baseline

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
DVD	-0.116	-0.107	0.051	-0.201	-0.060
Cable TVOD	-0.259	-0.263	0.057	-0.337	-0.185
Online TVOD	0.646	0.656	0.069	0.545	0.727
Outside	-0.271	-0.282	0.049	-0.327	-0.195
Panel B: Movie					
DVD	-0.705	-0.624	0.299	-1.137	-0.367
Cable TVOD	-1.390	-1.408	0.381	-1.860	-0.812
Online TVOD	2.773	2.827	0.365	2.287	3.207
Outside	-0.678	-0.659	0.222	-0.987	-0.411

Notes: Changes in market shares when the buffer time for online TVOD is set to 0, relative to a baseline of 1.5 minutes for TV show and 11.5 minutes for the movie. Changes are in percentage points relative to the baseline.

Table 22: Experiment 1: equal buffer time for online and cable TVOD, higher baseline

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
DVD	-0.431	-0.414	0.167	-0.694	-0.238
Cable TVOD	-0.734	-0.760	0.190	-0.961	-0.464
Online TVOD	1.851	1.889	0.233	1.521	2.124
Outside	-0.687	-0.718	0.169	-0.873	-0.433
Panel B: Movie					
DVD	-2.208	-2.119	0.766	-3.245	-1.309
Cable TVOD	-3.195	-3.262	1.032	-4.436	-1.629
Online TVOD	6.930	6.928	1.175	5.445	8.481
Outside	-1.527	-1.446	0.549	-2.262	-0.885

Notes: Changes in market shares when the buffer time for online TVOD is set to 0, relative to a baseline of 6 minutes for the TV show and 46 minutes for the movie. Changes are in percentage points relative to the baseline.

Table 23: Median own and cross-price elasticities, equal buffer time for online and cable TVOD

Panel A: TV show			
	DVD	Cable TVOD	Online TVOD
DVD	-1.020	0.332	0.531
Cable TVOD	0.594	-2.598	0.693
Online TVOD	0.681	0.483	-2.213
Outside	0.841	0.140	0.295
Panel B: Movie			
	DVD	Cable TVOD	Online TVOD
DVD	-2.068	0.695	0.864
Cable TVOD	0.800	-2.618	0.885
Online TVOD	0.835	0.745	-2.311
Outside	0.763	0.398	0.583

Notes: Cell entires i,j where i indexes row and j column, give the percentage change in demand (choice probabilities) of option i following a 1 percent change in the price of platform j. Each entry represents the median of the elasticities across individuals. Download speed is set to zero for both cable and online TVOD. Changes are computed relative to the actual price of using the platform (TV show: 12.99 for DVD, 29.99 for cable, and 24.99 for online TVOD; movie: 16.96 for DVD, 21.99 for cable, 19.99 for online TVOD.)

Table 24: Experiment 2: equal buffer time and price for online and cable TVOD, with baseline cable prices for both

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
DVD	3.417	3.473	0.403	2.754	3.856
Cable TVOD	0.862	0.831	0.240	0.582	1.197
Online TVOD	-5.151	-5.109	0.704	-6.117	-4.306
Outside	0.872	0.835	0.331	0.466	1.316
Panel B: Movie					
DVD	1.053	1.050	0.275	0.722	1.430
Cable TVOD	-0.602	-0.595	0.341	-1.040	-0.136
Online TVOD	-0.729	-0.806	0.353	-1.126	-0.213
Outside	0.278	0.324	0.196	-0.013	0.491

Notes: Changes in market shares when the buffer time for online TVOD is set to 0 and its price is set equal to the price of cable. Changes are in percentage points relative to the baseline.

8.7 Weighted results

Table 25: Summary statistics of individual coefficients and WTP buffer time, weighted

	Mean	Median	St.dev.	10%	90%	N
TV show						
Price	-0.192	-0.175	0.104	-0.351	-0.075	154
Buffer time	-0.054	-0.005	0.263	-0.088	-0.002	154
WTP for buffer time	0.395	0.031	2.397	0.014	0.507	154
Movie						
Price	-0.269	-0.271	0.117	-0.379	-0.134	141
Buffer time	-0.013	-0.003	0.039	-0.043	-0.002	141
WTP for buffer time	0.055	0.015	0.124	0.005	0.189	141

Notes: Summary statistics for price and buffer time coefficient estimates from column (4) of Tables 15 and column (5) of Table 16 in the Appendix, and implied willingness to pay for buffer time.

Table 26: WTP for buffer time using model estimates in WTP space, weighted

	Mean	Median	St.dev.	10%	90%	N
TV show	0.975	0.065	4.141	0.018	1.095	154
Movie	0.106	0.017	0.257	0.006	0.253	141

Notes: WTP estimates from a model estimated in WTP space, assuming lognormally distributed WTP coefficients for both price and buffer time (see Train and Weeks, 2005). Estimation was performed using the mixlogitwtp command in Stata. The model also controls for demographic variables as described in the text.

Table 27: Predicted market shares at baseline, weighted

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
DVD	0.380	0.381	0.066	0.302	0.464
Cable TVOD	0.117	0.117	0.011	0.101	0.131
Online TVOD	0.194	0.198	0.029	0.153	0.227
Outside	0.310	0.310	0.051	0.249	0.373
Panel B: Movie					
DVD	0.308	0.307	0.071	0.222	0.397
Cable TVOD	0.160	0.151	0.070	0.072	0.248
Online TVOD	0.244	0.242	0.051	0.181	0.298
Outside	0.288	0.288	0.025	0.257	0.326

Notes: Predicted market shares (choice probabilities) under the baseline attribute values (see Table 6).

Table 28: Experiment 1: equal buffer time for online and cable TVOD, weighted

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
DVD	-0.229	-0.207	0.102	-0.397	-0.117
Cable TVOD	-0.484	-0.497	0.106	-0.624	-0.350
Online TVOD	1.185	1.210	0.124	1.014	1.332
Outside	-0.472	-0.581	0.094	-0.495	-0.321
Panel B: Movie					
DVD	-1.561	-1.431	0.603	-2.631	-0.801
Cable TVOD	-2.056	-1.960	0.716	-3.078	-0.992
Online TVOD	4.977	5.060	0.572	4.240	5.497
Outside	-1.360	-1.260	0.449	-2.212	-0.833

Notes: Changes in market shares when the buffer time for online TVOD is set to 0. Changes are in percentage points relative to the baseline.

Table 29: Experiment 2: equal buffer time and price for online TVOD and cable, weighted

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
DVD	-3.263	-3.278	0.528	-3.953	-2.584
Cable TVOD	5.888	5.942	0.528	5.239	6.554
Online TVOD	-0.978	-0.972	0.363	-1.512	-0.501
Outside	-1.647	-1.706	0.357	-2.147	-1.147
Panel B: Movie					
DVD	-3.013	-2.993	0.635	-3.837	-2.121
Cable TVOD	1.871	1.854	1.081	0.349	3.333
Online TVOD	3.377	3.355	0.835	2.328	4.512
Outside	-2.235	-2.307	0.418	-2.733	-1.669

Notes: Changes in market shares when the buffer time for online TVOD is set to 0, and simultaneously the price of cable is set equal to the price of online TVOD. Changes are in percentage points relative to the baseline.

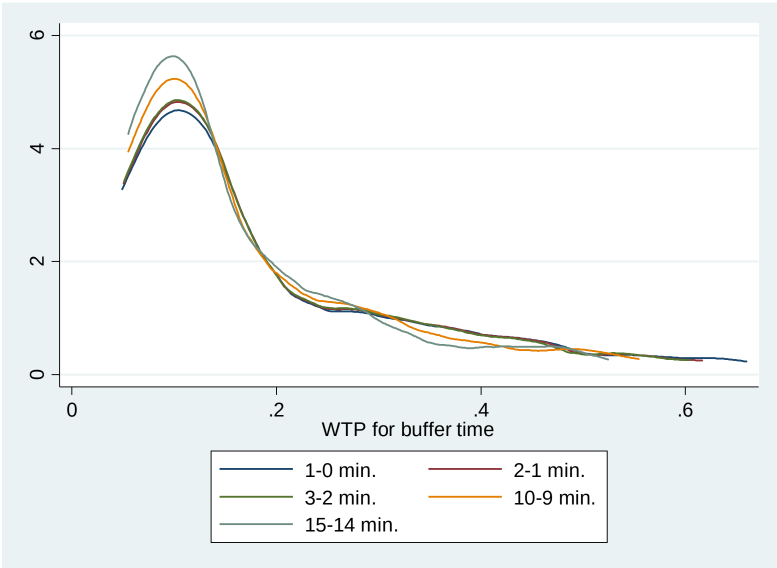
8.8 Nonlinear buffer time

We investigated whether allowing for a nonlinear buffer time effect would affect our estimates. To do this, we added the squared of buffer time to our preferred specifications (column 4 in Table 15 for the movie and column 5 in Table 16 for the TV show). We include a separate random coefficient on this new variable, assuming a Normal distribution. We estimate both the mean and the standard deviation of the new coefficient, and, for the specification on the TV show, we also estimate its covariances with the other two random coefficients in the model.

For the movie, our point estimate for the mean of the new random coefficient is 1.19×10^{-6}, with a std. error of 1.09×10^{-6}. Our estimate for the standard deviation is 1.04×10^{-7}, with a std. error of 7.21×10^{-8}. These estimates are neither statistically nor economically significant and reject the nonlinear model in favor of the linear specification.

For the TV show, our point estimates are also small, but they are statistically significant: 1.91×10^{-4} (std. error: 5.87×10^{-5}) for the mean and 3.76×10^{-4} (std. error: 8.40×10^{-5}) for the standard deviation. To see if this specification would cause large changes in our results, we computed the individual willingness to pay estimates for a 1 minute reduction in buffer time starting from different baseline levels. Figure 7 shows the distribution of these individual willingness to pay estimates for a change from 2 to 1 minute, 3 to 2 minutes, 11 to 10 minutes, and 15 to 14 minutes. Recall that our counterfactual exercise for the TV show is based on a reduction from 3 to 0 minutes. As can be seen WTP values for a 1 minute change in the 1-3 minute interval are indistinguishable from each other, and even changes from a baseline of 15 minutes (half the length of the TV show) cause little change in the distribution of the estimates. It appears that the nonlinear effects are small enough that they do not have a large impact for the relevant range of buffer times.

Figure 7: Distribution of individual WTP for time allowing for nonlinear time effects (TV show)



Notes: Distributions shown are for decreasing buffer time for the TV show by 1 minute from baselines of 1, 2, 3, 10 or 15 minutes. Values shown are for the 10-90 percentile range.

8.9 Results excluding the DVD option

The option to purchase a DVD differs from online and cable TVOD in that a consumer who chooses this option would have to travel to the store rather than simply wait for the download to complete. It is possible that, in real-world scenarios, some consumers would not consider this option. Thanks to the design of our experiment, it is possible to directly check the extent to which the presence of this option in the survey affects the results.

In each choice scenario, we asked participants to indicate both their first and second choice among the four options listed (this is similar to the design of Leung (2013)). To provide estimates without the DVD option, we can simply use the 2nd choice of those who indicated the DVD as their 1st choice in the experiment. (Since respondents who did not indicate the DVD as their 1st choice should make the same choice without the DVD option, we continue to use their 1st choice.)

The resulting estimates of individual coefficients and WTP for buffer time are summarized in Table 30, and Figure 8 shows the histogram of the WTP estimates.[27] Overall, the distribution of the individual coefficients is similar to those in Table 3. While values in the tails of the distribution lead to a larger mean WTP for buffer time for the TV show, comparing Figure 8 to Figure 6 shows that these distributions are also fairly similar.

Table 30: Summary statistics of individual coefficients and WTP for buffer time

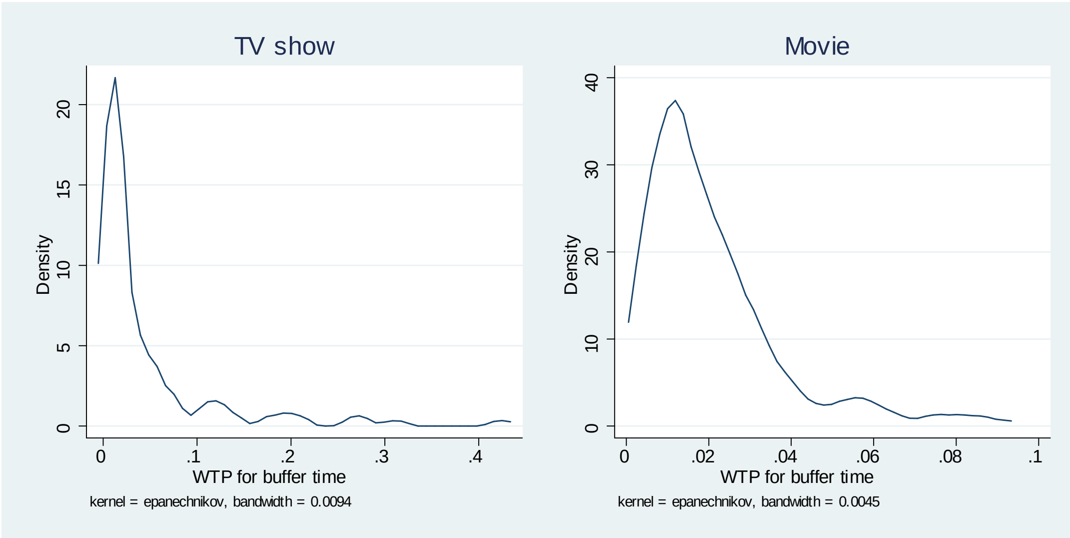
	Mean	Median	St.dev.	10%	90%	N
TV show						
Price	-0.176	-0.167	0.078	-0.291	-0.093	129
Buffer time	-0.390	-0.002	1.809	-0.076	-0.001	129
WTP for buffer time	2.285	0.015	13.469	0.004	0.424	129
Movie						
Price	-0.202	-0.183	0.089	-0.325	-0.106	125
Buffer time	-0.007	-0.003	0.018	-0.014	-0.001	125
WTP for buffer time	0.046	0.017	0.108	0.005	0.089	125

Notes: Summary statistics of the estimated individual-level price and buffer time coefficients based on column (4) of Table 15 (movie) and column (5) of Table 16 (TV show) in the Appendix, and implied willingness to pay for buffer time.

Table 31 shows the market shares predicted at the baseline price and buffer time values. Because the DVD option is excluded, the market shares of the other options are now higher. In Table 7 the median market share of the DVD was 42.4% for the TV show and 29.5%

[27] As before, we exclude respondents who always made the same choice among the included alternatives. In addition, we exclude observations where the DVD was indicated as the 1st choice but the 2nd choice is missing (1.7% of observations).

Figure 8: Distribution of individual WTP for buffer time



Notes: Individual WTP for buffer time computed using the parameter estimates in column (4) of Table 15 and column (5) of Table 16 in the Appendix. Values are for the 10-90 percentile range.

for the movie, and this is now allocated roughly equally among the remaining three options (cable, online TVOD, outside good).

Results of the two counterfactual experiments are described in Tables 32 and 33. When the buffer time for online TVOD is set to 0, some consumers switch to online TVOD from the other possible options (Table 32). As before, we find that consumers are particularly likely to switch from cable, both in the case of the TV show and the movie. Relative to our earlier estimates, the difference between the TV show and the movie is now smaller: cable loses 1.1 percentage points in market share for the TV show and 1.7 percentage points for the movie. As above, these findings highlight that an ISP/cable provider could gain by limiting the download speeds of competing online TVOD services.

When cable responds to the decline in online TVOD's buffer time by lowering its price, it gains customers (Table 33). Relative to our earlier estimates, the resulting increase in market shares is now larger for both the TV show (+11 percentage points) and the movie (+4.6 percentage points). This reinforces the idea that Net Neutrality may create an incentive for cable to lower its price and thereby increase price competition on the video on-demand market.

Table 31: Predicted market shares at baseline

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
Cable TVOD	0.249	0.249	0.028	0.206	0.285
Online TVOD	0.349	0.352	0.041	0.280	0.402
Outside	0.402	0.377	0.055	0.359	0.505
Panel B: Movie					
Cable TVOD	0.327	0.315	0.111	0.188	0.469
Online TVOD	0.340	0.336	0.069	0.265	0.426
Outside	0.333	0.325	0.062	0.259	0.410

Notes: Predicted market shares (choice probabilities) under the baseline attribute values (see Table 6).

Table 32: Experiment 1: equal buffer time for online and cable TVOD

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
Cable TVOD	-1.140	-1.204	0.177	-1.315	-0.810
Online TVOD	1.877	1.900	0.178	1.569	2.090
Outside	-0.738	-0.740	0.059	-0.802	-0.663
Panel B: Movie					
Cable TVOD	-1.706	-1.747	0.269	-1.944	-1.353
Online TVOD	2.636	2.685	0.275	2.347	2.920
Outside	-0.930	-0.925	0.329	-1.374	-0.539

Notes: Changes in market shares when the buffer time for online TVOD is set to 0. Changes are in percentage points relative to the baseline.

Table 33: Experiment 2: equal buffer time and price for online and cable TVOD

	Mean	Median	Std. dev.	10%	90%
Panel A: TV show					
Cable TVOD	11.049	11.082	0.924	9.295	12.119
Online TVOD	-5.482	-5.804	1.015	-6.452	-3.499
Outside	-5.567	-5.636	0.363	-6.027	-5.019
Panel B: Movie					
Cable TVOD	4.584	4.718	1.004	3.169	5.715
Online TVOD	-1.215	-1.233	0.804	-2.167	-0.083
Outside	-3.369	-3.459	0.300	-3.748	-3.011

Notes: Changes in market shares when the buffer time for online TVOD is set to 0, and simultaneously the price of cable is set equal to the price of online TVOD. Changes are in percentage points relative to the baseline.