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The Effect of Binge-Watching on the Subscription of Video on Demand: Results from Randomized Experiments

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Abstract. We analyze the outcomes of two randomized field experiments to study the effect of binge-watching on subscription to video on demand. In both cases, we offered access to subscription VoD (SVoD) to a random set of households for several weeks and used another random set of households as a control group. In both cases, we find that the households that binge-watch TV shows are less likely to pay for SVoD after these free trials. Our results suggest that binge-watchers deplete the content of interest to them very quickly, which reduces their short-term willingness to pay for SVoD. We also show that recommendation reminders aimed at widening the content preferences of households offset the negative effect of binge-watching and lessen the concerns of binge-watchers with lack of content refresh. We discuss that these recommendation reminders may help content providers manage supply costs, which may otherwise become prohibitive with frequent updates to SVoD catalogs.

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Keywords: binge-watching • subscription video on demand • recommendation reminders • randomized experiment • content

1. Introduction

Binge-watching refers to watching videos, usually TV shows, for an extended period in one sitting. In 2013, Harris Interactive surveyed 3,078 U.S. adults on behalf of Netflix, of whom 1,496 reported streaming TV shows at least once per week. Seventy-three percent of the latter defined binge-watching as watching two or more episodes of the same TV show in sequence (Spangler 2013). Seventy-six percent of respondents reported that binge-watching multiple episodes of a great TV show is a refuge from their busy lives, and 79% reported that binge-watching makes the TV shows more enjoyable. More recently, in 2016, Deloitte surveyed 2,131 U.S. consumers, of whom 73% reported binge-watching an average of six episodes, or five hours, per sitting. Ninety percent of millennials reported having binge-watched before, and 38% of them reported doing so every week (Deloitte 2016).

Some degree of binge-watching has existed since the 1990s. Binge-watching became possible with the DVD format, but only recently has binge-watching become a notable cultural and social phenomenon (Matrix 2014, Richmond 2014). Nowadays, many industry reports cite binge-watching as a regular practice among U.S. consumers (Statista 2016). In the world of linear TV, in which episodes of the same TV show are, for the most part, aired on a weekly or a daily basis, binge-watching is possible only if episodes are broadcast back-to-back, which is seldom the case. Video streaming technologies that are now prevalent both online (Matrix 2014) and on TV (Abreu et al. 2017, Belo et al. 2019) triggered the shift toward binge-watching. These technologies allow consumers to optimize their schedules and watch their preferred content whenever they want. Streaming technologies also allow content providers to make several episodes of the same TV show available at once, which is necessary for binge-watching.

The introduction of binge-watching can have significant implications for the entertainment industry. Besides the already visible changes on the demand side, binge-watching can significantly affect the supply side of the market. In particular, binge-watching is already affecting the creative process and the programming and distribution strategies of content providers, calling for changes to the business models used to monetize content. For example, some screenwriters now write "highly serialized" stories that consumers can appreciate better when viewed in multiepisode sessions (Jurgensen 2012, Barton 2015). Some content distributors encourage binge-watching using novel video-on-demand (VoD) client features such as automatically starting the next episode of a particular TV show when one episode ends. Some content distributors even release all episodes of the same TV show season at once (Schweidel and Moe 2016), inviting consumers to watch full seasons in only a few days.

The entertainment industry has been moving quickly to embrace business models that support binge-watching despite the lack of studies looking at the effects that may arise from such practice. Content providers and distributors have been keen to implement strategies that promote binge behavior without knowing in detail the potential problems that they may trigger. For example, consuming more content per unit of time can lead consumers to deplete the content of interest to them faster. Faster content depletion by consumers may increase the cost that firms have to incur to add new titles to their catalogs in order to keep consumers engaged. This paper aims to address this knowledge gap by studying the effect of binge-watching during free trials on subscription to video-on-demand services.

In this paper, we explore the results from two randomized field experiments, run in partnership with a large telecommunications provider, which we call TELCO. In our first experiment, several households were offered access for free to a channel that broadcast movies and TV shows 24/7, hereafter called the TV Show Channel (TVSC). A random subset of households was offered access to the TVSC with time-shift TV (TSTV). The remainder were offered access to this channel without TSTV. Another independent random subset of households was held out for control purposes. The first set of households could use TSTV to binge-watch TV shows by going back in time and consuming several episodes of the same TV show in the same sitting. We find that offering access to the TVSC increased its overall consumption and that doing so with TSTV increased its use in binge mode. We also find that offering access to this channel without TSTV did not change the households' likelihood of subscribing to the TVSC after the experiment. However, offering access to the TVSC with TSTV reduced the latter by about 10%. We then use the random assignment of treatments during this experiment as instruments for the time that households spent watching this channel in binge and nonbinge modes. This strategy allows us to show that the reduction in the subscription probability of this channel resulted from the time that households spent binge-watching it during the experiment. At this stage, the fact that binge-watching reduced consumers' willingness to subscribe to VoD after a free trial is a surprising result for practitioners, who embraced the binge-watching culture, potentially ignoring this negative outcome.

In our second randomized experiment, we study in more detail the mechanisms by which binge-watching reduces the likelihood of VoD subscription. To this end, we study TELCO-SVoD, a streaming subscription VoD (SVoD) service similar to Netflix, Hulu, and Amazon Prime. Several households, selected at random, were offered access to this service for free for three months. Another random set of households was used as a control group and did not get this gift. Again, we observe that households offered this gift subscribed to the service less after the experiment, a result driven by the households that binge-watched TELCO-SVoD content. The reduction in subscriptions to TELCO-SVoD after this experiment is in line with the findings of our first experiment.

Our results suggest that households who binge-watched in our second experiment subscribed less to TELCO-SVoD because they depleted the content that was of interest to them faster. TELCO-SVoD was an attractive product to consumers at the beginning of the experiment but became less so as time passed without TELCO adding new content to the catalog at a fast enough pace. This result has significant implications for firms in the entertainment industry. Indexing the rate at which providers add content to SVoD libraries to the rate at which consumers watch content is likely to address this concern but may become exaggeratedly expensive with binge-watching. For example, Netflix has been adding original titles to its SVoD catalog at an unprecedented pace. Netflix more than doubled its long-term debt in 2017 to $4.8 billion and increased its long-term obligations, such as those with rolling licensing agreements, to $15.7 billion (Ng 2017).

To keep binge-watchers engaged with their SVoD service, distributors may try to expose households to content that is already in the VoD catalog but that they would not otherwise consider. Such a strategy is cheaper than continually refreshing the catalog at the rate of consumption. Consumers typically browse SVoD catalogs to form a consideration set and then choose content to watch from this smaller set of options (Honka and Chintagunta 2016, Chen and Yao 2017). Recommendation reminders can influence the consideration sets of consumers, in particular, if consumers would not organically look for the content recommended. Such recommendations may widen consumer preferences in ways that increase the enjoyment that consumers can derive from the existing catalog, ultimately leading them to pay for the service. By carefully matching recommendations of existing content to consumers, content providers may be able to slow the rate at which their existing SVoD libraries need to be refreshed. Such a strategy could allow them to manage costs more judiciously.

However, not all types of recommendation reminders may effectively achieve this objective. During TELCO's experiment with TELCO-SVoD, a subset of households selected at random received generic reminders telling them that they could use TELCO-SVoD to watch movies and TV shows. These reminders aimed at attracting consumers to TELCO-SVoD without giving them any suggestions for specific content to watch. Another subset of households, also selected at random, received customized reminders telling them that they could use TELCO-SVoD to watch particular TV shows. The specific TV shows suggested to each household were determined using a state-of-the-art recommender system. The remaining households did not receive any reminders. Reminders were sent out by text message every other week during the experiment. We find that customized reminders steered viewership toward content that households would not have organically chosen to watch. We also find that the households that received these reminders did not reduce their likelihood of subscribing to TELCO-SVoD after the experiment. The households that did not receive reminders or that received generic reminders still subscribed to TELCO-SVoD less after the experiment than did the corresponding control households. These results show that carefully crafted reminders may offset the reduction in the subscriptions to SVoD services that arises because of binge-watching. Therefore, our findings suggest that firms issuing recommendations for VoD content should prioritize targeting binge-watchers.

The fact that binge-watching may lead consumers to subscribe to SVoD less may seem puzzling at first, in particular given the significant investment of content providers and distributors to allow it. However, several reasons may explain why firms allow this behavior. First, binge-watching is becoming a mainstream mode of video consumption across all types of demographics, and being in business without serving binge-watchers may be disadvantageous. Second, consumers are usually willing to pay more for an SVoD service that allows for binge-watching. TELCO surveyed a random sample of households to learn their willingness to pay for binge-watching. Households in the survey reported being willing to pay \$1.90 for their favorite TV show if all its episodes were released weekly (one by one). These same households reported being willing to pay an additional \$7.10 if they could access all episodes of this TV show at once. These statistics show that content distributors may consider adding titles to SVoD libraries at a rate similar to the rate at which consumers watch it by sharing some of the additional costs with them, that is, having consumers pay more to binge-watch.

TELCO ran another survey to households included in the TELCO-SVoD experiment asking them whether they subscribed to the service after the experiment and if not, why. A disproportionate number of binge-watchers indicated lack of content refresh and a high service price as their main reasons for not subscribing. This self-reported assessment comes in line with the idea that content depletion is a problem in managing SVoD catalogs. The answers to this survey show that TELCO-SVoD lost value during the experiment, and more so for binge-watchers, who were no longer interested in paying \$9.50 per month to keep the service after the experiment. In contrast, households who received customized reminders did not indicate a lack of content refresh as a concern as often as other consumers. This difference provides additional evidence that customized recommendation reminders influenced the consideration sets of TELCO's consumers and increased the value they associated with the outstanding TELCO-SVoD catalog after the experiment. Our results provide a surprising perspective on the potential effect of binge-watching on the entertainment industry, inviting managers to consider the implications of allowing for binge-watching carefully. Although it may be too late to eradicate binge-watching altogether, managers may consider new business strategies to reduce consumers' ability to binge-watch, such as staggering the release of content, instead of allowing them to consume full TV show seasons during a free trial.

We provide additional results in the form of robustness checks that dismiss alternative reasons that could lead binge-watchers to subscribe to SVoD less than other households after a free trial. For example, we show that households were unlikely to exhaust their time budget to watch TV during the free trial of the TVSC. In our setting, content satiation does not seem to be the root cause of what we find in this experiment. We also find that the households offered access to TELCO-SVoD enjoyed more their overall experience with the VoD system at TELCO. They issued more likes per piece of content watched in the VoD system than control households, and the increment in this statistic comes from titles included in TELCO-SVoD. Therefore, content dislike was not the reason for which households that obtained access to this SVoD library canceled it after the free trial. We also show that past access to TVSC and TELCO-SVoD free trials did not change the likelihood of subscribing to them after our experiments. These results provide empirical evidence that in our setting, gifts did not reduce consumers' reference prices, which, if true, could lead to a reduction in subscription rates.

We organize the remainder of this paper as follows. The next section reviews the relevant literature on binge behavior, free trials, and recommendations. Section 3 studies the outcomes of our first randomized experiment and analyzes the effects of consumption and binge-watching on the likelihood of subscribing to SVoD. Section 4 studies the outcomes of our second randomized experiment and analyzes the effect of catalog exhaustion and reminders on the latter. Section 5 concludes.

2. Literature Review

2.1. Binge Behavior

Binge-watching is an accelerated rate of consumption over a short period (Schweidel and Moe 2016). In the medical literature, binge behavior is linked to addiction. For example, Kubey and Csikszentmihalyi (2002) study the addictive nature of watching TV. These authors find that viewing begets more viewing, because individuals want to maintain a passive and relaxed state of mind when they watch TV. Therefore, individuals engage in long viewing sessions to avoid the stress that they experience when TV viewing ends. Economists rationalize binge behavior in a utility maximization framework and suggest that when people binge, they optimize their consumption schedule for enjoyment purposes (Becker and Murphy 1988). However, marketing research shows that people adapt to repetitions of the same stimuli and that people are particularly bad at predicting hedonic adaptation (Loewenstein and Frederick 1997, Nelson and Meyvis 2008). For example, people adapt to regions that they enjoy (Schkade and Kahneman 1998), to repeated consumption of their preferred ice cream (Kahneman and Snell 1990), to repeated exposure to a song that they like (Galak et al. 2011), or to watching a TV show that they enjoy several times (Nelson et al. 2009). Frederick and Loewenstein (1999) discuss that with some exceptions, the process of adaptation reduces the enjoyment associated with positive experiences over time, which hints at the fact that binge behavior may be a suboptimal strategy for consumers to maximize their medium- to long-term utility. This stream of research on adaptation and on the progression of affect suggests that individuals choose to consume too quickly goods that they enjoy because they fail to self-control or hold incorrect beliefs (or misapply correct beliefs) about the benefits of longer interconsumption intervals (Galak et al. 2013). In this paper, we study the effect of binge-watching TV shows on consumers' enjoyment of and on their willingness to pay for a service that allows for binge-watching. This question is now pertinent to the entertainment industry because new business models based on SVoD have flourished in recent years, such as Netflix, Hulu, and Amazon Instant Video, which have been encouraging binge-watching at an unprecedented rate (Wilbur 2008, Bronnenberg et al. 2010, Schweidel and Moe 2016).

The increased rate of video consumption with binge-watching may trigger unforeseen consequences for the entertainment industry. For example, consumers are not likely to pay for SVoD catalogs that do not refresh at a reasonable pace. Binge-watchers deplete SVoD catalogs faster, exacerbating this problem. Furthermore, consumers have limited attention spans (Johnson et al. 2012), and each consumer is usually interested in only a relatively small subset of today's large SVoD catalogs (Godinho de Matos et al. 2018). To the best of our knowledge, Schweidel and Moe (2016) is the only paper that studies the impact of binge-watching TV shows, in this case, on the consumption of advertising. The authors characterize the drivers of binge-watching behavior and focus on its impact on the consumption of ads on Hulu.com. The study uses observational data and concludes that (1) viewing begets more viewing; (2) exposure to advertising discourages binge-watching; (3) binge-watching is affected by situational factors, such as content previously consumed and the individual's inherent tendency to engage in binge-watching; and (4) binge-watching has a negative impact on the response to advertising that worsens with the length of the viewing session.

2.2. Free Trials and Price Discounts

Our research is also tightly related to studies on free trials and price discounts. We find that free trials in SVoD cannibalize future subscriptions, and we link this result to the binge behavior of consumers during the trial period. Free trials are a common strategy to reduce consumers' uncertainty about new products (Datta et al. 2015). Price discounts are a frequent business practice to entice consumers, with free trials being a particular case in which consumers are allowed to experience the product at zero price for some amount of time. Trying out the product before purchase should lead consumers who like it to buy it and consumers who do not like the product not to buy. Therefore, free trials enable better matches, and thus improve market efficiency, assuming that the costs associated with them are negligible (which is usually the case in online platforms).

A related strategy to entice consumers to purchase new products is to allow for long free trials. This business practice, called freemium, is prevalent in the software industry Niculescu and Wu (2014) and in online settings (Bapna et al. 2016). In freemium business models, both a free and a premium paid version of the product are available in the market. The former offers only basic features, which usually cater to the majority of users, whereas the latter includes enhanced features usually tailored to the more demanding consumers. Fremium services allow consumers to experience the product as much as they want without giving them a deadline to decide on purchasing. Such an extended experimental period prevents forcing consumers to decide but, on the other hand, leads many of them to stay with the free version, which may hurt the firm's profit. Indeed, prior research in the online streaming of experience goods argues that freemium works best only when tied to additional triggers to entice purchases. Bapna and Umyarov (2015) provide an example showing how peer influence between premium and freemium consumers is critical to increasing conversion from freemium to premium.

The marketing literature has established that how consumers use products during free trials affects their subsequent purchase behavior. Foubert and Gijsbrechts (2016) link usage patterns during the free trial to whether such use accelerates, increases, or cannibalizes sales. Our study complements this line of research, highlighting that binge-watching TV shows during free trials can be detrimental for the post-free-trial subscription of video-on-demand products.

The literature in information systems and marketing also shows that allowing consumers to try products at reduced prices may backfire. Thaler (1985) and Klein and Oglethorpe (1987) argue that consumers formulate a reference price for how much they expect to pay for a product. These results suggest that price discounts accelerate purchases in the short term because consumers perceive a benefit associated with the gap between the reference price and the reduced list price, but may be detrimental for profitability in the long term. For example, Pauwels and Weiss (2008) show that consumers exposed to frequent price promotions adjust their reference price downward and are more likely to purchase the product only when discounted. These results show that price promotions and free trials can affect consumers' willingness to pay through mechanisms unrelated to how consumers use the products during the free-trial periods. Hence, studying the effect of how usage during free trials affects consumption requires a setting in which researchers can partial out these effects. We accomplish this in our paper. For example, when measuring the effect of binge-watching on the subscription of SVoD, we also look at whether past free trials moderate this effect.

Past literature also established that price promotions and free trials appeal to specific subsets of consumers. For example, Anderson and Simester (2004) show that, in some contexts, customers acquired using catalogs with discounted items exhibit higher long-term value (choose cheap, but buy more). Lewis (2006) shows that, in other contexts, customers acquired through promotions exhibit lower repurchase rates and smaller lifetime values. Datta et al. (2015) develop a structural model of consumer decision making in which they argue that customers acquired through free trials should exhibit lower retention rates and lower value, but should also be more responsive to marketing interventions.

Overall, the fact that free trials affect specific segments of the population implies that to study the effect of binge-watching during a free trial on the posttrial likelihood of service subscription requires running randomized field experiments. That is what we accomplish in our work to avoid self-selection into these trials.

2.3. Recommendation Reminders

Finally, our paper also draws on and contributes to the literature on recommendation reminders. We highlight how regular SVoD service reminders, enriched with content recommendations, may help consumers discover new content in the SVoD catalog and reduce the content-depletion effect that binge-watching causes. The Over-the-Top (OTT) Video Market Tracker presented at the 2016 National Association of Broadcasters show by Parks Associates suggests that the content library essentially determines the perceived value of an SVoD service. The focus on the content library should not be a problem for today's entertainment industry because content catalogs are now orders of magnitude larger than those offered by the traditional brick-and-mortar stores from a decade ago (Resnick and Varian 1997, Brynjolfsson et al. 2003, Anderson 2006). However, the same report shows that many households subscribe to SVoD services from particular providers because specific content is available there, and that they terminate the contract right after watching such content. This platform-hopping behavior arises in a world where consumers know what they want to watch beforehand, fetch the content that interests them quickly, watch it, and leave (Chernev 2003). Using a particular OTT platform to browse for new content to watch becomes only secondary—a process sometimes characterized as dull and time-consuming (Mullins 2016, Bolluyt 2017).

Psychology literature predicts that consumers might not be inclined to search too much for content, in particular, because individuals have limited cognitive processes, they have short attention spans, and they have difficulty processing new information (Camerer et al. 2003, Thaler and Sunstein 2008). It is therefore probable that individuals subscribing to SVoD services are unaware of the depth of the content library available to them and that they are unaware of the content that they could enjoy but never heard about. In this paper, we hypothesize that highlighting such content to consumers may increase the value that they associate with SVoD.

To highlight content to consumers, we rely on content recommendation systems. Recommendation systems help consumers navigate large sets of alternatives (Resnick and Varian 1997). At their core, recommendation systems change product saliency (Ferreira et al. 2020). They highlight particular products to consumers at the expense of others that become less visible. Häubl and Trifts (2000) discuss the challenges that consumers face when evaluating large product assortments. They run a controlled experiment using a simulated online store, and they find that recommendations reduce the search effort of consumers to fetch product information. They also find that recommendations shorten consideration sets but increase the quality of the products placed in these sets, improving the quality of purchase decisions. We find a similar phenomenon in our setting.

Many studies detail that the design of the recommendation system is critical to determining the quality of the matches that consumers can find via recommendations. For example, Fleder and Hosanagar (2009) use an analytical model and simulations to show that some recommender systems help individuals find new products but bias choice toward popular content, thus generating rich-get-richer phenomena that reduce aggregate diversity. Lee and Hosanagar (2019) show that collaborative filter recommendations increase the diversity of purchases at the individual level but move similar consumers to explore similar products, decreasing diversity across aggregate sales. On the other hand, content-based recommender systems have been shown to reduce the concentration of sales. Several authors find empirical evidence of this fact, for example, in Amazon's bookstore (Oestreicher-Singer and Sundararajan 2010), in the context of wedding service vendors (Tucker and Zhang 2011), in niche home video products (Elberse and Oberholzer-Gee 2007), and in the sales of music (Chellappa et al. 2007, Dewan and Ramaprasad 2012).

Although studies highlight that different recommendation algorithms have different impacts on sales diversity, the fact that these systems increase sales seems to be present everywhere. For example, in a set of three laboratory experiments, Adomavicius et al. (2017) show that willingness to pay for songs increases with recommendations even when the songs recommended are chosen at random or even when they are computed by a state-of-the-art recommender system but their ratings are scrambled randomly.

In parallel, the academic literature has also established that nudges and reminders help consumers overcome inattention by highlighting information about products that consumers incorporate in their decision-making processes (Häubl and Murray 2006, Johnson et al. 2012). For example, Karlan et al. (2016) developed and tested a model of limited attention in intertemporal choice in the context of savings decisions. In three field experiments, they showed that reminders increased savings for clients who had recently opened a savings account and that messages mentioning savings goals and financial incentives worked particularly well. In another field experiment, Calzolari and Nardotto (2017) showed that simple weekly reminders led users to increase gym attendance substantially. They also showed that, in their setting, users responded to reminders immediately and recurrently.

Furthermore, reminders are cheap, can scale up, and are not usually coercive, because individuals retain the freedom to ignore them (Momsen and Stoerk 2014). Reminders were shown to be effective in many different contexts, such as managing energy consumption (Allcott and Mullainathan 2010), adhering to healthcare treatments (Raifman et al. 2014), and even improving credit ratings (Bracha and Meier 2014). Therefore, we hypothesize that combining content recommendations with reminders—that is, issuing regular recommendations to consumers—may help consumers to discover new content in an SVoD catalog. Our paper studies how carefully crafted recommendation reminders may affect the subscription rates of SVoD in a real-world setting.

3. The Effect of Consumption and of Binge-Watching on SVoD Subscription

3.1. Experimental Design

Our industry partner, called TELCO, is a large multinational telecommunications provider. TELCO focuses on selling pay-TV services in the country we analyze, serving more than one million households.

In addition to TV, internet, and telephony, TELCO offers video on demand, both transactional (pay per item viewed) and subscription-based (monthly fee with unlimited viewership), as well as TSTV. TSTV allows consumers to watch past TV broadcasts on demand. It is a feature that comes bundled with most TV channels that TELCO distributes. The primary TV service offered by TELCO includes 100 TV channels and access to a transactional video-on-demand library with more than 2,000 movies and TV shows.

TELCO also offers additional services à la carte, which can be purchased separately. In particular, TELCO sells the TVSC—for \$6.5/month—which broadcasts popular TV shows 24/7. The commercial version of the TVSC comes bundled with TSTV. Households that purchase the TVSC can watch TV shows live, but they can also look back seven days in the programming of the TVSC broadcast. TSTV allows households to pause, rewind, and fast-forward through content and to watch episodes that aired at any time in the past week.

We use a random sample of 30,000 households in an experiment that focuses on the TVSC in the summer of 2015. These households did not subscribe to the TVSC in the month before this experiment. One-third of these households, from now on called the control, selected at random, were held out from any intervention. The other two-thirds, from now on called the Gift group, were offered access to the TVSC for six consecutive weeks. We split this group of households into two subgroups of equal size. The households in the Gift LinearTV group were offered access to the TVSC without TSTV; that is, they could access content aired on this channel during its live broadcast. We note that in the commercial offer of TELCO, the TVSC is not available without the TSTV feature. TELCO planned this offer specifically to enable this experiment and discontinued it right after. The households in the Gift TSTV group were offered access to this channel with TSTV; that is, they could access the content aired in this channel both live and using TSTV.

Households in the Gift TSTV group could binge-watch the content aired on this channel because going back in time allowed them to watch several episodes of the same TV show in the same sitting. Households in the Gift LinearTV group could watch more than one episode of the same TV show in the same sitting only if these episodes were broadcast sequentially in live mode. Therefore, comparing households in the Gift TSTV group to households in the Gift LinearTV group allows for measuring the incremental effect associated with the (potential) additional viewership in binge mode done by the latter set of households because of TSTV. Activating the TVSC gift, with and without TSTV, did not require any action from the households in the experiment. Households received an email and a text message notifying them of the temporary offer, which was readily available to use. During this experiment, the TVSC broadcast 52 distinct TV shows and 58 seasons with 454 distinct episodes. The content aired included popular titles such as *House of Cards*, *Fargo*, and *Suits*. After the experiment, households could only buy the TVSC bundled with TSTV. Therefore, we can consider that TVSC service mimics an SVoD service with a small catalog of good quality.

3.2. Descriptive Statistics

Table 1 establishes the contrast between households that binge-watched and those that did not. These statistics are irrespective of whether such households received access to TSTV. The table shows that the consumption of the TVSC across households that binge-watched it during the experiment was very different from the consumption of those that watched this channel but that did not binge-watch it. Roughly 40% of the Gift households ((5,963 + 2,106)/20,000) watched the TVSC during the experiment. Roughly 26% of them binge-watched content on the TVSC at least once during the experiment. We follow the definition used in the 2013 Netflix survey and define binging as watching two or more episodes in a row of the same TV show in the same sitting (Spangler 2013). On average, the number of TV show episodes watched by binge-watchers was four times that watched by non-binge-watchers. Binge-watchers spent roughly five times more time watching the TVSC during the experiment. On average, 25.5% of the time they spent watching the TVSC was binge-watching.

Table 2 provides descriptive statistics that split households according to the treatment group they belong to. Following (Schweidel and Moe 2016), we define a session as a period of VoD streaming separated by one or more hours of inactivity. The number of binge two (B2) sessions, that is, sessions in which households watched two or more episodes of the same TV show, is 10% (0.209/0.189) higher across households in the Gift TSTV group compared with households in the Gift LinearTV group. The number of binge three (B3) sessions, that is, sessions in which households watched three or more episodes of the same TV show, is 37% (0.220/0.161) higher. The significant jump in this statistic from B2 sessions to B3

Table 1. Consumption of the TVSC During the Experiment Across Gifted Households and Broken Down by Whether They Binge-Watched It

	Variable	Mean	St. dev.	Median	Q05	Q95
No binge (5,963 households)	Number of episodes	3.375	3.174	2.000	1.000	9.900
	Number of seasons	3.124	2.675	2.000	1.000	8.000
	Number of TV shows	3.101	2.637	2.000	1.000	8.000
	Watch time (hours)	1.395	1.490	0.908	0.164	4.231
	Fraction of binge time	0.000	0.000	0.000	0.000	0.000
Binge (2,106 households)	Number of episodes	12.973	12.984	9.000	2.000	39.000
	Number of seasons	8.428	6.719	7.000	1.000	22.000
	Number of TV shows	8.114	6.352	7.000	1.000	21.000
	Watch time (hours)	6.403	7.418	3.998	0.943	19.886
	Fraction of binge time	0.433	0.255	0.377	0.110	1.000

Note. St. dev., Standard deviation; Q05, 5th percentile of the distribution; Q95, 95th percentile of the distribution.

Table 2. Consumption of the TVSC During the Experiment Across All Experimental Groups

			Sessions				Watch time (hours)		
Group	# episodes	# households	#	%	%B2+	%B3+	All	Other	Binge
Gift control	1	829	1,265	0.786	0	0	0.094	0.084	0.010
	2	198	229	0.142	0.214	0			
	3+	98	115	0.071	0.339	0.148			
Gift LinearTV	1	2,801	7,024	0.656	0	0	0.695	0.587	0.108
	2	1,426	2,285	0.213	0.189	0			
	3+	944	1,402	0.131	0.389	0.161			
Gift TSTV	1	3,025	7,200	0.649	0	0	0.746	0.604	0.142
	2	1,467	2,301	0.207	0.209	0			
	3+	1,065	1,594	0.144	0.462	0.220			

Note. "%Bx+" indicates the percentage of sessions in which households watched x or more episodes of the same TV show.

sessions arises because the TVSC broadcast live two episodes of the same TV show back-to-back relatively often during our experiment (and less so three episodes of the same TV show back-to-back), thus inducing some level of light binge-watching (two episodes only) across households in the Gift LinearTV group. Finally, and on average, a significant difference between households in the Gift TSTV group and households in the Gift LinearTV group is the time that they spent binge-watching the TVSC. Households in the latter group spent 31% (0.142/0.108) more time binge-watching this channel during the experiment than households in the former group.

Finally, Table 3 shows the averages of several covariates during the month before the experiment for households in the control group. We show data for how long the household subscribed to TV and internet from TELCO, its monthly bill, whether it pays the monthly bill using direct deposit, the amount of traffic exchanged over the internet (both download and upload), and whether the household received free TVSC offers in the past. The F-statistic and the associated p-value are for the analysis of variance comparing the averages of these covariates across all experimental groups in our experiment (control, Gift LinearTV, and Gift TSTV).

Overall, the statistics presented in this subsection suggest that our random assignment of TSTV across households was effective at changing the binge-watching behavior of households in our experiment. Furthermore, the statistics provided also show that our randomized schedule for placing households in experimental conditions achieved balance in the covariates that we observed before the experiment took place.

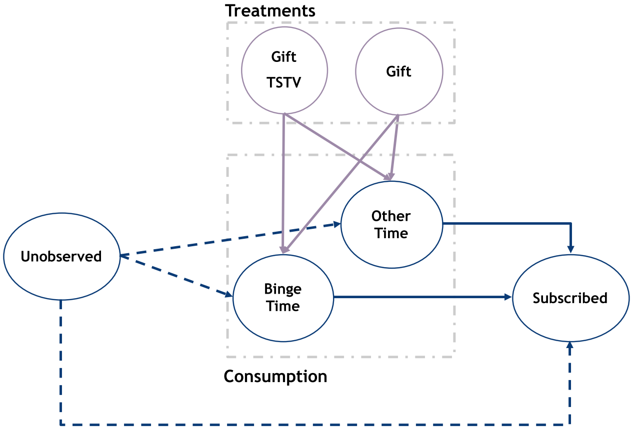
3.3. Empirical Strategy

The direct acyclic graph (DAG) in Figure 1 illustrates the setup of our experiment. Offering access to the TVSC (*Gift*) is likely to affect the time that households spend watching this channel both in binge mode (*Binge_Time*) and in nonbinge mode (*Other_Time*). Likewise, when access to this channel is offered with time-shift TV (*Gift_TSTV*), the time that households spend watching the TVSC, both in binge mode and in nonbinge mode, is likely to affect whether they subscribe to this channel after the experiment (*Subscribe*). Finally, unobservables (*Unobserved*) affect both the consumption of this channel and subscription to it, rendering the time that households spend watching the TVSC, both in binge mode and in nonbinge mode, endogenous in our setting. This DAG also helps clarify our identification strategy.

Table 3. Analysis of Variance for Pretreatment Covariates Comparing Households Across All Experimental Groups

Covariate	Mean control group	F-statistic	p-value
TV tenure (month)	77.350	0.210	0.811
Internet tenure (month)	52.200	0.250	0.779
Bill (USD/month)	66.790	0.279	0.757
Direct deposit	0.345	1.541	0.214
Download traffic (Gb/month)	44.246	1.895	0.150
Upload traffic (Gb/month)	11.040	0.379	0.684
Past TVSC gift	0.321	0.885	0.413

Figure 1. (Color online) Direct Acyclic Graph Describing the Setup of Our TVSC Experiment



First, we measure the intention to treat (ITT) effect. ITT is the average effect of the treatment on the outcome of interest, obtained using ordinary least squares. ITT averages the outcome across all treated households irrespective of their compliance with treatment, that is, across households that used TSTV to binge-watch and households that did not. Second, we look at the causal effect of binge-watching, that is, the effect across the subset of households that used TSTV to binge-watch the TVSC. In randomized control trials, this is called the local average treatment effect (LATE), and to obtain the LATE, we use our exogenous and random assignment of treatments to households (*Gift* and *Gift_TSTV*) as an instrument for the time they spend watching the TVSC. For a detailed treatment of the theory about ITT, LATE, and noncompliance, please refer to Imbens and Angrist (1994).

Table 4 describes all covariates used in this section of our paper. We note that we use TVSC subscription within three months after the experiment as our outcome variable of interest because this is the key metric of performance used by TELCO to study the outcomes of its marketing experiments. The rationale for this choice is related to the fact that TELCO's marketing campaigns have a mourning period of three months; that is, to avoid excessive targeting, TELCO excludes households from marketing campaigns for three months after any major marketing intervention. All households in our experiment, irrespective of their experimental condition, were subject to this mourning period. Therefore, their behavior during these three months was not influenced by any potentially endogenous subsequent actions taken by the firm.

We can identify the effect of offering access to the TVSC with and without TSTV on the likelihood of subscription using the following:

$$Subscribed_i = \alpha_0 + \alpha_1 Gift_i + \alpha_2 Gift\_TSTV_i + \epsilon_i. \quad (1)$$

In this specification, α_0 measures the subscription rate for TVSC in the control group, thus absent of any intervention; α_1 measures the change in the subscription rate for households offered access to the TVSC as part of our experiment; and α_1 averages the impact across households that were offered access to the TVSC with and without TSTV. We anticipate a small coefficient for this parameter, given that the potential positive effect of watching the TVSC live during the free trial may be attenuated by the potential negative effect of binge-watching it. The term α_2 measures the change in the subscription rate for the TVSC due to the effect of TSTV. Thus, we expect this coefficient to be negative if binge-watching reduces the posttrial likelihood of subscription. This specification measures the effect of the ITT across households with access to the TVSC, with and without TSTV. We can also measure the effect of watching the TVSC on the posttrial likelihood of subscription across households in our experiment, which is the LATE, obtained using the following:

$$\begin{aligned} Watch\_Time\_Other_i &= \psi_0 + \psi_1 Gift_i \\ &\quad + \psi_2 Gift\_TSTV_i + \epsilon_i, \quad (2) \\ Watch\_Time\_Binge_i &= \beta_0 + \beta_1 Gift_i \\ &\quad + \beta_2 Gift\_TSTV_i + \nu_i, \quad (3) \\ Subscribed_i &= \gamma_0 + \gamma_1 Watch\_T\hat{i}me\_Other_i \\ &\quad + \gamma_2 Watch\_T\hat{i}me\_Binge_i + \eta_i. \quad (4) \end{aligned}$$

Equations (2) and (3) measure how offering access to the TVSC with and without TSTV changes the time that households spend watching the gifted channel during our experiment. As described in the previous section, offering access to the TVSC with TSTV incentivized households in the Gift TSTV group to

Table 4. Covariates Used in Our Analysis of the TVSC Experiment

Variable name	Variable description
Subscribed (0/1)	Household subscribed to the TVSC within three months after the experiment
Gift (0/1)	Household offered the TVSC with or without TSTV
Gift_TSTV (0/1)	Household offered the TVSC with TSTV
Watch_Time_Other (hours)	Time household spends watching the TVSC in nonbinge mode
Watch_Time_Binge (hours)	Time household spends watching the TVSC in binge mode
Watch_Time_All (hours)	Time household spends watching the TVSC

binge-watch more than households in the Gift LinearTV group. Households in the latter group could only binge-watch when more than one episode of the same TV show was broadcast back to back in the live stream; that is, we expect β_1 in Equation (3) to be positive, reflecting the additional consumption in binge mode that households in the Gift LinearTV group can perform, as well as β_2, accounting for the additional binge-watching that households in the Gift TSTV can perform. We expect a positive coefficient for ψ_1, given that, on average, offering access to the TVSC without TSTV should increase its live consumption. Also, we expect ψ_2 to be small, given that offering access to the TVSC with TSTV is unlikely to increase its viewership live, although it could happen in practice. In addition, if the TVSC content is attractive, we expect γ_1 to be positive, given that watching more of it should further attract consumers. However, we expect γ_2 to be negative if binge-watching the TVSC content reduces the posterior likelihood of SVoD subscription.

Finally, we acknowledge that offering access to the TVSC may affect the posterior likelihood of subscription in ways that are unrelated to the consumption of this channel. If gifts affected subscriptions directly (not through usage), the DAG of Figure 1 should be expanded to include a new arrow from *Gift* and/or *Gift_TSTV* to *Subscribe*. For example, and as discussed in Section 2, there are marketing and information systems research studies that provide evidence that free trials may reduce reference prices (Pauwels and Weiss 2008), which can lead to lower consumption. Therefore, in our case, a lower rate of subscription across treated households could be associated with the fact that these households, once given the gift, could see there a signal that future gifts may come by and thus postpone subscription. To dismiss this possibility, we perform a robustness check that measures the effect of the TSTV feature independent of the effect of the gift. We contrast the group of households that had access to the TVSC without TSTV against the group of households that had access to the TVSC with TSTV. In this case, we control for any effects that the gift may have triggered that are unrelated to how households used it (given that all households in this subsample had the gift). For this purpose, we use the following:

$$Subscribed_i = \zeta_0 + \zeta_1 Gift\_TSTV_i + \epsilon_i, \tag{5}$$

$$Watch\_Time\_Binge_i = \delta_0 + \delta_1 Gift\_TSTV_i + \nu_i, \tag{6}$$

$$Subscribed_i = \lambda_0 + \lambda_1 Watch\_T\hat{i}me\_Binge + \eta_i, \tag{7}$$

where Equation (5) provides an ITT estimate, and Equation (6) provides the first stage for the LATE estimate in Equation (7). In line with the above, we expect ζ_1 to be negative if offering access to the TVSC with TSTV reduces subscription rates. We also expect λ_1 to be negative if this reduction in the subscription rate is driven by the amount of binge-watching. Finally, we expect δ_1 to be positive given that offering access to the TVSC with TSTV should increase the amount of binge-watching. Online Appendix E provides another robustness check to address this same concern. In this appendix, we test whether having had access for free to the TVSC before our experiment affected the posttrial likelihood of subscription. If, in our setting, gifts of the TVSC reduced reference prices, one would expect that similar prior gifts would yield a statistically significant effect. Finally, Online Appendix B shows that we do not find empirical evidence that households in our experiment exhausted their time budget to watch TV during the experiment, which could also confound the effect of binge-watching.

3.4. Results and Discussion

Table 5 shows that offering access to the TVSC without TSTV did not change the likelihood of subscription after the experiment. However, offering access to the TVSC with TSTV reduced this likelihood. The results in columns (1) and (2) indicate that, on average, for households receiving the gift with TSTV, the probability of subscribing to TVSC after the experiment declined by 0.008 percentage points from the baseline purchase probability of 0.082 of the control group. This change corresponds to a 10% drop in the probability of subscription. Columns (3) and (4) in this table show that offering access to the TVSC without TSTV increased its consumption in both binge and nonbinge modes. The former increased roughly nine times, and the latter increased approximately six times when compared with households in the control group. As expected, offering access to this channel with TSTV increased its consumption in binge mode even more. The increase was approximately 12 times when compared with households in the control group, and there is no statistically significant change in the time that these households spent watching it in nonbinge mode.

Households without the gift binge-watched the TVSC 12% of the time that they spent watching it. Binge-watching across households with no gift was possible because, in our setting, TELCO did not block households from organically subscribing to the TVSC, and some of the households in the control group subscribed to it. Subscription by control households is an instantiation of noncompliance on the control side of our experiment, addressed in our analyses by using LATE. This statistic increases to 19% and 15.5% for the households offered access to this channel with and without TSTV, respectively. Finally, columns (5) and (6) in this

Table 5. Effect of Offering Access to the TVSC with and Without TSTV on the Time That Households Spent Watching It During the Experiment in Binge and Nonbinge Modes and on the Posttrial Subscription Level

			Watch Time			
	Subscribed		*Other*	*Binge*	*Subscribed*	
	ITT	ITT	1STG	1STG	LATE	LATE
	LPM	Probit	OLS	OLS	2SLS	IV Probit
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.082***	–1.394***	0.084***	0.011***	0.080***	–1.406***
	(0.003)	(0.018)	(0.004)	(0.002)	(0.003)	(0.024)
Gift	0.001	0.008	0.503***	0.097***		
	(0.004)	(0.026)	(0.015)	(0.005)		
Gift_TSTV	–0.008**	–0.057**	0.017	0.034***		
	(0.004)	(0.026)	(0.020)	(0.008)		
Watch_Time_Other (hours)					0.055*	0.377*
					(0.032)	(0.213)
Watch_Time_Binge (hours)					–0.275*	–1.875**
					(0.141)	(0.930)
Num. obs.	30,000	30,000	30,000	30,000	30,000	30,000
RMSE	0.271		1.184	0.461	0.293	
AIC		16,667.791				
Log likelihood		–8,330.896				

Notes. Heteroskedasticity-consistent standard errors are in parentheses. Columns (1) and (2) correspond to Equation (1). Column (3) corresponds to Equation (2). Column (4) corresponds to Equation (3). Columns (5) and (6) correspond to Equation (4). LPM, Linear probability model; 1STG, first stage; 2SLS, two-stage least squares; OLS, ordinary least squares; IV, instrumental variable; Num. obs., number of observations; RMSE, root mean squared error; AIC, Akaike information criterion.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

table show that the more households watched the TVSC in nonbinge mode, the more likely they were to subscribe to it after the experiment. However, the more they binge-watched the TVSC during the experiment, the less likely they were to subscribe to it. The negative effect of binge-watching on the posterior likelihood of subscription that we report here is identified in our regressions from the difference in the amount of binge-watching that households in the Gift TSTV and the Gift LinearTV groups did during our experiment. Thus, in our experimental setting, this is the incremental effect of binge-watching on the posttrial subscription rate for the TVSC.

Table 6 compares only households in the Gift group. Columns (1) and (2) show that households in the Gift TSTV group subscribed to the TVSC less than households in the Gift LinearTV group after the experiment. The results in column (1) indicate a reduction of 0.84% in this likelihood from a baseline subscription rate of 8.3%, thus, a 10% decline. Columns (3) and (4) show that TSTV contributed only to increase the consumption of the TVSC in binge mode. Households in the Gift TSTV group spent 31.5% more time binge-watching the TVSC than households in the Gift LinearTV group.

Columns (5) and (6) show that the lower likelihood of TVSC subscription after the experiment across households in the former group came from the additional time they spent binge-watching this channel during the experiment. The negative coefficient in column (6) of Table 6 associated with the time spent binge-watching arises from the binge-watchers without TSTV that would otherwise binge-watch much more if given TSTV. The results in column (6) show that consumers who binge-watched the TVSC for more than six hours during the experiment (which corresponds to approximately eight episodes of the same TV show) were unlikely to subscribe to the TVSC after the experiment (their likelihood of subscription reduced to 0.1% from a baseline of 12.7%). In sum, our results show that binge-watching reduces the likelihood of SVoD subscription.

Finally, the appendices to our paper provide several robustness checks to our results, increasing our confidence in our findings. Table 15 in Online Appendix B shows that all households in our experiment watched the same amount of TV during the three months after the experiment. This table provides some empirical evidence that households that binge-watched during the experiment did not exhaust their time budget to consume TV.

Table 6. Effect of Offering Access to the TVSC with and Without TSTV on the Time That Households Spent Watching It During the Experiment in Binge and Nonbinge Modes and on the Posttrial Subscription Level Only Across Households Offered Access to the TVSC

			Watch Time			
	Subscribed		*Other*	*Binge*	*Subscribed*	
	ITT	ITT	1STG	1STG	LATE	LATE
	LPM	Probit	OLS	OLS	2SLS	IV Probit
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.083***	–1.386***	0.587***	0.108***	0.109***	–1.205***
	(0.003)	(0.018)	(0.014)	(0.005)	(0.016)	(0.107)
Gift_TSTV	–0.008**	–0.057**	0.017	0.034***		
	(0.004)	(0.026)	(0.020)	(0.008)		
Watch_Time_Binge (hours)					–0.246**	–1.681**
					(0.125)	(0.855)
Num. obs.	20,000	20,000	20,000	20,000	20,000	20,000
RMSE	0.269		1.424	0.554	0.302	
AIC		11,012.594				
Log likelihood		–5504.297				

Notes. Heteroskedasticity-consistent standard errors are in parentheses. Columns (1) and (2) correspond to Equation (5). Column (4) corresponds to Equation (6). Columns (5) and (6) correspond to Equation (7). LPM, Linear probability model; 1STG, first stage; 2SLS, two-stage least squares; OLS, ordinary least squares; IV, instrumental variable; Num. obs., number of observations; RMSE, root mean squared error; AIC, Akaike information criterion.

$^{**}p < 0.05$; $^{***}p < 0.01$.

If they did, then one would expect their consumption of TV to reduce immediately after the experiment. Table 18 in Online Appendix E shows that past access to free trials of the TVSC before our experiment did not change the likelihood of TVSC subscription after the experiment. Therefore, we do not find evidence that these trials reduce the consumers' willingness to pay for the TVSC, which could confound the negative effect of binge-watching that we report above. Table 16 in Online Appendix C shows that our results remain unchanged when we look at subscription rates one and two months after the experiment ended, thus providing robustness to the definition of our outcome variable. Finally, Table 17 in Online Appendix D shows that our results remain unchanged when we employ different definitions for marking households as having binge-watched during the experiment, thus providing additional robustness to the definition of our endogenous variable of interest.

4. The Role of Catalog Exhaustion and of Reminders on SVoD Subscription

4.1. Experimental Design

The TVSC experiment analyzed in the previous section shows that binge-watching during a free trial reduces the posttrial likelihood of subscription. This section discusses results from a second experiment that we use to provide additional insights about why binge-watching does so. This experiment focuses on TELCO-SVoD, a SVoD service that could be purchased for $9.5/month. TELCO-SVoD competes with online content streaming services such as Netflix, Hulu, and Amazon Prime. When our study took place, TELCO-SVoD offered access to approximately 1,300 movies and 75 TV shows covering a total of 133 seasons. The average IMDb rating for the content available on TELCO-SVoD was 7.5/10, and, on average, the release date of the first season for the TV shows available was in 2012. According to Unogs.com, the size of the catalog provided by TELCO-SVoD was comparable to Netflix's in several European countries, Russia, India, and South Africa in 2015. The TELCO-SVoD catalog changes every month, with some TV shows and seasons removed and new ones coming in. The pace of content refresh varies widely and depends on title availability and long-term deals established with content distributors. For the benefit of our study and to help us isolate the mechanism of content depletion that we identified in the TV Show Channel experiment, TELCO was able to hold their catalog static during the experiment we describe below.

TELCO selected a random sample of 30,000 households that did not subscribe to TELCO-SVoD in the month before this experiment. A subset of 15,000 of them, selected at random, hereafter called treated, were offered access to TELCO-SVoD for free for three consecutive months (October, November, and December 2016). The remaining 15,000 households, hereafter called control, did not receive such an offer. Some households, both treated and control, were selected to receive recommendation reminders. A subset of 5,000 treated households and a subset of 5,000 control households, in both cases selected at random, were sent no reminders. A subset of 5,000 treated households and a subset of 5,000 control households, in both cases selected at random, were sent generic recommendation reminders. Reminders were sent by text message every other week during the experiment and included the following text: "With TELCO-SVoD you have unlimited access to thousands of movies, complete TV-shows, and content for kids that you can watch on TV or using our app in any mobile device." Finally, the remainder of the treated households (5,000) and control households (5,000) were sent customized recommendation reminders. These reminders were also sent by text message every other week during the experiment. They included the following text: "You can watch all episodes of TV Show [X] using TELCO-SVoD, you can watch on TV or using our app in any mobile device." "X" in this message represents the title of the TV show recommended by TELCO. Our study did not attempt to optimize these recommendation reminders, which could be done by adjusting their frequency, the text in the message, or the recommendation algorithm used to compute show X. Furthermore, we note that these reminders did not change the interface of the TELCO-SVoD service. In particular, if consumers wanted to watch the suggested titles, they would still need to search for them at TELCO-SVoD. These reminders were sent to TELCO households to try to affect the frequency with which they consumed content from TELCO-SVoD, either in binge or nonbinge mode. Online Appendix G provides additional details about the engine used by TELCO during this experiment to issue recommendations.

We consider only 12 weeks of data out of the 14 weeks that the experiment lasted. We exclude from the analysis the first experimental week because it took time to activate TELCO-SVoD, and not all treated households had access to it during this week (a maximum number of households could be activated per day to reduce the strain in the network). We also exclude from the analysis the last experimental week because it coincided with Christmas, and between December 23 and December 25, TELCO launched a mass marketing campaign priming households to try TELCO-SVoD during the Christmas break.

Finally, treated households received a brief survey two weeks after the experiment. The survey asked whether the household subscribed to TELCO-SVoD after the gift period. If not, a follow-up question asked the household to choose reasons why they did not subscribe among the following options: high price, lack of time, lack of interest, lack of content refresh, or other (under which a field for running text was available).

4.2. Descriptive Statistics

Table 7 shows statistics for the consumption of TELCO-SVoD for treated and control households that watched TELCO-SVoD at least once during the experiment. Note that in our setting, and similarly to the TVSC experiment, households in the control group could organically subscribe TELCO-SVoD and thus watch and binge-watch it. Offering access to TELCO-SVoD increased more than fourfold the number of households watching it (2,990/706). Treated households exhibit significantly more sessions, TV shows, episodes,

Table 7. Consumption of TELCO-SVoD Content During the Experiment Across All Households that Watched TELCO-SVoD Content

	Variable	Mean	St. dev.	Median	Q05	Q95
Control (706 households)	TELCO-SVoD viewing sessions	5.445	8.265	2.000	1.000	21.000
	TELCO-SVoD TV shows	0.435	1.405	0.000	0.000	2.750
	TELCO-SVoD TV show episodes	1.851	8.662	0.000	0.000	8.000
	TELCO-SVoD movies	3.479	8.477	1.000	0.000	17.000
	TELCO-SVoD total titles	8.667	16.571	2.000	1.000	34.750
	TELCO-SVoD watch time (hours)	7.024	14.651	1.485	0.003	27.977
Treated (2,990 households)	TELCO-SVoD viewing sessions	8.923	13.464	4.000	1.000	35.550
	TELCO-SVoD TV shows	0.780	1.611	0.000	0.000	3.000
	TELCO-SVoD TV show episodes	5.318	18.538	0.000	0.000	30.000
	TELCO-SVoD movies	8.365	15.234	3.000	0.000	35.000
	TELCO-SVoD total titles	17.751	29.934	6.000	1.000	72.750
	TELCO-SVoD watch time (hours)	13.179	24.525	4.208	0.016	55.426

Note. St. dev., Standard deviation; Q05, 5th percentile of the distribution; Q95, 95th percentile of the distribution.

and movies watched. They also spent 87% more time watching TELCO-SVoD content.

Table 8 shows additional statistics about how households consume TELCO-SVoD content during the experiment. Consistent with the previous experiment, we defined a session as a period of TELCO-SVoD streaming separated by one or more hours of inactivity (Schweidel and Moe 2016). We observe a total of 30,525 TELCO-SVoD sessions in our data, 87.5% of which are from treated households. Viewing sessions for treated and control households originate from 2,990 and 706 unique households, respectively. Among treated households, 46.6% of TELCO-SVoD sessions include a single title (a TV show episode or a movie), 21.9% include two titles, and 11.9% include three titles. These statistics are 57.3%, 20.4%, and 9.5%, respectively, for control households, showing that treated households tend to exhibit longer sessions. We observe 6,184 B2 sessions (sessions that include two or more episodes of the same TV show) and 3,600 B3 sessions (sessions that include three or more episodes of the same TV show) across treated households. They correspond to 23.2% and 13.5% of all sessions from treated households, respectively. These statistics are 12.2% and 7.2% for control households, showing that treated households tend to binge-watch TELCO-SVoD relatively more. Treated households that watched TELCO-SVoD content, that is, that started a TELCO-SVoD stream during the experiment, watched, on average, 0.780 different TELCO-SVoD TV shows and an average of 5.318 different TV show episodes. The households that watched more TV shows (top 5%) watched three different TV shows. These statistics show that households tend to watch several episodes of a few TV shows. Finally, treated households spent much more time than their control counterparts watching TELCO-SVoD content. In particular, the amount of time they spent binge-watching was 15 times that of control households (0.878/0.059).

Table 9 shows the averages of several covariates during the month before the experiment for households in the control group. We report covariates similar to those in the TVSC experiment. The F-statistics and the associated P-values are for the analysis of variance comparing the average of these covariates across all experimental groups in our experiment, namely, Control No Reminders, Control Generic Reminders, Control Customized Reminders, Treated No Reminders, Treated Generic Reminders, and Treated Customized Reminders. These columns show that our randomized schedule for placing households in experimental conditions achieved good balance in the covariates that we observe before the experiment took place. The table shows the means for all households in the Control No Reminders group.

4.3. Empirical Strategy

The direct acyclic graph in Figure 2 illustrates the setup of our experiment. Offering access to TELCO-SVoD (*Gift*) is likely to affect the time that households

Table 8. Consumption of TELCO-SVoD Content During the Experiment Across Experimental Groups

			Sessions				Watch time (hours)		
Group	Episodes	Households	#	%	#B2+	#B3+	All	Other	Binge
Control	1	633	2,204	57.336	0	0	0.279	0.221	0.059
	2	313	785	20.421	153	0			
	3	187	364	9.469	114	95			
	4	101	180	4.683	78	71			
	5	81	116	3.018	46	40			
	6	42	69	1.795	28	23			
	7	30	34	0.884	16	16			
	8	24	26	0.676	8	8			
	9	15	17	0.442	8	7			
	10+	27	49	1.275	18	17			
Treated	1	2,669	12,436	46.610	0	0	3.073	2.160	0.878
	2	1,686	5,837	21.877	2,179	0			
	3	1,180	3,172	11.889	1,438	1,259			
	4	864	1,804	6.761	871	764			
	5	599	1,079	4.044	523	488			
	6	450	727	2.725	380	346			
	7	326	452	1.694	227	213			
	8	229	321	1.203	157	145			
	9	174	219	0.821	110	105			
	10+	328	634	2.376	299	280			

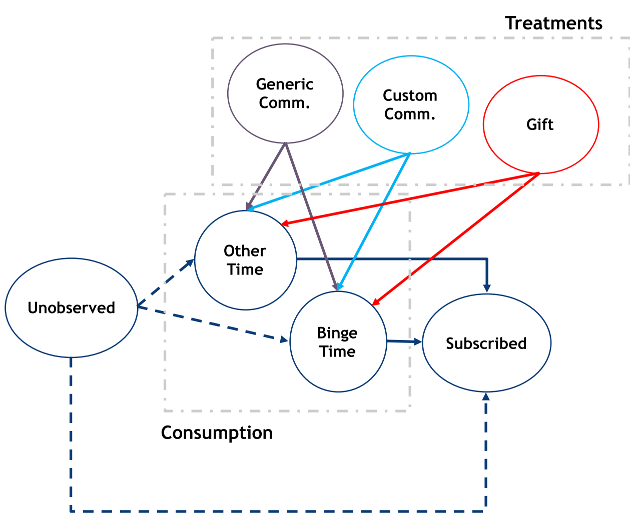
Note. #Bx+ indicates the number of sessions in which households watch x or more episodes of the same TV show.

Table 9. Analysis of Variance for Pretreatment Covariates Comparing Households Across All Experimental Groups

Covariate	Mean of Control No Reminders	*F*-statistic	*p*-value
TV tenure (month)	79.569	0.656	0.657
Internet tenure (month)	51.078	0.663	0.652
Bill (USD/month)	66.781	1.749	0.120
Direct deposit	0.349	1.016	0.406
Download (Gb/month)	37.621	0.375	0.866
Upload (Gb/month)	6.581	0.626	0.680
Past TELCO-SVoD gift	0.145	1.745	0.121

spend watching it both in binge mode (*Binge_Time*) and in nonbinge mode (*Other_Time*). Targeting households with reminders, both generic (*Generic_Reminders*) and customized (*Customized_Reminders*), may affect the time that households spend watching TELCO-SVoD content, both in binge mode (*Binge_Time*) and in nonbinge (*Other_Time*) mode. The time that households spend watching TELCO-SVoD, both in binge mode and in nonbinge mode, is likely to affect whether they subscribe to the service after the free trial (*Subscribe*). Finally, unobservable factors (*Unobserved*) may affect both consumption of the TELCO-SVoD service during the experiment and posttrial subscription to the TELCO-SVoD service. The consequence is that the time households spend watching TELCO-SVoD content, both in binge and in nonbinge mode, may be endogenous in our setting. This DAG also shows that our identification strategy will rely on using the exogenous and random assignment of the free trial and communication reminders as instruments for the endogenous variables. Table 10 describes all covariates used in this section of our paper.

Figure 2. (Color online) Direct Acyclic Graph Describing the Setup of Our TELCO-SVoD Experiment



Note. Comm., Communication.

We can identify the effect of offering access to TELCO-SVoD on the likelihood of subscription after the experiment using the following:

$$Subscribed_i = \alpha_0 + \alpha_1 Gift_i + \epsilon_i. \tag{8}$$

In this setting, we can also identify the effect of watching TELCO-SVoD on the posterior likelihood of subscription using a LATE estimator:

$$Watch\_Time\_All_i = \lambda_0 + \lambda_1 Gift_i + \epsilon_i, \tag{9}$$

$$Subscribed_i = \gamma_0 + \gamma_1 Watch\_\hat{T}ime\_All_i + \eta_i. \tag{10}$$

In this specification, Equation (9) provides the first-stage estimates for Equation (10). In another specification, we split *Watch_Time_All* into *Watch_Time_Other* and *Watch_Time_Binge* to identify the effects of binge- and non-binge-watching of TELCO-SVoD content on the posterior likelihood of subscription:

$$\begin{aligned} Watch\_Time\_Other_i \\ = \alpha_0 + \alpha_1 Gift_i + \alpha_2 Generic\_Reminders_i \\ + \alpha_3 Customized\_Reminders_i \\ + \alpha_4 Gift_i \times Generic\_Reminders \\ + \alpha_5 Gift_i \times Customized\_Reminders + \epsilon_i, \end{aligned} \tag{11}$$

$$\begin{aligned} Watch\_Time\_Binge_i \\ = \beta_0 + \beta_1 Gift_i \\ + \beta_2 Generic\_Reminders_i \\ + \beta_3 Customized\_Reminders_i \\ + \beta_4 Gift_i \times Generic\_Reminders \\ + \beta_5 Gift_i \times Customized\_Reminders + \nu_i, \end{aligned} \tag{12}$$

$$\begin{aligned} Subscribed_i = \gamma_0 + \gamma_1 Watch\_Ti\hat{m}e\_Other_i \\ + \gamma_2 Watch\_Ti\hat{m}e\_Binge_i + \eta_i. \end{aligned} \tag{13}$$

Equations (11) and (12) provide the first stages for Equation (13). Including *Generic_Reminders* and

Table 10. Covariates Used in the TELCO-SVoD Experiment

Variable name	Variable description
Subscribed (0/1)	Household subscribes TELCO-SVoD within three months after the experiment
Gift (0/1)	Household offered TELCO-SVoD
Watched (0/1)	Household watched TELCO-SVoD content at least once
Binged (0/1)	Household binge-watched TELCO-SVoD content at least once
Watch_Time_Other (hours)	Time household spends watching TELCO-SVoD in nonbinge mode
Watch_Time_Binge (hours)	Time household spends watching TELCO-SVoD in binge mode
Watch_Time_All (hours)	Time household spends watching TELCO-SVoD
N_Episodes (number)	Number of distinct TELCO-SVoD episodes that household watches
N_TV_Shows (number)	Number of distinct TELCO-SVoD shows that household watches
Generic Reminders (0/1)	Household received generic reminders
Customized Reminders (0/1)	Household received customized reminders

Customized_Reminders alone allows for controlling for the "direct" effect of reminders in our setting (i.e., their potential effect on the posterior likelihood of subscription that is unrelated to using the gift). Including their interactions with *Gift* allows for measuring their potential effect beyond the "direct" effect of the free trial itself (i.e., the effect of the free trial without reminders).

In another model, we replace *Watch_Time_Other* with *Watched*, and *Watch_Time_Binge* with *Binged*. The term $Watched_i$ indicates whether household i watched TELCO-SVoD content at least once during the experiment (any positive amount), and $Binged_i$ indicates whether household i binge-watched TELCO-SVoD content during our experiment, that is, whether it began streams for two or more episodes of the same TV show in the same sitting at least once during our experiment. Finally, we measure how reminders mediate the effect of offering access and watching TELCO-SVoD on the posterior likelihood of TELCO-SVoD subscription using the following:

$$\begin{aligned} Subscribed_i &= \alpha_0 + \alpha_1 Gift_i + \alpha_2 Generic\_Reminders_i + \alpha_3 Customized\_Reminders_i \\ &\quad + \alpha_4 Gift_i \times Generic\_Reminders + \alpha_5 Gift_i \times Customized\_Reminders + \epsilon_i, \end{aligned} \tag{14}$$

$$\begin{aligned} Watch\_Time\_All_i &= \alpha_0 + \alpha_1 Gift_i + \alpha_2 Generic\_Reminders_i + \alpha_3 Customized\_Reminders_i \\ &\quad + \alpha_4 Gift_i \times Generic\_Reminders + \alpha_5 Gift_i \times Customized\_Reminders + \epsilon_i, \end{aligned} \tag{15}$$

$$\begin{aligned} Subscribed_i &= \alpha_0 + \alpha_1 Watch\_\hat{T}ime\_All_i + \alpha_2 Generic\_Reminders_i + \alpha_3 Customized\_Reminders_i \\ &\quad + \alpha_4 Watch\_\hat{T}ime\_All_i \times Generic\_Reminders \\ &\quad + \alpha_5 Watch\_\hat{T}ime\_All_i \times Customized\_Reminders + \epsilon_i. \end{aligned} \tag{16}$$

We also show results for Equation (15) replacing *Watch_Time_All* with *N_Episodes* and with *N_TV_Shows*, which indicate the number of distinct episodes and TV shows that households watched from TELCO-SVoD during the experiment, respectively. Analyzing these outcomes allows us to understand how reminders affect the type of content consumed during our experiment.

4.4. Results and Discussion

Table 11 shows that after the experiment, treated households subscribed to TELCO-SVoD less than control households did. The results in column (1) and (2), which are the same for the linear probability model and for the probit specification respectively, indicate that the likelihood of subscribing to this service after the experiment was 0.28% lower for the former households from a baseline of 1.7%, thus, a reduction of 16%. Column (3) shows that the gift increased the time spent watching TELCO-SVoD content by 10 times (2.758/0.279). The results in columns (4) and (5) show that the more households watched TELCO-SVoD content, the less they subscribed to the service after the experiment. In particular, the marginal effect of the instrumental-variable probit reported in column (5) indicates that, compared with households that did not receive the TELCO-SVoD gift,

Table 11. Impact of the TELCO-SVoD on Overall TELCO-SVoD Use During the Experiment and Impact of Overall TELCO-SVoD Use on TELCO-SVoD Subscription After the Experiment

	Subscribed	*Subscribed*	What_Time_All	*Subscribed*	*Subscribed*
	OLS	Probit	OLS	2SLS	IV Probit
	ITT	ITT	1STG	LATE	LATE
	(1)	(2)	(3)	(4)	(5)
Intercept	0.017***	−2.129***	0.279***	0.017***	−2.130***
	(0.001)	(0.025)	(0.035)	(0.001)	(0.029)
Gift	−0.003**	−0.072*	2.758***		
	(0.001)	(0.037)	(0.123)		
Watch_Time_All (hours)				−0.001*	−0.044***
				(0.001)	(0.014)
Num. obs.	29,950	29,950	29,950	29,950	29,950
RMSE	0.122		10.632	0.125	
AIC		4,721.703			
Log likelihood		−2,358.852			

Notes. Heteroskedasticity-consistent standard errors are in parentheses. Columns (1) and (2) correspond to Equation (8). Column (3) corresponds to Equation (9). Columns (4) and (5) correspond to Equation (10). 2SLS, Two-stage least squares; OLS, ordinary least squares; IV, instrumental variable; ITT, intent-to-treat; 1STG, first stage; LATE, local average treatment effect; Num. obs., number of observations; RMSE, root mean squared error; AIC, Akaike information criterion.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

households that watched 14.6 hours of TELCO-SVoD (the average time spent watching across those that used it) reduced the likelihood of TELCO-SVoD subscription after the experiment by 1.5% from a baseline of 1.7% across the control group.

Table 12 separates the effect of binge-watching TELCO-SVoD content during the experiment on the likelihood of subscribing the service after the experiment from the effect of not binge-watching it. Columns (1) and (2) show that offering access to TELCO-SVoD increased the time that households spent both binge- and non-binge-watching TELCO-SVoD content. These columns also show that customized reminders increased the time they spent watching TELCO-SVoD content in nonbinge mode. Column (3) shows coefficients with the expected signs for the effect of binge-watching and the effect of not binge-watching TELCO-SVoD content during the experiment. However, these coefficients are not statistically significant.

The distributions of *Watch Time Binge* and *Watch Time Other* are highly skewed, have several outliers, and the shocks introduced by reminders on TELCO-SVoD consumption during our experiment are underpowered to separate these effects, which are measured on aggregate in column (5) of Table 11. We reduce the skewness of these distributions and limit the impact that outliers may have on our estimation procedure (without discarding any data points) by replacing *Watch Time Binge* and *Watch Time Other* with *Binged* and *Watched*, respectively, and then by estimating a multivariate Probit using the GJRM R package provided by (Marra and Radice 2017, Marra et al. 2017). The term *Binged* is a dummy variable equal to 1 for households that have positive *Watch Time Binge*, and *Watched* is a dummy variable equal to 1 for households that have positive *Watch Time Other*.

Columns (4) and (5) in Table 12 provide the necessary first-stage estimates, and column (6) shows our second-stage results. The latter column shows that watching TELCO-SVoD during the experiment increased the probability of subscribing to the service after the experiment. However, binge-watching TELCO-SVoD during that period reduced the likelihood of subscribing to the service after the experiment. In particular, the coefficient associated with *Binged* in the last column of this table shows that the likelihood of subscribing to TELCO-SVoD after the experiment for the households that binge-watched TELCO-SVoD content during our experiment reduced 1.5% because of the gift, from a baseline of 1.7% .[1]

Table 13 shows the effect of reminders on the likelihood of subscribing to TELCO-SVoD after the experiment. Columns (1) and (2) show that generic reminders did not change this likelihood, but that customized reminders did. The latter increased this likelihood (+0.180 in the probit specification) and offset the negative effect of the gift reported before (−0.163 in the probit specification). Columns (3) and (4) show that customized reminders did not slow the consumption of TELCO-SVoD content during the experiment. On the contrary, these reminders increased the number of distinct TELCO-SVoD

Table 12. The Effects of Binge-Watching and Not Binge-Watching TELCO-SVoD Content on the Posttrial Likelihood of TELCO-SVoD Subscription

	What_Time_Other	What_Time_Binge	*Subscribed*	*Watched*	*Binged*	*Subscribed*
	OLS	OLS	IV Probit	Probit	Probit	Tri. Probit
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.27**	0.06	−2.16***	−1.82***	−2.60***	−2.17***
	(0.11)	(0.09)	(0.06)	(0.03)	(0.06)	(0.04)
Gift	1.65***	0.68***		0.91***	0.87***	
	(0.15)	(0.12)		(0.04)	(0.07)	
Generic_Communication	−0.08	0.00		−0.04	−0.08	
	(0.15)	(0.12)		(0.05)	(0.09)	
Custom_Communication	-0.07	−0.01		−0.04	−0.14	
	(0.15)	(0.12)		(0.05)	(0.10)	
Gift × *Generic_Communication*	0.34	0.24		0.10*	0.09	
	(0.21)	(0.17)		(0.06)	(0.10)	
Gift × *Custom_Communication*	0.53**	0.18		0.10*	0.15	
	(0.21)	(0.17)		(0.06)	(0.10)	
Watch_Time_Other (hours)			0.27			
			(0.49)			
Watch_Time_Binge (hours)			−0.80			
			(1.16)			
Watched						0.33***
						(0.09)
Binged						−0.76***
						(0.09)
Num. obs.	29,950	29,950	29,950	29,950	29,950	29,950
RMSE	7.57	6.01				
AIC						26,557.68
Log likelihood						−13,260.84

Notes. Heteroskedasticity-consistent standard errors are in parentheses. Column (1) corresponds to Equation (11). Column (2) corresponds to Equation (12). Column (3) corresponds to Equation (13). Columns (4), (5), and (6) correspond to Equations (11), (12), and (13), but we replace *Watch_Time_Other* with *Watched* and *Watch_Time_Binge* with *Binged*, which are all binary outcomes. This transformation allows the joint estimation of the three equations using a multivariate probit framework. OLS, Ordinary least squares; IV, instrumental variable; Tri, trivariate; Num. obs., number of observations; RMSE, root mean squared error; AIC, Akaike information criterion.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

episodes that treated households watched as well as the number of distinct TV shows. Online Appendix G provides additional analyses about the effect of reminders on TELCO-SVoD consumption, showing that customized reminders steered consumption toward TELCO-SVoD content that households would unlikely consider organically. Columns (5) and (6) in this table show that the effect of reminders on the likelihood of TELCO-SVoD subscription after the experiment comes from the households that indeed watched TELCO-SVoD content during the free trial.

To conclude the analysis of the TELCO-SVoD experiment, we look at the survey extended to all treated households after the experiment.

The survey allows us to collect additional information about why many households refrained from subscribing TELCO-SVoD after the experiment and about why customized reminders may have affected their decisions to do so. A total of 296 answers were collected from the 15,000 treated households that were targeted with the survey. Figure 3 shows the relative importance of each answer, that is, how many households cited each answer among those that binge-watched and those that did not binge-watch TELCO-SVoD content during the experiment. High price and lack of content refresh are the only two answers that drew larger shares among binge-watchers. The shares of households indicating a lack of time and lack of interest are actually larger among non-binge-watchers. Online Appendix H shows that TELCO consumers are willing to pay more for a service that allows for binge-watching. Therefore, we find some evidence that lack of content refresh seems to be a major reason why binge-watchers exhibit a lower likelihood of

Table 13. Mediating Effect of Recommendation Reminders on Consumption of TELCO-SVoD Content During the Experiment and on Posttrial Subscription to TELCO-SVoD

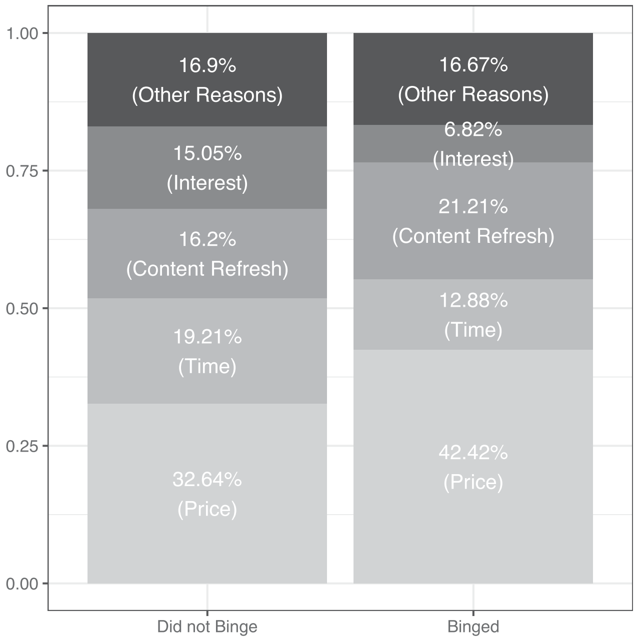
	Subscribed		*N_Episodes*	*N_TV_Shows*	*Subscribed*	
	OLS	Probit	OLS	OLS	2SLS	IV Probit
	ITT	ITT	ITT	ITT	LATE	LATE
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.018***	−2.106***	0.489***	0.053***	0.018***	−2.090***
	(0.002)	(0.043)	(0.073)	(0.006)	(0.002)	(0.051)
Gift	−0.006**	−0.163**	4.201***	0.174***		
	(0.002)	(0.066)	(0.349)	(0.016)		
Generic_Communication	−0.000	−0.000	−0.033	−0.011	−0.001	−0.017
	(0.003)	(0.061)	(0.106)	(0.009)	(0.003)	(0.071)
Custom_Communication	−0.003	−0.074	−0.028	−0.021**	−0.004	−0.099
	(0.003)	(0.063)	(0.126)	(0.009)	(0.003)	(0.073)
Gift × *Generic_Communication*	0.003	0.089	0.659	0.018		
	(0.003)	(0.091)	(0.494)	(0.021)		
Gift × *Custom_Communication*	0.007*	0.180*	0.850*	0.065***		
	(0.003)	(0.092)	(0.500)	(0.023)		
Watch_Time_All (hours)					−0.003**	−0.090***
					(0.001)	(0.030)
Watch_Time_All (hours) × *Generic_Communication*					0.002	0.048
					(0.001)	(0.038)
Watch_Time_All (hours) × *Custom_Communication*					0.003**	0.077**
					(0.001)	(0.038)
Num. obs.	29,950	29,950	29,950	29,950	29,950	29,950
RMSE	0.122		17.578	0.782	0.125	
AIC		4,725.031				
Log likelihood		−2,356.516				
Deviance		4,713.031				

Notes. Heteroskedasticity-consistent standard errors are in parentheses. Columns (1) and (2) correspond to Equation (14). Columns (3) and (4) correspond to Equation (15), but replacing *Watch_Time_All* with *N_Episodes* and with *N_TV_Shows*, respectively. Columns (5) and (6) correspond to Equation (16). 2SLS, Two-stage least squares; OLS, ordinary least squares; IV, instrumental variable; Num. obs., number of observations; RMSE, root mean squared error; AIC, Akaike information criterion.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TELCO-SVoD subscription after the experiment. The fact that binge-watchers report high price as a concern is also aligned with this idea. Binge-watchers burn more content during the experiment. Therefore, the VoD catalog loses more value for them. As a consequence, they identify high price as a concern for posttrial subscription, even though they would pay more for the service allowing for binge-watching.

Finally, if customized reminders leveled off the likelihood of TELCO-SVoD subscription after the experiment because they incentivized consumers to consider titles that they otherwise would have not browsed or watched, leading them to realize that there remained interesting content to watch in the outstanding TELCO-SVoD catalog that could be worth paying for, then one may expect that the consumers who received these reminders during the experiment were less concerned with the lack of content refresh. We use the answers collected from the postexperimental survey to analyze whether this is the case. Table 14 shows the results obtained from coding the different reasons for not subscribing to TELCO-SVoD after the experiment as dummy variables and using logistic regressions to test whether receiving generic and customized communications changed the likelihood of choosing each of them. These results provide strong evidence that customized reminders changed consumers' perceptions about how much TELCO refreshed the TELCO-SVoD catalog during the experiment. In line with our previous results, we find that generic communications had no effect on the reasons that consumers reported for not subscribing to TELCO-SVoD after the experiment, but that customized communications reduced by 15%–17% the likelihood of reporting lack of content refresh as a driver for not doing so.

Figure 3. Reasons Why Treated Households Did Not Subscribe TELCO-SVoD After the Experiment (296 Survey Respondents)



Note. Each column indicates the percentage of households that selected each answer.

5. Conclusions

Binge-watching has recently become a widespread cultural and social phenomenon. It disrupts the traditional model of linear TV, which was based on tight broadcast schedules, by shifting control to consumers. Propelled by advanced content distribution networks over the internet, OTT platforms such as Netflix, Hulu, and Amazon Prime allow consumers to watch what they want when they want. Content is available at all times from SVoD services, whose catalogs now offer an unprecedented number of movies and TV shows. In many cases, content providers upload several episodes of the same TV show at once, allowing for binge-watching. In some cases, they even upload all the episodes of the same TV show season at once, allowing consumers to view entire seasons over short periods of time, whereas in the past consumers needed several months to get to season finales. Content providers and content distributors have raced very quickly to provide SVoD services allowing for binge-watching. However, it is unclear whether content providers and content distributors fully anticipated all the potential consequences of such a shift. For example, with SVoD services that allow for binge-watching, consumers watch more content per unit of time. These higher rates of consumption can lead them to deplete VoD catalogs faster and can reduce their interest in and, consequently, their willingness to pay for the outstanding VoD catalog, at least in the short run until new content is added to the SVoD library.

Our paper provides evidence of this mechanism at work. We partner with a major telecommunications provider—that we call TELCO—to study the impact of binge-watching on the likelihood of an SVoD subscription. We report results from two randomized control trials, in both cases showing that binge-watching reduces the latter. In our first experiment, some households were offered access to a TV channel that broadcast movies and TV shows 24/7. A random subset of these households was offered access to this channel with TSTV,

Table 14. Effect of Recommendation Reminders on the Reasons to Not Subscribe to TELCO-SVoD After the Experiment

	Price	*Interest*	*Time*	*Content Refresh*	*Price*	*Interest*	*Time*	*Content Refresh*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.557***	−1.253***	−0.836***	−0.504***	0.182	−1.312***	−0.981**	−0.431
	(0.163)	(0.189)	(0.171)	(0.162)	(0.350)	(0.426)	(0.391)	(0.356)
Generic Communication					0.476	0.074	0.181	−0.092
					(0.396)	(0.475)	(0.435)	(0.400)
Custom_Communication	−0.102	0.213	0.285	−0.739***	0.273	0.272	0.430	−0.812**
	(0.241)	(0.273)	(0.248)	(0.263)	(0.392)	(0.469)	(0.430)	(0.412)
dy/dx								
Custom_Communication	−0.024	0.039	0.063	−0.153***	0.063	0.050	0.095	−0.167**
	(0.057)	(0.050)	(0.055)	(0.052)	(0.089)	(0.086)	(0.095)	(0.082)
Num. Obs.	296	296	296	296	296	296	296	296
Log likelihood	−195.734	−162.769	−187.283	−178.558	−195.018	− 162.757	−187.194	−178.531
AIC	395.467	329.538	378.565	361.116	396.037	331.513	380.389	363.063

Notes. Columns (1–8) estimate using logistic regression. Heteroskedasticity-consistent standard errors are in parentheses. dy/dx, the average marginal effect of the logistic regression for the impact of Customized_Reminders on the survey reponses; Num. obs., number of observations; AIC, Akaike information criterion.

$^{**}p < 0.05$; $^{***}p < 0.01$.

and the remainder could only watch this channel live. A third random set of households was used as a control group. Using TSTV, the second set of households could binge-watch by going back in time and consuming several episodes of the same TV show in the same sitting. We find that households offered access to this channel for free subscribed to it less than households that did not receive the gift. This result is driven by the fact that the former set of households used TSTV to binge-watch this channel during the experiment.

The fact that binge-watching reduces the posttrial likelihood of subscription may seem, at first glance, surprising. Therefore, we ran a second experiment to better understand the drivers of this result. Our second experiment studies the behavior of households offered access to TELCO-SVoD, an SVoD service similar to Netflix, Hulu, and Amazon Prime. A subset of households, selected at random, was offered access to TELCO-SVoD for free for three months. The remaining households were not offered this gift and were used as a control group. TELCO did not update the content in the TELCO-SVoD library during this experiment. We find that the households that binge-watched TELCO-SVoD were less likely to subscribe to it after the experiment. However, they also enjoyed (proxied by likes per piece of content watched) more their overall experience with the VoD system at TELCO, ruling out the potential confounder that the content offered as part of TELCO-SVoD was unattractive.

The lower likelihood of SVoD subscription in the short run across binge-watchers may be an undesired outcome for content providers and content distributors and may be troublesome now that binge-watching has become a prevalent way to consume video. Although our analyses are only about the effect of binge-watching on acquiring consumers with free trials, we anticipate that results may be similar in contexts of consumer retention. Binge-watching by existing consumers is also likely to lead them to exhaust the VoD catalog of interest to them more quickly, and to change how much they are willing to pay to continue subscribing to such services. In any case, studies looking specifically at how binge-watching affects churn rates in VoD might be a relevant area for future research. We also study whether recommendation reminders, aimed at expanding the preferences of consumers for existing content, could help address this concern. Enticing consumers to view content that is already available in the SVoD catalog that they would not otherwise browse or watch could lead them to enjoy the SVoD service more, keeping them engaged for more extended periods. These strategies are likely to allow content providers to better manage the potentially prohibitive costs associated with a demanding schedule to create and distribute new content.

During our experiment with TELCO-SVoD, a subset of households used in the experiment, selected at random, received generic reminders. Another subset of households, also selected at random, received customized reminders. The previous messages reminded consumers of TELCO-SVoD, whereas the latter suggested particular TV shows that could be watched using TELCO-SVoD that households did not watch before. We find that consumers who received customized reminders did not reduce their likelihood of subscribing to TELCO-SVoD after the experiment. On the other hand, consumers who did not receive these reminders were significantly less likely to subscribe to the service after the experiment. Therefore, carefully crafted reminders may help keep binge-watchers engaged with SVoD services. The fact that, on average, customized reminders may completely offset the negative effect of binge-watching may also be surprising given their relative simplicity and cost-effectiveness.

A postexperimental survey of consumers treated with TELCO-SVoD confirmed a lack of content refresh and a high price as the main reasons leading binge-watchers not to subscribe to the service after the experiment. However, consumers are willing to pay more for a SVoD service that allows for binge-watching. Furthermore, consumers who received customized reminders during our experiment reported lack of content refresh as a concern less frequently, which provides additional evidence of the critical role that such reminders may play in helping to manage the supply of VoD content. Consequently, VoD platforms may want to consider prioritizing recommendations to binge-watchers, in particular, those who use third-party services to manage recommendations, given that the latter usually charge according to the size of the targeted population.

We also acknowledge that our study has some limitations. For example, TELCO was able to collect answers from only a few consumers who self-selected to answer the survey run after our second experiment, and therefore our data do not represent the average households included in this experiment. Also, during this experiment, we measure the effect of recommendation reminders using a single recommender system, specific text messages, and using a fixed schedule for issuing them. Thus, our results pertain to these conditions and may be different in other settings. Still, we show that customized reminders help keep binge-watchers engaged, which we believe provides a good signal for firms to invest in better recommendation technologies targeted at binge-watchers. Also, we acknowledge that a good experimental design to further test the effect of catalog depletion on SVoD subscription rates would be to randomize, at the household level, the rate at which the content provider/distributor adds new content to the SVoD catalog. Unfortunately, this was not possible at TELCO, for both business and technical reasons; therefore, we leave this idea for future research. Potentially, such analyses may even allow one to determine the optimal refresh rate for content in the catalog in the presence of binge-watching.

In addition, we note that after these experiments, TELCO offered the products featured in them to consumers at the usual market prices. Therefore, our results are pegged to such prices and could change were other prices to be implemented. In any case, we note that price sensitivity cannot drive our findings, because households were randomly assigned to treatment and control groups and, therefore, that the price sensitivity is, on average, similar across the groups of households that we compare in our analyses. Likewise, the free trials in our experiments ran for specific periods, namely, six weeks and three months. Although the free-trial durations are standard in the country where TELCO operates, we still acknowledge that our results are pegged to these managerial choices. Future work may attempt to study the effect of different free-trial durations on the posttrial likelihood of product subscription.

Finally, we acknowledge that our paper looks only at the short-term effects of binge-watching on the likelihood of VoD consumption. We also note that in many respects, we were limited in the types of manipulations we could have, on the sample size we could obtain, in the timing, and in the services we could use in our experiment. Given the constraints of deploying an experiment in a real business setting, we focused on studying the average effect of binge-watching on an SVoD subscription, and we did not plan our study to explore heterogeneous treatment responses. Although we believe that our contribution is novel and valuable for both academics and practitioners, we leave much on the table for others to explore in the future. We believe that it will be valuable to explore moderators of binge-watching behavior to provide further insights into how and when firms can pace the consumption behavior of households and minimize the negative business effects of binge-watching that we identified in our research.

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Endnote

[1] We calculate the treatment effect in the multivariate probit using posterior simulation. The calculation measures the average difference in outcomes under treatment (the binary predictor or treatment assumes value 1) and under control (the binary treatment assumes value 0). For the econometric details, please see (Marra and Radice 2011). For the code implementation see (Marra and Radice 2017)

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