The Effects of Binge-Watching on Media Franchise Engagement *

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Abstract

We quantify the effects of binge-watching on consumers' engagement with media franchises in two areas: interactive and personal engagement. The former involves a user's content generation related to a focal media product and the latter concerns the adoption of franchise extensions (sequels and other extensions). Our novel data come from an online anime (Japanese cartoons) platform containing individual-level data on users' anime adoptions and their user-generated content. We find that binge-watching has a negative effect on the production of user-generated content. The effect of binge-watching on the adoption of franchise extensions critically depends on both the availability of franchise extensions at the time of watching the focal anime and the extension type: if it is available, binge-watching increases (decreases) the probability that a user watches the sequel (other franchise extensions). If it is not available, binge-watching has no effect on (decreases) the probability that a user watch the sequel (other franchise extensions). Our results are directionally robust using data from five continents. We discuss managerial implications for TV networks and online streaming services regarding the timing of content release.

Keywords: Binge-Watching, Media Franchise, Consumer Engagement, Online Movie Streaming

JEL Classification: L82, M31

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1 Introduction

The global entertainment and media industry reported revenues of $1.72 trillion in 2015 (Statistica 2016*b*) with $38.3 billion coming from the box office and $286 billion from the TV and video industry (Statistica 2016*a*). A notable trend on both big and small screens is the rising success of media franchises. For example, the top-grossing movies of 2015 all belonged to franchises such as Star Wars, Jurassic World and Avengers. Franchise series also ruled the small screen as witnessed by the exploding online streaming traffic at Netflix drawn by Breaking Bad and House of Cards. We broadly define "media franchise" as a collection of media in which several derivative works have been developed in response to the popularization of an original creative work and the commercial exploitation of such through licensing agreements (Aarseth 2006). For example, the media franchise of the American sitcom "Friends" consists of ten seasons of the TV series and a spin-off TV series named "Joey;" the media franchise of the Japanese anime "Pokemon" began as two video games and now spans into animated TV shows and movies, trading card games, comic books, and toys.

Although industry observers have regarded media franchises as the overt success recipe for Hollywood because of the built-in awareness and interest with audiences (Garrahan 2014; Gonzales 2014), little is known about the factors that contribute to consumers' engagement with a media franchise. Marketing scholars and business practitioners have long been interested in consumer engagement or customer brand engagement which highlights customers' interactive and co-creative experiences with firms and other customers (e.g. Bowden 2009; Van Doorn et al. 2010; Mollen and Wilson 2010; Vivek et al. 2012). Empirical studies have shown that engaged customers play a key role in viral marketing activities by providing product referrals and recommendations, in new product development, and in co-creating experiences and value (e.g., Nambisan and Nambisan 2008; Brakus et al. 2009; Hoyer et al. 2010) across various industries. However, to the best of our knowledge, no empirical study to date has systematically examined consumer engagement in the context of media franchises.

Another prominent recent trend in the entertainment and media industry is the immense popularity of binge-watching, i.e., the practice of watching multiple episodes (of a series) in rapid succession. The percentage of consumers who indicate that they binge-watch increased from 62% in 2013 (Shannon-Missal 2013) to 92% in 2015 (TiVo 2015). Anecdotal evidence is abundant that binge-watching might increase viewer engagement with sequels and spin-offs. For example, Breaking Bad creator Vince Gilligan previously told Mashable that the show "may have met its demise after season two, had it not been for streaming video on demand. It ushered in new viewers and encouraged time-starved individuals to keep watching at their own pace resulting in enormous growth from season to season" that reached its climactic end in September 2013 with 10.3 million viewers (the show's highest viewership ever) (Hernandez 2014). Similarly, for popular series such as "Supernatural," Netflix starts streaming previous season(s) shortly before the release of a new season (on traditional TV).

Despite what anecdotes and common practice suggest, there is little systematic empirical evidence to support the claim that binge-watching increases consumer engagement with a media franchise. Furthermore, how this engagement manifests itself is of interest to both academics and practitioners. Calder et al. (2009) identify two types of engagement with media: personal engagement such as enjoyment and relaxation, and interactive engagement such as socialization and participation in a community. They associate the former with intrinsic motivation that leads an individual to getting caught up in the flow of an activity and being absorbed by it (Csikszentmihalyi 1997), and the latter with extrinsic motivation that leads to an individual's content generation and promotion of a focal media product. Therefore, increased engagement with a TV series might result in the viewer watching subsequent series, i.e. sequels, or other franchise extensions of the same series and/or in the viewer promoting the TV series and producing user-generated content (UGC) about it. We explore these questions in this paper.

If binge-watching increases consumer engagement with a media franchise, this finding would have important implications for both online streaming services and traditional TV

networks. For online streaming services, it would validate their practice of releasing a whole season of a series at once and thereby making it bingeable. For TV networks, it would provide support for their new strategy of promoting a new season shown on traditional TV by making older seasons available through online streaming services. This strategic tool could represent an especially important benefit for TV networks since it would not only increase immediate profits through higher advertising revenues (for the new season on traditional TV), but also extend the "life" of a series, making it more likely to reach five seasons at which point the series is a candidate for syndication, a very profitable path for networks.

If binge-watching does not increase media franchise engagement or if it does not do so for all series or consumers, it is important to understand why and when this is the case. For example, does the timing of the release through online streaming services matter? Or does the type of franchise extensions matter, for example, sequels might benefit more from binge-watching than other types of franchise extensions such as spin-offs? Furthermore, given the varying popularity of online streaming and binge-watching across different countries, are consumers from some countries affected more by binge-watching than consumers from other countries? In this paper, we provide systematic empirical evidence of this new mode of viewing and its effects on consumers' media franchise engagement.

Our data come from MyAnimeList.net, an online forum that attracts anime (Japanese cartoons) fans from all over the world. We observe a user's adoption of animes including information on the number of days it took a user to watch the whole season of an anime. This allows us to classify user-anime combinations into "binged" and "not binged" cases. Further, we observe a user's self-generated content about an anime in the form of posts on the discussion forum and recommendations. Our data also contain information on a user's decision to watch the next season (sequel) of an adopted anime and to watch other franchise extensions such as summaries, spin-offs, side stories, and remakes.[1] And lastly, we have a large set of control variables including a user's rating of watched animes and the user's

[1] We define each of these types of franchise extension in the Data Section.

geographic location.

We use bivariate binary probit models to quantify the effects of binge-watching on a user's actions related to media franchise engagement. The first binary probit equation describes the effects of binge-watching and the second binary probit equation models the user's decision to binge. We incorporate an instrumental variable that satisfies the exclusion criterion in the latter equation to account for the potential endogeneity of the decision to binge-watch. By simultaneously modeling the decision to binge and the decision to engage with a media franchise, we allow correlated unobservables to drive both decisions.

Our results for North American consumers show that binge-watching reduces a user's probability of producing UGC. The effect of binge-watching on a user's franchise adoption, however, largely depends on both the availability of the franchise at the time of watching the focal series and the type of franchise extensions. If the franchise extension is available, bingeing the prior season significantly increases a user's probability of watching the subsequent season (sequel), but decreases the adoption of other franchise extensions. If the franchise is not available at the time of watching the focal series, bingeing decreases the probability of watching other types of franchise extensions, but has no effect on the adoption probability of the sequels. We extend our analysis using data on consumers from other continents (South America, Europe, Asia and Oceania). We find the effects of binge-watching to be qualitatively consistent across the five regions if the coefficient estimates are statistically significant.

Our paper makes the following contributions. First, we contribute to the vast consumer engagement literature by systematically examining the factors that drive consumer engagement in the context of a media franchise. By quantifying the effect of binge-watching on consumer engagement with a media franchise in two broad areas, interactive and personal engagement, our paper provides empirical evidence that the modus of consumption, on top of product adoption, influences consumer brand engagement. And second, our paper adds to the small but rapidly growing literature on binge-watching and online streaming. To

the best of our knowledge, we are the first to establish the effects of binge-watching on consumers' subsequent media consumption and word-of-mouth behavior. Our results have important managerial implications for both online streaming services and traditional TV networks regarding content provision and the timing thereof.

The remainder of the paper is organized as follows: In the next section, we discuss the relevant literature. In Sections 3 and 4, we describe our data, introduce our model and estimation approach. We present our results in Section 5. In Section 6, we conduct robustness checks and discuss limitations and future research in the following section. Finally, we conclude by summarizing our findings and discussing managerial implications in the last section.

2 Relevant Literature

In this section, we review relevant streams of literature on customer engagement, binge-watching, and online movie streaming.

2.1 User Engagement

Customer "engagement" has been extensively studied in the marketing literature (e.g., Bowden 2009; Mollen and Wilson 2010; Van Doorn et al. 2010; Vivek et al. 2012).[2] It differs from similar relational concepts such as participation or involvement in that it highlights customers' interactive and co-creative experiences in networked relationships with multiple stakeholders including service personnel, firms, and/or other customers (Brodie et al. 2011). Empirical studies have shown that engaged customers play a key role in viral marketing activities by generating referrals and recommendations for products and services, in new product development, and in co-creating experiences and value across various industries (e.g., Nambisan and Nambisan 2008; Brakus et al. 2009; Hoyer et al. 2010). However, to the

[2] We refer readers to Brodie et al. (2011) for an extensive review of the marketing literature on engagement.

best of our knowledge, no empirical studies to date have systematically examined consumer engagement in the context of media franchises. Wei (2016) studies the movie industry's decision of producing original vs. imitative work and rationalizes the industry's exceeding reliance on sequels and franchises as a result of firms attempting to reduce demand uncertainty and securing finances for new movies. Despite the popularity and success enjoyed by media franchises on both big and small screens, little is known about the factors that contribute to consumers' engagement with a media franchise.

In a separate stream of literature, Calder et al. (2009) define engagement in terms of the different motivational experiences that consumers have with a media product. Using a confirmatory factor analysis, they identify two types of engagement with media, personal engagement and interactive engagement. The former includes individualistic experiences such as enjoyment and relaxation, while the latter is especially relevant to online media and includes experiences such as socialization and participation in a community. While personal engagement with a media product is associated with intrinsic motivation, i.e. the individual getting caught up in the flow of consuming the product and being absorbed by it (Csikszentmihalyi 1997), interactive engagement is associated with extrinsic motivation, i.e. the individual creating content and voluntarily engaging in media promotion activities. Following Calder et al. (2009), we study users' interactive and personal engagement with a media franchise. In our empirical context of an online anime platform, the former includes a user's content generation and promotion of a focal media product, e.g. a user's recommendations, comments, and responses published in a community discussion forum regarding a TV series. The latter includes a user's self-enjoyment of the focal product and the adoption of its franchised extensions including sequels, spin-offs, summaries, side stories, and remakes.

2.2 Binge-Watching

The Merriam-Webster dictionary defines binge-watching as "Watch(ing) many episodes (of a television program) in rapid succession, typically by means of DVDs or digital stream-

ing (Merriam-Webster.com 2017)." This definition is consistent with Schweidel and Moe (2016) who consider "the consumption of multiple episodes of a television series in a short period of time" as binge watching. Many regard the element of control as an essential part of binge-watching, which distinguishes binge-watching from watching marathon releases of series episodes back to back on regular TV channels (Jenner 2015; Pittman and Sheehan 2015). In other words, binge-watching is not only about watching multiple episodes in one sitting, but it is also about a user's control and decision on when and what to watch. In addition, the presence or absence of interruptions such as commercials separates marathon releases on TV channels from binge-watching by means of DVDs or digital streaming (Jenner 2015).

There is disagreement on how much watching is considered binge-watching. Many studies rely on respondents' perception of what is considered binge-watching without defining a specific amount (e.g., Devasagayam 2014; Pena 2015). Based on a survey of their users, Netflix defines binge-watching as watching at least two episodes in one sitting (Netflix 2013). This is in line with the idea that binge-watching is a violation of what is considered the norm, regular TV watching or "appointment watching" (Jenner 2015). The number of two episodes is not agreed upon by everyone though. For example, Amazon made the first 3 episodes of its series "Alpha House" available to its viewers at once, implying that it considers 3 episodes as a bingeable amount. Some studies view binge-watching as watching with the purpose of finishing a whole season in a short period of time (Devasagayam 2014; Pena 2015). However, this view is not necessarily supported by consumer surveys. In a MarketCast study, 71% of respondents indicated that they do not plan on bingeing, but they end up doing so. Furthermore, these definitions focus on the number of episodes without differentiating between one-hour dramas (about 40 minutes without commercials) and 30-minute sitcoms (about 20 minutes without commercials). It is debatable whether watching 8 episodes of a sitcom corresponding to about 2.5 hours is considered binge-watching. In this paper, we suggest a clear definition of binge-watching which is based on the time spent

watching a whole season and test its robustness.

Many reasons have been found for binge-watching. People binge to catch up on a series they missed when it was aired on TV (MarketCast 2013; TiVo 2015) or to be able to participate in the word-of-mouth created by the series (Pittman and Sheehan 2015). According to TiVo's annual binge behavior report, 32% of respondents indicated that they postpone watching a series until it has aired completely so that they can binge the whole season (TiVo 2015). This finding is consistent with MarketCast (2013)'s finding that one of the main reasons for binge-watching is that viewers cannot or do not want to wait for each next episode. The TiVo (2015) study also finds that 39% of the respondents consider it more enjoyable to binge a series as opposed to appointment watch it (Pittman and Sheehan 2015; TiVo 2015). Some people binge-watch TV to relax (Devasagayam 2014; Pittman and Sheehan 2015). For example, after a week of hard work, they binge-watch during the weekend to restore or as a reward to the point that they even plan for it beforehand. On the other hand, on weekends, holidays, or summer holidays for students, people might binge-watch because they are bored, have no better alternative, or feel lonely and want to compensate for their limited social life (Devasagayam 2014; Pittman and Sheehan 2015; Sung et al. 2015).

The underlying mechanism that drives binge-watching is related to the concept of "flow" (e.g., Hoffman and Novak 1996), which describes a state of focus concentration, intrinsic enjoyment, and time distortion. Previous research has found that users who experience the flow are more likely to repeat their behaviors or even become addicted (e.g., Kubey and Csikszentmihalyi 2002; Chou and Ting 2003). This mechanism also provides a plausible explanation for the interplay between advertisements and binge-watching as documented in Schweidel and Moe (2016): Advertisements in a viewing session discourage binge-watching and binge-watchers are less responsive to advertisements compared to non-binge-watchers.

While there has been a considerable amount of research on the reasons for binge-watching, few studies have focused on the consequences of binge-watching. In the TiVo (2015) study, 52% of respondents indicated that they felt sad when they finished bingeing a series; 31%

reported that they have lost sleep due to binge-viewing. Binge-watching - due to the intensity of the experience and the flow it creates - has been suggested to create loyalty to a series, lead to fandom or, at the very least, behavior similar to fandom such as purchasing ancillary materials, creating fandom pages or posting or creating content (Jenner 2015). However, empirical evidence supporting these claims is very limited. To the best of our knowledge, this paper is the first to carry out a systematic empirical examination on the effects of binge-watching on user engagement with a media franchise.

2.3 Online Movie Streaming

Despite its wide popularity, research on online movie streaming is scarce. Cha and Chan-Olmsted (2012) study the plausible cannibalization effect of online video platforms on traditional TV by examining the perceived substitutability between the former and the latter. They find that users of online video platforms believe that online video platforms have unique functionality and therefore are not substitutes for traditional TV. However, non-users of online video platforms perceive online video platforms as substitutes for traditional TV because of their perceived similar functionality. Cha (2013) finds that the more consumers perceive online video platforms to differ from traditional TV in satisfying their needs, the more likely they are to use online video platforms.

Studying consumer behavior within online streaming services, Ameri et al. (2016) investigate the drivers of consumers' anime adoption decisions. They find average anime ratings and popularity rank from the community network to have larger effects on consumers' adoption decisions compared to the same type of information obtained from the personal network. Zhang et al. (2013) develop a new class of "clumpiness" measures and, using data from Hulu.com, show that the "clumpiness phenomenon" is widely prevalent in digital content consumption. In a separate study, Zhang et al. (2015) extend the traditional recency/frequency/monetary value (RFM) segmentation framework to include the clumpiness measure (RFMC). In particular, they show that the RFMC framework can help companies

with bingeable content (such as online streaming platforms) uncover previously unseen customer segments. And lastly and most closely related to this paper, Schweidel and Moe (2016) simultaneously examine the drivers of users' binge-watching behavior and their responses to advertisements using data provided by Hulu.com. They find that binge-watchers are less responsive to advertising compared to non-binge-watchers.

3 Data

Our data come from MyAnimeList.net. This website was established in November 2004, but its main activities did not begin until 2007 when the website moved to a public domain and its user base started to grow rapidly (see Figure 1). At the point in time when we started the data collection (March 2015), there were more than 2.5 million users on the website.

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Insert Figure 1 about here

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MyAnimeList.net is a consumption-related online community where online interactions are based upon shared enthusiasm for a specific consumption activity (Kozinets 1999). MyAnimeList.net was created to allow anime fans to gather and share their excitement and opinions about animes. Over the years, the website has developed into one of the most comprehensive online sources of information about animes (Japanese cartoons). On MyAnimeList.net, both animes and users have their own pages. On a user's page, information about the animes the user has adopted (including the dates), her opinion about adopted animes (via numerical ratings), and forum posts and recommendations is shown in addition to her personal characteristics such as the user's geographic location or the website join date.

Users can create a list of animes that they plan to watch or have watched (we refer to this list as "watch list" throughout this paper).[3,4] Note that users add animes to their watch

[3]We do not account for platform choice in this paper because, in general, users can watch animes either legally or illegally through a number of different channels such as netflix.com, hulu.com, funimation.com, crunchyroll.com, aniplexusa.com and others.

[4]Our adoption data are self-reported. Thus accuracy in the reporting of adoptions is a potential concern.

lists using a search function so that all animes are correctly and uniquely identified. Further, users can also indicate their opinion about the animes on their watch list by rating them on a scale ranging from 1 to 10 (10 being the highest rating). Throughout this paper, we refer to ratings given to animes on watch lists as "user ratings." Lastly, users can indicate the date they started watching an anime series, the date they finished watching an anime series and the website also automatically registers the date users last updated the entry for an anime. We use these dates to infer the time of adoption.

3.1 Data Cleaning

We scraped data on 370,000 users from the website through snowball sampling. Not all users list start dates for (all or any) animes they have adopted on their watch list. After excluding all anime-user combinations for which we did not have start dates, we were left with 92,273 users. We then dropped (i) animes for which we did not have the release date or information on the number of episodes; (ii) anime-user combinations for which the watch period seemed unreasonably long, i.e. more than 3,000 days; (iii) observations for days on which users indicated to have watched more than 24 hours of animes; (iv) observations with start dates before 2008 since, although the website was launched in 2004, its main activities did not start until mid 2007 (see Figure 1); (v) observations with start dates after the end of 2014. Using the remaining 89,422 users and 4,896 animes (3,481,664 user-anime combinations), we took the following steps to get to our final data.

First, we dropped animes that would take less than 3 hours to watch. Table 1 shows the distribution of animes with respect to their number of episodes and durations. Movies or short anime series generally take less than 3 hours to be watched and thus, according to our operationalization of binge-watching (see Section "Binge-Watching"), cannot be binged.

We address this concern when discussing Figure 4. Further note that in contrast to incentivized surveys, there are no incentives for users on MyAnimeList.net to falsely report their true anime watching behavior. Furthermore, in the similar setting of TV shows, Lovett and Staelin (2016) compare survey panelists' self-reported viewing data and the actual streaming data and find that people tend to correctly report their actual watching behavior. Thus we are confident that the self-reported adoption data are reliable in our context.

Note that even if a user watches 3 movies back to back, since they are not part of a series, we do not consider this instance as binge-watching. Second, we dropped cases in which a user did not watch the whole season. Even if a user binge-watches the first half of a season, her behavior might be different compared to someone who finished the whole season. To be able to attribute the difference in behavior to the viewing modus of binge-watching and not the completion of the whole season, we only consider cases in which the user finished watching the whole season.

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Insert Table 1 about here

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Third, we only consider cases in which users have the option to binge the anime, but may choose not to do so, i.e. we only consider watching incidences after the season finale of an anime has been aired. It is noteworthy that most of our observations are for such cases (see Figure 2). After these three steps, our final data sample for the empirical analysis related to UGC contains 73,346 users and 2,715 animes (1,298,786 user-anime combinations). Next, to study user engagement in the form of watching franchise extensions, we only consider animes that have a franchise extension, i.e. next season (sequel) or other franchise extensions (side story, spin-off, summary, remakes). Note that some animes have multiple franchise extensions such as a spin-off and a summary. We consider adoption of each type of franchise extensions as a separate adoption, but only consider the first adoption out of multiple adoptions of the same type.

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3.2 Engagement

We study a user's engagement with a series in two areas: interactive and personal engagement. First, a user might engage with an anime by producing UGC in the form of recom-

mendations and posts on the discussion forum. On the platform, users can communicate with other users about the anime on an anime's discussion forum page. We operationalize communication engagement as two indicator variables: whether a use wrote (at least) one recommendation and whether a user wrote (at least) one post on the discussion forum.[5]

Second, a user who is engaged with an anime might get more caught up in the story line and be more likely to watch its franchise extensions. Our data contain information on whether a user watched the next season (sequel) and/or other franchise extensions, including spin-offs, summaries, side stories, and remakes. A "side story" is a short story related to the main characters in the context of the focal series. For example, the movie "Sherlock: The Abominable Bride" is a side story for the "Sherlock" series. A "spin-off" is a story taken from the focal series, however, unrelated to the main story. It usually tells the story of a secondary character following a different storyline, almost like a new series. For example, the "Joey" series is a spin-off from the popular sitcom series "Friends." A "summary" is a short series or a movie summarizing the events of the focal series. For example, the "Pink Panther" movie is a summary of the events in the identically titled TV series. A "remake" is a remake of the series, usually with small differences in the plot or a different ending. For example, there are several "Batman" series that are remakes of the same story. We operationalize personal engagement as an indicator variable: whether a user watched the franchise extension (at any point in time in the future).

3.3 Binge-Watching

We define a user as having binge-watched an anime if the user watches the series for over 3 hours on a single day, a more conservative measure than Netflix's.[6] In the Robustness Section, we test the robustness of this definition with respect to shorter and longer watch times. To differentiate binge from non-binge incidences, we use the average daily time that

[5]Conditional on writing at least one recommendation or at least one forum post, the median number of recommendations and forum posts users write are 1 and 2, respectively.

[6]Netflix defines binge-watching as watching at least two episodes in one sitting (Netflix 2013).

a user spent watching a series (calculated by dividing the total length of the series by the number days that it took the user to finish watching the series). For example, if a user watches more than an average of 3 hours a day (corresponding to about 8 25-minutes long episodes, excluding the few minutes of openings and endings), we mark this incidence as binge-watching.[7]

We use information on the start and end dates from users' watch lists to measure "watch period," the number of days it took a user to watch an anime season. We have both pieces of information for 93% of user-anime combinations. For the remaining 7% of user-anime combinations, we have the start date, but not the finish date. However, the website automatically registers the last time a user made a change to an anime on her watchlist, i.e. for each individual anime the website registers when the user made the last change in the entry for that specific anime. We use this registered last update in lieu of the finish date for the user-anime cases in which the user did not provided a finish date.[8]

3.4 Data Description

Figure 3 shows the distribution of watch periods (in days) in our sample. More than 50% of the user-anime cases are watched within 5 days, with 18.62% of user-anime combinations being watched within a day or two. While our classification into binged vs. non-binged animes depends on the length of a season in terms of hours (which Figure 3 does not take into account), Figure 3 shows that a potentially significant portion of user-anime cases are being binged.

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[7]Note that a user might have watched more than 3 hours on a Sunday, but it took him Monday to Friday to gradually watch the remaining 3 episodes (about 1 hour) and finish the series. Our data do not allow us to identify the watching behavior on Sunday as binge-watching.

[8]The only change a user can make after indicating that she has completed the series is adding a rating. In such cases, we might label a binge-watching case as a non-binge-watching case if the period between start date and the last update date is long.

In Figures 4(a) and 4(b), we display the total number of hours individuals watched animes on a day during which they binged and did not binge, respectively. Note that the total number of hours includes everything the user watched, i.e. all animes the user binged on that day *and* any other animes the user might have watched on that day. On days during which users binge-watched, the vast majority of users watched between 3 and 6 hours with a second, smaller group of users watching between 9 and 11 hours. While the distribution has a long right tail, very few users report watching more than 16 hours a day. This gives us confidence in the accuracy of the self-reported watching behavior (see also Netflix (2013)). On days during which users do not binge-watch, almost all users watch less than 3 hours. This is *not* a direct result of our definition of binge-watching since Figure 4 shows the total number of hours users spent on anime watching. For example, users who watch 7 episodes of one anime series and 7 episodes of another anime series would not be classified as bingeing on that day, but would have watched more than 3 hours.

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Insert Figure 4 about here

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Figure 5 shows the distribution of the fraction of animes on a user's watch list that can be classified as binged vs. not binged using the 3-hour cut-off. About 41.8% of users do not binge-watch at all, while for 6.5% of users bingeing is how they watch all animes. This implies that, although some users can be called binge-watchers and others non-binge-watchers, most of the users binge some and gradually watch other animes. This empirical observation is consistent with previous findings (e.g., MarketCast 2013; Schweidel and Moe 2016). On average, we classify 20.4% of animes on a user's watch list as binged with a standard deviation of 28% and a median of 8.3%.

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Figure 6 displays how the number of binged vs. non-binged cases has evolved over time. Up until about 2013, both the number of binged and the number of non-binged cases is gradually increasing. Starting in 2013, the number of binged cases continues to increase, while the number of non-binged cases starts to decrease, implying that more users are bingeing animes instead of gradually watch them. This pattern of an increasing proportion of users who binge-watch is consistent with findings reported in several survey studies (e.g., TiVo 2015).

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Insert Figure 6 about here

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In Table 2, we report statistics related to users' engagement measures between binged and not binged cases across the five continents. We first describe the data patterns in UGC behavior for North American users. 11% of users who binged made at least one forum post about the anime they watched, while this percentage is 14% for users who did not binge (difference is statistically significant at $p < 0.001$). Furthermore, 5% of users who binged wrote a recommendation for the anime, while 6% of users who did not binge wrote a recommendation. This difference is statistically significant at $p < 0.005$. Both results suggest that users who binge are less likely to produce content. The data patterns for the other regions are very similar.

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Next, we discuss user behavior related to franchise extensions. On average, 69% of anime-user combinations that binged a season watched the next season (sequel), while this percentage is 67% for non-bingeing cases (not shown in Table 2). However, the data patterns related to the adoption of the sequel crucially depend on the availability of the next season at the time of the viewership of the prior season. In Table 2, we show the percentage of

adoptions of the next season for binged and not binged cases depending on whether the next season was (not) available. If the sequel was available, a person who binged the prior season was significantly more likely to watch the next season compared to someone who did not binge (72% vs. 69%; difference is statistically significant at $p < 0.001$). However, if the sequel was not available yet, users who binged and did not binge were equally likely to adopt the next season (once it became available). For other franchise extensions, the proportions of users who watch these franchise extensions are similar across binge-watchers and non-binge-watchers. We find similar patterns across the five continents.[9]

In Table 3, we compare the timing of when users produce UGC and/or watch franchise extensions depending on whether they binged the focal anime. On average, users who binged posted in the forum section 4 days after they started to watch, while users who did not binge posted in the forum section 8 days after they started to watch (difference is statistically significant at $p < 0.001$). Users who binged wrote recommendations for a series 167 days after starting to watch, while users who did not binge wrote recommendations 194 days after starting to watch (difference is statistically significant at $p < 0.001$). If the sequel was not available at the time of watching the prior season, users who binged started watching the next season 77 days (median) after its release while users who did not binge the prior season started watching the next season 72 days (median) after its release. The difference, however, is not statistically significant. If the sequel was available at the time of watching the prior season, binge-watchers started watching it earlier than non-binge-watchers (a median of 1 vs. 2 days after finishing the prior season; difference statistically significant at $p < 0.001$). We find a similar pattern for other franchise extensions.

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Insert Table 3 about here

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[9]In Tables C-1 and C-2 in Appendix B, we show the same statistics for alternative definitions of binge-watching (2 and 4 hours compared to our main specification of 3 hours). Our empirical findings are mostly robust to these alternative definitions.

Figure 7 compares the distributions of ratings for binged and non-binged cases. Both distributions are very similar with slightly more ratings of 9 and 10 for the binged cases. The average ratings for binged and non-binged cases are 7.85 and 8.04, respectively. Even though the difference in average ratings is small, the average ratings are significantly different at $p < 0.001$. This implies that a person who binges an anime either thinks better of the anime because of bingeing it and/or has higher intrinsic interest in the anime and therefore binges it compared to someone who does not binge. This empirical observation is consistent with previous findings on reasons for binge-watching (e.g. Pittman and Sheehan 2015).

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Insert Figure 7 about here

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4 Model and Estimation

We quantify the effects of binge-watching on two areas of users' media franchise engagement: (1) production of user-generated content, i.e. comments in the discussion forum and recommendations, and (2) viewership of franchise series, i.e. watching of the next season (sequel) or other franchise extensions (spin-offs, side stories, summaries, and remakes). User i's propensity to take an action related to anime j is a latent continuous variable and denoted by y^*_{ij}. In the data, we observe user i to take an action y_{ij} for anime j (e.g. writing of a recommendation or watching of the next season) if her propensity supersedes a threshold. User i's propensity to produce UGC is given by

$$\begin{aligned} y^*_{ij} &= \alpha_i + \beta Binge_{ij} + \delta C_{ij} + \gamma G_j + \lambda T + \epsilon_{ij} \\ y_{ij} &= \begin{cases} 1 & y^*_{ij} > 0 \\ 0 & otherwise \end{cases}, \end{aligned} \tag{1}$$

where α_i is a user-specific intercept which comes from a normal distribution with $N(\overline{\alpha}, \sigma^2_\alpha)$ and $Binge_{ij}$ is a dummy variable indicating whether user i binge-watched anime j. Further,

we include other variables whose effects we control for. C_{ij} contains a dummy variable indicating whether user i submitted a rating for anime j and, if so, the rating user i gave to anime j, the popularity rank of anime j based on the number of users who have adopted it, and the average user rating given to anime j by all adopters on the website by the time of adoption of user i. Note that all these variables are publicly visible on the platform. G_j consists of anime-specific variables, namely, anime j's genre dummies, the number of episodes in a season, and the length of each episode in minutes. And lastly, T contains year dummies.

User i's propensity to adopt a franchise extension of anime j is modeled similarly. In addition to controlling for C_{ij}, G_j, and T, we also include a dummy variable for series type (sequel or not) and an interaction term between series type and binge watching, i.e.

$$\begin{aligned} y^*_{ij} &= \alpha_i + \beta Binge_{ij} + \eta Sequel_j + \psi Binge_{ij} \times Sequel_j + \delta C_{ij} + \gamma G_j + \lambda T + \epsilon_{ij} \\ y_{ij} &= \begin{cases} 1 & y^*_{ij} > 0 \\ 0 & otherwise \end{cases}, \end{aligned} \tag{2}$$

where $Sequel_j$ is a dummy variable indicating whether the franchise extension is a sequel.

The effects of binge-watching on users' franchise adoptions (next season and other franchise extensions) depend on the availability of the franchise extension at the time of the viewership of the focal anime (see Table 2). Consequently, we estimate separate models for the effects of binge watching on franchise extension adoptions when the extension is and is not available. Furthermore, in the case that the franchise extension is not available, we control for the number of days the user has to wait after finishing the focal anime until the franchise is released.

Potential endogeneity of the decision to binge-watch is a concern. To account for this concern, we simultaneously model user i's decision to binge-watch the focal anime and to produce UGC or to adopt a franchise series, respectively, allowing for the error terms across

the two equations to be correlated (see Heckman 1978, Maddala 1983, p. 123-159, Wilde 2000, Wooldridge 2010, p. 595-507). User i's decision whether to binge-watch anime j is given by

$$Binge^*_{ij} = \alpha'_i + \beta' w_{ij} + \delta' \widetilde{C}_{ij} + \gamma' G_j + \lambda' T + \epsilon'_{ij}$$
$$Binge_{ij} = \begin{cases} 1 & Binge^*_{ij} > 0 \\ 0 & otherwise \end{cases}, \tag{3}$$

where $Binge^*_{ij}$ is the underlying latent variable capturing user i's propensity of binge-watching anime j. The variable $Binge_{ij}$ (whose realizations we observe in the data) equals 1 if $Binge^*_{ij}$ is positive and 0 otherwise. $Binge^*_{ij}$ is a function of user random effects α'_i, a weekend dummy w_{ij}, and $\widetilde{C}_{ij}$ which contains the popularity rank of anime j based on the number of users who have adopted it at the time of adoption of user i, and the average user rating given to anime j by all adopters by the time of adoption of user i. Additionally, we control for G_j and T which contain the same sets of variables as described for equation (1). And lastly, we allow the two error terms in equations (1) and (3) and equations (2) and (3) to be correlated, i.e. $\epsilon_{ij}, \epsilon'_{ij} \sim N(0, \Sigma)$ with $\Sigma = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$.

We include a weekend dummy, w_{ij}, as an exclusion variable in equation (3). We expect users to have more time on weekends and thus to be more likely to binge-watch, while this variable should have no effect on users' subsequent adoption of franchise extensions and production of UGC. Table 4 shows the distribution of weekdays when users start to watch animes. Both binge-watching and non-binge-watching cases occur more often on weekends compared to weekdays (average of 15.78% vs. 13.69%). However, binge-watching is 1.76% more likely to happen on weekends (32.44% vs. 30.68%).

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Insert Table 4 about here

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A potential concern is that users might not only (binge-)watch the focal anime during a

weekend, but also show more engagement with the media franchise during the same weekend, i.e. that the weekend dummy might not be a valid exclusion variable. Descriptive statistics in Table 3 provide evidence for the validity of our instrument. Our data show that, even if a franchise series is available, the mean number of days until a user starts watching a franchise series from when she finishes the focal anime is significantly greater that two days.

Equations (1) and (3) and equations (2) and (3) constitute bivariate probit models. We estimate the models using Simulated Maximum Likelihood Estimation (SMLE). The likelihood of each model is given by

$$L = \prod_{i=1}^{N} \int_{-\infty}^{+\infty} \left[\prod_{j=1}^{J} P(y_{ij} = 1 \mid X, \Theta, \Sigma, \alpha_i) \cdot P(Binge_{ij} = 1 \mid X, \Theta, \Sigma, \alpha_i') \right] d\alpha_i d\alpha_i' d\Sigma, \quad (4)$$

where $\Theta = \{\alpha, \alpha', \beta, \beta', \eta, \psi, \delta, \delta', \gamma, \gamma', \lambda, \lambda', \rho\}$ is the vector of coefficients to be estimated and $X = \{Binge_{ij}, C_{ij}, \widetilde{C}_{ij}, w_{ij}, G_j, T\}$ represents the vector of covariates.

5 Results

We start by discussing the results for North America (Table 5).[10] The lower half of Table 5 shows the results from the probit models capturing the decision to binge. Across the four probit regressions, the coefficient estimates have the expected signs and most of them are significant: our exclusion variable, a weekend dummy, has the expected significant positive effect in three of the four regressions. The lower the popularity rank of the focal season (i.e. a better rank), the more likely it is that a user will binge it. More and longer episodes also increase the probability of binge-watching. Lastly, we find evidence for a significant amount of unobserved heterogeneity across users.

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Insert Table 5 about here

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[10] We show the results from univariate probit regressions ignoring the potential endogeneity of the binge-watching decision in Table A-1 in Appendix A.

The top half of Table 5 shows the results of the probit regressions describing users' engagement actions. In general, compared to other types of franchise extensions, sequels have a higher probability of being adopted. The effects of binge-watching on users' franchise adoptions (next season and other franchise extensions) differ depending on the type of franchise extension and on whether the franchise was available at the time of the binge: if it was, binge-watching significantly increases the probability of watching the next season (at $p < 0.05$), while it decreases the probability of watching other franchise extensions (at $p < 0.01$).[11] These mixed findings on the effects of binge-watching are consistent with our expectation that the "flow" created by binge-watching is closely related to the story line involving the main characters in the binged series. Previous research indicates that users who experience the flow are more likely to repeat their behaviors or even become addicted in order to stay in the flow (e.g., Kubey and Csikszentmihalyi 2002; Chou and Ting 2003). Among the different kinds of franchise extensions, sequels, i.e. next seasons, are the ones that continue the same story line of and share the same main characters with the prequel or previous season. Other franchise extensions may have a different story line or center around different characters (e.g., "Better Call Soul," as a spin off of "Breaking Bad," follows the story of a lawyer who was a secondary character in "Breaking Bad.").[12] As a result, the natural way for users to continue the flow after bingeing a season is to watch the next season. The significant negative effect of binge-watching on other franchise extensions can be attributed to the net effect of enjoyment or immersion in the flow and the physical/mental burden of bingeing (Grøntved and Hu 2011; Matrix 2014; Sung et al. 2015). For sequels, the flow is strongly continued in sequels. As a result, despite the fatigue, a user is more likely to adopt the sequel. In the case of other franchise extensions, however, the flow is disrupted by a new story line introduced in the extension. Consequently, a user has less motivation to

[11]The effect of binge-watching on other franchise extensions is captured by the binge-dummy. The effect of binge-watching on sequels is the combined effect of the binge dummy and the interaction terms between the binge and sequel dummies. In the text, we describe the combined effect in terms of its size, direction, and significance when refering to the effects of binge-watching on sequels.

[12]Other examples are "Frasier" as a spin-off of "Cheers," "Joey" as a spin-off of "Friends" and "The Good Fight" as a spin-off of "The Good Wife."

overcome the fatigue and to spend more time watching shows.

If the franchise extension is not available at the time of the binge, binge-watching significantly decreases the probability of adopting another franchise series (at $p < 0.05$), while it does not affect the adoption of sequels. The flow can only continue if the next season of the series is available at the time when users adopt the focal season.

Next, we discuss the effects of binge-watching on the production of UGC. For both forum posts and recommendations, we find that bingeing decreases the probability that a user produces content. The effect is significant is at $p < 0.001$ for forum posts and at $p < 0.10$ for recommendations ($p < 0.10$ not shown in Table 5). This result can also be explained by bingers' inclination to stay in the flow. Therefore they tend to avoid any activities that distract them from watching. This avoidance tendency is also manifested in Schweidel and Moe (2016) where the authors find that binge-watchers are less responsive to advertisements compared to non-binge-watchers. Another plausible explanation is that, compared to binge-watchers, it takes non-binge-watchers a longer time and more viewing sessions to complete an anime season. The more frequent (yet not as deep) interaction with the media product may lead to a higher likelihood to generate product-related UGC.

Our control variables related to the focal anime (own rating, rating dummy, popularity rank, community rating) have consistent effects across the four regressions and are mostly significant. The wait time until the franchise extension becomes available in regression (ii) has a significant negative effect, i.e. the longer users have to wait for a franchise extension to become available, the less likely they are to watch it. And lastly, we find a significant amount of unobserved heterogeneity across users.

Lastly, we discuss the results for the other geographic regions included in our data: South America, Europe, Asia, and Oceania.[13] Table 6 shows the coefficient estimates for the binge effects for all engagement measures and all continents.[14] The complete sets of results showing

[13]Note that our data are much smaller for South America, Oceania, and Asia than for North America and Europe.

[14]We show the corresponding results from univariate probit regressions ignoring the potential endogeneity of the binge-watching decision in Table A-2 in Appendix A.

all coefficient estimates can be found in Appendix B. Across the five regions, consumers are significantly more likely to watch sequels than other franchise extensions. Consistent with the results for North America, binge-watching significantly increases the adoption probability of sequels (if those are available) in Asia (at $p < 0.001$) and the estimates are directionally consistent but insignificant for the other continents (see footnote 11 for a description of how these effects were calculated). If the next season is not available, the effect of binge-watching on the adoption probability of sequels is insignificant across all regions. And lastly, the effect of binge-watching on the adoption of other franchise extensions is consistently negative (if significant).

6 Robustness Checks

We assess the robustness of our main data pattern in Appendix C. Recall that we define a user as having binged if she watches more than 3 hours of an anime series per day. In Appendix C, we explore two alternative definitions of binge-watching, namely, having watched more than 2 hours and having watched more than 4 hours of an anime series per day. Tables C-1 and C-2 show the probabilities of producing UGC and watching franchise extensions under these two alternative definitions of binge-watching. Overall, we find data patterns under the alternative definitions that are similar to the data patterns under our main definition.

7 Limitations and Future Research

There are several limitations to our research. First, a media franchise can also include merchandising items that are available for purchase, such as posters, coffee mugs, toys, and trading card games. In our data, we do not observe (offline) purchases of such ancillary products. It is left for future research to investigate whether the viewing modus of bingeing affects (offline) purchases. Second, even though we provide evidence for the validity of our data, measurement error in our binge-watching variable remains a potential concern.

Measurement error might be due to the self-reported character of the data or due to the usage of the date of the last update in cases in which the finish date is missing (see Data Section). It is well-known that measurement error in an independent variable leads to attenuation bias, i.e. a bias of the coefficient towards zero. Thus our results should be interpreted as a lower bound of the effects of binge-watching.

Third, some shows have a higher probability of being binged than others. While we quantify the effects of variables such as weekend or ratings on the probability that a user binges, we do not model the effects of different creative content. It is left for future research to study whether and how different characteristics such as story line characteristics, episode openings and endings make a show more or less bingeable. And lastly, different methods or channels of watching such as online streaming websites, streaming platforms, DVDs, or piracy websites might produce varying degrees of bingeing behavior. Channels deploy different interfaces, advertising methods, and sequential watching strategies, which can influence binge-watching behavior.

8 Conclusion

With the introduction of video-on-demand services during the last decade, binge-watching has become very common among TV viewers. An open empirical question is whether the viewing modus has implications for user engagement compared to the traditional, linear way of watching TV. Built on extant literature, we argue that binge-watchers would want to stay in the "flow," a state of concentrated focus created by binge-watching. In this paper, using novel data coming from an online anime platform containing information on individual users' adoptions of different animes and their user-generated content, we quantify the effects of binge-watching on consumers' engagement with a media franchise as related to user-generated content and the adoption of franchise extensions. Our paper thus adds to the small but rapidly growing body of literature on consumers' digital media consumption

as well as on the online streaming industry. To the best of our knowledge, our paper is the first systematic empirical examination of the effects of binge-watching on user engagement with a media franchise.

Our results show that binge-watching decreases the production of UGC. For the video elements of the media franchise, the effect of binge-watching crucially depends on both the type and the availability of franchise extensions at the time of watching the focal anime series. If the franchise extension is available, binge-watching increases the probability that a user watches the next season, while it has the opposite effect for other franchise extensions. If the franchise extension is not available, binge-watching decreases the probability of other franchise extensions being adopted and has no effect on the adoption of sequels. Our results are directionally consistent across the five continents if the coefficients are significant.

Our results offer the following important managerial implications for TV channels and online streaming platforms. First, binge-watching can boost viewership of subsequent seasons (sequels). However, the availability of the subsequent season plays a crucial role. Companies have started to recognize this by making prior seasons available (for binge-watching) shortly before the release of the next season. Figure 8 shows several examples from Netflix.

Second, binge-watching does not boost viewership of all franchise extensions. Which franchise extensions would benefit from a bingeable prior season depends on whether the franchise extension would help continue the flow viewers experience when bingeing the prior season. Franchise extensions that differ significantly in story lines and/or main characters may not attract binge-watchers of the prior season. The general lackluster performance of spin-offs speaks to the importance of staying close to the successful original series when developing franchised extensions.[15]

Third, online streaming networks such as Netflix have been aggressive in expanding their services beyond the home country. Our study provides first empirical evidence regarding the similarities and differences in consumers' media consumption and engagement behaviors

[15]Wikipedia lists 1,142 TV spin-offs on its website (https://en.wikipedia.org/wiki/List_of_television_spin-offs). Only 135 spin-offs (12%) ran for 5 or more seasons. 413 spin-offs (36%) ran for one season or less.

across five continents. Specifically, we find that the effect of binge-watching are directionally consistent across the different regions. These findings provide valuable information that helps online steaming companies decide to what extent their content strategy in general and content release timing strategy in particular should be customized to accommodate local consumers' preferences.

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Figures and Tables

Table 1: Number of Episodes in and Duration of a Season

Number of Episodes	Freq.	Percent	Duration of Series (Hours)	Freq.	Percent
1	78	1.59	less than 1	867	17.71
2	740	15.09	1 - 2	906	18.50
3 - 7	892	18.19	2 - 3	307	6.27
8 - 11	192	3.92	3 - 4	142	2.90
12	691	14.09	4 - 5	715	14.60
13	627	12.79	5 - 6	440	8.99
14 - 27	956	19.50	6 - 10	417	8.52
28 - 56	566	11.54	10 - 15	495	10.11
57 and more	161	3.28	15 - 20	252	5.15
			20 and more	355	7.25

Table 2: Probability of Engagement Action

	Next Season		Other Franchises		UGC	
	Available	Not Available	Available	Not Available	Forum Posts	Recommendation
North America						
Non-Binge-Watch	0.689	0.543	0.280	0.307	0.139	0.058
Binge-Watch	0.724	0.537	0.287	0.299	0.111	0.050
South America						
Non-Binge-Watch	0.722	0.557	0.345	0.345	0.113	0.037
Binge-Watch	0.762	0.557	0.345	0.341	0.082	0.040
Europe						
Non-Binge-Watch	0.708	0.545	0.325	0.328	0.095	0.047
Binge-Watch	0.755	0.536	0.329	0.317	0.081	0.044
Asia						
Non-Binge-Watch	0.702	0.551	0.306	0.319	0.105	0.035
Binge-Watch	0.749	0.522	0.304	0.298	0.085	0.049
Oceania						
Non-Binge-Watch	0.683	0.558	0.288	0.343	0.135	0.044
Binge-Watch	0.757	0.566	0.291	0.353	0.119	0.036

Table 3: Timing of Engagement Actions

	Median (Days)	Obs
Next Season		
After Release of Focal Season If Next Season Is not Available		
Non-Binge-Watching	72	59,420
Binge-Watching	77	13,036
After Finishing Focal Season If Next Season Is Available		
Non-Binge-Watching	2	213,848
Binge-Watching	1	53,504
Other Franchises		
After Release of Focal Season If Franchise Is not Available		
Non-Binge-Watching	105	28,288
Binge-Watching	121	6,469
After Finishing Focal Season If Franchise Is Available		
Non-Binge-Watching	4	164,577
Binge-Watching	1	46,369
UGC		
Posting in Discussion Forum After Starting to Watch		
Non-Binge-Watching	8	13,035
Binge-Watching	4	2,510
Posting Recommendation After Starting to Watch		
Non-Binge-Watching	194	1,185
Binge-Watching	167	313

Table 4: Weekday Frequencies of Start Dates

Weekday	Percent	Percent
	Non-Binge-Watch	*Binge-Watch*
Monday	14.64	14.22
Tuesday	13.96	13.51
Wednesday	13.73	13.17
Thursday	13.49	13.08
Friday	13.51	13.57
Saturday	14.84	15.89
Sunday	15.84	16.55

Table 5: Results - North America

	Franchises		UGC	
	Franchise Available	Franchise Not Available	Forum Post	Recommendation
	(i)	(ii)	(iii)	(iv)
Engagement Equation				
Binge Dummy	-0.139**	-0.151*	-0.535***	-0.590
	(0.047)	(0.073)	(0.134)	(0.308)
Sequel Dummy	1.399***	0.762***		
	(0.021)	(0.028)		
Binge Dummy × Sequel Dummy	0.152***	0.117***		
	(0.023)	(0.034)		
Own Rating of Focal Season	0.140***	0.176***	0.048***	0.050*
	(0.004)	(0.008)	(0.008)	(0.023)
Own Rating Dummy[b]	-0.954***		-0.119	-0.005
	(0.038)		(0.091)	(0.323)
Popularity Rank of Focal Season[a]	-0.100***	-0.081***	-0.047***	0.004
	(0.004)	(0.01)	(0.009)	(0.031)
Community Rating of Focal Season	-0.153***	-0.103***	-0.047*	-0.142
	(0.011)	(0.022)	(0.024)	(0.085)
Wait Time Until Franchise Series Available		-0.160***		
When Started Watching Focal Season[a]		(0.007)		
Number of Episodes of Focal Season	-0.038**	0.200***	0.370***	0.278**
	(0.010)	(0.025)	(0.029)	(0.092)
Duration of an Episode[a]	-0.193***	0.354***	0.210*	0.225
	(0.036)	(0.084)	(0.085)	(0.281)
Constant	1.718***	-1.536***	-2.360***	-1.972
	(0.154)	(0.343)	(0.37)	(1.218)
Variance of User Random Effects	0.425***	0.571***	0.758***	0.229***
	(0.016)	(0.035)	(0.059)	(0.051)
Genre Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Binge Decision Equation				
Weekend Dummy	0.061***	0.037*	0.050**	0.067
	(0.010)	(0.017)	(0.017)	(0.055)
Popularity Rank of Focal Season[a]	-0.063***	-0.070***	-0.035***	-0.048
	(0.005)	(0.009)	(0.008)	(0.028)
Community Rating of Focal Season	-0.009	0.029	0.037	0.032
	(0.012)	(0.02)	(0.02)	(0.071)
Number of Episodes of Focal Season	0.233***	-0.251***	0.294***	0.326***
	(0.012)	(0.024)	(0.023)	(0.077)
Duration of an Episode[a]	0.281	-0.164	0.630***	0.780*
	(0.050)	(0.084)	(0.082)	(0.356)
Constant	-2.853***	0.546	-4.458***	-4.875***
	(0.197)	(0.336)	(0.353)	(1.316)
Variance of User Random Effects	1.147***	0.886***	0.651***	0.617***
	(0.046)	(0.053)	(0.06)	(0.143)
Genre Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Error Correlation	0.120**	0.071	0.298**	0.416
	(0.032)	(0.048)	(0.099)	(0.266)
Number of Observations	164,666	44,346	57,965	6,224
AIC	308,517.224	92,990.404	82,869.404	8,609.047
BIC	309,648.543	93,973.479	83,864.807	9,329.817
Log Likelihood	-154,145.612	-46,382.202	-41,323.702	-4,197.524

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] Measured on logarithmic scale.

[b] Not estimated in all models due to collinearity.

Table 6: Effects of Binge-Watching Across Different Regions

	Franchises		UGC	
	Available	Not Available	Forum Posts	Recommendation
North America				
Binge Dummy	-0.139**	-0.151*	-0.535***	-0.590
	(0.047)	(0.073)	(0.134)	(0.308)
Sequel Dummy	1.399***	0.762***		
	(0.021)	(0.028)		
Binge Dummy × Sequel Dummy	0.152***	0.117***		
	(0.023)	(0.034)		
South America				
Binge Dummy	-0.204*	0.045	-0.568	-0.830
	(0.100)	(0.061)	(0.376)	(0.486)
Sequel Dummy	1.238***	0.744***		
	(0.039)	(0.035)		
Binge Dummy × Sequel Dummy	0.205***	0.012		
	(0.044)	(0.078)		
Europe				
Binge Dummy	-0.131*	-0.091	-0.298*	-0.002
	(0.038)	(0.087)	(0.129)	(0.076)
Sequel Dummy	1.228***	0.914***		
	(0.015)	(0.032)		
Binge Dummy × Sequel Dummy	0.198***	0.032		
	(0.016)	(0.044)		
Asia				
Binge Dummy	0.124	-0.288	-0.563	0.148
	(0.087)	(0.200)	(0.324)	(0.143)
Sequel Dummy	1.273***	0.904***		
	(0.038)	(0.065)		
Binge Dummy × Sequel Dummy	0.172***	-0.023		
	(0.040)	(0.075)		
Oceania				
Binge Dummy	-0.205	-0.038	-1.038	-1.553
	(0.151)	(0.295)	(0.723)	(1.662)
Sequel Dummy	1.265***	0.876***		
	(0.060)	(0.100)		
Binge Dummy × Sequel Dummy	0.330***	-0.014		
	(0.060)	(0.013)		

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1: Dates Users Joined MyAnimeList.Net

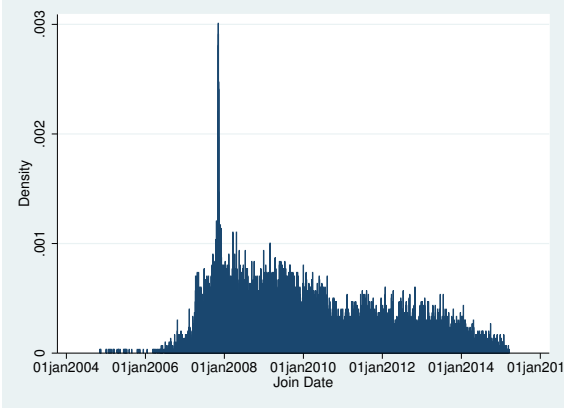
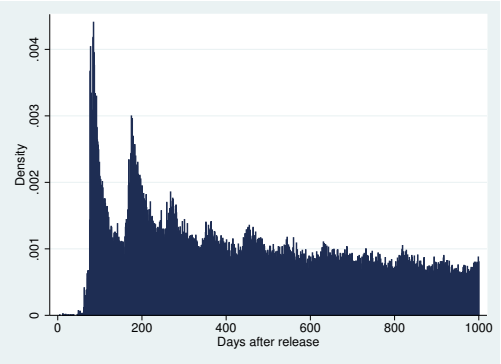
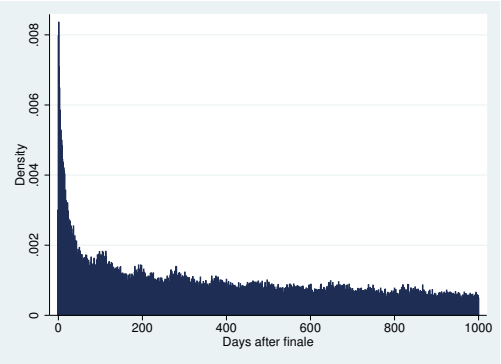


Figure 2: Number of Days After Release of First or Final Episode in a Season That Animes Were Watched

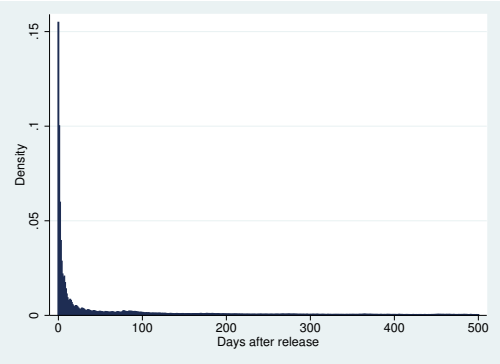
(a) Binge-watchers: Number of days after first episode (truncated at 1,000 days)



(b) Binge-watchers: Number of days after season finale (truncated at 1,000 days)



(c) Non-binge-watchers: Number of days after first episode (truncated at 500 days)



(d) Non-binge-watchers: Number of days after season finale (truncated at 500 days)

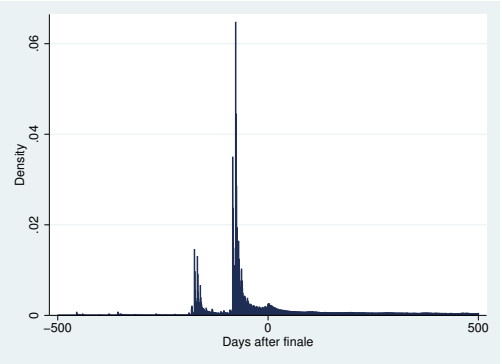


Figure 3: Watch Period Distribution (truncated at 200 days)

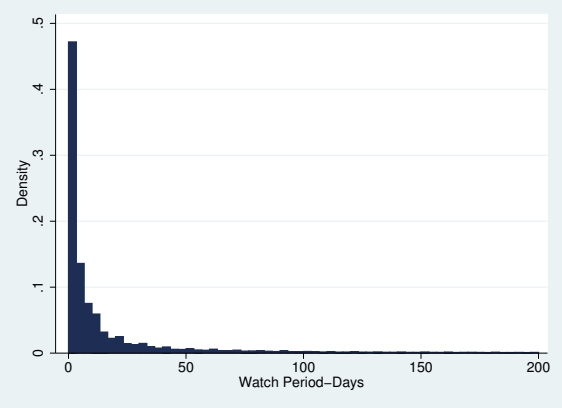


Figure 4: Number of Hours Watched Per Day

(a) Days with Binge-Watching **(b) Days with No Binge-Watching**

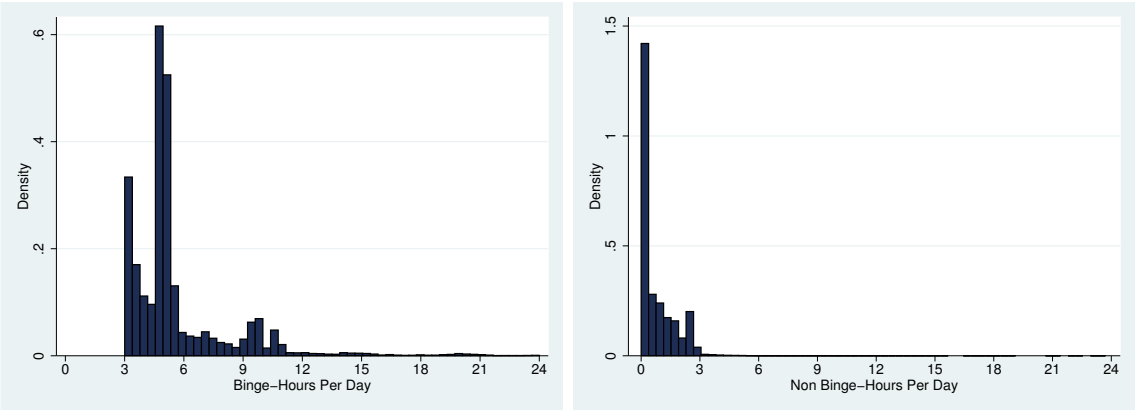


Figure 5: Percentage of A User's Watch List That Is Binge-Watched

(a) Including 0% and 100% **(b) Excluding 0% and 100%**

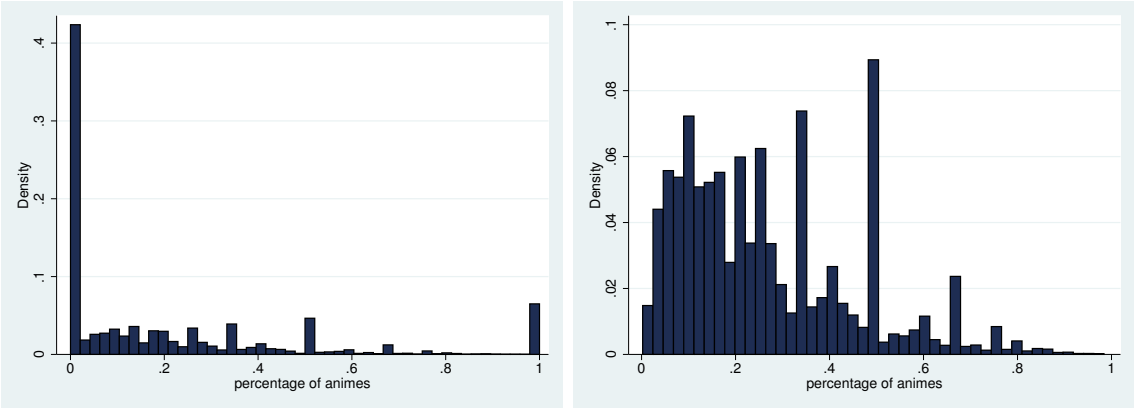


Figure 6: Binge-Watching vs Non-Binge-Watching Across Time

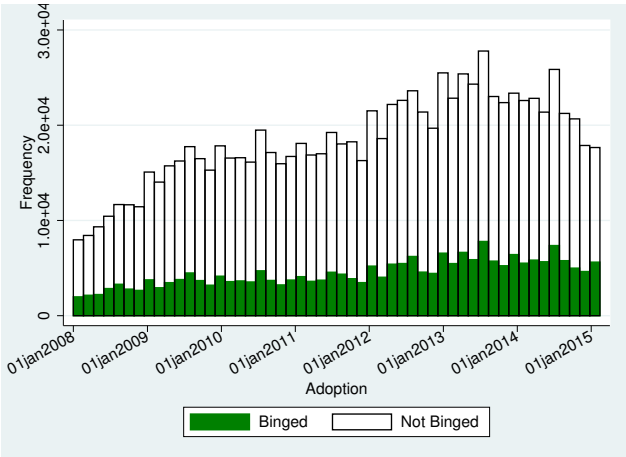
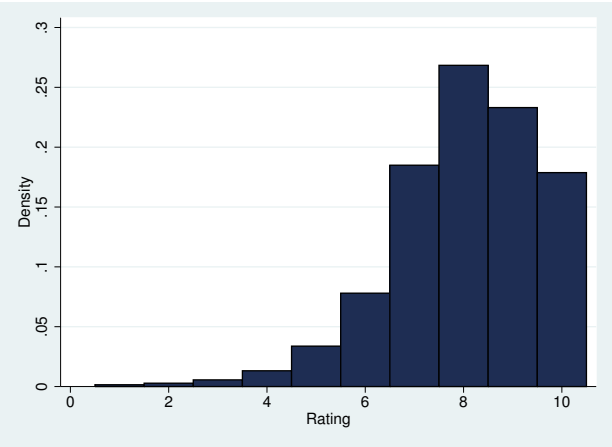


Figure 7: Distribution of Ratings for Binged vs. Non-Binged Cases

(a) Binged Cases



(b) Non-Binged Cases

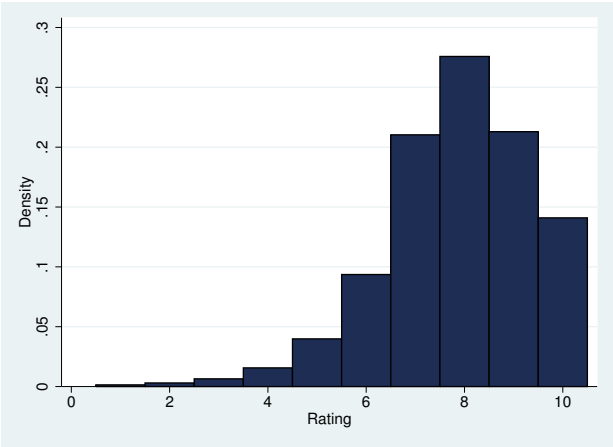


Figure 8: Examples of Release Dates on Netflix

Appendix A: Probit Results

Table A-1: Probit Results - North America

	Franchises		UGC	
	Franchise Available	Franchise Not Available	Forum Post	Recommendation
	(i)	(ii)	(iii)	(iv)
Binge Dummy	0.038**	-0.004	-0.077***	-0.017
	(0.012)	(0.031)	(0.023)	(0.067)
Sequel Dummy	1.263***	0.780***		
	(0.009)	(0.019)		
Binge Dummy × Sequel Dummy	0.143***	0.031		
	(0.020)	(0.040)		
Own Rating of Focal Season	0.137***	0.170***	0.043***	0.042*
	(0.003)	(0.007)	(0.007)	(0.018)
Own Rating Dummy				
Popularity Rank of Focal Season[a]	-0.090***	-0.082***	-0.055***	-0.068**
	(0.004)	(0.009)	(0.008)	(0.025)
Community Rating of Focal Season	-0.151***	-0.114***	-0.001	0.010
	(0.010)	(0.022)	(0.021)	(0.065)
Wait Time Until Franchise Extension Available When Started Watching Focal Season[a]		-0.156***		
		(0.006)		
Number of Episodes of Focal Season[a]	-0.035***	0.239***	0.299***	0.164**
	(0.009)	(0.025)	(0.019)	(0.063)
Duration of an Episode[a]	-0.206***	0.525***	0.148*	0.115
	(0.033)	(0.090)	(0.072)	(0.213)
Constant	0.700***	-2.112***	-2.326***	-2.256*
	(0.137)	(0.358)	(0.295)	(0.879)
Log Variance of User Random Effects	-0.137	(0.358)	-0.474***	-1.808***
	(0.026)	(0.044)	(0.045)	(0.167)
Genre Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Number of Observations	173,025	36,859	57,523	8,661
AIC	186,931.685	42,740.038	36,282.44	3,795.95
BIC	187,505.173	43,225.385	36,775.23	4,170.48
Log Likelihood	-93,408.842	-21,313.019	-18,086.22	-1,844.98

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] Measured on logarithmic scale.

Table A-2: Effects of Binge-Watching Across Different Regions

	Franchises		UGC	
	Franchise Available	Franchise Not Available	Forum Post	Recommendation
	(i)	(ii)	(iii)	(iv)
North America				
Binge Dummy	0.038**	-0.004	-0.077***	-0.017
	(0.012)	(0.031)	(0.023)	(0.067)
Sequel Dummy	1.263***	0.780***		
	(0.009)	(0.019)		
Binge Dummy × Sequel Dummy	0.143***	0.031		
	(0.020)	(0.040)		
South America				
Binge Dummy	0.017	0.045	0.071	-0.202
	(0.024)	(0.061)	(0.076)	(0.238)
Sequel Dummy	1.159***	0.744***		
	(0.016)	(0.035)		
Binge Dummy × Sequel Dummy	0.199***	0.012		
	(0.041)	(0.078)		
Europe				
Binge Dummy	0.024**	0.029	-0.035	-0.025
	(0.009)	(0.022)	(0.023)	(0.070)
Sequel Dummy	1.172***	0.741***		
	(0.007)	(0.014)		
Binge Dummy × Sequel Dummy	0.192***	-0.004		
	(0.015)	(0.028)		
Asia				
Binge Dummy	0.020	-0.004	0.064	0.074
	(0.023)	(0.055)	(0.047)	(0.113)
Sequel Dummy	1.218***	0.829***		
	(0.019)	(0.037)		
Binge Dummy × Sequel Dummy	0.167***	-0.016		
	(0.038)	(0.069)		
Oceania				
Binge Dummy	-0.043	0.145	0.024	-0.471
	(0.033)	(0.094)	(0.065)	(0.291)
Sequel Dummy	1.206***	0.826***		
	(0.025)	(0.061)		
Binge Dummy × Sequel Dummy	0.318***	-0.006		
	(0.057)	(0.122)		

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix B: Complete Results for Other Continents

Table B-1: Results - South America

	Franchises		UGC	
	Franchise Available	Franchise Not Available	Forum Post	Recommendation
	(i)	(ii)	(iii)	(iv)
Engagement Equation				
Binge Dummy	-0.204*	0.045	-0.568	-0.830
	(0.100)	(0.061)	(0.376)	(0.486)
Sequel Dummy	1.238***	0.744***		
	(0.039)	(0.035)		
Binge Dummy × Sequel Dummy	0.205***	0.012		
	(0.044)	(0.078)		
Own Rating of Focal Season	0.152***	0.164***	0.047*	0.080
	(0.008)	(0.013)	(0.023)	(0.108)
Own Rating Dummy[b]				
Popularity Rank of Focal Season[a]	-0.099***	-0.062***	0.062*	0.307
	(0.008)	(0.017)	(0.031)	(0.262)
Community Rating of Focal Season	-0.091***	-0.060	-0.128	-0.378
	(0.019)	(0.039)	(0.080)	(0.61)
Wait Time Until Franchise Series Available		-0.179***		
When Started Watching Focal Season[a]		(0.012)		
Number of Episodes of Focal Season	-0.028	0.325***	0.456***	0.414
	(0.018)	(0.048)	(0.087)	(1.026)
Duration of an Episode[a]	0.080	1.068***	-0.084	3.895
	(0.069)	(0.184)	(0.253)	(6.398)
Constant	-0.615*	-4.374***	-1.675	-12.993
	(0.282)	(0.699)	(1.081)	(20.372)
Variance of User Random Effects	0.460***	0.540***	0.960***	0.050
	(0.034)	(0.046)	(0.21)	(0.168)
Genre Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Binge Decision Equation				
Weekend Dummy	0.099***	0.030	0.054	-0.405
	(0.020)	(0.037)	(0.064)	(0.428)
Popularity Rank of Focal Season[a]	-0.040***	0.011	-0.007	-0.896
	(0.009)	(0.020)	(0.031)	(0.588)
Community Rating of Focal Season	0.078***	0.167***	0.143	1.249
	(0.023)	(0.045)	(0.079)	(1.903)
Number of Episodes of Focal Season	0.196***	0.084	0.250**	0.251
	(0.022)	(0.053)	(0.080)	(2.157)
Duration of an Episode[a]	0.229*	0.210	0.742*	-10.587
	(0.099)	(0.208)	(0.353)	(17.041)
Constant	-3.501***	-3.815***	-6.085***	27.652
	(0.391)	(0.812)	(1.458)	(49.485)
Variance of User Random Effects	1.173***	0.851***	0.999***	1.123***
	(0.094)		(0.263)	
Genre Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Error Correlation	0.145*	0.000	0.507	0.000
	(0.068)	(0.000)	(0.334)	(0.000)
Number of Observations	49,592	12,561	6,077	184
AIC	86,828.260	21,995.063	7,892.839	455.723
BIC	87,850.404	22,798.405	8,617.763	722.563
Log Likelihood	-43,298.130	-10,889.531	-3,838.419	-144.862

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] Measured on logarithmic scale.

[b] Not estimated in all models due to collinearity.

Table B-2: Results - Europe

	Franchises		UGC	
	Franchise Available	Franchise Not Available	Forum Post	Recommendation
	(i)	(ii)	(iii)	(iv)
Engagement Equation				
Binge Dummy	-0.131*	-0.091	-0.298*	-0.002
	(0.038)	(0.087)	(0.129)	(0.076)
Sequel Dummy	1.228***	0.914***		
	(0.015)	(0.032)		
Binge Dummy × Sequel Dummy	0.198***	0.032		
	(0.016)	(0.044)		
Own Rating of Focal Season	0.173***	0.170***	0.056***	0.123***
	(0.003)	(0.009)	(0.008)	(0.022)
Own Rating Dummy[b]		-1.209***		
		(0.088)		
Popularity Rank of Focal Season[a]	-0.085***	-0.067***	-0.047***	-0.041
	(0.003)	(0.011)	(0.009)	(0.029)
Community Rating of Focal Season	-0.128***	-0.012	-0.062**	-0.210**
	(0.008)	(0.026)	(0.023)	(0.080)
Wait Time Until Franchise Series Available		-0.157***		
When Started Watching Focal Season[a]		(0.008)		
Number of Episodes of Focal Season	-0.017*	0.280***	0.331***	-0.050
	(0.007)	(0.031)	(0.026)	(0.086)
Duration of an Episode[a]	-0.108***	0.644***	0.179*	-0.304
	(0.025)	(0.099)	(0.076)	(0.276)
Constant	0.055	-2.516***	-2.627***	0.726
	(0.104)	(0.431)	(0.337)	(1.180)
Variance of User Random Effects	0.420***	0.543***	0.524***	0.142***
	(0.012)	(0.038)	(0.042)	(0.027)
Genre Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Binge Decision Equation				
Weekend Dummy	0.054***	0.048*	0.047**	0.058
	(0.007)	(0.022)	(0.015)	(0.050)
Popularity Rank of Focal Season[a]	-0.045***	-0.032*	-0.040***	-0.036
	(0.003)	(0.013)	(0.007)	(0.025)
Community Rating of Focal Season	0.063***	0.082**	0.098***	0.073
	(0.009)	(0.029)	(0.018)	(0.066)
Number of Episodes of Focal Season	0.184***	0.147***	0.207***	0.383***
	(0.008)	(0.032)	(0.019)	(0.074)
Duration of an Episode[a]	0.272***	0.150	0.785***	0.502
	(0.034)	(0.129)	(0.073)	(0.326)
Constant	-3.174***	-2.957***	-5.168***	-4.503***
	(0.137)	(0.521)	(0.330)	(1.267)
Variance of User Random Effects	1.019***	1.008***	0.619***	0.565***
	(0.033)	(0.075)	(0.055)	(0.000)
Genre Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Error Correlation	0.100*	0.063	0.174*	0.000
	(0.025)	(0.056)	(0.088)	(0.000)
Number of Observations	305,262	34,276	68,513	5,709
AIC	554,671.635	63,873.605	87,177.215	7,267.988
BIC	555,883.333	64,836.016	88,182.040	7,946.267
Log Likelihood	-277,221.818	-31,822.802	-43,478.607	-3,531.994

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] Measured on logarithmic scale.

[b] Not estimated in all models due to collinearity.

Table B-3: Results - Asia

	Franchises		UGC	
	Franchise Available	Franchise Not Available	Forum Post	Recommendation
	(i)	(ii)	(iii)	(iv)
Engagement Equation				
Binge Dummy	-0.124	-0.288	-0.563	0.148
	(0.087)	(0.200)	(0.324)	(0.143)
Sequel Dummy	1.273***	0.904***		
	(0.038)	(0.065)		
Binge Dummy × Sequel Dummy	0.172***	-0.023		
	(0.040)	(0.075)		
Own Rating of Focal Season	0.154***	0.155***	0.122***	-0.001
	(0.008)	(0.017)	(0.024)	(0.048)
Own Rating Dummy[b]				
Popularity Rank of Focal Season[a]	-0.090***	-0.078***	0.032	0.084
	(0.008)	(0.021)	(0.025)	(0.068)
Community Rating of Focal Season	-0.071***	-0.067	-0.261***	-0.247
	(0.021)	(0.044)	(0.065)	(0.224)
Wait Time Until Franchise Series Available		-0.158***		
When Started Watching Focal Season[a]		(0.016)		
Number of Episodes of Focal Season	-0.025	0.467***	0.384***	0.539**
	(0.020)	(0.063)	(0.079)	(0.191)
Duration of an Episode[a]	-0.216*	1.540***	0.518	-1.759
	(0.085)	(0.277)	(0.317)	(1.655)
Constant	-0.049	-6.118***	-2.850*	4.901
	(0.328)	(1.006)	(1.155)	(5.796)
Variance of User Random Effects	0.427***	0.579***	0.780***	0.064
	(0.032)	(0.082)	(0.145)	(0.042)
Genre Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Binge Decision Equation				
Weekend Dummy	0.037*	0.019	0.056	0.043
	(0.019)	(0.037)	(0.040)	(0.132)
Popularity Rank of Focal Season[a]	-0.043***	-0.053*	-0.053*	-0.137
	(0.009)	(0.021)	(0.021)	(0.071)
Community Rating of Focal Season	0.056*	0.115**	0.084	-0.020
	(0.022)	(0.044)	(0.049)	(0.234)
Number of Episodes of Focal Season	0.292***	0.208***	0.369***	0.768***
	(0.022)	(0.054)	(0.061)	(0.216)
Duration of an Episode[a]	0.520***	0.558*	0.187	-0.285
	(0.121)	(0.284)	(0.281)	(1.689)
Constant	-4.320***	-4.222***	-3.621***	-1.877
	(0.444)	(1.027)	(1.047)	(6.106)
Variance of User Random Effects	1.187***	0.885***	0.804***	0.790***
	(0.093)	(0.135)	(0.182)	
Genre Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Error Correlation	0.095	0.198	0.481	0.000
	(0.058)	(0.146)	(0.293)	(0.000)
Number of Observations	41,774	11,751	10,162	808
AIC	78,942.647	22,679.711	15,678.752	1,513.000
BIC	79,910.330	23,497.969	16,459.204	1,958.983
Log Likelihood	-39,359.324	-11,228.855	-7,731.376	-661.500

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] Measured on logarithmic scale.

[b] Not estimated in all models due to collinearity.

Table B-4: Results - Oceania

	Franchises		UGC	
	Franchise Available	Franchise Not Available	Forum Post	Recommendation
	(i)	(ii)	(iii)	(iv)
Engagement Equation				
Binge Dummy	-0.205	-0.038	-1.038	-1.553
	(0.151)	(0.295)	(0.723)	(1.662)
Sequel Dummy	1.265***	0.876***		
	(0.060)	(0.100)		
Binge Dummy × Sequel Dummy	0.330***	-0.014		
	(0.060)	(0.129)		
Own Rating of Focal Season	0.190***	0.204***	0.092**	0.221
	(0.013)	(0.028)	(0.031)	(0.156)
Own Rating Dummy[b]				
Popularity Rank of Focal Season[a]	-0.096***	-0.070*	0.075*	-0.998
	(0.012)	(0.032)	(0.035)	(0.832)
Community Rating of Focal Season	-0.180***	-0.191*	-0.286**	-15.734
	(0.031)	(0.076)	(0.106)	(8.256)
Wait Time Until Franchise Series Available		-0.154***		
When Started Watching Focal Season[a]		(0.024)		
Number of Episodes of Focal Season	-0.013	0.386***	0.612***	-32.050
	(0.028)	(0.095)	(0.168)	(19.397)
Duration of an Episode[a]	-0.104	1.491**	0.602	-155.213
	(0.106)	(0.504)	(0.380)	(98.063)
Constant	0.136	-5.113**	-2.829	859.468
	(0.433)	(1.766)	(1.514)	(509.339)
Variance of User Random Effects	0.483***	0.720***	0.890**	NA
	(0.055)	(0.149)	(0.313)	
Genre Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Binge Decision Equation				
Weekend Dummy	-0.039	0.124*	-0.026	0.940
	(0.026)	(0.058)	(0.068)	(0.746)
Popularity Rank of Focal Season[a]	-0.047***	-0.059	-0.031	0.120
	(0.012)	(0.031)	(0.033)	(0.945)
Community Rating of Focal Season	0.070*	0.128	-0.009	-3.184
	(0.032)	(0.074)	(0.086)	(7.728)
Number of Episodes of Focal Season	0.177***	0.096	0.358**	2.358
	(0.030)	(0.083)	(0.109)	(3800.451)
Duration of an Episode[a]	0.190	-0.136	0.383	-70.462
	(0.151)	(0.320)	(0.403)	(1864.914)
Constant	-3.230***	-2.202	-3.988*	233.623
	(0.571)	(1.271)	(1.730)	(3595.251)
Variance of User Random Effects	1.001***	0.703***	0.762*	0.000
	(0.121)	(0.166)	(0.331)	(0.000)
Genre Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Error Correlation	0.103	0.129	0.849	0.524
	(0.098)	(0.208)	(0.771)	(1.29)
Number of Observations	22,713	4,995	4,940	143
AIC	41,728.857	9,072.505	8,004.589	370.712
BIC	42,628.294	9,795.802	8,707.142	625.517
Log Likelihood	-20,752.428	-4,425.252	-3,894.294	-99.356

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] Measured on logarithmic scale.

[b] Not estimated in all models due to collinearity.

Appendix C: Alternative Classifications of Binge-Watching

Table C-1: Probability of Engagement Action – Binge-Watching Definition: More than 2 Hours

	Next Season		Other Franchises		UGC	
	Available	Not Available	Available	Not Available	Forum Posts	Recommendation
North America						
Non-Binge-Watch	0.677	0.543	0.276	0.308	0.146	0.058
Binge-Watch	0.733	0.542	0.292	0.294	0.112	0.052
South America						
Non-Binge-Watch	0.709	0.560	0.339	0.345	0.119	0.033
Binge-Watch	0.765	0.556	0.360	0.332	0.078	0.048
Europe						
Non-Binge-Watch	0.693	0.550	0.321	0.325	0.098	0.044
Binge-Watch	0.760	0.535	0.336	0.322	0.079	0.050
Asia						
Non-Binge-Watch	0.687	0.552	0.304	0.325	0.113	0.034
Binge-Watch	0.755	0.534	0.307	0.296	0.084	0.044
Oceania						
Non-Binge-Watch	0.670	0.562	0.284	0.347	0.141	0.045
Binge-Watch	0.748	0.553	0.298	0.331	0.115	0.035

Table C-2: Probability of Engagement Action – Binge-Watching Definition: More than 4 Hours

	Next Season		Other Franchises		UGC	
	Available	Not Available	Available	Not Available	Forum Posts	Recommendation
North America						
Non-Binge-Watch	0.693	0.546	0.283	0.311	0.139	0.057
Binge-Watch	0.710	0.526	0.279	0.280	0.103	0.045
South America						
Non-Binge-Watch	0.724	0.562	0.347	0.350	0.113	0.036
Binge-Watch	0.739	0.536	0.340	0.319	0.069	0.033
Europe						
Non-Binge-Watch	0.712	0.549	0.326	0.331	0.094	0.046
Binge-Watch	0.741	0.520	0.324	0.308	0.073	0.044
Asia						
Non-Binge-Watch	0.708	0.552	0.310	0.322	0.105	0.038
Binge-Watch	0.745	0.514	0.292	0.284	0.081	0.041
Oceania						
Non-Binge-Watch	0.688	0.558	0.291	0.349	0.135	0.042
Binge-Watch	0.749	0.564	0.287	0.324	0.117	0.039