Binge-Watching and Media Franchise Engagement *

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Abstract

We investigate the relationship between binge-watching and consumers' engagement with media franchises in two areas: personal and interactive engagement. The former involves consumers' adoption and consumption of franchise extensions and the latter concerns consumers' content generation related to a focal media product they watched. Our novel data come from an online anime (Japanese cartoons) platform containing individual-level information on consumers' anime watching behavior and their user-generated content. We find that the effects of binge-watching on personal engagement critically depend on the availability of a franchise extension at the time of watching the focal media product and the type of franchise extension (sequels versus other types of extensions). For interactive engagement, our results show that binge-watching is associated with lower submission rates but higher valence of anime ratings, the most prevalent form of UGC on the platform. Furthermore, we explore five common sources of heterogeneity: age, gender, geography, usage, and experience. 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

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1 Introduction

The global entertainment and media industry reported revenues of $1.72 trillion in 2015 (Statistica 2016*a*) with $38.3 billion coming from the box office and $286 billion from the TV and video industry (Statistica 2016*b*). A notable trend on both big and small screens is the rising success of media franchises.[1] For example, the three top-grossing movies of 2015 all belonged to franchises such as "Star Wars," "Jurassic World," and "Avengers."[2] Franchise series also ruled the small screen as witnessed by the exploding traffic on Netflix drawn to "Breaking Bad" and "House of Cards." We define "media franchise" as a collection of media products 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 sitcom "Friends" consists of ten seasons of the TV series and a spin-off TV series named "Joey" (two seasons); the media franchise of "Ice Age" consists of five sequel movies and seven short films.

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. At the same time, across various other industries, marketing scholars and business practitioners have shown extensive interest in consumer engagement or customer brand engagement which highlights customers' interactive and co-creative experiences with firms and other customers (e.g., Bowden 2009; Mollen and Wilson 2010; Van Doorn et al. 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 in multiple industries (e.g., Nambisan and Nambisan 2008; Brakus et al. 2009; Hoyer et al. 2010). However, to the best of our knowledge, no empirical study to date has systematically examined consumer engagement in

[1]In 1994, 1 out of the 10 top grossing movies was a franchise. In 2014, 7 out of the 10 top grossing movies were franchises (https://www.ft.com/content/192f583e-7fa7-11e4-adff-00144feabdc0?mhq5j=e5).

[2]The total historic revenue from the "Star Wars" franchise was $42 billion (by 2015), $25 billion (by 2016) for the "Harry Potter" franchise, and $6 billion (by 2016) for the "Ice Age" franchise.

the context of media franchises despite of its significance in modern society. This discrepancy is partly driven by the complexity in how consumer engagement with media products manifests itself and how one can measure it using behavioral data.

In this study, we adopt the categorization developed by Calder et al. (2009) and identify two types of consumer engagement with media products: "personal engagement" such as enjoyment and relaxation directly derived from consuming the product and "interactive engagement" such as socialization and participation in a community facilitated by consuming the product. Calder et al. (2009) associate the former with an individual's internal state of getting caught up in the flow of an activity and being absorbed by it (Csikszentmihalyi 1997) and the latter with an individual's voluntary content generation and promotion of a focal media product. Therefore, increased engagement with a TV series might result in the viewer watching subsequent seasons or other types of franchise extensions[3] of the same series (i.e., personal engagement) and/or in the viewer promoting the TV series and producing user-generated content (UGC) about it (i.e., interactive engagement).

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.[4] For example, "Breaking Bad" creator Vince Gilligan previously told Mashable that the show

[3]We study five types of franchise extensions in this paper: sequels, side stories, spin-offs, summaries, and remakes. Frequently, we divide franchise extensions into two groups: sequels and "other types of franchise extensions" (i.e., side stories, spin-offs, summaries, and remakes). A "sequel" is a story that is a direct continuation of the focal series and usually carries on elements of the original story, often with the same characters and settings. For example, season 8 of "Game of Thrones" is a sequel to season 7 of "Game of Thrones." 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.

[4]The empirical context of this paper are anime (Japanese cartoon) series. Thus we use the terms "next season" and "sequel" interchangeably.

"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 (versus watching at a slower pace) increases consumer engagement with a media franchise. In this paper, taking advantage of novel data containing individual-level information on consumers' media watching behavior and user-generated content, we empirically examine the relationship between binge-watching (versus watching at a slower pace) and consumers' personal and interactive engagement with a media franchise. More specifically, we are interested in assessing whether bingeing a focal media product indeed increases personal engagement by enhancing a consumer's adoption and consumption of other media products belonging to the same franchise. At the same time, we also investigate whether bingeing affects consumers' interactive engagement by altering their content generation behaviors related to the focal media product.

If binge-watching increases consumers' 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 shows or all consumers, it is important to understand when and why this is the case. Does the timing of the release through online streaming services matter? Or does the type of franchise extension matter? For example, do sequels 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 bingeing than consumers from other countries? Similarly, are consumers with certain demographic and behavioral characteristics such as older or inexperienced consumers more susceptible to the effect of binge-watching than other consumers? In this paper, through a systematic empirical investigation, we provide a description of this new mode of watching and its relation to 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 an individual's adoption of animes including the number of days it took a consumer to watch the whole season of an anime. This information allows us to classify consumer-anime combinations into "binged" and "not binged" cases. Further, we observe an individual's self-generated content about an anime in the form of published posts on the discussion forum as well as submitted ratings and recommendations. Our data also contain information on a consumer's decision to watch the next season (sequel) of an adopted anime and/or to watch other types of franchise extensions such as summaries, spin-offs, side stories, and remakes. And lastly, we observe a consumer's demographic and behavioral characteristics, including the individual's geographic location, age, gender, domain expertise, and recent anime watching activities. These consumer-specific traits allow us to explore whether and how the effects of binge-watching vary across different consumer segments.

We mostly use bivariate binary probit models to study the relationship between binge-watching and a consumer's actions related to media franchise engagement.[5] The first equation describes the user's decision to binge and the second equation models the relation between binge-watching and consumer engagement. Further, we incorporate two exclusion variables

[5]For a few continuous engagement variables, we use a linear regression model together with a binary probit model allowing for a correlation in the error terms across the two equations, i.e. we use an analogue of the bivariate binary probit model with one of the equations being a linear instead of a probit model.

that can be interpreted as instruments in the binge 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 also allow correlated unobservables to affect both decisions.

Our results show that the effect of binge-watching on an individual's personal engagement largely depends on both the availability of a franchise extension at the time of watching the focal season and the type of franchise extension. If the franchise extension is available, bingeing the prior season significantly increases a consumer's probability of watching the subsequent season (sequel), but decreases the probability of adopting another type of franchise extension. If the franchise extension is not available at the time of watching the focal season, bingeing decreases the adoption probability of both sequels and other types of franchise extensions. However, conditional on adopting a franchise extension, we find that bingeing has a significant positive effect on the likelihood of finishing to watch the franchise extension – regardless of the type of franchise extension. In addition, we find that consumers who binge a focal anime are more likely to watch a franchise extension immediately next than those who do not binge and that this effect is stronger when the franchise is a sequel (versus another type of franchise extension).

Regarding the relationship between binge-watching and interactive engagement, i.e., the production of UGC, we find that the effect of bingeing varies with the type of UGC: it decreases the likelihood of submitting a rating, increases the likelihood of making a recommendation, and does not affect the likelihood of publishing a forum post. Given that ratings are the most prevalent type of UGC and recommendations are very rare on this platform, our results provide partial support for the general avoidance tendency of binge-watchers proposed and documented in previous literature (e.g., Schweidel and Moe 2016). We also find that consumers who binge rate the focal anime higher, suggesting that bingeing positvely affects consumers' liking of a media product.

We extend our analysis to explore five common sources of heterogeneity: age, gender, geography, usage, and experience. Geographic heterogeneity is mostly captured by different behaviors of consumers in and outside of North America: consumers in North America are more likely to binge, less likely to engage personally, and more likely to engage interactively than consumers outside of North America. Further, if North American consumers binge, they are less likely to watch a franchise extension immediately next than bingeing consumers from outside of North America. We find a limited amount of heterogeneity related to age and gender: older consumers are less likely to binge and produce related UGC than younger consumers. Women are more likely to write forum posts and submit ratings, but these forum posts are shorter and ratings are worse than those written and submitted by men. Among our two behavioral segmentation criteria of experience and recent usage, our results indicate that more experienced consumers and consumers with higher recent usage are less likely to binge than less experienced consumers and consumers with no recent usage. Lastly, we find that the effects of binge-watching on interactive engagement vary with experience and usage: more experienced consumers and consumers with higher recent usage who binge tend to generate more forum posts and/or recommendations related to a media franchise than less experienced consumers and consumers with no recent usage who binge.

Our paper makes the following two contributions. First, we contribute to the 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 study the relationship between binge-watching and 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 present our theoretical framework. 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 explore five potential sources of heterogeneity and discuss limitations and future research in the following section. Finally, we conclude by summarizing our findings and discussing managerial implications in Section 8.

2 Theoretical Background

In this section, we focus on providing a theoretical foundation for the effects of binge-watching on customer engagement with a media franchise. To do so, we draw from relevant streams of literature on customer engagement with a media franchise, on binge-watching, and on online movie streaming. We then discuss how past research in these three domains informs us about the relationship between binge-watching and consumer engagement with a media franchise.

2.1 Customer Engagement with a Media Franchise

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).[6] 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 across various industries 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 (e.g., Nambisan and Nambisan 2008; Brakus et al. 2009; Hoyer et al. 2010). However, to the best of our knowledge, no empirical study to date has systematically examined customer engagement in the context of media franchises.

To understand what drives customer engagement with media franchises, the first question is how customer engagement with a media product should be measured. In this regard, Calder et al. (2009) define media engagement in terms of the different motivational experiences that

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

consumers have with a media product. Using confirmatory factor analysis, they identify two types of media engagement: personal engagement and interactive engagement. Personal engagement is associated with intrinsic motivation and includes individualistic experiences such as enjoyment and relaxation directly derived from consuming a media product. More specifically, a consumer's personal engagement with a media product is driven by the "transportation" motive, i.e., by consuming a media product a consumer aims to be transported into a different state (e.g., from bored to happy) or to be transported into taking part in an activity, such as being absorbed into a story and shutting out the real world. Csikszentmihalyi (1997) describes a more general variant of the "transportation" experience as the internal state of an individual getting caught up in the "flow" of an activity and being absorbed by it.

The second type of media engagement, interactive engagement, is associated with extrinsic motivation and includes interactive experiences especially relevant to online media such as socialization and participation in a community facilitated by the consumption of a media product. For example, after finishing to watch a movie, a consumer may have the urge to generate online word-of-mouth related to the movie by submitting a rating, publishing a review, or participating in discussion forums on various social media platforms. This online word-of-mouth has been shown to be effective in raising awareness and influencing opinions of other consumers, through which it increases the adoption of the movie (Ameri et al. 2019).

In this study, we follow the categorization by Calder et al. (2009) when examining consumers' personal and interactive engagement with media franchises. In our empirical context of an online anime platform, we measure a user's personal engagement with a media franchise by examining her self-enjoyment of the focal media product and the adoption of its franchised extensions including sequels, spin-offs, summaries, side stories, and remakes. We assess her interactive engagement through her content generation and promotion of a focal media product, i.e., her decision to submit recommendations, ratings, and comments in a community discussion forum regarding the focal anime series.

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 streaming" (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, i.e., the consumer's control over whether to watch more episodes, as an essential part of binge-watching. The element of control distinguishes binge-watching from watching marathon releases of series episodes back to back on regular TV channels (Jenner 2015; Pittman and Sheehan 2015). To put it differently, binge-watching is not only about watching multiple episodes in one sitting, but also about a consumer's control and decision of 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 should be considered as 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 aired on TV (MarketCast 2013; TiVo 2015) or to be able to participate in the word-of-mouth related to 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). Similarly, MarketCast (2013) also finds that one of the main reasons for binge-watching is that viewers cannot or do not want to wait for each next episode. Another finding in the TiVo (2015) study is 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). All these findings suggest that instant gratification may be a main driver for the binge-watching behavior (Wertenbroch 1998). Some people binge 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, individuals 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; Hi et al. 2015; Pittman and Sheehan 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 feel sad when they finish bingeing a series; 31% reported that they have lost sleep due to bingeing. Binge-watching - due to the intensity of the experience and the flow it creates - has been suggested to create loyalty to a series, to lead to fandom, and to help the formation of one-sided, unconscious bonds between viewers and characters or, at the very least, behavior similar to fandom such as purchasing ancillary materials, creating fandom pages or posting or creating content (Devasagayam 2014; 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 of the effects of binge-watching on consumer 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 to 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, 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. Ameri et al. (2019) investigate the drivers of consumers' anime adoption decisions in the context of online streaming. They find the average anime rating and the popularity rank from the community network, i.e., the platform, to have larger effects on consumers' adoption decisions than the same two types of information obtained from the personal network, i.e., a consumer's friends. 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 from Hulu.com. They find that binge-watchers are less responsive to advertising compared to non-binge-watchers.

2.4 Theoretical Synthesis

In this subsection, we provide a theoretical synthesis of prior research in the three relevant domains based on which we develop a set of predictions for our empirical context. We first discuss the relationship between binge-watching and personal engagement and conclude this subsection by examining the relationship between binge-watching and interactive engagement.

Bingeing can affect consumers' personal engagement in two distinct ways. On the one hand, media consumers who experience the flow created by binge-watching are more likely to repeat their behavior or even become addicted in order to stay in the flow (e.g., Kubey and Csikszentmihalyi 2002; Chou and Ting 2003). One would expect that a natural way for consumers to continue the flow after bingeing a focal media product is to watch its franchise extensions when they are available at the time of bingeing the focal media product. By watching franchise extensions, consumers can remain in the state concentrated around the same characters and their story shown in the focal media product. Therefore, binge-watching may elevate consumers' probability of choosing a franchise extension of the focal media product as the *next* media product to watch compared to choosing an unrelated media product next. Similarly, bingeing may also affect the overall likelihood of consumers adopting a franchise extension of the focal media product *at any point in the future*, as a means of continuing the immersive experience and maintain the one-sided relationship with the characters in the focal media series. And lastly, conditional on starting to watch a franchise extension, bingeing may also increase consumers' probability of finishing to watch the franchise extension so that they can continue staying in the flow.

On the other hand, by watching and finishing a season in a short amount of time, binge-watching may also cause "satiation" or boredom with the focal media product. Satiation propels consumers to move away from related media products such as franchise extensions. For example, consumers may seek for variety by watching something unrelated to the focal series *next*, they may completely move away from consuming any franchise extensions of the focal media product *at any point in the future*, and/or they may not finish watching a franchise extension.

These two effects of binge-watching on personal engagement work in opposite directions. Therefore the net effect of binge-watching depends on how consumers balance the flow created by bingeing against the satiation that is also brought about by bingeing. Whether binge-watching enhances or weakens a consumer's personal engagement with media franchises is therefore an empirical question that we set out to answer in this paper.

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 may be centered 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").[7] Therefore, we expect the flow created by bingeing a media product to be best continued by sequels. In other words, we expect that consumers experience a stronger flow effect when they watch a sequel relative to other types of franchise extensions (i.e., spin-offs, side stories, remakes, and summaries). However, for exactly the same reason, after bingeing the focal media product, consumers may also experience stronger satiation when watching a sequel. In the current study, we empirically examine how the net effect of binge-watching on personal engagement varies across different

[7]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."

types of franchise extensions.

And lastly, we discuss the relationship between binge-watching and interactive engagement. Due to bingers' inclination to stay in the flow, they tend to avoid any activities that distract them from watching the focal media product, including interactive engagement activities such as content creation and promotion of the focal media product.[8] This avoidance tendency is manifested in Schweidel and Moe (2016) where the authors find that binge-watchers are less responsive to advertisements compared to non-binge-watchers. Many industry observers also accredit Netflix's no disruption design (for example, getting rid of the opening credits at the start of an episode if you are watching more than one episode) as one of the main reasons for the wide spread of binge-watching (Vidar 2015). Thus, we conjecture that consumers who binge a focal media product are less likely to generate related content than consumers who watch the product without bingeing. However, if these consumer ever generate content about the focal media product, we suspect this content might be more favorable than content generated by consumers who do not binge-watch. This is because binge-watching is suggested to induce loyalty or fandom-like behaviors (Devasagayam 2014; Jenner 2015).

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 in 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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[8]We use the terms "bingers" and "non-bingers" as follows in this paper: bingers are individuals who ended up binge-watching an anime series *on a specific occasion*. Non-bingers are defined similarly. Across all instances that we observe an individual in our data, the individual can be classified as a binger on some occasions and as a non-binger on other occasions depending on her pace of watching a focal media product.

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

Users can create a list of animes that they have watched or plan to watch (we refer to this list as "watch list" throughout this paper).[9,10] Note that users add animes to their watch 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 "ratings." Lastly, users can indicate the date they started watching an anime series and the date they finished watching an anime series. We use the start and end dates to infer the beginning and end of a user's watch period for an anime series.

3.1 Binge-Watching

We define an individual as having binged an anime season if the individual watches the series for over 3 hours a day – a more conservative measure than Netflix's.[11, 12] To differentiate binge

[9]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.

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

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

[12]In Web Appendix A, we test the robustness of this definition with respect to shorter and longer watch times of 2 and 4 hours, respectively. Our results are qualitatively robust to these alternative operationalizations of binge-watching.

from non-binge incidences in our data, we use the average daily time that an individual spent watching a season of an anime series, i.e., we divide the total duration of the anime season (measured in hours) by the number days that it took the individual to watch all episodes of the anime season. 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.[13]

3.2 Engagement

We investigate three aspects of an individual's personal engagement with media franchises by examining her consumption decisions related to franchise extensions of a focal anime season. First, bingeing an anime season might affect a user's likelihood of watching its franchise extension (at any point in time in the future). Second, conditional on watching a franchise extension, the viewing modus might affect a consumer's likelihood of finishing to watch the franchise extension. And lastly, if a franchise extension is available at the time of watching the focal anime, bingeing might also affect the likelihood of watching a franchise extension immediately next versus an unrelated anime. We operationalize these three aspects of personal engagement as binary indicator variables: (i) whether a user watched a franchise extension (at any point in time in the future), (ii) whether a user finished watching the franchise extension (conditional on starting to watch a franchise extension), and (iii) whether a user watched a franchise extension next (conditional on a franchise extension being available).

We examine an individual's interactive engagement with media franchises by looking at her decisions to produce UGC related to adopted anime seasons. We investigate three types of UGC: recommendations, ratings, and posts on the discussion forum. Recommendations on this platform exhibit the following pattern: "If you like anime A, you will like anime B because of XYZ." In that sense, individuals give a recommendation for which two animes are *similar*, but not necessarily a recommendation that an anime is particularly good. Posts on the

[13]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 season. Our data do not allow us to identify the watching behavior on Sunday as binge-watching.

discussion forum typically discuss topics such as new season release dates, voice cast decisions, story lines, specific characters, awards, or anime adaptations. Ratings are different from the two previously mentioned forms of UGC in that they are numerical and a higher rating clearly indicates a more favorable opinion towards the rated anime season. Furthermore, while ratings are publicly visible to everybody, they are recorded by a user on her watch list and help her remember her preference for or liking of a particular anime.

For each type of UGC, we study whether the viewing modus affects UGC incidence, i.e. whether bingeing affects the likelihood of (a) writing (at least) one recommendation, (b) submitting a numerical rating, or (c) publishing (at least) one post on the discussion forum related to the focal anime season. Conditional on UGC incidence, we further investigate whether the viewing modus also affects UGC valence of (d) ratings or (e) forum posts. In addition, since a user can submit more than one recommendation and more than one forum post about an anime series, we also study whether the viewing modus affects (f) the number of recommendations and (g) the number of forum posts submitted by the individual, conditional on incidence. And lastly, for forum posts only, we also investigate whether bingeing affects (h) the average length of submitted forum posts. Variables (a) - (c) are operationalized as indicator variables and variables (d) - (h) are treated as continuous variables.

3.3 Estimation Sample

We scraped data on 370,000 individuals from the website. Not all users list start dates for (all or any) anime series they have adopted on their watch list. After excluding all user-anime combinations for which we did not have start dates, we were left with 92,273 individuals.[14] We then dropped (i) animes for which we did not have the release date or information on the number of episodes; (ii) user-anime combinations for which the watch period seemed unreasonably long, i.e. more than 3,000 days; (iii) observations for days on which individuals indicated to have watched animes for more than 24 hours; (iv) observations with start dates before 2008 since,

[14]Individuals' behavior on MyAnimeList.net is consistent with the well-known 90-9-1 rule in social media (see e.g. https:www.nngroup.comarticlesparticipation-inequality): a large proportion of individuals is inactive.

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 individuals and 4,896 animes (3,481,664 user-anime combinations), we took the following steps to get to our final data.

First, we dropped anime series for which it would take an individual less than 3 hours to watch the whole season. Table 1 shows the frequency distribution of anime series with respect to their number of episodes and durations of a season in hours. Movies or short anime series generally take less than 3 hours to be watched and thus, according to our operationalization of binge-watching, cannot be binged. Note that, even if an individual watches 3 movies back to back, if they are not part of a franchise, we do not consider this instance as binge-watching. Second, we dropped user-anime combinations in which an individual did not watch the whole season. Even if a user binges the first half of a season (and does not watch the second half of the season), her behavior might be different from someone who binged and finished the whole season. To be able to attribute the difference in user behavior to the viewing modus of binge-watching and not to the completion of the whole season, we only consider cases in which the individual finished watching the whole season.

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Insert Table 1 about here

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Third, we only consider user-anime combinations 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. In Figure 2, we show the number of days (after the original airing of the first and last episode in a season, respectively) after which individuals who ended up bingeing the anime and individuals who did not binge the anime started to watch it. For example, Figure 2(b) shows that individuals, who ended up not bingeing the anime, did not start watching it immediately after the original airing of the first episode, but instead waited until the season finale aired.[15] Note that access to the anime after its original airing is *not* a reason for the delayed watching: almost all animes are available through online streaming within 3 days of the original episode airing (see also Ameri et al. 2019). And lastly, we dropped individuals for whom we do not have their geographic location. This type of information is needed to control for national holidays and weekends and to explore geographic heterogeneity. After these steps, our final data sample for the empirical analysis of interactive engagement contains 37,694 individuals and 2,562 animes with 693,173 user-anime combinations.[16]

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Insert Figure 2 about here

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For personal engagement, we need to constrain the final data sample further. More specifically, we can only consider anime series that have a franchise extension, i.e. next season (sequel) or another type of franchise extension (i.e. side story, spin-off, summary or remake). After dropping anime series that do not have any franchise extension, the data sample contains 35,447 individuals and 1,250 animes with 490,717 user-anime combinations, i.e. unique user-(focal)-anime combinations. Sometimes, anime series have multiple types of franchise extensions (e.g., a spin-off and a summary). In such cases, we model the adoption of each type of franchise extension as a separate potential adoption. Sometimes, anime series have multiple franchise extensions of the *same* type (e.g., two spin-offs). In such cases, we only model the first potential adoption among franchise extensions of the same type. Because of these two issues, the number of observations in the model estimation is 764,666.

3.4 Data Description

We present summary statistics for the 37,694 individuals in our final sample in Table 2. 20,167 individuals in our final sample report their age. Among these individuals, the average age is

[15] A large number of animes have 13 or 26 episodes in a season (see also Table 1). The two spikes around days 91 and 182 after the original airing of the first episode in Figures 2(a) and (b) are consistent with these two frequent season lengths.

[16] Because of missing values in one of our explanatory variables (popularity rank), the number of observations in the model estimation is 663,963.

19 years. 42% of users are female and 41% of individuals are male with the remaining 17% of individuals not specifying their gender. 46% of individuals live in Europe, 34% come from North America, 9% from South America, 8% from Asia, and 4% from Oceania. Users, on average, have watched 2 animes during the last 30 days and 57 animes over the course of their membership on the platform. Note that both distributions exhibit positive skewness and long right tails. We use the number of watched animes during the last 30 days to measure consumers' recent product usage and the number of watched animes over the course of the platform membership to measure consumer experience. Further, we find that users, on average, started watching 31% and 3% of the animes on their watch lists on weekends and holidays, respectively. Given that, for example, weekend days represent 28.57% of days in our data, we observe that users are over-proportionally more likely to start watching animes on weekends (similar results hold for holidays). And lastly, users are significantly more likely to binge on weekends and holidays than to binge during the workweek or on non-holidays providing support for us modeling the binge decision as a function of the weekend and holiday dummies. For example, on any given day during the workweek and on any given day during the weekend, 13.56% and 16.09% of users, respectively, binge (similar results hold for holidays). To summarize, we find that users are more likely to start watching and more likely to binge on weekends and holidays than during the workweek or on non-holidays.

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Insert Table 2 about here

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Figure 3 shows the distribution of watch periods, i.e., the number of days between watching the first and last episode of an anime season, in our estimation sample. In more than 50% of the user-anime combinations, the individual watched a complete anime season within 5 days, with 18.62% of user-anime combinations being watched within a day or two. While Figure 3 does *not* account for the length of a season in terms of the number of episodes, i.e., whether a season consists of 13 or 26 episodes, or the length of episodes (in minutes), it nevertheless shows the possibility that a significant portion of user-anime combinations might be binged.

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Insert Figure 3 about here

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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 (using our 3-hour operationalization of binge-watching). Note that the total number of hours in this figure 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-watch, the vast majority of users watches between 3 and 6 hours with a second, smaller group of individuals 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 individuals 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 watching *any* anime. For example, users who watch 7 20-minutes episodes of one anime series and 7 20-minutes 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 anime series on a user's watch list that can be classified as binged vs. not binged using our 3-hour operationalization. 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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Insert Figure 5 about here

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Figure 6 displays how the number of binged vs. non-binged user-anime combinations has evolved over time. Up until about 2013, both the number of binged and the number of non-binged user-anime combinations gradually increased. Starting in 2013, the number of binged cases continued to increase, while the number of non-binged cases started to decrease, implying that the proportion of binged animes among all animes a user watches is increasing. 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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Next, we discuss our engagement variables. Table 3 shows statistics for our personal engagement variables. In the data, we observe that personal engagement crucially depends on (i) the type of franchise extension (sequel vs. another type) and (ii) the availability of a franchise extension at the time of watching the focal media product. We therefore show the three personal engagement variables for each of the four possible combinations of franchise type and availability separately in Table 3. If a sequel is available at the time of watching the focal anime, individuals who binge the focal anime season are more likely to watch the sequel, to finish watching it, and to watch it immediately next than individuals who do not binge (all three differences are statistically significant at $p < 0.01$). If another type of franchise extension is available at the time of watching the focal anime, individuals who binge the focal anime season are more likely to watch this other type of franchise extension immediately next and to finish watching it (both differences are significant at $p < 0.01$), but are not more likely to watch it than individuals who do not binge. And lastly, if another type of franchise is not available at the time of watching the focal anime, individuals who binge are less likely to watch the franchise extension once it becomes available than consumers who do not binge (difference significant at $p < 0.01$).

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Insert Table 3 about here

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In Figure 7, we report statistics related to users' interactive engagement. Note that, out of the three types of UGC on this platform (i.e., forum posts, ratings, and recommendations), ratings are the dominant form of UGC in terms of user participation: the submission rate is 92.66% for ratings compared to 0.68% for forum posts and 0.18% for recommendations. Further, we find that users who binge an anime season are less likely to post on the discussion forum (difference statistically significant at $p < 0.01$). Conditional on posting on the discussion forum, users who binge an anime season make longer and more negative posts (both differences statistically significant at $p < 0.01$). Further, users who binge an anime season are less like to rate it, but conditional on rating, they rate it higher (both differences statistically significant at $p < 0.01$). We do not observe significant differences between users who binge and users who do not binge in their recommendation behaviors.

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Insert Figure 7 about here

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4 Models and Estimation

We investigate the relationship between binge-watching and a consumer's personal and interactive media franchise engagement. Potential endogeneity of the decision to binge is a concern. To account for it, we simultaneously model an individual's decision to binge the focal anime season and to engage with the franchise allowing for the error terms across the two equations to be correlated (see Heckman 1978, Maddala 1983, Wilde 2000, Wooldridge 2010).

We start by describing the binge equation.[17] Let $i = 1, ..., N$ denote consumers and $j = 1, ..., J$ denote animes. Individual i's decision on whether to binge anime j is given by

$$\begin{aligned} B_{ij}^{*} &= \alpha_i^B + \beta_1^B w_{ij} + \beta_2^B h_{ij} + \delta^B C_{ij}^B + \gamma^B G_j^B + \lambda^B T + \epsilon_{ij}^B \\ B_{ij} &= \begin{cases} 1 & B_{ij}^{*} > 0 \\ 0 & otherwise \end{cases}, \end{aligned} \tag{1}$$

where B_{ij}^{*} is the underlying latent variable capturing consumer i's utility of bingeing anime j. The variable B_{ij} (whose realizations we observe in the data) equals 1 if B_{ij}^{*} is positive and 0 otherwise. B_{ij}^{*} is a function of individual-specific random effects α_i^B following a normal distribution $N\left(\overline{\alpha}^B, \sigma_{\alpha^B}^2\right)$, a weekend dummy w_{ij}, a holiday dummy h_{ij}, control variables C_{ij}^B, anime-specific variables G_j^B, time dummies T, and an error term ϵ^B that follows a standard normal distribution.[18] The control variables C_{ij}^B consist of the popularity rank and the community rating of anime j with both variables being measured at the time of user i's adoption of the focal anime season.[19] G_j^B contains anime-specific variables, namely, anime j's genre dummies, the number of episodes in a season, and the length of each episode in minutes. Note that an anime typically belongs to three to four genres and the genre assignment is done by the platform. And lastly, T contains calendar year dummies.

Next, we describe how we model a consumer's personal engagement with a media franchise. All three personal engagement variables under study are operationalized as binary indicator variables. Thus consumer i's utility from personally engaging with the media franchise is given by

[17]Note that the binge equation always includes the same set of variables as described in Equation (1). However, for each personal and each interactive engagement variable, we re-estimate the binge equation together with the engagement equation for each engagement variable allowing for a correlation between the two error terms.

[18]The weekend and holiday indicators, w_{ij} and h_{ij}, can be interpreted as exclusion variables. We expect users to have more time on weekends and on holidays and thus to be more likely to binge-watch, while these variables should have no/less effect on users' subsequent personal and interactive engagement.

[19]The popularity rank is based on the number of users who adopted the anime. The community rating is the average rating of users who watched the anime. Users can see both variables on the platform.

$$y_{ij}^* = \alpha_i + \Big(\beta_1 + \beta_2 S_j + \beta_3 A_{ij} + \beta_4 S_j A_{ij}\Big) B_{ij} + \kappa_1 S_j + \kappa_2 A_{ij} + \kappa_3 S_j A_{ij} + \delta C_{ij} + \gamma G_j + \lambda T + \epsilon_{ij}$$

$$y_{ij} = \begin{cases} 1 & y_{ij}^* > 0 \\ 0 & otherwise \end{cases} . \tag{2}$$

The variable y_{ij} (whose realizations we observe in the data) equals 1 if y_{ij}^* is positive and 0 otherwise. The underlying personal engagement utility y_{ij}^* is a function of individual-specific random effects α_i following a normal distribution $N(\overline{\alpha}, \sigma_\alpha^2)$ and a dummy variable B_{ij} indicating whether user i binge-watched anime j. Because both the type and the availability of a franchise extension play important roles in precisely pinning down the effects of binge-watching (see also Section 3.4), we not only estimate a main effect of bingeing, but also interact it with a dummy variable S_j indicating whether the franchise extension is a sequel and with a dummy variable A_{ij} indicating whether the franchise extension was available at the time of user i watching the focal anime season. Furthermore, we account for the main and interaction effects of the sequel dummy S_j and the availability dummy A_{ij}.[20] Our control variables C_{ij} include the popularity rank and community rating of anime j both measured at the time of user i watching the focal anime season and, if the franchise extension was not available at the time of user i watching the focal anime season, the wait time until the franchise became available in days. And lastly, G_j contains genre dummies for anime j, T contains calendar year dummies, and ϵ_{ij} is an error term following a standard normal distribution.

Given that both the binge variable described in Equation (1) and the three personal engagement variables described in Equation (2) are indicator variables, the three models – one for each personal engagement variable – are estimated as bivariate probit models.

And lastly, we describe how we model a consumer's interactive engagement with a media franchise. As we describe in Section 3.2, we operationalize three UGC incidence variables as

[20] Note that for the personal engagement form of whether to watch a franchise extension *immediately next* after watching the focal anime, we condition on the availability of a franchise extension at the time of watching the focal anime. Thus, for that equation, we are not able to estimate the effects of availability.

binary indicator variables and the remaining five UGC valence, count, and length variables (conditional on UGC incidence) as continuous variables. For the UGC incidence variables (e.g., forum post indicator), consumer i's engagement is modeled as follows:

$$\begin{aligned} y_{ij}^* &= \alpha_i + \beta B_{ij} + \delta C_{ij} + \gamma G_j + \lambda T + \epsilon_{ij} \\ y_{ij} &= \begin{cases} 1 & y_{ij}^* > 0 \\ 0 & otherwise. \end{cases} \end{aligned} \tag{3a}$$

If the variable capturing interactive media engagement is continuous (e.g., rating valence), consumer i's engagement is modeled as

$$y_{ij}^* = \alpha_i + \beta B_{ij} + \delta C_{ij} + \gamma G_j + \lambda T + \epsilon_{ij}. \tag{3b}$$

α_i is an individual-specific random effect following a normal distribution $N(\overline{\alpha}, \sigma_\alpha^2)$ and B_{ij} is a dummy variable indicating whether user i binge-watched anime j. C_{ij} contains control variables including the popularity rank, the average community rating, and the number of previous forum posts about, ratings of or recommendations for anime j at the time of individual i's adoption of the focal anime season. For dependent variables related to forum posts only, we also control for whether consumer i has ever published a forum post and the time since the last forum post on anime j published by anyone. G_j contains anime-specific variables such as the number of episodes in a season and genre dummies, and T contains calendar year dummies. Lastly, ϵ_{ij} is the error term following a standard normal distribution.

If the interactive media engagement variable is binary as described in Equation (3a), we jointly estimate the binge equation and the interactive media engagement equation using a bivariate probit model with correlated errors. If the interactive media engagement variable is continuous as described in Equation (3b), we jointly estimate the binge equation and the interactive media engagement equation using a probit and a linear model with correlated errors.

5 Results

5.1 Binge Decision

We start by discussing the results for consumers' binge decisions. The lower halves of Tables 4 and 5 show the results from the model parts capturing the decision to binge. Across the eleven sets of results shown in Tables 4 and 5, the coefficient estimates have the expected signs and most of them are significant: the coefficients for the weekend and holiday dummies are, as expected, positive. The lower the popularity rank of the focal anime season (i.e. the better the rank), the more likely it is that an individual binges it. Higher rated anime series with more and longer episodes also increase the probability of binge-watching. We also find evidence for a significant amount of unobserved heterogeneity across users. Lastly, six out of eleven correlations between the binge and engagement decisions are statistically significant with some correlations being positive and some being negative.

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Insert Tables 4 and 5 about here

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5.2 Personal Engagement

The top half of Table 4 shows the parameter estimates from the model parts describing consumers' personal engagement actions. Column (i) describes an individual's decision of whether to watch a franchise extension (at any point in time). We find the main effect of binge-watching as well as all four interaction effects (three two-way interactions and one three-way interaction) to be statistically significant, suggesting that the effect of bingeing critically depends on the type of franchise extension (sequel versus other type) and its availability at the time of watching the focal media product. To facilitate interpretation of the effects of binge-watching in each of the four scenarios (sequel/available, sequel/not available, other type/available, other type/not available), we separately show the effects of binge-watching (taking all main and interaction effects of the binge dummy into account) for each scenario in column (i) in Table 6.[21]

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Insert Table 6 about here

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When a franchise extension is available, we find that bingeing the focal media product (compared to watching it at a slower pace) significantly increases the likelihood of adopting a sequel, while it significantly decreases the likelihood of adopting other types of franchise extensions. This finding is consistent with consumers experiencing a stronger and more seamless flow effect by watching a sequel compared to watching other types of franchise extensions. A sequel is a continuation of the main plot and has the same main characters as the focal media product, while other types of franchise extensions may have a different story line or may be centered around different characters. In the case of a sequel, the stronger flow created by bingeing overcomes the satiation with the media franchise and therefore leads to a positive net effect on adopting this specific type of franchise extension. For other types of franchise extensions, since the flow is not as strong due to the weaker connection to the focal media product, the satiation effect dominates resulting in a negative net effect on adoption.

When a franchise extension is not available at the time of watching the focal media product, we find that bingeing (compared to watching at a slower pace) significantly decreases the adoption probability for both sequels and other types of franchise extensions (once the media franchise becomes available). Given the separation in time between watching the focal media product and the possibility of adopting its franchise extension due to its initial unavailability, the flow effect is not strong in this situation. As a result, the net effect of bingeing is mainly driven by the satiation. This is why we find the adoption probabilities of both sequels and other types of franchise extensions to decrease when they are not available at the time of watching the focal anime season.

We further examine whether bingeing affects a consumer's probability of finishing to watch the franchise extension (conditional on starting to watch a franchise extension) in column (ii) of

[21]For example, we calculate the effect of bingeing for the sequel/available scenario as follows: $0.069 = -0.142 + 0.036 + 0.030 + 0.145$. We use the Delta method to calculate the standard errors.

Table 4. Again, we calculate the effect of bingeing (taking all main and interaction effects into account) for each of the four scenarios separately and show them in column (ii) in Table 6. We find that, after starting to watch a franchise extension, users who binge the focal media product are significantly more likely to finish watching the franchise extension than users who watch it at a slower pace in all four scenarios. These results suggest that, once consumers overcome their satiation (with the media franchise) and start watching a franchise extension, the positive flow effect dominates which increases the probability of finishing to watch the franchise extension.

Lastly, we examine how binge-watching affects the more immediate media watching behavior. In column (iii) of Table 4, we pin down how bingeing affects a consumer's probability of watching a franchise extension (compared to an unrelated media product) immediately next (conditional on it being available at the time of watching the focal media product). We find that individuals who binge a focal anime season are more likely to watch a franchise extension immediately next than individuals who do not binge, and that this effect is stronger when the franchise extension is a sequel (versus another type – see column (iii) in Table 6). This result again speaks to the consumers' tendency to continue the flow created by bingeing the focal media product. A natural way to do so is to watch its franchise extensions if one is available. Relative to other types of franchise extensions, sequels benefit more from the binge effect because of the stronger flow they create.

To summarize, our results for personal engagement show that bingeing only increases a consumer's probability of watching a franchise extension (at any point in time in the future) if that franchise extension is a sequel *and* available at the time of watching the focal media product. Otherwise, bingeing decreases the adoption probability of a franchise extension. However, conditional on starting to watch a franchise extension, bingeing increases the probability that a consumer finishes to watch it in all four scenarios. And lastly, bingeing also increases the probability that a consumer watches a franchise extension immediately next after watching the focal media product.

5.3 Interactive Engagement

Next, we discuss the results for interactive engagement shown in the upper half of Table 5. Columns (i) to (iv) in Table 5 display the coefficients for estimations related to forum posts. Our results in columns (i) and (iii) indicate that bingeing (compared to watching at a slower pace) does not significantly affect a user's probability of making forum posts – neither the incidence nor the number of forum posts. Whether a user contributes to the discussion forum and the number of her contributions rather appear to be largely driven by unobserved consumer heterogeneity. Conditional on contributing to the discussion forum, if an individual binges, she makes more negative but longer posts (columns (ii) and (iv)). However, it is important to note that this negative effect on valence does *not* necessarily mean that consumers who binge have a more negative opinion of the focal media product as a consequence of the modus of consumption. As mentioned before, discussion threads cover a wide range of topics related to the focal anime season, including new season release dates, voice cast decisions, story lines, specific characters, awards, and anime adaptations. It is possible that, if an individual binges, she likes the focal media product more, but makes a more negative post in a thread on the discussion forum, for example, about the wait time until the next season becomes available.

Columns (vii) and (viii) in Table 5 show the results for recommendations – another form of verbal UGC. Recall that recommendations on this platform exhibit the following pattern: "If you like anime A, you will like anime B because of XYZ." In that sense, individuals give a recommendation for which two animes are *similar*, but not necessarily an endorsement that either of these two animes is particularly good. Giving such a recommendation is likely to be driven by a consumer's higher interest level in an anime. We find that consumers who binge are significantly more likely to write a recommendation for the focal media product than consumers who do not binge, but conditional on submitting a recommendation, the former group does not write more recommendations than the latter group of consumers. Here, it is also important to note that our estimation sample for the recommendation count is very small since only a very small fraction of users make any recommendations and an even smaller fraction of users makes more than one recommendation.

Ratings are different from the two previously mentioned forms of UGC in that they are numerical and in that a higher rating clearly indicates a more favorable opinion towards the rated anime. Furthermore, while ratings are publicly visible to everybody like the two other forms of UGC, they are recorded by a user on her watch list and help her remember her preference for or liking of a particular anime. This partly explains why ratings are the dominant form of UGC in terms of user participation on this platform. Our results in columns (v) and (vi) in Table 5 show that, if an individual binges, she is significantly less likely to rate the focal media product, but if she does rate it, she gives it a more positive rating than an individual who does not binge.

To summarize, our results show that forum post incidence and frequency are rather driven by unobserved consumer heterogeneity than bingeing. Further, conditional on making forum posts, consumers make more negative but longer posts. We also find that bingeing increases the probability that an individual writes a recommendation for the focal media product. And lastly, we find that consumers are less likely to rate an anime if they binge, but conditional on rating it, they give it a more positive rating.

Given that consumers who binge are less likely to rate animes, we interpret our results as providing partial support for bingeing having a negative effect on the amount of UGC produced. We acknowledge that bingeing increases the probability of writing a recommendation. However, ratings are a far more frequent form of interactive engagement on this platform (and on most UGC platforms in general). We believe the negative effect of bingeing on the rating submission can be explained by bingers' inclination to stay in the flow and to avoid any activity that distracts from or interrupts the watching, which is also consistent with the avoidance tendency of bingeing individuals towards advertisements documented in Schweidel and Moe (2016).

Furthermore, we believe that our results provide some evidence that bingeing increases consumers' liking of an anime. This is because individuals who binge rate the focal anime higher. This positive effect of bingeing on consumers' liking of an anime is consistent with previous research which has suggested that bingeing induces loyalty and fandom-like behavior

(Devasagayam 2014, Jenner 2015).

6 Heterogeneity

In this section, we explore the extent of heterogeneity in our results with respect to five common segmentation criteria: geography, age, gender, usage, and experience.[22] We explore three manifestations of heterogeneity: (i) in the decision to binge, (ii) in the baseline probability to engage, and (iii) in the effect of binge-watching.

We start by exploring heterogeneity in the decision to binge.[23] We find that consumers outside of North America are less likely to binge than consumers in North America. Older (above 25 years), more experienced consumers, and consumers with higher recent usage are also less likely to binge than younger, less experienced consumers, and consumers with no recent usage, respectively.

Next, we describe heterogeneity in both the baseline probability to engage and in the effects of binge-watching on consumers' personal and interactive engagement. A summary of the results is shown in Table 7. Note that the table contains the results from a large number separate regressions – one for each of the five sources of heterogeneity and each dependent variable. The complete regression results with all coefficient estimates for all regressions can be found in Web Appendix B. Further note that, since we are interested in the extent of heterogeneity, we show the *differential effects* in Table 7, i.e. the estimates displayed in Table 7 indicate *by how much* an effect is *different* from the baseline and whether this difference is statistically significant. *Intuitively speaking, significant effects in Table 7 mean that there is heterogeneity and insignificant effects mean that there is no heterogeneity.*[24] And lastly, in Table 7, we show

[22]We operationalize all heterogeneity variables as dummy variables. For experience, we conduct a median-split and operationalize experience as a high-experience dummy variable. Similarly, for usage, we conduct a 3rd quartile split and operationalize usage as a high-usage dummy variable. We use the 3rd quartile as the split cutoff for usage because the median is 0. Geography and gender vary across individuals; age, usage, and experience vary across individuals and time.

[23]Coefficient estimates for the heterogeneity variables (quantifying the effects of the heterogeneity variables on consumers' decision to binge) are shown in the lower halves of Tables B-1 to B-10 in Web Appendix B.

[24]We acknowledge that, strictly speaking, a statistically insignificant differential effect means that we cannot reject the null hypothesis of no heterogeneous effect and a statistically significant differential effect means that we can reject the null hypothesis of no heterogeneous effect.

both how the baseline probabilities to engage vary with consumer characteristics – these effects are denoted by, for example, "Differential Effect of Europe" or "Differential Effect of Being Female" – and how the effects of binge-watching vary with consumer characteristics – these effects are denoted by, for example, "Differential Effect of Bingeing in Europe" or Differential Effect of Bingeing for Females."

In the following, we use a few examples to illustrate how the estimates in Table 7 should be interpreted. For example, the baseline for the regressions exploring geographic heterogeneity is North America (see 2nd line in Table 7). The differential effect of bingeing in Europe (as compared to North America) for "Sequel & Available" is -0.021 and statistically insignificant (see column (i) in Table 7). This means that, while the effect of binge-watching in the case of "Sequel & Available" is smaller for European consumers than for North American consumers by -0.021, this difference is statistically insignificant.[25] To put it differently, the effect of binge-watching on whether consumers watch a franchise extension in case of "Sequel & Available" is the same for consumers in Europe and North America. To give a second example, the differential effect of bingeing in Asia (as compared to North America) on forum post incidence is 0.189 and significant at $p < 0.05$ (see column (iv) in Table 7).[26] This means that the effect of binge-watching on forum post incidence is larger in Asia than in North America by 0.189 and that this difference is statistically significant. In other words, Asian consumers who binge are significantly more likely to post on the discussion forum than North American consumers who binge. And lastly, we also show the differential effects of the heterogeneity variables on the baseline engagement probabilities. For example, the "Differential Effect of Europe" on watching a franchise extension is 0.126 and significant at $p < 0.001$ (see column (i) in Table 7).[27] This means that consumers in Europe are significantly more likely to watch a franchise

[25] The differential effect of bingeing in Europe for "Sequel & Available" was calculated as follows using the coefficient estimates from column (i) in Table B-1 in Web Appendix B: Europe $\times$ Binge + Europe $\times$ Binge $\times$ Sequel + Europe $\times$ Binge $\times$ Available + Europe $\times$ Binge $\times$ Sequel $\times$ Available $= 0.005 + (-0.093) + 0.017 + 0.050 = -0.021$.

[26] The differential effect of bingeing in Asia on forum post incidence equals the coefficient estimate for Asia $\times$ Binge in column (i) in Table B-2 in Web Appendix B.

[27] The differential effect of Europe on watching a franchise extension equals the coefficient estimate for the Europe dummy in column (i) in Table B-1 in Web Appendix B.

extension than consumers in North America.

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Insert Table 7 about here

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Our results suggest a limited amount of heterogeneity in the baseline probabilities of engaging with a media franchise which are captured by the differential effects of the heterogeneity variables in Table 7 such as “Differential Effect of Europe” or “Differential Effect of Female.” We find that consumers outside of North America are more likely to personally engage, but less likely to interactively engage with a media franchise than consumers in North America. Female consumers are more likely to finish watching a franchise extension, to submit ratings, and to publish posts on the discussion forum than male consumers. However, the length of forum posts and valence of ratings submitted by women is lower than the length of forum posts and valence of ratings submitted by men. Older consumers, in general, are less likely to interactively engage with a media franchise than younger consumers, as indicated by their lower participation in all three forms of UGC. Further, we find very little to no heterogeneity in the engagement probabilities related to experience and recent usage.

Lastly, we discuss the amount of heterogeneity in the effects of binge-watching. Regarding personal engagement, consumers outside of North America who binge are generally more likely to watch a franchise extension immediately next than consumers in North America who binge (see column (iii) in Table 7). With regard to interactive engagement, consumers in Europe and Oceania who binge write more forum posts than consumer in North America who binge. Consumers in South America and Asia who binge submit fewer ratings and worse ratings, respectively, than consumers in North America who binge. We only find two heterogeneous effects of binge-watching related to age: the effect of bingeing on watching a franchise that is neither a sequel nor available is smaller for people older than 20 years old than younger people and the effect of bingeing on watching a franchise that is not sequel immediately next is larger for the age group of 20 to 25 years than for younger consumers. Regarding our two behavioral segmentation criteria of experience and recent usage, our results show that consumers with a lot of experience who binge are less likely to finish a franchise extension (that is unavailable and of other type) than consumers with little experience who binge. Further, we find that the effect of bingeing on interactive engagement varies with experience: consumers with more experience who binge write more forum posts and more recommendations than consumers with little experience who binge. However, consumers with more experience who binge also give worse ratings than consumers with little experience who binge. And lastly, similar to the finding for experience, we also find that consumers with high recent usage who binge write more recommendations than consumers with no recent usage who binge.

To summarize, geographic heterogeneity is mostly captured by different behaviors of consumers in and outside of North America: consumers outside of North America are less likely to binge, more likely to engage personally, and less likely to engage interactively than consumers in North America. Further, if consumers outside of North America binge, they are more likely to watch a franchise extension immediately next than bingeing consumers from North America. We find a limited amount of heterogeneity related to age and gender: older consumers are less likely to binge and produce UGC related to a media franchise than younger consumers. Women are more likely to write forum posts and submit ratings, but these forum posts are shorter and ratings are worse than those written and submitted by men. Among our two behavioral segmentation criteria of experience and recent usage, our results indicate that more experienced consumers and consumers with higher recent usage are less likely to binge than less experienced consumers and consumers with no recent usage. Lastly, we find that the effects of binge-watching on interactive engagement vary with experience and usage: more experienced consumers and consumers with higher recent usage who binge tend to generate more forum posts and/or recommendations related to a media franchise than less experienced consumers and consumers with no recent usage who binge.

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 due to its self-reported nature remains a potential concern. 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 creative content. It is left for future research to study whether and how different content characteristics such as features of the story line, 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. An interesting direction for future research is to explore how these different channels should design and deploy user interfaces, advertising methods, and sequential watching strategies to 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 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 examine the relationship between binge-watching and 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 the effect of binge-watching on personal engagement crucially depends on both the type and the availability of franchise extensions at the time of watching the focal media product. 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 adoption probability for both sequels and other types of franchise extensions. However, conditional on starting to watch a franchise extension, bingeing increases the probability that a consumer finishes to watch it in all four scenarios. We also find that bingeing increases the probability that a consumer watches a franchise extension immediately after watching the focal media product. We believe these effects are driven by the balance between the flow and the satiation, two forces created by binge-watching but operating in opposite directions. Regarding interactive engagement, our results suggest binge-watching decreases the submission of ratings, the most dominant form of UGC on the platform, providing partial support for the avoidance tendency of binge-watchers proposed and documented in previous literature.

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.

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Insert Figure 8 about here

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Second, binge-watching does not boost viewership of all franchise extensions. Which franchise extensions benefit from a bingeable prior season depends on whether the franchise extension helps to 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.[28]

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 across five continents. Specifically, we find that the effects of binge-watching are present and robust across the different regions, with a stronger effect on personal engagement for consumers outside of North America. 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.

[28]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.

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Figures and Tables

Figure 1: Dates Users Joined MyAnimeList.Net

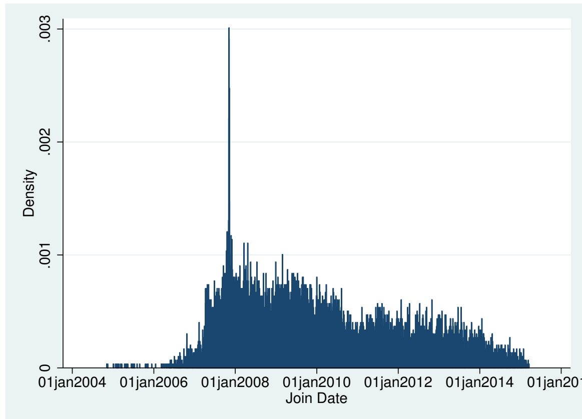
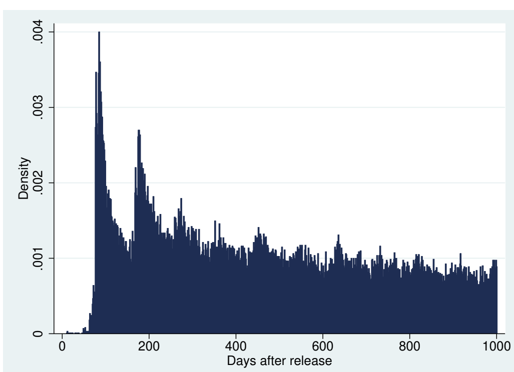
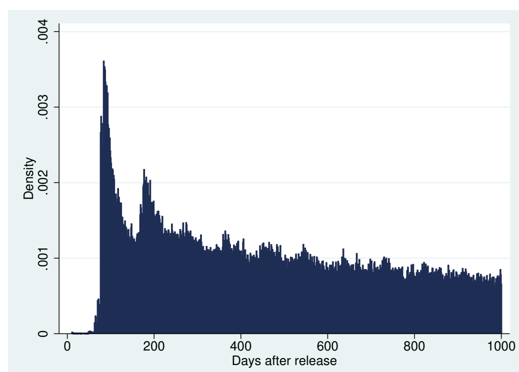


Figure 2: Number of Days After Release of First or Final Episode in a Season That Animes Were Watched

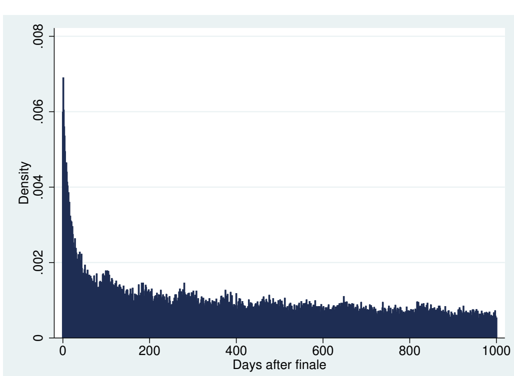
(a) Binged: Number of days after FIRST episode in a season (truncated at 1,000 days)



(b) NOT Binged: Number of days after FIRST episode in a season (truncated at 500 days)



(c) Binged: Number of days after LAST episode in a season (truncated at 1,000 days)



(d) NOT Binged: Number of days after LAST episode in a season (truncated at 500 days)

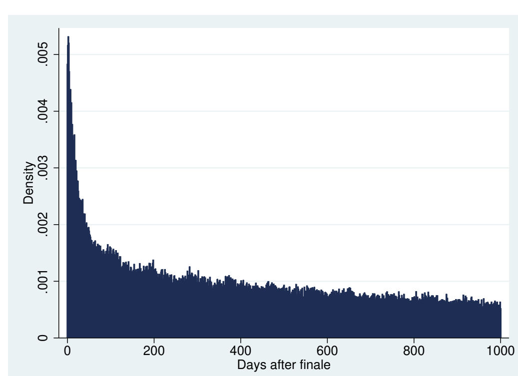


Figure 3: Watch Period Distribution (truncated at 200 days)

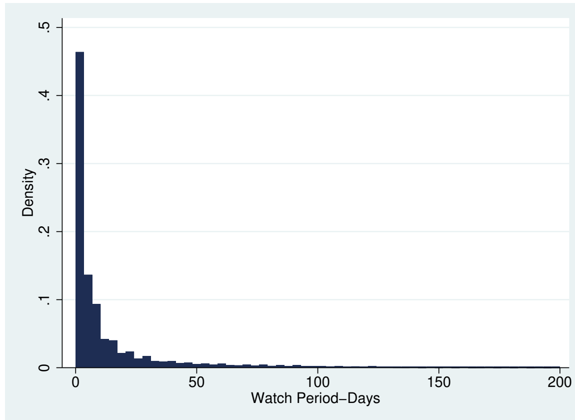
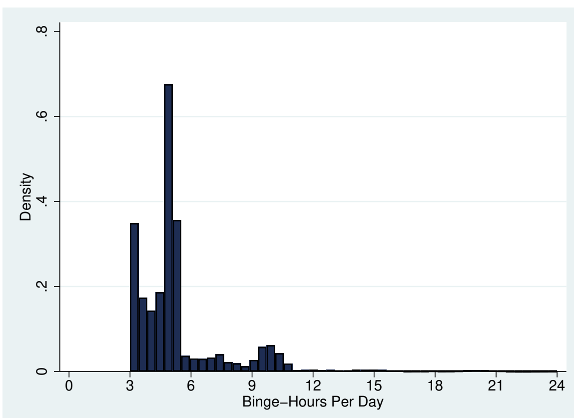


Figure 4: Number of Hours Watched Per Day

(a) Days with Binge-Watching



(b) Days with No Binge-Watching

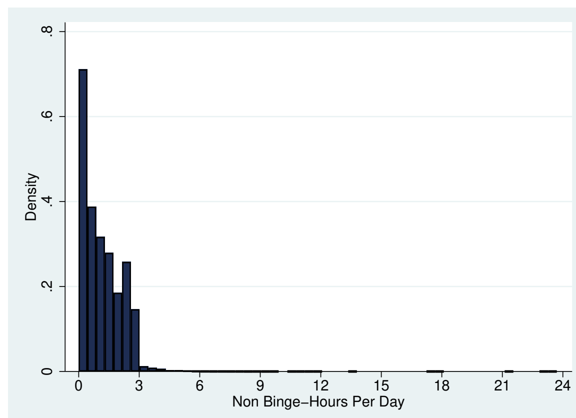
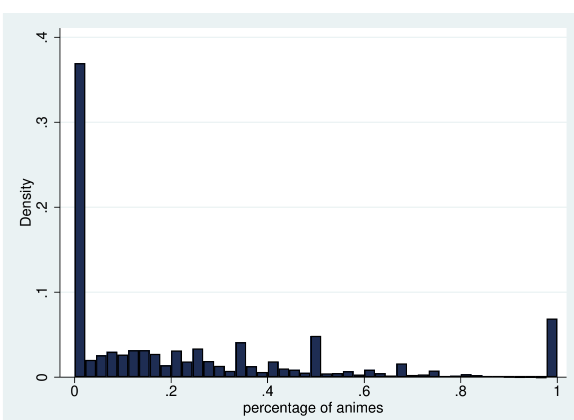


Figure 5: Percentage of A User's Watch List That Is Binged

(a) Including 0% and 100%



(b) Excluding 0% and 100%

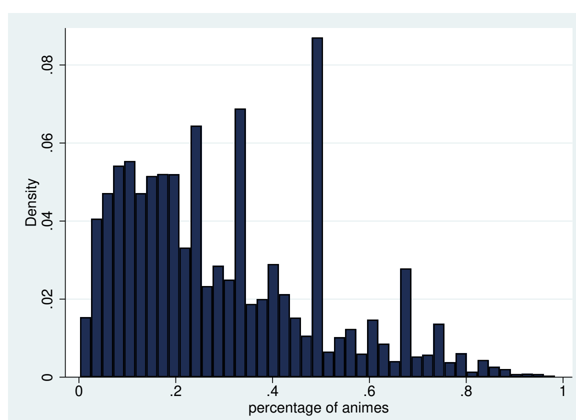


Figure 6: Binge-Watching vs Non-Binge-Watching Across Time

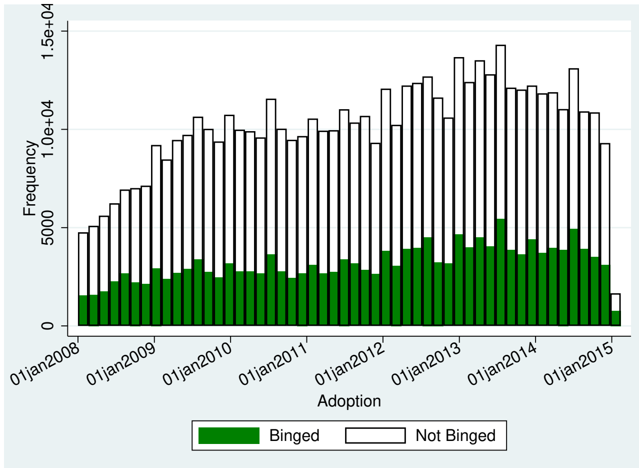
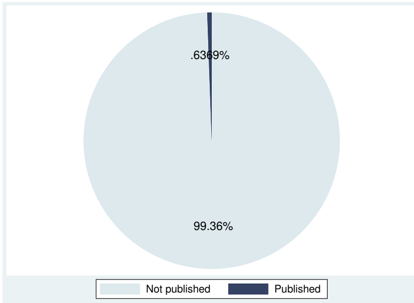
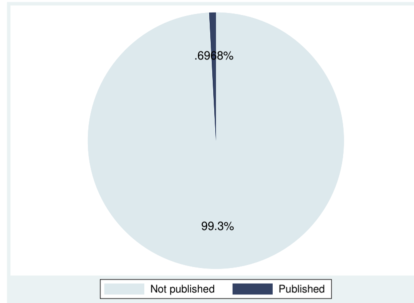


Figure 7: Distribution of UGC for Binged vs. Non-Binged Cases

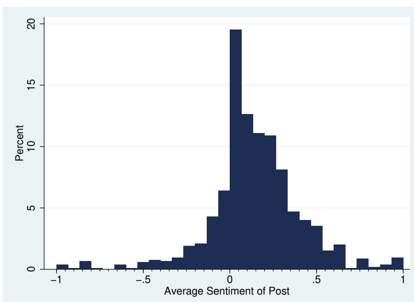
(a) Binged: Publishing Forum Posts



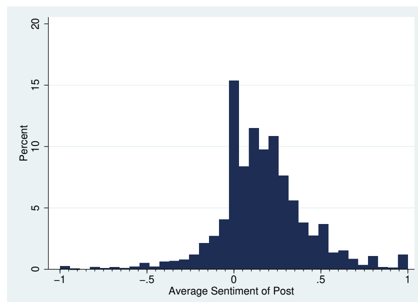
(b) Not Binged: Publishing Forum Posts



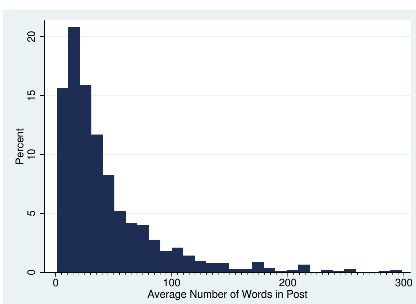
(c) Binged: Average Sentiment of Forum Posts



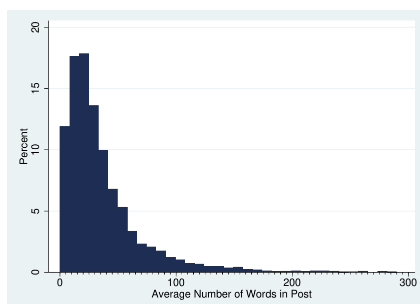
(d) Not Binged: Average Sentiment of Forum Posts



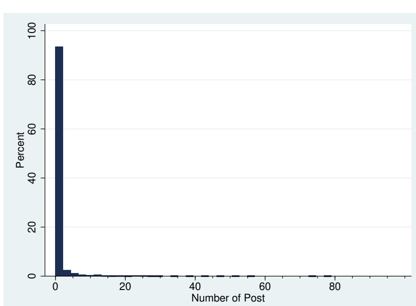
(e) Binged: Average Number of Words in Forum Posts



(f) Not Binged: Average Number of Words in Forum Posts



(g) Binged: Average Number of Forum Posts



(h) Not Binged: Average Number of Forum Posts

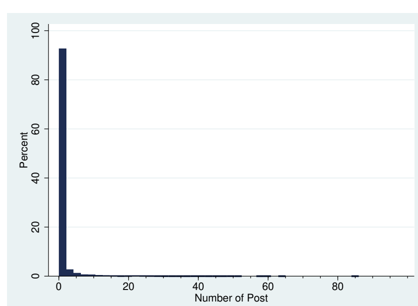
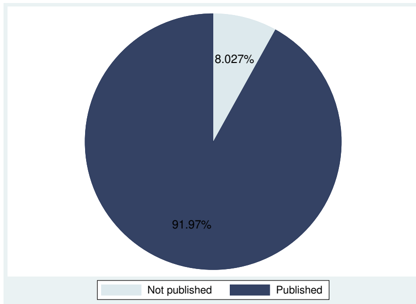
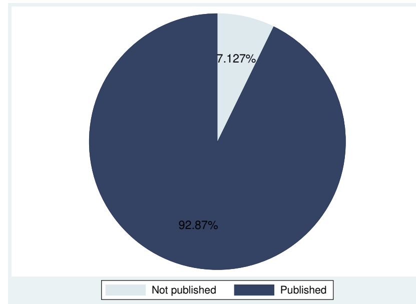


Figure 7: Distribution of UGC for Binged vs. Non-Binged Cases (Continued)

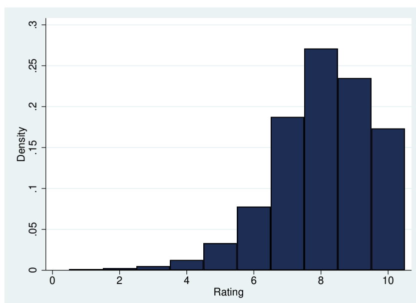
(i) Binged: Publishing a Rating



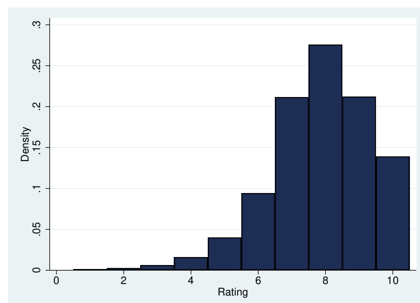
(j) Not Binged: Publishing a Rating



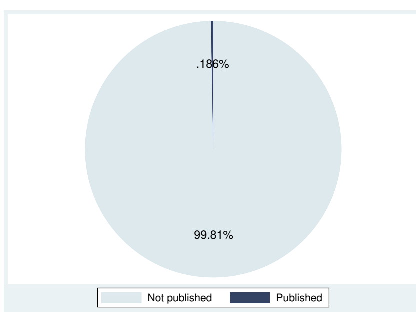
(k) Binged: Distribution of Ratings



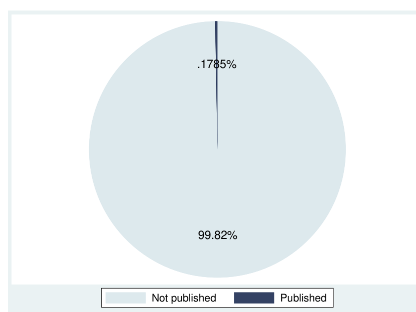
(l) Not Binged: Distribution of Ratings



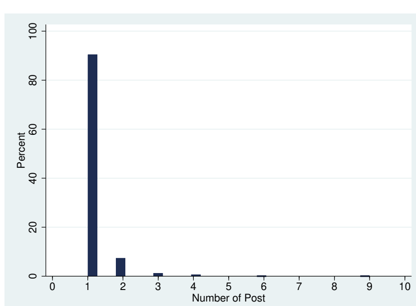
(m) Binged: Publishing a Recommendation



(n) Not Binged: Publishing a Recommendation



(o) Binged: Distribution of Number of Recommendations



(p) Not Binged: Distribution of Number of Recommendations

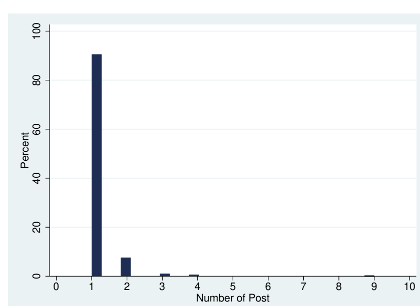


Figure 8: Examples of Release Dates on Netflix

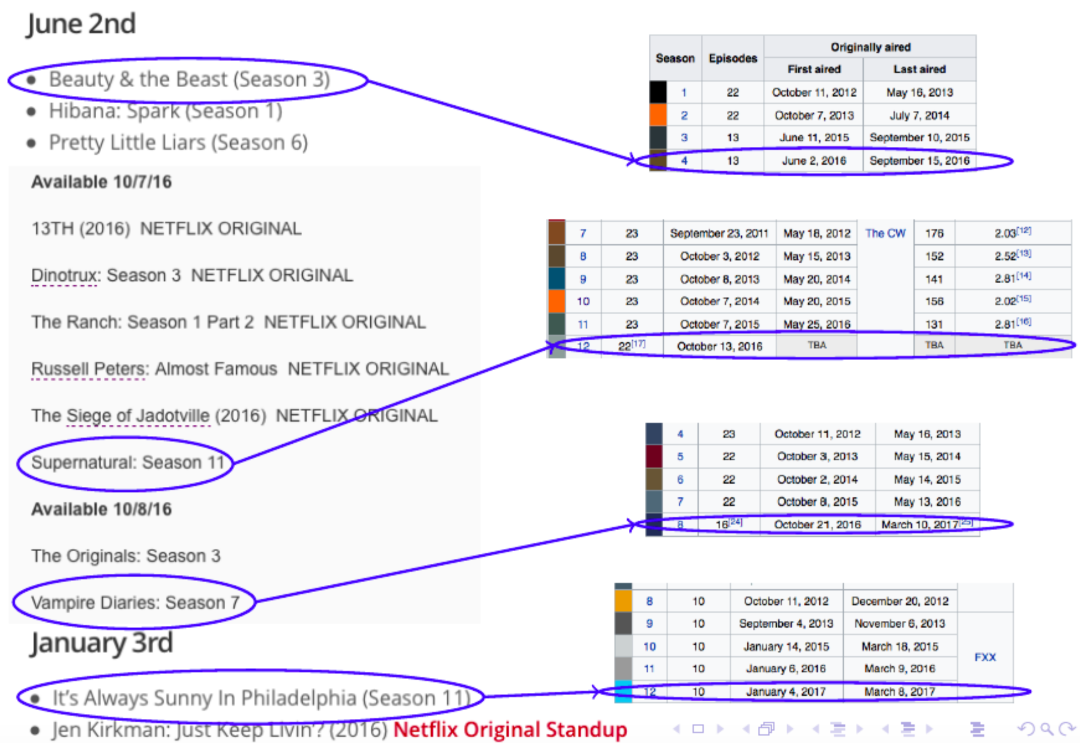


Table 1: Number of Episodes in and Duration of a Season

Number of Episodes	Freq.	Percent	Duration of Season (in 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: Descriptive Statistics

	Mean	Std. Dev.	Min	Median	Max	N
Age	18.96	4.607371	6.01	18.57	71.06	20,167
Number of Animes in Last 30 Days	1.63	7.22	0	0	298.56	37,694
Number of Total Animes Watched	56.63	138.37	0	0	3927	37,694

	Proportion in %	N
Gender		
Females	42	37,694
Males	41	37,694
Not Specified	17	37,694
Geography		
North America	34	37,694
South America	9	37,694
Europe	46	37,694
Asia	8	37,694
Oceania	4	37,694
Animes Watched Over Weekend	31	37,694
Animes Watched Over Holiday	3	37,694

Table 3: Distribution of Personal Engagement for Binged vs. Non-Binged Cases

Whether Franchise was	Watched (in %)	
	Binged	Not Binged
Sequel & Available	75.3	70.4
Sequel & Not Available	54.0	54.7
Other Type & Available	31.8	31.8
Other Type & Not Available	31.4	33.1
Whether Franchise was	Finished (in %)	
	Binged	Not Binged
Sequel & Available	69.8	65.0
Sequel & Not Available	52.2	52.9
Other Type & Available	23.0	19.2
Other Type & Not Available	23.6	22.9
Whether Franchise was	Watched Next (in %)	
	Binged	Not Binged
Sequel & Available	4.3	0.4
Sequel & Not Available	-	-
Other Type & Available	2.2	0.5
Other Type & Not Available	-	-

Table 4: Results - Personal Engagement

Note that all three variables "Binge," "Sequel," and "Availability" are dummy variables.
The model in column (ii) is estimated using user-anime observations for which the user decided to watch a franchise extension, i.e. conditional on watching (any type of) franchise extension. The model in column (iii) is estimated using user-anime observations for which (at least) one franchise is available at the time of watching the focal anime, i.e. conditional on a franchise being available.

	Whether Franchise was		
	Watched	Finished	Watched Next
	(i)	(ii)	(iii)
Engagement Equation			
Binge	-0.142***	0.185***	0.781***
	(0.020)	(0.035)	(0.035)
Binge × Sequel	0.036*	-0.044	0.416***
	(0.017)	(0.029)	(0.026)
Binge × Availability	0.030*	0.093***	
	(0.014)	(0.026)	
Binge × Sequel × Availability	0.145***	0.076*	
	(0.020)	(0.032)	
Sequel	0.648***	1.045***	-0.061**
	(0.009)	(0.014)	(0.020)
Availability	-0.784***	-0.385***	
	(0.016)	(0.018)	
Sequel × Availability	0.500***	0.554***	
	(0.010)	(0.015)	
Wait Time Until Franchise Available When Started Watching Focal Season[a]	-0.147***	-0.048***	
	(0.003)	(0.003)	
Popularity Rank[a,b]	-0.065***	-0.011***	0.016*
	(0.002)	(0.003)	(0.007)
Community Rating[b]	0.061***	0.071***	-0.011
	(0.004)	(0.007)	(0.016)
Number of Episodes[b]	0.028***		-0.513***
	(0.004)		(0.019)
Constant	0.141***	-1.768***	-1.357***
	(0.042)	(0.065)	(0.159)
Standard Deviation of User Random Effect	0.593***	0.762***	0.252***
	(0.004)	(0.006)	(0.013)
Genre Dummies	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes
Binge Equation			
Weekend Dummy	0.045***	0.044***	0.045***
	(0.004)	(0.006)	(0.005)
Holiday Dummy	0.027**	0.014	0.025
	(0.010)	(0.016)	(0.014)
Popularity Rank[a,b]	-0.050***	-0.044***	-0.037***
	(0.002)	(0.003)	(0.003)
Community Rating[b]	0.045***	0.073***	0.049***
	(0.005)	(0.007)	(0.006)
Number of Episodes[b]	0.042***	0.045***	0.053***
	(0.005)	(0.007)	(0.006)
Duration of an Episode[a]	0.132***	0.179***	0.181***
	(0.019)	(0.028)	(0.025)
Constant	-1.938***	-2.287***	-2.076***
	(0.076)	(0.115)	(0.099)
Standard Deviation of User Random Effect	0.948***	0.921***	0.791***
	(0.005)	(0.007)	(0.006)
Genre Dummies	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes
Error Correlation	0.096***	-0.100***	-0.126***
	(0.010)	(0.016)	(0.020)
Number of Observations	764,666	345,108	396,928
AIC	1,524,347.41	671,905.76	408,906.11
BIC	1,525,698.43	673,142.20	410,125.95
Log Likelihood	-762,056.71	-335,837.88	-204,341.05

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
[a] Measured on logarithmic scale.
[b] Of focal season.

Table 5: Results - Interactive Engagement

Note that the variable "Binge" is a dummy variable.

The models in column (ii), (iii), and (iv) are estimated using user-anime observations for which the user made (at least) one forum post, i.e. conditional on a forum post. The model in column (vi) is estimated using user-anime observations which the user rated, i.e. conditional on a rating. The model in column (viii) is estimated using user-anime observations for which the user wrote a recommendation, i.e. conditional on a recommendation.

	Forum Posts				Ratings		Recommendations	
	Incidence (i)	Valence (ii)	Number (iii)	Length (iv)	Incidence (v)	Valence (vi)	Incidence (vii)	Number (viii)
Engagement Equation								
Binge	0.132	-0.077*	-0.069	0.227*	-0.243***	0.128***	0.118*	0.005
	(0.083)	(0.031)	(0.079)	(0.099)	(0.030)	(0.009)	(0.049)	(0.012)
Ever-Made-a-Forum-Post Indicator	0.116***	0.006	0.073*	-0.064				
	(0.034)	(0.011)	(0.030)	(0.041)				
Time Since Last Forum Post[a]	-0.026**	-0.003	-0.008	-0.012				
	(0.008)	(0.004)	(0.008)	(0.011)				
Number of Forum Posts[a,c]	0.020**	-0.005	-0.001	-0.032**				
	(0.007)	(0.004)	(0.009)	(0.012)				
Number of Ratings[a,c]					0.004	0.003		
					(0.007)	(0.002)		
Number of Recommendations[a,c]							0.282***	0.015
							(0.038)	(0.010)
Popularity Rank[a,b]	0.095***	0.004	0.024*	0.013	-0.059***	0.057***	0.045	0.005
	(0.009)	(0.004)	(0.010)	(0.013)	(0.012)	(0.004)	(0.028)	(0.007)
Community Rating[b]	0.046*	0.044***	0.039	-0.022	0.123***	1.034***	0.098	-0.004
	(0.020)	(0.009)	(0.022)	(0.030)	(0.028)	(0.008)	(0.056)	(0.013)
Number of Episodes[b]	0.360***	-0.012	0.273***	0.095***				
	(0.018)	(0.008)	(0.020)	(0.027)				
Constant	-6.159***	-0.098	-0.189	3.369***	3.693***	-0.318***	-5.856***	0.682***
	(0.193)	(0.085)	(0.205)	(0.272)	(0.274)	(0.080)	(0.534)	(0.118)
Standard Deviation of User Random Effect	1.424***	0.067***	0.329***	0.510***	2.861***	0.764***	1.078***	0.044***
	(0.027)	(0.009)	(0.012)	(0.020)	(0.034)	(0.003)	(0.011)	(0.004)
Genre Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Binge Equation								
Weekend Dummy	0.053***	0.043	0.038	0.039	0.053***	0.052***	0.053***	0.055
	(0.004)	(0.057)	(0.058)	(0.058)	(0.011)	(0.009)	(0.010)	(0.148)
Holiday Dummy	0.024*	0.311*	0.304*	0.305*	0.025	0.022	0.024	-0.289
	(0.011)	(0.132)	(0.134)	(0.134)	(0.029)	(0.024)	(0.026)	(0.370)
Popularity Rank[b]	-0.030***	-0.089***	-0.089***	-0.088***	-0.030***	-0.031***	-0.031***	0.018
	(0.002)	(0.026)	(0.026)	(0.026)	(0.005)	(0.004)	(0.005)	(0.067)
Community Rating[b]	0.054***	0.027	0.023	0.025	0.054***	0.058***	0.055***	0.363*
	(0.005)	(0.064)	(0.064)	(0.064)	(0.012)	(0.010)	(0.011)	(0.182)
Number of Episodes[b]	0.052***	-0.045	-0.049	-0.044	0.051***	0.052***	0.051***	-0.064
	(0.005)	(0.058)	(0.058)	(0.058)	(0.012)	(0.010)	(0.011)	(0.171)
Duration of an Episode[a]	0.380***	0.493	0.480	0.493	0.382***	0.379***	0.379***	0.482
	(0.017)	(0.285)	(0.285)	(0.285)	(0.045)	(0.038)	(0.040)	(0.986)
Constant	-2.728***	-2.367*	-2.288*	-2.376*	-2.727***	-2.772***	-2.728***	-5.413
	(0.069)	(1.083)	(1.087)	(1.084)	(0.186)	(0.155)	(0.164)	(3.541)
Standard Deviation of User Random Effect	0.774***	0.963***	0.976***	0.981***	0.780***	0.753***	0.758***	0.867***
	(0.005)	(0.071)	(0.072)	(0.073)	(0.005)	(0.005)	(0.005)	(0.131)
Genre Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Error Correlation	-0.073	0.176	0.039	-0.126	0.144***	0.007***	-0.048*	0.033
	(0.050)	(0.090)	(0.093)	(0.087)	(0.007)	(0.002)	(0.020)	(0.048)
Number of Observations	663,963	4,564	4,564	4,564	663,963	615,325	663,963	1,215
AIC	649,332.48	4,941.87	13,031.46	15,649.22	744,916.84	2,539,647.62	625,884.76	193.45
BIC	650,176.52	5,655.15	13,744.74	16,362.51	746,205.71	2,540,939.23	627,128.01	729.21
Log Likelihood	-324,592.24	-2,359.93	-6,404.73	-7,713.61	-372,345.42	-1,269,709.81	-312,833.38	8.28

Standard errors in parentheses.

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

[a] Measured on logarithmic scale.

[b] Of focal season.

[c] At the time of watching focal anime season.

Table 6: Effects of Binge-Watching

	Whether Franchise was		
	Watched	Finished	Watched Next
	(i)	(ii)	(iii)
Sequel & Available	0.069*	0.310***	1.197***
	(0.036)	(0.061)	(0.044)
Sequel & Not Available	-0.106***	0.141***	
	(0.026)	(0.045)	
Other Type & Available	-0.112***	0.278***	0.781***
	(0.024)	(0.044)	(0.035)
Other Type & Not Available	-0.142***	0.185***	
	(0.020)	(0.035)	

Standard errors in parentheses.

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

Table 7: Sources of Heterogeneity - Differential Effects

	PERSONAL ENGAGEMENT			INTERACTIVE ENGAGEMENT							
	Whether Franchise was			Forum Posts				Ratings		Recommendations	
	Watched	Finished	Watched Next	Incidence	Valence	Number	Length	Incidence	Valence	Incidence	Number
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)
GEOGRAPHY											
Baseline: North America (not shown)											
Differential Effect of Bingeing in *EUROPE*...				0.025	-0.028	0.120*	0.122	-0.110	-0.008	-0.097	-0.019
				(0.046)	(0.022)	(0.054)	(0.072)	(0.058)	(0.018)	(0.110)	(0.026)
... for Sequel & Available	-0.021	0.012	0.246***								
	(0.061)	(0.107)	(0.055)								
... for Sequel & Not Available	-0.088*	0.029									
	(0.041)	(0.072)									
... for Other Type & Available	0.022	-0.021	0.201***								
	(0.036)	(0.069)	(0.040)								
... for Other Type & Not Available	0.005	0.008									
	(0.025)	(0.047)									
Differential Effect of Bingeing in *OCEANIA*...				0.049	0.007	0.283*	-0.014	-0.218	-0.023	-0.189	-0.018
				(0.103)	(0.046)	(0.113)	(0.150)	(0.165)	(0.053)	(0.288)	(0.069)
... for Sequel & Available	0.020	-0.008	0.368*								
	(0.178)	(0.297)	(0.144)								
... for Sequel & Not Available	0.038	0.088									
	(0.119)	(0.201)									
... for Other Type & Available	-0.084	-0.023	0.139								
	(0.105)	(0.189)	(0.101)								
... for Other Type & Not Available	0.177*	-0.063									
	(0.072)	(0.129)									
Differential Effect of Bingeing in *ASIA*...				0.189*	-0.022	0.046	-0.039	-0.094	-0.067*	0.046	0.018
				(0.078)	(0.035)	(0.087)	(0.115)	(0.132)	(0.033)	(0.151)	(0.038)
... for Sequel & Available	-0.038	0.111	0.271**								
	(0.113)	(0.199)	(0.098)								
... for Sequel & Not Available	-0.049	0.122									
	(0.075)	(0.135)									
... for Other Type & Available	-0.035	-0.086	0.112								
	(0.067)	(0.128)	(0.069)								
... for Other Type & Not Available	0.012	-0.164									
	(0.046)	(0.088)									
Differential Effect of Bingeing in *SOUTH AMERICA*...				0.061	-0.076	0.149	-0.058	-0.344***	-0.039	-0.270	-0.029
				(0.127)	(0.061)	(0.156)	(0.211)	(0.097)	(0.035)	(0.285)	(0.074)
... for Sequel & Available	-0.029	-0.008	0.121								
	(0.126)	(0.213)	(0.102)								
... for Sequel & Not Available	-0.114	-0.007									
	(0.084)	(0.144)									
... for Other Type & Available	0.015	-0.041	0.212**								
	(0.074)	(0.136)	(0.069)								
... for Other Type & Not Available	-0.024	-0.005									
	(0.051)	(0.093)									
Differential Effect of...											
... Europe	0.126***	0.174***	0.113***	-0.579***	-0.006	-0.119***	-0.101*	-0.067*	-0.052***	-0.352***	-0.005
	(0.010)	(0.014)	(0.025)	(0.039)	(0.011)	(0.033)	(0.046)	(0.032)	(0.010)	(0.053)	(0.012)
... Oceania	0.054*	0.057	0.073	-0.083	-0.005	-0.126*	-0.086	0.148	-0.023	-0.088	-0.028
	(0.023)	(0.032)	(0.056)	(0.085)	(0.022)	(0.064)	(0.090)	(0.081)	(0.026)	(0.118)	(0.028)
... Asia	0.084***	0.244***	0.110**	-0.315***	0.010	-0.011	-0.102	0.049	0.270***	0.011	-0.007
	(0.017)	(0.026)	(0.041)	(0.070)	(0.020)	(0.057)	(0.079)	(0.063)	(0.018)	(0.081)	(0.021)
... South America	0.196***	0.263***	0.151***	-0.756***	-0.007	-0.077	-0.287**	-0.384***	0.211***	-0.422***	-0.030
	(0.016)	(0.023)	(0.038)	(0.081)	(0.023)	(0.066)	(0.093)	(0.052)	(0.017)	(0.101)	(0.026)
GENDER											
Baseline: Male (not shown)											
Differential Effect of Bingeing for *FEMALES*...				-0.064	0.014	-0.035	0.013	0.009	-0.008	0.167	0.046
				(0.046)	(0.021)	(0.051)	(0.068)	(0.063)	(0.018)	(0.104)	(0.025)
... for Sequel & Available	-0.017	-0.005	0.031								
	(0.061)	(0.107)	(0.054)								
... for Sequel & Not Available	0.013	-0.021									
	(0.041)	(0.072)									
... for Other Type & Available	-0.007	-0.045	0.024								
	(0.036)	(0.069)	(0.038)								
... for Other Type & Not Available	0.036	-0.075									
	(0.025)	(0.047)									
Differential Effect of Being Female	0.012	0.032*	-0.024	0.162***	0.009	0.029	-0.116**	0.069*	-0.029**	0.048	-0.003
	(0.009)	(0.013)	(0.022)	(0.037)	(0.011)	(0.031)	(0.043)	(0.031)	(0.010)	(0.051)	(0.012)

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

Table 7: Sources of Heterogeneity - Differential Effects

	PERSONAL ENGAGEMENT			INTERACTIVE ENGAGEMENT							
	Whether Franchise was			Forum Posts				Ratings		Recommendations	
	Watched	Finished	Watched Next	Incidence	Valence	Number	Length	Incidence	Valence	Incidence	Number
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)
AGE											
Baseline: Age < 20 (not shown)											
Differential Effect of bingeing				0.076	-0.031	-0.081	-0.071	-0.066	-0.015	0.081	0.025
for *AGE: 20 - 25...*				(0.066)	(0.030)	(0.073)	(0.097)	(0.084)	(0.025)	(0.134)	(0.034)
... for Sequel & Available	-0.020	0.064	0.025								
	(0.088)	(0.160)	(0.076)								
... for Sequel & Not Available	-0.049	0.020									
	(0.060)	(0.108)									
... for Other Type & Available	-0.011	-0.049	0.104*								
	(0.053)	(0.103)	(0.053)								
... for Other Type & Not Available	-0.086*	-0.079									
	(0.037)	(0.071)									
Differential Effect of bingeing				0.076	0.054	0.063	0.080	-0.098	-0.015	-0.174	-0.005
for *AGE > 25...*				(0.065)	(0.029)	(0.072)	(0.097)	(0.084)	(0.025)	(0.158)	(0.039)
... for Sequel & Available	-0.008	0.030	-0.013								
	(0.086)	(0.153)	(0.076)								
... for Sequel & Not Available	-0.040	0.085									
	(0.058)	(0.103)									
... for Other Type & Available	0.004	0.007	0.054								
	(0.051)	(0.098)	(0.053)								
... for Other Type & Not Available	-0.104**	0.014									
	(0.035)	(0.067)									
Differential Effect of...											
... Age: 20 - 25	0.015	-0.019	-0.001	-0.134**	-0.001	-0.015	0.022	-0.068	-0.013	-0.110	0.010
	(0.009)	(0.014)	(0.031)	(0.043)	(0.016)	(0.042)	(0.058)	(0.044)	(0.013)	(0.075)	(0.018)
... Age > 25	-0.016	-0.017	0.046	-0.132**	-0.009	-0.042	-0.018	-0.137**	0.012	-0.172*	0.001
	(0.011)	(0.017)	(0.030)	(0.049)	(0.015)	(0.043)	(0.061)	(0.042)	(0.013)	(0.074)	(0.018)
EXPERIENCE											
Baseline: Little Experience (not shown)											
Differential Effect of Bingeing with				0.064	0.009	0.141*	0.073	0.098	-0.020*	0.098	0.051*
LARGE EXPERIENCE...				(0.052)	(0.023)	(0.057)	(0.075)	(0.078)	(0.009)	(0.078)	(0.025)
... for Sequel & Available	-0.038	0.022	0.065								
	(0.071)	(0.128)	(0.058)								
... for Sequel & Not Available	-0.092	0.100									
	(0.048)	(0.087)									
... for Other Type & Available	-0.005	-0.055	0.047								
	(0.042)	(0.083)	(0.040)								
... for Other Type & Not Available	-0.056	-0.198***									
	(0.029)	(0.057)									
Differential Effect of Large Experience	-0.002	0.015	0.005	-0.067	0.009	-0.050	-0.008	0.024	-0.021	0.024	-0.007
	(0.007)	(0.011)	(0.023)	(0.037)	(0.013)	(0.035)	(0.049)	(0.050)	(0.011)	(0.050)	(0.014)
USAGE											
Baseline: No Recent Usage (not shown)											
Differential Effect of bingeing				-0.012	0.008	-0.006	0.058	0.014	-0.015	0.113	0.060*
with *HIGH RECENT USAGE...*				(0.067)	(0.030)	(0.074)	(0.098)	(0.035)	(0.011)	(0.094)	(0.029)
... for Sequel & Available	-0.051	0.012	0.024								
	(0.088)	(0.159)	(0.076)								
... for Sequel & Not Available	-0.033	0.116									
	(0.059)	(0.108)									
... for Other Type & Available	-0.028	-0.045	0.004								
	(0.052)	(0.102)	(0.052)								
... for Other Type & Not Available	-0.035	-0.117									
	(0.036)	(0.070)									
Differential Effect of High Recent Usage	0.002	0.026*	-0.018	-0.052	-0.005	-0.064	-0.021	-0.017	-0.017*	0.019	-0.015
	(0.007)	(0.011)	(0.029)	(0.038)	(0.015)	(0.040)	(0.054)	(0.023)	(0.007)	(0.054)	(0.016)

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

Web Appendix A: Results with Alternative Operationalizations of Binge-Watching

Table A-1: Personal Engagement - 2 Hours

Note that all three variables "Binge," "Sequel," and "Availability" are dummy variables.
The model in column (ii) is estimated using user-anime observations for which the user decided to watch a franchise extension, i.e. conditional on watching (any type of) franchise extension. The model in column (iii) is estimated using user-anime observations for which (at least) one franchise is available at the time of watching the focal anime, i.e. conditional on a franchise being available.

	Whether Franchise was		
	Watched	Finished	Watched Next
	(i)	(ii)	(iii)
Engagement Equation			
Binge	-0.082***	0.296***	0.986***
	(0.018)	(0.032)	(0.033)
Binge × Sequel	0.017	0.005	0.298***
	(0.015)	(0.025)	(0.026)
Binge × Availability	0.064***	0.077***	
	(0.012)	(0.023)	
Binge × Sequel × Availability	0.154***	0.134***	
	(0.017)	(0.028)	
Sequel	0.656***	1.029***	-0.027
	(0.009)	(0.015)	(0.022)
Availability	-0.799***	-0.381***	
	(0.017)	(0.018)	
Sequel × Availability	0.064***	0.536***	
	(0.012)	(0.016)	
Wait Time Until Franchise Available When Started Watching Focal Season[a]	-0.148***	-0.048***	
	(0.003)	(0.003)	
Popularity Rank[a,b]	-0.067***	-0.002	0.017**
	(0.002)	(0.003)	(0.006)
Community Rating[b]	0.059***	0.072***	-0.005
	(0.004)	(0.007)	(0.015)
Number of Episodes[b]	0.030***		-0.407***
	(0.004)		(0.018)
Constant	0.157***	-1.837***	-1.762***
	(0.042)	(0.065)	(0.150)
Standard Deviation of User Random Effect	0.593***	0.764***	0.215***
	(0.004)	(0.006)	(0.014)
Genre Dummies	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes
Binge Equation			
Weekend Dummy	0.040***	0.026***	0.041***
	(0.004)	(0.005)	(0.005)
Holiday Dummy	0.015	0.012	0.009
	(0.010)	(0.014)	(0.013)
Popularity Rank[a,b]	-0.050***	-0.044***	-0.040***
	(0.002)	(0.003)	(0.002)
Community Rating[b]	0.010*	0.029***	0.015*
	(0.004)	(0.007)	(0.006)
Number of Episodes[b]	-0.134***	-0.143***	-0.111***
	(0.004)	(0.006)	(0.006)
Duration of an Episode[a]	0.059**	0.097***	0.101***
	(0.018)	(0.026)	(0.023)
Constant	-0.521***	-0.741***	-0.698***
	(0.069)	(0.104)	(0.091)
Standard Deviation of User Random Effect	0.886***	0.847***	0.745***
	(0.004)	(0.006)	(0.005)
Genre Dummies	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes
Error Correlation	0.066***	-0.188***	-0.331***
	(0.009)	(0.015)	(0.020)
Number of Observations	790,138	356,162	409,535
AIC	1,709,238.53	757,027.55	496,089.18
BIC	1,710,593.39	758,267.61	497,312.53
Log Likelihood	-854,502.27	-378,398.78	-247,932.59

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
[a] Measured on logarithmic scale.
[b] Of focal season.

Table A-2: Interactive Engagement - 2 Hours

Note that the variable "Binge" is a dummy variable.

The models in column (ii), (iii), and (iv) are estimated using user-anime observations for which the user made (at least) one forum post, i.e. conditional on a forum post. The model in column (vi) is estimated using user-anime observations which the user rated, i.e. conditional on a rating. The model in column (viii) is estimated using user-anime observations for which the user wrote a recommendation, i.e. conditional on a recommendation.

	Forum Posts				Ratings		Recommendations	
	Incidence	Number	Length	Valence	Incidence	Valence	Incidence	Number
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Engagement Equation								
Binge	-0.544***	-0.048	-0.090	0.124	-0.534***	0.188***	-0.189*	0.001
	(0.063)	(0.028)	(0.066)	(0.093)	(0.037)	(0.016)	(0.095)	(0.021)
Ever-Made-a-Forum-Post Indicator	0.130***	0.004	0.080**	-0.066				
	(0.030)	(0.010)	(0.029)	(0.041)				
Time Since Last Forum Post[a]	-0.030***	-0.002	-0.005	-0.012				
	(0.008)	(0.003)	(0.008)	(0.011)				
Number of Forum Posts[a,c]	0.021**	-0.005	-0.003	-0.033**				
	(0.007)	(0.004)	(0.009)	(0.012)				
Number of Ratings[a,c]					-0.012*	0.001		
					(0.005)	(0.002)		
Number of Recommendations[a,c]							0.281***	0.014
							(0.022)	(0.008)
Popularity Rank[a,b]	0.086***	0.003	0.025**	0.014	-0.058***	0.060***	0.045**	0.005
	(0.008)	(0.004)	(0.009)	(0.013)	(0.005)	(0.002)	(0.017)	(0.005)
Community Rating[b]	0.055**	0.042***	0.040	-0.013	0.130***	1.034***	0.101**	-0.003
	(0.019)	(0.009)	(0.022)	(0.029)	(0.010)	(0.003)	(0.033)	(0.011)
Number of Episodes[b]	0.338***	-0.012	0.270***	0.100***				
	(0.018)	(0.008)	(0.020)	(0.026)				
Constant	-5.778***	-0.090	-0.202	3.302***	3.542***	-0.315***	-5.829***	0.680***
	(0.193)	(0.083)	(0.203)	(0.267)	(0.105)	(0.034)	(0.336)	(0.101)
Standard Deviation of User Random Effect	1.349***	0.067***	0.331***	0.508***	2.713***	0.751***	1.082***	0.044***
	(0.024)	(0.008)	(0.011)	(0.020)	(0.033)	(0.003)	(0.032)	(0.004)
Genre Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Binge Equation								
Weekend Dummy	0.049***	0.026	0.024	0.023	0.049***	0.048***	0.049***	0.103
	(0.004)	(0.055)	(0.055)	(0.055)	(0.004)	(0.004)	(0.004)	(0.104)
Holiday Dummy	0.013	0.319*	0.310*	0.315*	0.015	0.013	0.015	-0.098
	(0.010)	(0.126)	(0.127)	(0.127)	(0.010)	(0.010)	(0.010)	(0.259)
Popularity Rank[b]	-0.037***	-0.095***	-0.097***	-0.095***	-0.036***	-0.037***	-0.037***	-0.029
	(0.002)	(0.024)	(0.024)	(0.024)	(0.002)	(0.002)	(0.002)	(0.048)
Community Rating[b]	0.034***	0.001	-0.005	-0.001	0.034***	0.036***	0.034***	0.150
	(0.004)	(0.060)	(0.060)	(0.060)	(0.004)	(0.004)	(0.004)	(0.127)
Number of Episodes[b]	-0.112***	-0.179**	-0.188***	-0.179**	-0.112***	-0.111***	-0.111***	-0.137
	(0.004)	(0.057)	(0.057)	(0.057)	(0.004)	(0.005)	(0.004)	(0.127)
Duration of an Episode[a]	0.183***	0.252	0.227	0.253	0.191***	0.186***	0.185***	0.347
	(0.016)	(0.266)	(0.264)	(0.265)	(0.016)	(0.016)	(0.016)	(0.656)
Constant	-1.083***	-0.836	-0.676	-0.834	-1.098***	-1.116***	-1.091***	-2.400
	(0.064)	(1.010)	(1.009)	(1.009)	(0.064)	(0.067)	(0.064)	(2.399)
Standard Deviation of User Random Effect	0.728***	0.977***	0.984***	0.979***	0.737***	0.725***	0.723***	0.878***
	(0.004)	(0.065)	(0.066)	(0.066)	(0.004)	(0.004)	(0.004)	(0.121)
Number of Observations	682,787	4,703	4,703	4,703	682,787	632,455	682,787	1,243
AIC	789,276.56	5,537.25	13,969.04	16,651.51	887,745.53	2,722,318.63	764,257.37	342.47
BIC	790,580.03	6,260.31	14,692.11	17,374.58	889,037.57	2,723,613.37	765,503.67	880.63
Log Likelihood	-394,524.28	-2,656.62	-6,872.52	-8,213.76	-443,759.77	-1,361,045.31	-382,019.68	-66.24

Standard errors in parentheses.

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

[a] Measured on logarithmic scale.

[b] Of focal season.

[c] At the time of watching focal anime season.

Table A-3: Personal Engagement - 4 Hours

Note that all three variables “Binge,” “Sequel,” and “Availability” are dummy variables.
The model in column (ii) is estimated using user-anime observations for which the user decided to watch a franchise extension, i.e. conditional on watching (any type of) franchise extension. The model in column (iii) is estimated using user-anime observations for which (at least) one franchise is available at the time of watching the focal anime, i.e. conditional on a franchise being available.

	Whether Franchise was		
	Watched	Finished	Watched Next
	(i)	(ii)	(iii)
Engagement Equation			
Binge	-0.146***	0.291***	1.008***
	(0.025)	(0.046)	(0.040)
Binge × Sequel	-0.007	-0.044	0.456***
	(0.020)	(0.035)	(0.027)
Binge × Availability	0.046**	0.057	
	(0.017)	(0.032)	
Binge × Sequel × Availability	0.113***	0.108**	
	(0.023)	(0.039)	
Sequel	0.676***	1.056***	-0.054**
	(0.008)	(0.013)	(0.019)
Availability	-0.793***	-0.365***	
	(0.016)	(0.018)	
Sequel × Availability	0.504***	0.558***	
	(0.009)	(0.014)	
Wait Time Until Franchise Available When Started Watching Focal Season[a]	-0.150***	-0.049***	
	(0.003)	(0.003)	
Popularity Rank[a,b]	-0.070***	-0.011***	0.008
	(0.002)	(0.003)	(0.007)
Community Rating[b]	0.057***	0.072***	-0.023
	(0.004)	(0.007)	(0.016)
Number of Episodes[b]	0.049***		-0.401***
	(0.004)		(0.021)
Constant	0.137**	-1.750***	-1.481***
	(0.042)	(0.065)	(0.160)
Standard Deviation of User Random Effect	0.592***	0.767***	0.217***
	(0.004)	(0.006)	(0.015)
Genre Dummies	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes
Binge Equation			
Weekend Dummy	0.081***	0.083***	0.074***
	(0.005)	(0.007)	(0.006)
Holiday Dummy	0.020	0.013	0.017
	(0.012)	(0.018)	(0.016)
Popularity Rank[a,b]	-0.040***	-0.036***	-0.029***
	(0.002)	(0.003)	(0.003)
Community Rating[b]	-0.001	0.029***	-0.004
	(0.005)	(0.008)	(0.007)
Number of Episodes[b]	-0.056***	-0.060***	-0.031***
	(0.005)	(0.008)	(0.007)
Duration of an Episode[a]	0.070**	0.084*	0.133***
	(0.024)	(0.036)	(0.032)
Constant	-1.512***	-1.770***	-1.636***
	(0.092)	(0.139)	(0.120)
Standard Deviation of User Random Effect	0.925***	0.868***	0.723***
	(0.006)	(0.008)	(0.007)
Genre Dummies	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes
Error Correlation	0.081***	-0.171***	-0.179***
	(0.012)	(0.021)	(0.022)
Number of Observations	780,073	351,602	403,712
AIC	1,390,319.93	606,052.55	328,305.42
BIC	1,391,673.29	607,291.13	329,527.16
Log Likelihood	-695,042.97	-302,911.28	-164,040.71

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
[a] Measured on logarithmic scale.
[b] Of focal season.

Table A-4: Interactive Engagement - 4 Hours

Note that the variable "Binge" is a dummy variable.

The models in column (ii), (iii), and (iv) are estimated using user-anime observations for which the user made (at least) one forum post, i.e. conditional on a forum post. The model in column (vi) is estimated using user-anime observations which the user rated, i.e. conditional on a rating. The model in column (viii) is estimated using user-anime observations for which the user wrote a recommendation, i.e. conditional on a recommendation.

	Forum Posts				Ratings		Recommendations	
	Incidence (i)	Number (ii)	Length (iii)	Valence (iv)	Incidence (v)	Valence (vi)	Incidence (vii)	Number (viii)
Engagement Equation								
Binge	-0.411***	-0.074	0.850***	0.249*	-0.354***	-1.008***	-0.287	-0.004
	(0.108)	(0.052)	(0.043)	(0.115)	(0.047)	(0.013)	(0.148)	(0.028)
Ever-Made-a-Forum-Post Indicator	0.140***	0.004	0.068*	-0.071				
	(0.033)	(0.010)	(0.028)	(0.041)				
Time Since Last Forum Post[a]	-0.027***	-0.002	-0.006	-0.016				
	(0.008)	(0.004)	(0.008)	(0.011)				
Number of Forum Posts[a,c]	0.024***	-0.005	0.000	-0.029*				
	(0.007)	(0.004)	(0.009)	(0.012)				
Number of Ratings[a,c]					-0.012*	-0.002		
					(0.005)	(0.002)		
Number of Recommendations[a,c]							0.280***	0.014
							(0.022)	(0.009)
Popularity Rank[a,b]	0.088***	0.005	0.034***	0.012	-0.052***	0.060***	0.046**	0.005
	(0.009)	(0.004)	(0.010)	(0.012)	(0.005)	(0.002)	(0.017)	(0.005)
Community Rating[b]	0.043*	0.047***	0.029	-0.022	0.130***	1.040***	0.103**	-0.003
	(0.020)	(0.009)	(0.024)	(0.029)	(0.011)	(0.004)	(0.034)	(0.011)
Number of Episodes[b]	0.365***	-0.016	0.285***	0.109***				
	(0.018)	(0.009)	(0.022)	(0.027)				
Constant	-5.900***	-0.123	-0.302	3.369***	3.981***	-0.118***	-5.901***	0.684***
	(0.195)	(0.083)	(0.220)	(0.266)	(0.114)	(0.035)	(0.337)	(0.101)
Standard Deviation of User Random Effect	1.314***	0.066***	0.305***	0.505***	3.155***	0.745***	1.094***	0.044***
	(0.028)	(0.009)	(0.012)	(0.021)	(0.047)	(0.003)	(0.032)	(0.004)
Genre Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Binge Equation								
Weekend Dummy	0.076***	0.116	0.074	0.114	0.076***	0.066***	0.076***	0.341**
	(0.005)	(0.067)	(0.048)	(0.067)	(0.005)	(0.004)	(0.005)	(0.132)
Holiday Dummy	0.021	0.264	0.150	0.262	0.022	0.016	0.022	0.025
	(0.012)	(0.152)	(0.108)	(0.153)	(0.012)	(0.012)	(0.012)	(0.338)
Popularity Rank[b]	-0.024***	-0.028	-0.028	-0.023	-0.024***	-0.019***	-0.025***	-0.055
	(0.002)	(0.031)	(0.024)	(0.031)	(0.002)	(0.002)	(0.002)	(0.063)
Community Rating[b]	0.012*	0.051	0.029	0.051	0.011*	0.049***	0.012*	0.147
	(0.005)	(0.075)	(0.059)	(0.075)	(0.005)	(0.005)	(0.005)	(0.167)
Number of Episodes[b]	-0.032***	-0.106	-0.197***	-0.105	-0.033***	-0.071***	-0.033***	0.095
	(0.006)	(0.072)	(0.057)	(0.072)	(0.006)	(0.005)	(0.006)	(0.161)
Duration of an Episode[a]	0.172***	0.336	0.319	0.346	0.175***	0.129***	0.173***	-0.210
	(0.023)	(0.367)	(0.268)	(0.367)	(0.023)	(0.022)	(0.023)	(0.802)
Constant	-1.830***	-2.830*	-1.914	-2.901*	-1.836***	-1.909***	-1.834***	-2.580
	(0.087)	(1.357)	(1.017)	(1.359)	(0.087)	(0.086)	(0.087)	(3.006)
Standard Deviation of User Random Effect	0.710***	0.852***	0.401***	0.868***	0.712***	0.662***	0.702***	0.873***
	(0.005)	(0.078)	(0.045)	(0.079)	(0.005)	(0.005)	(0.005)	(0.168)
Genre Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Error Correlation	0.204**	0.132	-1.138***	-0.153	0.137***	0.589***	0.145	0.076
	(0.067)	(0.135)	(0.058)	(0.091)	(0.026)	(0.008)	(0.091)	(0.122)
Number of Observations	671,223	4,646	4,646	4,646	671,223	621,871	671,223	1,237
AIC	521,418.48	3,536.74	11,814.93	14,502.38	617,857.76	2,432,588.69	497,165.19	-290.50
BIC	522,708.59	4,239.11	12,517.30	15,204.75	619,147.86	2,433,881.50	498,409.62	247.15
Log Likelihood	-260,596.24	-1,659.37	-5,798.47	-7,142.19	-308,815.88	-1,216,180.34	-248,473.59	250.25

Standard errors in parentheses.

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

[a] Measured on logarithmic scale.

[b] Of focal season.

[c] At the time of watching focal anime season.

Web Appendix B: Complete Heterogeneity Results

Table B-1: Personal Engagement - Geography

Note that all three variables "Binge," "Sequel," and "Availability" are dummy variables.

	Whether Franchise was		
	Watched	Finished	Watched Next
	(i)	(ii)	(iii)
Engagement Equation			
Binge	-0.091***	0.293***	0.859***
	(0.025)	(0.045)	(0.043)
Binge × Sequel	0.090***	-0.077	0.382***
	(0.025)	(0.042)	(0.034)
Binge × Availability	0.031	0.100*	
	(0.020)	(0.039)	
Binge × Sequel × Availability	0.110***	0.079	
	(0.028)	(0.046)	
Europe × Binge	0.005	0.008	0.201***
	(0.025)	(0.047)	(0.040)
Europe × Binge × Sequel	-0.093**	0.021	0.045
	(0.032)	(0.055)	(0.038)
Europe × Binge × Availability	0.017	-0.029	
	(0.026)	(0.050)	
Europe × Binge × Sequel × Availability	0.050	0.012	
	(0.037)	(0.061)	
Oceania × Binge	0.177*	-0.063	0.139
	(0.072)	(0.129)	(0.101)
Oceania × Binge × Sequel	-0.139	0.151	0.229*
	(0.095)	(0.154)	(0.103)
Oceania × Binge × Availability	-0.261***	0.040	
	(0.076)	(0.138)	
Oceania × Binge × Sequel × Availability	0.243*	-0.136	
	(0.108)	(0.170)	
Asia × Binge	0.012	-0.164	0.112
	(0.046)	(0.088)	(0.069)
Asia × Binge × Sequel	-0.061	0.286**	0.159*
	(0.059)	(0.102)	(0.069)
Asia × Binge × Availability	-0.047	0.078	
	(0.049)	(0.093)	
Asia × Binge × Sequel × Availability	0.058	-0.089	
	(0.069)	(0.113)	
South America × Binge	-0.024	-0.005	0.212**
	(0.051)	(0.093)	(0.069)
South America × Binge × Sequel	-0.090	-0.002	-0.091
	(0.067)	(0.110)	(0.075)
South America × Binge × Availability	0.039	-0.036	
	(0.054)	(0.099)	
South America × Binge × Sequel × Availability	0.046	0.035	
	(0.077)	(0.122)	
Sequel	0.648***	1.042***	-0.062**
	(0.009)	(0.014)	(0.020)
Availability	-0.782***	-0.386***	
	(0.016)	(0.018)	
Sequel × Availability	0.501***	0.554***	
	(0.010)	(0.015)	
Wait Time Until Franchise Available	-0.147***	-0.048***	
When Started Watching Focal Season[a]	(0.003)	(0.003)	
Popularity Rank[a,b]	-0.065***	-0.010***	0.015*
	(0.002)	(0.003)	(0.007)
Community Rating[b]	0.061***	0.069***	-0.014
	(0.004)	(0.007)	(0.016)
Number of Episodes[b]	0.027***		-0.526***
	(0.004)		(0.019)
Europe	0.126***	0.174***	0.113***
	(0.010)	(0.014)	(0.025)
Oceania	0.054*	0.057	0.073
	(0.023)	(0.032)	(0.056)
Asia	0.084***	0.244***	0.110**
	(0.017)	(0.026)	(0.041)
South America	0.196***	0.263***	0.151***
	(0.016)	(0.023)	(0.038)
Constant	0.041	-1.896***	-1.369***
	(0.043)	(0.066)	(0.158)
Standard Deviation of	0.589***	0.751***	0.214***
User Random Effect	(0.004)	(0.006)	(0.014)
Genre Dummies	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes

	Whether Franchise was		
	Watched	Finished	Watched Next
	(iv)	(v)	(vi)
Binge Equation			
Weekend Dummy	0.045***	0.043***	0.046***
	(0.004)	(0.006)	(0.005)
Holiday Dummy	0.022*	0.004	0.013
	(0.010)	(0.016)	(0.014)
Popularity Rank[a,b]	-0.050***	-0.045***	-0.037***
	(0.002)	(0.003)	(0.003)
Community Rating[b]	0.045***	0.074***	0.047***
	(0.005)	(0.007)	(0.006)
Number of Episodes[b]	0.043***	0.049***	0.057***
	(0.005)	(0.007)	(0.006)
Duration of an Episode[a]	0.133***	0.186***	0.185***
	(0.019)	(0.028)	(0.025)
Europe	-0.659***	-0.634***	-0.602***
	(0.012)	(0.015)	(0.013)
Oceania	-0.651***	-0.673***	-0.594***
	(0.030)	(0.034)	(0.031)
Asia	-0.483***	-0.437***	-0.416***
	(0.020)	(0.027)	(0.023)
South America	-0.798***	-0.743***	-0.726***
	(0.021)	(0.025)	(0.022)
Constant	-1.509***	-1.896***	-1.683***
	(0.076)	(0.115)	(0.098)
Standard Deviation of	0.899***	0.861***	0.727***
User Random Effect	(0.005)	(0.007)	(0.006)
Genre Dummies	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes
Error Correlation	0.064***	-0.156***	-0.247***
	(0.011)	(0.017)	(0.022)
Number of Observations	764,666	345,108	396,928
AIC	1,520,053.89	669,119.07	405,943.97
BIC	1,521,682.05	670,613.54	407,338.09
Log Likelihood	-759,885.95	-334,420.53	-202,843.99

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
[a] Measured on logarithmic scale.
[b] Of focal season.

Table B-2: Interactive Engagement - Geography

Note that the variable "Binge" is a dummy variable.

	Forum Posts				Ratings		Recommendations	
	Incidence	Valence	Number	Length	Incidence	Valence	Incidence	Number
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Engagement Equation								
Binge	-0.528***	-0.081*	-0.144	0.189	-0.170***	0.236***	-0.110	0.002
	(0.079)	(0.033)	(0.082)	(0.106)	(0.045)	(0.014)	(0.065)	(0.016)
Europe × Binge	0.025	-0.028	0.120*	0.122	-0.110	-0.008	-0.097	-0.019
	(0.046)	(0.022)	(0.054)	(0.072)	(0.058)	(0.018)	(0.110)	(0.026)
Oceania × Binge	0.049	0.007	0.283*	-0.014	-0.218	-0.023	-0.189	-0.018
	(0.103)	(0.046)	(0.113)	(0.150)	(0.165)	(0.053)	(0.288)	(0.069)
Asia × Binge	0.189*	-0.022	0.046	-0.039	-0.094	-0.067*	0.046	0.018
	(0.078)	(0.035)	(0.087)	(0.115)	(0.132)	(0.033)	(0.151)	(0.038)
South America × Binge	0.061	-0.076	0.149	-0.058	-0.344***	-0.039	-0.270	-0.029
	(0.127)	(0.061)	(0.156)	(0.211)	(0.097)	(0.035)	(0.285)	(0.074)
Ever-Made-a-Forum-Post Indicator	0.150***	0.006	0.071*	-0.070				
	(0.031)	(0.011)	(0.030)	(0.042)				
Time Since Last Forum Post[a]	-0.029***	-0.003	-0.008	-0.011				
	(0.008)	(0.004)	(0.008)	(0.011)				
Number of Forum Posts[a,c]	0.022**	-0.005	0.000	-0.031**				
	(0.007)	(0.004)	(0.009)	(0.012)				
Number of Ratings[a,c]					0.000	0.001		
					(0.007)	(0.002)		
Number of Recommendations[a,c]							0.281***	0.015
							(0.037)	(0.010)
Popularity Rank[a,b]	0.086***	0.004	0.024*	0.013	-0.060***	0.058***	0.043	0.005
	(0.009)	(0.004)	(0.010)	(0.013)	(0.011)	(0.004)	(0.027)	(0.007)
Community Rating[b]	0.064**	0.044***	0.039	-0.022	0.124***	1.033***	0.105	-0.002
	(0.020)	(0.009)	(0.022)	(0.030)	(0.026)	(0.008)	(0.055)	(0.013)
Number of Episodes[b]	0.359***	-0.011	0.273***	0.094***				
	(0.018)	(0.008)	(0.020)	(0.027)				
Europe	-0.579***	-0.006	-0.119***	-0.101*	-0.067*	-0.052***	-0.352***	-0.005
	(0.039)	(0.011)	(0.033)	(0.046)	(0.032)	(0.010)	(0.053)	(0.012)
Oceania	-0.083	-0.005	-0.126*	-0.086	0.148	-0.023	-0.088	-0.028
	(0.085)	(0.022)	(0.064)	(0.090)	(0.081)	(0.026)	(0.118)	(0.028)
Asia	-0.315***	0.010	-0.011	-0.102	0.049	0.270***	0.011	-0.007
	(0.070)	(0.020)	(0.057)	(0.079)	(0.063)	(0.018)	(0.081)	(0.021)
South America	-0.756***	-0.007	-0.077	-0.287**	-0.384***	0.211***	-0.422***	-0.030
	(0.081)	(0.023)	(0.066)	(0.093)	(0.052)	(0.017)	(0.101)	(0.026)
Constant	-5.609***	-0.097	-0.137	3.421***	3.573***	-0.340***	-5.563***	0.677***
	(0.197)	(0.085)	(0.206)	(0.273)	(0.253)	(0.081)	(0.523)	(0.119)
Standard Deviation of User Random Effect	1.289***	0.067***	0.327***	0.505***	2.726***	0.756***	1.021***	0.043***
	(0.027)	(0.009)	(0.011)	(0.021)	(0.027)	(0.003)	(0.010)	(0.004)
Genre Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Binge Equation								
Weekend Dummy	0.053***	0.046	0.040	0.042	0.053***	0.052***	0.053***	0.046
	(0.004)	(0.057)	(0.057)	(0.057)	(0.010)	(0.009)	(0.010)	(0.145)
Holiday Dummy	0.016	0.275*	0.267*	0.267*	0.016	0.014	0.017	-0.277
	(0.011)	(0.131)	(0.133)	(0.133)	(0.027)	(0.024)	(0.026)	(0.363)
Popularity Rank[b]	-0.030***	-0.086***	-0.087***	-0.085**	-0.030***	-0.030***	-0.030***	0.017
	(0.002)	(0.026)	(0.026)	(0.026)	(0.005)	(0.004)	(0.005)	(0.066)
Community Rating[b]	0.053***	0.039	0.032	0.035	0.053***	0.055***	0.053***	0.357*
	(0.005)	(0.063)	(0.064)	(0.064)	(0.012)	(0.010)	(0.011)	(0.178)
Number of Episodes[b]	0.056***	-0.029	-0.038	-0.032	0.055***	0.060***	0.055***	-0.059
	(0.005)	(0.058)	(0.058)	(0.058)	(0.011)	(0.010)	(0.011)	(0.168)
Duration of an Episode[a]	0.381***	0.492	0.475	0.489	0.386***	0.385***	0.383***	0.443
	(0.017)	(0.283)	(0.282)	(0.282)	(0.042)	(0.038)	(0.040)	(0.958)
Europe	-0.612***	-0.494***	-0.493***	-0.497***	-0.611***	-0.612***	-0.616***	-0.600***
	(0.011)	(0.092)	(0.092)	(0.092)	(0.011)	(0.010)	(0.011)	(0.155)
Oceania	-0.596***	-0.569**	-0.566**	-0.566**	-0.597***	-0.580***	-0.601***	-0.690
	(0.027)	(0.191)	(0.193)	(0.193)	(0.026)	(0.025)	(0.025)	(0.363)
Asia	-0.421***	-0.073	-0.065	-0.067	-0.419***	-0.433***	-0.442***	-0.070
	(0.020)	(0.149)	(0.150)	(0.150)	(0.020)	(0.018)	(0.018)	(0.228)
South America	-0.769***	-0.809***	-0.796***	-0.800***	-0.745***	-0.759***	-0.735***	-1.049**
	(0.018)	(0.208)	(0.210)	(0.210)	(0.019)	(0.017)	(0.018)	(0.379)
Constant	-2.324***	-2.292*	-2.158*	-2.254*	-2.337***	-2.387***	-2.331***	-4.973
	(0.070)	(1.076)	(1.080)	(1.076)	(0.172)	(0.156)	(0.164)	(3.442)
Standard Deviation of User Random Effect	0.704***	0.926***	0.938***	0.939***	0.705***	0.692***	0.700***	0.815***
	(0.004)	(0.069)	(0.070)	(0.070)	(0.005)	(0.004)	(0.004)	(0.128)
Genre Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Error Correlation	0.311***	-1.395***	-0.579***	-0.312***	0.152***	0.135***	0.109***	-1.978***
	(0.053)	(0.014)	(0.012)	(0.014)	(0.007)	(0.001)	(0.021)	(0.021)
Number of Observations	663,963	4,564	4,564	4,564	663,963	615,325	663,963	1,215
AIC	645,482.33	4,917.61	12,963.63	15,584.36	742,547.78	2,534,801.25	621,749.81	189.00
BIC	646,919.49	5,708.00	13,754.03	16,374.75	743,973.52	2,536,228.81	623,129.94	785.99
Log Likelihood	-322,615.17	-2,335.81	-6,358.82	-7,669.18	-371,148.89	-1,267,274.62	-310,753.91	22.50

Standard errors in parentheses.

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

[a] Measured on logarithmic scale.

[b] Of focal season.

[c] At the time of watching focal anime season.

Table B-3: Personal Engagement - Age

Note that all three variables "Binge," "Sequel," and "Availability" are dummy variables.

	Whether Franchise was		
	Watched	Finished	Watched Next
	(i)	(ii)	(iii)
Engagement Equation			
Binge	-0.139***	0.157***	0.796***
	(0.025)	(0.045)	(0.042)
Binge × Sequel	0.008	0.013	0.411***
	(0.026)	(0.043)	(0.035)
Binge × Availability	0.016	0.109**	
	(0.021)	(0.039)	
Binge × Sequel × Availability	0.160***	0.013	
	(0.030)	(0.048)	
Age: 20 - 25 × Binge	-0.086*	-0.079	0.104*
	(0.037)	(0.071)	(0.053)
Age: 20 - 25 × Binge × Sequel	0.037	0.099	-0.079
	(0.047)	(0.082)	(0.054)
Age: 20 - 25 × Binge × Availability	0.075*	0.030	
	(0.038)	(0.075)	
Age: 20 - 25 × Binge × Sequel × Availability	-0.046	0.014	
	(0.053)	(0.090)	
Age > 25 × Binge	-0.104**	0.014	0.054
	(0.035)	(0.067)	(0.053)
Age > 25 × Binge × Sequel	0.064	0.071	-0.067
	(0.046)	(0.078)	(0.055)
Age > 25 × Binge × Availability	0.108**	-0.007	
	(0.037)	(0.072)	
Age > 25 × Binge × Sequel × Availability	-0.076	-0.048	
	(0.052)	(0.087)	
AgeMissing × Binge	0.023	0.049	-0.064
	(0.028)	(0.051)	(0.043)
AgeMissing × Binge × Sequel	0.022	-0.130*	0.048
	(0.036)	(0.060)	(0.044)
AgeMissing × Binge × Availability	-0.022	-0.030	
	(0.029)	(0.054)	
AgeMissing × Binge × Sequel × Availability	0.006	0.107	
	(0.041)	(0.066)	
Sequel	0.648***	1.046***	-0.061**
	(0.009)	(0.014)	(0.020)
Availability	-0.784***	-0.385***	
	(0.016)	(0.018)	
Sequel × Availability	0.501***	0.554***	
	(0.010)	(0.015)	
Wait Time Until Franchise Available When Started Watching Focal Season[a]	-0.147***	-0.048***	
	(0.003)	(0.003)	
Popularity Rank[a,b]	-0.066***	-0.011***	0.016*
	(0.002)	(0.003)	(0.007)
Community Rating[b]	0.061***	0.071***	-0.011
	(0.004)	(0.007)	(0.016)
Number of Episodes[b]	0.028***		-0.513***
	(0.004)		(0.019)
Age: 20 - 25	0.015	-0.019	-0.001
	(0.009)	(0.014)	(0.031)
Age > 25	-0.016	-0.017	0.046
	(0.011)	(0.017)	(0.030)
AgeMissing	0.005	0.000	0.003
	(0.009)	(0.013)	(0.025)
Constant	0.139**	-1.762***	-1.364***
	(0.043)	(0.066)	(0.159)
Standard Deviation of User Random Effect	0.593***	0.763***	0.252***
	(0.004)	(0.006)	(0.013)
Genre Dummies	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes
Binge Equation			
Weekend Dummy	0.045***	0.044***	0.045***
	(0.004)	(0.006)	(0.005)
Holiday Dummy	0.027**	0.014	0.025
	(0.010)	(0.016)	(0.014)
Popularity Rank[a,b]	-0.050***	-0.044***	-0.037***
	(0.002)	(0.003)	(0.003)
Community Rating[b]	0.045***	0.073***	0.049***
	(0.005)	(0.007)	(0.006)
Number of Episodes[b]	0.042***	0.045***	0.053***
	(0.005)	(0.007)	(0.006)
Duration of an Episode[a]	0.132***	0.180***	0.181***
	(0.019)	(0.028)	(0.025)
Age: 20 - 25	0.019	0.017	0.013
	(0.010)	(0.014)	(0.013)
Age > 25	-0.040**	-0.033	-0.040*
	(0.013)	(0.018)	(0.016)
AgeMissing	0.020	0.005	0.003
	(0.011)	(0.014)	(0.013)
Constant	-1.942***	-2.287***	-2.073***
	(0.076)	(0.115)	(0.099)
Standard Deviation of User Random Effect	0.945***	0.919***	0.791***
	(0.005)	(0.007)	(0.006)
Genre Dummies	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes
Error Correlation	0.103***	-0.096***	-0.126***
	(0.010)	(0.016)	(0.020)
Number of Observations	764,666	345,108	396,928
AIC	1,524,541.99	671,980.22	408,905.44
BIC	1,526,100.86	673,410.18	410,255.99
Log Likelihood	-762,136.00	-335,857.11	-204,328.72

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
[a] Measured on logarithmic scale.
[b] Of focal season.

Table B-4: Interactive Engagement - Age

Note that the variable "Binge" is a dummy variable.

	Forum Posts				Ratings		Recommendations	
	Incidence	Valence	Number	Length	Incidence	Valence	Incidence	Number
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Engagement Equation								
Binge	0.183*	-0.052	-0.128	0.225*	-0.252***	0.132***	0.108	-0.029
	(0.087)	(0.034)	(0.083)	(0.108)	(0.048)	(0.014)	(0.086)	(0.020)
Age: 20 - 25 × Binge	0.076	-0.031	-0.081	-0.071	-0.066	-0.015	0.081	0.025
	(0.066)	(0.030)	(0.073)	(0.097)	(0.084)	(0.025)	(0.134)	(0.034)
Age > 25 × Binge	0.076	0.054	0.063	0.080	-0.098	-0.015	-0.174	-0.005
	(0.065)	(0.029)	(0.072)	(0.097)	(0.084)	(0.025)	(0.158)	(0.039)
AgeMissing × Binge	-0.120*	-0.045*	0.080	-0.004	0.040	0.018	0.118	0.042
	(0.051)	(0.022)	(0.056)	(0.074)	(0.070)	(0.020)	(0.112)	(0.027)
Ever-Made-a-Forum-Post Indicator	0.143***	0.005	0.079**	-0.070				
	(0.033)	(0.011)	(0.030)	(0.042)				
Time Since Last Forum Post[a]	-0.026**	-0.003	-0.007	-0.011				
	(0.008)	(0.003)	(0.008)	(0.011)				
Number of Forum Posts[a,c]	0.019**	-0.004	0.000	-0.032**				
	(0.007)	(0.004)	(0.009)	(0.012)				
Number of Ratings[a,c]					0.004	0.004*		
					(0.007)	(0.002)		
Number of Recommendations[a,c]							0.282***	0.015
							(0.037)	(0.010)
Popularity Rank[a,b]	0.096***	0.004	0.025*	0.013	-0.059***	0.058***	0.045	0.005
	(0.009)	(0.004)	(0.010)	(0.013)	(0.012)	(0.004)	(0.027)	(0.007)
Community Rating[b]	0.045*	0.043***	0.040	-0.023	0.122***	1.033***	0.100	-0.004
	(0.020)	(0.009)	(0.022)	(0.030)	(0.027)	(0.008)	(0.055)	(0.013)
Number of Episodes[b]	0.361***	-0.012	0.271***	0.094***				
	(0.018)	(0.008)	(0.020)	(0.027)				
Age: 20 - 25	-0.134**	-0.001	-0.015	0.022	-0.068	-0.013	-0.110	0.010
	(0.043)	(0.016)	(0.042)	(0.058)	(0.044)	(0.013)	(0.075)	(0.018)
Age > 25	-0.132**	-0.009	-0.042	-0.018	-0.137**	0.012	-0.172*	0.001
	(0.049)	(0.015)	(0.043)	(0.061)	(0.042)	(0.013)	(0.074)	(0.018)
AgeMissing	0.028	0.023	-0.076*	-0.040	0.058	-0.010	0.082	-0.014
	(0.037)	(0.012)	(0.033)	(0.046)	(0.034)	(0.011)	(0.056)	(0.013)
Constant	-6.146***	-0.109	-0.143	3.401***	3.548***	-0.310***	-5.853***	0.699***
	(0.194)	(0.085)	(0.206)	(0.273)	(0.265)	(0.080)	(0.523)	(0.118)
Standard Deviation of User Random Effect	1.424***	0.068***	0.327***	0.510***	2.770***	0.763***	1.045***	0.044***
	(0.027)	(0.009)	(0.011)	(0.021)	(0.030)	(0.003)	(0.010)	(0.004)
Genre Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Binge Equation								
Weekend Dummy	0.053***	0.041	0.035	0.036	0.053***	0.052***	0.053***	0.049
	(0.004)	(0.057)	(0.058)	(0.058)	(0.011)	(0.009)	(0.010)	(0.146)
Holiday Dummy	0.025*	0.310*	0.300*	0.301*	0.025	0.021	0.024	-0.264
	(0.011)	(0.133)	(0.134)	(0.134)	(0.028)	(0.024)	(0.026)	(0.365)
Popularity Rank[b]	-0.030***	-0.090***	-0.090***	-0.089***	-0.031***	-0.031***	-0.031***	0.017
	(0.002)	(0.026)	(0.026)	(0.026)	(0.005)	(0.004)	(0.005)	(0.066)
Community Rating[b]	0.054***	0.026	0.020	0.023	0.054***	0.058***	0.055***	0.360*
	(0.005)	(0.064)	(0.064)	(0.064)	(0.012)	(0.010)	(0.011)	(0.178)
Number of Episodes[b]	0.051***	-0.047	-0.053	-0.048	0.051***	0.052***	0.052***	-0.077
	(0.005)	(0.058)	(0.058)	(0.058)	(0.012)	(0.010)	(0.011)	(0.169)
Duration of an Episode[a]	0.379***	0.489	0.468	0.485	0.382***	0.380***	0.379***	0.492
	(0.017)	(0.287)	(0.286)	(0.286)	(0.045)	(0.037)	(0.041)	(0.983)
Age: 20 - 25	-0.001	0.256*	0.252*	0.253*	-0.005	0.001	0.001	0.055
	(0.010)	(0.116)	(0.116)	(0.116)	(0.016)	(0.014)	(0.015)	(0.204)
Age > 25	-0.031*	0.247*	0.251*	0.251*	-0.039**	-0.034**	-0.032*	-0.314
	(0.013)	(0.121)	(0.122)	(0.122)	(0.015)	(0.013)	(0.014)	(0.228)
AgeMissing	0.028**	-0.191*	-0.193*	-0.194*	0.017	0.031**	0.026*	0.175
	(0.011)	(0.095)	(0.095)	(0.095)	(0.013)	(0.011)	(0.012)	(0.157)
Constant	-2.737***	-2.266*	-2.134	-2.243*	-2.734***	-2.786***	-2.739***	-5.449
	(-0.070)	(1.090)	(1.092)	(1.089)	(0.184)	(0.154)	(0.168)	(3.519)
Standard Deviation of User Random Effect	0.768***	0.972***	0.980***	0.984***	0.776***	0.747***	0.763***	0.836***
	(0.005)	(0.071)	(0.072)	(0.072)	(0.005)	(0.004)	(0.005)	(0.129)
Genre Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Error Correlation	-0.072	-1.400***	-0.578***	-0.311***	0.151***	0.134***	-0.085***	-1.980***
	(-0.049)	(0.014)	(0.012)	(0.014)	(0.007)	(0.001)	(0.020)	(0.022)
Number of Observations	663,963	4,564	4,564	4,564	663,963	615,325	663,963	1,215
AIC	649,479.72	4,939.00	13,000.68	15,630.06	745,703.37	2,539,484.43	625,408.78	201.25
BIC	650,426.42	5,710.11	13,771.79	16,401.18	747,094.90	2,540,878.01	626,754.68	782.93
Log Likelihood	-324,656.86	-002,349.50	-6,380.34	-7,695.03	-372,729.69	-1,269,619.22	-312,586.39	13.38

Standard errors in parentheses.

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

[a] Measured on logarithmic scale.

[b] Of focal season.

[c] At the time of watching focal anime season.

Table B-5: Personal Engagement - Gender

Note that all three variables “Binge,” “Sequel,” and “Availability” are dummy variables.

	Whether Franchise was		
	Watched	Finished	Watched Next
	(i)	(ii)	(iii)
Engagement Equation			
Binge	-0.133***	0.197**	0.797***
	(0.034)	(0.061)	(0.052)
Binge × Sequel	0.000	-0.011	0.408***
	(0.039)	(0.065)	(0.048)
Binge × Availability	0.501***	0.105	
	(0.010)	(0.058)	
Binge × Sequel × Availability	0.138**	0.033	
	(0.045)	(0.072)	
Female × Binge	0.036	-0.075	0.024
	(0.025)	(0.047)	(0.038)
Female × Binge × Sequel	-0.023	0.054	0.007
	(0.032)	(0.055)	(0.039)
Female × Binge × Availability	-0.043	0.030	
	(0.026)	(0.050)	
Female × Binge × Sequel × Availability	0.013	-0.014	
	(0.037)	(0.061)	
GenderMissing × Binge	-0.030	0.021	-0.031
	(0.034)	(0.063)	(0.050)
GenderMissing × Binge × Sequel	0.054	-0.067	0.007
	(0.045)	(0.075)	(0.052)
GenderMissing × Binge × Availability	0.037	-0.030	
	(0.036)	(0.067)	
GenderMissing × Binge × Sequel × Availability	0.003	0.058	
	(0.051)	(0.083)	
Sequel	0.648***	1.045***	-0.061**
	(0.009)	(0.014)	(0.020)
Availability	-0.783***	-0.385***	
	(0.016)	(0.018)	
Sequel × Availability	0.018	0.555***	
	(0.032)	(0.015)	
Wait Time Until Franchise Available When Started Watching Focal Season[a]	-0.147***	-0.048***	
	(0.003)	(0.003)	
Popularity Rank[a,b]	-0.065***	-0.011***	0.016*
	(0.002)	(0.003)	(0.007)
Community Rating[b]	0.061***	0.071***	-0.011
	(0.004)	(0.007)	(0.016)
Number of Episodes[b]	0.028***		-0.513***
	(0.004)		(0.019)
Female	0.012	0.032*	-0.024
	(0.009)	(0.013)	(0.022)
GenderMissing	0.008	-0.012	0.021
	(0.012)	(0.017)	(0.030)
Constant	0.128**	-1.771***	-1.365***
	(0.043)	(0.067)	(0.160)
Standard Deviation of User Random Effect	0.594***	0.761***	0.253***
	(0.004)	(0.006)	(0.013)
Genre Dummies	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes
Binge Equation			
Weekend Dummy	0.045***	0.044***	0.045***
	(0.004)	(0.006)	(0.005)
Holiday Dummy	0.028**	0.014	0.025
	(0.010)	(0.016)	(0.014)
Popularity Rank[a,b]	-0.051***	-0.044***	-0.037***
	(0.002)	(0.003)	(0.003)
Community Rating[b]	0.045***	0.073***	0.049***
	(0.005)	(0.007)	(0.006)
Number of Episodes[b]	0.041***	0.045***	0.053***
	(0.005)	(0.007)	(0.006)
Duration of an Episode[a]	0.132***	0.180***	0.181***
	(0.019)	(0.028)	(0.025)
Female	0.014	-0.008	-0.008
	(0.011)	(0.015)	(0.013)
GenderMissing	0.018	0.006	-0.009
	(0.015)	(0.019)	(0.017)
Constant	-1.955***	-2.290***	-2.065***
	(0.077)	(0.116)	(0.100)
Standard Deviation of User Random Effect	0.938***	0.924***	0.791***
	(0.005)	(0.007)	(0.006)
Genre Dummies	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes
Error Correlation	0.097***	-0.098***	-0.126***
	(0.010)	(0.016)	(0.020)
Number of Observations	764,666	345,108	396,928
AIC	1,524,682.82	671,778.76	408,890.18
BIC	1,526,172.41	673,144.21	410,197.16
Log Likelihood	-762,212.41	-335,762.38	-204,325.09

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
[a] Measured on logarithmic scale.
[b] Of focal season.

Table B-6: Interactive Engagement - Gender

Note that the variable “Binge” is a dummy variable.

	Forum Posts				Ratings		Recommendations	
	Incidence	Valence	Number	Length	Incidence	Valence	Incidence	Number
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Engagement Equation								
Binge	0.254**	-0.047	-0.101	0.114	-0.243***	0.094***	0.083	-0.056
	(0.095)	(0.038)	(0.096)	(0.123)	(0.070)	(0.021)	(0.136)	(0.031)
Female × Binge	-0.064	0.014	-0.035	0.013	0.009	-0.008	0.167	0.046
	(0.046)	(0.021)	(0.051)	(0.068)	(0.063)	(0.018)	(0.104)	(0.025)
GenderMissing × Binge	-0.113	-0.045	0.059	0.121	0.014	-0.003	-0.074	0.038
	(0.066)	(0.029)	(0.073)	(0.098)	(0.081)	(0.024)	(0.159)	(0.036)
Ever-Made-a-Forum-Post Indicator	0.111**	0.006	0.074*	-0.066				
	(0.034)	(0.011)	(0.030)	(0.041)				
Time Since Last Forum Post[a]	-0.026**	-0.003	-0.008	-0.011				
	(0.008)	(0.004)	(0.008)	(0.011)				
Number of Forum Posts[a,c]	0.021**	-0.004	-0.001	-0.032**				
	(0.007)	(0.004)	(0.009)	(0.012)				
Number of Ratings[a,c]					0.002	0.003		
					(0.007)	(0.002)		
Number of Recommendations[a,c]							0.283***	0.016
							(0.037)	(0.010)
Popularity Rank[a,b]	0.094***	0.004	0.024*	0.012	-0.059***	0.058***	0.045	0.005
	(0.009)	(0.004)	(0.010)	(0.013)	(0.012)	(0.004)	(0.027)	(0.007)
Community Rating[b]	0.047*	0.043***	0.039	-0.021	0.121***	1.034***	0.099	-0.002
	(0.020)	(0.009)	(0.022)	(0.030)	(0.028)	(0.009)	(0.054)	(0.013)
Number of Episodes[b]	0.359***	-0.012	0.273***	0.095***				
	(0.018)	(0.008)	(0.020)	(0.027)				
Female	0.162***	0.009	0.029	-0.116**	0.069*	-0.029**	0.048	-0.003
	(0.037)	(0.011)	(0.031)	(0.043)	(0.031)	(0.010)	(0.051)	(0.012)
GenderMissing	0.089	0.003	-0.039	0.027	0.106**	-0.002	0.083	-0.017
	(0.059)	(0.016)	(0.046)	(0.064)	(0.040)	(0.013)	(0.077)	(0.017)
Constant	-6.282***	-0.101	-0.166	3.391***	3.468***	-0.291***	-5.971***	0.692***
	(0.199)	(0.086)	(0.209)	(0.278)	(0.270)	(0.083)	(0.522)	(0.118)
Standard Deviation of User Random Effect	1.397***	0.067***	0.329***	0.507***	2.751***	0.765***	1.081***	0.043***
	(0.027)	(0.009)	(0.012)	(0.021)	(0.030)	(0.003)	(0.010)	(0.004)
Genre Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Binge Equation								
Weekend Dummy	0.053***	0.041	0.035	0.037	0.053***	0.052***	0.053***	0.047
	(0.004)	(0.057)	(0.058)	(0.058)	(0.011)	(0.009)	(0.010)	(0.148)
Holiday Dummy	0.024*	0.301*	0.294*	0.295*	0.025	0.022	0.024	-0.266
	(0.011)	(0.132)	(0.134)	(0.134)	(0.029)	(0.024)	(0.025)	(0.369)
Popularity Rank[b]	-0.030***	-0.088***	-0.089***	-0.088***	-0.030***	-0.031***	-0.031***	0.017
	(0.002)	(0.026)	(0.026)	(0.026)	(0.005)	(0.004)	(0.005)	(0.067)
Community Rating[b]	0.054***	0.028	0.022	0.025	0.054***	0.058***	0.054***	0.364*
	(0.005)	(0.064)	(0.064)	(0.064)	(0.012)	(0.010)	(0.011)	(0.181)
Number of Episodes[b]	0.052***	-0.043	-0.049	-0.044	0.051***	0.050***	0.052***	-0.056
	(0.005)	(0.058)	(0.058)	(0.058)	(0.012)	(0.010)	(0.011)	(0.171)
Duration of an Episode[a]	0.380***	0.478	0.464	0.475	0.382***	0.379***	0.379***	0.452
	(0.017)	(0.284)	(0.284)	(0.284)	(0.045)	(0.038)	(0.039)	(0.963)
Female	-0.015	-0.238**	-0.237**	-0.238**	-0.009	-0.010	-0.013	0.215
	(0.011)	(0.089)	(0.087)	(0.087)	(0.011)	(0.010)	(0.010)	(0.148)
GenderMissing	0.004	-0.072	-0.073	-0.075	0.001	0.015	0.006	-0.195
	(0.015)	(0.122)	(0.123)	(0.123)	(0.015)	(0.013)	(0.014)	(0.208)
Constant	-2.723***	-2.171*	-2.071	-2.152*	-2.724***	-2.774***	-2.726***	-5.252
	(0.071)	(1.087)	(1.092)	(1.088)	(0.186)	(0.156)	(0.163)	(3.475)
Standard Deviation of User Random Effect	0.779***	0.962***	0.976***	0.980***	0.781***	0.751***	0.759***	0.861***
	(0.005)	(0.070)	(0.071)	(0.072)	(0.005)	(0.005)	(0.005)	(0.131)
Genre Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Error Correlation	-0.069	-1.398***	-0.577***	-0.311***	0.135***	0.134***	-0.036	-1.981***
	(0.047)	(0.014)	(0.012)	(0.014)	(0.007)	(0.001)	(0.020)	(0.021)
Number of Observations	663,963	4,564	4,564	4,564	663,963	615,325	663,963	1,215
AIC	649,175.53	4,939.02	13,036.41	5,653.70	745,537.02	2,538,913.89	626,080.96	193.76
BIC	650,544.25	5,690.86	13,788.25	16,405.53	746,894.33	2,540,273.48	627,392.65	760.14
Log Likelihood	-324,467.77	-2,352.51	-6,401.21	-7,709.85	-372,649.51	-1,269,336.94	-312,925.48	14.12

Standard errors in parentheses.

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

[a] Measured on logarithmic scale.

[b] Of focal season.

[c] At the time of watching focal anime season.

Table B-7: Personal Engagement - Experience

Note that all four variables "Binge," "Sequel," "Availability," and "Large Experience" are dummy variables.

	Whether Franchise was		
	Watched	Finished	Watched Next
	(i)	(ii)	(iii)
Engagement Equation			
Binge	-0.135***	0.215***	0.780***
	(0.021)	(0.037)	(0.036)
Binge × Sequel	0.045*	-0.100**	0.412***
	(0.019)	(0.031)	(0.028)
Binge × Availability	0.021	0.070*	
	(0.015)	(0.028)	
Binge × Sequel × Availability	0.143***	0.116***	
	(0.021)	(0.035)	
Large Experience × Binge	-0.056	-0.198***	0.047
	(0.029)	(0.057)	(0.040)
Large Experience × Binge × Sequel	-0.036	0.298***	0.018
	(0.038)	(0.066)	(0.042)
Large Experience × Binge × Availability	0.051	0.143*	
	(0.031)	(0.060)	
Large Experience × Binge × Sequel × Availability	0.003	-0.221**	
	(0.043)	(0.072)	
Sequel	0.648***	1.045***	-0.061**
	(0.009)	(0.014)	(0.020)
Availability	-0.785***	-0.385***	
	(0.016)	(0.018)	
Sequel × Availability	0.501***	0.554***	
	(0.010)	(0.015)	
Wait Time Until Franchise Available When Started Watching Focal Season[a]	-0.147***	-0.048***	
	(0.003)	(0.003)	
Popularity Rank[a,b]	-0.065***	-0.011***	0.016*
	(0.002)	(0.003)	(0.007)
Community Rating[b]	0.061***	0.071***	-0.011
	(0.004)	(0.007)	(0.016)
Number of Episodes[b]	0.028***		-0.513***
	(0.004)		(0.019)
Large Experience	-0.002	0.015	0.005
	(0.007)	(0.011)	(0.023)
Constant	0.141***	-1.764***	-1.348***
	(0.042)	(0.065)	(0.159)
Standard Deviation of User Random Effect	0.594***	0.762***	0.251***
	(0.004)	(0.006)	(0.013)
Genre Dummies	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes
Binge Equation			
Weekend Dummy	0.045***	0.044***	0.045***
	(0.004)	(0.006)	(0.005)
Holiday Dummy	0.028**	0.014	0.025
	(0.010)	(0.016)	(0.014)
Popularity Rank[a,b]	-0.050***	-0.045***	-0.037***
	(0.002)	(0.003)	(0.003)
Community Rating[b]	0.045***	0.073***	0.049***
	(0.005)	(0.007)	(0.006)
Number of Episodes[b]	0.042***	0.046***	0.054***
	(0.005)	(0.007)	(0.006)
Duration of an Episode[a]	0.133***	0.180***	0.182***
	(0.019)	(0.028)	(0.025)
Large Experience	-0.051***	-0.101***	-0.084***
	(0.008)	(0.012)	(0.011)
Constant	-1.932***	-2.283***	-2.071***
	(0.076)	(0.115)	(0.099)
Standard Deviation of User Random Effect	0.940***	0.916***	0.788***
	(0.005)	(0.007)	(0.006)
Genre Dummies	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes
Error Correlation	0.099***	-0.097***	-0.132***
	(0.010)	(0.016)	(0.020)
Number of Observations	764,666	345,108	396,928
AIC	1,524,821.60	672,136.30	408,817.87
BIC	1,526,241.90	673,437.25	410,081.29
Log Likelihood	-762,287.80	-335,947.15	-204,292.94

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
[a] Measured on logarithmic scale.
[b] Of focal season.

Table B-8: Interactive Engagement - Experience

Note that the variables "Binge" and "Large Experience" are dummy variables.

	Forum Posts				Ratings		Recommendations	
	Incidence (i)	Valence (ii)	Number (iii)	Length (iv)	Incidence (v)	Valence (vi)	Incidence (vii)	Number (viii)
Engagement Equation								
Binge	0.103	-0.078*	-0.094	0.214*	0.112	0.126***	0.112	-0.010
	(0.084)	(0.032)	(0.081)	(0.099)	(0.116)	(0.019)	(0.116)	(0.025)
Large Experience × Binge	0.064	0.009	0.141*	0.073	0.098	-0.020*	0.098	0.051*
	(0.052)	(0.023)	(0.057)	(0.075)	(0.078)	(0.009)	(0.078)	(0.025)
Ever-Made-a-Forum-Post Indicator	0.117***	0.006	0.074*	-0.064				
	(0.034)	(0.011)	(0.030)	(0.041)				
Time Since Last Forum Post[a]	-0.026**	-0.003	-0.008	-0.012				
	(0.008)	(0.004)	(0.008)	(0.011)				
Number of Forum Posts[a,c]	0.020**	-0.005	0.000	-0.032**				
	(0.007)	(0.004)	(0.009)	(0.012)				
Number of Ratings[a,c]					0.282***	0.008**		
					(0.022)	(0.003)		
Number of Recommendations[a,c]							0.282***	0.014
							(0.022)	(0.009)
Popularity Rank[a,b]	0.095***	0.004	0.025*	0.013	0.044**	0.057***	0.044**	0.005
	(0.009)	(0.004)	(0.010)	(0.013)	(0.017)	(0.002)	(0.017)	(0.006)
Community Rating[b]	0.046*	0.043***	0.039	-0.023	0.097**	1.034***	0.097**	-0.003
	(0.020)	(0.009)	(0.022)	(0.030)	(0.034)	(0.004)	(0.034)	(0.011)
Number of Episodes[b]	0.359***	-0.012	0.273***	0.095***				
	(0.018)	(0.008)	(0.020)	(0.027)				
Large Experience	-0.067	0.009	-0.050	-0.008	0.024	-0.021	0.024	-0.007
	(0.037)	(0.013)	(0.035)	(0.049)	(0.050)	(0.011)	(0.050)	(0.014)
Constant	-6.146***	-0.096	-0.181	3.376***	-5.892***	-0.322***	-5.892***	0.691***
	(0.193)	(0.085)	(0.205)	(0.272)	(0.337)	(0.034)	(0.337)	(0.103)
Standard Deviation of User Random Effect	0.771***	0.963***	0.976***	0.980***	0.754***	0.751***	0.754***	0.871***
	(0.005)	(0.071)	(0.072)	(0.073)	(0.005)	(0.005)	(0.005)	(0.131)
Genre Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Binge Equation								
Weekend Dummy	0.053***	0.043	0.038	0.039	0.053***	0.052***	0.053***	0.054
	(0.004)	(0.057)	(0.058)	(0.058)	(0.004)	(0.004)	(0.004)	(0.111)
Holiday Dummy	0.025*	0.310*	0.304*	0.304*	0.024*	0.021	0.024*	-0.302
	(0.011)	(0.132)	(0.134)	(0.134)	(0.011)	(0.011)	(0.011)	(0.289)
Popularity Rank[b]	-0.030***	-0.088***	-0.088***	-0.088***	-0.031***	-0.030***	-0.031***	0.017
	(0.002)	(0.026)	(0.026)	(0.026)	(0.002)	(0.002)	(0.002)	(0.051)
Community Rating[b]	0.054***	0.027	0.023	0.026	0.055***	0.058***	0.055***	0.363**
	(0.005)	(0.064)	(0.064)	(0.064)	(0.005)	(0.005)	(0.005)	(0.138)
Number of Episodes[b]	0.052***	-0.044	-0.048	-0.043	0.052***	0.052***	0.052***	-0.060
	(0.005)	(0.058)	(0.058)	(0.058)	(0.005)	(0.005)	(0.005)	(0.130)
Duration of an Episode[a]	0.381***	0.495	0.483	0.494	0.380***	0.380***	0.380***	0.498
	(0.017)	(0.285)	(0.285)	(0.285)	(0.017)	(0.017)	(0.017)	(0.757)
Large Experience	-0.088***	-0.066	-0.048	-0.048	-0.080***	-0.079***	-0.080***	0.103
	(0.009)	(0.099)	(0.098)	(0.098)	(0.008)	(0.008)	(0.008)	(0.157)
Constant	-2.722***	-2.378*	-2.308*	-2.387*	-2.727***	-2.765***	-2.727***	-5.474*
	(0.069)	(1.082)	(1.088)	(1.084)	(0.069)	(0.073)	(0.069)	(2.720)
Standard Deviation of User Random Effect	0.771***	0.963***	0.976***	0.980***	0.754***	0.751***	0.754***	0.871***
	(0.005)	(0.071)	(0.072)	(0.073)	(0.005)	(0.005)	(0.005)	(0.131)
Genre Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Error Correlation	-0.063	-1.398***	-0.578***	-0.311***	-0.056	0.134***	-0.056	-1.978***
	(0.050)	(0.014)	(0.012)	(0.014)	(0.069)	(0.001)	(0.069)	(0.022)
Number of Observations	663,963	4,564	4,564	4,564	663,963	615,325	663,963	1,215
AIC	649,312.75	4,946.16	13,030.54	15,654.55	625,864.47	2,539,112.05	625,864.47	194.70
BIC	650,647.25	5,678.72	13,763.10	16,387.10	627,141.94	2,540,437.65	627,141.94	745.77
Log Likelihood	-324,539.37	-2,359.08	-6,401.27	-7,713.27	-312,820.24	-1,269,439.03	-312,820.24	10.65

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
[a] Measured on logarithmic scale.
[b] Of focal season.
[c] At the time of watching focal anime season.

Table B-9: Personal Engagement - Usage

Note that all four variables "Binge," "Sequel," "Availability," and "High Recent Usage" are dummy variables.

	Whether Franchise was		
	Watched	Finished	Watched Next
	(i)	(ii)	(iii)
Engagement Equation			
Binge	-0.140***	0.198***	0.781***
	(0.021)	(0.036)	(0.036)
Binge × Sequel	0.036*	-0.069*	0.414***
	(0.018)	(0.030)	(0.027)
Binge × Availability	0.029	0.086**	
	(0.015)	(0.027)	
Binge × Sequel × Availability	0.148***	0.095**	
	(0.020)	(0.033)	
High Recent Usage × Binge	-0.035	-0.117	0.004
	(0.036)	(0.070)	(0.052)
High Recent Usage × Binge × Sequel	0.002	0.233**	0.020
	(0.047)	(0.082)	(0.055)
High Recent Usage × Binge × Availability	0.007	0.072	
	(0.038)	(0.074)	
High Recent Usage × Binge × Sequel × Availability	-0.025	-0.176	
	(0.053)	(0.090)	
Sequel	0.648***	1.045***	-0.061**
	(0.009)	(0.014)	(0.020)
Availability	-0.784***	-0.385***	
	(0.016)	(0.018)	
Sequel × Availability	0.501***	0.555***	
	(0.010)	(0.015)	
Wait Time Until Franchise Available When Started Watching Focal Season[a]	-0.147***	-0.048***	
	(0.003)	(0.003)	
Popularity Rank[a,b]	-0.065***	-0.011***	0.016*
	(0.002)	(0.003)	(0.007)
Community Rating[b]	0.061***	0.071***	-0.011
	(0.004)	(0.007)	(0.016)
Number of Episodes[b]	0.028***		-0.513***
	(0.004)		(0.019)
High Recent Usage	0.002	0.026*	-0.018
	(0.007)	(0.011)	(0.029)
Constant	0.140***	-1.769***	-1.354***
	(0.042)	(0.065)	(0.159)
Standard Deviation of User Random Effect	0.593***	0.762***	0.253***
	(0.004)	(0.006)	(0.013)
Genre Dummies	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes
Binge Equation			
Weekend Dummy	0.045***	0.044***	0.045***
	(0.004)	(0.006)	(0.005)
Holiday Dummy	0.027**	0.014	0.025
	(0.010)	(0.016)	(0.014)
Popularity Rank[a,b]	-0.050***	-0.044***	-0.037***
	(0.002)	(0.003)	(0.003)
Community Rating[b]	0.045***	0.073***	0.049***
	(0.005)	(0.007)	(0.006)
Number of Episodes[b]	0.042***	0.045***	0.054***
	(0.005)	(0.007)	(0.006)
Duration of an Episode[a]	0.132***	0.180***	0.182***
	(0.019)	(0.028)	(0.025)
High Recent Usage	-0.009	-0.029*	-0.035***
	(0.008)	(0.012)	(0.010)
Constant	-1.938***	-2.288***	-2.076***
	(0.076)	(0.115)	(0.099)
Standard Deviation of User Random Effect	0.947***	0.921***	0.790***
	(0.005)	(0.007)	(0.006)
Genre Dummies	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes
Error Correlation	0.098***	-0.100***	-0.126***
	(0.010)	(0.016)	(0.020)
Number of Observations	764,666	345,108	396,928
AIC	1,524,444.24	671,881.24	408,954.55
BIC	1,525,864.55	673,182.18	410,217.96
Log Likelihood	-762,099.12	-335,819.62	-204,361.27

Standard errors in parentheses.

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

[a] Measured on logarithmic scale.

[b] Of focal season.

Table B-10: Interactive Engagement - Usage

Note that the variables "Binge" and "High Recent Usage" are dummy variables.

	Forum Posts				Ratings		Recommendations	
	Incidence (i)	Valence (ii)	Number (iii)	Length (iv)	Incidence (v)	Valence (vi)	Incidence (vii)	Number (viii)
Engagement Equation								
Binge	0.123	-0.078*	-0.074	0.219*	-0.217***	0.126***	0.097	-0.006
	(0.083)	(0.031)	(0.079)	(0.099)	(0.042)	(0.018)	(0.115)	(0.025)
High Recent Usage × Binge	-0.012	0.008	-0.006	0.058	0.014	-0.015	0.113	0.060*
	(0.067)	(0.030)	(0.074)	(0.098)	(0.035)	(0.011)	(0.094)	(0.029)
Ever-Made-a-Forum-Post Indicator	0.115***	0.006	0.074*	-0.064				
	(0.033)	(0.011)	(0.030)	(0.041)				
Time Since Last Forum Post[a]	-0.026**	-0.003	-0.008	-0.012				
	(0.008)	(0.004)	(0.008)	(0.011)				
Number of Forum Posts[a,c]	0.020**	-0.005	-0.001	-0.032**				
	(0.007)	(0.004)	(0.009)	(0.012)				
Number of Ratings[a,c]					-0.001	0.005*		
					(0.005)	(0.002)		
Number of Recommendations[a,c]							0.282***	0.014
							(0.022)	(0.009)
Popularity Rank[a,b]	0.095***	0.004	0.024*	0.013	-0.059***	0.057***	0.044**	0.005
	(0.009)	(0.004)	(0.010)	(0.013)	(0.005)	(0.002)	(0.017)	(0.006)
Community Rating[b]	0.046*	0.044***	0.040	-0.022	0.123***	1.034***	0.098**	-0.005
	(0.020)	(0.009)	(0.022)	(0.030)	(0.011)	(0.004)	(0.034)	(0.011)
Number of Episodes[b]	0.360***	-0.012	0.273***	0.095***				
	(0.018)	(0.008)	(0.020)	(0.027)				
High Recent Usage	-0.052	-0.005	-0.064	-0.021	-0.017	-0.017*	0.019	-0.015
	(0.038)	(0.015)	(0.040)	(0.054)	(0.023)	(0.007)	(0.054)	(0.016)
Constant	-6.151***	-0.098	-0.198	3.372***	3.507***	-0.316***	-5.866***	0.699***
	(0.192)	(0.085)	(0.205)	(0.272)	(0.109)	(0.034)	(0.338)	(0.104)
Standard Deviation of User Random Effect	0.775***	0.964***	0.977***	0.981***	0.780***	0.751***	0.759***	0.867***
	(0.005)	(0.071)	(0.072)	(0.073)	(0.005)	(0.005)	(0.005)	(0.130)
Genre Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Binge Equation								
Weekend Dummy	0.053***	0.043	0.038	0.039	0.053***	0.052***	0.053***	0.055
	(0.004)	(0.057)	(0.058)	(0.058)	(0.004)	(0.004)	(0.004)	(0.111)
Holiday Dummy	0.024*	0.310*	0.303*	0.304*	0.025*	0.021	0.024*	-0.294
	(0.011)	(0.132)	(0.134)	(0.134)	(0.011)	(0.011)	(0.011)	(0.289)
Popularity Rank[b]	-0.030***	-0.088***	-0.088***	-0.087***	-0.030***	-0.030***	-0.031***	0.017
	(0.002)	(0.026)	(0.026)	(0.026)	(0.002)	(0.002)	(0.002)	(0.051)
Community Rating[b]	0.054***	0.028	0.024	0.027	0.054***	0.058***	0.055***	0.363**
	(0.005)	(0.064)	(0.064)	(0.064)	(0.005)	(0.005)	(0.005)	(0.138)
Number of Episodes[b]	0.052***	-0.043	-0.048	-0.042	0.051***	0.052***	0.052***	-0.060
	(0.005)	(0.058)	(0.058)	(0.058)	(0.005)	(0.005)	(0.005)	(0.130)
Duration of an Episode[a]	0.380***	0.496	0.482	0.496	0.382***	0.380***	0.380***	0.484
	(0.017)	(0.284)	(0.285)	(0.285)	(0.017)	(0.017)	(0.017)	(0.753)
High Recent Usage	-0.035***	-0.142	-0.130	-0.125	-0.033***	-0.030***	-0.034***	0.067
	(0.008)	(0.110)	(0.110)	(0.110)	(0.008)	(0.008)	(0.008)	(0.179)
Constant	-2.722***	-2.396*	-2.312*	-2.405*	-2.725***	-2.768***	-2.730***	-5.426*
	(0.069)	(1.081)	(1.086)	(1.083)	(0.069)	(0.073)	(0.069)	(2.705)
Standard Deviation of User Random Effect	0.775***	0.964***	0.977***	0.981***	0.780***	0.751***	0.759***	0.867***
	(0.005)	(0.071)	(0.072)	(0.073)	(0.005)	(0.005)	(0.005)	(0.130)
Genre Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Error Correlation	-0.067	-1.397***	-0.577***	-0.311***	0.129***	0.134***	-0.044	-1.978***
	(0.050)	(0.014)	(0.012)	(0.014)	(0.024)	(0.001)	(0.069)	(0.022)
Number of Observations	663,963	4,564	4,564	4,564	663,963	615,325	663,963	1,215
AIC	649,282.16	4,946.07	13,032.12	15,652.58	745,668.08	2,539,240.71	625,703.13	195.18
BIC	650,616.66	5,678.62	13,764.68	16,385.14	746,991.17	2,540,566.31	626,980.60	746.25
Log Likelihood	-324,524.08	-2,359.03	-6,402.06	-7,712.29	-372,718.04	-1,269,503.36	-312,739.57	10.41

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
[a] Measured on logarithmic scale.
[b] Of focal season.
[c] At the time of watching focal anime season.