Watching Intensity and Media Franchise Engagement *

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Abstract

The rapid adoption of online streaming and over-the-top services has fundamentally changed at-home entertainment media consumption and given rise to new behaviors which are often characterized by a high intensity of watching (e.g., binge-watching). In this paper, we investigate how the watching intensity affects 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. Using individual-level data from an online anime (Japanese cartoons) platform, we find inverse U-shaped effects of watching intensity with the largest effects around three to five hours of watching per day on personal engagement and two to four hours a day on interactive engagement. The positive effects of watching intensity are larger for sequels than other types of franchise extensions. For interactive engagement, our results show that conditional on rating submission, higher watching intensity is associated with higher valence of anime ratings, the most prevalent form of UGC on the platform. We interpret this result as evidence that watching intensity can induce liking.

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

JEL Classification: L82, M31

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1 Introduction

The global at-home media entertainment industry has fundamentally changed during the last 15 years due to online streaming, a new technology brought about by high-speed Internet. Prior to online streaming, at-home media consumption was mostly characterized by "appointment watching" or "linear watching" of TV programs, i.e., consumers turning to a specific TV channel to watch a show on a day and at a time determined by the TV network. While appointment watching still exists, its importance has declined. At-home media consumption through TV channels and satellite TV has been – to a large extent – replaced by over-the-top (OTT) media consumption.[1] OTT media services allow consumers to freely choose when and how much of a movie or TV series to watch. Consumers have overwhelmingly embraced this new technology giving rise to new media consumption behaviors such as "binge-watching," which is characterized by rapid consumption of media content in a short period of time. This new technology has also changed the structure of the at-home media entertainment industry: streaming services such as Netflix and Hulu have emerged as major players in distributing and creating media content, traditional TV networks have launched their own streaming platforms, and new contenders such as Apple and Disney have launched their own OTT services.

Another notable trend in the entertainment and media industry is the rising success of media franchises on both big and small screens.[2] 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, all 10 top-grossing movies of 2022 in the U.S. belonged to franchises such as "Avengers," "Jurassic World," and "Top Gun."[3] Franchise series also ruled the small screen as witnessed by the exploding traffic on Netflix drawn to "Breaking Bad" or "Bridgerton," original

[1]An OTT media service is a streaming service that delivers film, TV, and video content directly to viewers over the internet without requiring users to subscribe to traditional cable or satellite pay TV. By 2022, over 85% of U.S. households subscribed to at least one video streaming service (https://www.kantar.com/north-america/inspiration/technology/85-per-cent-of-us-households-have-a-video-subscription-service). In the U.S., streaming captured more than 38% of total TV viewing in 2020 and audiences streamed more than 19 million years worth of content (https://www.nielsen.com/insights/2023/streaming-services-remain-most-popular-destination-for-tv-viewing-in-december/).

[2]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). In 2022, all 10 top grossing movies were franchises (https://www.boxofficemojo.com/year/2022/).

[3]The total historic revenue from the "Star Wars" franchise was $69 billion (by mid 2021), $32 billion (by mid 2021) for the "Harry Potter" franchise, and $22 billion (by mid 2021) for the "Toy Story" franchise (https://www.statista.com/statistics/1257650/media-franchises-revenue/).

series created by the streaming service.

Anecdotal evidence and common industry practices suggest that intensive media consumption might increase viewer engagement with media franchise series. For example, "Breaking Bad" creator Vince Gilligan previously told Mashable that the show "may have met its demise after season two, had it not been for streaming video on demand. It ushered in new viewers and encouraged time-starved individuals to keep watching at their own pace resulting in enormous growth from season to season" that reached its climactic end in September 2013 with 10.3 million viewers (the show's highest viewership ever) (Hernandez 2014). Similarly, for popular series such as "Supernatural," Netflix starts streaming previous season(s) shortly before the release of a new season (on traditional TV).[4]

However, there is little systematic examination into the relationship between a consumer's media consumption intensity and her engagement with a media franchise.[5] In this paper, we aim to fill this gap. To do so, we estimate the effects of different watching intensities ranging from low- to high-intensity watching. In general, low-intensity or slow watching (of a series) over an extended time period can encompass both appointment watching (on TV) and consumer-driven gradual viewing of a series (through an OTT service). High-intensity or "fast" watching of a series over a short time period may apply to both marathon releases (on TV) and consumer-driven intensive viewing of a series (through an OTT service). Higher levels of watching intensity therefore include but are not restricted to binge-watching.[6]

To measure consumer engagement with media products, we adopt the categorization developed by Calder et al. (2009). They identify two types of consumer engagement: "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

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

[5]Note that *all* users in our estimation sample watch the whole anime season and that all episodes in a season are available for watching in our estimation sample. However, some finish watching the whole season in fewer days than others, i.e., we study the effects of watching intensity conditional on season completion.

[6]Recently, a process-based definition of binge-watching has been suggested (see, e.g., Schweidel and Moe 2016, Lu et al. 2017). It poses that streaming data are necessary to classify viewing behavior as binge-watching, i.e., the researcher has to observe that a consumer watched at least two episodes of a series directly in a row. Our data contain information on how many minutes of a series a consumer watched on average per day, but we do not observe whether this watching happened in one sitting. For more details, please see Sections 2.2 and 3.1.

latter with an individual's voluntary content generation and promotion of a focal media product. Therefore, increased consumption intensity might result in the viewer watching subsequent seasons or other types of franchise extensions (see Table 1 for definitions and examples) 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).

Table 1: Types of Franchise Extensions

Types of Franchise Extensions	Definition	Example
Sequel	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	Season 8 of "Game of Thrones" is a sequel to season 7 of "Game of Thrones."
Other Types of Franchise Extensions		
Side Story	A short story related to the main characters in the context of the focal series	The movie "Sherlock: The Abominable Bride" is a side story for the "Sherlock" series.
Spin-off	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.	The "Joey" series is a spin-off from the popular sitcom series "Friends."
Summary	A short series or a movie summarizing the events of the focal series	The "Pink Panther" movie is a summary of the events in the identically titled TV series.
Remake	A remake of a series, usually with small differences in the plot or a different ending	The American "The Office" series is a remake of the British "The Office" series.

If watching intensity increases consumers' engagement with a media franchise, this finding would have important implications for media companies' content production and release strategies. First, in line with this finding, both online streaming platforms and traditional TV networks could use watching intensity levels of a focal media product as an additional predictor for the success of its sequels and other types of franchise extensions, thus making the production planning more informed. Second, for online streaming services, the finding 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 content release strategy of promoting a new season shown on traditional TV by making older seasons available through online streaming services. This strategy could garner 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.[7]

If watching intensity does not always increase media franchise engagement or if it does not do so for all shows, it is important to understand when and why this is the case. Does the level of watching intensity matter such that excessive watching would actually hurt consumer engagement with the media franchise? Does the timing of the release through online streaming services play a role? Or does the type of franchise extension make a difference? In this paper, through a systematic empirical investigation, we provide a nuanced description of consumers' different levels of watching intensities and how they affect consumer engagement with media franchises.

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 timing of anime including the number of days it took a consumer to watch the whole season of an anime.[8] This information allows us to calculate the watching intensity for each consumer-anime combination. 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 (see Table 1 for definitions and examples of franchise extensions). And lastly, we observe a consumer's demographic characteristics, including the individual's geographic location, age, and gender.

Our goal is to understand how the watching intensity (conditional on viewing the whole season) impacts a consumer's actions related to media franchise engagement. Potential endogeneity of a user's decision on how intensively to watch an anime is a concern for the causal interpretation of the estimated effects. Omitted variables, i.e., variables that are not observed in the data but are correlated with an individual's watching intensity and influence their engagement, are the cause of the concern (see, e.g., Angrist and Pischke 2009). In this paper, we address endogeneity concerns by exploiting our unique and rich individual-level data that allow us to incorporate a large number

[7] https://www.cnbc.com/2018/08/15/netflix-cost-plus-model-tv-shows-revenue-upside.html
[8] The term "anime season" also subsumes movies, i.e., an anime season with one episode.

of fixed effects to control for various types of omitted variables (see, e.g., Wooldridge 2001). The idea of the fixed effects approach is to partition the variation in watching intensity into that which is "clean" and that which is not and only use the clean portion of variation to estimate the effect of watching intensity (see Allenby and Rossi 2019). Specifically, our model incorporates the following fixed effects: anime, month, user-genre, and user-weekend/holiday fixed effects. Our interpretation of the effects of watching intensity as causal therefore relies on the assumption that, conditional on these fixed effects and control variables, the watching intensity decision is independent of the error term. We discuss in detail in Section 4.1 why we believe that these fixed effects together with the control variables address potential endogeneity concerns.

Our results show that a watching intensity of more than one hour per day, i.e., at a higher level than typically in linear watching, increases an individual user's probability of watching a franchise extension (at any point in time in the future), and that the positive effects of watching intensity are larger for sequels than other types of franchise extensions. More interestingly, we find the effects of watching intensity to exhibit an inverse U-shaped pattern with the largest effects around three to five hours of watching per day. Additionally, the effects of watching intensity on an individual's likelihood of finishing to watch a franchise extension critically depend on the availability of a franchise extension at the time of watching the focal season: the probability that a user finishes to watch a franchise extension only increases if the franchise extension was available at the time when the user watched the focal anime and, in that case, also follows an inverse U-shaped pattern. And lastly, watching intensity of more than three hours a day increases the probability that a user watches a franchise extension immediately next after watching the focal media product, and this effect is stronger when the franchise extension is a sequel.

Regarding the relationship between watching intensity and interactive engagement, i.e., the production of UGC, we find that intermediate levels of watching intensity around two to four hours per day increase the number of recommendations and ratings a user produces compared to the baseline of watching less than an hour per day. At the same time, our results also reveal that excessive watching intensity (i.e., more than five hours a day) can have a negative effect on UGC submission in the case of forum posts. We also find that, conditional on submitting a rating, consumers who intensively watch the focal anime rate it higher, suggesting that watching intensity positively affects consumers' liking of a media product.

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 watching intensity 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 watching intensity, binge-watching, and online streaming. To the best of our knowledge, we are the first to study the relationship between watching intensity 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 review the relevant literature. In Sections 3 and 4, we describe our data, introduce our model and estimation approach. We present our results in Section 5. In Section 6, we discuss managerial implications and examine limitations and future research in the following section. Finally, we conclude by summarizing our findings in Section 8.

2 Relevant Literature

In this section, we draw from relevant streams of literature on customer engagement with a media franchise, watching intensity, and online movie streaming.

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).[9] 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 gen-

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

erating 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 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. Interactive engagement, on the other hand, is associated with extrinsic motivation and includes interactive experiences such as socialization and participation in a community facilitated by the consumption of a media product. For example, after watching 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 social media. 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.

2.2 Watching Intensity

We adopt a time-based definition of watching intensity: average number of hours of watching the focal media product per day (conditional on the completion of watching the focal media product). While this definition results in a continuous measure of watching intensity, in our empirical models (see Section 4.2), we estimate separate coefficients for different watching intensity levels. Low-intensity watching, by our definition, encompasses both appointment watching (on TV) and consumer-driven slow viewing of a series (through an OTT service); while high-intensity watching, by our definition, includes watching of both marathon releases (on TV) and consumer-driven intensive viewing of a series (through an OTT service).

We would like to point out that by our definition, watching intensively includes, but is not restricted to binge-watching, i.e., the practice of watching multiple episodes (of a series) in one sitting.[10] There is disagreement in previous literature on how much watching is considered binge-watching. Based on a survey of their users, Netflix defines binge-watching as watching at least two episodes in one sitting (Netflix 2013). 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. Schweidel and Moe (2016) and Lu et al. (2017) use process-level streaming data to define binge-watching. For example, Schweidel and Moe (2016) consider "the consumption of multiple episodes of a television series in a short period of time" as binge-watching. Other studies rely on respondents' perception of what is considered binge-watching without defining a specific amount (e.g., Devasagayam 2014; Pena 2015).

These definitions rely 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. To circumvent these obstacles, in this study, we

[10]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. In other words, 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. Thus a consumer watching a marathon release on TV would *not* count as binge-watching.

measure watching intensity based on the time spent watching a whole season. This definition is in line with the idea that watching a show very intensively is a violation of what is considered the norm, regular TV watching such as "appointment watching" or "linear watching."

The underlying mechanism that drives high-intensity watching is related to the concept of flow (e.g., Hoffman and Novak 1996), which describes a state of focused 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 high-intensity watching, few studies have focused on the consequences of high-intensity 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 watching intensity on consumer engagement with a media franchise.

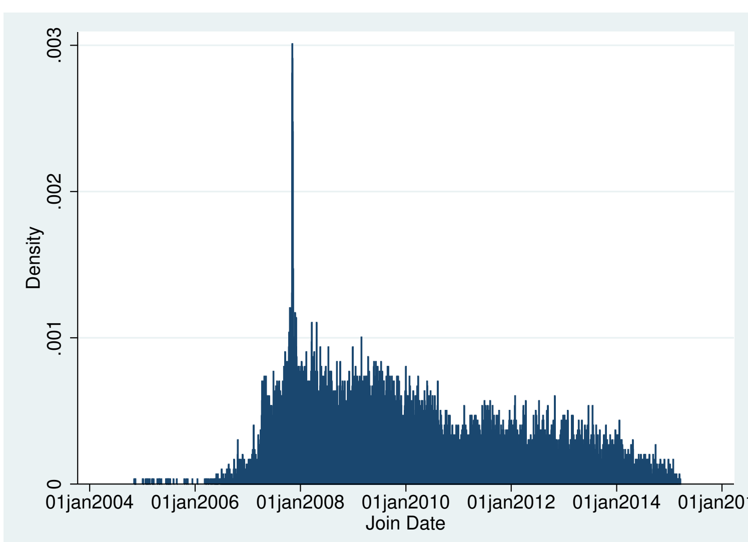
2.3 Online Streaming

Despite its wide popularity, research on online movie streaming is scarce. 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.

3 Data

Our data come from MyAnimeList.net. This website is a consumption-related online community where online interactions are based upon shared enthusiasm for a specific consumption activity (Kozinets 1999). It was created to allow anime fans to gather and share their excitement and opinions about animes. 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.

Figure 1: Dates Users Joined MyAnimeList.Net



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).[11] 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 season and the date they finished watching an anime season. We use the start and end dates to infer the beginning and end of a user's watch period for an anime season.

3.1 Self-Reported Watching Data

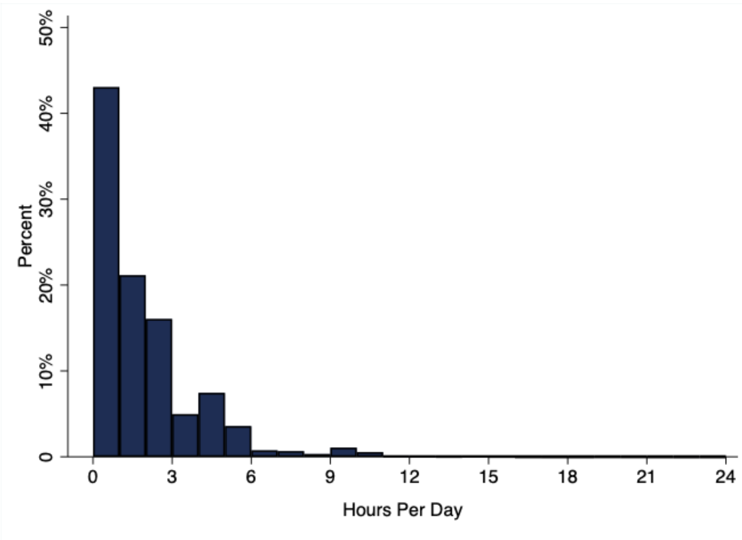
Our anime watching data are self-reported. Thus, accuracy in the reporting of anime adoptions could be a potential concern due to factors such as social desirability noted by previous literature on response bias in survey research (e.g., Furnham 1986; Fisher 1993; Steenkamp et al. 2010). However, in contrast to surveys, that usually provide incentives for participation and have participants answer previously-determined questions, users' self-reporting on anime-related behaviors on MyAnimeList.net is entirely voluntary. Therefore, there are no obvious incentives for them to falsely report their true anime watching behavior. Additionally, empirical evidence provided by Lovett and Staelin (2016) through a comparison of survey panelists' self-reported viewing data and the actual streaming data in the similar setting of TV shows supports that people tend to correctly report their actual watching behavior.

To further check the reliability of our self-reported anime watching data, we display the total number of hours per day users in our data reported having watched animes (conditional on watching) in Figure 2. Note that the number of hours in this figure includes *everything* the user watched, i.e., all animes watched that day (whether they belong to any franchise or not). The distribution is

[11] 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.

skewed with more than 40% of observations being for less than an hour of watch time. While there is heterogeneity in the number of hours per day, the data only contain a relatively small number of observations with watch times of more than six hours and essentially none with watch times of more than 11 hours.

Figure 2: Number of Hours Per Day



And lastly, we accessed data from the 2014 American Time Use Survey collected by the Department of Labor.[12]. Using these data, we created a figure showing the distribution of the number of hours individuals report watching TV per day. The distribution based on the 2014 American Time Use Survey (shown as Figure C-1 in Web Appendix C) exhibits a similar shape to one shown in Figure 2. Thus, we are confident that the self-reported adoption data are reliable in our context.

3.2 Estimation Samples

We scraped data on 370,000 individuals from the website. Not all users list start dates for (all or any) animes 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.[13] 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

[12] https://www.bls.gov/tus/data/datafiles_2014.htm

[13] 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.

3,000 days; (iii) observations for days on which individuals indicated to have watched animes for more than 24 hours or a single anime for more than 16 hours; (iv) observations with start dates before 2008 since, although the website was launched in 2004, its main activities did not start until mid 2007 (see Figure 1); (v) individuals with unknown geographic location; (vi) observations with start dates after the end of 2014. Using the remaining 47,557 individuals and 4,364 animes (1,872,404 user-anime combinations), we took the following steps to get to our final data.

First, we dropped animes for which it would take an individual less than 2 hours to watch the whole season. Table 2 shows the frequency distributions for the 4,364 animes with respect to their number of episodes and durations of a season in hours.[14] Movies, i.e., animes with one episode, or short anime series generally take less than 2 hours to be watched and thus cannot be watched at higher intensity levels. Note that, even if an individual watches 3 movies back to back, if they are not part of the same franchise, we do not consider this instance as intense watching. Therefore, looking at the right half of Table 2, we dropped 1,626 animes in the first step because their season duration was less than 2 hours.

Table 2: Number of Episodes in and Duration of a Season

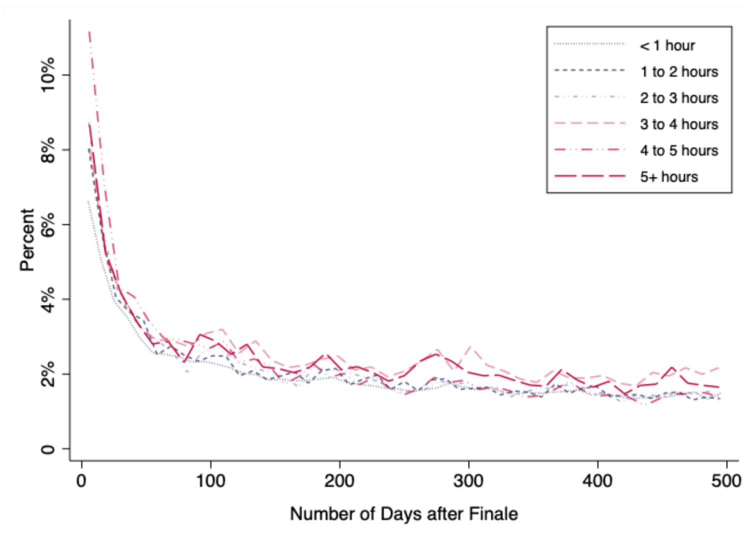
Number of Episodes	Freq.	Percent	Duration of Season (in Hours)	Freq.	Percent
1	9	.21	less than 1	722	16.54
2	766	17.55	1 - 2	904	20.71
3 - 7	. 940	21.54	2 - 3	311	7.13
8 - 11	178	4.08	3 - 4	132	3.02
12	541	12.40	4 - 5	590	13.52
13	426	9.76	5 - 6	353	8.09
14 - 27	767	17.58	6 - 10	331	7.48
28 - 56	559	12.81	10 - 15	426	9.76
57 and more	178	4.08	15 - 20	248	5.68
			20 and more	347	7.95

Second, we dropped user-anime combinations in which an individual did not watch the whole season. Even if a user intensively watches the first half of a season (and does not watch the second half of the season), her behavior might be different from someone who intensively watched and finished the whole season. To be able to attribute the difference in user behavior to the watching intensity and not to the completion of the whole season, we only consider cases in which the individual finished watching the whole season.

[14] A large number of animes have 13 or 26 episodes in a season.

And third, we only consider user-anime combinations in which users have the option to intensively watch the anime, but may not 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 3, we show the number of days (after the original airing of the last episode in a season) after which individuals, who watched the anime at different intensity levels, started to watch it. 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). After these steps, our final data sample for the empirical analysis related to interactive engagement contains 39,630 individuals and 2,467 animes with 739,969 user-anime combinations.[15]

Figure 3: Number of Days After Season Finale That Animes Were Watched (truncated at 500 days)



For personal engagement, we need to constrain the final data sample further. More specifically, we can only consider animes 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 animes that do not have any franchise extension, the data sample contains 37,516 individuals and 1,246 animes with 536,505 user-anime combinations, i.e., unique user-(focal)-anime combinations. Sometimes, animes have multiple types of franchise extensions (e.g., a spin-off and a summary). In such

[15]Because of missing values in one of our explanatory variables (popularity rank), the number of observations in the model estimation is 658,542.

cases, we model the adoption of each type of franchise extension as a separate potential adoption. Sometimes, animes 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 reasons, the number of observations in the model estimation is 641,424.

3.3 Definitions of Watching Intensity and Engagement Variables

We compute the watching intensity variable for each user-anime combination as follows: total duration of the anime season (measured in hours) divided by the number of days that it took the individual to watch all episodes of the anime season.[16] Thus, watching intensity is a continuous variable. In our main empirical analysis, we will use six dummy variables that capture the essence of the continuous watching intensity variable: whether a user spent less than 1 hour, between 1 to 2 hours, 2 to 3 hours, 3 to 4 hours, 4 to 5 hours, or more than 5 hours a day watching the anime season. In Section 5.3, we show that this simpler operationalization of watching intensity produces very similar results as using the continuous version of this variable.

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, watching an anime season intensively 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 watching intensity 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, watching intensively 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:

[16] Note that a user might have watched more than 3 hours on a Sunday, but it took her Monday to Friday to gradually watch the remaining 3 episodes (about 1 hour) and finish the season. Our data do not allow us to compute different watching intensities *within* a user-anime combination.

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 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 other two 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 forum posts and recommendations, we study whether the watching intensity affects the number of posts and recommendations, respectively. For forum posts, we also investigate whether watching intensity affects the average sentiment and average length of submitted forum posts. For ratings, we examine whether the watching intensity impacts whether an individual submits a rating and its valence.

3.4 Data Description

We present summary statistics for the $39,630$ individuals in our final sample in Table 3. 18,372 individuals in our final sample report their age. Among these individuals, the average age is 19 years. 42% of users are female and 41% of individuals are male with the remaining 17% of individuals not specifying their gender. 45% live in Europe, 32% come from North America, 8% from South America, 11% from Asia, and 4% from other geographies. Users, on average, have watched 1 anime during the last 30 days and a total of 75 animes over the course of their membership on the platform. Further, users, on average, started watching 31% and 3% of the animes on their watch lists on weekends and holidays, respectively.

Table 3: Descriptive Statistics

	Mean	Std. Dev.	Min	Median	Max	N
Age (If Disclosed)[a]	19.33	4.38	12.01	18.79	71.06	18,372
Number of Animes in Last 30 Days[a]	0.88	4.78	0	0	296	39,630
Total Number of Animes Watched	74.88	169.14	0	0	4,157	39,630

	Proportion in %	N
Gender		
Females	42	39,630
Males	41	39,630
Not Specified	17	39,630
Geography		
North America	32	39,630
South America	8	39,630
Europe	45	39,630
Asia	11	39,630
Other	4	39,630
Watched Animes During Weekend	31	39,630
Watched Animes During Holiday	3	39,630

[a] Variable is the average value for an individual during observation period.

Figure 4 shows the distribution of watching periods, i.e., the number of days between watching the first and last episode of an anime season, in our estimation sample. In 49% of the user-anime combinations, the individual watched a complete anime season within 5 days, with 27% of user-anime combinations being watched within a day or two. While Figure 4 does *not* account for the length of a season in terms of the number of episodes or the length of an episode (in minutes), it nevertheless shows the possibility that a significant portion of user-anime combinations might be watched intensively.

Figure 4: Watching Periods (truncated at 100 days)

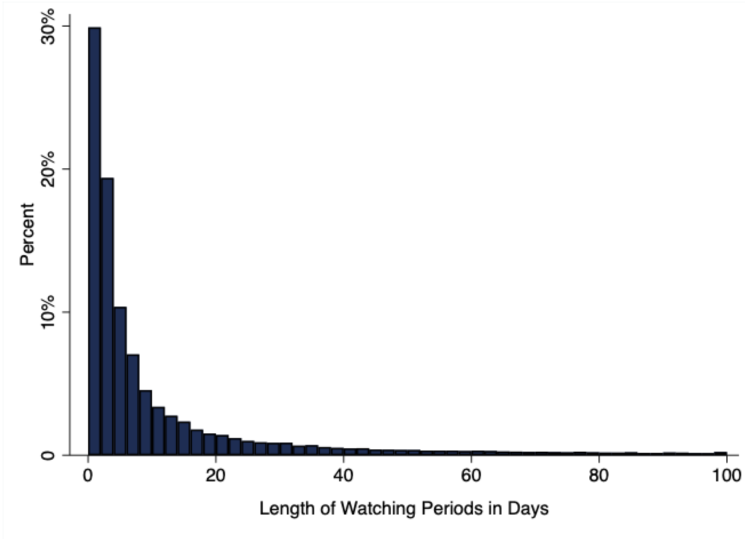
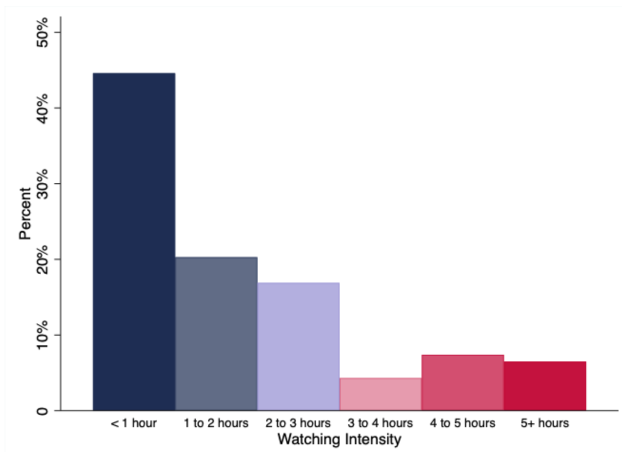


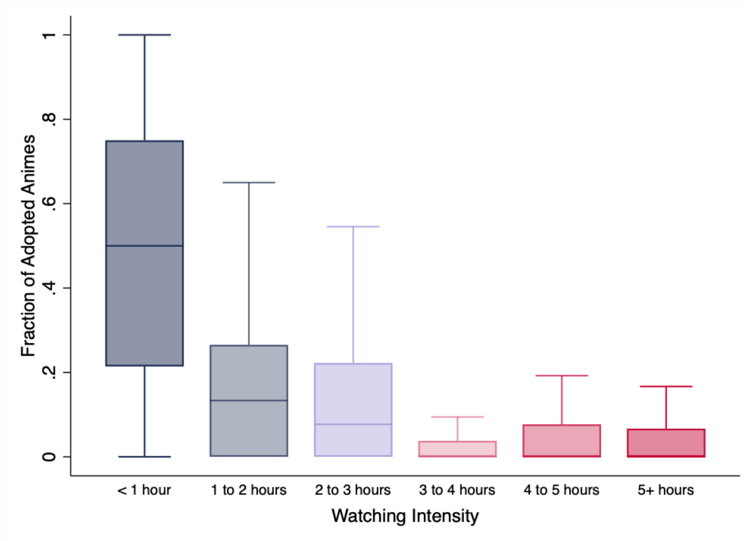
Figure 5 shows the distribution of the watching activity that was done at different intensity levels. In about 45% of user-anime combinations, users watch the anime for less than an hour each day, while users viewed the anime at the highest intensity, spending 5 or more hours per day watching it, in 7% of user-anime combinations.

Figure 5: Watching Intensity



The boxplots in Figure 6 show the fractions of adopted animes that were watched at each intensity level. The median user watches about 45% of adopted animes for less than an hour a day, about 18% of adopted animes for 1 to 2 hours a day, and about 10% of adopted animes for 2 to 3 hours a day. However, as the boxplots also show, there is significant variation in the fractions across users as shown by the large range of the 5th and 95th percentiles of the distributions. This empirical observation is consistent with previous findings (e.g., MarketCast 2013; Schweidel and Moe 2016).

Figure 6: Fraction of Users' Adopted Animes Watched at Each Intensity Level



Next, we discuss our engagement variables. Table 4 shows statistics for our personal engagement variables. We observe several patterns in the table. First, 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 observe the highest engagement when a sequel is available at the time of watching the focal anime for all three engagement variables. Second, watching intensity generally increases a user's likelihood of starting to watch a franchise extension, of finishing to watch it, and of watching it immediately next. However, for the first two engagement variables, the positive effect seems to diminish at the highest watching intensity levels. This observation highlights the potential non-linearity in the effect of watching intensity on personal engagement.

Table 4: Personal Engagement by Watching Intensity

	Watching Intensity of Focal Anime					
	< 1 hour	1 to 2 hours	2 to 3 hours	3 to 4 hours	4 to 5 hours	5+ hours
	Whether Franchise was Started (in %)					
Sequel & Available	66.5	75.7	76.2	80.2	73.4	75.2
Sequel & Not Available	54.0	56.6	54.0	61.4	48.6	58.4
Other Type & Available	30.5	33.7	33.5	33.1	33.8	30.0
Other Type & Not Available	32.9	33.9	31.8	35.7	29.2	31.5
	Whether Franchise was Finished (in %)					
Sequel & Available	57.7	67.9	66.8	73.1	70.6	69.6
Sequel & Not Available	49.1	54.4	51.9	52.7	53.0	51.3
Other Type & Available	17.6	20.6	17.8	29.4	22.8	21.0
Other Type & Not Available	21.3	24.1	20.6	27.6	22.6	22.1
	Whether Franchise was Started Next (in %)					
Sequel & Available	.4	.4	.6	1.7	6.6	7.1
Sequel & Not Available	-	-	-	-	-	-
Other Type & Available	.4	.4	.9	.6	2.8	3.5
Other Type & Not Available	-	-	-	-	-	-

In Table 5, we display 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 92.76% for ratings compared to 0.67% for forum posts and 0.18% for recommendations. In terms of forum posts, users who watch an anime for 3 to 4 hours per day are most likely to post on the discussion forum. Conditional on posting on the forum, users who watch an anime season intensively make longer and more negative posts. In terms of anime ratings, users who watch an anime season for more than 4 hours per day are less likely to submit a rating compared to those who watch it at a very slow rate (e.g., less than 1 hour per day), but, conditional on submitting a rating, rate it higher. We do not observe significant differences between users who watch intensively and users who watch slowly in their recommendation behaviors.

Table 5: Interactive Engagement by Watching Intensity

	Focal Anime Watching Intensity					
	< 1 hour	1 to 2 hours	2 to 3 hours	3 to 4 hours	4 to 5 hours	5+ hours
	Mean (Std. dev.)	Mean (Std. dev.)	Mean (Std. dev.)	Mean (Std. dev.)	Mean (Std. dev.)	Mean (Std. dev.)
Users' Forum Posts for Focal Anime						
Number of Posts	0.03	0.02	0.02	0.05	0.01	0.02
	(0.79)	(0.85)	(0.64)	(1.84)	(0.42)	(0.55)
Avg. Sentiment	0.16	0.17	0.17	0.12	0.14	0.12
	(0.26)	(0.25)	(0.25)	(0.27)	(0.27)	(0.27)
Avg. Number of Words	38.17	37.22	41.25	43.34	44.98	49.38
	(44.51)	(38.90)	(64.06)	(43.10)	(45.75)	(55.20)
Users' Recommendations for Focal Anime						
Number of Recommendations	0.00	0.00	0.00	0.00	0.00	0.00
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)
Users' Rating of Focal Anime						
Incidence (%)	92.5	93.6	92.9	93.3	92.1	91.2
Valence	7.77	7.93	7.94	8.26	7.95	8.08
	(1.54)	(1.48)	(1.49)	(1.42)	(1.50)	(1.50)

4 Models and Estimation

We investigate the relationship between the watching intensity and a consumer's personal and interactive media franchise engagement. Potential endogeneity of the watching intensity is a concern. We first discuss how we address this concern and then present our empirical specification.

4.1 Potential Endogeneity of Watching Intensity

Potential endogeneity of a user's decision on how intensively to watch an anime is a concern when estimating the effects of watching intensity on media franchise engagement. Omitted variables, i.e., variables that are not observed in the data but are correlated with an individual's watching intensity and influence their engagement, are the cause of the concern (see, e.g., Angrist and Pischke 2009). In this paper, we address endogeneity concerns by exploiting our unique and rich individual-level data that allow us to incorporate a large number of fixed effects to control for various types of omitted variables (see, e.g., Wooldridge 2001). Under the assumption that, conditional on the fixed effects (and control variables), the watching intensity decision is independent of the error term, the coefficient estimates for the watching intensity variable can be interpreted as causal.

The idea of the fixed effects approach is to partition the variation in watching intensity into that which is "clean" and that which is not and only use the clean portion of variation to estimate the effect of watching intensity (see Allenby and Rossi 2019). Our specification includes the following fixed effects: anime, month, user-genre, and user-weekend/holiday. In the following, we discuss potential sources of endogeneity concerns and how our fixed effects address them.

First, the anime fixed effects control for time- and user-invariant and anime-specific unobservables that might affect users' watching intensity. For example, some animes might have teasers at the end of each episode that induce individual viewers to watch more intensively.[17] Second, the month fixed effects control for anime- and user-invariant and month-specific unobservables that might influence individual users' watching intensity. For example, during summer months, individual users might have more leisure time that they can spend watching animes due to summer breaks and vacations. Third, the user-genre fixed effects control for each user's intrinsic preference for a specific genres of anime.[18] For example, a user might like romance and action animes the best, and tend to watch these two genres of animes more intensively. And lastly, the user-weekend/holiday fixed effects account for individual users' preference or lifestyle which may lead to the user watching animes more during weekdays or weekends/holidays.[19]

To summarize, we rely on fixed effects to control for various types of omitted variables that may cause endogeneity concerns. Conditional on the fixed effects (and other control variables), we interpret the estimated effects of the watching intensities as casual.

4.2 Empirical Specification

We start by describing how we model a consumer's personal engagement with a media franchise. The three personal engagement variables under study are operationalized as binary indicator variables and we estimate a linear probability model for each of the three dependent variables. Let $i = 1, ..., N$ denote consumers and $j = 1, ..., J$ denote animes. Consumer i's utility from personally

[17] Note that we also control for an anime's time-varying popularity and (perceived) quality by using rankings and ratings as control variables.

[18] MyAnimeList.net assigns each anime to 3 - 4 out of 44 available genres (e.g., action, comedy, fantasy). We use this genre assignment to construct the user-genre fixed effects.

[19] Note that users are located all around the world and that we use the local holidays and weekend definitions when constructing the variable.

engaging with the media franchise is given by

$$y_{ijt} = \alpha + \beta_1 B_{ij}^{1-2} + \beta_2 B_{ij}^{2-3} + \beta_3 B_{ij}^{3-4} + \beta_4 B_{ij}^{4-5} + \beta_5 B_{ij}^{5+} + \delta C_{ijt} + \gamma_j + \lambda_t + \tau_{ig} + \nu_{it} + \epsilon_{ijt} \quad (1)$$

The variable y_{ij} (whose realizations we observe in the data) equals 1 if user i, depending on the personal engagement variable of interest, watched at least one episode of the franchise extension, watched all the episodes of the franchise extension, or watched the franchise extension next without watching any other anime in between. In each case, y_{ij} equals 0 otherwise. B_{ij}^{k}, $k \in \{1-2, 2-3, 3-4, 4-5, 5+\}$, are dummy variables for watching intensity, indicating whether user i watched anime j for k number of hours on average per day. The baseline is set at less than one hour of watching anime j per day. By using this non-parametric specification to model the effects of watching intensity, we explore the potential non-linearity in the relationship between an individual user's watching intensity and their franchise engagement behaviors. 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[20] 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, γ_j contains anime fixed effects, λ_t contains calendar month fixed effects, τ_{ig} contains user-genre fixed effects, ν_{it} contains user-weekend/holiday fixed effects, and ϵ_{ij} is an error term following a standard normal distribution.

Furthermore, because both the type and the availability of a franchise extension play important roles in precisely pinning down the effects of watching intensity (see also Section 3.4), we estimate the effects of watching intensity conditional on the type and the availability of a franchise extension. That is, we partition our data into four scenarios: when a franchise extension is a sequel and was available at time of user i watching the focal anime season, when a franchise extension is not a sequel and was available, when a franchise extension is a sequel and was not available, and when a franchise is not a sequel and was not available, and estimate the model separately under these four scenarios.[21]

[20] 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.

[21] Note that for the personal engagement form of whether to watch a franchise extension *immediately next* after watching the focal anime, we condition on a franchise extension being available at the time of watching the focal anime. Thus, for that equation, we only estimate the effects of watching intensity under two scenarios: when the extension is a sequel, and when the extension is not a sequel.

And lastly, we describe how we model a consumer's interactive engagement with a media franchise. We operationalize the UGC variables as described in Section 3.3 and estimate linear regressions. For all UGC variables, consumer i's engagement is modeled as follows:

$$y_{ij}^{*} = \alpha + \beta_1 B_{ij}^{1-2} + \beta_2 B_{ij}^{2-3} + \beta_3 B_{ij}^{3-4} + \beta_4 B_{ij}^{4-5} + \beta_5 B_{ij}^{5+} + \delta C_{ij} + \gamma_j + \lambda_t + \tau_{ig} + \nu_{it} + \epsilon_{ij}. \quad (2)$$

B_{ij}^{k}, $k \in \{1-2, 2-3, 3-4, 4-5, 5+\}$, are the same dummy variables for watching intensity as we describe in equation (1) indicating whether user i watched anime j intensively for a number of k hours per day. 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. Lastly, ϵ_{ij} is the error term following a standard normal distribution.

5 Results

5.1 Personal Engagement

We present the parameter estimates from our personal engagement models in Table 6. Columns (i) to (iv) describe an individual's decision of whether to start watching a franchise extension (at any point in time) under varying scenarios of franchise extension type and availability. Recall that we estimate five coefficients allowing for non-linear effects of different watching intensities. Compared to the baseline of watching the focal anime for less than an hour a day, watching it for more than one hour per day increases an individual user's likelihood of starting to watch a franchise extension of the focal anime. As an illustration, in Figure 7, we plot the point estimates of the effects of different watching intensity levels on personal engagement variables for scenarios of franchise extension type and availability for which coefficients are statistically significant. As shown in Figures 7(a), (b), (c) and (d), the effect sizes generally follow an inverse U-shaped pattern with the largest effect size when the individual watches between three to five hours per day.

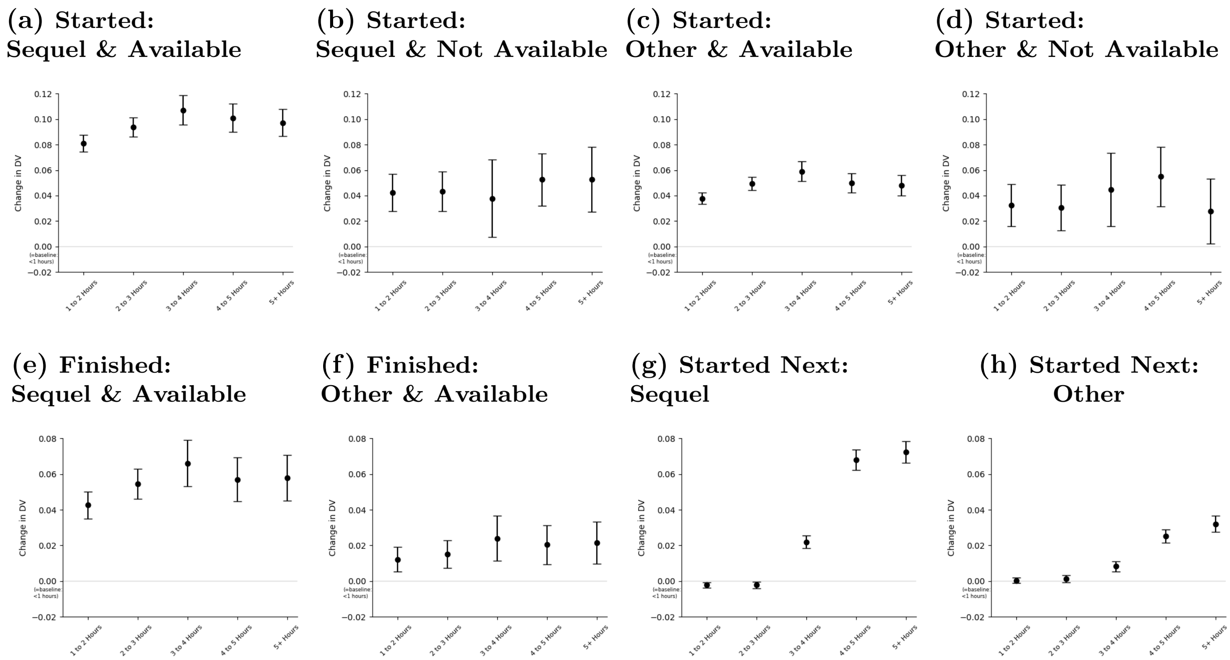
Table 6: Results - Personal Engagement

The models in columns (v) to (viii) 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 columns (ix) and (x) are 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.

Type of Franchise Extension Availability When Watching Focal Anime	Sequel Available	Sequel Not Available	Other Available	Other Not Available	Sequel Available	Sequel Not Available	Other Available	Other Not Available	Sequel Available	Other Available
	Whether Franchise Extension was									
	Started				Finished				Started Next	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
Average Daily Number of Hours Spent Watching the Focal Anime										
1 to 2 Hours	0.081***	0.042***	0.038***	0.032***	0.043***	0.002	0.012***	0.006	-0.002**	0.000
	(0.003)	(0.007)	(0.002)	(0.008)	(0.004)	(0.012)	(0.004)	(0.016)	(0.001)	(0.001)
2 to 3 Hours	0.094***	0.043***	0.050***	0.031***	0.055***	0.013	0.015***	-0.002	-0.002*	0.001
	(0.004)	(0.008)	(0.003)	(0.009)	(0.004)	(0.013)	(0.004)	(0.019)	(0.001)	(0.001)
3 to 4 Hours	0.107***	0.038*	0.059***	0.045**	0.066***	0.021	0.024***	0.019	0.022***	0.008***
	(0.006)	(0.016)	(0.004)	(0.015)	(0.007)	(0.025)	(0.007)	(0.029)	(0.002)	(0.002)
4 to 5 Hours	0.101***	0.053***	0.050***	0.055***	0.057***	-0.002	0.020***	-0.033	0.068***	0.025***
	(0.006)	(0.011)	(0.004)	(0.012)	(0.006)	(0.017)	(0.006)	(0.025)	(0.003)	(0.002)
5+ Hours	0.097***	0.053***	0.048***	0.028*	0.058***	0.015	0.022***	0.021	0.072***	0.032***
	(0.005)	(0.013)	(0.004)	(0.013)	(0.007)	(0.022)	(0.006)	(0.026)	(0.003)	(0.002)
Other Variables										
Wait Time Until Franchise Available		-0.014***		-0.008*		-0.007		0.008		
		(0.004)		(0.003)		(0.006)		(0.008)		
Popularity Rank[a,b]	-0.004	0.016	-0.024***	-0.045	-0.019*	-0.005	0.012	0.147**	0.000	0.003
	(0.007)	(0.019)	(0.004)	(0.025)	(0.009)	(0.030)	(0.006)	(0.055)	(0.002)	(0.002)
Community Rating[b]	0.060*	-0.036	0.136***	-0.153*	0.052	-0.102	-0.098**	0.047	-0.011	0.012
	(0.029)	(0.059)	(0.019)	(0.065)	(0.044)	(0.107)	(0.031)	(0.122)	(0.009)	(0.007)
Constant	0.229	0.798	-0.682***	1.816**	0.373	1.524	0.945***	-0.871	0.094	-0.104
	(0.236)	(0.493)	(0.157)	(0.558)	(0.363)	(0.892)	(0.258)	(1.097)	(0.072)	(0.054)
User-Genre FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Anime FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
User-Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	166,514	43,974	393,777	37,159	111,345	17,927	103,556	7,128	160,470	148,339
AIC	68,686.35	14,456.18	242,662.05	3,246.12	24,069.45	2,957.72	8,301.61	-1,843.70	-304,109.70	-341,694.08
BIC	68,756.51	14,525.71	242,738.23	3,314.31	24,136.80	3,020.07	8,368.44	-1,788.73	-304,039.80	-341,624.73
Log Likelihood	-34,336.18	-7,220.09	-121,324.02	-1,615.06	-12,027.73	-1,470.86	-4,143.80	929.85	152,061.85	170,854.04

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

Figure 7: Point Estimates for Different Levels of Watching Intensity



Watching an anime series for three to five hours a day fits into an evening after work or school. The inverse U-shaped pattern is consistent with consumers initially experiencing a stronger flow when watching the focal anime more intensively, while satiation and fatigue kick in after watching the same anime for several hours. Comparing across the four extension types and availability scenarios (sequel/available, sequel/not available, other type/available, other type/not available), the effect of watching intensity on the adoption of a franchise extension is the largest when the extension is a sequel and was available at time when the user watched the focal anime (column (i) compared to columns (ii) - (iv) in Table 6). This finding is consistent with our expectation that consumers tend to experience a stronger and more seamless flow effect when watching a sequel compared to watching other types of franchise extensions. 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 extension may have a different story line or center around different characters (e.g., “Better Call Saul,” a spin-off of “Breaking Bad,” tells the story of a lawyer who was a secondary character in “Breaking Bad”). As a result, it is natural for users to continue the flow after watching a season intensively by starting to watch the next season.

Next, we examine whether the watching intensity affects a user's probability of finishing to watch the franchise extension (conditional on starting to watch a franchise extension) in columns (v) to (viii) of Table 6. Interestingly, the watching intensity of a focal anime increases a user's probability of finishing to watch a franchise extension only if the extension was available for watching when the user watched the focal anime (see columns (vi) and (viii) in Table 6 and Figures 7(e) and (f)). In this case, we observe a similar inverse U-shaped pattern of the effect of watching intensity: the effect is the largest when the individual watches the focal anime for three to four hours a day. If the franchise extension was not available at the time when the user watched the focal anime, the watching intensity does not have a significant effect on the user's probability of finishing to watch the extension. One explanation that can account for these results is that the positive flow effect due to intensive watching is transient. In other words, it disappears if the user cannot adopt the franchise extension right away due to its unavailability.

Lastly, we examine how the watching intensity of the focal anime affects the more immediate media watching behavior. In columns (ix) and (x) of Table 6, we pin down how the watching intensively affects a user's probability of watching a franchise extension (compared to an unrelated media product) *immediately* next (conditional on a franchise extension being available at the time of watching the focal media product). We find that individuals who watch a focal anime season for more than three hours a day are more likely to watch a franchise extension immediately next than individuals who watch at a slower pace, and that this effect is stronger when the franchise extension is a sequel (see also Figures 7(g) and (h)). This result again speaks to the consumer's tendency to continue the flow created by watching the focal media product intensively. A natural way to do so is to watch its franchise extension if one is available. Relative to other types of franchise extensions, sequels benefit more from the effect of watching intensity because of the stronger flow they create.

To summarize, watching intensity of more than one hour per day increases a user's probability of watching a franchise extension (at any point in time in the future). Interestingly, the positive effects of watching intensity exhibit an inverse U-shaped pattern with the largest effects around three to five hours of watching per day. Further, conditional on starting to watch a franchise extension, watching intensity increases the probability that a user finishes to watch the extension only if it was available at the time when the user watched the focal anime. In this case, we find similar inverse U-shaped effects of watching intensity with the largest effect around three to four hours of watching per day. And lastly, watching intensity of more than three hours a day increases the probability that a user watches a franchise extension immediately next after watching the focal media product.

5.2 Interactive Engagement

We now discuss the results for interactive engagement shown in Table 7. For illustrative purposes, in Figure 8, we plot the point estimates of the effects of different watching intensity levels on interactive engagement variables that are significantly impacted by watching intensity. Columns (i) to (iii) in Table 7 display the coefficients for estimations related to forum posts. Our results in columns (i) indicate that watching intensity does not affect the number of forum posts a user will write about the focal anime with the exception of very intensive watching behavior: if a user watches the focal anime more than five hours a day, she will make significantly *fewer* forum posts about the anime. At this high level of watching intensity, satiation and potentially fatigue are likely reasons for the smaller number of forum posts. Conditional on contributing to the discussion forum, the watching intensity does not affect the valence or length of posts.

Table 7: Results - Interactive Engagement

The models in column (ii) and (iii) 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 (v) is estimated using user-anime observations which the user rated, i.e., conditional on a rating.

	Forum Posts			Recommendations	Ratings	
	Number	Valence	Length	Number	Incidence	Valence
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Average Daily Number of Hours Spent Watching Focal Anime						
1 to 2 Hours	0.000	0.009	-0.031	0.000	0.005***	0.216***
	(0.000)	(0.023)	(0.085)	(0.000)	(0.001)	(0.005)
2 to 3 Hours	-0.001	-0.032	-0.052	0.001**	0.006***	0.286***
	(0.001)	(0.036)	(0.114)	(0.000)	(0.001)	(0.006)
3 to 4 Hours	0.001	0.006	0.056	0.001*	0.006***	0.293***
	(0.001)	(0.042)	(0.149)	(0.000)	(0.001)	(0.009)
4 to 5 Hours	0.000	-0.032	0.015	0.000	0.006***	0.280***
	(0.001)	(0.050)	(0.138)	(0.000)	(0.001)	(0.009)
5+ Hours	-0.002*	-0.031	0.145	0.000	0.004***	0.258***
	(0.001)	(0.048)	(0.181)	(0.000)	(0.001)	(0.010)
Other Variables						
Ever-Made-a-Forum-Post Indicator	0.002	-0.065	0.046			
	(0.002)	(0.055)	(0.172)			
Time Since Last Forum Post[a]	-0.001***	0.000	0.041			
	(0.000)	(0.010)	(0.030)			
Number of Forum Posts[a,c]	0.003***	0.032	-0.098			
	(0.001)	(0.021)	(0.065)			
Number of Ratings[a,c]				0.000		
				(0.000)		
Number of Recommendations[a,c]					0.000	-0.004
					(0.001)	(0.003)
Popularity Rank[a,b]	0.003**	-0.122**	0.500**	-0.000	0.004***	0.063***
	(0.001)	(0.046)	(0.153)	(0.000)	(0.001)	(0.010)
Community Rating[b]	0.004	0.338	-0.304	0.001	0.008*	0.300***
	(0.003)	(0.199)	(0.537)	(0.001)	(0.004)	(0.036)
Constant	-0.048	-2.138	3.526	-0.003	0.848***	5.024***
	(0.024)	(1.695)	(4.414)	(0.007)	(0.034)	(0.298)
User-Genre FE	Yes	Yes	Yes	Yes	Yes	Yes
Anime FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year FE	Yes	Yes	Yes	Yes	Yes	Yes
User-Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	658,542	1,641	1,641	658,542	658,542	610,567
AIC	-1,356,748.58	-2,326.81	1,441.50	-2,825,479.93	-1,020,379.42	1,727,389.35
BIC	-1,356,634.60	-2,272.78	1,495.53	-2,825,388.75	-1,020,288.24	1,727,479.93
Log Likelihood	678,384.29	1,173.40	-710.75	1,412,747.97	510,197.71	-863,686.68

Clustered standard errors in parentheses.

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

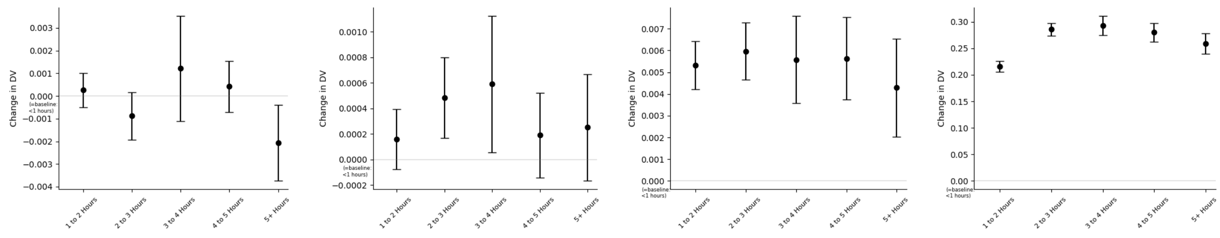
[a] Measured on logarithmic scale.

[b] Of focal season.

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

Figure 8: Point Estimates for Different Levels of Watching Intensity

(a) Number of Forum Posts **(b) Number of Recommendations** **(c) Rating Incidence** **(d) Rating Valence**



Column (vi) in Table 7 shows the results for recommendations – another form of 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. As shown in Figure 8(b), the familiar inverse U-shaped pattern emerges: watching two to four hours a day significantly increases the number of recommendations a user submits compared to watching more or less intensively. Albeit we acknowledge that the effect size is small.

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 observable by everybody, just like the other two 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 (iv) and (v) in Table 7 (and illustrated in Figure 8(c) and (d)) again show an inverse U-shaped pattern in the effects of watching intensity: if an individual watches a focal anime for two to four hours a day, she is significantly more likely to rate the focal media product. Furthermore, conditional on submitting a rating, the effect of watching intensity on the valence of the rating is the largest for users who watch two to four hours day. We believe that this result suggests that watching intensity increases consumers' liking of an anime (compared to the baseline of watching less than an hour a day). This finding is consistent with previous research which suggests that bingeing induces loyalty and fandom-like behavior (Devasagayam 2014, Jenner 2015). However, at the same time, our results also show that too intensive watching of more than four hours a day decreases this effect, likely due to satiation and potentially fatigue, compared to more intermediate levels of watching intensity.

In summary, intermediate levels of watching intensity (in our case, around two to four hours per day) increase the quantity of UGC a user produces compared to the baseline case of watching less than one hour per day. However, excessively high levels of watching intensity (more than five hours per day) result in less UGC production in the case of forum posts. Our results also reveal that consumers who intensively watch the focal anime rate it higher conditional on submitting a rating, suggesting that watching intensity positively affects consumers' liking of a media product.

5.3 Robustness Checks

In this section, we demonstrate the robustness of our results with respect to using a different operationalization of the watching intensity variable in the model and a different model specification. In the first robustness check, we include the continuous version of the watching intensity variable in the model, but estimate separate coefficients for each of the six hourly intervals. This specification utilizes more granular information as naturally contained in the continuous watching intensity measure (compared to the dummy variable operationalization in our main analysis) and also allows for potential non-linearity in the effects without assuming a specific functional form.

Formally, we estimate the following equations for personal and interactive engagements, respectively:

$$\begin{aligned} y_{ijt} = \alpha &+ \beta_1 B_{ij}^{<1} \cdot w_{ij} + \beta_2 B_{ij}^{1-2} \cdot w_{ij} + \beta_3 B_{ij}^{2-3} \cdot w_{ij} \\ &+ \beta_4 B_{ij}^{3-4} \cdot w_{ij} + \beta_5 B_{ij}^{4-5} \cdot w_{ij} + \beta_6 B_{ij}^{5+} \cdot w_{ij} \\ &+ \delta C_{ijt} + \gamma_j + \lambda_t + \tau_{ig} + \nu_{it} + \epsilon_{ijt} \end{aligned} \tag{3}$$

and

$$\begin{aligned} y_{ij}^* = \alpha &+ \beta_1 B_{ij}^{<1} \cdot w_{ij} + \beta_2 B_{ij}^{1-2} \cdot w_{ij} + \beta_3 B_{ij}^{2-3} \cdot w_{ij} \\ &+ \beta_4 B_{ij}^{3-4} \cdot w_{ij} + \beta_5 B_{ij}^{4-5} \cdot w_{ij} + \beta_6 B_{ij}^{5+} \cdot w_{ij} \\ &+ \delta C_{ij} + \gamma_j + \lambda_t + \tau_{ig} + \nu_{it} + \epsilon_{ij}. \end{aligned} \tag{4}$$

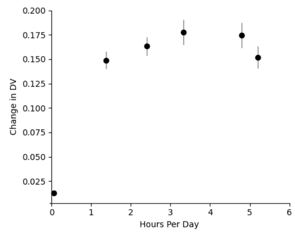
B_{ij}^k, $k \in \{<1, 1-2, 2-3, 3-4, 4-5, 5+\}$, are dummy variables for watching intensity indicating whether user i watched anime j for k number of hours per day (similar to the dummy variables we described in equation (1)). w_{ij} is the number of hours per day user i spent watching anime j. The associated coefficients, e.g., β_1, β_2, β_3, β_4, β_5, and β_6, estimate the marginal effect of watching intensity for each of the six hourly intervals separately. All remaining variables are defined as in equations (1) and (2).

Tables A-1 and A-2 in Web Appendix A show the coefficient estimates. The results are largely consistent with the results from our main analysis. For personal engagement, watching intensity increases a user's probability of starting to watch a franchise extension (at any point in time in the future) for all six hourly intervals. However, watching intensity only positively affects a user's likelihood of finishing to watch a franchise extension when the extension was available at the time when the user watched the focal anime. And lastly, watching intensity of more than three hours a day increases a user's likelihood of watching a franchise extension immediately next after watching the focal media product. For interactive engagement, the effect of watching intensity on UGC production depends on the type of UGC: it decreases the number of forum posts but increases the recommendation and rating submissions. Conditional on submitting a rating, it also positively affects rating valence.

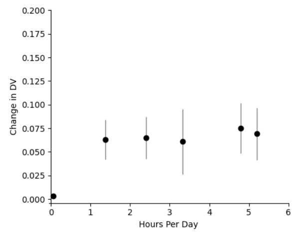
It is important to recognize that the estimated coefficients for each level of watching intensity indicate the slope of the effect of watching intensity on the dependent variable during each of the six hourly intervals. By comparing the magnitudes of these coefficients, we can determine whether the marginal effect of watching intensity (e.g., another 6 minutes or 0.1 hour) on the dependent variable increases or decreases as we move from one hourly interval of watching intensity to the next. However, these coefficients do *not* directly translate to a change in the level of engagement across the hourly watching intensity intervals. To understand the absolute changes in engagement at each intensity level, we calculate the predicted change in the dependent variable at the median value of watching intensity for each hourly interval. When plotting these changes in Figures 9 and 10, we observe the familiar inverse U-shaped effects of watching intensity similar to those displayed in Figures 7 and 8.

Figure 9: Predicted Change in Personal Engagement for Median Watching Intensity by Hourly Interval

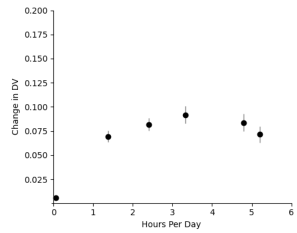
(a) Started: Sequel & Available



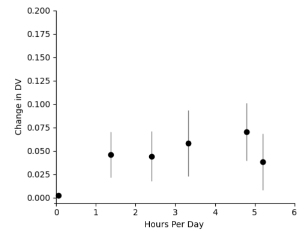
(b) Started: Sequel & Not Available



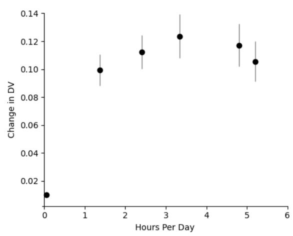
(c) Started: Other & Available



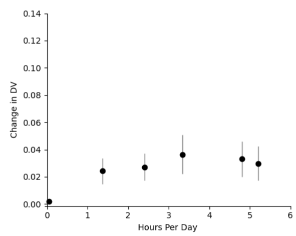
(d) Started: Other & Not Available



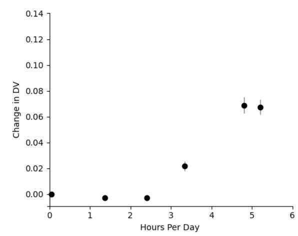
(e) Finished: Sequel & Available



(f) Finished: Other & Available



(g) Started Next: Sequel



(h) Started Next: Other

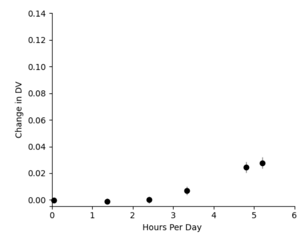
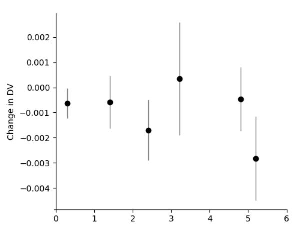
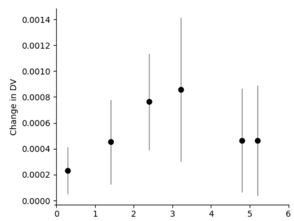


Figure 10: Predicted Change in Interactive Engagement for Median Watching Intensity by Hourly Interval

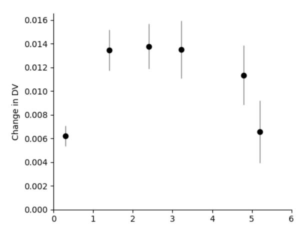
(a) Number of Forum Posts



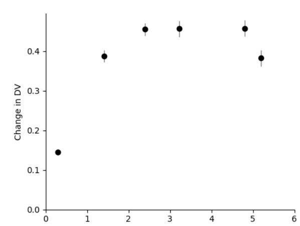
(b) Number of Recommendations



(c) Rating Incidence



(d) Rating Valence



In a second robustness check, we also utilize the continuous watching intensity variable and assume that it enters our model linearly and quadratically, i.e.,

$$y_{ijt} = \alpha + \beta_1 w_{ij} + \beta_2 w_{ij}^2 + \delta C_{ijt} + \gamma_j + \lambda_t + \tau_{ig} + \nu_{it} + \epsilon_{ijt} \tag{5}$$

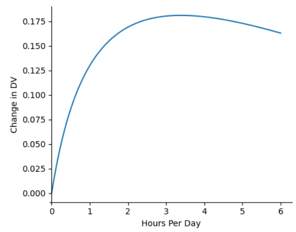
and

$$y_{ij}^* = \alpha + \beta_1 w_{ij} + \beta_2 w_{ij}^2 + \delta C_{ij} + \gamma_j + \lambda_t + \tau_{ig} + \nu_{it} + \epsilon_{ij}. \tag{6}$$

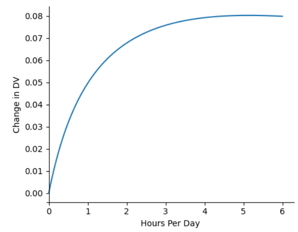
The coefficient estimates are shown in Tables B-1 and B-2 in Web Appendix B and Figures 11 and 12 display the familiar illustrations exhibiting an inverse U-shaped pattern (with the exception of Figures 11(g) and (h) just as in our main analysis).

Figure 11: Effects of Watching Intensity on Personal Engagement

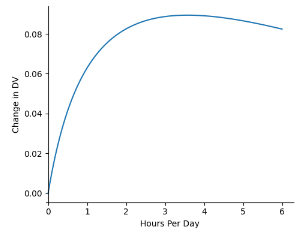
(a) Started: Sequel & Available



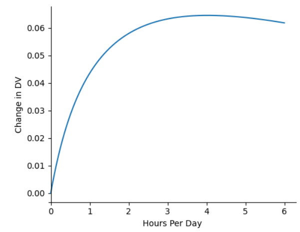
(b) Started: Sequel & Not Available



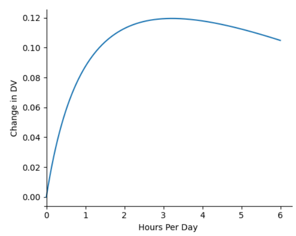
(c) Started: Other & Available



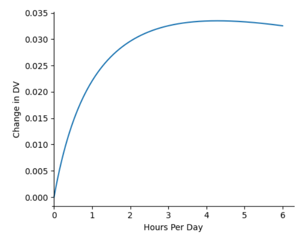
(d) Started: Other & Not Available



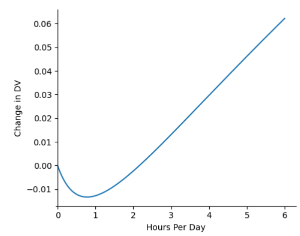
(e) Finished: Sequel & Available



(f) Finished: Other & Available



(g) Started Next: Sequel



(h) Started Next: Other

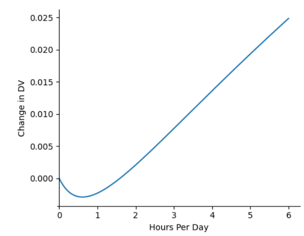
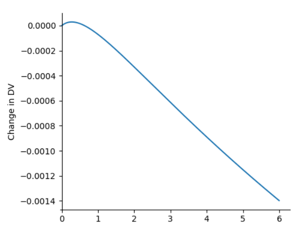
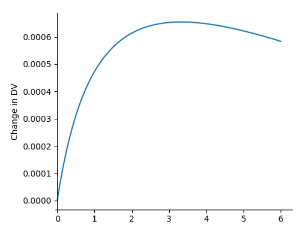


Figure 12: Effects of Watching Intensity on Interactive Engagement

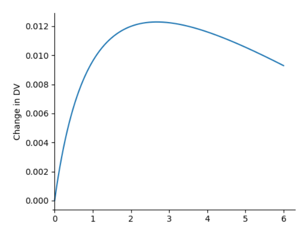
(a) Number of Forum Posts



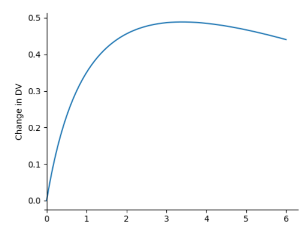
(b) Number of Recommendations



(c) Rating Incidence



(d) Rating Valence



6 Managerial Implications

Our results offer important managerial implications for TV channels and online streaming platforms. First, watching a media product for more than an hour a day (compared to watching it for less than an hour day, e.g., once a week on a traditional schedule) has overall positive effects on both personal and interactive engagement with the media franchise. To put it differently, while the magnitudes of the effects of watching intensity vary depending on whether an individual watches a media product for, e.g., 1-2 or 3-4 hours a day, the effects of higher watching intensities are all positive compared to watching a media product less than an hour a day. This finding suggests that content providers should make larger amounts of content available at once.

Second, the generally positive effect of watching intensity on personal engagement suggests that content providers can use watching intensity of the current season as a reliable predictor for the success of future franchise extensions in addition to the viewer count of the current season. This information can be particularly useful when the decision of renewing a show has to be made right after the opening weekend, which is the case for many streaming platforms.[22]

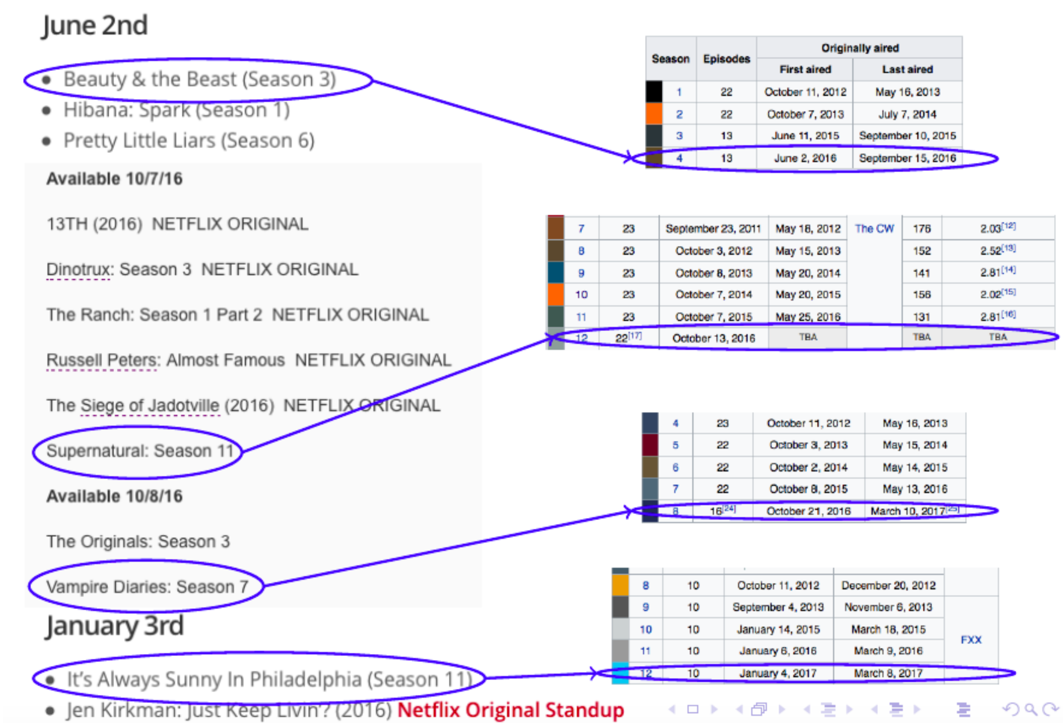
Third, taking a closer look at our results, the effect of watching intensity on personal and interactive engagement does not exhibit a straightforward linear relationship. Rather, we find inverse U-shaped effects of watching intensity on several key engagement measures with the largest impact typically found in the interval of 2 to 4 hours of watching an anime per day. This finding provides a rationale for the recently increasing popularity of mini series, a format that is longer than a movie but shorter than a typical season and can be finished in 6 to 8 hours of watching (e.g., on a weekend), right on the sweet spot when the maximum effect of watching intensity would be induced. This finding also validates the content release strategy of dropping the first few episodes of a new season all at once to hook the audience and then switch to a more linear fashion of releasing the remaining episodes one by one. For example, Amazon commonly drops the first three episodes of a season at once and then switches to a weekly release schedule (e.g., seasons 2 and 3 of "The Boys," seasons 1 and 2 of "Wheel of Time").[23]

Fourth, watching intensity can boost viewership of franchise extensions. However, the availability of the franchise extension plays a crucial role. Media content providers have started to recognize this by making prior seasons available (for intensive viewing) shortly before the release of the next season. Figure 13 shows several examples from Netflix.

[22]Industry experts confirmed this practice in conversations.

[23]Zhao et al. (2023) also suggest such a release strategy for online fiction.

Figure 13: Examples of Release Dates on Netflix



Fifth, watching intensity does not boost viewership of all franchise extensions equally. Sequels benefit from a prior season that is available for intensive viewing more than other types of franchise extensions because sequels continue the flow viewers experience when watching the prior season intensively. Franchise extensions that differ significantly in story lines and/or main characters may not attract viewers who watched the prior season intensively. The historical lackluster performance of spin-offs speaks to the importance of staying close to the successful original series when developing franchised extensions.[24]

And lastly, watching more intensively induces liking and content providers can target and encourage users who watched a show more intensively to generate favorable word-of-mouth.

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.

[24] 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.

In our data, we do not observe purchases of such ancillary products. It is left for future research to investigate whether the watching intensity affects such purchases. Second, even though we provide evidence for the validity of our data, measurement error in watching intensity 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 watching intensity.

Third, some TV shows or movies have a higher probability of being watched intensively than others due to their creative content, which we do not consider in our model. It is left for future research to study whether and how different content characteristics make a show more or less suitable for intensive viewing. Fourth, watching intensity of the media franchise can also be impacted by the watching intensity of the focal show. Our data only allows us to observe whether a user has started and finished watching a particular media franchise, and not the intensity of watching the franchise. More granular data on the intensity with which users watch the franchise would add further depth and nuance to our understanding of users' engagement. And lastly, watching intensity may differ significantly depending on the methods or channels of watching such as online streaming websites, streaming platforms, DVDs, or piracy websites. 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 individuals' watching intensity.

8 Conclusion

With the introduction of high-speed Internet during the last 15 years, watching media products intensively – also known as binge-watching – has become very common. An open empirical question is whether the watching intensity has implications for user engagement compared to the traditional, linear way of watching. In this paper, using novel data coming from an online anime platform containing information on individual users' adoptions of different animes and their UGC, we examine the relationship between watching intensity and consumers' engagement with a media franchise as related to UGC 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 watching intensity on user engagement with a media franchise.

Our results show that watching intensity increases the probability that a user watches a franchise extension and that the positive effects exhibit an interesting inverse U-shaped pattern with the largest effect around three to five hours per day. However, conditional on starting to watch a franchise extension, watching intensity only increases the probability that a user finishes to watch it if the extension was available at the time when the user watched the focal media series. We also find that watching intensity increases the probability that a consumer watches a franchise extension immediately after watching the focal media product if the user watched the focal media series for more than three hours per day. We believe these effects are driven by the balance between flow and satiation, two forces created by watching intensity but operating in opposite directions. Regarding interactive engagement, our results suggest excessive watching (i.e., more than five hours per day) decreases the number of forum posts a user writes, providing partial support for the avoidance tendency of binge-watchers proposed and documented in previous literature. However, intermediate levels of watching intensity positively affect the submission of recommendations and ratings, the most dominant form of UGC in our empirical context. Moreover, we also find that intermediate watching intensity increases rating valence conditional on rating submission.

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Web Appendix A:
Continuous Operationalization of Watching Intensity

Table A-1: Results - Personal Engagement

The models in columns (v) to (viii) 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 columns (ix) and (x) are 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.

Type of Franchise Extension Availability When Watching Focal Anime	Sequel Available	Sequel Not Available	Other Available	Other Not Available	Sequel Available	Sequel Not Available	Other Available	Other Not Available	Sequel Available	Other Available
	Whether Franchise Extension was									
	Started				Finished				Started Next	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
Average Daily Number of Hours Spent Watching the Focal Anime										
<1 Hour[a]	0.223***	0.057**	0.104***	0.039	0.176***	0.027	0.038***	0.055	-0.002	-0.003
	(0.009)	(0.022)	(0.006)	(0.027)	(0.012)	(0.035)	(0.010)	(0.053)	(0.002)	(0.002)
1 to 2 Hours[a]	0.172***	0.073***	0.080***	0.053***	0.115***	0.015	0.028***	0.031	-0.003**	-0.001
	(0.005)	(0.012)	(0.004)	(0.015)	(0.007)	(0.020)	(0.006)	(0.030)	(0.001)	(0.001)
2 to 3 Hours[a]	0.133***	0.053***	0.067***	0.036**	0.092***	0.018	0.022***	0.015	-0.002*	0.000
	(0.004)	(0.009)	(0.003)	(0.011)	(0.005)	(0.015)	(0.004)	(0.023)	(0.001)	(0.001)
3 to 4 Hours[a]	0.121***	0.041***	0.063***	0.040**	0.084***	0.020	0.025***	0.027	0.015***	0.005***
	(0.005)	(0.012)	(0.003)	(0.012)	(0.005)	(0.020)	(0.005)	(0.024)	(0.001)	(0.001)
4 to 5 Hours[a]	0.099***	0.043***	0.048***	0.040***	0.067***	0.004	0.019***	-0.007	0.039***	0.014***
	(0.004)	(0.008)	(0.003)	(0.009)	(0.004)	(0.012)	(0.004)	(0.019)	(0.002)	(0.001)
5+ Hours[a]	0.083***	0.038***	0.039***	0.021*	0.058***	0.008	0.016***	0.020	0.037***	0.015***
	(0.003)	(0.008)	(0.002)	(0.008)	(0.004)	(0.013)	(0.004)	(0.017)	(0.002)	(0.001)
Other Variables										
Wait Time Until Franchise Available		-0.015***		-0.008*		-0.008		0.008		
		(0.004)		(0.003)		(0.006)		(0.008)		
Popularity Rank[a,b]	-0.003	0.019	-0.023***	-0.045	-0.020*	-0.004	0.012	0.145**	0.000	0.003
	(0.007)	(0.019)	(0.004)	(0.025)	(0.009)	(0.030)	(0.006)	(0.055)	(0.002)	(0.002)
Community Rating[b]	0.054	-0.041	0.133***	-0.157*	0.047	-0.104	-0.100**	0.036	-0.011	0.012
	(0.029)	(0.059)	(0.019)	(0.065)	(0.044)	(0.108)	(0.031)	(0.122)	(0.009)	(0.007)
Constant	0.200	0.810	-0.691***	1.834**	0.354	1.529	0.943***	-0.788	0.093	-0.104
	(0.237)	(0.493)	(0.157)	(0.558)	(0.365)	(0.893)	(0.258)	(1.094)	(0.072)	(0.054)
User-Genre FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Anime FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
User-Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	166,514	43,974	393,777	37,159	111,345	17,927	103,556	7,128	160,470	148,339
AIC	67,691.34	14,440.46	242,245.90	3,243.26	23,632.70	2,959.50	8,285.07	-1,843.51	-304,179.89	-341,655.35
BIC	67,771.52	14,518.68	242,332.97	3,319.96	23,709.66	3,029.64	8,361.45	-1,781.67	-304,100.01	-341,576.10
Log Likelihood	-33,837.67	-7,211.23	-121,114.95	-1,612.63	-11,808.35	-1,470.75	-4,134.54	930.76	152,097.95	170,835.68

Clustered 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: Results - Interactive Engagement

The models in column (ii) and (iii) 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 (v) is estimated using user-anime observations which the user rated, i.e., conditional on a rating.

	Forum Posts			Recommendations	Ratings	
	Number	Valence	Length	Number	Incidence	Valence
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Average Daily Number of Hours Spent Watching Focal Anime						
<1 Hour[a]	-0.003*	0.037	0.174	0.001*	0.018***	0.556***
	(0.001)	(0.067)	(0.227)	(0.000)	(0.002)	(0.015)
1 to 2 Hours[a]	-0.001	0.031	0.036	0.001**	0.012***	0.442***
	(0.001)	(0.034)	(0.138)	(0.000)	(0.001)	(0.009)
2 to 3 Hours[a]	-0.001**	-0.010	-0.002	0.001***	0.009***	0.372***
	(0.001)	(0.029)	(0.111)	(0.000)	(0.001)	(0.007)
3 to 4 Hours[a]	0.000	0.014	0.080	0.001**	0.008***	0.317***
	(0.001)	(0.030)	(0.101)	(0.000)	(0.001)	(0.007)
4 to 5 Hours[a]	0.000	-0.010	0.042	0.000*	0.006***	0.261***
	(0.000)	(0.032)	(0.089)	(0.000)	(0.001)	(0.006)
5+ Hours[a]	-0.002**	-0.005	0.101	0.000*	0.005***	0.211***
	(0.001)	(0.025)	(0.101)	(0.000)	(0.001)	(0.006)
Other Variables						
Ever-Made-a-Forum-Post Indicator	0.002	-0.067	0.039			
	(0.002)	(0.055)	(0.174)			
Time Since Last Forum Post[a]	-0.001***	0.000	0.040			
	(0.000)	(0.010)	(0.030)			
Number of Forum Posts[a,c]	0.003***	0.033	-0.097			
	(0.001)	(0.021)	(0.065)			
Number of Ratings[a,c]				0.000		
				(0.000)		
Number of Recommendations[a,c]					0.000	-0.003
					(0.001)	(0.003)
Popularity Rank[a,b]	0.003**	-0.122**	0.505**	0.000	0.004***	0.065***
	(0.001)	(0.046)	(0.154)	(0.000)	(0.001)	(0.010)
Community Rating[b]	0.004	0.332	-0.320	0.001	0.007	0.288***
	(0.003)	(0.200)	(0.535)	(0.001)	(0.004)	(0.035)
User-Genre FE	Yes	Yes	Yes	Yes	Yes	Yes
Anime FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year FE	Yes	Yes	Yes	Yes	Yes	Yes
User-Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	658,542	1,641	1,641	658,542	658,542	610,567
AIC	-1,356,756.70	-2,324.99	1,441.91	-2,825,488.34	-1,020,621.29	1,724,722.90
BIC	-1,356,631.32	-2,265.55	1,501.34	-2,825,385.76	-1,020,518.71	1,724,824.80
Log Likelihood	678,389.35	1,173.49	-709.96	1,412,753.17	510,319.64	-862,352.45

Clustered 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:
Linear and Quadratic Specification of Watching Intensity

Table B-1: Results - Personal Engagement

The models in columns (v) to (viii) 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 columns (ix) and (x) are 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.

Type of Franchise Extension Availability When Watching Focal Anime	Sequel Available	Sequel Not Available	Other Available	Other Not Available	Sequel Available	Sequel Not Available	Other Available	Other Not Available	Sequel Available	Other Available
	Whether Franchise Extension was									
	Started				Finished				Started Next	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
Average Daily Number of Hours Spent Watching the Focal Anime										
Hours Watching Per Day[a]	0.245***	0.089***	0.118***	0.080***	0.166***	0.063*	0.040***	0.039	-0.046***	-0.012***
	(0.008)	(0.018)	(0.005)	(0.021)	(0.010)	(0.029)	(0.008)	(0.043)	(0.003)	(0.002)
Hours Watching Per Day Squared[a]	-0.083***	-0.024**	-0.039***	-0.025*	-0.058***	-0.029*	-0.012**	-0.019	0.040***	0.013***
	(0.004)	(0.009)	(0.003)	(0.010)	(0.004)	(0.014)	(0.004)	(0.020)	(0.002)	(0.001)
Other Variables										
Wait Time Until Franchise Available		-0.016***		-0.008*		-0.009		0.008		
		(0.004)		(0.003)		(0.006)		(0.008)		
Popularity Rank[a,b]	-0.003	0.019	-0.023***	-0.045	-0.019*	-0.003	0.012	0.147**	0.000	0.003
	(0.007)	(0.019)	(0.004)	(0.025)	(0.009)	(0.030)	(0.006)	(0.055)	(0.002)	(0.002)
Community Rating[b]	0.054	-0.041	0.133***	-0.157*	0.047	-0.111	-0.100**	0.042	-0.011	0.012
	(0.029)	(0.059)	(0.019)	(0.065)	(0.044)	(0.108)	(0.031)	(0.122)	(0.009)	(0.007)
Constant	0.203	0.807	-0.692***	1.830**	0.357	1.568	0.942***	-0.839	0.095	-0.103
	(0.236)	(0.493)	(0.157)	(0.558)	(0.362)	(0.894)	(0.258)	(1.097)	(0.073)	(0.054)
User-Genre FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Anime FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
User-Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	166,514	43,974	393,777	37,159	111,345	17,927	103,556	7,128	160,470	148,339
AIC	67,614.99	14,444.30	242,202.40	3,242.78	23,628.88	2,946.22	8,274.96	-1,844.79	-303,127.10	-341,385.75
BIC	67,655.08	14,487.76	242,245.94	3,285.39	23,667.36	2,985.19	8,313.15	-1,810.43	-303,087.16	-341,346.12
Log Likelihood	-33,803.50	-7,217.15	-121,097.20	-1,616.39	-11,810.44	-1,468.11	-4,133.48	927.40	151,567.55	170,696.87

Clustered 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: Results - Interactive Engagement

The models in column (ii) and (iii) 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 (v) is estimated using user-anime observations which the user rated, i.e., conditional on a rating.

	Forum Posts			Recommendations	Ratings	
	Number	Valence	Length	Number	Incidence	Valence
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Average Daily Number of Hours Spent Watching Focal Anime						
Hours Watching Per Day[a]	0.000	0.002	-0.017	0.001**	0.019***	0.660***
	(0.001)	(0.048)	(0.211)	(0.000)	(0.002)	(0.013)
Hours Watching Per Day Squared[a]	-0.001	-0.006	0.032	0.000*	-0.007***	-0.223***
	(0.001)	(0.024)	(0.105)	(0.000)	(0.001)	(0.006)
Other Variables						
Ever-Made-a-Forum-Post Indicator	0.002	-0.061	0.053			
	(0.002)	(0.054)	(0.171)			
Time Since Last Forum Post[a]	-0.001***	0.000	0.042			
	(0.000)	(0.010)	(0.030)			
Number of Forum Posts[a,c]	0.003***	0.030	-0.096			
	(0.001)	(0.021)	(0.064)			
Number of Ratings[a,c]				0.000		
				(0.000)		
Number of Recommendations[a,c]					0.000	-0.003
					(0.001)	(0.003)
Popularity Rank[a,b]	0.003**	-0.123**	0.506**	0.000	0.004***	0.065***
	(0.001)	(0.045)	(0.154)	(0.000)	(0.001)	(0.010)
Community Rating[b]	0.004	0.333	-0.325	0.001	0.007	0.286***
	(0.003)	(0.202)	(0.538)	(0.001)	(0.004)	(0.035)
Constant	-0.048	-2.075	3.627	-0.004	0.845***	4.943***
	(0.024)	(1.695)	(4.441)	(0.007)	(0.033)	(0.294)
User-Genre FE	Yes	Yes	Yes	Yes	Yes	Yes
Anime FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year FE	Yes	Yes	Yes	Yes	Yes	Yes
User-Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	658,542	1,641	1,641	658,542	658,542	610,567
AIC	-1,356,734.80	-2,327.76	1,438.99	-2,825,488.00	-1,020,648.15	1,724,363.41
BIC	-1,356,655.01	-2,289.94	1,476.81	-2,825,431.01	-1,020,591.16	1,724,420.02
Log Likelihood	678,374.40	1,170.88	-712.50	1,412,749.00	510,329.07	-862,176.70

Clustered 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 C: Daily Watching Behavior in 2014 American Time Use Survey

Data are available on the Department of Labor website at https://www.bls.gov/tus/data/datafiles_2014.htm.

Figure C-1: Daily Watching - American Time Use Survey 2014