Word-of-Mouth, Observational Learning, and Product Adoption: Evidence from an Anime Platform *

Current version: September 2016

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Abstract

We quantify the effects of word-of-mouth and observational learning on consumers' product adoptions. Understanding whether these two forces provide different and unique information or whether one is redundant in the presence of the other is crucial for companies' information provision strategies. We differentiate between the effects of word-of-mouth and observational learning from friends ("personal network") and the effects of word-of-mouth and observational learning from the whole community ("community network"). The relative importance of word-of-mouth and observational learning at each network level provides guidance for companies regarding their platform design. Our unique data come from an online anime platform containing individual-level data on users' networks, product adoptions, and ratings of animes. Our results reveal two segments of users: a small segment of "Enthusiasts" who tend to watch more animes and to adopt them earlier, and a larger segment of "Regular Watchers" who tend to watch fewer animes and to adopt them later. For both segments of users, word-of-mouth from the community network is the largest driver of users' product adoptions followed by observational learning from the community network. Thus our results show that word-of-mouth and observational learning provide unique and different information that individuals use in their product adoption decisions and that the community network is the primary source of information. Lastly, using our results, we test for image utility, for observational learning creating product awareness versus transferring unobserved quality information, and for rational herding.

Keywords: Word-of-Mouth, Observational Learning, Product Adoption, Movie Industry, Social Networks

JEL Classification: D83, L82, M31

*All errors are our own. We thank Pradeep Chintagunta, Brett Gordon, Brett Hollenbeck, Yong Liu, Dina Mayzlin, Peter Rossi, Ananya Sen, Brad Shapiro, Sanjay Sood, Jinhong Xie, Nathan Yang, Jurui Zhang; the participants of the 2016 TX PhD Research Conference, the 2016 UC/USC Colloquium, the 34th Annual UH Doctoral Symposium, the 14th ZEW Conference on The Economics of ICT, and the 2016 SICS Conference; and the seminar participants at UT Dallas, UC Berkeley, University of Iowa, London Business School, and McGill University for their comments. Mina Ameri and Elisabeth Honka gratefully acknowledge support by the Morrison Family Center for Marketing Studies and Data Analysis.

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1 Introduction

Social learning has been shown to play an important role in consumers' product adoptions (e.g., Aral and Walker 2011; Chen et al. 2011). Consumers can learn from and be influenced by their social interactions with others through two different mechanisms, namely, through word-of-mouth (WOM hereafter) and through observational learning (OL hereafter). In WOM, consumers extract product information directly from others' opinions, while in OL, consumers infer information about products from others' previous actions indirectly. Numerous studies have shown that volume, valence, and dispersion of WOM can have a significant impact on consumers' purchase and adoption behaviors (to name a few, Godes and Mayzlin 2004; Chevalier and Mayzlin 2006; Liu 2006; Moe and Trusov 2011; Lovett and Staelin 2015). Although OL has not been studied to that extent in the marketing literature, a few recent empirical papers have shown that OL can affect consumers' decisions leading to information cascades and herding behavior (e.g., Cai et al. 2009; Zhang 2010; Herzenstein et al. 2011; Zhang and Liu 2012).

Although both WOM and OL have been separately studied as elements of social learning, there remain important questions unanswered. First, almost all extant literature has studied either WOM or OL as the single social learning device that influences consumers' product adoptions (e.g., Godes and Mayzlin 2004; Zhang 2010). To the best of our knowledge, Chen et al. (2011) is the only paper that studies the effects of both WOM and OL. Although the authors find that both WOM and OL influence aggregate product sales, it is an open question whether this result found at the aggregate level is driven by all consumers being influenced by both WOM and OL or different groups of consumers being influenced by either WOM or OL. The answer to this question has important implications for companies' information provision strategies.

Both scenarios described in the previous paragraph are possible and plausible and data at the individual level are needed to differentiate between them. On the one hand, one may expect both WOM and OL to have a significant impact on individual consumers' product adoptions because the two forces provide information about product quality in different forms and therefore may complement each other in reinforcing consumers' beliefs about product quality (Kirmani and Rao 2000). On the other hand, individual consumers may interpret and therefore respond to WOM and OL information differently. Some consumers may argue that actions speak louder than words. In the presence of OL, the product information a consumer can obtain from consumer reviews may seem unreliable or redundant and therefore the role of WOM may be diminished. At the same time other consumers may believe that, compared with OL, WOM conveys more diagnostic information about product quality; therefore they may rely on WOM as the dominant mechanism for social learning. To the best of our knowledge, no study has simultaneously examined the differential effects of information from WOM versus OL on individual consumers' adoption decisions.

Furthermore, both WOM and OL can operate at different levels of a network. Many online platforms provide various tools and functions to facilitate socialization among their users. Users can become friends with each other and form their own personal social networks within the larger community. In this context, a user can be influenced by his friends' actions and/or opinions, while, at the same time, he can also observe product adoptions, online reviews, and ratings by users beyond his personal network. Throughout this paper we refer to a user's network of friends as the "personal" network and to the network as a whole (which includes his personal network) as the "community" network. Although extant empirical studies have led support for the significant effects of WOM or OL from either the community or the personal network (e.g., Godes and Mayzlin 2004; Zhang 2010; Nair et al. 2010; Aral and Walker 2011), it remains an unanswered empirical question whether and to what extent WOM and OL influence product adoptions when both types of information are available from both network levels. The answer to this question will provide useful guidance for companies' platform design.

On the one hand, friends' actions and opinions may be viewed as more informative and provide more relevant guidance (Zhang et al. 2015). This is because, when users make their product adoption decisions based on both personal preferences and product quality, the higher certainty in preferences of the personal network makes the extraction of quality information easier. On the other hand, when community networks are large, they provide more "accurate" information in terms of being less prone to cascades than personal networks (Zhang et al. 2015). The finding whether one network level is dominant or both network levels are equally important will carry important implications for the socialization tools and functions that should be made available to consumers on a platform.

In this paper, we aim to answer these questions in the empirical context of the rapidly expanding market of online streaming. We choose this market as our empirical context for the following two reasons. First, online streaming of movies and (TV) shows has grown rapidly over the last decade.[1] In 2015, over 40% of U.S. households subscribed to at least one video streaming service.[2] 70% of North American internet traffic in 2015 consisted of streaming video and audio content and Netflix alone accounted for 37% of all internet traffic in North America.[3] Despite its size and growth, there is a lack of marketing research studying the online streaming market, especially of forces and factors influencing individual consumers' movie watching decisions. Second, movies and shows are cultural products. In an environment such as the online streaming market, facing an overwhelmingly large and constantly growing choice set, consumers tend to rely on various informational cues to learn about product availability as well as to lower their ex-ante uncertainty about product utility. Moreover, in contrast to other online markets, the product price is zero in online streaming.[4] Therefore product popularity and rating information from social networks are likely to play significant roles in consumers' product adoptions, making it an ideal context to study social learning.

We obtain our data from a special interest online community website for animes (Japanese cartoons) called MyAnimeList.net. This website provides a gathering place for anime fans to share their enthusiasm and exchange their opinions about animes. Aside from online ratings, rankings, and news, the website provides a platform for users to interact with each other and to form friendships. Furthermore, users can not only create their personal watch lists, i.e. a list of animes that they have watched, and rate the movies on their watch list, but they can also check other users' watch lists and the ratings these users have submitted. Users receive information whether an anime was watched by their friends through automatic updates about their friends' recent activities, by looking at friends' watch lists, and by reading an anime's list of adopters; all three means contain friends' adoptions and the ratings thereof. Users can also see information about animes in form of community-wide popularity rankings (based on the number of adoptions) and community-wide average rating scores. This dual nature enables us to tease apart different sources of information and to study their separate influence on users' product adoptions.

[1] Throughout this paper, we use the terms "movies," "(TV) shows," and "series" interchangeably.

[2] http://www.nielsen.com/us/en/insights/reports/2015/the-total-audience-report-q4-2014.html

[3] https://www.sandvine.com/pr/2015/12/7/sandvine-over-70-of-north-american-traffic-is-now-streaming-video-and-audio.html

[4] Through legal channels, there are usually fixed costs of online streaming through subscription fees.

We model users' adoption decisions for 103 animes using a latent segments discrete time parametric hazard model. Using a discrete time hazard model allows us to take advantage of the abundant information provided by event histories in our data. In addition, although adoptions happen in continuous time, we only observe them at discrete times. To make our model as close to the continuous data generating process as possible, we use a complementary log-log link function. This model has the additional advantage that it can handle event history data with low event rates. In this model, a log-log transformation of the event rate is assumed to be a linear function of WOM and OL observed from both the users' personal and community networks.

One of the major challenges of working with network data is distinguishing between correlation and causation. As Nair et al. (2010) point out correlation in behavior can be due to three different reasons: Endogenous group formation, homophily, and simultaneity. To solve the challenge of endogenous group formation, we only look at users who have been in the network for more than one year before the release of the first anime under study since our data indicate that users mostly form their friendships in the first six months after joining. To account for common shocks that lead to simultaneity, we use the cumulative number of news pieces collected from MyAnimeList.net and other websites as a variable affecting the adoption rate of all users under the assumption that online news are the main common shock that influences users. To address homophily, we use product adoptions of users before the release of each anime as a measure of their preferences (and prior influence by friends). Lastly, to ensure that the effects of friends' adoptions we find are not due to insufficient handling of the reflection problem (Manski 1993), we follow a standard approach first suggested by Bramoullé et al. (2009) and De Giorgi et al. (2010) and show that users are influenced by their peers' actions.

Our results reveal two distinct segments of anime watchers: a small segment of "Enthusiasts" (26%) who tend to watch more animes and adopt them earlier, and a larger segment of "Regular Watchers" (74%) who tend to watch fewer animes and adopt them later. We find that both WOM and OL have significant effects on users' anime adoptions. Within the community network, we find that average community ratings have a significant positive effect on users' adoptions. Furthermore, OL has a significant effect on product adoptions: as an anime climbs up in the community popularity rank, users become more likely to watch the anime. These results hold true for both segments of users. Within the personal network, the effects of OL are positive and significant for both user segments, while WOM valence has a significant positive effect for "Regular Watchers" but an insignificant effect for "Enthusiasts." Comparing the OL and WOM elasticities across both network levels and both segments, we find that WOM valence from the community network is the largest adoption driver related to social learning followed by OL from the community network. Further, we do not find evidence consistent with image utility in the context of anime watching. Next, we find OL to both create awareness for an anime and to let users learn about the unobserved quality of an anime. And lastly, our empirical results are consistent with rational herding.

The contribution of this paper is three-fold. First, we contribute to the social learning and product adoption literatures by disentangling the effects of WOM and OL, the two prevalent social learning devices. Our findings provide empirical support for the differential and unique effects that product information inferred from WOM versus OL has on consumers' product adoption decisions. In particular, our result that the effect of community WOM overshadows the effect of community OL is consistent with the predominant business practice to display average product ratings. Second, we demonstrate the relative importance of social learning at different network levels: the community network versus the personal network. Our finding that social learning from the community network has a much larger impact on consumer product adoption than social learning from the personal network corroborates the theoretical prediction from Zhang et al. (2015) that community networks provide more accurate information to consumers than personal networks when they are sufficiently large. And lastly, to the best of our knowledge, our paper is the first to study product adoption in the fast growing online streaming market. By showing how social learning shapes consumers' watching decisions, we gain a valuable understanding of the adoption drivers in this unique market.

The remainder of the paper is organized as follows: In the next section, we discuss the relevant literature. In Sections 3 and 4, we describe our data, introduce our model and estimation approach. We present and discuss our results in Section 5. In the following section, we examine limitations of the current work and opportunities for future research. Finally, we conclude by summarizing our findings in Section 7.

2 Relevant Literature

In this section, we review relevant streams of literature on word-of-mouth (WOM), observational learning (OL), and the movie industry, and delineate the positioning of our research vis-a-vis the findings from extant research.

2.1 Word-Of-Mouth

WOM has been largely studied in the context of reviews and online opinions. There is strong empirical support for the positive effect of online opinions in different industries: TV shows (Godes and Mayzlin 2004; Lovett and Staelin 2015), movies (Liu 2006; Dellarocas et al. 2007; Duan et al. 2008; Chintagunta et al. 2010), books (Chevalier and Mayzlin 2006; Li and Hitt 2008), bath and beauty (Moe and Trusov 2011), and video games (Zhu and Zhang 2010). The consensus of these studies is that WOM created by community networks influences consumers' product adoptions. At the same time, there are few papers that have studied the effects of WOM within personal networks. Aral and Walker (2011) study consumers' app adoptions. They find WOM in the form of active-personalized messaging to be more effective than in the form of passive broadcasting viral messaging in encouraging adoption per message. Brown and Reingen (1987) trace referral WOM of music teachers in local neighborhoods and quantify the effects of WOM in weak and strong ties. They find that strong ties are likely to be used as sources for product related information.

While these studies show the significant effect of WOM on adoption at both the community and the personal network level, how these two levels of WOM influence an individual's decision simultaneously is not clear. Zhang and Godes (2013) study how decision quality improves based on information received from strong and weak ties while controlling for aggregate valence and variance. However, they neither observe the valence nor the content of information individuals receive from their personal networks and instead they use the number of ties as a proxy for the amount of information. In the current study, we treat WOM extracted from the community network and WOM received from one's own personal network as separate information sources and identify their relative importance in driving individuals' product adoption behavior.

2.2 Observational Learning

With limited information available, people use others' observed prior decisions in addition to their private information to shape their beliefs and to make decisions (Banerjee 1992; Bikhchandani et al. 1992). This can lead to information cascades (Bikhchandani et al. 1992) and herding behavior. This effect is stronger when consumers are uncertain about the product, have imperfect information, and infer their own utility from observing others' prior decisions (Cai et al. 2009; Duan et al. 2009). Zhang (2010) uses data from the kidney market to show that patients draw negative quality inferences from earlier refusals by unknown people in the queue even though they themselves do not have information about the quality of the kidney. Cai et al. (2009) show that displaying popularity of dishes in a restaurant increases orders of those dishes. Zhang and Liu (2012) study lenders' funding decisions using data from an online microloan platform and find evidence for rational herding among lenders. Studying individual choices under the influence of personal networks, Nair et al. (2010) and Wang et al. (2013) show that the volume of usage, expertise, or popularity of friends are key factors that affect adoptions in medicine, technology, and fashion goods, respectively.

However, the influences of the community and personal networks have not been recognized as two different sources of OL until recently. Zhang et al. (2015) employ a game-theoretical approach to study OL in networks of friends vs. strangers. They define friends as groups of users with homogenous preferences and strangers as groups of users with heterogeneous preferences. They show that, when the network is small, friends' actions provide more information, while the network of strangers becomes more effective as it grows in size. Sun et al. (2012) study herding behavior of consumers under the influence of friends' and the community's choices. In their specific context, users do not infer quality information about a choice, just the popularity of a choice. They show that people are more likely to diverge from the popular choice among their friends as the adoption rate of a choice increases, but do not respond to the popular choice in the community. This is because the community does not form an opinion about the person whereas friends do. These two studies suggest that OL can happen at both the personal and the community network level. In this paper, we observe choices of individuals when they receive product popularity information from both their personal and the community network and study how each of these two sources influences consumers' product adoptions simultaneously.

2.3 Word-Of-Mouth versus Observational Learning

To the best of our knowledge, almost all extant marketing literature has either studied WOM or OL as the single mechanism through which consumers extract product information to facilitate their adoption decisions. The only exception is Chen et al. (2011) in which the authors examine the role of both WOM and OL on aggregate online product sales at Amazon.com. They find that, while negative WOM is more influential than positive WOM, positive OL information significantly increases sales but negative OL information has no effect.

No study that we are aware of has investigated the effects of WOM and OL simultaneously on individual consumers' product adoptions. Although information about product quality can be extracted or inferred from both mechanisms, consumers may still interpret WOM and OL information differently. One can argue that compared with OL, WOM conveys more diagnostic information about product quality; therefore it should play a more prominent role. Alternatively, actions speak louder than words; although indirect, OL information may be more credible than WOM information. In this study, we aim to fill in the gap by examining the differential effects of information from WOM versus OL on individual consumers' adoption decisions.

2.4 Movie Industry

There is a large body of literature in marketing studying the motion picture industry. It primarily focuses on finding the determinants for and influencers of box office success of movies (e.g., Prag and Casavant 1994; Eliashberg and Shugan 1997), and forecasting sales and demand for movies (e.g., Lehmann and Weinberg 2000).

Several papers have studied the role of WOM in form of online reviews in the movie industry. Since movies are experience goods, peers' opinions constitute an important source of information for consumers (Eliashberg and Shugan 1997). However, there is no consensus regarding the effects of WOM on movie sales across various empirical studies. On the one hand, Elberse and Eliashberg (2003) show that more positive reviews correspond to more opening revenue; Liu (2006) and Dellarocas et al. (2007) among others also find a positive influence of movie critics on movies' box office performance. On the other hand, Duan et al. (2008) find the ratings from online user reviews not to have a statistically significant impact on movies' box office revenues.

Aside from online reviews, the internet has also provided a platform for online streaming.

Online streaming is becoming more and more popular given the increasing number of internet-based movie streaming providers such as Netflix or Hulu.[5] The online streaming market is different from the traditional movie market in that the movie price is zero in the former market. This unique feature may make WOM and OL more or less salient in the online streaming market as compared to the traditional movie market. To the best of our knowledge, our paper is the first one that explicitly studies the drivers underlying consumers' movie adoption decisions in the context of online movie streaming.

3 Data

Our data come from MyAnimeList.net. This website is a consumption-related online community (Kozinets 1999) where online interactions are based upon shared enthusiasm for a specific consumption activity. MyAnimeList.net was created to allow anime fans to gather and share their excitement and opinions about animes. In addition, the website has developed into one of the most comprehensive online sources of information about animes (Japanese cartoons) and mangas (Japanese comics). In this paper, we focus on animes. On MyAnimeList.net, both animes and users have their own pages. Figure 1 shows an example of an anime page. Each anime page contains detailed information such as a content summary, an episode guide, production details, ratings, and rankings.

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Insert Figure 1 about here

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Figure 2 shows an example of a user page. Note that all information on users' pages is available to the public.[6] On a user page, one can see information about the animes and mangas the user has adopted (including the dates), his opinion about adopted animes and mangas, the website join date, his in-site activities, the identities of his friends and other information. Users can become friends with other users upon mutual acceptance of a friendship request. Users make friends as it allows them to see automatic updates about friends' recent in-site

[5] The Sky is Rising: A Closer Look At Growth In The Major Entertainment Industries (Technical report 2014 available at https://www.ccianet.org/wp-content/uploads/2014/10/Sky-Is-Rising-2014.pdf

[6] Users have the option to hide their profile page from the public, but less then 5% of users use this option.

activities on their own page and instant-messaging and communication tools are provided to enable in-site communication between two friends.

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Insert Figure 2 about here

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Users can create a list of animes that they plan to watch or have watched (we refer to this list as "watch list" throughout this paper).[7] Figure 3 shows an example of a user's watch list. Note that users add animes to their watch lists using a search function so that all animes are correctly and uniquely identified. Users can assign different stati to the animes on their watch list: "watched," "watching," "on hold," "dropped," or "plan to watch." We define a user as having adopted an anime if the anime is on his watch list under any of the first four stati.[8] While this definition of adoption might seem very broad, note that the stati "watched," "watching," "on hold," and "dropped" all imply that the user has at least started to watch, i.e. adopted, the anime.[9] Further, users can also indicate their opinion about the animes on their watch list by rating them on a scale ranging from 1 to 10 (10 being the highest rating). Throughout this paper, we refer to ratings given to animes on watch lists as "user ratings." Lastly, users can indicate the date they started watching an anime and the website also automatically registers the date users last updated the entry for an anime. We use these two dates to infer the time of adoption.[10]

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Insert Figure 3 about here

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[7] 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.

[8] Our adoption data are self-reported. Thus accuracy in the reporting of adoptions is a potential concern. Note that in contrast to incentivized surveys, there are no incentives for users on MyAnimeList.net to falsely report their true anime watching behavior. Furthermore, in the similar setting of TV shows, Lovett and Staelin (2015) compare survey panelists' self-reported viewing data and the actual streaming data and find that people tend to correctly report their actual watching behavior. Thus we are confident that the self-reported adoption data are reliable in our context.

[9] In an additional model, we differentiate between observational learning coming from positive and negative product adoption experiences. To do so, we define positive OL as product adoptions under the stati "watched," "watching," and "on hold" and negative OL as product adoptions under the status "dropped." We discuss the results from this additional model in Section 5.2.

[10] Our data contain the start dates and the dates of the last updates for 34% and 66% of observations, respectively. The different modeling implications of the start dates and the dates of the last updates are discussed in Section 4.2.

We aim at quantifying the effects of WOM and OL from both the personal and the community network on product adoption. We use the number of friends who adopted the anime to measure OL from the personal network.[11] Further, we operationalize WOM valence from the personal network as the average rating of the anime given by the user's friends. Following previous literature (e.g. Chintagunta et al. 2010; Moe and Trusov 2011), we measure the dispersion in WOM using a function of the variance of WOM ratings, namely, its standard deviation. With regard to the community network, users see an anime's rank (based on the number of adoptions) on the anime page (see "Popularity" in the bottom left corner in Figure 1) - this is our measure of OL. Similarly, users also see the average rating for an anime based on ratings submitted by all users on the anime page (see "Score" in the bottom left corner in Figure 1) - this is our measure of WOM valence.[12] And lastly, users can see the distribution of ratings from the community network on another tab of the anime page. We use the standard deviation of ratings to capture the dispersion in community WOM.[13]

3.1 Data Collection, Cleaning, and (Re-)Construction

MyAnimeList.net 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 4). At the point in time when we started the data collection (March 2015), there were more than 2.5 million users on the website. Many users are standalone users with no friends and little to no activity. Since we are interested in the effects of social learning on product adoption, we collected data on a network of nearly 380,000 users.[14]

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Insert Figure 4 about here

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[11]We test the robustness of our results by using the percentage of friends (instead of the number of friends) who adopted the anime as our measure of OL from the personal network. We find our results to be qualitatively similar (see model (i) in Table B-1 in Online Appendix C).

[12]Note that there is also an alternative measure of WOM from the community network: users can see the rank of an anime based on its average rating from all users (see "Ranked" in the bottom left corner of Figure 1). We estimated our model using this alternative measure of WOM from the community network and our results are robust (see model (ii) in Table B-1 in Online Appendix C).

[13]Note that all our WOM variables from both the personal and the community network are conditional on friends' and all users' adoptions, respectively.

[14]This is the largest and oldest network on MyAnimeList.net. It includes the website owner and users who were members of the website before 2007.

There are over 10,000 animes listed on the website. These animes range from short 20-minutes single-episode animes to anime series with more than 50 episodes. We use data on 103 anime series to study the effects of WOM and OL on product adoption. These animes were selected based on release dates, being the first season of an anime (if multiple seasons exist), and viewership. More specifically, all animes were released between July 2012 and January 2014 and the release dates of these animes are scattered. We focus on the first season to avoid potential spillover effects from a previous season. Based on these two criteria we narrowed the list of animes down to 535 animes. Among these 535 animes, 103 animes have been viewed by more than 50,000 users of MyAnimeList.net and are included in our final data.[15]

We define the period under study as the time period from the release of an anime until the release of the second season (if multiple seasons exist) or 52 weeks (one year) after the release, whichever is shorter. Thus the study period varies from 19 to 52 weeks across the 103 animes.[16]

We took the following steps to arrive at the set of users to be included in the final data set: First, to avoid the simultaneity of tie formation and product adoption, we dropped all users who had joined the network less than one year prior to the release date of the first anime under study.[17] The choice of a one year cut-off was driven by the data. In Figure 5, we show the average percentage of friends added over the years for different groups of users based on their join date. Users grow their friendship network mostly during the first six months after joining the website. We chose a conservative cut-off of one year.

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Insert Figure 5 about here

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Second, we removed users who showed no activity after the release of the last anime. We define activity as an update to the watch list. For these users, we would not be able to differentiate between them not adopting an anime under study because they did not want to or due to their inactivity. Therefore, we look at users who added at least one anime (not necessarily one of the selected animes in this study) to their watch list after the release of the

[15]The 103 animes have a market share of 68% (in terms of viewership) among the 535 animes.

[16]74% of adoptions across the 103 animes happen during the study period as compared to the total observation period, i.e. from release until March 2015. Note that the observation period is, on average 2.7 times longer than the study period (with a minimum of 1.4 and a maximum of 7.4 times longer). Thus we conclude that the adoption rate is significantly higher during the study period when compared to the total observation period.

[17]We refer the reader to Section 4.1 where we discuss in detail why this is necessary.

last anime under study. Third, we dropped users who reported fewer than 10 adoptions of any anime (not only the ones selected for this study) over the entire observation period (i.e. at least 4 years). This is a very conservative criterion which ensures a minimal interest and activity level.

Fourth, for some users we do not have data on all their friends' adoptions e.g. because one of their friends' watch list is not public. Therefore we restrict our data to users for whom we have adoption data on more than 95% of their friends. Note that this only affects a small number of users. And lastly, we condition on users having adopted at least 20 animes out of the 103 animes under study. We do so for two reasons, namely, to ensure minimal interest in the 103 animes under study and to have sufficient variation in the dependent variable (see discussion in Section 4.1). After applying these five criteria, the remaining data contain information on 15,456 users with nearly 60 million weekly observations. We use data on a random sample of 800 users with 2,747,954 weekly observations for the empirical analysis.[18]

To account for common shocks on adoption, we gathered two types of data for each anime: the number of online news articles and the number of posts in the news sections of MyAnimeList.net. To collect data on online news, we used google.com/news search results. One advantage of using Google news is that Google also provides information on whether the same news article was published on several webpages or not. This allows us to not only follow the number of news for each anime over time, but also to capture the volume of news at each point in time. Figures 6(a) and 6(b) show the average cumulative number of online news articles and the average cumulative number of posts in the news sections of MyAnimeList.net, respectively, for the animes under study over time.[19]

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Further, we also considered another type of common shock: the availability of an anime through legal online streaming channels. However, we found that more than 90% of the animes under study were available for online streaming within hours to up to three days after their

[18]We compare the characteristics of the final data set to the characteristics of two larger data sets (the eligible population not conditioning on at least 20 adoptions, i.e. users satisfying data cleaning steps 1 - 4, and all 380,000 users) in Online Appendix A.

[19]The grey shaded areas in Figures 6(a) and 6(b) show the areas between the 5th and 95th percentile.

original airing in Japan.[20] Since our data are at the weekly level, we conclude that availability through legal channels is synonymous with original episode airings and do not include it as a separate variable in our empirical model.

3.2 Data Description

Table 1 summarizes key statistics of our data. On average, a user has 20 friends, watches 131 animes per year, and has adopted 40 of the 103 animes under study. Figures 7(a), 7(b), 7(c), and 7(d) show histograms of the number of friends, the average number of adopted animes per year, the number of adopted animes among those under study, and the adoption weeks across all users and all 103 animes (each relative to its own release date), respectively. Note that there is considerable variation in all four variables and that the distributions have very long right tails. Further, 30% of users indicate their gender as "Female," 55% as "Male," and the remainder did not specify their gender. On average, users adopt an anime in week 14 with a median adoption week of 13. Two spikes in adoptions around week 13 and week 26 are noticeable. Note that most animes have 13 or 26 episodes and are aired on a weekly basis. Thus these two spikes are likely due to a significant number of users waiting for all episodes in a season to be available before they start to watch an anime.

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Insert Table 1 about here

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Insert Figure 7 about here

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In Figure 8, we show the average levels (across users and animes) of our six key variables capturing WOM and OL from the personal and community networks across time. The shaded area in each graph displays the 5th and 95th percentiles at any point in time. Figure 8a shows the average cumulative number of friends who adopted the anime (this is our measure of OL from the personal network). Figures 8c and 8e show the average and the standard deviation, respectively, of ratings given by friends (these are our measures of WOM valence and WOM

[20] Animes were mostly available for immediate online streaming on the international website crunchyroll.com.

dispersion from the personal network). Figures 8b, 8d and 8f show the logarithm of rank, the average community rating, and the standard deviation of community rating, respectively.[21] These last three variables capture OL, WOM valence, and WOM dispersion from the community network. The graphs show that our key variables vary considerably across time. More importantly, the shaded areas displaying the 5th and 95th percentiles at each point in time indicate that there is also considerable variation in our key variables across animes and users, especially for the personal network measures. For example, the cumulative number of friends who watched an anime ranges from 0 to 19 across users and animes by the end of week 1 and the average rating given by friends varies from 1 to 10 across users and animes by the end of week 1. These patterns suggest that we have sufficient variation in all our WOM and OL measures to identify their effects on product adoptions.

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Insert Figure 8 about here

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Additionally, we use eight genre-specific similarity indices to capture users' preferences (and potentially past influence by friends on past product adoptions) before the release of an anime. The animes listed on the website are typically associated with three to five different genres out of the 44 genres listed on the website. The assignment of an anime to genres is done by the website and the animes under study belong to 36 genres. Since including 36 genre similarity indices would significantly increase the number of parameters to be estimated and the computational burden, we focus on the eight main genres into which all animes under study fall.[22] First, we identify which of the eight main genres each of the 103 animes under study falls. Then we collect information on the genres of past adoptions for each user in our final data. Putting these two pieces of information together, we calculate the eight genre-specific similarity indices for each user/anime combination. They describe how similar each of the selected animes under study is to a user's past adoptions (in terms of each of the eight main genres). A higher value of a genre-specific similarity index for an anime/user combination shows more similarity between the user's past adoptions and that anime in terms of genres, i.e. the user has watched many

[21] See Online Appendix B for details on these variables.

[22] These genres are action (34 animes), comedy (55 animes), school (43 animes), romance (37 animes), supernatural (25 animes), fantasy (32 animes), slice of life (21 animes), and shounen (19 animes). "Shounen" means "young boy" in Japanese.

animes of that genre in the past. If a user watches animes of different genres, the genre-specific similarity indices for a specific anime will be lower compared to a user who mainly watches animes of the same genre as that anime. We provide details on how the genre-specific similarity indices are calculated in Online Appendix B.

4 Model and Estimation

In this section, we first discuss the three challenges we face in modeling choice interdependence in networks. Subsequently, we discuss an estimation challenge that also influences our modeling decisions. Finally, we present the model and discuss our estimation approach.

4.1 Challenges

We face four main challenges in modeling and estimating product adoption in networks: Endogenous group formation, simultaneity, homophily, and an extremely low event rate. In this section, we explain how these issues pose a challenge and how we address each of them.

Social ties can be formed to facilitate sharing common interests among people (Kozinets 1999). Observing others' past actions can be used as a source of information to find individuals with similar interests. To study how people influence each other, we have to take into account that, while friends influence each others' product adoptions, friendships themselves are formed under the influence of previous product adoptions. To solve the challenge of the endogeneity of tie formation, we focus on users who have been a member of the website for at least one year before the release of the first anime. As mentioned in Section 3.1, we observe users to form friendships mostly during the first six months. Using data on users who have been members for at least one year enables us to assume that the networks are exogenous and fixed.

The simultaneity problem is caused by common shocks that influence both users' and their friends' product adoptions. In such a case, even if both the user and his friend adopt the product due to the shock, it can be mistaken as the user who adopted the product earlier influencing his friend. To account for common shocks, we use two variables that can affect the adoption decisions of all users: the number of online news pieces collected from different websites and the number of posts about an anime on the news section of MyAnimeList.net. Since animes are available through legal online streaming immediately after airing in Japan and the users of the website are located all over the world, we believe online news and posts in the news sections of MyAnimeList.net are two of the main sources of common shocks. Note that the anime-specific correlations between the cumulative number of online news articles and the cumulative number of posts on the anime site for the same anime are very high with a median of 0.90. Therefore we use a combined cumulative online news count, i.e. the cumulative sum of online and in-website news, to control for common shocks.[23]

The third difficulty arises when ties among friends are formed because users share the same interests. While two friends adopting the same product might be due to one influencing the other, it might as well be due to those similar interests. To tease homophily apart from influence, we control for users' preferences for anime genres. We do so by creating genre-specific similarity indices (see Section 3.1 and Online Appendix B for details) which capture how similar, in terms of genre, an anime is to prior adoptions by the user. These past adoptions are due to a user's personal interests (and potentially due to past influence by friends on past product adoptions). By controlling for genre similarity of an anime with past adoptions, we are able to control for a user's interests at the time of release of an anime.[24]

For linear-in-means models, the economics literature (e.g. Bramoullé et al. 2009; De Giorgi et al. 2010; Claussen et al. 2014) has proposed using friends of a user's friends who are not friends with that user as an instrument for that user's friends' adoptions to solve the reflection problem in social networks (Manski 1993) and to identify peer effects.[25] While the adoption of friends of friends is correlated with friends' adoption, it does not directly influence that user's adoption. We construct the instrument by counting the number of friends of friends who have adopted each anime by each week and estimate a user's weekly adoption decision as a linear probability model using two-stage-least-square (2SLS). The result of this 2SLS regression is shown in Table 2 as model (i).[26] The coefficient for the cumulative number of friends who

[23]We also estimated our model including only the cumulative number of online news and including only the cumulative number of posts in the news sections of MyAnimeList.net and our results are robust. The results are available from the authors upon request.

[24]We also created genre-specific similarity indices capturing a user's interests/adoptions prior to the first friend and our model results are robust (see model (iii) in Table B-1 in Online Appendix C).

[25]We refer the reader to Bramoullé et al. (2009) and De Giorgi et al. (2010) for details on this approach.

[26]We do not use this model as our main model because the hazard model allows us to explicitly model adoptions of users for whom we do not observe the start date, but only the date of the last update (see Sections 3 and 4.2).

adopted – our measure of peer effects – is positive and significant.

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Insert Table 2 about here

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Next, we estimated a homogenous version of our main hazard model (see Section 4.2) in which – to keep the specification consistent with the linear probability model – we control for simultaneity and homophily using the cumulative number of news and genre-specific similarity indices. The results are shown in Table 2 as model (ii). To compare the magnitudes of the peer effects, we calculate the elasticities of OL from friends for both models. We find the OL elasticity from the 2SLS regression to be larger than the OL elasticity from the hazard model. Thus we conclude that our approach is sufficiently addressing the reflection problem and, if anything, we estimate a lower bound for the peer effects.

Lastly, our data are at the weekly level. Despite conditioning on at least 20 adoptions (see Section 3.1), the vast majority of users in our data adopts fewer than 40 animes (see Figure 7(c)). Conditional on adopting an anime, the vast majority of users adopt an anime 10 or more weeks after its release (see Figure 7(d)). Both these characteristics of our data create the well-known problem of low event rate, i.e. the proportion of 1's among all observations of the binary dependent variable is very small (see also King and Zeng 2001*a*,*b*). This challenge is especially prevalent in our data: The event rate is 1.2% and the adoption rate, i.e. proportion of animes adopted at any point in time, is 38.5% across all 103 animes. It has been well-documented that a low event rate causes biased estimates in logit models and is also challenging for hazard models using a logit link function (e.g. King and Zeng 2001*b*).

Several approaches have been suggested by past research to overcome this challenge. First, using only data conditional on adoptions has been suggested (e.g. Hannan et al. 1978). However, this approach has the disadvantage that information from non-adopters is lost. In our data, given that the adoption rate is 38.5%, we would have to discard about 61.6% of our data. Second, aggregating the data to longer periods has been suggested (e.g. Hannan et al. 1978; Allison 1982). While in some contexts this approach might be reasonable, in our data, it would eliminate a substantial part of the variation which occurs on a weekly basis especially during the first few weeks after release (see e.g. Figure 8). And lastly, oversampling adopters versus non-adopters and using representativeness weights in the estimation has been suggested (e.g.

King and Zeng 2002). However, due to the severity of the low event rate problem and the multidimensionality of adoption decisions within a user and across the animes under study, this approach is not feasible in our data. We conclude that, for the reasons discussed above, none of these three approaches works in our data.

Instead, we use a combination of a specific hazard model that can accommodate a low event rate and a very large data set to overcome the challenge of an extremely low event rate. More specifically, we use a discrete time parametric hazard model with a complementary log log ("cloglog") link function. These models are particularly well-suited for situations in which the event rate is very low (e.g. Allison 1982; Buckley and Westerland 2004). We combine this model with a large data set which ensures sufficient variation in the dependent variable despite the very low event rate to empirically identify our parameters of interest.

4.2 Model Description

The set-up of the model is as follows: Suppose there are $i = 1, ..., N$ individuals and $j = 1, ...J$ animes that an individual can adopt at time $t_j = 1, ..., \bar{T}_j$. We observe each individual i until his adoption of anime j in time period T_{ij} or until the end of the study period for anime j, $\bar{T}_j$, if individual i does not adopt anime j (uncensored observations). We assume that the end of the study period is independent of an individual's adoption, i.e. there is no censoring of time. Given that we as researchers chose the length of the study period ex post, this assumption is reasonable. Note that, for some individual/anime combinations, we do not observe the exact week the anime was adopted. Instead, we observe that the adoption happened some time before or at T'_{ij} (left censored observations). We describe later in this section how we account for the left censoring in our model.

The discrete time hazard rate of individual i's adoption of anime j at time t conditional on not having adopted anime j before time t is defined as

$$h_{ijT_{ij}} = \Pr\left(T_{ij} = t \mid T_{ij} \geq t, X_{ijt}, Z_{jt}, C_{ijt}\right) \tag{1}$$

where T_{ij} is a discrete random variable giving the uncensored time of adoption and X_{ijt}, Z_{jt}, and C_{ijt} are covariates.

We use a complementary log log link function to link the hazard of adoption to time and other covariates. This link functions allows for the utilization of a large number of observations despite the very low rate of adoption while, at the same time, it does not assume duration independency, proportionality or symmetric probability of adoption. The link function between the adoption hazard and the covariates including time is given by

$$\log\left(-\log\left(1-h_{ijt}\right)\right)=\alpha\,\log\left(t\right)+X_{ijt}\beta_1+Z_{jt}\beta_2+C_{ijt}\beta_3 \tag{2}$$

where X_{ijt} contains WOM and OL from the personal network, Z_{jt} includes WOM and OL from the community network, and C_{ijt} contains other variables whose effects we control for, namely, the genre similarity indices, the number of animes adopted by individual i in week t, a dummy variable indicating whether a user has also read the manga associated with the anime, a dummy variable indicating whether the season finale was aired in week t, and the cumulative number of news published about anime j by week t. β_1 and β_2 describe the effects of WOM and OL from both the personal and the community network. Our model-free evidence supports the assumption of a monotonically decreasing hazard rate over time. Therefore we use $\log(t)$ to account for time since release; $\log(t)$ implies a Weibull distribution for the hazard rate.[27]

For left censored individuals, i.e. those for whom we know the adoption happened some time before or on T'_{ij} but for whom we do not observe the exact time, the probability of adoption happening before or on T'_{ij} is given by $F\left(T'_{ij}\right)$ where F is the cumulative distribution of adoption probability over time. $F\left(T'_{ij}\right)$ equals $1-S\left(T'_{ij}\right)$ with S being the survival function or, in other words, the individual not surviving beyond T'_{ij}. Thus $S\left(T'_{ij}\right)$ is given by

$$S\left(T'_{ij}\right)=\left(1-h_{ij1}\right)\left(1-h_{ij2}\right)...\left(1-h_{ijT'}\right)=\prod_{t\leqslant T'_{ij}}\left(1-h_{ijt}\right). \tag{3}$$

Lastly, we account for unobserved heterogeneity in our key parameter β_1 and β_2 via latent segments. The probability that individual i belongs to segment k is given by

$$p_k=\frac{exp\left(\gamma_0+W_i\gamma\right)}{1+\sum_{k=1}^{K-1}exp\left(\gamma_0+W_i\gamma\right)} \tag{4}$$

where γ_0 is the intercept and W_i contains two individual-specific time-invariant variables, namely, the total number of friends and the average number of yearly adopted animes. The inclusion of these variables is motivated by our goal to test for image utility (Toubia and Stephen 2013) and rational herding (Banerjee 1992; Bikhchandani et al. 1992) (see Sections 5.2 and 5.3

[27] We also estimated a model with different coefficients for $\log(t)$ for animes with 26 or more episodes in a season and for animes with fewer than 26 episodes in a season. The two coefficients for $\log(t)$ are very similar and our results are quantitatively and qualitatively robust. The results are available from the authors upon request.

for details). Finally, $\theta = (\alpha, \beta_1, \beta_2, \beta_3, \gamma_0, \gamma)$ is the set of parameters to be estimated.

4.3 Estimation

We estimate our model using maximum likelihood. For uncensored observations, the likelihood of individual i adopting anime j at time T_{ij} is given by

$$l_{ij}^{uc} = \prod_{t=1}^{T_{ij}} \left(\frac{h_{ijt}}{1 - h_{ijt}} \right)^{y_{ijt}} \cdot (1 - h_{ijt}) \tag{5}$$

where y_{ijt} is a dummy variable which equals one if individual i adopts anime j in week t and zero otherwise. The likelihood for a left censored observation, i.e. individual i adopting anime j at some point before or on T'_{ij} is given by

$$l_{ij}^{lc} = F\left(t \leqslant T'_{ij}\right) = 1 - S\left(T'_{ij}\right). \tag{6}$$

Then the likelihood of the model is given by

$$L = \prod_{i=1}^{N} \sum_{k=1}^{K} p_k \prod_{j=1}^{J} \left(l_{ij|k}^{uc}\right)^{1-\delta_{ij}} \left(l_{ij|k}^{lc}\right)^{\delta_{ij}} \tag{7}$$

where δ_{ij} is a dummy variable that takes the value one when the adoption of anime j by individual i is left censored and zero otherwise.

5 Results and Discussion

Table 3 shows the estimation results for the homogenous (model (i)) and the 2-latent segments model (model (ii)). The model fit improves after the inclusion of latent segments. Further, both the AIC and the BIC support the inclusion of unobserved heterogeneity. Therefore we focus on the 2-latent segments model in interpreting the results.

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Insert Table 3 about here

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We first discuss the parameter estimates for the control variables that share common coefficients across the two segments. The parameters for the number of adopted animes in week t, the manga adoption dummy, the season finale dummy, and the cumulative number of news are, as expected, all positive and, with the exception of the manga dummy, significant. We find a significant negative effect of the logarithm of the number of weeks indicating that users become less likely to adopt an anime as time goes by (absent the effects of other variables). And lastly, we find significant positive effects for all eight genre-specific similarity indices suggesting that familiarity with a genre increases the adoption probability of animes that fall into the same genre.

Our results reveal two distinct segments of users: segment 1 consists of 74% of users and segment 2 consists of the remaining 26% of users (see Table 4).[28] Users in segment 1, on average and when compared to users in segment 2, have more friends (20 versus 18), watch fewer animes per year (110 versus 186), adopt fewer animes among those under study (29 versus 60), and also adopt later (week 15 versus week 12).[29] Therefore we term users belonging to segment 1 as "Regular Watchers" and users belonging to segment 2 as "Enthusiasts."

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Insert Table 4 about here

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5.1 Effects of Word-Of-Mouth and Observational Learning

Next, we discuss the effects of our key variables of WOM and OL from the personal and the community network for both segments. We first start with the community network. The coefficients on community rank, which capture the effects of OL from the whole community, are negative and significant. Note that, the lower the rank is, the more popular the anime is. Therefore, as expected, our result suggests that the more popular an anime gets, the more likely it will be adopted by an individual. Further, as expected, community ratings have a significant positive effect on users' anime adoptions. Recall that community ratings capture the valence of WOM since they are the average ratings given to animes by the whole community. We capture the dispersion of community WOM using its standard deviation. The effects are negative and significant for both segments, i.e. users are more likely to adopt animes with less dispersed ratings.

[28] We assign users to a segment using posterior segment probabilities and a cut-off of .5.

[29] All the differences are significant at $p < .001$ except for the average number of friends.

Our results for the community network indicate that OL and WOM provide users with different and unique information that influences individuals' product adoptions. Thus the effects of social learning are not fully captured when only WOM or only OL are included in an empirical study. We calculate WOM and OL elasticities (see Table 5) to judge the relative magnitudes of the effects.[30] For both segments, WOM valence is the largest driver followed by OL and WOM dispersion. Across the two segments, we observe "Regular Watchers" to be influenced by WOM valence and OL to a larger extent than "Enthusiasts" are influenced by these two social learning devices. The effect sizes of WOM dispersion are similar for both segments.

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Insert Table 5 about here

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We now turn to the effects of WOM and OL from the personal network. The effects of OL are positive and significant for both segments: as the number of friends who have watched an anime increases, an individual becomes more likely to adopt the anime. We use three variables to capture the effects of WOM from the personal network: a friends' rating dummy which equals one if at least one friend in an individual's personal network has submitted a rating for the anime and zero otherwise; friends' average rating (capturing WOM valence) conditional on the friends' rating dummy being one; and the standard deviation of friends' ratings (capturing WOM dispersion). We use the dummy variable because, for some users, we observe a time period after the release when none of their friends has rated the anime yet. Given this data pattern, the friends' rating dummy captures the effect of the first rating submitted by a friend and friends' average rating captures the valence of the ratings.[31] For both segments, we find the effects of the friends' rating dummies to be insignificant, while WOM valence has a significant positive effect for "Regular Watchers" and an insignificant effect for "Enthusiasts." The effects of WOM dispersion are positive and significant for both segments. This last result is in line with previous research that has found mixed effects of WOM dispersion.[32]

[30]We first calculate the elasticities for each user/week combination, then the average elasticity for each user, and, finally, the average elasticity for all users in a segment.

[31]A dummy of similar nature could be used for the average rating from the community network as well, but due to the large number of users in the network, all 103 animes under study have at least one rating in the first week after release.

[32]For example, Chintagunta et al. (2010) find an insignificant effect, while Moe and Trusov (2011) find a significant positive and Zhang and Godes (2013) find a significant negative effect.

Thus, similar to the community network, we find that users derive different and unique information from WOM and OL from the personal network. However, in contrast to the community network, OL from friends has a larger effect on users' adoption decisions than WOM valence or WOM dispersion (see Table 5). Across the two segments, the effect of OL (WOM valence) is larger (smaller) for "Enthusiasts" than for "Regular Watchers." WOM dispersion only plays a small role for both segments.

Lastly, we compare the effects of WOM valence and OL across the two network levels.[33] For both segments of users, WOM valence from the community network has a much larger influence than WOM valence from the personal network. In fact, it is the largest adoption driver related to social learning overall – both across network levels and learning mechanisms (i.e. OL versus WOM). Similar to WOM valence, OL from the community network has a much larger influence than OL from the personal network. Our results are consistent with the findings from Zhang et al. (2015): When community networks are large, they provide more information to individuals than personal networks.

5.2 Image Utility

Intrinsic utility is the consumption utility a user receives, while image utility is the utility a user receives from the image he creates of himself for his friends. This concept was first introduced by Toubia and Stephen (2013) who find that both intrinsic and image utility are present in the context of Twitter posts. Using the number of friends a user has, we test for the existence of image utility in the context of anime adoptions. If image utility plays a role in the adoption of animes, we expect individuals with more friends to belong to a segment that adopts more animes and/or adopts animes sooner.

We find a positive significant coefficient in the segment probability for the number of friends a user has (see model (ii) in Table 3), i.e. the more friends a user has, the more likely he is to be a "Regular Watcher." At the same time, it is the segment of "Enthusiasts" who adopt more animes and adopt them earlier (see Table 4). Thus we conclude that image utility does not play a role in the adoption of animes.

[33] We focus on WOM valence and OL since the effects of WOM dispersion are relatively small.

5.3 Rational versus Irrational Herding

Rational herding occurs as a result of OL among consumers (Banerjee 1992; Bikhchandani et al. 1992), while irrational herding can happen when consumers blindly follow others' decisions or conform to prevalent choices as the social norm (Zhang and Liu 2012). In this subsection, we distinguish between rational and irrational herding by investigating whether the effects of OL differ with a user's expertise with animes. If the observed effects of OL are indeed driven by rational herding, we expect that inexperienced anime watchers are subject to the influence of OL to a larger extent than experienced anime watchers. This is because experienced anime watchers can make a better or more certain judgment about anime quality due to their expertise in the domain area.

We find mixed evidence for rational herding. The coefficient for the average number of yearly adopted animes in the segment probability – our measure of expertise – is negative and significant, i.e. individuals who watch more animes are more likely to belong to segment 2 ("Enthusiasts"). The effect of OL from the community network is smaller for "Enthusiasts" than for "Regular Watchers." This result suggests that experienced anime watchers are less influenced by the popular anime choices of strangers – a result that is consistent with the rational herding explanation. In contrast, the effect of OL from the personal network is larger for "Enthusiasts" than for "Regular Watchers." This finding suggests that experienced anime watchers are more influenced by their friends' anime adoptions than their less experienced counterparts - a result that is inconsistent with rational herding.

5.4 Positive and Negative Observational Learning

As discussed in Section 3, users can assign different stati to the animes on their watch list: "watched," "watching," "on hold," "dropped," or "plan to watch." While we define a user as having adopted an anime if the anime is on his watch list under any of the first four stati in our main model, the four stati contain different information about product adoptions. More specifically, while the adoption information can be viewed as either positive or neutral for the stati "watched," "watching," and "on hold," it is clearly negative for the status "dropped." We use this information on stati to estimate an additional model in which we differentiate between OL coming from positive and negative product adoption experiences within the personal network.

To do so, we define positive OL as product adoptions under the stati "watched," "watching," and "on hold" and negative OL as product adoptions under the status "dropped."[34]

The results are shown as model (i) in Table 6. As expected, we find significant positive coefficients for positive OL from friends for both segments of users. However, negative OL only has a significant negative effect on "Regular Watchers" and is insignificant for "Enthusiasts." We conclude that individuals use the differential informational content in their friends' adoption stati when making their own watching decisions.

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Insert Table 6 about here

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5.5 Awareness versus Learning about Unobserved Quality

OL from the personal network can influence a user in his decision whether to watch an anime in two ways: A user can become aware of an anime through his friends' adoptions and/or he can learn about the unobserved quality of an anime from his friends' adoptions (see also Fafchamps et al. 2016). When a user first observes that a friend has watched an anime, this can both create awareness for the anime and let the user learn about the unobserved quality of the anime. However, friends' subsequent adoptions only inform a user about the unobserved quality and do not create awareness for the anime since that has already been achieved through the first adoption by a friend. To turn this around, if we do not find a significant effect of the first adoption by a friend, but a significant effect for friends' subsequent adoptions, it implies that quality information transfer and not awareness creation is the underlying mechanism for the effect of OL from friends in our setting.

We estimate an additional model in which we incorporate separate coefficients for the first adoption by a friend and for subsequent adoptions by friends. The results are shown as model (ii) in Table 6. For both segments of users, our results reveal significant positive coefficients for both the first and subsequent adoptions by friends. This finding implies that users both become aware of an anime and learn about its unobserved quality through OL from the personal

[34] Note that our definition of positive and negative OL is different from Chen et al. (2011). Chen et al. (2011) use data from Amazon.com and consider the OL signal for a camera to be positive (negative) if the market share of this camera is sufficiently high (too low) to be listed under the "What do customers ultimately buy after viewing this item?" section.

network and is similar to the results found in Fafchamps et al. (2016) in the context of an airtime transfer service.

6 Limitations and Future Research

There are several limitations to our research. First, we do not account for competition stemming from other animes that could potentially be adopted beyond controlling for the number of animes watched in each week. A model that explicitly accounts for competition would improve our understanding of individuals' decisions of which anime to watch. Second, we only have data on online WOM and OL. While in our context of animes, online information is likely to be the primary source of information due to the special interest nature of animes, accounting for offline WOM and OL might be important in other contexts.

Third, while we observe five different stati ("watched," "watching," "on hold," "dropped" and "plan to watch") for each anime, we only model initial adoptions of an anime (episode) and do not investigate what drives individuals to watch multiple episodes, take a break in watching a series or drop it altogether. We leave this for future research to study. And finally, to solve the challenge of endogenous group formation, we focus on users who have been members of MyAnimeList.net for at least one year in our empirical analysis. Studying the co-evolution of one's personal network and product adoption decisions during the first year of website membership would be an interesting direction for future research.

7 Conclusion

Advances in technology have enabled firms to directly facilitate and manage social interactions and information sharing among consumers. A good understanding of the differential and unique effects of various social learning devices at different levels of a network is essential for firms to develop successful information provision strategies and efficiently design their websites. In this paper, we study the role of social learning in individual consumers' product adoptions. Drawn from the previous literature, we conceptualize that an individual can learn from and be affected by peers in his personal network as well as all other users in the community network through two different mechanisms, namely, WOM and OL. Utilizing a unique data on individual users' friendship networks and movie watching decisions from an anime website, we examine the effects of both WOM and OL simultaneously on users' product adoptions and quantify the relative importance of information obtained from one's personal network as compared to the information obtained from the community network. Our study thus complements the growing body of literature investigating the role of social learning in individuals' online purchases and consumption decisions.

Our empirical analysis reveals two segments of users with varying degrees of susceptibility to the influence of WOM and OL: an "Enthusiasts" segment consisting 26% of users and a "Regular Watcher" segment containing the remaining 74% of users. For both segments of users, WOM from the community network is the largest driver of users' product adoptions followed by OL from the community network. Thus our results highlight that WOM and OL provide unique and different information that individuals use in their product adoption decisions. We also find that social learning from the community network has a much larger impact on individuals' product adoption than social learning from one's immediate personal network. This result is consistent with the theoretical prediction in Zhang et al. (2015) that community networks provide more accurate information to consumers when they are sufficiently large.

Our results offer noteworthy policy implications for firms operating online streaming platforms. First, the predominant business practice in the online streaming industry has been to only display community level movie ratings and popularity statistics. For a short time period in 2013, Netflix gave users the option to link their Netflix to their Facebook accounts and thus enabled direct information sharing about movies between friends. Currently, to the best of our knowledge, none of the major online streaming services in the US provides users with the tools necessary to form personal networks. Our results suggest that the less significant role the personal network plays vis-a-vis the community network in individuals' movie watching behavior may explain online streaming platforms' strategic decision not to provide information from personal networks within the platform.

Second, we find that the effect of community WOM is the largest adoption driver and overshadows the effect of community OL. These results are consistent with the current product information provision practice found in leading online streaming platforms. The top four US online streaming platforms, i.e., Netflix, Hulu, Amazon and HBO Now, all provide average user ratings for movies and (TV) shows available at their websites. Netflix and Hulu also provide some information partially based on adoptions: Netflix shows “Top Picks” which are based on viewership and customization to an individual’s tastes and “Trending Now.” Hulu has a “Popular Shows/Episodes” and a “Popular Networks” category. However, it is unclear how and to what extent actual adoptions by individuals influence these featured categories. Our results suggest that, from the perspective of enhancing movie watching, it might be worthwhile for Amazon and HBO Now to provide popularity information for their movies and (TV) shows alongside the average ratings. Online streaming platforms can also consider displaying OL information directly in terms of adoptions, rankings, or similar metrics to encourage adoptions more efficiently.

References

Allison, Paul D. (1982), 'Discrete-time methods for the analysis of event histories', *Sociological Methodology* **13**(1), 61–98.

Aral, Sinan and Dylan Walker (2011), 'Creating social contagion through viral product design: A randomized trial of peer influence in networks', *Management Science* **57**(9), 1623–1639.

Banerjee, Abhijit V. (1992), 'A simple model of herd behavior', *The Quarterly Journal of Economics* **107**(3), 797–817.

Bikhchandani, Sushil, David Hirshleifer and Ivo Welch (1992), 'A theory of fads, fashion, custom, and cultural change as informational cascades', *Journal of Political Economy* **100**(5), 992–1026.

Bramoullé, Yann, Habiba Djebbari and Bernard Fortin (2009), 'Identification of peer effects through social networks', *Journal of Econometrics* **150**(1), 41–55.

Brown, Jacqueline Johnson and Peter H. Reingen (1987), 'Social ties and word-of-mouth referral behavior', *Journal of Consumer Research* **14**(3), 350–362.

Buckley, Jack and Chad Westerland (2004), 'Duration dependence, functional form, and corrected standard errors: Improving eha models of state policy diffusion', *State Politics & Policy Quarterly* **4**(1), 94–113.

Cai, Hongbin, Yuyu Chen and Hanming Fang (2009), Observational learning: Evidence from a randomized natural field experiment, Technical Report 3.

Chen, Yubo, Qi Wang and Jinhong Xie (2011), 'Online social interactions: A natural experiment on word of mouth versus observational learning', *Journal of Marketing Research* **48**(2), 238–254.

Chevalier, Judith A. and Dina Mayzlin (2006), 'The effect of word of mouth on sales: Online book reviews', *Journal of Marketing Research* **43**(3), 345–354.

Chintagunta, Pradeep K., Shyam Gopinath and Sriram Venkataraman (2010), 'The effects of online user reviews on movie box office performance: Accounting for sequential rollout and aggregation across local markets', *Marketing Science* **29**(5), 944–957.

Claussen, Jörg, Benjamin Engelstätter and Michael R Ward (2014), 'Susceptibility and influence in social media word-of-mouth', *ZEW-Centre for European Economic Research Discussion Paper* (14-129).

De Giorgi, Giacomo, Michele Pellizzari and Silvia Redaelli (2010), 'Identification of social interactions through partially overlapping peer groups', *American Economic Journal: Applied Economics* **2**(2), 241–275.

Dellarocas, Chrysanthos, Zhang Xiaoquan and Neveen F. Awad (2007), 'Exploring the value of online product reviews in forecasting sales: The case of motion pictures', *Journal of Interactive Marketing* **21**(4), 23–45.

Duan, Wenjing, Bin Gu and Andrew B. Whinston (2008), 'Do online reviews matter? an empirical investigation of panel data', *Decision Support Systems* **45**(4), 1007–1016.

Duan, Wenjing, Bin Gu and Andrew B. Whinston (2009), 'Informational cascades and software adoption on the internet: An empirical investigation', *MIS Quarterly* **33**(1), 23–48.

Elberse, Anita and Jehoshua Eliashberg (2003), 'Demand and supply dynamics for sequentially released products in international markets: The case of motion pictures', *Marketing Science* **22**(3), 329–354.

Eliashberg, Jehoshua and Steven M. Shugan (1997), 'Film critics: Influencers or predictors?', *Journal of Marketing* **61**(2), 68–78.

Fafchamps, Marcel, Mans Soderbom and Monique vanden Boogaart (2016), Adoption with social learning and network externalities, Working Paper 22282, National Bureau of Economic Research.

Godes, David and Dina Mayzlin (2004), 'Using online conversations to study word-of-mouth communication', *Marketing Science* **23**(4), 545–560.

Hannan, Michael T., Nancy B. Tuma and Lyle P. Groeneveld (1978), 'Income and independence effects on marital dissolution: Results from the seattle and denver income-maintenance experiments', *American Journal of Sociology* **84**(3), 611–633.

Herzenstein, Michal, Utpal M. Dholakia and Rick L. Andrews (2011), 'Strategic herding behavior in peer-to-peer loan auctions', *Journal of Interactive Marketing* **25**(1), 27 – 36.

King, Gary and Langche Zeng (2001*a*), 'Explaining rare events in international relations', *International Organization* **55**(03), 693–715.

King, Gary and Langche Zeng (2001*b*), 'Logistic regression in rare events data', *Political Analysis* **9**(2), 137–163.

King, Gary and Langche Zeng (2002), 'Estimating risk and rate levels, ratios and differences in case-control studies', *Statistics in Medicine* **21**(10), 1409–1427.

Kirmani, Amna and Akshay R. Rao (2000), 'No pain, no gain: A critical review of the literature on signaling unobservable product quality', *Journal of Marketing* **64**(2), 66–79.

Kozinets, Robert V. (1999), 'E-tribalized marketing?: The strategic implications of virtual communities of consumption', *European Management Journal* **17**(3), 252–264.

Lehmann, Donald R. and Charles B. Weinberg (2000), 'Sales through sequential distribution channels: An application to movies and videos', *Journal of Marketing* **64**(3), 18–33.

Li, Xinxin and Lorin M. Hitt (2008), 'Self-selection and information role of online product reviews', *Information Systems Research* **19**(4), 456–474.

Liu, Yong (2006), 'Word of mouth for movies: Its dynamics and impact on box office revenue', *Journal of Marketing* **70**(3), 74–89.

Lovett, Mitchell J. and Richard Staelin (2015), 'The role of paid and earned media in building entertainment brands: Reminding, informing, and enhancing enjoyment', *Forthcoming at Marketing Science* .

Manski, Charles F. (1993), 'Identification of endogenous social effects: The reflection problem', *The Review of Economic Studies* **60**(3), 531–542.

Moe, Wendy W. and Michael Trusov (2011), 'The value of social dynamics in online product ratings forums', *Journal of Marketing Research* **48**(3), 444–456.

Nair, Harikesh S., Puneet Manchanda and Tulikaa Bhatia (2010), 'Asymmetric social interactions in physician prescription behavior: The role of opinion leaders', *Journal of Marketing Research* **47**(5), 883–895.

Prag, Jay and James Casavant (1994), 'An empirical study of the determinants of revenues and marketing expenditures in the motion picture industry', *Journal of Cultural Economics* **18**(3), 217–235.

Sun, Monic, Xiaoquan Michael Zhang and Feng Zhu (2012), 'To belong or to be different? evidence from a large-scale field experiment in china', *NET Institute Working Paper* .

Toubia, Olivier and Andrew T. Stephen (2013), 'Intrinsic vs. image-related utility in social media: Why do people contribute content to twitter?', *Marketing Science* **32**(3), 368–392.

Wang, Jing, Anocha Aribarg and Yves F. Atchadé (2013), 'Modeling choice interdependence in a social network', *Marketing Science* **32**(6), 977–997.

Zhang, Juanjuan (2010), 'The sound of silence: Observational learning in the u.s. kidney market', *Marketing Science* **29**(2), 315–335.

Zhang, Juanjuan and Peng Liu (2012), 'Rational herding in microloan markets', *Management Science* **58**(5), 892–912.

Zhang, Jurui, Yong Liu and Yubo Chen (2015), 'Social learning in networks of friends versus strangers', *Marketing Science* **34**(4), 573–589.

Zhang, Yuchi and David Godes (2013), 'Learning from online social ties', *Available at ssrncode 2277580* .

Zhu, Feng and Xiaoquan (Michael) Zhang (2010), 'Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics', *Journal of Marketing* **74**(2), 133–148.

Figures and Tables

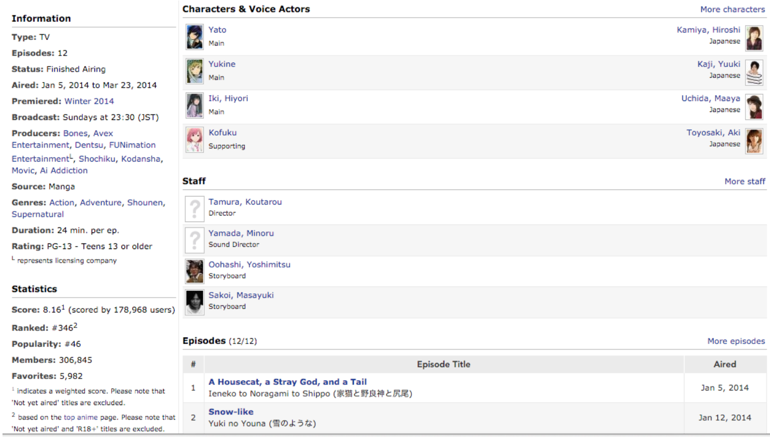


Figure 1: Example of an Anime Page

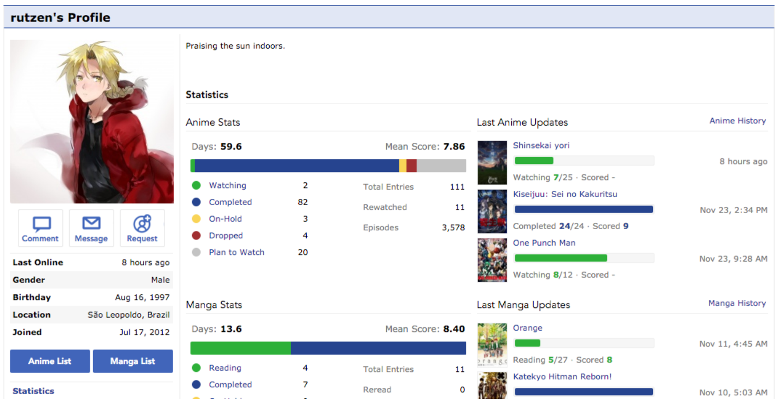


Figure 2: Example of a User Page

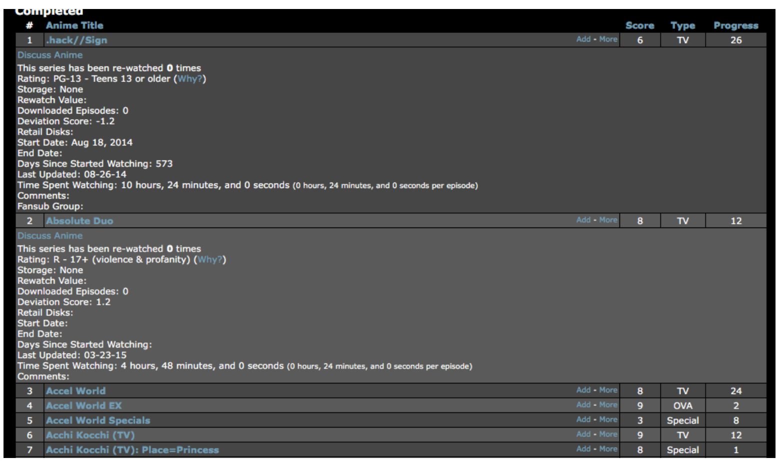


Figure 3: Example of a User Watch List

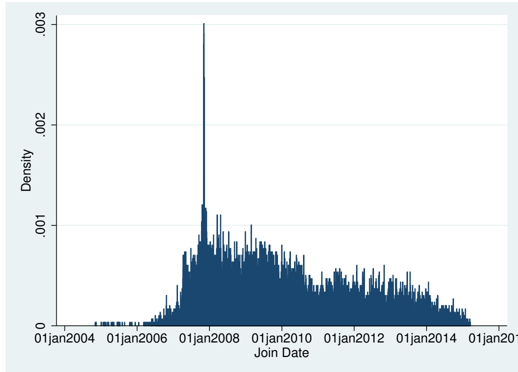


Figure 4: Dates Users Joined MyAnimeList.Net

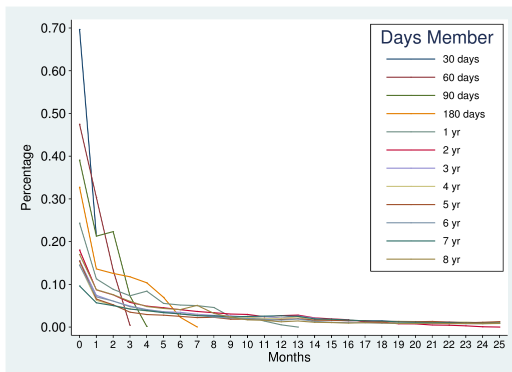


Figure 5: Percentage of Friends Added During First 2 Years After Joining MyAnimeList.net (Grouped by the Number of Days of Membership)

(a) Average Cumulative Number of News Articles Outside Of MyAnimeList.net

(b) Average Cumulative Number of News Articles on MyAnimeList.net

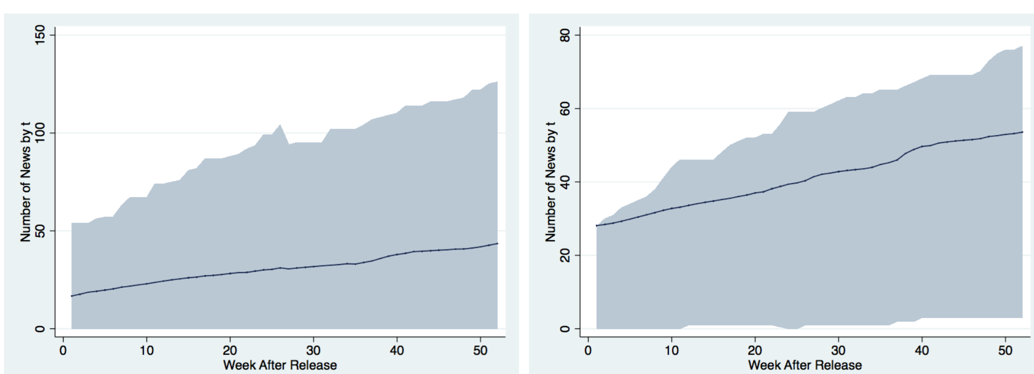
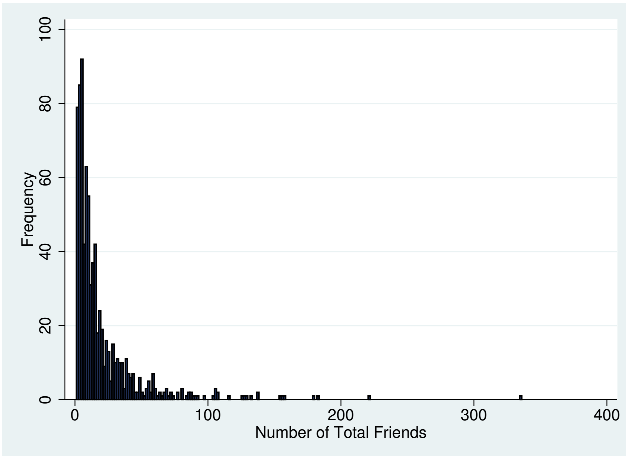
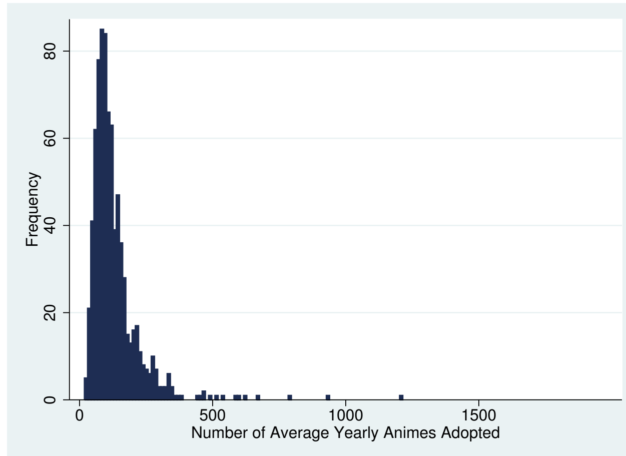


Figure 6: Average Cumulative Number of News Articles

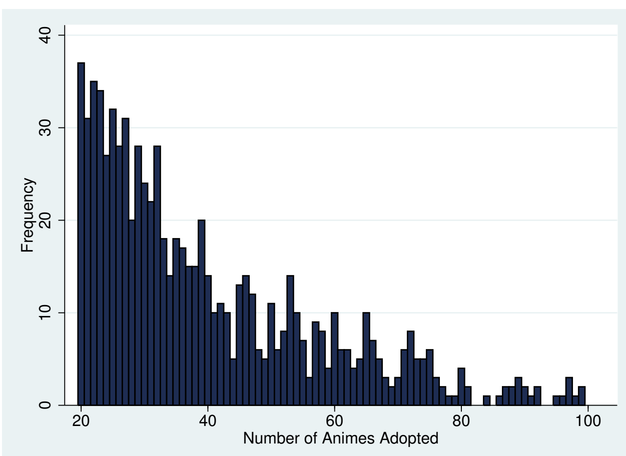
(a) Number of Friends
(truncated at 200 friends)



(b) Average Number of Animes Adopted Per Year
(truncated at an annual average of 1,000 animes)



(c) Number of Adopted Animes Among Animes Under Study



(d) Adoption Week (Relative to Each Anime's Release Date)

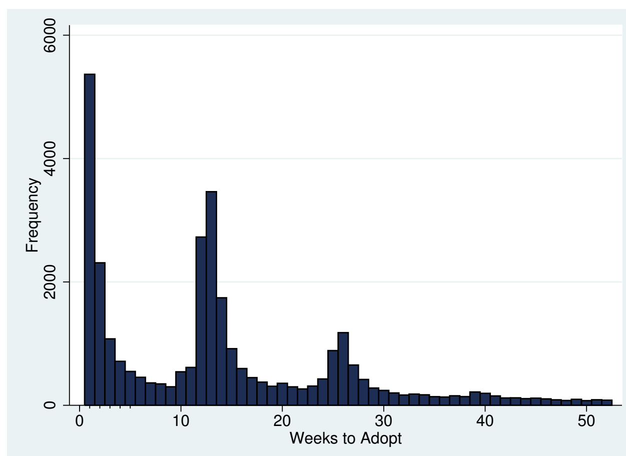
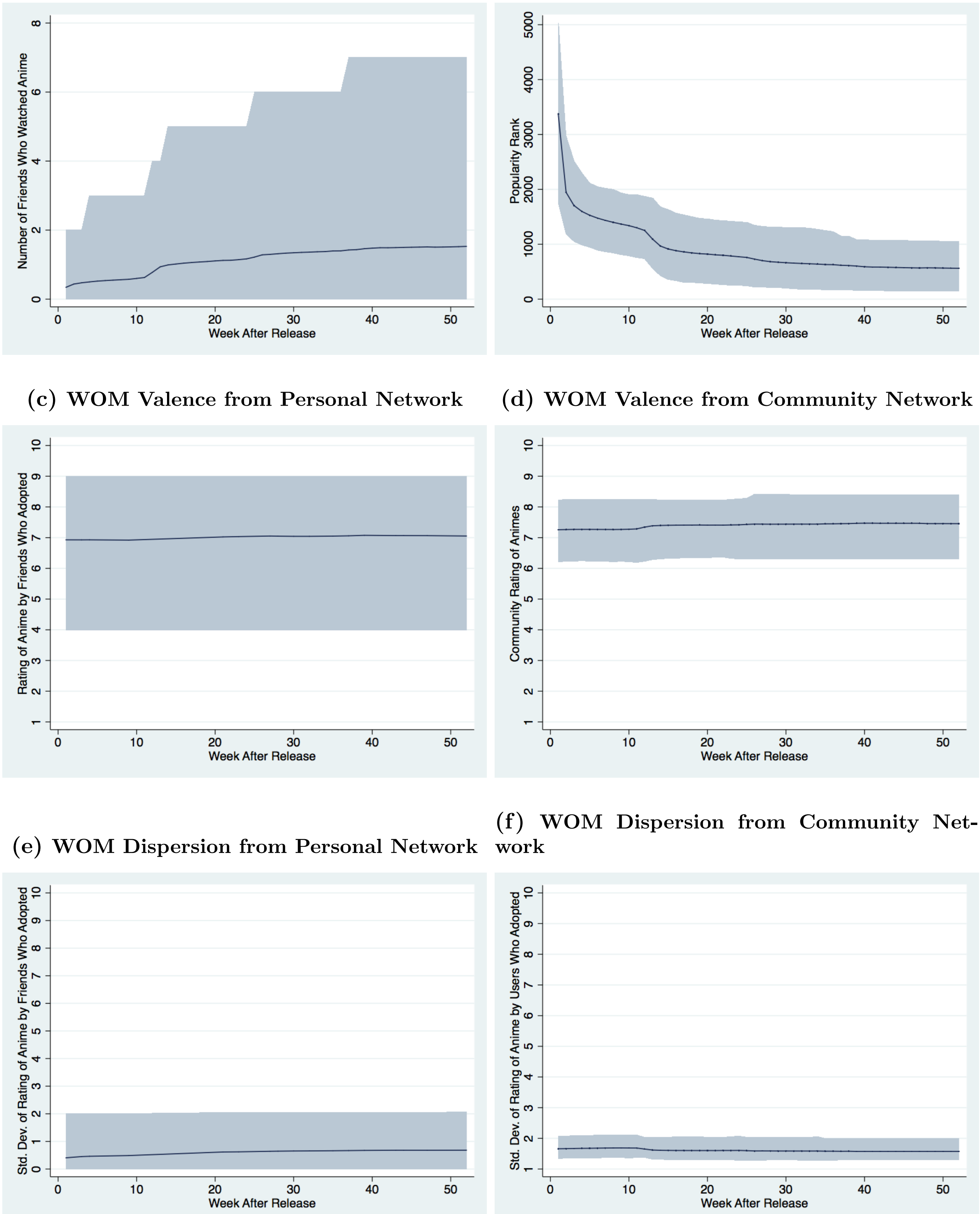


Figure 7: Histograms of the Number of Friends and of Descriptives Related to Adoption



(a) OL from Personal Network

(b) OL from Community Network

(c) WOM Valence from Personal Network

(d) WOM Valence from Community Network

(e) WOM Dispersion from Personal Network

(f) WOM Dispersion from Community Network

Figure 8: WOM and OL from Personal and Community Networks

	Mean	Std. Dev.	Min	Median	Max	N
Age	23	5	13	22	78	505
Gender (% Females)	30					800
Gender (% Males)	55					800
Gender (% Not Specified)	15					800
Number of Friends	20	28	1	11	336	800
Average Number of Animes Adopted per Year	131	97	18	105	1,214	800
Number of Animes Adopted Among Animes Under Study	40	18	20	34	99	800
Adoption Week (Conditional on Adoption)	14	12	1	13	52	31,467

Table 1: Descriptive Statistics

	(i) Linear-in-means-model	(ii) Homogeneous hazard model
Word-of-Mouth		
Friends' Av. Rating Dummy	−0.003***	0.007
	(0.000)	(0.039)
Friends' Av. Rating Interaction	0.000***	0.022***
	(0.000)	(0.005)
Friends' Rating Std. Deviation	−0.001***	0.057***
	(0.000)	(0.017)
Community Rating	0.004***	0.193***
	(0.000)	(0.009)
Community Rating Std. Deviation	0.002***	−0.266***
	(0.000)	(0.029)
Observational Learning		
Cum. Number of Friends Who Adopted[a]	0.004***	0.064***
	(0.000)	(0.017)
Community Rank[a]	−0.002***	−0.480***
	(0.000)	(0.012)
Other Parameters		
Number of Animes Watched During the Week[a]	0.018***	0.654***
	(0.000)	(0.007)
Manga Adoption Dummy	−0.001	0.009
	(0.001)	(0.063)
Season Finale Dummy	0.040***	1.098***
	(0.000)	(0.058)
Cum. Number of Online News[a]	0.002***	0.108***
	(0.000)	(0.005)
log(Week)	−0.009***	−1.830***
	(0.000)	(0.010)
Genre-Specific Similarity Indices		
Action		1.071***
		(0.043)
Comedy		0.096***
		(0.028)
School		0.380***
		(0.059)
Romance		1.007***
		(0.041)
Supernatural		−0.188***
		(0.06)
Fantasy		0.344***
		(0.061)
Slice of Life		1.098***
		(0.098)
Shounen		0.499***
		(0.068)

Standard errors in parentheses

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

[a] Measured on logarithmic scale.

Table 2: Peer Effect Identification

	(i)	(ii)	
	Homogenous Model	Latent Segments Model	
		Segment 1: Regular Watchers	Segment 2: Enthusiasts
Word-of-Mouth			
Friends' Av. Rating Dummy	0.007	−0.067	0.072
	(0.039)	(0.049)	(0.070)
Friends' Av. Rating Interaction	0.022***	0.037***	0.002
	(0.005)	(0.006)	(0.009)
Friends' Rating Std. Deviation	0.057***	0.048***	0.133***
	(0.017)	(0.021)	(0.036)
Community Rating	0.193***	0.276***	0.088***
	(0.009)	(0.011)	(0.015)
Community Rating Std. Deviation	−0.266***	−0.158***	−0.420***
	(0.029)	(0.036)	(0.045)
Observational Learning			
Cum. Number of Friends Who Adopted[a]	0.064***	0.079***	0.150***
	(0.017)	(0.022)	(0.033)
Community Rank[a]	−0.480***	−0.614***	−0.263***
	(0.012)	(0.014)	(0.020)
Other Parameters			
Number of Animes Watched During the Week[a]	0.654***	0.575***	
	(0.007)	(0.008)	
Manga Adoption Dummy	0.009	0.021	
	(0.063)	(0.064)	
Season Finale Dummy	1.098***	1.053***	
	(0.058)	(0.059)	
Cum. Number of Online News[a]	0.108***	0.110***	
	(0.005)	(0.005)	
log(Week)	−1.830***	-1.834***	
	(0.010)	(0.010)	
Genre-Specific Similarity Indices			
Action	1.071***	1.134***	
	(0.043)	(0.044)	
Comedy	0.096***	0.115***	
	(0.028)	(0.029)	
School	0.380***	0.383***	
	(0.059)	(0.061)	
Romance	1.007***	1.082***	
	(0.041)	(0.042)	
Supernatural	−0.188***	-0.135***	
	(0.060)	(0.061)	
Fantasy	0.344***	0.444***	
	(0.061)	(0.063)	
Slice of Life	1.098***	1.152***	
	(0.098)	(0.100)	
Shounen	0.499***	0.548***	
	(0.068)	(0.070)	
Segment Membership Probability:			
Constant		9.886***	
		(0.964)	
Number of Friends[a]		0.263***	
		(0.100)	
Avg. Number of Yearly Adopted Animes[a]		-1.967***	
		(0.201)	
Loglikelihood	−72,449.67	-70,164.59	
AIC	144,939.33	140,389.18	
BIC	145,195.86	140,773.98	

Standard errors in parentheses

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

[a] Measured on logarithmic scale.

Table 3: Model Results

	Regular Watchers 74%	Enthusiasts 26%
Av. Number of Friends Who Adopted in Adoption Week	1.9	1.3
Av. Friends' Rating in Adoption Week	7.5	7.4
Av. Community Rank in Adoption Week	1,243	1,510
Av. Community Rating in Adoption Week	7.5	7.4
Av. Number of Friends	20.1	17.6
Annual Av. Number of Animes Watched	109.5	185.8
Av. Number of Weeks until Adoption	15	12
Segment Adoption Rate (out of 103)	29	60

Table 4: Segment Characteristics

	Regular Watchers 74%	Enthusiasts 26%
Word-Of-Mouth		
Friends' Av. Rating	0.09	-
Friends' Rating Std. Deviation	0.01	0.03
Community Rating	2.02	0.64
Community Rating Std. Deviation	-0.26	-0.26
Observational Learning		
Cum. Number of Friends Who Adopted	0.08	0.15
Community Rank	-0.61	-0.26

Table 5: WOM and OL Elasticities

	(i) Asymmetric OL Model		(ii) Awareness Model	
	Segment 1: Regular Watchers	Segment 2: Enthusiasts	Segment 1: Regular Watchers	Segment 2: Enthusiasts
Word-of-Mouth				
Friends' Av. Rating Dummy	−0.038	0.083	0.050	0.099***
	(0.051)	(0.069)	(0.026)	(0.034)
Friends' Av. Rating Interaction	0.025***	−0.008	−0.062	0.069
	(0.007)	(0.01)	(0.049)	(0.071)
Friends' Rating Std. Deviation	0.041	0.102***	0.037***	0.003
	(0.023)	(0.037)	(0.006)	(0.009)
Community Rating	0.276***	0.088***	0.277***	0.088***
	(0.011)	(0.015)	(0.011)	(0.015)
Community Rating Std. Deviation	−0.139***	−0.415***	−0.155***	−0.419***
	(0.036)	(0.045)	(0.036)	(0.045)
Observational Learning				
Cum. Number of Friends Who Adopted[a]			0.060***	0.102***
			(0.022)	(0.037)
Cum. Number of Friends Who Watched[a]	0.169***	0.232***		
	(0.028)	(0.043)		
Cum. Number of Friends Who Dropped[a]	−0.162***	0.058		
	(0.042)	(0.053)		
Dummy for First Adoption by Friend			0.045***	0.135***
			(0.022)	(0.039)
Community Rank[a]	−0.617***	−0.263***	−0.615***	−0.262***
	(0.014)	(0.020)	(0.014)	(0.020)
Other Parameters				
Number of Animes Watched During the Week[a]	0.578***		0.575***	
	(0.008)		(0.008)	
Manga Adoption Dummy	0.017		0.024	
	(0.064)		(0.064)	
Season Finale Dummy	1.059***		1.049***	
	(0.059)		(0.060)	
Cum. Number of Online News[a]	0.110***		0.110***	
	(0.005)		(0.005)	
log(Week)	-1.836***		-1.834***	
	(0.010)		(0.010)	
Genre-Specific Similarity Indices				
Action	1.131***		1.127***	
	(0.044)		(0.044)	
Comedy	0.112***		0.114***	
	(0.029)		(0.029)	
School	0.378***		0.378***	
	(0.061)		(0.061)	
Romance	1.079***		1.075***	
	(0.042)		(0.042)	
Supernatural	-0.129***		-0.137***	
	(0.061)		(0.061)	
Fantasy	0.441***		0.443***	
	(0.063)		(0.063)	
Slice of Life	1.149***		1.155***	
	(0.100)		(0.100)	
Shounen	0.544***		0.545***	
	(0.070)		(0.070)	
Segment Membership Probability:				
Constant	9.921***		9.896***	
	(0.960)		(0.962)	
Number of Friends[a]	0.211***		0.237***	
	(0.097)		(0.098)	
Avg. Number of Yearly Adopted Animes[a]	-1.951***		-1.957***	
	(0.199)		(0.200)	
Loglikelihood	-70,140.31		-70,159.24	
AIC	140,344.62		140,378.48	
BIC	140,755.07		140,763.27	

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

Table 6: Asymmetric OL and Awareness Model Result

Appendix A: Original and Final Data

In this appendix, we compare the characteristics of the final data to two other data sets, namely, (i) a data set that conditions on the same criteria as our final data with the exception of the conditioning on at least 20 anime adoptions among the animes under study and (ii) the data set containing all 380,000 users for whom we have data. The top half of Table A-1 shows the descriptive statistics for the former and the bottom half of Table A-1 displays the descriptive statistics for the latter data set.

	Mean	SD	Min	Median	Max	N
Eligible Population Not Conditioning On At Least 20 Adoptions						
Age	26	4	13	25	84	34,545
Gender (% Females)	33					48,291
Gender (% Males)	51					48,291
Gender (% Not Specified)	16					48,291
Number of Friends	14	32	1	6	2,334	48,290
Average Number of Animes Adopted per Year	75	70	1	57	1,942	48,290
Number of Animes Adopted Among Animes Under Study	16	17	0	10	103	48,290
Adoption Week (Conditional on Adoption)	16	13	1	13	52	708,614
Population of 380,000 Users						
Age	23	7	12	22	84	218,130
Gender (% Females)	26					377,644
Gender (% Males)	40					377,644
Gender (% Not Specified)	34					377,644
Number of Friends	9	26	1	3	3,731	377,644
Average Number of Animes Adopted per Year	55	65	0	32	330	377,644
Number of Animes Adopted Among Animes Under Study	11	15	0	3	103	377,644
Adoption Week (Conditional on Adoption)	21	14	1	17	52	1,368,846

Table A-1: Descriptive Statistics

Users in our final data are similar to users in data sets (i) and (ii) on all but four characteristics: users in our final data watch, on average, more animes per year (131 versus 75 and 55, respectively) and adopt more animes among those under study (40 versus 16 and 11, respectively). The difference between the number of adopted animes among those under study between the final data and data sets (i) and (ii) is likely due to us conditioning on at least 20 adoptions among the animes under study – thus users who generally adopt more are overrepresented in our final data. Further, users in our final data have, on average, more friends (20 versus 14 and 9, respectively) and adopt earlier (week 14 versus 16 and 21, respectively). The difference between the total number of friends between the final data and data set (ii) is likely due to us conditioning on a longer website membership in the final data and data set (i) as compared to data set (ii). Recall that we require users to have been a member of the website for at least one year before the release of the first anime under study to be included in the final data and data set (i).

Appendix B: Variable (Re-)Construction

In this appendix, we describe the process through which we (re-)constructed several variables used in the estimation, namely, the WOM and OL variables from the community network and the genre-specific similarity indices. For the WOM and OL variables from the community network, this re-construction was necessary because MyAnimeList.net only shows the current levels of these variables, but no historical values. Thus we had information on the number of adoptions, the rank based on the number of adoptions, average rating, and the distribution of ratings from the community network in March 2015 (start date of the data collection), but not earlier to that.

Community Rank

The variable "Community Rank" captures the weekly rank of an anime among all the animes on the website based on the cumulative number of adoptions by all users. Note that a lower rank is a "better" rank. On MyAnimeList.net, this popularity rank is explained as:

"This popularity is measured according to the number of users who have the title in their list. The more users that have the title shown in their Anime or Manga list, the higher it will be ranked."

We used our complete collected data containing the adoption histories of nearly 380,000 users to re-construct the weekly rank data based on users' adoption behavior using the following steps: First, for each anime on the website and each week, we calculated the cumulative number of users who had adopted the anime. Second, for each week, we sorted all animes in a decreasing order based on the cumulative number of adoptions. Thus, for each week, the position of each anime in the sorted list indicates the rank of that anime among all animes.

To test the accuracy of the re-constructed rank data, we compared the re-constructed ranks of several randomly selected animes in the first week of March 2015 to the ranks provided by the website at that point in time. The comparison showed that we are able to closely recover anime ranks.

Community Rating

The variable "Community Rating" captures the average of user ratings from all users in the community network. We re-constructed the community rating for each week using the ratings from all users who had adopted and rated the anime among the nearly 380,000 users. For each week, we calculated the average rating based on the ratings submitted by all users by that week. Then we compared the re-constructed values of the "Community Rating" variable for several randomly selected animes in the first week of March 2015 to those shown on the website at the same point in time and found our re-constructed "Community Ratings" to be close to those shown on the website.

We also check the robustness of our results by estimating an additional model (see model (ii) in Online Appendix C) using an alternative operationalization of the "Community Rating" variable, namely, the rank of an anime based on ratings submitted by the whole community. MyAnimeList.net reports the method used to calculate these weighted ranks:

"Only scores where a user has completed at least 1/5 of the anime/manga are calculated. Example: If you watched a 26 episode series, this means you would had to have watched at least 5 episodes (26/5.2)=5. We're using 5.2 instead of 5 so we get a whole number for "most" series. The formula used is:
$WeightedRank(WR) = (v/(v+m)) * S + (m/(v+m)) * C$
S = Average score for the Anime (mean).
v = Number of votes for the Anime = (Number of people scoring the Anime).
m = Minimum votes/scores required to get a calculated score (currently 50 scores required).
C = The mean score across the entire Anime DB."

We applied this formula and calculated weekly weighted ranks for all animes. To test the accuracy of the re-constructed rank data, we compared the re-constructed ranks of several randomly selected animes in the first week of March 2015 to the ranks provided by the website at that point in time. The comparison showed that we are able to closely recover anime ranks.

Community Rating Std. Deviation

The variable "Community Rating Std. Deviation" captures the dispersion of user ratings from all users in the community network. We constructed the community rating std. deviation for each week using the ratings from all users who had adopted and rated the anime among the nearly 380,000 users. For each week, we calculated the std. deviation of ratings based on the ratings submitted by all users by that week. Then we compared the constructed values of the "Community Rating Std. Deviation" variable for several randomly selected animes in the first week of March 2015 to the implied std. deviation based on the distribution of ratings shown on the website at the same point in time and found our "Community Rating Std. Deviations" to be close to those implied by the distributions shown on the website.

Genre-Specific Similarity Indices

We use anime genres to capture users' preferences in terms of genres before the release of an anime. The animes listed on the website are typically associated with three to five different genres out of the 44 genres listed on the website. We use genres of users' past adoptions as a metric to build similarity indices that describe how similar a user's past adoptions in terms of genres are to each of the selected animes in the study. To construct these indices, we first count how many of the animes each user had watched were labeled with each of the 44 different genres. For example, if an anime belongs to the "si-fi," "action," and "mystery" genres, it would increase the counters for each of the three genres "si-fi," "action," and "mystery" by one. Note that since each anime is associated with more than one genre on the website, the sum of the 44 genre counters for each user will be larger than the total number of animes that the user had adopted. Next, we divided each genre counter by the total number of animes that the user has adopted. This gives us the percentage of animes that the user has watched that are of that genre. Back to our example, if a user has watched 50 animes and 30 of those are associated with the genre "action," 60% of the animes that this user has watched are of genre "action." Finally, for each of the 103 animes, we took the calculated percentages for any of the eight main genres, i.e. action, comedy, school, romance, supernatural, fantasy, slice of life, and shounen, as the genre-specific similarity indices of that user for that genre. Higher values of a user's genre-specific similarity index for a genre show more similarity between the user's past adoptions and the focal anime in terms of genres.

Appendix C: Robustness Checks

	(i) Alternative for Personal OL		(ii) Alternative for Community WOM		(iii) Alternative for Similarity Index	
	Segment 1: Regular Watchers	Segment 2: Enthusiasts	Segment 1: Regular Watchers	Segment 2: Enthusiasts	Segment 1: Regular Watchers	Segment 2: Enthusiasts
Word-of-Mouth						
Friends' Av. Rating Dummy	−0.022	0.115	−0.138***	0.069	−0.065	0.010
	(0.049)	(0.066)	(0.048)	(0.065)	(0.049)	(0.067)
Friends' Av. Rating Interaction	0.043***	0.005	0.049***	0.005	0.038***	0.015
	(0.006)	(0.009)	(0.006)	(0.009)	(0.006)	(0.009)
Friends' Rating Std. Deviation	0.079***	0.197***	0.072***	0.133***	0.059***	0.137***
	(0.019)	(0.032)	(0.021)	(0.036)	(0.021)	(0.035)
Community Rating	0.278***	0.094***	−0.197***	−0.109***	0.308***	0.097***
	(0.011)	(0.015)	(0.009)	(0.011)	(0.011)	(0.015)
Community Rating Std. Deviation	−0.150***	−0.398***			−0.091***	−0.411***
	(0.036)	(0.045)			(0.035)	(0.044)
Observational Learning						
Cum. Number of Friends	−0.032	0.072***	0.111***	0.147***	0.057***	0.134***
Who Adopted[a]	(0.018)	(0.025)	(0.022)	(0.034)	(0.021)	(0.033)
Community Rank[a]	−0.627***	−0.252***	−0.220***	−0.190***	−0.626***	−0.242***
	(0.015)	(0.021)	(0.009)	(0.011)	(0.014)	(0.02)
Other Parameters						
Number of Animes Watched	0.580***		0.589***		0.569***	
During the Week[a]	(0.008)		(0.008)		(0.007)	
Manga Adoption Dummy	0.018		0.051		0.025	
	(0.064)		(0.064)		(0.064)	
Season Finale Dummy	1.063***		1.004***		1.050***	
	(0.060)		(0.059)		(0.059)	
Cum. Number of Online News[a]	0.111***		0.142***		0.110***	
	(0.005)		(0.005)		(0.005)	
log(Week)	-1.833***		-1.722***		-1.837***	
	(0.010)		(0.008)		(0.010)	
Genre-Specific Similarity Indices						
Action	1.132***		1.125***		0.588***	
	(0.044)		(0.044)		(0.036)	
Comedy	0.118***		0.231***		-0.007	
	(0.029)		(0.029)		(0.025)	
School	0.385***		0.443***		0.090	
	(0.060)		(0.060)		(0.049)	
Romance	1.076***		1.010***		0.653***	
	(0.042)		(0.041)		(0.034)	
Supernatural	-0.136***		-0.128***		-0.075	
	(0.061)		(0.061)		(0.058)	
Fantasy	0.452***		0.482***		0.292***	
	(0.063)		(0.063)		(0.050)	
Slice of Life	1.147***		1.309***		0.478***	
	(0.100)		(0.100)		(0.084)	
Shounen	0.543***		0.444***		0.315***	
	(0.070)		(0.070)		(0.055)	
Segment Membership Probability:						
Constant	9.895***		9.930***		4.438***	
	(0.963)		(0.971)		(0.583)	
Number of Friends[a]	0.215***		0.326***		0.136	
	(0.097)		(0.099)		(0.091)	
Avg. Number of Yearly Adopted	-1.945***		-2.013***		-0.715***	
Animes[a]	(0.200)		(0.203)		(0.105)	
Loglikelihood	-70,175.10		-70,386.15		-70,469.29	
AIC	140,410.20		140,828.30		140,998.57	
BIC	140,794.99		141,187.44		141,383.36	

Standard errors in parentheses

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

[a] Measured on logarithmic scale.

Table B-1: Robustness Model Results