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

Current version: January 2018

Mina Ameri† Elisabeth Honka‡ Ying Xie§

Abstract

We quantify the effects of observational learning and word-of-mouth (volume and valence) on consumers' product adoptions. Understanding whether these two social learning devices 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 (Japanese cartoon) platform containing individual-level data on users' networks, anime adoptions, forum posts, and ratings of animes. Our results reveal that both word-of-mouth (volume and valence) and observational learning from the community network have significant and positive effects on individual users' anime adoption decisions. Furthermore, this finding also holds true for word-of-mouth and observational learning coming from the personal network. Comparing the magnitudes word-of-mouth and observational learning effects across both network levels, we find that word-of-mouth valence from the community network is the largest adoption driver among the social learning forces we study. 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 asymmetric observational learning from positive and negative actions and observational learning creating product awareness versus transferring unobserved quality information.

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

JEL Classification: D83, L82, M31

*We thank Eric Bradlow, Pradeep Chintagunta, Brett Gordon, Brett Hollenbeck, Yong Liu, Dina Mayzlin, Peter Rossi, Ananya Sen, Brad Shapiro, Sanjay Sood, Christophe Van den Bulte, 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 Center for Marketing and Data Analysis. All errors are our own.

†University of Texas at Dallas, mina.ameri@utdallas.edu.

‡University of California Los Angeles, elisabeth.honka@anderson.ucla.edu.

§University of Texas at Dallas, ying.xie@utdallas.edu.

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 and valence 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 2016). 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). Although information about product quality can be extracted or inferred from both mechanisms, consumers may still interpret WOM and OL information differently and therefore be influenced by these two forces to varying degrees. On the one hand, one can argue that, compared with OL, WOM conveys more diagnostic information about product quality; therefore it should play a more prominent role. On the other hand, 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. To the best of our knowledge, Chen et al. (2011) is the only paper that studies the effects of both WOM and OL at the aggregate product sales level. No study that we are aware of has simultaneously examined the differential effects of information from WOM versus OL on individual consumers' adoption decisions.[1]

[1] Note that our definition of OL in this paper differs from the classic definition of OL used by previous literature (e.g. Cai et al. 2009; Zhang 2010; Herzenstein et al. 2011; Zhang and Liu 2012): In the classic definition, OL is conceptualized as observations of adoptions without additional information. In our paper, OL is conceptualized as observations of adoptions after controlling for WOM information (see also Chen et al. 2011). We thank an anonymous reviewer for pointing this out.

Second and more importantly, 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 provide useful information to guide companies' platform design decisions on what socialization tools and functions should be made available to consumers.

In this paper, we aim to answer these questions in the empirical context of anime (Japanese cartoon) watching. We choose this market as our empirical context for the following reasons: Movies and shows such as animes are cultural products. With the rapid expansion of online streaming services in recent years,[2] consumers face an overwhelmingly large and constantly

[2]Online streaming of movies and (TV) shows has grown rapidly over the last decade (see McKinsey&Company's Global Media Report 2015). In 2015, over 40% of U.S. households subscribed to at least one video streaming service (http://www.nielsen.com/us/en/insights/reports/2015/the-total-audience-report-q4-2014.html). 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 (https://www.sandvine.com/pr/2015/12/7/sandvine-over-70-of-north-american-traffic-is-now-streaming-video-and-audio.html).

growing choice set when deciding which specific movies or shows to watch. In this scenario, 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 marginal product price is zero in online streaming.[3] 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 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, forum posts, 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 about their friends' anime adoptions and the ratings thereof through three means: through automatic updates about their friends' recent activities, by looking at friends' watch lists, and by checking the adopter list for an anime. Users can also check community-wide popularity (based on the number of adoptions) and average rating scores for all animes listed on the platform. This dual nature enables us to tease apart different sources of information and to study their separate influence on users' product adoptions.

One of the major challenges of working with network data is distinguishing between correlation and causation. As Hartmann et al. (2008) discuss correlation in behavior can be due to three different reasons: endogenous group formation, correlated unobservables, and simultaneity. We take two steps to solve the challenge of endogenous group formation: first, 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. And second, to address the issue of homophily which arises due to endogenous group formation, we exploit the rich panel structure of our data and include user-anime fixed effects to control for each user's preference for a specific anime and user-release week fixed effects to control for each user's propensity to adopt earlier as opposed to later in our model. To account for common shocks that lead to correlated unobservables, we include

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

(calendar) week fixed effects and the number of news pieces collected from MyAnimeList.net and other websites in our model. To address simultaneity, we use lagged versions of variables describing friends' actions and opinions.

We model users' adoption decisions for 103 animes using a linear probability model to be able to accommodate the large number of fixed effects in our model specification (e.g. Bandiera and Rasul 2006; Nair et al. 2010; Bollinger and Gillingham 2012). Our results reveal that both WOM and OL have significant effects on users' anime adoptions. At the community network level, while both WOM valence and WOM volume have significant positive effects on users' adoptions, the effect of WOM valence is larger than the effect of WOM volume. Furthermore, OL also has a significant, albeit smaller than WOM valence, positive effect on product adoptions: as an anime gains more popularity in the community, users become more likely to watch the anime. Similarly, at the personal network level, both WOM (volume and valence) and OL from friends have significant positive effects on users' adoptions with WOM volume having the largest effect among the three. Comparing the magnitudes WOM and OL effects across both network levels based on our predictive exercise results, we find that WOM valence from the community network is the largest adoption driver related to social learning. Further, we find evidence that users differentiate between positive OL (from their friends' positive actions) and negative OL (from their friends' negative actions). And finally, we find OL to both create awareness for an anime and to let users learn about the unobserved quality of an anime.

The contribution of this paper is two-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 valence overshadows the effect of community OL is consistent with the predominant business practice to display average product ratings. And 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 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.

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 and observational learning and delineate the positioning of our research vis-a-vis the findings from extant research.

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 2016), 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 an individual's (purchase) decision quality improves based on information received from strong and weak ties in the network while controlling for WOM valence and variance at the community network level. While Zhang and Godes (2013) have data from an online community similar to the one under study in this paper, they do not have information on product adoptions (neither from friends nor the whole community). Therefore Zhang and Godes (2013) are not able to study OL and, instead, focus on WOM as the main social learning device. In addition, they also do not observe either the valence or the content of information individuals receive from their personal networks and instead use the number of ties as a proxy for the quantity of information received. In the current study, we study the effect of both WOM and OL on an individual's product adoption decisions. Furthermore, 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.

Next, we discuss the relevant literature on OL. 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.

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. 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.

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 about the anime including a content summary, an episode guide, production details, user ratings, and rankings.

===========================

Insert Figure 1 about here

===========================

Figure 2 shows an example of a user page. Note that all information contained in a user's page is available to the public.[4] On a user page, one can see information about the animes and mangas the user has adopted and the adoption dates, his opinion about adopted animes and mangas, his 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. After becoming friends, users can see automatic updates about friends' recent in-site activities on their own pages. Moreover, instant-messaging and communication tools are provided to enable in-site communication between two friends.

===========================

Insert Figure 2 about here

===========================

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).[5] Figure 3 shows an example of a user's watch list. Note that that all animes on the watch list are correctly and uniquely identified because users are required to use a search function to add animes to the list. 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 assigned to any of the first four stati on his watchlist.[6] 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.[7] Further, users can indicate their opinion

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

[5]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.

[6]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 (2016) compare survey panelists' self-reported viewing data and the actual streaming data and find that people tend to correctly report their actual watching behavior. Thus we are confident that the self-reported adoption data are reliable in our context.

[7]In an additional model, we differentiate between OL 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.

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." Users can also discuss the animes they have watched in the forum section of the website. 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.[8]

=========================

Insert Figure 3 about here

=========================

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.[9] Further, we use the average rating of an anime given by the user's friends to measure WOM valence from the personal network. Following previous literature (e.g. Godes and Mayzlin 2004; Chintagunta et al. 2010), we measure WOM volume from the personal network using the number of ratings and forum posts submitted by the user's friends. With regard to the community network, users see the community-wide total number of adoptions for an anime on the anime page (see "Members" in the bottom left corner in Figure 1) - this is our measure of community OL for the anime. 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 community WOM valence.[10] And lastly, users can see the number of ratings from the community network and the number of forum posts on another tab of the anime page. We use the total number of ratings and forum

[8]Our data contain the start dates and the dates of the last updates for 95% and 5% of observations, respectively. As a robustness check, we move the adoption dates of the 5% of observations for whom we only have the dates of the last update one week, i.e. mark the adoption time as one week prior to the date of the last update. We then re-estimate our model using these modified adoption times for observations with last updates and find our results to be robust (see column (iv) in Table C-1 in Online Appendix C).

[9]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 C-1 in Online Appendix C).

[10]Note that there is also an alternative measure of OL from community network: popularity rank (based on the number of adoptions) on the anime page (see "Popularity" in the bottom left corner in Figure 1). Similarly, there is an alternative measure of WOM valence 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 these two alternative measures of OL and WOM valence from the community network and our results are robust (see models (ii) and (iii) in Table C-1 in Online Appendix C).

posts to measure community WOM volume.[11]

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 2.6 million users on the website among which were about 2.2 million stand-alone users with no friends and little to no activity.[12] Since we are interested in the effects of social learning on product adoption, we collected data on a network of nearly 380,000 users.[13]

==========================

Insert Figure 4 about here

==========================

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 in our analysis. These animes were selected based on release dates, being the first season of an anime (if multiple seasons exist), and viewership. More specifically, we chose animes that were released between July 2012 and January 2014 and 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 (among the 2.6 million users and over a period of at least two years; i.e. by at least 2% of users) and together account for 68% of viewership market share. We include these 103 animes in our final sample.

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.[14]

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

[12]The 2.2 million inactive stand-alone users represent a characteristic of this social media platform that is consistent with the well-known 90-9-1 rule in social media (see e.g. https:www.nngroup.comarticlesparticipation-inequality).

[13]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.

[14]74% of adoptions across the 103 animes happen during the study period as compared to the total observation

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.[15] 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.

==========================

Insert Figure 5 about here

==========================

Second, we removed users who showed no activity after the release of the last anime. We define activity as any 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 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. And lastly, for some users we do not have data on all their friends' adoptions e.g. because one of their friends' watch lists 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. After applying these four criteria, the remaining data contain information on 39,652 users with nearly 170 million weekly observations. We use data on a random sample of 5,000 users with 21,853,295 weekly observations for the empirical analysis.

To account for the effects of common shocks on adoption, we gathered data on the number of news published for each anime online and on 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

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.

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

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. Figure 6 shows the average number of news articles online and on MyAnimeList.net for the animes under study over time.[16]

==========================

Insert Figure 6 about here

==========================

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 original airing in Japan.[17] 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, users have 18 friends, watch 76 animes per year, and adopt 17 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 (for each anime 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, 35% of users indicate their gender as “Female,” 53% as “Male,” and the remainder did not specify their gender. On average, users adopt an anime in week 16 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.

==========================

Insert Table 1 about here

==========================

[16] The grey shaded area in Figure 6 shows the area between the 5th and 95th percentile.

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

===========================

Insert Figure 7 about here

===========================

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 of ratings given by friends and the volume of ratings and forum posts by friends (these are our measures of WOM valence and WOM volume from the personal network). Figures 8b, 8d and 8f show the number of community adoptions, the average community rating, and the number of community ratings and forum posts, respectively.[18] These last three variables capture OL, WOM valence, and WOM volume 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 2 across users and animes by the end of week 1 and from 0 to 5 by the end of week 20. The average rating given by friends varies from 3.5 to 10 across users and animes by the end of week 1 and from 4 to 9.5 by the end of week 20. These patterns suggest that we have sufficient variation in all our WOM and OL measures to identify their effects on product adoptions.

===========================

Insert Figure 8 about here

===========================

4 Model and Estimation

In this section, we start by discussing the three challenges we face in modeling choice interdependence in networks. Subsequently, we present the model and discuss our estimation approach.

[18]We refer the reader to Online Appendix B for details on these variables.

4.1 Challenges

We face three main challenges in modeling and estimating the effects of social learning on product adoptions with network data: endogenous group formation, correlated unobservables, and simultaneity (Hartmann et al. 2008). In this section, we explain how these issues pose challenges and how we address each of them.

The challenge of endogenous group formation has two aspects. First, 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 this part 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 (see Figure 5). Using data on users who have been members for at least one year enables us to assume that the networks are exogenous and fixed.

Second, additional difficulty arises due to the existence of homophily,[19] i.e. friendship ties among users have been 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 need to control for both each user's intrinsic preference for a specific anime and each user's propensity to adopt earlier as opposed to later. We do so by taking advantage of the rich panel structure of our data (Hartmann et al. 2008) and by incorporating user-anime and user-release week fixed effects in our model.[20]

The correlated unobservables problem[21] 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

[19] Homophily, which Manski (1993) referred to as "correlated effects," is the more prominent aspect of the endogenous network formation challenge.

[20] Our empirical strategy of including user-anime and user-release week fixed effects goes beyond previous literature's approach of including group fixed effects (Lee 2007; Lee et al. 2010; Ma et al. 2014). Note that the user-anime and user-release week fixed effects subsume any group and/or any group-anime and/or any group-release week fixed effects. Further, because the user-anime fixed effects subsume *any* group (and *any* group-anime) fixed effects, our identification approach for peer effects does not rely on a specific definition/operationalization of "group" and even allows the "group" to vary from one anime to another.

[21] Manski (1993) referred to this issue as "exogenous (contextual) effects."

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 the following two approaches. First, we control for a variable that can affect the adoption decisions of all users: the number of online news pieces collected from MyAnimeList.net and other websites. 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 in-site news posts on MyAnimeList.net are the main sources of common shocks.[22] Therefore we use previous week's number of online and in-site news to control for common shocks. And second, to account for other unobserved shocks that are common among all users (e.g. seasonality or platform malfunction), we incorporate (calendar) week fixed effects in our model.

The simultaneity problem, which is also known as the "reflection problem" (Manski 1993), arises due to a potentially simultaneous decision-making by a user and his friends. In other words, a user might be influenced by his friends and, at the same time, influence those friends. We are able to address this challenge by using the lagged versions of variables capturing aggregated friends' actions.

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 $t = 1, ..., \bar{T}_j$. We define each time period t as the t^{th} week since release of anime 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. 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. The adoption status of anime j by user i at time t is shown by y_{ijt}. If user i adopts anime j at week t, y_{ijt} equals 1 and 0 otherwise. We model users' adoption decisions using a linear probability model. In other words, y_{ijt} is given by

[22]Note that the platform was created mainly to provide fans with an environment to connect to other fans. It was a non-profit, commercial free, and completely user-driven platform until 2016 (i.e. until after the end of our observation period). No targeted actions or similar strategies (display ads, emails, or any other kind of targeting tools) were employed by the platform. Similarly, the platform did not provide users with any product or friend recommendations during the observation period.

$$y_{ijt} = \alpha_{ij} + \gamma_{it} + \delta_t^{cal} + X_{ijt}\beta_1 + Z_{jt}\beta_2 + C_{ijt}\beta_3 + \epsilon_{ijt} \tag{1}$$

where α_{ij} are user-anime fixed effects, γ_{it} are user-release week fixed effects, δ_t^{cal} are calendar week fixed effects, X_{ijt} contains WOM and OL variables from the personal network, and Z_{jt} includes WOM and OL variables from the community network.[23] C_{ijt} contains other variables whose effects we control for, namely, the number of animes adopted by individual i in week t, the number of news published about anime j in week $t-1$, a dummy variable indicating whether the season finale was aired in week t or $t-1$, and the interactions of the season finale dummy with each of the community OL and WOM variables. We include interaction effects between the season finale dummy and the community WOM and OL variables to control for sudden jumps in the community WOM and OL variables due to increased adoptions around the season finale. β_1 and β_2 capture the effects of WOM and OL from the personal and the community networks, respectively. ϵ_{ijt} is the error term and is assumed to follow a standard normal distribution. Finally, $\theta = \left(\alpha_{ij}, \gamma_{it}, \delta_t^{cal}, \beta_1, \beta_2, \beta_3\right)$ is the set of parameters to be estimated.

5 Results and Discussion

The estimation results for our main model are presented in column (ii) in Table 2. For comparison, we also show the results of a model without user-anime, user-release week, and calendar week fixed effects in column (i) of Table 2. In interpreting our results, we focus on our main model shown in column (ii). We start by discussing the parameter estimates for the control variables. The parameters for the number of adopted animes in week t and the number of online news are, as expected, both positive and significant. We find that the season finale dummy has a significant negative main effect and significant positive interaction effects with the community WOM and OL variables. For a typical anime, the total effect of the season finale is positive.

==========================

Insert Table 2 about here

==========================

[23]Note we use one-week lagged versions of our WOM and OL variables to avoid the simultaneity problem.

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 networks. We first start with the community network. As expected, community ratings have a significant positive effect on a user's anime adoption decisions. Recall that community ratings capture the valence of WOM since they are the average ratings given to animes by the whole community, while the community-wide number of ratings and forum posts for an anime captures the volume of community WOM. We find both WOM valence and volume to have positive and significant effects. In other words, users are more likely to adopt animes that generate more buzz and more positive buzz in the community. The coefficient for the number of adoptions in the community, which captures the effect of OL from the whole community, is positive and significant. Therefore, as expected, our result suggests that the more popular an anime gets, the more likely it will be adopted by an individual. Note that, the significant positive effect of OL is after controlling for WOM valence and volume, suggesting that OL provides additional information to users.

To judge the relative magnitudes of the effects, we use our parameter estimates to predict adoption probabilities for several scenarios. Specifically, we evaluate the changes in the likelihood of adopting an anime resulting from a 1% increase (calculated at the mean levels) in WOM (valence and volume) and OL due to incoming adoptions, ratings, and posts. For OL, this is represented by 80 additional adoptions; for WOM volume, this is represented by 50 additional ratings and posts about an anime; and for WOM valence, this is represented by 49 additional ratings with an average of 7.55 for these additional ratings.[24] For each of these three scenarios, we predict the change in average adoption likelihood (across all users and all animes) and find the average adoption likelihoods to increase by 0.49%, 0.03%, and 0.6% due to a 1% increase in OL, WOM volume, and WOM valence, respectively. To put it in words, the 1% increase in WOM valence produces the largest increase in adoptions followed by the increase in OL and WOM volume.

We now turn to the effects of WOM and OL from the personal network. 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

[24] 49 additional ratings represent 1% of the mean number of ratings (4,911) submitted for an anime. The mean rating in our sample is 7.48, i.e. the additional 49 ratings are 1% higher than the mean rating.

rating for the anime and zero otherwise; friends' average rating conditional on the friends' rating dummy being one to capture WOM valence within the personal network; and the number of friends' ratings and forum posts to capture WOM volume within the personal network. We include the friend rating dummy variable because, for some users, we observe a time period after the anime release when none of their friends have 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.[25]

We find the effect of the friends' rating dummy to be negative and significant, while both WOM valence and WOM volume from friends have significant positive effects on a user's anime adoption decisions. We also find the effect of OL from one's personal network to be positive and significant: as the number of friends who have watched an anime increases, an individual becomes more likely to adopt the anime. These results for the personal network indicate that OL and WOM provide users with different and unique information and have separate influences on individuals' product adoption decisions. Thus the influence of social learning is not fully captured when only WOM or only OL is considered in an empirical study.

Similar to the predictive exercise we conducted for WOM and OL from the community network, we evaluate the changes in anime adoption likelihood resulting from a 1% increase at the average WOM valence, WOM volume and OL levels from the personal network. However, in contrast to the community network, the 1% change in WOM volume from friends has a larger effect on users' adoption decisions (with an average increase in adoption likelihood of 0.27%) than those of OL or WOM valence (with average increases in adoption likelihoods of 0.21% and 0.01%, respectively).

Lastly, using the results from the prediction exercises, we compare the effects of WOM valence and OL across the two network levels. 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 larger influence than OL from the personal network. This is probably due to the fact that

[25] 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.

the community of MyAnimeList.net is a large one consisting of more than 2.6 million users. As Zhang et al. (2015) point out: When community networks are large, they provide more information to individuals than personal networks.

5.2 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." 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. However, one can argue that 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" as this status suggests product abandonment after trial. We therefore use this more nuanced information on adoption 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 the act of adopting the product under the stati "watched," "watching," and "on hold" and negative OL as the act of adopting and abandoning the product under the status "dropped."

The results are shown in column (iii) in Table 2. As expected, we find a significant positive coefficient for positive OL from friends. We also find a significant positive, albeit significantly smaller coefficient for negative OL. This finding is consistent with our expectation that the effect of positive OL is indeed larger than that of negative OL. In other words, users do pay attention to the differential informational content in their friends' adoption stati when making their own watching decisions. However, to our surprise, the negative OL still enhances users' adoption likelihood of an anime. One plausible explanation is that, compared to animes that no friend would even want to (watch and then) drop, animes with negative OL from friends are perceived to be of better quality because they crossed some friends' bar for an initial trial.

5.3 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). To put it differently, 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 in column (iv) in Table 2. 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 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 only have data on online WOM and OL. While in our empirical 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. Second, 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.

Third, the influence of WOM and OL may vary across users. We view not modeling the varying degree of susceptibility to peer effects across users as a limitation of our study and leave this very interesting question for future research. And finally, we chose to focus on studying the adoption behavior of users who have at least one friend in the anime community in this paper. This decision is largely due to little to no activity and very sparse adoption behavior among stand-alone users in the anime community and implies that our paper does not address questions related to the adoption behavior of stand-alone users. We leave the topic of social learning of stand-alone users 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 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 that both OL and WOM (both valence and volume) have significant and positive effects on individual user's anime adoption decisions. Moreover, this finding holds true for WOM and OL information coming from both the community network and the personal 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 larger impact on individuals' product adoptions 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 among friends. Currently, to the best of our knowledge, none of the major online streaming services in the U.S. 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 decisions 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 valence is the largest adoption driver and overshadows the effect of community OL (and also WOM volume). This result is consistent with the current product information provision practice found among leading online streaming platforms. The top four U.S. 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 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

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.

Bandiera, Oriana and Imran Rasul (2006), 'Social networks and technology adoption in northern mozambique', *The Economic Journal* **116**(514), 869–902.

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.

Bollinger, Bryan and Kenneth Gillingham (2012), 'Peer effects in the diffusion of solar photovoltaic panels', *Marketing Science* **31**(6), 900–912.

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

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.

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.

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.

Hartmann, Wesley, Puneet Manchanda, Harikesh Nair, Matthew Bothner, Peter Dodds, David Godes, Kartik Hosanagar and Catherine Tucker (2008), 'Modeling social interactions: Identification, empirical methods and policy implications', *Marketing Letters* **19**(3-4), 287–304.

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.

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

Lee, Lung-fei (2007), 'Identification and estimation of econometric models with group interactions, contextual factors and fixed effects', *Journal of Econometrics* **140**(2), 333–374.

Lee, Lung-fei, Xiaodong Liu and Xu Lin (2010), 'Specification and estimation of social interaction models with network structures', *The Econometrics Journal* **13**(2), 145–176.

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 (2016), 'The role of paid and earned media in building entertainment brands: Reminding, informing, and enhancing enjoyment', *Marketing Science* **35**(1), 142–157.

Ma, Liye, Ramayya Krishnan and Alan Montgomery (2014), 'Latent homophily or social influence? an empirical analysis of purchase within a social network', *Management Science* **61**(2), 454–473.

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.

Sun, Monic, Xiaoquan Michael Zhang and Feng Zhu (2012), To belong or to be different? evidence from a large-scale field experiment in china, Technical report.

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', *Working Paper* .

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

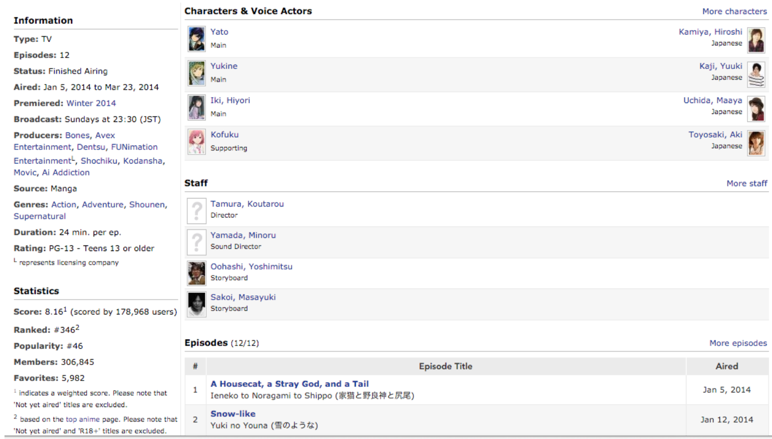

Figure 1: Example of an Anime Page

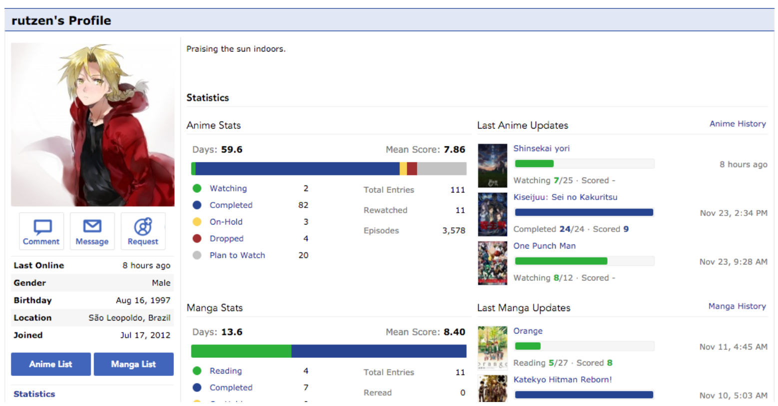

Figure 2: Example of a User Page

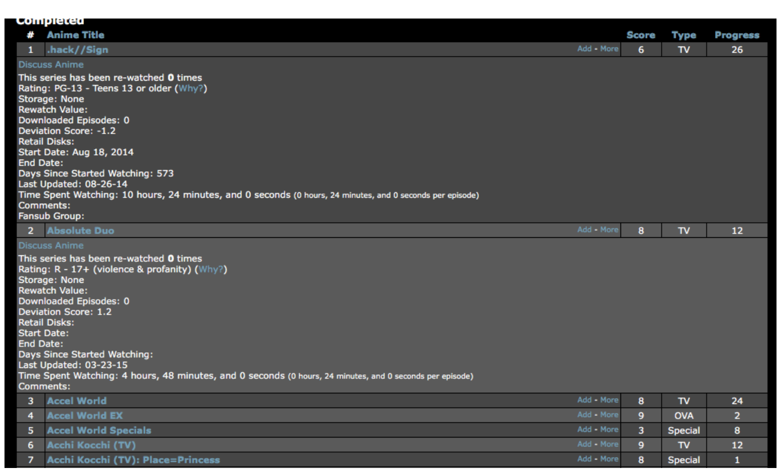

Figure 3: Example of a User Watch List

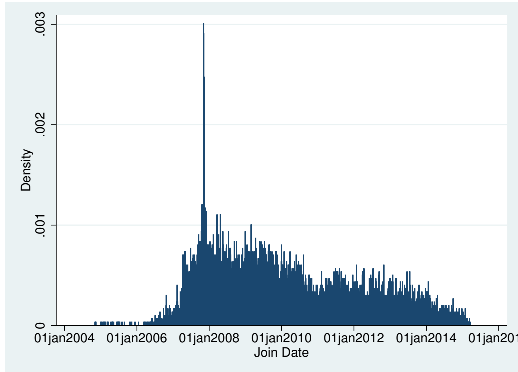

Figure 4: Dates Users Joined MyAnimeList.Net

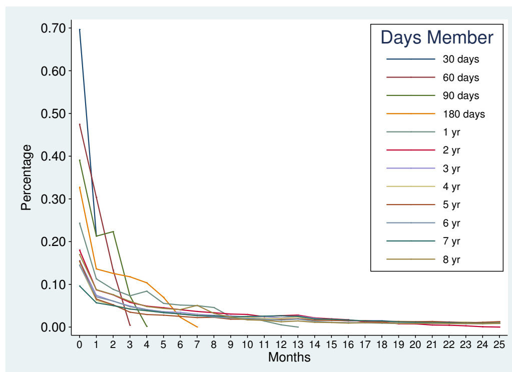

Figure 5: Percentage of Friends Added During First 2 Years After Joining MyAnimeList.net (grouped by length of membership)

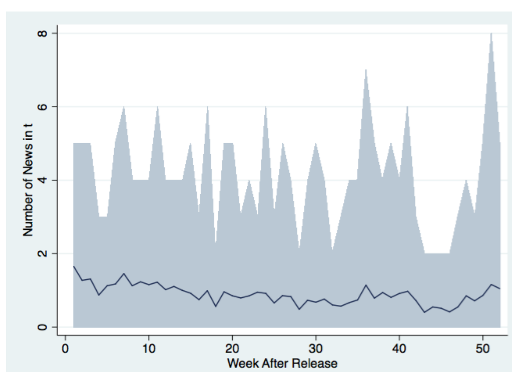

Figure 6: Average Number of News Articles
(shaded area denotes 5th and 95th percentiles)

(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)

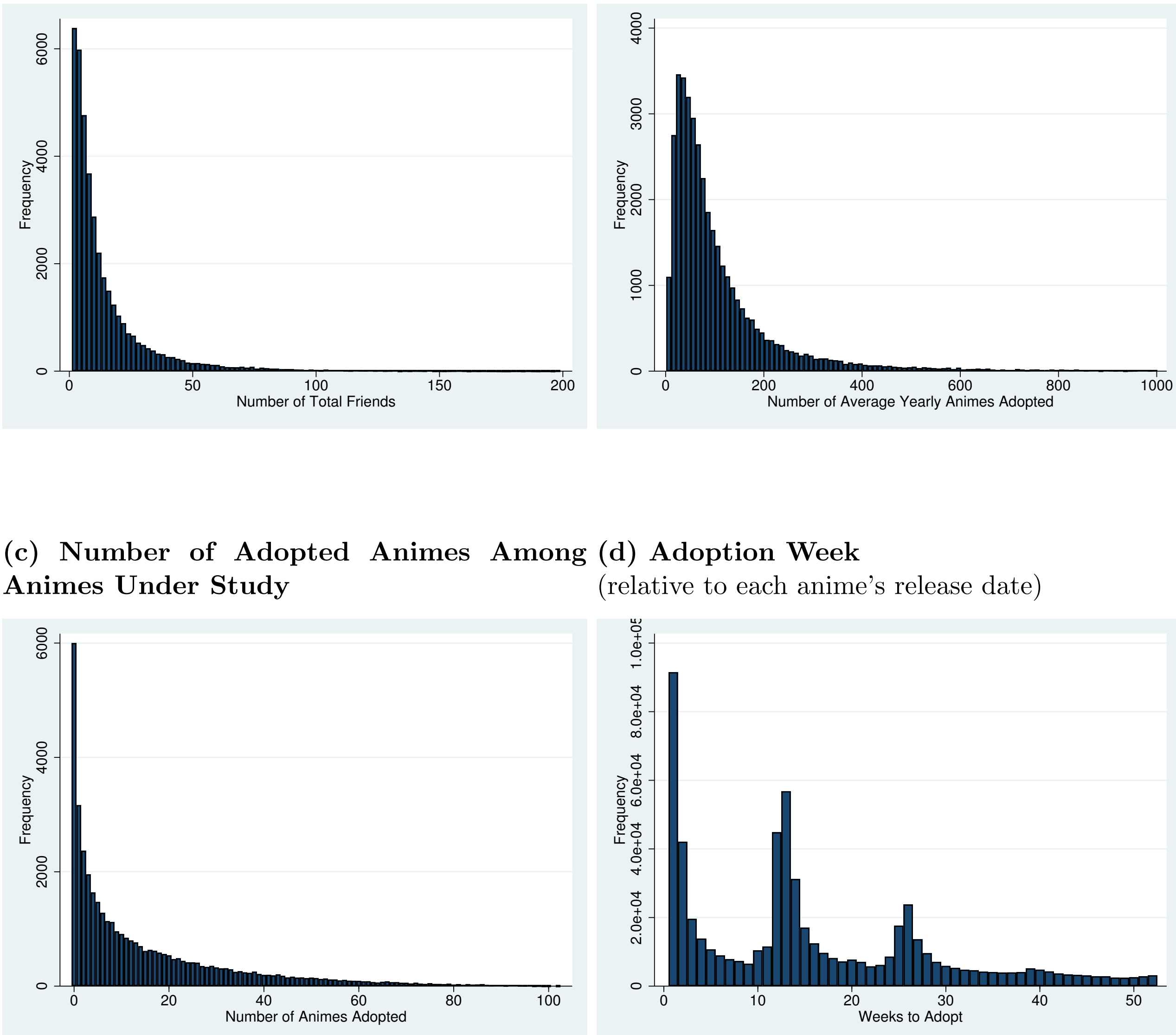

Figure 7: Histograms of the Number of Friends and of Descriptives Related to Adoption

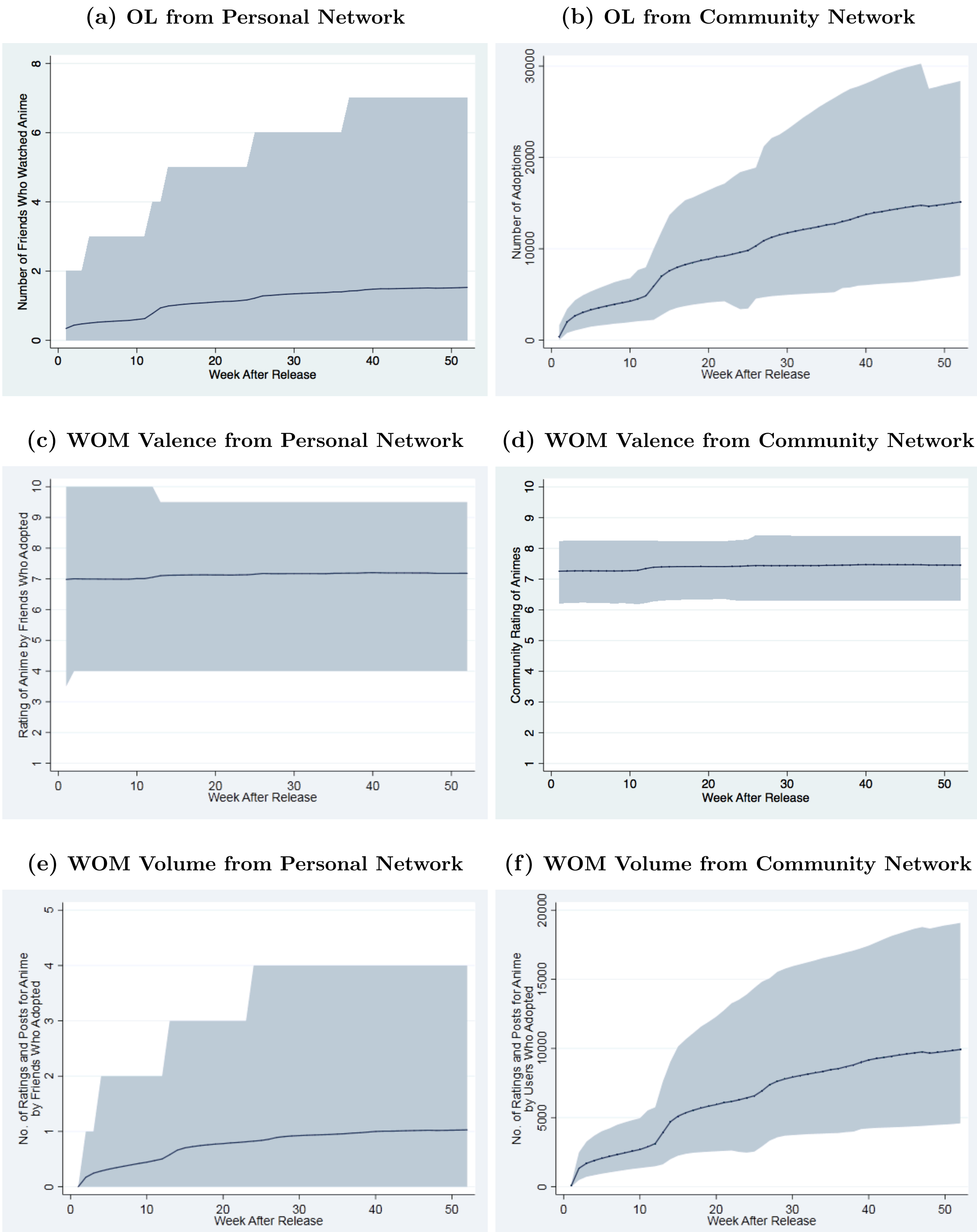

Figure 8: WOM and OL from Personal and Community Networks

	Mean	Std. Dev.	Min	Median	Max	N
Age	23	6	11	23	84	24,584
Gender (% Females)	35					39,652
Gender (% Males)	53					39,652
Gender (% Not Specified)	13					39,652
Number of Friends	18	31	1	9	1,720	39,652
Average Number of Animes Adopted per Year	76	68	1	58	2,144	39,652
Number of Animes Adopted Among						
Animes Under Study	17	18	0	8	103	39,652
Adoption Week (Conditional on Adoption)	16	13	1	13	52	614,048

Table 1: Descriptive Statistics

	(i) Homogenous Model	(ii) Main Model	(iii) Asymmetric OL Model	(iv) Awareness Model
Word-of-Mouth				
Friends' Av. Rating Dummy	−0.0010***	−0.0044***	−0.0042***	−0.0043***
	(0.0000)	(0.0002)	(0.0002)	(0.0002)
Friends' Av. Rating Interaction	0.0002***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Friends' Number of Ratings	−0.0001	0.0038***	0.0038***	0.0037***
and Forum Posts[a]	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Community Rating	0.0009***	0.0214***	0.0214***	0.0209***
	(0.0000)	(0.0002)	(0.0002)	(0.0002)
Community Number of Ratings	−0.0027***	0.0002***	0.0002***	0.0003***
and Forum Posts[a]	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observational Learning				
Cum. Number of Friends Who Adopted[a]	0.0007***	0.0029***		0.0035***
	(0.0000)	(0.0001)		(0.0001)
Cum. Number of Friends Who Watched[a]			0.0026***	
			(0.0001)	
Cum. Number of Friends Who Dropped[a]			0.0020***	
			(0.0002)	
Dummy for First Adoption by Friend				0.0032***
				(0.0001)
Cum. Number of Community Users	0.0012***	0.0030***	0.0030***	0.0029***
Who Adopted[a]	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Other Parameters				
Number of Animes Watched During the Week[a]	0.0118***	0.0078***	0.0078***	0.0078***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Number of Online News[a]	0.0009***	0.0001***	0.0001***	0.0001***
	(0.0011)	(0.0000)	(0.0000)	(0.0000)
Season Finale Dummy	−0.1585***	−0.1192***	−0.1192***	−0.1192***
	(0.0000)	(0.0010)	(0.0010)	(0.0010)
Season Finale Dummy × Community Rating	0.0017***	0.0019***	0.0019***	0.0019***
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Season Finale Dummy × Community Number	0.0182***	0.0137***	0.0137***	0.0137***
of Ratings and Forum Posts[a]	(0.0000)	(0.0002)	(0.0002)	(0.0002)
Season Finale Dummy × Cum. Number	0.0014***	0.0007**	0.0007**	0.0007**
of Community Users Who Adopted[a]	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Constant	0.0042***			
	(0.0000)			
User-Anime Fixed Effects	No	Yes	Yes	Yes
User-Release Week Fixed Effects	No	Yes	Yes	Yes
Calendar Week Fixed Effects	No	Yes	Yes	Yes
Adjusted R-Squared	0.0186	0.1238	0.1238	0.1239
Number of Observations	21,853,295	21,853,295	21,853,295	21,853,295

Standard errors in parentheses

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

[a] Measured on logarithmic scale.

Table 2: Results

Online Appendix A: Original and Final Data

In this appendix, we compare the characteristics of the eligible population of 40,000 users to the (i) data set containing all 380,000 users from the same network and to a (ii) data set containing nearly 80,000 users from the same network who have the same "platform lifetime," i.e. joined the platform before July 2011, as our eligible population.[26] Comparing our eligible population not only to all users from the same network, but also to users with the same platform lifetime is necessary since some of the descriptive statistics such as the number of friends change with users' length of membership on the platform. The difference between the eligible population and the population of users with the same lifetime is that the latter also includes users who showed little to no activity during the study period, i.e. added fewer than 10 animes to their watch list (any anime; not necessarily one of the animes under study).

Panel A of Table A-1 shows the descriptive statistics for the population of 380,000 users, Panel B of Table A-1 displays the descriptive statistics for the same-platform-lifetime population of nearly 80,000 users, and Panel C of Table A-1 shows the descriptive statistics for the eligible population of 40,000 users. In terms of demographics (age and gender), users in Panels B and C are similar. Users in Panel C compared to users in Panel B watch, on average, more animes per year and adopt more animes among those under study. However, this difference is to be expected since Panel B includes users with little to no activity during the study period. Lastly, conditional on adopting, users in Panels B and C adopt animes at the same time.[27]

We conclude that users in our eligible population are representative active users on the platform.

[26]For users to be included in the last data set (ii), we also require them to show some type of activity after the release of the last anime under study in January 2014, i.e. that they add at least one anime to their watch list (any anime; not necessarily one of the animes under study).

[27]Comparing Panels A and C, we find that newer users are less likely to report their gender. Users in Panel A have fewer friends which is likely due to them having been a member of the platform for a significantly shorter time period. Further, users in Panel A watch fewer animes per year and adopt fewer animes among those under study than users in Panel C – this difference is due to Panel A including users who show little to no acitivity. Lastly, users in Panel A watch animes conditional on adoption about 4 weeks later than users in Panel C.

	Mean	Std. Dev.	Min	Median	Max	N
PANEL A: 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
PANEL B: Same-Platform-Lifetime Population						
Age	24	5	12	23	84	25,500
Gender (% Females)	33					76,069
Gender (% Males)	45					76,069
Gender (% Not Specified)	22					76,069
Number of Friends	13	33	1	4	3,077	76,069
Average Number of Animes Adopted per Year	45	58	0	28	2,633	76,069
Number of Animes Adopted Among Animes Under Study	7	14	0	0	103	76,069
Adoption Week (Conditional on Adoption)	17	13	1	14	52	738,969
PANEL C: Eligible Population						
Age	23	6	11	23	84	24,584
Gender (% Females)	35					39,652
Gender (% Males)	52					39,652
Gender (% Not Specified)	13					39,652
Number of Friends	18	31	1	9	1,720	39,652
Average Number of Animes Adopted per Year	76	68	1	58	2,144	39,652
Number of Animes Adopted Among Animes Under Study	17	18	0	8	103	39,652
Adoption Week (Conditional on Adoption)	16	13	1	13	52	614,048

Table A-1: Descriptive Statistics

Online Appendix B: Variable (Re-)Construction

In this appendix, we describe the process through which we (re-)constructed several variables used in the estimation of the main model and robustness checks, namely, the WOM and OL variables from the community network. 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 not historical values. Thus we had information on the number of adoptions, the rank based on the number of adoptions, the average rating, the rank based on the average rating, and the number of ratings and forum posts from the community network in March 2015 (start date of the data collection), but not earlier to that.

Community OL

The variable "Cumulative Number of Community Users Who Adopted" is our main measure of OL from the community network and, as the name indicates, captures the cumulative number of users from the community network who have adopted the anime. We used our complete collected data containing the adoption histories of 380,000 users to re-construct the cumulative number of users who adopted each anime for each week.

The variable "Community Rank" is our alternative measure of OL from the community network and 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 WOM Valence

The variable "Community Rating" is our main measure of WOM valence from the community network and captures the average of user ratings for an anime from all users in the community network. We re-constructed the community rating for each week using the ratings for an anime 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.

The variable "Community Rating Rank" is our alternative measure of WOM valence from the community network and describes the rank of an anime based on ratings submitted by the whole community. MyAnimeList.net reports the method used to calculate these weighted ranks as:

"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 WOM Volume

The variable "Community Number of Ratings and Forum Posts" is our measure of WOM volume from the community network and, as the name indicates, captures the cumulative number of ratings and forum posts published about an anime. Since each rating and forum post is dated, i.e. has a calendar date, we re-constructed this variable by calculating the cumulative number of ratings and forum posts for each anime and each week.

Online Appendix C: Robustness Checks

Alternative Operationalizations for ...	(i) Personal OL	(ii) Community OL	(iii) Community WOM	(iv) Adoption Time
Word-of-Mouth				
Friends' Av. Rating Dummy	−0.0043***	−0.0029***	−0.0035***	−0.0038***
	(0.0000)	(0.0002)	(0.0002)	(0.0002)
Friends' Av. Rating Interaction	0.0003***	0.0001***	0.0001***	0.0002***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Friends' No. Ratings and Forum Posts[a]	0.0056***	0.0033***	0.0039***	0.0035***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Community Rating	0.0216***	0.0136***		0.0074***
	(0.0001)	(0.0002)		(0.0002)
Community Rating Rank[a]			−0.0030***	
			(0.0001)	
Community Number Ratings and Forum Posts[a]	0.0002***	0.0012***	0.0011***	0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observational Learning				
Cum. Number of Friends Who Adopted[a]		0.0022***	0.0035***	0.0030***
		(0.0001)	(0.0001)	(0.0001)
Cum. Percentage of Friends Who Adopted	0.0025***			
	(0.0001)			
Cum. Number of Community Users Who Adopted[a]	0.0030***		0.0021***	0.0023***
	(0.0001)		(0.0001)	(0.0001)
Community Rank[a]		−0.0056***		
		(0.0001)		
Other Parameters				
Number of Animes Watched During the Week[a]	0.0078***	0.0078***	0.0078***	0.0011***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Number of Online News[a]	0.0001***	0.0001***	0.0000	−0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Season Finale Dummy	−0.1192***	−0.0909***	−0.0997***	−0.1271***
	(0.0010)	(0.0044)	(0.0012)	(0.0010)
Season Finale Dummy × Community Rating	0.0019***	0.0024***		0.0023***
	(0.0001)	(0.0001)		(0.0001)
Season Finale Dummy × Community Rating Rank			−0.0012***	
			(0.0001)	
Season Finale Dummy × Community Number of Ratings and Forum Posts[a]	0.0137*** (0.0002)	0.0132*** (0.0003)	0.0150*** (0.0003)	0.0141*** (0.0002)
Season Finale Dummy × Cum. Number of Community Users Who Adopted[a]	0.0007** (0.0002)		−0.0001 (0.0003)	0.00017*** (0.0002)
Season Finale Dummy × Community Rank[a]		−0.0030***		
		(0.0000)		
User-Anime Fixed Effects	Yes	Yes	Yes	Yes
User-Release Week Fixed Effects	Yes	Yes	Yes	Yes
Calendar Week Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.1238	0.1240	0.1234	0.1258
Number of Observations	21,853,295	21,853,295	21,853,295	21,808,418

Standard errors in parentheses

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

[a] Measured on logarithmic scale.

Table C-1: Robustness Checks