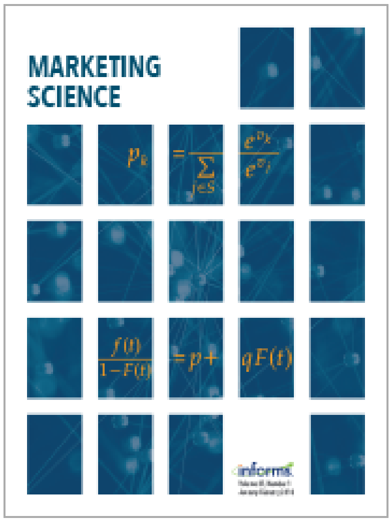

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Word of Mouth, Observed Adoptions, and Anime-Watching Decisions: The Role of the Personal vs. the Community Network

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Abstract. We quantify the effects of others' adoptions and word of mouth (volume and valence) on consumers' product adoption decisions. We differentiate between the effects of word of mouth and observed adoptions from friends (*personal network*) and the effects of word of mouth and observed adoptions from the whole community (*community network*). Understanding the relative importance of word of mouth and observed adoptions at each network level provides crucial guidance for companies regarding their information provision and platform design strategies. 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 anime series. Our results reveal that both word of mouth (volume and valence) and observed adoptions from the community network have significant positive effects on individual users' anime-watching decisions. Furthermore, this finding also holds true for word of mouth and observed adoptions coming from the personal network. Comparing the magnitudes of the effects of word of mouth and observed adoptions across both network levels, we find that word-of-mouth valence from the community network is the largest driver among the social learning forces we study. Thus our results show that word of mouth and observed adoptions provide unique and different information that individuals use in their anime-watching decisions and that the community network is the primary source of information driving anime adoptions.

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Keywords: word of mouth • observed adoptions • social learning • product adoption • social networks

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 in two different ways: they can extract product information directly from others' opinions, or they can infer information about products indirectly from observing others' previous product adoption decisions. Numerous studies have shown that the volume and valence of others' opinions, often termed *word of mouth* (WOM) by marketing researchers, can have a significant impact on consumers' purchase and adoption behaviors (Godes and Mayzlin 2004, Chevalier and Mayzlin 2006, Liu 2006, Moe and Trusov 2011, Lovett and Staelin 2016, to name a few). Although social learning through observed product adoptions of others (OA hereafter) has not been studied to that extent in the marketing literature, a few recent empirical papers have shown that others' purchase decisions can affect consumers' own 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 OA have been separately studied as elements of social learning, there remain important unanswered questions. First, almost all extant literature has studied either WOM or OA 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 either source, consumers may still interpret information contained in WOM and OA differently and therefore be influenced by both forces to varying degrees. On the one hand, one can argue that compared with OA, 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 OA, 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 empirical paper that studies the effects of both WOM and OA at the aggregate product sales level. No empirical study that we are aware of has simultaneously examined the differential effects of information extracted from WOM versus OA on individual consumers' adoption decisions.[1]

Second, and more important, both WOM and OA information can be extracted by consumers 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 or her friends' opinions and/or actions while, at the same time, he or she can also observe product adoptions, online reviews, and ratings by users beyond his or her 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 or her personal network) as the *community* network. Although extant empirical studies have lent support for the significant effects of WOM or OA from either the community or the personal network (e.g., Godes and Mayzlin 2004, Nair et al. 2010, Zhang 2010, Aral and Walker 2011), it remains an unanswered empirical question whether and to what extent WOM and OA influence product adoptions when both types of information are available from both network levels.

On the one hand, friends' opinions and actions 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 which 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 anime are cultural products. With the rapid expansion of online streaming services in recent years,[2] consumers face an overwhelmingly large and constantly 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 in online streaming is zero.[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 anime called *MyAnimeList.net*. This website provides a gathering place for anime fans to share their enthusiasm and exchange their opinions about anime series. 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, not only can users create their personal watch lists (i.e., a list of anime series that they have watched) and rate the movies on their watch list, but they can also check other users' watch lists and the ratings those users have submitted. Users receive information about their friends' anime adoptions and the ratings thereof by 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 anime series 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 come from three different sources: endogenous group formation, correlated unobservables, and simultaneity. We take two steps to solve the challenge of endogenous group formation: First, we look only at users who have been in the network for more than one year before the release of the first anime under study because 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 as a result of 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. In addition, we include stand-alone users (i.e., users without friends) in our estimation sample to aid the identification of social influence effects from personal networks. To account for common shocks that lead to correlated unobservables, we include (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 anime series 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 OA have significant effects on users' anime adoptions. At the community network level, whereas both WOM valence and WOM volume have significant positive effects on users' adoptions, the elasticity of WOM valence is larger than the elasticity of WOM volume. Furthermore, OA also has a significant, albeit smaller, positive effect on product adoptions (in terms of elasticity): as an anime series gains more popularity in the community, users become more likely to watch it. Similarly, at the personal network level, both WOM (volume and valence) and OA from friends have significant positive effects on users' adoptions, with WOM valence having the largest elasticity among the three forces. Comparing the magnitudes of WOM and OA effects across both network levels based on elasticity calculations, we find that WOM valence from the community network is the largest adoption driver related to social learning. Furthermore, we find evidence that users differentiate between positive OA (from their friends' positive actions) and negative OA (from their friends' negative actions). And finally, we find OA to both create awareness for an anime series and to let users learn about the unobserved quality of an anime series.

The contribution of this paper is twofold. First, we contribute to the social learning and product adoption literatures by disentangling the effects of WOM and OA, the two prevalent social learning devices. Our findings provide empirical support for the differential and unique effects that product information inferred from WOM versus OA has on consumers' product adoption decisions. In particular, our result that the effect of community WOM valence overshadows the effect of community OA 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 does 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 this paper is organized as follows. In the next section, we discuss the relevant literature. In Sections 3 and 4, we describe our data and 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 social learning through WOM and OA, and we delineate the positioning of our research vis-à-vis the findings from extant research.

WOM has largely been studied in the context of reviews and online opinions. There is strong empirical support for the positive effect of online opinions on product adoptions 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 from personal networks. Aral and Walker (2011) find WOM in the form of active-personalized messaging to be more effective than in the form of passive broadcasting viral messaging in encouraging consumers' app adoption decisions per message. Brown and Reingen (1987) trace referral WOM of music teachers in local neighborhoods and quantify the effects of WOM coming from weak versus strong ties. They find that strong ties are likely to be used as sources for product-related information.

Although these studies show the significant effect of WOM on adoption at both the community and the personal network levels, how these two levels of WOM influence an individual's decision simultaneously is not clear. Zhang and Godes (2018) study how an individual's (purchase) decision quality improves based on information received from strong and weak ties in a network while controlling for WOM valence and variance at the community network level. Although Zhang and Godes (2018) 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 from the whole community). Therefore, Zhang and Godes (2018) are not able to study OA and, instead, focus on WOM as the main social learning device. In addition, they observe neither the valence nor 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 this study, we examine the effects of both WOM and OA 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 social learning by observing others' product-related decisions. 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). The resulting *observational learning* can lead to information cascades (Bikhchandani et al. 1992) and herding behavior. This observational learning 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).[4] 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 the popularity of dishes in a restaurant increases orders of those dishes. Tucker and Zhang (2011) show that product popularity information has a greater influence on consumers when they shop for niche products than when they shop for broad-appeal products. Zhang and Liu (2012) study lenders' funding decisions using data from an online microloan platform and find evidence for rational herding among lenders. Whereas the previous papers investigate the effects of OA from the community, Nair et al. (2010) and Wang et al. (2013) study the effects of OA from personal networks. These two papers show that the volume of usage, expertise, and popularity of friends are key factors that affect adoptions in medicine, technology, and fashion goods, respectively.

However, OA from the community network and OA from the personal network have not been recognized as two different influences until recently. Zhang et al. (2015) employ a game-theoretical approach to study the role of observational learning in networks of friends versus strangers. They show that when the network is small, friends' actions provide more information, whereas the network of strangers becomes more effective as it grows in size. Sun et al. (2019) 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 consumers can be influenced by others' adoption behaviors at either the personal network level or 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 networks and study how each of these two sources influences consumers' product adoptions simultaneously.

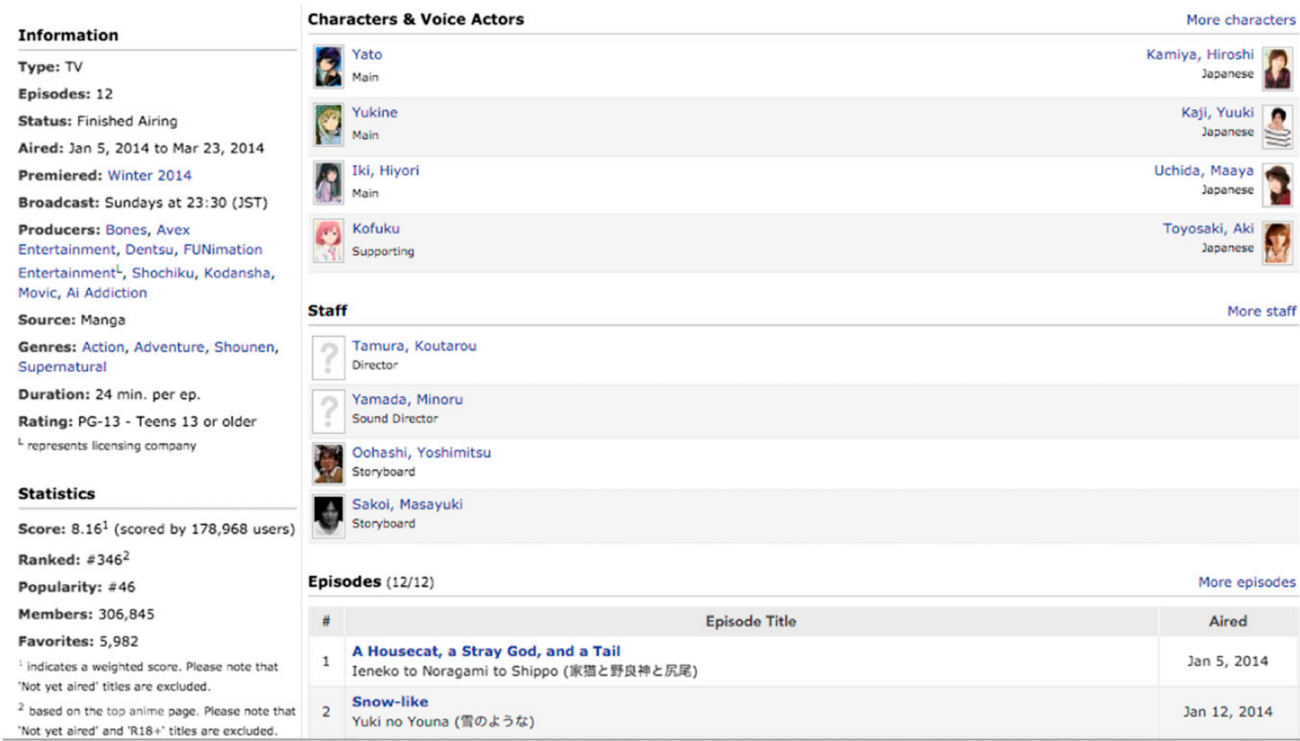
To the best of our knowledge, almost all extant marketing literature has either studied WOM or OA as the single mechanism through which consumers extract product information to facilitate their adoption decisions. The only exception is Chen et al. (2011), in which the authors examine the effects of both WOM and OA on aggregate online product sales at Amazon.com. They find that whereas negative WOM is more influential than positive WOM, positive OA significantly increases sales, but negative OA has no effect. No study that we are aware of has investigated the effects of WOM and OA simultaneously on individual consumers' product adoptions. Although information about product quality can be extracted or inferred from either source, consumers may still interpret information extracted from WOM and OA differently. In this study, we aim to fill this gap by examining the differential effects of information from WOM versus OA 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 on shared enthusiasm for a specific consumption activity. MyAnimeList.net was created to allow anime fans to gather and share their excitement and opinions about anime. In addition, the website has developed into one of the most comprehensive online sources of information about anime and *manga* (Japanese comics). In this paper, we focus on anime. On MyAnimeList.net, both anime series and users have their own pages. Figure 1 shows an example of an anime page. Each anime page contains detailed information about the anime series, including a content summary, an episode guide, production details, user ratings, and rankings.

Figure 2 shows an example of a user page. Note that all information contained in a user's page is available to the public.[5] On a user page, one can see information about the anime and manga the user has adopted and the adoption dates, his or her opinion about adopted anime and manga series, his or her website join date, his or her in-site activities, the identities of his or her friends, and other information. Users can become

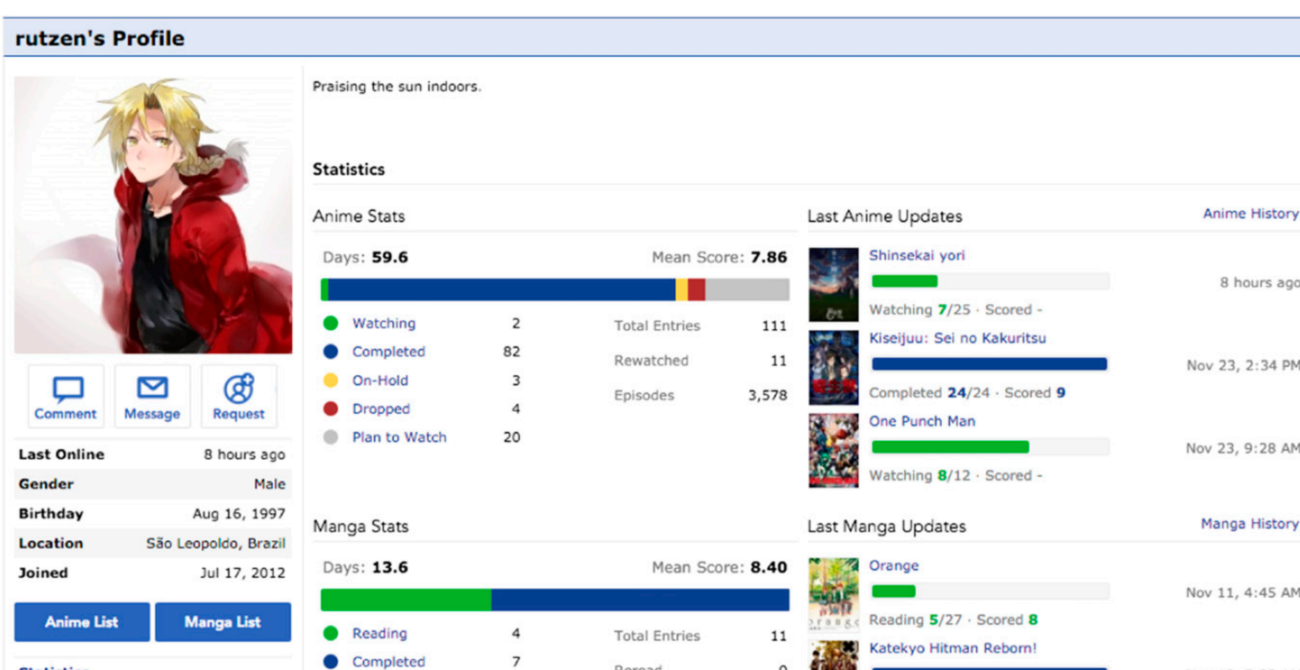
Figure 1. (Color online) Example of an Anime Page



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.[6]

Users can create a list of anime series that they plan to watch or have watched (we refer to this list as the

Figure 2. (Color online) Example of a User Page



watch list throughout this paper).[7] Figure 3 shows an example of a user's watch list. Note that all anime series on the watch list are correctly and uniquely identified because users are required to use a search function to add anime series to the list. Users can assign different statuses to the anime series on their watch list: "watched," "watching," "on hold," "dropped," or "plan to watch." We define a user as having adopted an anime series if the anime series is assigned to any of the first four statuses on his or her watchlist.[8] Although this definition of adoption might seem very broad, note that the statuses "watched," "watching," "on hold," and "dropped" all imply that the user has at least started to watch (i.e., adopted) the anime series.[9] Furthermore, users can indicate their opinion about the anime series 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 anime series on watch lists as *user ratings*. Users can also discuss the anime they have watched in the forum section of the website. Finally, users can indicate the date they started watching an anime series, and the website also automatically registers the date users last updated the entry for an anime series. We use these two dates to infer the time of adoption.[10]

We aim at quantifying the effects of WOM and OA from both the personal and the community networks on product adoption. We use the number of friends who adopted the anime series to measure OA from the personal network.[11] Furthermore, we use the average rating of an anime series 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 series on the anime page (see "Members" in the bottom left corner in Figure 1); this is our measure of community OA for the anime series. Similarly, users also see the average rating for an anime series 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.[12] And finally, 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 posts to measure community WOM volume.[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 2.6 million users

Figure 3. (Color online) Example of a User Watch List

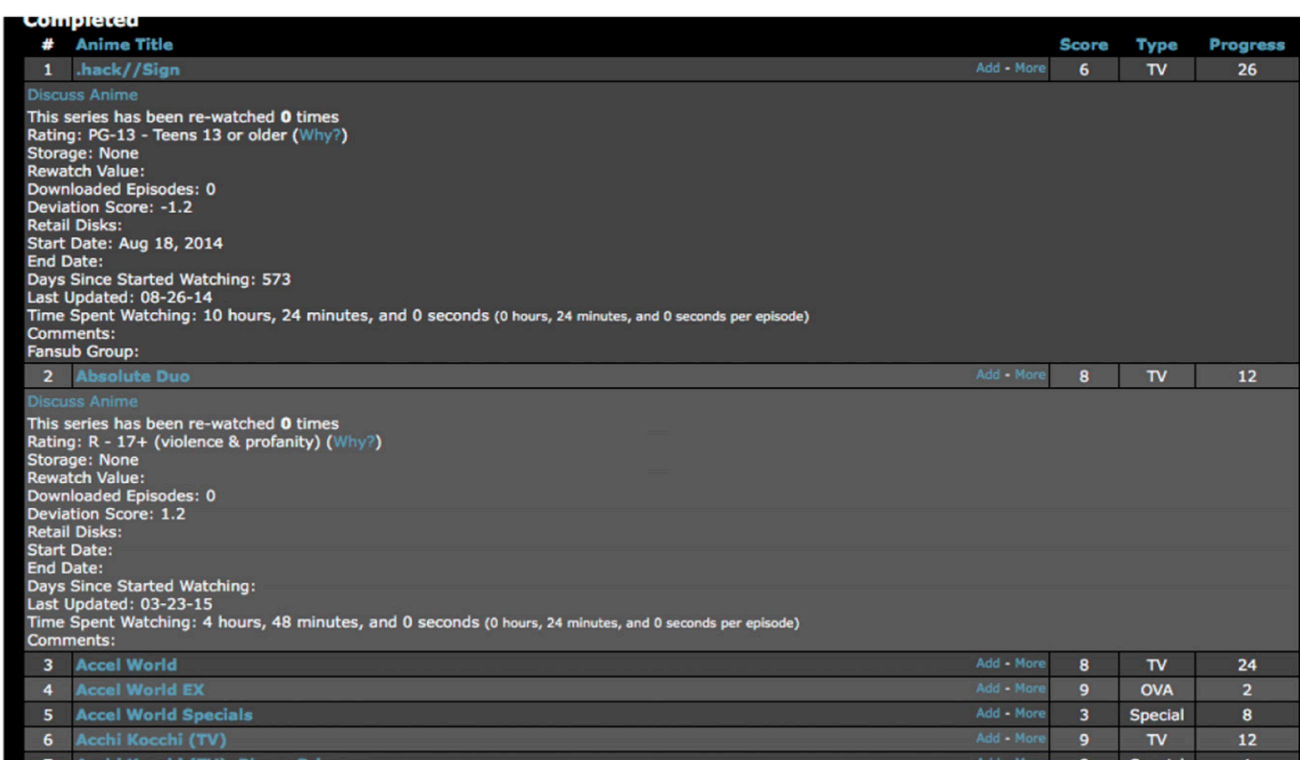
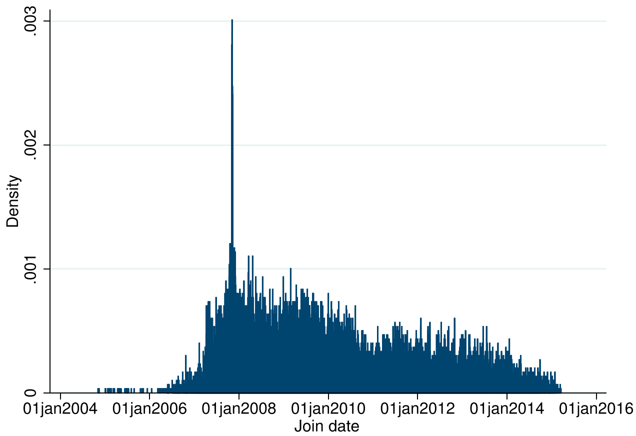


Figure 4. (Color online) Dates Users Joined MyAnimeList.net



on the website, among which were about 2.2 million stand-alone users with no friends and mostly little to no activity.[14] Because we are interested in the effects of social learning on product adoption, we collected data on a network of nearly 380,000 users.[15]

There are more than 10,000 anime series listed on the website. These anime series range from short 20-minute single-episode anime series to anime series with more than 50 episodes. We use data on 103 anime series in our analysis. These anime series were selected based on release dates, being the first season of an anime series (if multiple seasons exist), and viewership. More specifically, we chose anime series 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. On the basis of these two criteria, we narrowed the list of anime series down to 535 anime series. Among these 535 anime series, 103 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 anime series in our final sample.

We define the period under study as the time period from the release of an anime series until the release of the second season (if multiple seasons exist) or 52 weeks (one year) after the release, whichever is shorter.[16] Thus the study period varies from 19 to 52 weeks across the 103 anime series.[17]

We took the following steps to arrive at the set of network users (i.e., users with at least one friend) to be included in the final estimation sample: 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 series under study.[18] The choice of a one-year cutoff 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 the conservative cutoff of one year.

Second, we removed users who showed no activity after the release of the last anime series. 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 series under study because they did not want to or because of their inactivity. Therefore, we limit our data to include only users who added at least one anime (not necessarily one of the selected anime series in this study) to their watch list after the release of the last anime series under study.

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

Fourth, for some users, we do not have data on all their friends' adoptions, for example, 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 restriction affects only a small number of users.

Fifth, and finally, if a user adopts an anime series, we drop all observations for the user–anime combination following the week of adoption. After applying these five criteria, the remaining data contain information on 39,652 network users with nearly 170 million weekly observations. We use data on a random sample of 4,000 such users with 17,512,541 weekly observations for the empirical analysis.

We enrich our random sample of 4,000 users with friends with a random sample of 1,000 stand-alone

Figure 5. (Color online) Percentage of Friends Added During First Two Years After Joining MyAnimeList.net (Grouped by Length of Membership)

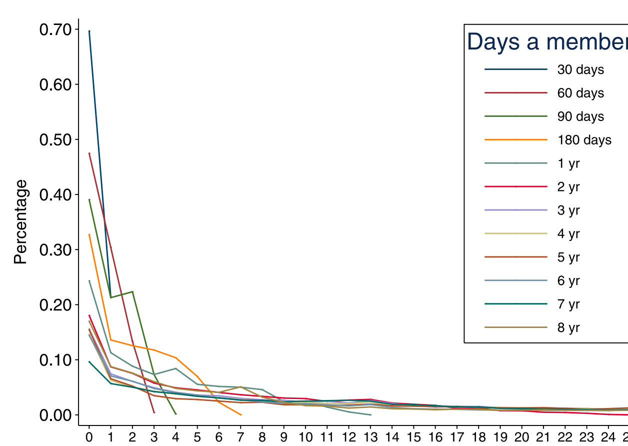


Table 1. Descriptive Statistics

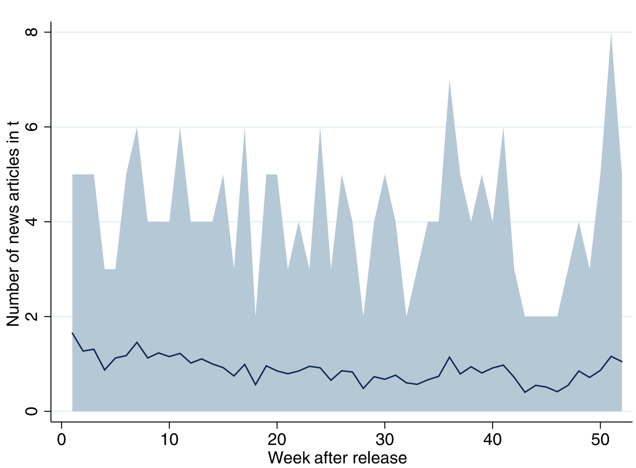
Variable	Mean	Standard deviation	Min	Median	Max	*N*
Age	20	7	12	21	85	4,154
Gender (% Females)	34					1,557
Gender (% Males)	52					2,373
Gender (% Not Specified)	14					626
Number of Friends[a]	17	31	1	8	635	4,000
Average Number of Anime Series Adopted per Year	68	57	1	53	817	5,000
Number of Anime Series Adopted Among Anime Series Under Study	12	17	0	5	98	5,000
Adoption Week (Conditional on Adoption)	16	13	1	13	52	61,582

[a]Calculated only using network users.

users (i.e., users who do not have any friends on MyAnimeList.net); this adds 4,867,940 weekly observations to our sample. These stand-alone users have to satisfy the same anime-watching recency and frequency requirements as do users with friends (i.e., the second and third data-cleaning steps). Although these stand-alone users are not subject to friends' influence, they are still exposed to WOM and OA information at the community level. Including these stand-alone users together with network users in our estimation sample helps us further identify the social learning forces coming from the personal network versus the community network.[19] Thus our final data set contains 5,000 users and 22,380,481 weekly observations.

To account for the effects of common shocks on adoption, we gathered data on the number of news articles published for each anime series 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 web pages. This allows us not only to follow the number of news articles for each anime series 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 anime series under study over time.

Figure 6. (Color online) Average Number of News Articles (Shaded Area Denotes 5th and 95th Percentiles)

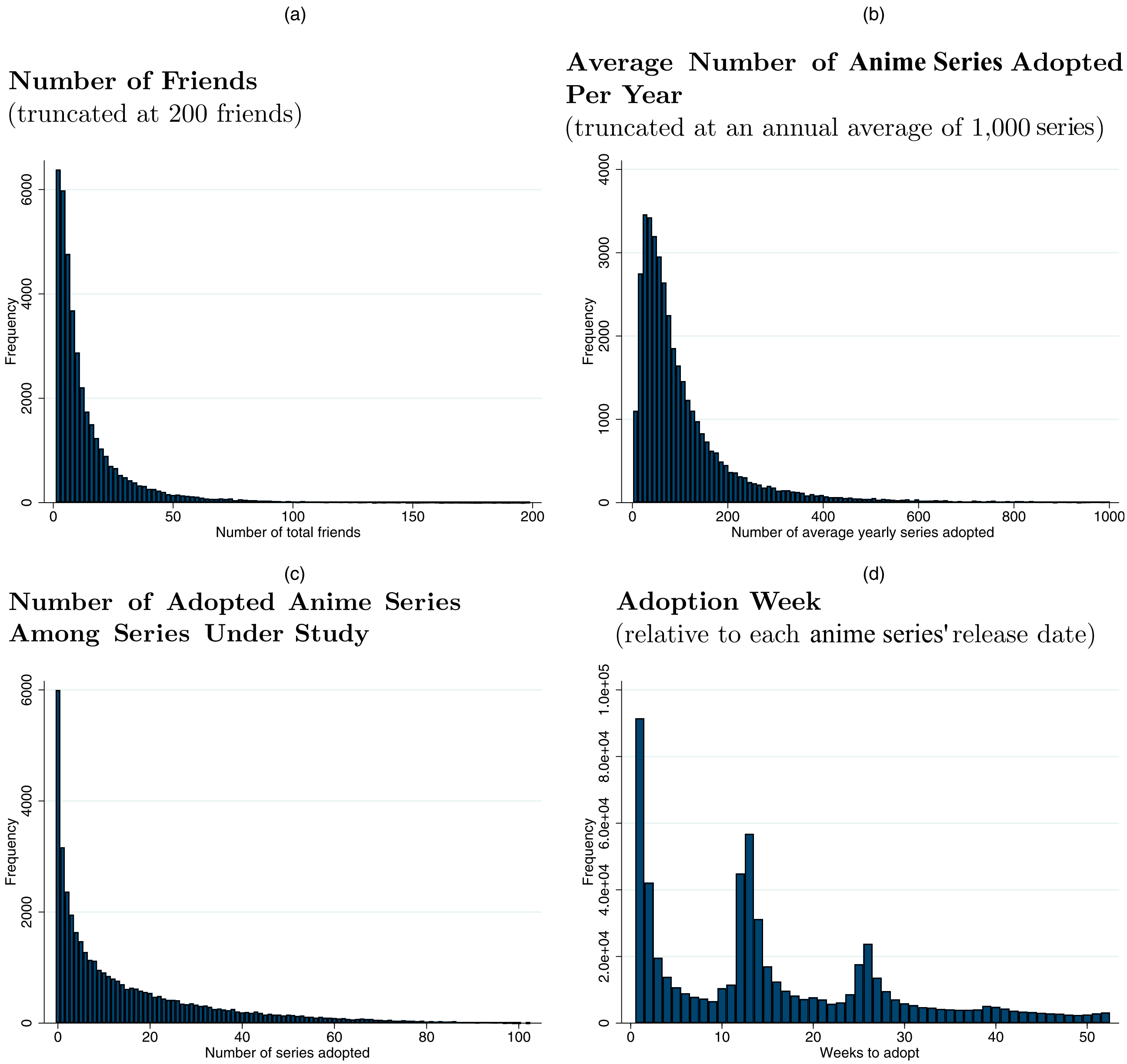


Furthermore, we also considered another type of common shock: the availability of an anime series through legal online streaming channels. However, we found that more than 90% of the anime series under study were available for online streaming within hours to up to three days after their original airing in Japan.[20] Because our data are at the weekly level, we conclude that availability through legal channels is synonymous with original episode airing and do not include it as a separate variable in our empirical model.

3.2. Data Description

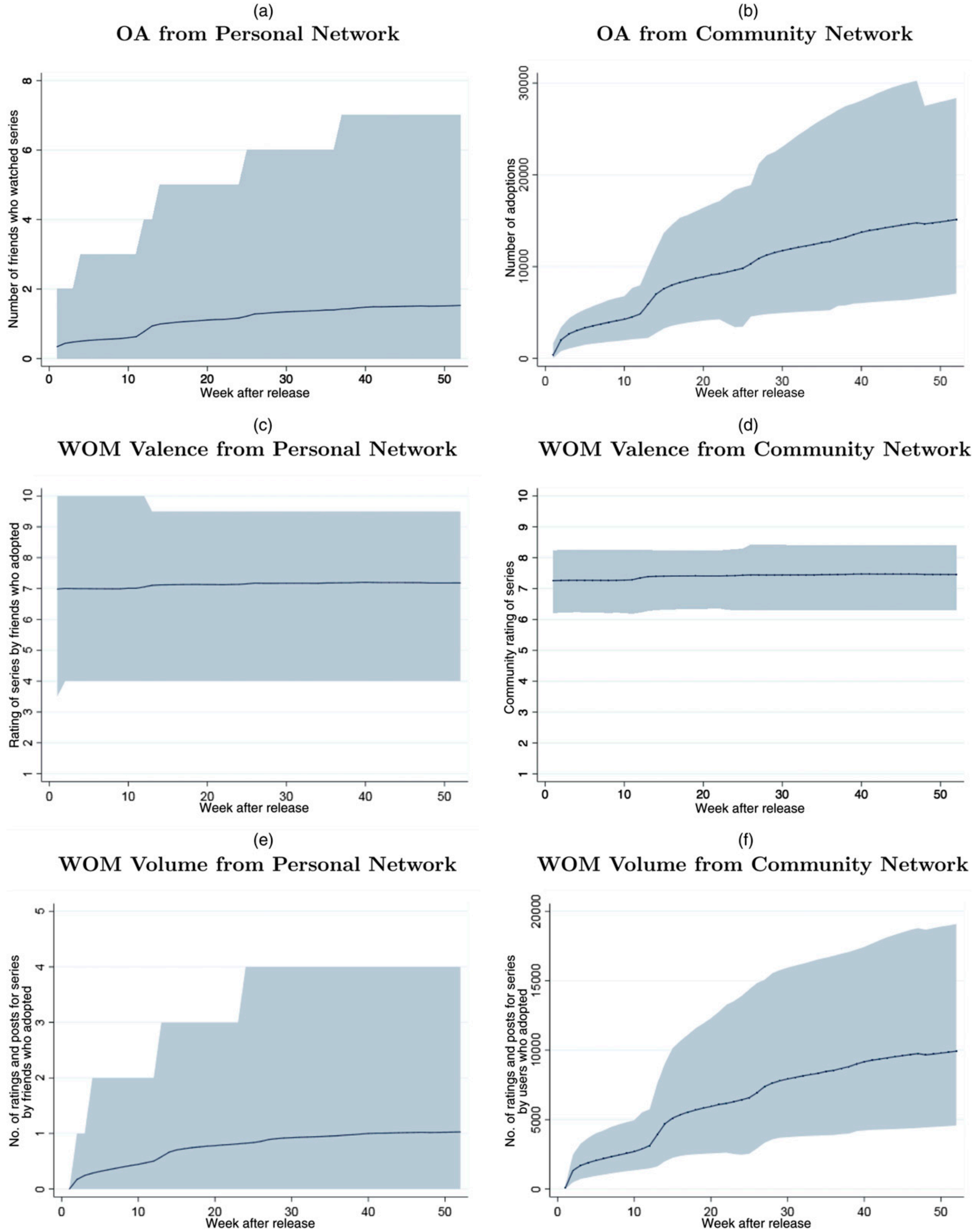
Table 1 summarizes key statistics of our data. On average, users watch 68 anime series per year and adopt 12 of the 103 anime series under study. Network users have, on average, 17 friends. Figure 7, (a)–(d), shows histograms of the number of friends, the average number of adopted anime series per year, the number of adopted anime series among those under study, and the adoption weeks (for each anime series 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. Furthermore, 34% of users indicate their gender as female, 52% as male, and the remainder did not specify their gender. On average, users adopt an anime series 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 anime series 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 series.

Figure 7. (Color online) Histograms of the Number of Friends and of Descriptives Related to Adoption



In Figure 8, we show the average levels (across users and anime series) of our six key variables capturing WOM and OA 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 8(a) shows the average cumulative number of friends who adopted the anime series (this is our measure of OA from the personal network). Figure 8, (c) and (e), shows the average of ratings given by friends and the volume of ratings and forum posts by friends, respectively (these are our measures of WOM valence and WOM volume from the personal network). Figure 8, (b), (d), and (f), shows the number of community adoptions, the average community rating, and the number of community ratings and forum posts, respectively.[21] These last three variables capture OA, WOM valence, and WOM volume from the community network. The graphs show that our key variables vary considerably across time. More important, 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 anime series and users, especially for the personal network measures. For example, the cumulative number of friends who watched an anime series ranges from 0 to 2 across users and anime series 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

Figure 8. (Color online) WOM and OA from Personal and Community Networks



and anime series 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 OA measures to identify their effects on product adoptions.

4. Model and Estimation

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

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 although 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 series. As mentioned in Section 3.1, we observe that users 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 as a result of the existence of homophily;[22] that is, friendship ties among users have been formed because users share the same interests. Whereas two friends adopting the same product might be the result of one influencing the other, it might as well be the result of those similar interests. To tease homophily apart from influence, we need to control for each user's intrinsic preference for a specific anime series 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.[23] Additionally, we also include stand-alone users (i.e., users without friends) in our estimation sample. Although these users are subject to social influence from the community network, they are not subject to social influence from personal networks and provide an additional source of variation.

The correlated unobservables problem[24] 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 or her friend adopt the product because of the shock, it can be mistaken as the user who adopted the product earlier influencing his or her friend. One example of such common shocks might be targeted actions by the platform. Note that the platform was created mainly to provide fans with an environment to connect with other fans. It was a nonprofit, 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.

To account for other 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. Because anime series 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 that online news and in-site news posts on MyAnimeList.net are the main sources of common shocks. Therefore, we use the previous week's number of online and in-site news articles 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 as a result of potentially simultaneous decision making by a user and his or her friends. In other words, a user might be influenced by his or her friends and, at the same time, influence those friends. We are able to address this challenge by using the lagged versions of variables capturing friends' actions.

4.2. Model Description

The setup of the model is as follows: suppose that there are $i = 1, \ldots, N$ individuals and $j = 1, \ldots, J$ anime series that an individual can adopt at time $t = 1, \ldots, \bar{T}_j$. We define each time period t as the tth week since the release of anime series j. We observe each individual i until his or her adoption of anime series j in time period T_{ij} or until the end of the study period for anime series j, $\bar{T}_j$, if individual i does not adopt anime series j. We assume that the end of the study period is independent of an individual's adoption; that is, there is no censoring of time. Given that we, as researchers, chose the length of the study period ex post, this assumption is reasonable. Let y_{ijt} capture the adoption status of anime series j by user i at time t. If user i adopts anime series j at week t, y_{ijt} equals 1; otherwise, it equals 0. We model users' adoption decisions using a linear probability model (e.g., Bandiera and Rasul 2006, Tucker 2008, Lambrecht and Tucker 2013). In other words, y_{ijt} is given by

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

where α_{ij} are user–anime fixed effects, γ_{it} are user–release week fixed effects, δ_t^{cal} are calendar week fixed effects, and X_{ijt} contains WOM and OA variables from the personal network. In addition, we also include a dummy variable indicating whether a user is a stand-alone user in X_{ijt}. This variable helps to distinguish a stand-alone user from a network user whose friends have not adopted a specific anime series. The term Z_{jt} includes WOM and OA variables from the community network;[25] C_{ijt} contains other variables whose effects we control for, namely, the number of anime series adopted by individual i in week t, the number of news articles published about anime series 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 OA and WOM variables. We include interaction effects between the season finale dummy and the community WOM and OA variables to control for sudden jumps in the community WOM and OA variables as a result of an increased number of adoptions around the season finale. Furthermore, β_1 and β_2 capture the effects of WOM and OA from the personal and community networks, respectively. The error term ϵ_{ijt} is assumed to follow a standard normal distribution. Finally, $\theta = (\alpha_{ij}, \gamma_{it}, \delta_t^{cal}, \beta_1, \beta_2, \beta_3)$ is the set of parameters to be estimated.

5. Results and Discussion

The estimation results for our main model are presented in column (2) of 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 (1) of Table 2. In interpreting our results, we focus on our main model shown in column (2).[26] We start by discussing the parameter estimates for the control variables. The parameters for the number of adopted anime series in week t and the number of online news articles 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 OA variables. For a typical anime series, the total effect of the season finale is positive.

5.1. Effects of WOM and OA

Next, we discuss the effects of our key variables of WOM and OA 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 because they are the average ratings given to an anime series by the whole community, whereas the community-wide number of ratings and forum posts for an anime series 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 anime series 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 OA from the whole community, is also positive and significant. Therefore, as expected, our result suggests that the more popular an anime series gets, the more likely it will be adopted by an individual. Note that the significant positive effect of OA is after controlling for WOM valence and volume, suggesting that OA provides additional information to users.

To judge the relative magnitudes of the effects, we use our parameter estimates to calculate elasticities for the three social influence variables at the community network level. We find that the average adoption likelihoods increase by 0.86%, 0.15%, and 3.45% as a result of a 1% increase in OA, WOM volume, and WOM valence, respectively. To put it differently, a 1% increase in WOM valence produces the largest increase in adoptions, followed by the increases in OA and WOM volume.

We now turn to the effects of WOM and OA from the personal network. We use three variables to capture the effects of WOM from the personal network: a friends' rating dummy, which equals 1 if at least one friend in an individual's personal network has submitted a rating for the anime and 0 otherwise; friends' average rating conditional on the friends' rating dummy being 1 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 series release when none of their friends had rated the anime series yet. Given this data pattern, the friends' rating dummy captures the effect of the first rating submitted by a friend, and the friends' average rating captures the valence of the ratings.[27] In addition, to distinguish stand-alone users, who by definition have zero inputs in all WOM and OA variables from the personal network, from network users whose friends have not made any observed adoptions or produced any WOM for a specific anime (and therefore also have zero inputs in WOM and OA variables from the personal network for that anime series), we include a dummy variable indicating whether a user is a stand-alone user in the model.

We find the effect of the friends' rating dummy to be negative and significant, whereas 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 OA from one's personal network to be positive and significant: as the number of friends who have watched an anime series increases, an individual becomes more likely to adopt the anime series. These results for the personal network indicate that OA and WOM provide users with different and unique information and have separate

Table 2. Results

Variables	(1) Homogeneous model	(2) Main model	(3) Asymmetric OA model	(4) Awareness model
Word of mouth				
Friends' Rating Dummy	−0.0011***	−0.0034***	−0.0031***	−0.0032***
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Friends' Avg. Rating Interaction	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Friends' Number of Ratings and Forum Posts[a]	0.0003***	0.0034***	0.0031***	0.0030***
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Community Rating	0.0008***	0.0012***	0.0011***	0.0011***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Community Number of Ratings and Forum Posts[a]	−0.0021***	0.0004***	0.0004***	0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observed adoptions				
Cum. Number of Friends Who Adopted[a]	0.0000	0.0030***		0.0040***
	(0.0000)	(0.0001)		(0.0001)
Cum. Number of Friends Who Watched[a]			0.0029***	
			(0.0001)	
Cum. Number of Friends Who Dropped[a]			0.0018***	
			(0.0001)	
Dummy for First Adoption by Friend				0.0055***
				(0.0001)
Cum. Number of Community Users Who Adopted[a]	0.0010***	0.0021***	0.0021***	0.0021***
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Other parameters				
Number of Anime Series Watched During the Week[a]	0.0118***	0.0082***	0.0081***	0.0082***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Season Finale Dummy	−0.1283***	−0.1002***	−0.1002***	−0.0999***
	(0.0010)	(0.0009)	(0.0009)	(0.0009)
Number of Online News Articles[a]	0.0007***	0.0000**	0.0001*	0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Stand-alone User Dummy	0.0000	0.0061***	0.0056***	0.0077***
	(0.0000)	(0.0005)	(0.0010)	(0.0005)
Season Finale Dummy × Community Rating	0.0014***	0.0018***	0.0018***	0.0018***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Season Finale Dummy × Community Number of Ratings and Forum Posts[a]	0.0145***	0.0113***	0.0113***	0.0112***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Season Finale Dummy × Cum. Number of Community Users Who Adopted[a]	0.0013***	0.0006***	0.0006***	0.0008**
	(0.0002)	(0.0002)	(0.0002)	(0.0005)
Constant	0.0027***			
	(0.0002)			
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^2	0.0182	0.1164	0.1164	0.1240
Number of observations	22,369,620	22,369,620	22,369,620	22,369,620

Note. Standard errors are in parentheses.
$*p < 0.05$; $**p < 0.01$; $***p < 0.001$.
[a]Operationalized as $\ln(x + 1)$.

influences on individuals' product adoption decisions. Thus the influence of social learning is not fully captured when only WOM or only OA is considered in an empirical study.

Friendships can vary in their strength. As a result, the magnitude of peer effects can vary across friends. Private communication between users is likely a good measure of friendship tie strength. Because we do not observe these private communications, we cannot characterize friendships beyond their existence. In this context, the effects of OA and WOM should be interpreted as the average effects across friends. Finally, we also find a positive and significant effect for being a stand-alone user, suggesting that a stand-alone user is generally more likely to adopt a specific anime series than a network user whose friends have not adopted it.

To compare the relative magnitudes of the effects, we calculate elasticities for the three social influence variables at the personal network level. That is, we evaluate the percent changes in anime adoption likelihood resulting from a 1% increase in the average WOM valence, WOM volume, and OA levels from the personal network. Similar to the community network, the 1% change in WOM valence from friends has a larger effect on users' adoption decisions (with an average increase in adoption likelihood of 0.49%) than those of OA or WOM volume (with average increases in adoption likelihoods of 0.48% and 0.46%, respectively), even though the three elasticities are of similar magnitudes.

Finally, using the calculated elasticities, we compare the effect sizes of WOM valence and OA 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—across both network levels and learning mechanisms (i.e., OA versus WOM). Similar to WOM valence, OA from the community network has a larger influence than does OA from the personal network. This is probably because 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 do personal networks.

5.2. Positive and Negative Observed Adoptions

As discussed in Section 3, users can assign different statuses to the anime series on their watch list: "watched," "watching," "on hold," "dropped," or "plan to watch." We define a user as having adopted an anime series if it is on his or her watch list under any of the first four statuses in our main model. However, one can argue that the four statuses contain different information about product adoptions. More specifically, whereas the adoption information can be viewed as either positive or neutral for the statuses "watched," "watching," and "on hold," it is clearly negative for the status "dropped" because this status suggests product abandonment after trial. We therefore use this more nuanced information on adoption statuses to estimate an additional model in which we differentiate between OA coming from positive and negative product adoption experiences within the personal network. To do so, we define positive OA as the act of adopting the product under the statuses "watched," "watching," and "on hold" and negative OA as the act of adopting and abandoning the product under the status "dropped."

The results are shown in column (3) of Table 2. As expected, we find a significant positive coefficient for positive OA from friends. We also find a significant positive, albeit significantly smaller, coefficient for negative OA. This finding is consistent with our expectation that the effect of positive OA is indeed larger than that of negative OA. In other words, users do pay attention to the differential informational content in their friends' adoption statuses when making their own watching decisions. However, to our surprise, the negative OA still enhances users' adoption likelihood of an anime series. One plausible explanation is that compared with anime series that no friend would even want to (watch and then) drop, anime series with negative OA from friends are perceived to be of better quality because they crossed some friends' bar for an initial trial.

5.3. Awareness vs. Learning About Unobserved Quality

OA from the personal network can influence a user in his or her decision as to whether to watch an anime series in two ways: a user can become aware of an anime series through his or her friends' adoptions, and he or she can learn about the unobserved quality of an anime series from his or her friends' adoptions (see also Fafchamps et al. 2016). To put it differently, when a user first observes that a friend has watched an anime series, this can both create awareness for the anime series and let the user learn about the unobserved quality of the anime series. However, friends' subsequent adoptions only inform a user about the unobserved quality and do not create awareness for the anime series because 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, this implies that quality information transfer and not awareness creation is the underlying mechanism for the effect of OA 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 (4) of 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 OA from the personal network; this 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 OA. Although in our empirical context of anime series, online information is likely to be the primary source of information because of the special-interest nature of anime, accounting for offline WOM and OA might be important in other contexts.

Second, although we observe five different statuses (“watched,” “watching,” “on hold,” “dropped,” and “plan to watch”) for each anime series, we model only initial adoptions of an anime series 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, users might vary in their befriending strategies—that is, how selective they are in accepting friendship requests, and the strength or closeness of friendships. It represents a limitation of our data that we do not observe the incidence and/or content of private communication between friends and are not able to qualify friendships and their formation beyond existence.

Fourth, we study adoption behavior at the weekly level. In some contexts, a more granular study of user behavior (e.g., at the daily level) might be of interest. Because of computational limitations, we can estimate our model with daily data only using a small sample of users, and we leave a larger empirical analysis for future research.

Fifth, and finally, the influence of WOM and OA 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.

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 peers in his or her personal network as well as all other users in the community network by observing their opinions (i.e., WOM) and/or actions (i.e., OA). 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 OA on users’ product adoptions and quantify the relative importance of information obtained from one’s personal network compared with 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 OA and WOM (both valence and volume) have significant and positive effects on individual users’ anime adoption decisions. Moreover, this finding holds true for WOM and OA information coming from both the community network and the personal network. Thus our results highlight that WOM and OA 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 United States provides users with the tools necessary to form personal networks. Our results suggest that the less significant role the personal network plays vis-à-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 OA (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—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” category 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. More generally, online streaming platforms can consider displaying movie popularity information directly in terms of adoptions, rankings, or similar metrics to encourage adoptions more efficiently.

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Endnotes

[1] Observational learning has been proposed as the underlying mechanism for the effect of OA. We defer the discussion of observational learning to the literature review section.

[2] Online streaming of movies and (TV) shows has grown rapidly over the last decade (see McKinsey & Company 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, accessed January 28, 2016). In 2015, 70% of North American internet traffic consisted of streaming video and audio content, and Netflix alone accounted for 37% of all internet traffic in North America (https://www.sandvine.com/press-releases/blog/sandvine-over-70-of-north-american-traffic-is-now-streaming-video-and-audio, accessed January 28, 2016).

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

[4] Note that our OA variables in this paper differ from the classic definition of OA used by the literature on observational learning: in the classic definition, OA is conceptualized as observations of adoptions without additional information. In our paper, OA 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.

[5] Users have the option to hide their profile page from the public, but less than 5% of users used this option at the time we started the data collection (March 2015).

[6] It is a limitation of our data that we do not observe private communication between friends. We discuss this data limitation in more detail in Sections 5 and 6.

[7] We do not account for platform choice in this paper because, in general, users can watch anime 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 (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.

[9] In an additional model, we differentiate between OA coming from positive and negative product adoption experiences. To do so, we define *positive* OA as product adoptions under the statuses "watched," "watching," and "on hold" and *negative* OA 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 95% and 5% of observations, respectively. As a robustness check, we move up the adoption dates of the 5% of observations for whom we only have the dates of the last update one week; that is, we mark the adoption time as one week prior to the date of the last update. We then reestimate 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).

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

[12] Note that there is also an alternative measure of OA from the community network: popularity rank (based on the number of adoptions) on the anime page (see "Popularity" in the bottom left corner of Figure 1). Similarly, there is an alternative measure of WOM valence from the community network: users can see the rank of an anime series 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 OA 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).

[13] Note that all our WOM variables from both the personal and the community networks are conditional on friends and all users, respectively, having adopted an anime series.

[14] The 2.2 million mostly 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.com/articles/participation-inequality/, accessed January 28, 2016).

[15] 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.

[16] Seventy-four percent of adoptions across the 103 anime series happen during the study period compared with 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 with the total observation period.

[17] Ideally, one would want to model adoption at the daily level. However, doing so would septuple our current estimation sample of 5,000 users with 22.4 million observations (saved in a 40-gigabyte [GB] text file) to a data sample with 156.7 million observations. Although we are still able to estimate our model with weekly data on a 12-core, 64-GB memory MacPro desktop, to estimate our model with daily data, a supercomputer would be needed. We estimated our main model with daily data for a (small) random sample of 500 users with 15.6 million observations, and our findings are robust (see model (v) in Table C-1 in Online Appendix C).

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

[19] In a set of robustness checks, we estimate our model using different mixes of these two types of users (i.e., network and stand-alone users), including a sample of (a) 5,000 network users, (b) 4,000 network and 1,000 stand-alone users (the same as our main results, shown for ease of comparison), (c) 3,000 network and 2,000 stand-alone users, and (d) 2,000 network and 3,000 stand-alone users. The

results are shown in Table C-2 in Online Appendix C, and our main findings are qualitatively robust.

[20] Anime series were mostly available for immediate online streaming on the international website Crunchyroll.com.

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

[22] Homophily, which Manski (1993, p. 533) referred to as "correlated effects," is the more prominent aspect of the endogenous network formation challenge.

[23] 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, any group–anime, and/or any group–release week fixed effects. Furthermore, 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 or operationalization of *group*, and it even allows a so-called group to vary from one anime series to another.

[24] Manski (1993, p. 532) referred to this issue as "exogenous (contextual) effects."

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

[26] Because of data size issues (see also Endnote 17), we use weekly data to estimate our main model. Using a small sample of 500 users (15.6 million observations), we also estimated our main model using daily data, and our findings are robust (see model (v) in Table C-1 in Online Appendix C).

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

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