Article

Journal of Marketing
2019, Vol. 83(6) 93-112

DOI: 10.1177/0022242919875688
journals.sagepub.com/home/jmx

What Drives Herding Behavior in Online Ratings? The Role of Rater Experience, Product Portfolio, and Diverging Opinions

Sarang Sunder, Kihyun Hannah Kim, and Eric A. Yorkston

Abstract

Consumers' postpurchase evaluations have received much attention due to the strong link between ratings and sales. However, less is known about *how* herding effects from reference groups (i.e., crowd and friends) unfold in online ratings. This research examines the role of divergent opinions, rater experience, and firm product portfolio in attenuating/amplifying herding influences in online rating environments. Applying robust econometric techniques on data from a community of board gamers, we find that herding effects are significant and recommend a more nuanced view of herding. Highlighting the role of rater experience, the positive influence of the crowd is weakened and friend influences are amplified as the rater gains experience. Furthermore, divergent opinions between reference groups create herding and differentiation depending on the reference group and the rater's experience level. Finally, firms can influence online opinion through their product portfolio in profound ways. A broad and deep product portfolio not only leads to favorable quality inferences but also attenuates social influence. Implications for online reputation management, rating system design, and firm product strategy are discussed.

Keywords

diverging opinions, disagreement, herding effects, online ratings, product scope, rater experience, reflection problem

Online supplement: https://doi.org/10.1177/0022242919875688

User-generated online ratings and reviews play an important role in the consumer decision process. They act as a key source of quality information for consumers and have profound downstream market impact. With easy access to online reviews and ratings, consumers rely more and more on the opinions of others when making purchase decisions (Bernick 2017; Nielsen 2012). Academic work points to significant positive effects of online ratings on market outcomes, reputation, and purchase behavior across various business contexts (Ameri, Honka, and Xie 2019; Chevalier and Mayzlin 2006; Chintagunta, Gopinath, and Venkataraman 2010; Moe and Trusov 2011; Zhu and Zhang 2010). Given the positive consequences of online ratings, a great deal of recent interest has emerged among academics and practitioners in understanding the antecedents of ratings (Dellarocas and Narayan 2006; Godes and Silva 2012; Goes, Lin, and Yeung 2014; Moe and Schweidel 2012).

When generating an online rating or review, raters create an evaluation of a product that reflects their personal perception of the product's quality and qualities. However, most review sites (e.g., Yelp, TripAdvisor, Amazon) also expose raters to others' ratings. These prior ratings by others often influence current raters' evaluations, a process generally known as "herding."[1] In the recent past, several popular ratings platforms have begun to display friends' and crowd ratings distinctly on their websites. For example, Facebook Local allows individuals to rate and review places such as restaurants and other service establishments and share this information with their friend network (Lee

[1] A note on terminology. We use the general term "herding" to describe people's behaviors that follow the observed actions of others (Ding and Li 2018). The specific herding behavior that we uncover in this research has been referred to as "information-motivated herding" in prior literature (Li and Hitt 2008). Researchers have used the terms "social dynamics" (e.g., Moe and Schweidel 2012; Moe and Trusov 2011), "peer effects" and "social multipliers" (e.g., Nair, Manchanda, and Bhatia 2010), and "information cascades" (e.g., Lee, Hosanagar, and Tan 2015) to describe the same behavior.

Sarang Sunder is Assistant Professor of Marketing, Neeley School of Business, Texas Christian University, USA (email: s.sunder@tcu.edu). Kihyun Hannah Kim is Assistant Professor of Marketing, Rutgers Business School, Rutgers University, USA (email: kh.kim@business.rutgers.edu). Eric A. Yorkston is Associate Professor of Marketing, Neeley School of Business, Texas Christian University, USA (email: e.yorkston@tcu.edu).

2016). Yelp displays the ratings from the crowd and allows individuals to "connect with friends" to easily access their individual ratings. Other services, such as Netflix, Foursquare, and TripAdvisor, allow their accounts to be connected to popular social networks such as Facebook. This provides raters with multiple, often conflicting, sources of social information that can cause herding effects.

Recent Research on Herding in Online Rating Environments

Typically, research on herding in online ratings has focused on social influence arising from the online community as an aggregate whole (Dellarocas and Narayan 2006; Godes and Silva 2012; Goes, Lin, and Yeung 2014; Li and Hitt 2008; Muchnik, Aral, and Taylor 2013; Sridhar and Srinivasan 2012; Wu and Huberman 2008). Less work has focused on parsing out herding effects from multiple sources. A rater's friend network may exert a different kind of influence relative to that of the general public. For instance, a friend's rating may prove to be more salient than the rating of the crowd, especially when the friend's interests overlap with those of the rater. More recent research has stressed the importance of identifying and separating multiple sources of herding (Lee, Hosanagar, and Tan 2015; Zhang and Godes 2018). Still, scant research exists that explores the contingencies under which herding may or may not occur for these multiple sources. Our research relates to, and in many ways extends, the recent empirical work by Lee, Hosanagar, and Tan (2015) and Zhang and Godes (2018) highlighting differences in the herding effects across multiple reference groups. Lee, Hosanagar, and Tan uncovered the differences between crowd and friend herding effects. They found that although friends' ratings always induced herding effects, crowd ratings caused herding for popular products and differentiation for unpopular ones. We build on Lee, Hosanagar, and Tan by controlling for their moderators and covariates while breaking new ground by establishing the influential role that individual-level and firm-controllable factors play in moderating herding behavior. Furthermore, our research complements Zhang and Godes, who examined herding from the perspective of an individual's number of social ties and whether these ties are strong or weak. We control for the number of ties and instead study the important roles that the valence and consistency of opinions play in herding. A further notable difference from Zhang and Godes has to do with the operationalization of social ties. In their work, "weak ties" are represented by people a rater follows, whereas "strong ties" are bidirectional (i.e., exist when the rater and their peer follow each other). We expand this view to consider influences arising from self-declared friend networks and the overall community, not just people who a rater might choose to follow.

Our work aims to be the first to focus not only on the distinct herding effects produced by crowd and friend networks but also on understanding the contingencies that govern the herding influences. In addition to decomposing herding effects into influences exerted by in-group (i.e., friends) and out-group (i.e., crowd) networks on a rater's subsequent rating, we aim to (1) uncover key rater-level and firm-level factors that attenuate/amplify herding and (2) examine the role of "mixed" opinions (i.e., disagreement between crowd and friends) on the herding effect. Using the theory of herding (Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992) as our theoretical lens, we develop a conceptual framework to understand and evaluate the herding effects. We examine the aforementioned research objectives and test the proposed conceptual framework on unique data from an online community in the board gaming industry comprising 44,108 board gamers rating 5,138 games from 2,206 publishing firms spanning over ten years. Our data and modeling strategy allow us to exploit the timing of tie formation and exogenous variation created through partially overlapping network pairs (Bramoulle, Djebbari, and Fortin 2009) to credibly identify the herding effects. In the spirit of building on and extending previous work, we ensure that our findings are interpretable over and above what extant research has accomplished. Wherever appropriate, we include covariates, moderators, and other control variables that prior work has highlighted and then demonstrate our additional contributions. In Table 1, we juxtapose our research with prior work across dimensions including research scope, conceptualization, and application, placing our research in the context of extant literature on social influence in online ratings.

Overview of the Key Contributions

This article adds to a growing stream of academic work aimed at assessing social effects in online rating environments and highlighting the importance of distinguishing the herding influences exerted by weak (i.e., crowd) and strong (i.e., friend) ties. We find that crowd and friend effects are distinct, significant, and positive; there is indeed wisdom to be found in crowds *and* friends. We offer a more nuanced view of herding by making three important contributions. First, we find that the herding effect is not universal but depends on an individual's own experience level. All herding effects should not be treated equally, because rater experience attenuates the herding effect of the crowd but amplifies the herding effect of friends. Second, we demonstrate how firms can leverage their category-level experience in online rating environments through their product line strategy. A firm's product scope serves as an additional source of diagnostic information for raters and influences rater quality judgments both directly and indirectly. Ceteris paribus, not only do firms with greater product scope receive more favorable ratings, greater product scope also attenuates the herding effect. Third, we show that, in general, raters rely more on the crowd's opinions than on those of friends when the two reference groups disagree with each other. However, more experienced raters will rely more heavily on friends' ratings.

We believe this research has important implications for online reputation management, online rating platform design, and product strategy. First, our study suggests that firms can and should take advantage of herding in rating environments. Firms can manage their online reputations by strategically

Table 1. Representative Empirical Research on Herding Effects in Online Ratings.

Study	Main Effects			Moderating Effects		Level of Analysis	Data and Empirical Context
	Crowd	Friends/Peers	Divergence of Opinion	Rater Experience	Firm's Product Scope		
Moe and Trusov (2011)	Yes	No	Main effect only[a]	No	No	Aggregate	Online retail (500 products, one year)
Moe and Schweidel (2012)	Yes	No	Main effect only[a]	Yes	No	Individual	Online retail (4,974 raters, 1,811 products, six months)
Sridhar and Srinivasan (2012)	Yes	No	No	Main effect only	No	Individual	Hospitality (7,499 raters, 114 products, four years)
Muchnik, Aral, and Taylor (2013)	Yes	No	No	No	No	Individual	News (3,600 raters, 163 days)
Lee, Hosanagar, and Tan (2015)	Yes	Yes	No	Main effect only	No	Individual	Movies (28,160 raters, 149 products, 16 weeks)
Zhang and Godes (2018)	Only number of ties	Only number of ties	No	Yes	No	Individual	Books (5,389 raters, 16,595 products, 50 days)
This study	Yes	Yes	Divergence between reference groups + moderation effects	Main + moderation effects	Main + moderation effects	Individual	Board games (44,108 raters, 5,138 products, ten years)

[a]Considers only aggregate distribution (variance) of prior ratings, not divergence between specific reference groups.

targeting their review solicitations. Specifically, firms seeking more objective ratings should target experienced raters because they are less influenced by the herding effect. Firms that want to ride a positive bandwagon effect should solicit ratings from new users. Of course, managers must be careful, as we demonstrate that herding influences are a double-edged sword. Positive word of mouth results in more word of mouth that is positive, but the reverse is also true. Second, our research has implications for online rating platform design. Depending on prior product ratings and the goals of the website, friend and crowd information can be made more or less accessible. Third, this research provides guidance for portfolio planning, as a firm's product strategy has profound positive effects on online opinion, both directly and indirectly. Firms with broader and deeper product portfolios are viewed more favorably, and this higher product scope attenuates herding influences from both crowds and friends.

The rest of the article is organized as follows. We first introduce the theoretical lens of herding, which forms the basis of our conceptual framework and hypotheses describing the herding effects and key moderators on online rating behavior. Following this, we describe the empirical context and develop our measures. We then discuss the modeling framework that forms the basis of our hypothesis testing. After estimating the model, we report the empirical findings, test our hypotheses, and conduct a series of robustness analyses. Finally, we discuss the theoretical and managerial implications of this research before concluding with limitations and avenues for future research.

Theory and Conceptual Framework

The Theory of Herding

The theory of herding (Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992) guides how social influence manifests in online rating environments. Our application joins a long list of applied empirical work studying herding in purchase, adoption, and consumption decisions across various contexts in economics, finance, information systems, and marketing.[2] Herding can be explained as a response to an individual's perceived uncertainty about an action. That is, in an effort to minimize uncertainty about their own decisions, people tend to utilize information provided by others and converge on similar behaviors. An individual's decision is a reflection of two main sources of information: imperfect individual information and the sequential actions of others. The first source is the individual's own signal or preference that encompasses all the information that one is able to gather about the decision. The second source is the history of actions taken by other individuals who also were faced with the same decision. To reconcile these two sources, individuals weigh their own information against the sequential actions of others. When people are more certain

[2] Ding and Li (2018) provide an excellent review of research applying herding theory in various contexts.

about their preferences and quality assessment, their information dominates the herding effect.[3] On the other hand, in the presence of uncertainty (e.g., when individuals are unsure about their preferences), the theory of herding predicts that the observed sequential actions of others will play an enhanced role in forming a preference.

Our research is well suited to the theory of herding because it satisfies the two main criteria for rational herding to exist. First, ratings are based on preferences and quality judgments; two sources that are notoriously uncertain (Zhang, Liu, and Chen 2015; Zhao et al. 2012). Second, ratings arrive in a sequential order and are clearly visible to the individual. In our context, as in most online rating platforms, the ratings provided by the community are salient to the individual at the time of rating. Our framework enables us to extend this theory by allowing for multiple sources of sequential actions from friends and crowds in addition to demonstrating how firms can influence herding through their product strategy.

Conceptual Framework

Herding from reference groups. Individuals adjust their ratings of products in line with the online rating information of the crowd (Li and Hitt 2008; Muchnik, Aral, and Taylor 2013). That is, to conform to the crowd's opinion, rating behavior is positively related to prior crowd rating behavior. Conformance does not just exist with crowd behavior—herding has been demonstrated among friend networks as well (Lee, Hosanagar, and Tan 2015; Zhang and Godes 2018). The theory of herding supports these conclusions. Raters make use of the observed behaviors of the reference groups (i.e., crowd and friends) to adjust their own quality judgments in an effort to reduce uncertainty. In addition, there is often a social cost to having opinions that diverge from the community and reference groups. Although we do not formally hypothesize an effect, given the theoretical motivations along with prior literature, we expect that the rating valence of the reference groups, both crowd and friends, will be positively related to the subsequent valence of an individual's rating, resulting in a positive herding effect. As raters in an online community are exposed to more diagnostic information when rating a specific product online, their susceptibility to herding may shift. We focus on three factors that may govern the herding effect: rater experience, the firm's competencies as inferred through product portfolio scope, and the role that divergent opinions play in online ratings. In the following subsections, we offer theoretical arguments for each moderation effect and develop hypotheses for the same.

Rater's prior experience. As individuals develop their own preferences and gain knowledge of and expertise with a product category, they become more confident in their own evaluations and opinions (Ding and Li 2018). Highly experienced raters view themselves as opinion leaders and tend to be less affected by the crowd. Empirical work in the medical domain and physician prescription behavior has found asymmetric peer effects among physicians according to their perceived opinion leadership (Iyengar, Van den Bulte, and Valente 2011; Nair, Manchanda, and Bhatia 2010). We expect similar effects to exist among highly experienced raters. According to the theory of herding, experienced individuals gain confidence in their own preferences and information. As such, highly experienced raters should rely relatively less on others' ratings and more on their own experiences. In addition, experienced raters may find value in differentiation. In an online community context, where there are fewer individual markers to establish identity, experts try to signal divergence from the crowd (Berger and Heath 2007) in an effort to appear knowledgeable (Schlosser 2005) and display "good taste" (Holbrook and Addis 2007). Thus, we expect that as raters gain more experience by spending more time and rating more products, their reliance on the crowd will decrease.

Although diverging from the majority may be of social value, the same cannot be said for having separate opinions from friends. The potential cost of divergence of opinion is amplified when members belong to in-group networks (Bikhchandani, Hirshleifer, and Welch 1992). As a result, raters tend to conform strongly within self-selected friend networks. The stronger the in-group network grows over time, the more opinions coalesce, and the more attitudes shift to be consistent with the in-group (Mackie and Cooper 1984). From the perspective of social identity theory (Ashforth and Mael 1989), herding from known in-group networks such as friends is likely to be stronger among embedded individuals. That is, raters who are strongly embedded within a friend network share a common identity with the network and feel the need to signal this common shared identity. In the case of online social networks, it is expected that experienced raters, who have spent more time on the social network and carefully select their reference groups, are more embedded within their friend networks. This sharing of identity and norms within friend networks causes experienced raters to coalesce their opinions to signal common tastes and mutual respect with the friend groups (Ashforth and Mael 1989). Furthermore, these shared group norms create barriers to dissenting opinions (Fehr and Fischbacher 2004; Harmeling et al. 2017). Therefore, although we expect experienced raters to diverge from the "common" others (i.e., out-group networks), we expect them to coalesce with friends (i.e., in-group networks). A rater's prior experience will amplify the effect of self-declared friends' ratings on subsequent evaluations. In summary, we expect that the moderating influence of rater experience on crowd and friend influences acts in opposing directions.

> **H_1:** As an individual's prior rating experience increases, the crowd's influence on subsequent ratings decreases.

> **H_2:** As an individual's prior rating experience increases, the friends' influence on subsequent ratings increases.

[3] Note that individuals' information can be gained either through direct experience or by gathering information from external sources (e.g., the firm's reputation).

Divergent opinions. Although friends and crowds both exert herding influences on the individual, these two sources may not always agree with each other. One of our main objectives is to investigate the role that disagreements play on herding effects. As predicted by the theory of herding (Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992), when faced with mixed signals, the average rater calculates the cost of diverging from each reference group. The cost of divergence is not the same for the crowd and friends. The average rater shares some of their identity with their friend groups, but this shared identity is not strong enough to offset the cost of diverging from the majority opinion of the crowd. Notably, the average rater, by definition, is less motivated (than experienced raters) to signal strong self or shared identities and therefore has less incentive to diverge (Berger and Heath 2007; Schlosser 2005). Given this, the average rater would perceive a higher cost of divergence with the crowd (i.e., the majority opinion) than among friends (i.e., the minority opinion).

> **H_3:** When the divergence between crowd and friend ratings is high (vs. low), raters favor the crowd over friends such that (a) the crowd's herding influence increases and (b) friends' herding influence decreases.

Although, on average, we expect raters to coalesce with the crowd more than with friends, when faced with mixed opinions, the role of rater experience cannot be ignored. As raters gain experience, their relationships with their friend networks and their mutually held attitudes strengthen (Mackie and Cooper 1984). This makes disagreements with the strong in-group ties more costly, lending relatively more weight to the opinions of friends. Stronger in-group ties encourage the formation of behaviors and attitudes that minimize in-group differences while maximizing out-group differences (Terry and Hogg 1996). As we posit in H_2, experienced raters conform to their self-selected reference groups, thereby avoiding sanctions from the strong in-group network (Harmeling et al. 2017) and preventing the erosion of that group's shared identity (Ashforth and Mael 1989). Conversely, experienced raters gain less value from following the crowd, as it is through divergence from the crowd that raters can signal expertise and opinion leadership (Iyengar, Van den Bulte, and Valente 2011; Nair, Manchanda, and Bhatia 2010; Schlosser 2005). The combined result of these two competing influences is that experienced raters are less influenced by the crowd and are increasingly influenced by their friends, especially when these sources disagree. Formally,

> **H_4:** When the divergence between crowd and friend ratings is high (vs. low), as rater experience increases, raters favor friends over the crowd such that (a) the crowd's herding influence decreases and (b) friends' herding influence increases.

Scope of a firm's product portfolio. A firm's historical product launches and product strategy can play an important role in building its reputation (Kekre and Srinivasan 1990; Purohit and Srivastava 2001). One factor of success is past product production experience, where advantages come from both breadth and depth of the product line (Sorescu, Chandy, and Prabhu 2003). Specifically, having several products concentrated within one category (i.e., depth) enables a firm to learn through repetition of tasks and processes. Offering a wide range of products across multiple categories (i.e., breadth) enables a firm to learn through variation (Argote and Miron-Spektor 2011; Narayanan, Balasubramanian, and Swaminathan 2009; Schilling et al. 2003). The depth and breadth of a firm's product portfolio, its product scope, helps build its category-level experience. Raters interpret this scope as a diagnostic measure of competence and use this information when making quality judgments. Therefore, as firm product scope increases, raters see this as a direct cue of product success. One may also view the firm product scope effect through the lens of assemblage theory (DeLanda 2016; Deleuze and Guattari 1987), wherein "assemblages" refer to emergent wholes made up of heterogeneous components. Applying assemblage theory to the current context, a firm's product portfolio could be viewed as an assemblage of its various offerings that form its identity in the marketplace (Cayla and Peñaloza 2012; Lury 2009; Ramaswamy and Ozcan 2016). A firm with a broad and deep portfolio of offerings, when compared with a firm with a narrow and shallow product portfolio, is able to achieve a clearer, well-integrated assemblage, thus resulting in a stronger and clearer identity in the minds of raters. As a result, firms are able to signal their competencies through their assemblages, leading to more favorable inferences from consumers. Given these theoretical arguments, we hypothesize the following:

> **H_5:** Firm product scope is positively related to an individual's subsequent rating of the product.

Firm product scope provides another source of diagnostic information, albeit an external rather than an internal source, that acts in conjunction with herding. Following the theory of herding, firm product scope contributes to a rater's private information and weighs against herding effects (Ding and Li 2018). As firm product scope increases, the firm's identity is more clearly signaled and the relative diagnosticity of this information improves (Lury 2009; Ramaswamy and Ozcan 2016). The rater, thus, has more confidence in their judgment about a product and relies less on the herd's opinion. Formally,

> **H_6:** As firm product scope increases, the crowd's influence on individuals' subsequent ratings decreases.
>
> **H_7:** As firm product scope increases, the friends' influence on individuals' subsequent ratings decreases.

Data

Empirical Context

The empirical context of our research is the board gaming (i.e., tabletop gaming) industry. Despite operating alongside an increasingly digitized entertainment industry, board gaming has continued to grow. According to NPD Group, the board gaming industry grew 28% in 2016 and is currently valued at \$9.6 billion (Birkner 2017). The industry consists of very large publishing firms, such as Hasbro (which publishes Monopoly), as well as smaller competitors, such as the recently popular Cards Against Humanity. Our data come from BoardGameGeek (BGG), the largest online discussion community for the board gaming industry. Raters log into the free website to research and rate board games. Often, individuals form communities by self-declaring "GeekBuddies," which is a proxy for friend networks.[4] On the game page, individuals can see the average rating (i.e., crowd effects) that the game has received as well as view the GeekBuddy ratings (i.e., friends' effects). In addition, they can learn about the publishers and genres under which a game is classified. Games are classified into eight genres, and similarly to the movie context, a specific game can be classified into multiple genres. For example, the game Catan is classified as a "family" game as well as a "strategy" game. In addition, multiple publishers can collaborate and launch a game in various regions with multiple publisher names appearing on the game box (e.g., Catan is published by KOSMOS, Mayfair Games, and 999 Games, among others[5]). In our data, 60.8% of games are published by multiple firms.

Given our research focus, we restrict our sample to those who have declared online friends. This produces a sample size of 44,108 individuals with 2,218,574 ratings. Furthermore, the data include 2,206 firms publishing over 5,138 games. The structure of the data is as follows: We observe multiple publishers offering multiple games, which are subsequently rated by multiple raters. Our data are at the individual level, in conjunction with publisher- and game-level descriptive information. Each rater can leave only one rating for each game, and our data have a panel structure with a time stamp for each rating.

Measures

Dependent variable. The key dependent variable in our analysis is an individual's rating of a game. We define the dependent variable R_{ijt} as individual i's rating of product j at time t. Individuals rate games on a continuous scale of 1–10, unlike conventional rating scales that are typically discrete. Although most individuals do stick to a discrete rating value, close to 20% of the data consists of decimals. This informs our modeling approach as we elaborate in the "Methodology" section.

Independent variables. The independent variables of interest in this research include information regarding the social effects in the perceived quality information (i.e., crowd and friend rating), rater-level factors that describe relative experience (i.e., number of prior ratings), and publisher-level factors that describe the breadth and depth of a firm's product portfolio (i.e., product scope). To capture the overall valence of opinion within the community, we measure $\text{CrowdR}_{jt} = \sum_{\forall i'} R_{i'jt}/N$ as the average rating of all N individuals on the website who have rated game j prior to individual i's rating. Similarly, to capture the overall valence of opinion among friends, $\text{FriendR}_{ijt} = \sum_{\forall F_{it}} R_{i'jt}/N_{F_{it}}$ denotes the average rating level of game j by an individual's online friend network (F_{it}) computed just prior to individual i rating the product. $N_{F_{it}}$ is the size of individual i's network and can change over time. On the website, individuals declare their friend networks, which we capture separately. This information allows us to reliably identify an individual's friend network without using behaviors or location-based measures. This method of determining reference groups has advantages in terms of identification (Manski 1993) which we discuss in detail in the "Methodology" section.

Following Packard and Berger (2017), we measure a rater's cumulative experience (RaterEXP_{it}) as the number of ratings that the individual has submitted prior to time t. The rationale behind this measure of experience stems from the ideas that learning stems from consumption, and experience is known to be a particularly good proxy for consumer knowledge (Packard and Berger 2017). Measuring rater experience in this way is also supported by the literature on experiential learning (Nokes and Ohlsson 2005). That is, consumers, especially in online environments, gather knowledge and experience through repeated activity and learning by doing. In Web Appendix B, we test the robustness of the results using alternative definitions of rater experience—namely, average number of prior ratings and time since joining the site.

Our measure of a firm's product scope (PS_{ft}) is derived from organizational learning literature, which posits that a firm's accumulated knowledge bases need to capture the breadth and depth of its product portfolio (Argote and Miron-Spektor 2011; Narayanan, Balasubramanian, and Swaminathan 2009; Schilling et al. 2003). Following Sorescu, Chandy, and Prabhu (2003) and Thirumalai and Sinha (2011), we measure the product scope (PS_{ft}) as the product of the entropy of product offerings (breadth) and the number of products in the firm's product portfolio (depth) as follows[6]:

$$PS_{ft} = \underbrace{\sum_c p_{cft} \ln\left(\frac{1}{p_{cft}}\right)}_{\text{breadth/entropy}} \times \underbrace{N_{ft}}_{\text{overall depth}}, \quad (1)$$

[4] A screenshot of the typical interface (using the game Catan as an illustration) that users see on BGG is available in Web Appendix A.

[5] This is also similar to the movie industry, in which multiple production houses collaborate to produce a final movie. According to the Internet Movie Database (www.imdb.com), the movie *Dunkirk* was produced by seven production houses, including Warner Bros., Syncopy, and Dombey Street Productions. Similar examples exist in the video gaming industry as well.

[6] In a previous version of this manuscript, we used a measure of relevant product scope. In the spirit of parsimony, we use the more standard product scope measure for our main results and report the relevant product scope results in Web Appendix B.

where

f = publishing firm;
c = product category;
t = time;
p_{cft} = proportion of the firm f's products in c^{th} category relative to its overall product portfolio at time t; and
N_{ft} = overall number of products offered by firm f at time t.

Our final covariate of interest is the measure of divergence of opinion between crowd and friends which will be used to test H_3 and H_4. We begin by defining the absolute value of divergence between crowd and friend ratings as $ABS\_DIV_{ijt} = |CrowdR_{jt} - FriendR_{ijt}|$. We define $I\left(ABS\_DIV^{High}_{ijt}\right)$ as a categorical variable that takes the value of 1 if ABS_DIV_{ijt} is greater than its median and 0 otherwise.[7] Thus, $I_{ijt} = 1$ denotes relatively high divergence between friend and crowd while $I_{ijt} = 0$ describes relatively low divergence of opinion.

Control variables. We include a rich set of control variables at the rater and game level as well as temporal and sequential/volume effects that may influence the relationships. Following Godes and Silva (2012), we include the time (elapsed) since the first rating to capture temporal effects and volume of crowd ratings to capture sequence effects. In addition, we control for the volume of ratings from the friend networks for game j until time t to control for any volume effects arising specifically from the friend reference groups. Volume of crowd and volume of friend ratings allow us to control for some of the "popularity" effects described in Lee, Hosanagar, and Tan (2015). We also tested robustness of our results after including several two-way and three-way interactions between volume and valence that prior research has highlighted (Web Appendix B). As some raters may exhibit loyalty toward specific game publishers, we control rater–publisher loyalty by including publisher loyalty as the number of previous games from the publisher that the individual has previously rated. We include the number of friends the individual has in the online community at the time of rating to control for the size of one's social network.

Descriptive Statistics and Model-Free Evidence

Descriptives. In Table 2, we report the basic descriptive statistics for key variables in the data at the individual-product level, the individual level, and the product level. In our sample, an average individual has approximately 14.1 declared buddies/friends on the website. Given that the data span a period of over 10 years, we find that the average membership period is also quite high (≅7 years). However, the variation in membership length

Table 2. Descriptive Statistics.

Level of Analysis	Variable	M	SD	Min	Max
Individual level (44,108 users)	Number of ratings	50.3	100.8	1	2,216
	Number of friends	14.1	37.0	1	972
	Membership length (in months)	80.4	41.5	0	190
Product level (5,138 games)	Number of publishers per game	3.4	4.7	1	141
	Number of genres per game	1.2	0.4	1	3
Individual-product level (2,218,574 ratings)	Rating	6.9	1.5	1	10
	Crowd rating	7.2	0.7	1	10
	Friends' rating	7.1	1.3	1	10
	Product scope	46.0	36.1	0	227
	Rater experience	216.7	257.2	0	2,215

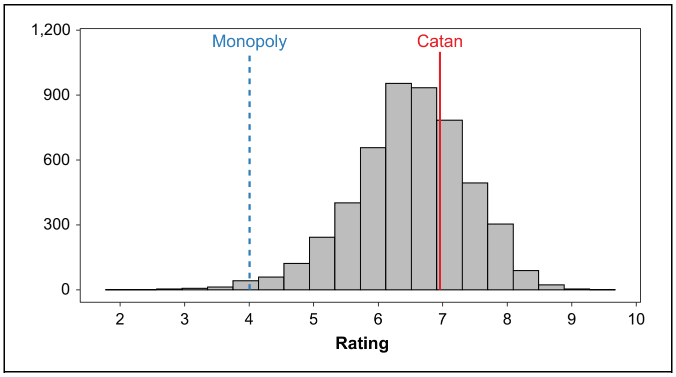

Figure 1. Distribution of ratings.

is also quite high, suggesting that there are several newer hobbyists interspersed within the older ones. Looking at the product-level descriptives, we find that the average number of publishers per game is 3.4, with a maximum of 141. Finally, we see that games are often classified into multiple categories (mean = 1.2), supporting our decision not to aggregate firm-level variables but to instead match a firm's accumulated experience with the product at the category level.

Figure 1 presents the distribution of the dependent variable and highlights the ratings of two popular games: Catan and Monopoly. Catan (average rating = 6.95) was much better received by the board gaming community than Monopoly (average rating = 4). As we can see from Figure 1, there is significant variation across games in terms of how individuals rate them. The distribution of ratings in our sample is consistent with previous work in online ratings (Chevalier and Mayzlin 2006; Lee, Hosanagar, and Tan 2015; Li and Hitt 2008; Sridhar and Srinivasan 2012).[8] The median individual rates 16 games (mean = 50.3 games), which may seem high but is realistic given the long time series span of the data (seven years per

[7] We present the categorical variable results here for ease of interpretability. The results remain robust even when considering the continuous variable, ABS_DIV_{ijt} (Web Appendix B).

[8] Web Appendix C describes temporal patterns in rating behavior for two games (Catan and Monopoly).

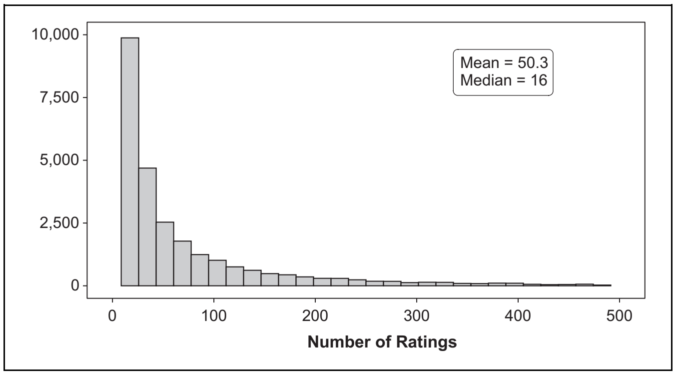

Figure 2. Distribution of rating frequency (per individual).

rater, on average). There is a large variation in the number of ratings provided (Figure 2).

Table 3 presents the full correlation matrix for all the variables used in the model. In a model-free sense, Table 3 suggests a positive correlation between crowd and friend ratings with the focal rating. In addition, product scope (PS_{ft}) is also positively correlated with rating valence. In the following subsection, we present more model-free evidence of patterns in the data that speak to the effects that we describe in this article.

Model-free evidence. In Figure 3, we plot an individual's rating of games at time t against the lagged average ratings of the two herding groups: the crowd and friends. In general, there is a positive correlation between crowd and friends' ratings with the focal rater's rating, suggesting that herding may indeed be prevalent in the data.

However, the rater does not always agree with the crowd or friends. To illustrate this, Figure 4 plots the individual correlations: rater versus friend and rater versus the crowd. The y-axis denotes the rater–friend correlation coefficient and the x-axis denotes the rater–crowd correlation coefficient, each computed at the individual level. On average, herding appears to exist in the data. However, there are raters who conform strongly with the crowd and others who conform strongly with friends. The question then becomes, What factor might drive this behavior? We posit that one such factor may be rater experience.

To explore this, we computed the mean absolute deviation (MAD) between the rater and the crowd/friends since the first month that the rater joined the website. If our hypotheses hold, as raters become more familiar and gain experience in rating products, they should deviate more from the crowd and less from friends' ratings. To visualize this in a model-free sense, we plotted the MAD between rater and the crowd/friends over time in Figure 5. As time progresses, raters deviate more from the crowd and less from friends, suggesting model-free support for our conceptual framework.

Of course, this model-free evidence is correlational at best, not causal. We need a robust methodology to causally identify the proposed herding effects. In the following section, we present our empirical strategy, the data variation that allows for identification, and the modeling approach used to estimate our hypothesized effects.

Methodology

Model

We model rating behavior using a linear specification that approximates it as a reduced form of the underlying data-generating process. A linear specification is more appropriate than an ordinal logit- or probit-style model because ratings in our data are not strictly discrete. Raters occasionally enter decimal values for their rating of games, thus violating the typical discrete nature of the dependent variable.[9] Furthermore, our objective is to explain ratings behavior and not to predict specific game ratings. As such, a linear regression is an approximation of the conditional expectation function even when the distribution of ratings may be discrete (Angrist and Pischke 2009). Finally, our conceptual framework and corresponding hypotheses require the use of interaction variables. Interpretation in nonlinear models is not straightforward and is especially complicated in the presence of interaction effects (Ai and Norton 2003). Given this, in the spirit of parsimony, we adopt a linear model to explain rating behavior. Thus, indexing the rater by i, product by j, and time with t, we can model rating valence (R_{ijt}) as follows:

$$\begin{aligned} R_{ijt} = {} & \beta_1 CrowdR_{jt} + \beta_2 FriendR_{ijt} + \beta_3 PS_{ft} + \beta_4 RaterEXP_{it} \\ & + \beta_5 I\left(ABS\_DIV_{ijt}^{High}\right) + \delta_1 CrowdR_{jt} \times RaterEXP_{it} \\ & + \delta_2 FriendR_{ijt} \times RaterEXP_{it} + \delta_3 CrowdR_{jt} \\ & \times I\left(ABS\_DIV_{ijt}^{High}\right) + \delta_4 FriendR_{ijt} \times I\left(ABS\_DIV_{ijt}^{High}\right) \\ & + \delta_5 CrowdR_{jt} \times I\left(ABS\_DIV_{ijt}^{High}\right) \times RaterEXP_{it} \\ & + \delta_6 FriendR_{ijt} \times I\left(ABS\_DIV_{ijt}^{High}\right) \times RaterEXP_{it} \\ & + \delta_7 CrowdR_{jt} \times PS_{ft} + \delta_8 FriendR_{ijt} \times PS_{ft} + \nu_{ijt}, \end{aligned} \tag{2}$$

where

$CrowdR_{jt}$ and $FriendR_{ijt}$ = the average rating for the crowd and the rater's friend network for product j up until time t,
PS_{ft} = product scope of firm f at time t,
$RaterEXP_{it}$ = rater i's cumulative experience in rating products (number of ratings provided) until time t,
$I\left(ABS\_DIV_{ijt}^{High}\right)$ = indicator variable describing the level of divergence between crowd and friend ratings, and
ν_{ijt} = unobserved factors that shift an individual's rating.

[9] Of the observed ratings, 19.8% contain decimal values. In the "Robustness Analyses" subsection, we show that our results are qualitatively consistent in an ordinal probit model even if we ignore the continuous nature of the data.

Table 3. Correlation Matrix.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1. Rating	1									
2. Crowd rating	.444*	1								
3. Friends' rating	.381*	.363*	1							
4. Product scope	.134*	.103*	.085*	1						
5. Rater experience	−.086*	−.064*	−.073*	.072*	1					
6. Rating order	−.101*	−.255*	−.132*	−.029*	−.148*	1				
7. Volume of friends' ratings	.021*	.020*	−.013*	−.037*	.314*	.088*	1			
8. Time since the first rating	.071*	.255*	.131*	.265*	−.063*	.366*	.124*	1		
9. Publisher loyalty	.006*	.015*	.001*	.207*	.373*	−.098*	.079*	−.064*	1	
10. Number of friends	−.082*	−.075*	−.079*	−.036*	.487*	−.146*	.387*	−.056*	.196*	1

*$p < .05$.

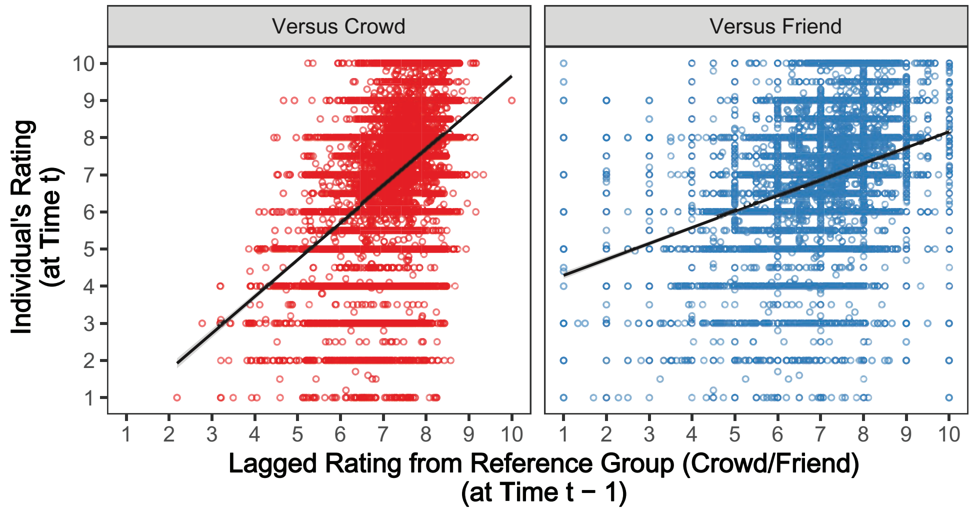

Figure 3. Relationship between rater versus reference group (crowd/friend) rating.
Notes: The solid line in both panels denotes the ordinary least squares regression line.

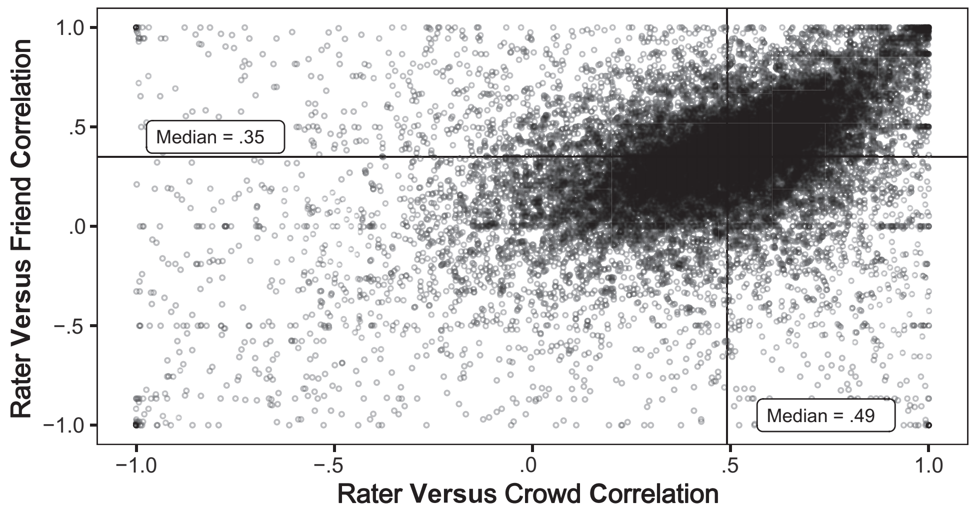

Figure 4. Correlations between rater and reference group at the individual level.

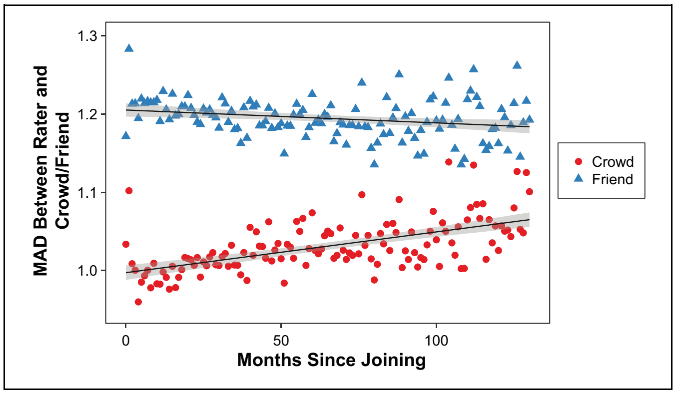

Figure 5. Deviation from reference group (crowd/friend).

The model is specified at the rater-game level; when a rater rates a product j, the covariates used are friend rating valence and crowd rating valence for the jth game. In Equation 2, β_1–β_5 capture the direction and magnitude of the main effects, while δ_1–δ_8 describe the effects of the moderators (product scope, rater experience, and divergence of opinions). δ_1 and δ_2 capture the moderating influences of rater experience on herding (H_1 and H_2), while δ_3–δ_6 assess the role of divergence of opinions on rating behaviors. The two-way interactions $\left(CrowdR_{jt} \times I\left(ABS\_DIV_{ijt}^{High}\right) \text{ and } FriendR_{ijt} \times I\left(ABS\_DIV_{ijt}^{High}\right)\right)$ inform how the herding effect may be amplified or attenuated when there is divergence between friend and crowd (δ_3 and δ_4). Specifically, this shows whether raters rely more heavily on friends or on the crowd when divergence exists (H_3). Similarly, three-way interactions between $FriendR_{ijt} \times I\left(ABS\_DIV_{ijt}^{High}\right) \times RaterEXP_{it}$ and $CrowdR_{jt} \times I\left(ABS\_DIV_{ijt}^{High}\right) \times RaterEXP_{it}$ provide insight into who experienced raters favor in the event of divergence between friends and the crowd (δ_5 and δ_6) (H_4). β_3, δ_7, and δ_8 capture the main and moderating effects of product scope (H_5, H_6, and H_7). In the following section, we discuss key identification challenges that must be addressed to causally infer the herding effects described in Equation 2.

Identification of Friend Effects: Challenges and Empirical Strategy

To establish causality, we need to address key endogeneity concerns that arise in studying friend effects due to the reflection problem (Manski 1993). Specifically, we need to address three main issues that confound the identification of causal peer effects: endogenous group formation, simultaneity, and other correlated unobservables. Before introducing and addressing these, we first comment on how we determine reference groups.

Determining reference groups. The first important challenge that a researcher faces in identifying a peer effect in nonexperimental data is the ability to clearly determine reference groups. That is, we need to identify the proper friends' networks for each agent exogenously, without using the behavior itself as a measure of reference groups (Manski 1993). Using behaviors to group users introduces an upward bias in the peer effects, while using geographic or location based grouping methods confounds the peer effects with other correlated unobservables. We make use of "sociometrics" in identifying reference groups to overcome these issues (Iyengar, Van den Bulte, and Valente 2011; Nair, Manchanda, and Bhatia 2010). Fortunately, in our data, raters self-identify their website friend networks, thus allowing us to determine reference groups without having to make any assumptions on friendships through geographic or behavioral similarities. Next, we discuss the identification issues that arise when studying herding effects using observational secondary data.

Endogenous group formation. Although the exogenous measure of reference groups resolves the issue of group determination, it does not address the endogeneity that can exist due to group formation. Endogenous group formation arises if raters self-select into reference groups due to similarities in tastes with friends. It is possible that the observed rating behavior is correlated with the friend behavior simply because the friends and the rater share common tastes that led to the formation of the friendship in the first place. As such, the unobserved part of a rater's behavior (ν_{ijt}) may be correlated with the peer effect ($FriendR_{ijt}$), resulting in bias due to endogeneity. Following guidance from Hartmann et al. (2008), we address the endogenous group formation issue by exploiting the panel structure of the data and specifying fixed effects at the individual level (α_i). The individual fixed effect α_i controls for the part of the random error that is related to the common tastes that a rater shares with their reference group (Nair, Manchanda, and Bhatia 2010). In essence, the variation caused by common tastes among raters within the same reference group is removed through the individual fixed effect.

Simultaneity. Social effects cannot be identified if the focal individual's ratings both influence and reflect peer ratings. This simultaneity problem makes it difficult for us to distinguish between the individual's effect on their peers versus the peers' effect on the individual. We adopt a three-pronged approach to address simultaneity. First, we leverage the panel nature of the data and impose temporal ordering between the peer covariate ($FriendR_{ijt}$) and the rater's rating (R_{ijt}). In Equation 2, we ensure that $FriendR_{ijt}$ is computed until time t (not including the current time period), thus ensuring that this relationship is not reversible. Second, we exploit the network formation timing and force temporal ordering such that a friend's influence is included only *after* tie formation. This is distinct from Lee, Hosanagar, and Tan (2015), who were unable to observe time of friendship formation and acknowledge this as a limitation. Although temporal ordering of friend

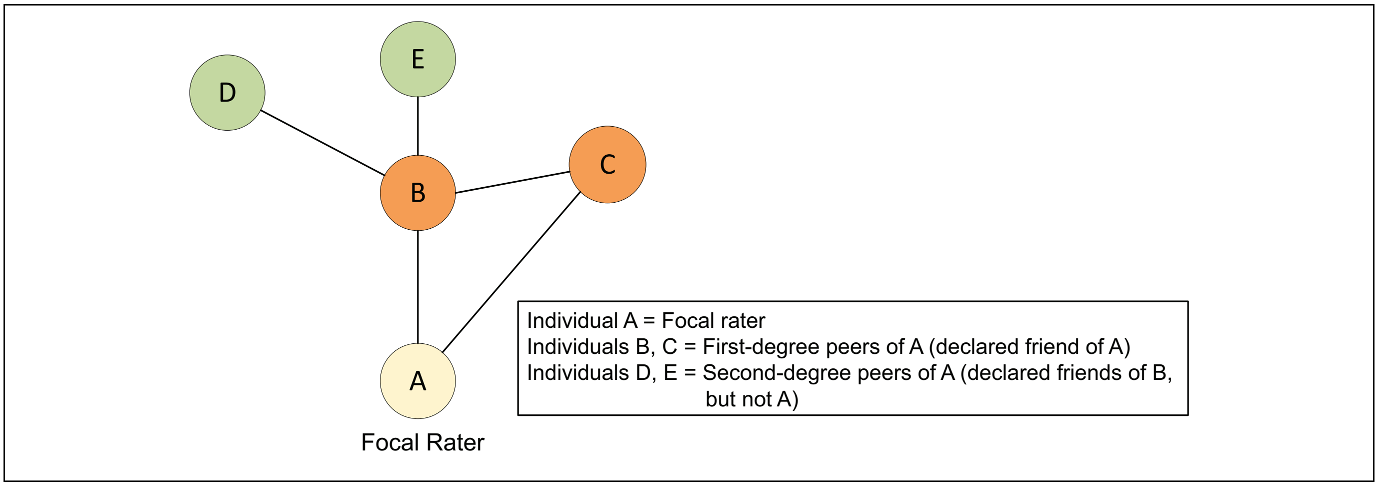

Figure 6. Illustration of intransitive triads (or) partially overlapping groups.

rating and tie formation controls for observable sources of simultaneity between peers and the individual, it does not account for the potential unobservable cues between individuals that may still cause simultaneity. Temporal ordering alone does not solve the simultaneity issue. Therefore, we use instruments with clear exclusion restrictions to address endogeneity arising from the peer variables.

To be a valid instrument, the proposed instrument candidate should satisfy criteria of exclusion and relevance. The exclusion criterion requires that the instrument be uncorrelated with the error term in Equation 2. Given the rich network information in the data, we exploit the availability of partially overlapping pairs or intransitive triads (Bramoulle, Djebbari, and Fortin 2009) to create exclusion restrictions that allow reliable identification of the peer effect. The intuition behind our instrument strategy is that the characteristics of friends' friends who are not also friends of the focal individual act as instruments for controlling endogeneity in the reflection problem. We illustrate this using a hypothetical five-person network (A, B, C, D, and E) in Figure 6. An intransitive triad exists when individual A is friends with B and C, but not D and E. In addition, B and D are friends and B and E are friends. We refer to D and E as second-degree peers of A, and the networks A, B, D and A, B, E form intransitive triads. These intransitive triads create an identifying condition whereby characteristics of individuals D and E affect A only through individual B, thus satisfying the exogeneity condition of the instruments. As long as individuals D and E are not friends of individual A, the exogeneity condition is satisfied.[10] Web Appendix C provides a visual representation of the network for two users in the data and highlights second-degree peers and overlapping peers.

The relevance criterion requires that the instrument be correlated with the peer covariate's rating behavior ($FriendR_{ijt}$). We use four characteristics of friends' friends (e.g., individuals D and E in Figure 6) as instruments for $FriendR_{ijt}$: (1) second-degree friends' volume of ratings, (2) second-degree friends' membership length, (3) second-degree friends' average network size, and (4) second-degree friends' declared groups/guilds. From a relevance standpoint, these variables are relevant to $FriendR_{ijt}$ because they influence valence of ratings. We empirically verify this using an instrument relevance test as well. To elaborate how the instruments are calculated, we refer to the example network described in Figure 6. Ignoring the t subscript for this static example, let W_A, W_B, W_C, W_D, and W_E denote the vector of instruments (describing characteristics of nodes A, B, C, D, and E) used in the regression. As we explained in the previous paragraph, because nodes D and E are second-degree peers of A, their characteristics can be used as instruments for A's behavior. That is, the average characteristics of friends' friends ($\bar{W}_{D,E} = (W_D + W_E)/2$) is used in instrument variable regression for node A. In addition, following Bramoulle, Djebbari, and Fortin (2009), $\bar{W}_{B,C}$ also enters the main regression equation for node A as a control variable. In the estimation, we adopt the control function approach to incorporate the instruments within the model framework. Specifically, the endogenous variable ($FriendR_{ijt}$) is expressed as a function of the instruments (denoted by $W_{i'jt}$) and the residuals from this regression (e^{IV}_{ijt}) are then introduced into Equation 2 as covariates for endogeneity correction.

Next, we address the data variation that allows identification of the hypothesized friend effects. Identification comes from data variation in the network size. Figure 7 presents evidence of significant data variation that allows reliable identification. Panel A in Figure 7 describes the distribution of friend network size across individuals and suggests that there is sufficient cross-sectional variation to aid identification. Raters have, on average, 14.1 friends, with a standard deviation of

[10] Bramoulle, Djebbari, and Fortin (2009) show that the exogeneity condition is met as long as some intransitive triads exist in the data. In our data, because we observe a large number of raters over a significant period, we are able to leverage this condition for identification.

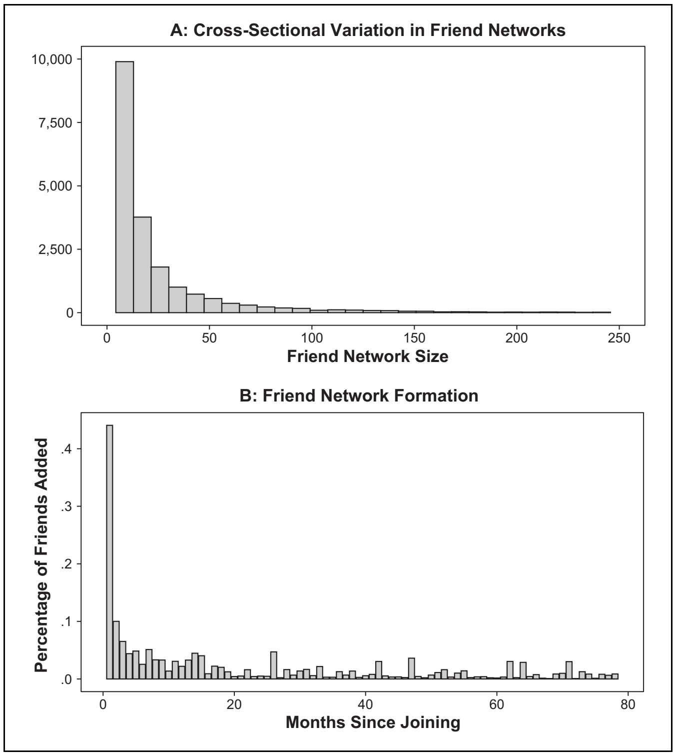

Figure 7. Variation in friend networks.

37. Panel B in Figure 7 plots the friend network growth over the tenure of the individual. As we see, most people form the majority of their friend networks within the first few months of joining; the network size after initial formation is relatively stable. Taken together, these patterns suggest sufficient cross-sectional variation in network size to identify the peer effects through exclusion restrictions arising from second-degree peers.

Correlated unobservables. A final concern is that there could be correlated, unobservable variables that influence the rater and peers simultaneously. A common approach to address correlated unobservables is to include a rich set of fixed effects. By including rater-level fixed effects (α_i), we control for the across-rater variation and use only within-rater variation for identification. Furthermore, as we elaborated previously, the individual fixed effects also help account for unobserved common tastes shared among raters within a reference group. Moreover, there could be correlated unobservables arising from game-level factors that influence the rater and reference groups simultaneously. These factors can reveal themselves as peer effects. By including game-level fixed effects (γ_j), we control for any across-game variations that may be causing endogeneity. We include year fixed effects (Year_t) to control for any macro-level trends such as website popularity that could influence the effects within the model. In addition, as we elaborate in the “Measures” subsection, we control for several game-level, rater-level, friend network–level, and temporal factors highlighted in prior work that may confound the findings. This not only controls for confounds but also demonstrates evidence of our proposed effects over and above what prior research has established.

Final Model Specification

We decompose the unobserved factors (ν_{ijt}) in Equation 4 into individual fixed effects (α_i); game-level fixed effects (γ_j); year fixed effects (Year_t); control variables Z_{ijt} (a $1 \times K$ row vector of control variables) and θ (a $K \times 1$ vector of parameters), where K is the number of control variables in the sample; and endogeneity correction (e_{ijt}^{IV}) as follows:

$$\nu_{ijt} = \alpha_i + \gamma_j + \text{Year}_t + Z_{ijt}\theta + \lambda e_{ijt}^{IV} + \varepsilon_{ijt}. \tag{3}$$

Notably, Z_{ijt} consists of all the control variables described in the “Measures” subsection as well as first-degree friend network–level controls as suggested in Bramoulle, Djebbari, and Fortin (2009). Substituting Equation 4 into Equation 3, we get the model equation for rating behavior.

$$\begin{aligned} R_{ijt} = {} & \beta_1 \text{CrowdR}_{jt} + \beta_2 \text{FriendR}_{ijt} \\ & + \beta_3 \text{PS}_{ft} + \beta_4 \text{RaterEXP}_{it} + \beta_5 I\left(\text{ABS\_DIV}_{ijt}^{High}\right) \\ & + \delta_1 \text{CrowdR}_{jt} \times \text{RaterEXP}_{it} + \delta_2 \text{FriendR}_{ijt} \\ & \times \text{RaterEXP}_{it} + \delta_3 \text{CrowdR}_{jt} \times I\left(\text{ABS\_DIV}_{ijt}^{High}\right) \\ & + \delta_4 \text{FriendR}_{ijt} \times I\left(\text{ABS\_DIV}_{ijt}^{High}\right) + \delta_5 \text{CrowdR}_{jt} \\ & \times I\left(\text{ABS\_DIV}_{ijt}^{High}\right) \times \text{RaterEXP}_{it} + \delta_6 \text{FriendR}_{ijt} \\ & \times I\left(\text{ABS\_DIV}_{ijt}^{High}\right) \times \text{RaterEXP}_{it} + \delta_7 \text{CrowdR}_{jt} \\ & \times \text{PS}_{ft} + \delta_8 \text{FriendR}_{ijt} \times \text{PS}_{ft} + \alpha_i + \gamma_j + \text{Year}_t \\ & + Z_{ijt}\theta + \lambda e_{ijt}^{IV} + \varepsilon_{ijt}. \end{aligned} \tag{4}$$

Equation 4 needs a few modifications to avoid estimation of an intractable number of parameters. As described previously, we difference out the game-level fixed effects rather than estimate the parameters. That is, we subtract the game-level means from each variable in the right-hand and left-hand side of Equation 4. After we subtract the game-level means, the game-level fixed effects (γ_j) drop out of the equation. Denoting the covariates on the right-hand side of Equation 5 as X_{ijt}, we can write the differenced equation as

$$\Delta R_{ijt} = \beta \Delta X_{ijt} + \Delta Z_{ijt}\theta + \Delta\alpha_i + \text{Year}_t + \lambda \Delta e_{ijt}^{IV} + \Delta\varepsilon_{ijt}. \tag{5}$$

Equation 5 uses fixed effects linear panel data specifications, and the year fixed effects are included after differencing. Next, we describe the estimation results and demonstrate the robustness of the results to alternative variable operationalizations, model specifications, and data considerations.

Results

The main findings are organized as follows. We begin by presenting the results describing the main effects (i.e., crowd, friends, and product scope) and the moderating effects (i.e., product scope, rater experience, and divergence of opinions) on the focal rater's behavior. We estimate a series of regressions progressively adding complexity through observed and unobserved heterogeneity and show the consistency of the results throughout. Finally, we conduct a series of robustness analyses to ensure that the findings are robust to alternative specifications such as the inclusion of a rating incidence model and an ordered probit estimation.

Estimation Results

Table 4 presents the results from the estimation of the fixed-effects linear specification outlined previously. We estimate four nested models for consistency: Model 1 (main + moderation effects only), Model 2 (main + moderation effects with observed heterogeneity), Model 3 (main + moderation effects with observed and unobserved heterogeneity [individual fixed effects]) and Model 4 (main + moderation effects with observed and unobserved heterogeneity [individual + game-level fixed effects]). We include year fixed effects in all the models. Notably, Model 1 ignores the endogeneity problem because it does not include the control function or any fixed effects, which helps us isolate the friend effect.

We first comment on the validity of the instruments. Table 4 shows that the endogeneity correction term is significant and negative across all the models. This provides some evidence that endogeneity is most likely an important concern that needs to be addressed in this context. We also conduct two tests to assess instrument strength and validity. First, we conduct an instrument relevance test using the results from the first-stage instrument regression (reported in Web Appendix D). The F-statistic is highly significant (F-statistic $= 5{,}144.93$, $p < .001$), which suggests that that the chosen instruments do not suffer from the weak instruments problem. Second, because we have more than two instruments to address one endogenous covariate, we also test for overidentifying restrictions. The Hansen J statistic of 1.69 is not significant ($p > .10$), thus indicating that overidentification is not a serious issue with our instruments.

Main effects. We find that significant herding from the crowd exists across all the estimated models. That is, an increase in the crowd's rating of a product leads to an increase in the focal rater's rating of the same product ($\beta_1 = .431$, $p < .001$). Similarly, herding is evident among friends. The rating patterns of the friends' network has a positive, significant effect on the individual ($\beta_2 = .188$, $p < .001$).[11] Taken together, the results provide evidence of herding influence in online rating behavior; individuals perceive wisdom in *both* the crowd and friends. An increase in crowd (friend) rating by 1 point leads to a .431- (.188-) unit increase in the subsequent rating. Interestingly, the results suggest that the friend effect is smaller than the crowd influence (also indicated in Figure 3). To explore this in more detail, we conducted a Wald test. The null hypothesis for the Wald test is that the coefficients for $FriendR_{ijt}$ and $CrowdR_{jt}$ are equal. The F-statistic of the Wald test is significant (F-statistic $= 288.98$, $p < .01$), thus rejecting the null hypothesis that the coefficients are equal. This suggests that the crowd effect is significantly greater than the friend effect *after* we control for volume of ratings (among other factors). One possible explanation is that this result is driven by the specific website design. As in many rating platforms (e.g., Yelp), BGG's crowd rating is more predominantly displayed and, thus, more salient than friend rating information.

In support of H_5, we find that a firm's product scope has a positive effect on the rater's own evaluation of the product ($\beta_3 = .079$, $p < .001$); the greater the firm's scope of product portfolio, the higher the rater's evaluation of its products. Thus, the firm's own product line strategy can act as a signal of its competence and achieve favorable quality ratings online. It is important to note that the diagnostic information here is not a firm's promotion strategy (e.g., advertising) but simply its product line strategy. Finally, although we did not hypothesize an effect, rater's own experience has a negative main effect on the subsequent evaluation ($\beta_4 = -.0005$, $p < .001$), in line with prior research (Moe and Schweidel 2012; Schlosser 2005). One potential explanation is that raters who consider themselves "experts" try to signal their identity by posting more negative opinions. These highly experienced gamers are much more confident of their own quality inferences about games and are thus likely to be more critical and strict in their evaluations. Finally, although not hypothesized, we find that raters adjust their evaluations of products downward when disagreement between the crowd and friends is high (vs. low; $\beta_5 = -.023$, $p < .001$), suggesting that mixed opinions lead to stricter ratings.

Moderating role of rater experience. Turning to the interaction effects presented in Table 4, some interesting patterns emerge. We theorized that the diagnosticity of herding would be influenced by rater- and firm-level factors. We find that the rater's own experience and the firm's relevant product scope significantly moderate the herding effect from the crowd. In support of H_1, we find that the individual's own rating experience negatively moderates the relationship between crowd rating and the individual's rating ($\delta_1 = -.001$, $p < .001$). As raters rely more on their own experience, they rely less on the wisdom of the crowd, and the herding effect is attenuated. However, greater rater experience amplifies the social influence of friends ($\delta_2 = .0002$, $p < .001$), confirming H_2. As raters gain more experience, they not only know their own preferences better but also learn to listen more to like-minded friends and less to the crowd.

[11] It is noteworthy that, although directionally similar, the effect size of the friend effect is overestimated when endogeneity is ignored. For Model 1, which ignores endogeneity as well as observed and unobserved heterogeneity, the estimated friend effect is .322, but after accounting for these factors in Model 4, we can see that the effect is much smaller.

Table 4. Main Estimation Results.

Variable	Hypotheses	Model 1 Estimate	Model 1 SE	Model 2 Estimate	Model 2 SE	Model 3 Estimate	Model 3 SE	Model 4 Estimate	Model 4 SE
Main Variables of Interest									
Crowd rating		.688***	.007	.734***	.007	.845***	.006	.431***	.013
Friends' rating		.322***	.007	.400***	.005	.264***	.005	.188***	.004
Rater experience		−.0005***	.00002	−.0006***	.00003	−.0007***	.00003	−.0005***	.00001
Divergence between friends and crowd		−.126***	.011	−.164***	.020	−.125***	.019	−.023***	.002
Crowd rating × Rater experience[a]	H_1 (−)	−.149***	.018	−.132***	.015	−.212***	.015	−1.008***	.052
Friends' rating × Rater experience[a]	H_2 (+)	.049***	.015	.028***	.006	.096***	.013	.163***	.021
Crowd rating × Divergence between friends and crowd	H_{3a} (+)	.146***	.007	.129***	.007	.071***	.006	.048**	.014
Friends' rating × Divergence between friends and crowd	H_{3b} (−)	−.127***	.007	−.107***	.006	−.056***	.005	−.031***	.004
Crowd rating × Rater experience × Divergence between friends and crowd[a]	H_{4a} (−)	−.064***	.017	−.034**	.012	−.074***	.012	−.042**	.015
Friends' rating × Rater experience × Divergence between friends and crowd[a]	H_{4b} (+)	.052***	.016	.042***	.011	.090***	.012	.047***	.009
Product scope	H_5 (+)	.008***	.0003	.009***	.0003	.008***	.0003	.079***	.001
Crowd rating × Product scope	H_6 (−)	−.001***	.00004	−.001***	.00004	−.001***	.00004	−.015***	.003
Friends' rating × Product scope	H_7 (−)	−.0003***	.00002	−.0003***	.00002	−.0003***	.00002	−.005***	.0005
Control Variables									
Rating order/volume of crowd ratings[a]				−.009***	.0003	−.015***	.0002	−.007***	.0003
Volume of friends' ratings				.0002**	.0001	.002***	.0001	.002***	.0001
Time since the first rating[a]				.019***	.001	.033***	.001	.039***	.002
Publisher loyalty				.003***	.0002	.004***	.0002	.005***	.0002
Number of friends[a]				.478***	.020	.238***	.047	.157**	.046
Average network size of friends[a]				.040*	.016	.019*	.009	.037*	.017
Number of groups friends are part of				−.003**	.001	−.002*	.001	.001	.001
Friends' average length of membership[a]				−.020***	.001	.005***	.001	.002	.001
Endogeneity correction				−.111***	.002	−.054***	.003	−.022***	.001
Intercept		−.294***	.016	−1.114***	.030	−.835***	.028	−.070***	.013
Individual-level fixed effect		No		No		Yes		Yes	
Game-level fixed effect		No		No		No		Yes	
Year fixed effect		Yes		Yes		Yes		Yes	

*$p < .05$.
**$p < .01$.
***$p < .001$.
[a]The coefficients and standard errors are rescaled (i.e., multiplied by 1,000) to improve readability.
Notes: All standard errors are bootstrapped and clustered at the individual level.

Role of diverging opinions. We investigate how divergence of opinion between key reference groups influences rating behavior. Furthermore, we examine whether the rater's experience again plays a moderating role. In support of H_3, we find that raters increasingly favor crowd ratings and decreasingly favor friends' ratings when disagreement exists between the two ($\delta_3 = .048, p < .01$; $\delta_4 = -.031, p < .001$). This is consistent with the greater herding influence of the crowd and may be driven by the "cost of divergence" (Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992), as raters do not want to appear to contradict the crowd. Turning to the three-way interaction with rater experience, we find support for H_4. That is, more experienced raters tend to decreasingly favor the crowd's rating ($\delta_5 = -.00004$, $p < .01$) but increasingly favor friend ratings ($\delta_6 = .00005$, $p < .001$) when disagreement exists between the two. This result further bolsters our initial finding that as raters gain experience in rating products, they coalesce with their friend group more easily than with the crowd, in an effort to indicate identity (Berger and Heath 2007) and conform to group norms within strong ties (Fehr and Fischbacher 2004; Harmeling et al. 2017). Taken together, this analysis provides a unique insight into how raters behave when faced with mixed signals from reference groups. We demonstrate that diverging opinions can create herding and differentiation depending on the reference group and the experience level of the rater.

Moderating role of product scope. We find support for H_6, as the firm's product scope negatively moderates the crowd effect ($\delta_7 = -.015$, $p < .001$). Raters view the firm's product scope as diagnostic information and are inclined to discount the wisdom of the crowd. The firm's product scope also negatively moderates the relationship between friends' rating behavior and own rating behavior ($\delta_8 = -.005$, $p < .001$), thus confirming H_7. With the main effect of product scope, these results underscore the importance of product line management, not just for bottom line growth but for improving quality perceptions as well. From the manager's perspective, a firm's product portfolio acts as strong diagnostic information and helps attenuate herding effects. While, historically, firms have viewed herding as beyond their control, we demonstrate that the effectiveness of herding can be influenced by firm actions through product portfolio decisions.

Overall, the results demonstrate that although herding effects exist in online opinion formation, the source matters. We find that the crowd effect on an average rater is greater than that of the friend effect and that herding effects are not always consistent. We identify key rater-level and firm-level factors that govern the role of herding in online opinion formation. On the rater's side, the results show that a rater's experience positively moderates the friend effect and negatively moderates the crowd effect. As raters gain more experience, they find value in conforming with like-minded friends and diverging from the more general crowd. The herding and differentiation effects are even more apparent when there is disagreement between reference groups. That is, we find that an average rater coalesces with the crowd's opinion more than with friends when faced with mixed signals. However, experienced raters differentiate from the crowd and conform to friends' opinions. On the firm's side, we show that the effect of herding is influenced by firm actions. Specifically, the results highlight the value of a firm's product portfolio in online rating environments. Even in the absence of promotional messaging or advertising, a firm can influence the perceived quality of its product through its product strategy both directly and indirectly. We find that, in addition to a main effect on online ratings, the firm's scope of expertise attenuates the herding influences from crowds and friends.

Control variables. Consistent with prior work, we find a negative influence of rating order/volume of crowd ratings ($\theta_1 = -.00001$, $p < .001$) but a positive influence of temporal effect on user ratings (time since first rating; $\theta_3 = .039$, $p < .001$) (Godes and Silva 2012; Li and Hitt 2008; Wu and Huberman 2008). That is, the average rating level of a game is shifted downward as more ratings arrive and upward as more time passes, suggesting that the results are not simply driven by rating distributions among the crowd and friends or solely by contextual factors. We find that the volume of ratings from the friend networks has a positive relationship with the user ratings, which indicates that when there are many friends who have rated the game, the rater is more positive toward a specific game ($\theta_2 = .002$, $p < .001$). Furthermore, we find that rater–publisher loyalty has a positive effect on rating behavior, suggesting that firms should work toward building loyalty among the user base. The positive loyalty effect also suggests that raters are quite aware of and have clear preferences about publishers ($\theta_4 = .005$, $p < .001$). Rating valence is not only influenced by the volume of friends' ratings; the size of the social network (i.e., the number of friends) also has a significant positive influence on subsequent rating ($\theta_5 = .0002$, $p < .05$; Zhang and Godes 2018). In summary, the results strongly support the hypotheses proposed in the conceptual framework.

Robustness Analyses

In view of the multiple modeling, data considerations, and variable operationalization decisions in our analysis, we conduct several robustness checks to ensure that our findings are not an artifact of the choices we made. We discuss these checks briefly here and report the full analyses in the Web Appendix. The robustness checks can be broadly classified into (1) alternative variable operationalizations, (2) alternative modeling considerations, and (3) sample considerations.

Alternative variable operationalizations. Our first set of robustness checks deals with variable operationalization. Specifically, we aim to demonstrate robustness of the results to alternative measures of rater experience, product scope, and the $CrowdR_{jt}$ variable. In the main results, the friend rating information was included within the $CrowdR_{jt}$ computation. We rerun the model after removing the friend information from the $CrowdR_{jt}$ variable and find that the results remain virtually unchanged. Next, we rerun the model considering two alternate measures of rater experience: the average number of prior ratings and time since joining the website. The results continue to be qualitatively consistent. Finally, we estimate the model using three additional measures of a firm's product portfolio: relevant product scope to capture the within-category product relevance to the game being evaluated, overall entropy to capture the breadth of a firm's product portfolio, and depth of a firm's product portfolio. Again, the estimation results remain robust. We present all model results of alternative operationalization in Web Appendix B.

Alternative modeling considerations. Our second set of robustness checks concerns model specifications. The results may be influenced by selection bias because rating valence could be correlated with an individual's propensity to rate (i.e., rating incidence). To address this concern, we employ a Tobit II estimation in which the first stage is a rating incidence model that precedes the rating valence model. Next, to examine the robustness of our results to functional form, we replicate the results using an ordinal model specification. Ignoring the continuous nature of the dependent variable in our context, we round the individual ratings to the nearest discrete value and then estimate an ordered probit model. Finally, to account for the possibility that firm-level heterogeneity is influencing the results, we reestimate the model with firm-level fixed effects. All models replicate the main findings, and we report full estimation results in Web Appendix E.

Sample considerations and other controls. Our final set of robustness analyses involve relaxing sample considerations and including additional control variables. First, we reestimate the model after including raters with no friends in the estimation sample. Although, this does not allow us to test the friend effect, it provides a robustness check for the crowd effect. The results remain qualitatively unchanged (see Web Appendix F). Next, we include an additional source of observed heterogeneity: friends' experience level. Though not hypothesized, we find that the interaction of friends' rating with average experience of friends is significant and positive. Raters are more likely to be influenced by friends when the friend network is more experienced. We also conduct a series of additional analyses investigating whether the effect of rater experience varies by the volume of ratings and synergies between friend and crowd herding effects. Throughout these analyses, we replicate our main findings. Due to page restrictions, we report and discuss these additional analyses in Web Appendix G. We also test for the possibility that a rater may not be aware of a firm's product portfolio through the website.[12] We rerun the main regression model considering only raters who had rated a publishers' game prior to the focal game rating, thus ensuring that the raters did indeed have some prior knowledge about the publisher. Although not perfect, this condition gives us more confidence that only raters who are aware of the publisher are included in the model. The results (presented in Web Appendix F) remain robust. Finally, we explore the possibility that, given the skewness in rating frequency, the results may be driven by outliers in the data. We reestimate the model after dropping the top 1% of raters in terms of rating frequency. The results, reported in Web Appendix F, remain qualitatively unchanged.

Discussion and Conclusion

Summary of Findings and Contribution

As an avenue for consumers to express their opinions and evaluations about products, online ratings have become a staple component of the customer experience. In this article, we carefully unpack herding into friend and crowd effects using a rich data set of board gamers' ratings and offer a nuanced view of herding in online rating environments. Our identification strategy exploits the timing of tie formation and exogenous variation created through partially overlapping network pairs (Bramoulle, Djebbari, and Fortin 2009) to parse out the friend effect. We put the findings through a battery of tests and demonstrate that our results are robust to alternative variable measurement, modeling choices, and sample considerations. Next, we summarize the key takeaways from this research and place our study in context within extant literature.

[12] Notably, raters have easy access to a firm's entire publishing history, categories, and so on through the website. Anecdotally, we confirmed with the data provider as well as several users on the website that raters do often click through to the firm's profile page (which details its publishing history).

1. *There is wisdom in the crowd and among friends, but source matters*: While not strictly a contribution, our results add to growing evidence (e.g., Lee, Hosanagar, and Tan 2015; Zhang and Godes 2018; Zhang, Liu, and Chen 2015) highlighting the importance of separating the herding influences of the crowd and friends, thus underscoring the role that in-groups and out-groups play in online ratings. We find multiple herding effects on online ratings that are positive and significant; there is indeed wisdom to be found in both the crowd and friends. However, the source matters. On average, crowds exert a stronger herding influence on the average rater.
2. *Brands/firms influence online opinion through their product portfolio in profound ways*: We uncover key boundary conditions under which herding effects may be attenuated or amplified. Notably, we contribute to the product strategy literature (Kekre and Srinivasan 1990; Palepu 1985; Sorescu, Chandy, and Prabhu 2003) by demonstrating how a firm's product line strategy can used as a positive signal in product evaluations. The depth and breadth of a firm's product portfolio acts as a strong proxy for firm competence. We apply this stream of thought to online ratings and demonstrate that consumers take note of product scope and this directly influences rating behavior. We show that a firm's product strategy creates advantages even in online rating forums and can significantly attenuate herding.
3. *Social influence varies by expertise/experience*: Although prior research on opinion leadership suggests that experienced users tend to differentiate from existing opinions (Iyengar, Van den Bulte, and Valente 2011; Nair, Manchanda, and Bhatia 2010; Schlosser 2005), we find that a more nuanced view is required when studying the role of rater experience in social contexts. Specifically, we find that rater experience creates herding and differentiation depending on the strength of the social bond. Experienced raters discount the crowd but continue to herd toward their friends.
4. *Diverging opinions between reference groups create herding and differentiation*: Much extant work studying dispersion or disagreement in online opinions has focused on aggregate measures of "variation" in word of mouth (e.g., Godes and Mayzlin 2004; Nagle and Riedl 2017; Sun 2012). Less is known about how diverging opinions between specific herding groups influence opinion. Our research finds that divergence between friend and crowd ties can create herding *and* differentiation, depending on the experience level of the rater. More specifically, we show that when the two reference groups disagree with each other, experienced raters coalesce more on friends' rating more than with the crowd. We believe this is the first research to show this phenomenon in a large-scale empirical analysis.

To visualize the effects presented in the article, we plot the marginal effects of herding at different levels of rater

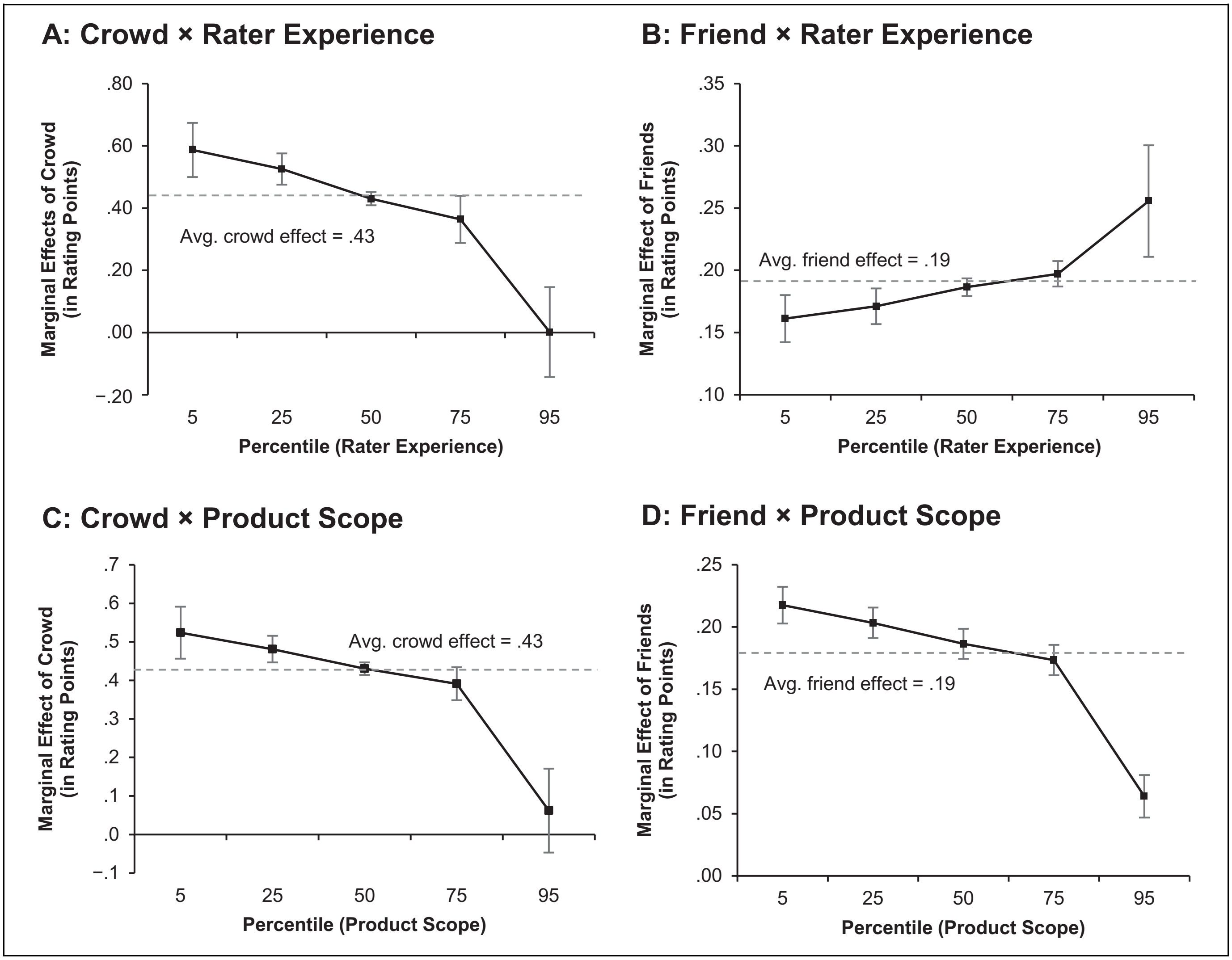

Figure 8. Visualizing the moderation effects.

Notes: The y-axis is the change in the herding effect measured as unit change in rating points. The dotted lines denote the marginal effect of the crowd (Panels A and C) and friends (Panels B and D) holding all other variables at their respective means. For a 1-unit change in crowd (friend) ratings, the corresponding change in the focal user's rating is .43 (.19) rating points. The points on the figure can be interpreted as the effect of the herding source at the corresponding moderating variable value. For instance, in Panel A, for a rater in the 95th percentile of rater experience, a 1-unit increase in crowd rating valence is expected to increase a focal rater's evaluation by only .13 rating points, whereas for a rater in the 5th percentile of rater experience, a 1-unit increase in crowd rating valence is expected lead to a .59 rating points increase in the focal rater's rating. Panels B, C, and D are interpreted similarly.

experience and firm product scope (see Figure 8). On average, we find that a 1-unit increase in crowd (friend) ratings will lead to a .43- (.19-) unit increase in the focal rater's rating represented by the dotted line in Figure 8, Panels A, B, C, and D. Panels A and B present the unit change in the crowd and friend effects for an increase in rater experience. As rater experience increases, the crowd effect clearly decreases (Panel A) but the friend effect increases (Panel B). Furthermore, the effects are most pronounced at the extremes. When a rater is highly experienced, the positive influence of the crowd on rating behavior *weakens* and the positive influence of the friend *strengthens*. That is, for a rater in the 95th percentile of experience level, a 1-unit increase in crowd rating is expected to result only a .13 rating points increase in rating valence (as opposed to a .43 rating point for the average rater). In fact, the confidence interval at the 95th percentile includes zero. Turning to the friend effect (Panel B), for a rater in the 95th percentile of experience level, a 1-unit increase in friend rating valence is expected to increase the focal rater's rating by .26 rating points (as opposed to a .19 rating point increase for the average rater). In contrast, for novice raters who have low rater experience (5th percentile), a 1-unit increase in crowd (friend) rating leads to approximately .59- (.16-) unit change in rating. Clearly, novice raters value the crowd much more than experienced raters.

Turning to the effects of firm product line scope (Panels C and D in Figure 8), we see the negative relationship between herding and a firm's product scope. When a firm cannot provide cues of domain competence to compete with herding (i.e., low product scope in Panels C and D), the positive influence of the crowd on an individual's rating behavior is strengthened compared with the average effect. In comparison, when a firm demonstrates domain competence through product scope (i.e., high product scope), the herding influence of the crowd on an individual's rating behavior weakens significantly. We find a similar pattern for the herding influence of friends.

Implications

This research provides actionable guidance to managers concerned with online reputation management, product strategy and planning, and the design of online rating platforms. We expand on these topics in the following subsections.

For online reputation management. Given the increased recent interest in review solicitation in online rating systems (Kremer, Mansour, and Perry 2014), our results suggest that even in the absence of conventional advertising strategies, firms can leverage reputation effects in ratings by strategically targeting their review solicitations. For instance, firms can get ratings that are more objective by targeting experienced raters as they are less influenced by the herding effect. Alternately, if managers are trying to ride a positive bandwagon effect, then new or less experienced reviewers should be targeted. The findings also have implications for reputation management when combatting negative online word of mouth as herding effects can be a double-edged sword. When faced with predominantly negative ratings, firms can try to identify and solicit favorable highly networked reviews to offset the effects of the average consumer. Finally, this research provides managers with guidance on where word of mouth is likely to be more impactful. A firm is more likely to be affected in product categories where their product lines are less deep, suggesting that when venturing into noncore products, firms should more closely monitor for online herding effects.

For product strategy and portfolio planning. We demonstrate that a firm's product scope is critical in influencing online rating behavior. Firms with greater product scope gain both directly and indirectly in terms of product evaluations. This provides firms with another example of the advantages of a product line that is both broad and deep. It also presents a dilemma for firms to consider: when one goes too broad, it becomes increasingly difficult to develop depth across multiple categories. Still, this work demonstrates the value of a "branded house"—firm scope not only increases the possibility of favorable online reviews but also can act as a counterbalance to the herding effect.

For online rating platform design. This research could have significant impact on online rating system designs. We find evidence of herding in online ratings, thus reducing the "objectivity" of online product evaluations. That is, herding from the crowd and friends can introduce some amount of bias in a user's online rating level. If the goal of an online rating system (e.g., Yelp, the Internet Movie Database) is to ensure independent, nonbiased reviews, then our results add to extant work that suggests the contrary often manifests (Lee, Hosanagar, and Tan 2015; Muchnik, Aral, and Taylor 2013). From a generalizability standpoint, we expect that the findings would be consistent for most medium- to high-involvement product categories (e.g., movies, restaurants, books, hotels, travel, health care; Ibbotson 2019). In a highly engaged and connected marketplace, consumers are increasingly turning to these online rating platforms to judge the "quality" of various services. This research adds to a growing body of work on herding effects in rating behavior by investigating contingent factors, both firm-controllable and rater-level, that may actually govern the herding effect. Finally, advertisers can use these results to decide what kind of social and product information to display to users when they rate products.

Limitations and Potential Directions for Future Research

Although the models and data utilized are rich and robust in many ways, our analysis does have its limitations. First, although we use various reduced-form econometric techniques to control for network formation, we do not formally model it. A structural model of network formation combined with the rating model presented here could create opportunities for interesting counterfactuals that we do not examine here. Second, there could be some underreporting of friend networks in our data. Although we expect that the inclusion of these data would only strengthen the results, we acknowledge this as a data limitation. Third, our measures of rater experience consider only online experience and are agnostic to offline knowledge gathering. As such, our results need to be interpreted in relative terms. Fourth, like many others before us, this research was conducted using data from one firm, in one industry. As such, future investigations could very easily adapt the proposed framework to different contexts and perhaps conduct a cross-industry study of herding effects. In addition, the data context, which is primarily offline consumption, does not include information on offline friendship networks that may also influence behaviors. A promising avenue for future research would be to compare the role of offline and online reference groups in online opinion formation. Finally, this study used only ratings and did not consider review text. While we expect that factors such as the complexity of ideas or the length of written reviews may affect subsequent ratings and provide alternative measures of rater experience, our data do not allow us to measure this. We leave such opportunities to future research.

Acknowledgments

The authors thank V. Kumar, Mark Houston, Sriram Thirumalai, and the audiences at the 2017 Marketing Science conference, the 2018 AMA Winter Academic Conference, University of Virginia Darden School of Business, Emory University, and Indian Institute of Management Bangalore for their valuable feedback on this research. They are also grateful to Scott Alden, Daniel Karp, and boardgamegeek.com for providing access to the data used in the study. Finally, the authors thank the *JM* review team for their thoughtful comments and feedback.

Associate Editor

Wendy Moe

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

ORCID iD

Sarang Sunder https://orcid.org/0000-0002-2875-9209

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