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Timing Matters: How Social Influence Affects Adoption Pre- and Post-Product Release

Sara B. Soderstrom,[a] Brian Uzzi,[b] Derek D. Rucker,[b] James H. Fowler,[c] Daniel Diermeier[d]

a) University of Michigan; b) Northwestern University; c) University of California, San Diego; d) University of Chicago

Abstract: Social influence is typically studied after a product is released. Yet, audience expectations and discussions begin before a product's release. This observation suggests a need to understand adoption processes over a product's life cycle. To explore pre- and postrelease social influence processes, this article uses survey data from Americans exposed to word of mouth for 309 Hollywood movies released over two and a half years. The data suggest pre- and postrelease social influences operate differently. Prerelease social influence displays a critical transition point with relation to adoption: before a critical value, any level of social influence is negligibly related to adoption, but after the critical value, the relationship between social influence and adoption is large and substantive. In contrast, postrelease social influence exhibits a positive linear relationship with adoption. Prerelease social influence is argued to require more exposures than postrelease social influence because of differences in the diagnosticity and accessibility of the information. To complement the survey data, computational models are used to test alternative hypotheses. Evidence from the computational models supports the proposed model of social influence.

Keywords: social influence; adoption; prerelease; diagnosticity; accessibility

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Daily conversations about companies and their innovations number in the billions. These conversations occur in various venues, from water cooler chatter to social media, but as much as 90 percent remains face-to-face (Keller and Fay 2012). These conversations allow for social influence to occur. In fact, one survey found that word-of-mouth (WOM) influences 70 percent of all buying decisions (Balter 2008). A single face-to-face conversation can even exert more impact on product judgments than public relations or marketing efforts (Herr, Kardes, and Kim 1991). These dynamics have led to growing efforts to understand social influence and its effect on corporate and consumer behavior (Aral and Walker 2011; Centola 2011; Cialdini and Goldstein 2004; Dubois, Rucker, and Tormala 2011; Salganik, Dodds, and Watts 2006).

Past research has traditionally emphasized "post-release" social influence—communications among consumers and stakeholders that follow their experience with an innovation or product (Banerjee et al. 2013; Foutz and Jank 2010; Walgrave and Wouters 2014). For example, early social influence research found that consumers were more likely to adopt a product when they heard about it from a current adopter (Coleman, Katz, and Menzel 1966). Subsequent research substantiated these effects with a range of explanations, including networks and social proofs (Goldenberg et al. 2009; Mahajan, Muller, and Bass 1990; Salganik et al. 2006). Yet, not all social influence is experience based. Social influence occurs throughout a product's life cycle, including before it is released. For example, social influence can set expectations for actual experiences and subsequent adoption processes (Banerjee et al. 2013; Gopinath, Chintagunta, and Venkataraman 2013). In this regard, prerelease social influence may be critical to postrelease adoption because it can shape expectations, subsequent postrelease conversations, and the size of the early adopter group—key factors predictive of the adoption rate and ultimate market share (Aral and Walker 2012; Salganik et al. 2006).

To expand our knowledge of the adoption life cycle, we investigate the relationship between prerelease social influence and adoption patterns. Specifically, we examine a nationwide random sample of Americans exposed to a major form of social influence—direct WOM exchanges with friends and network contacts. We draw on information processing work in psychology to suggest that prerelease WOM might be less accessible and diagnostic than postrelease WOM and that these differences change how WOM influences adoption behavior before and after a product is released. Specifically, based on proposed differences in the diagnosticity and accessibility of information (Feldman and Lynch 1988; Lynch 2006), we predict the relationship between WOM and subsequent adoption differs as a function of whether the WOM occurs during the pre- or postrelease of a product. We present two tests of our hypotheses. First, we test our hypotheses econometrically. These models estimate statistical relationships, functional forms, and effect sizes using proprietary company data on the prerelease WOM, postrelease WOM, and adoption of 309 Hollywood movies released over a two-and-a-half-year period from 1999–2001. Second, we use agent-based models to test whether dynamic person-level and network-level interactions, as outlined by our explanatory framework, account for the adoption rates and functional form patterns of adoption observed in the data. In addition, we evaluate how robust our findings are to alternative specifications. In this way, we seek evidence of the factors associated with pre- and postrelease adoption in equilibrium and the dynamic micro organizational processes that can produce the observed macro equilibrium.

Theory

Our theoretical predictions draw on information processing and network theories of diffusion. Information processing theory suggests that people are more inclined to act on information when it is accessible and diagnostic (Feldman and Lynch 1988; Lynch 2006). Accessibility refers to whether information is available in a person's mind, whereas diagnosticity refers to whether accessible information is viewed as sufficient to help a person reach a decision consistent with his or her goals (Lynch 2006). For example, a person deciding whether to purchase a car may have encountered many facts about the car. Not all facts are likely to be equally accessible when she is on the showroom floor. The handling of the car may be salient because of commercial ads, whereas crash test ratings may be less salient. In this example, the accessibility of the handling suggests it will be more likely to influence a person's decision. However, the fact that the handling of the car is salient is not necessarily sufficient for the person to act on this information. She has to decide if the information is diagnostic for the decision at hand. If the handling of the car is viewed as sufficiently diagnostic, then she may proceed with a purchase; if this feature is not diagnostic, then she may search her memory for additional information until she is satisfied with the diagnosticity of the accessible information (Lynch 2006).

Several factors can affect the accessibility and the diagnosticity of information (Feldman and Lynch 1988). For instance, the accessibility of information can be affected by how vivid information is. Vivid information, as compared to pallid information, is more likely to draw initial attention and provoke elaboration that can increase the memory for (and accessibility of) that information (Herr et al. 1991; Kisielius and Sternthal 1986). Thus, vividly presented information is more likely to be available to serve as an input to a subsequent adoption decision. Diagnosticity of information can be affected by direct or indirect experience with a product. Direct experience with a product is often more relevant and informative than indirect experience, and thus more diagnostic. For example, individuals were more likely to act on their opinions of food when they tasted it (direct experience) versus read about it (indirect experience) (Wu and Shaffer 1987). Indirect experience typically requires greater reinforcement to achieve a similar level of diagnosticity as direct experience. However, while the degree of exposures or number of inputs required may be different, both direct and indirect experiences may eventually surpass the required level of diagnosticity to make an adoption decision (Lynch 2006; Lynch, Marmorstein, and Weigold 1988; Wyer and Srull 1986).

We propose that social influence in the form of WOM may differ in accessibility and diagnosticity during different stages of a product's life cycle. By definition, prerelease WOM lacks firsthand, trial-based information. Prerelease WOM is based on speculation of what experience with an innovation or product might produce. This dynamic suggests that prerelease WOM lacks the vivid descriptions and testimonial reactions of an innovation or product that come with actual use, reducing the accessibility of prerelease WOM. By definition, the inherently speculative nature of prerelease WOM would seem to render it less diagnostic than postrelease WOM based on product use. Thus, we propose that prerelease WOM is often less diagnostic and less accessible than postrelease WOM. For example, within the movie context, prerelease WOM is likely to possess less vivid descriptions of specific scenes, storylines, and personal reactions to the overall quality of the movie than the same descriptions drawn from movie attendance.

Although, on average, prerelease WOM is likely to be less accessible and diagnostic than postrelease WOM, multiple exposures to information can raise its accessibility (Petrocelli, Tormala, and Rucker 2007). In addition, multiple exposures can also increase a message's diagnosticity. Specifically, even when the validity of a message is unverified, receiving it from multiple individuals can increase belief in the message, an effect observed in experiments (Salganik et al. 2006), legal decision making (Waters and Hans 2009), and attitudes in friendship networks (Fowler and Christakis 2008). As an anecdotal example, National Public Radio's tech news reported that Apple Inc. was releasing a new personal computing product to compete with the Kindle and the Nook, two electronic readers. Even without firsthand information about the product, the station had multiple reports from different sources which appeared sufficient for the station to report the name of Apple's to-be-released reader as the iSlate.[1] Thus, apparent social agreement may increase the diagnosticity of what was indirect and speculative information, while, at the same time, repeated exposure raises accessibility (Rosnow and Fine 1976; see also Dubois et al. 2011). The implication is that prerelease WOM will require exposure from multiple sources to be as effective as postrelease WOM.

Complex contagion theory (Centola and Macy 2007) complements the accessibility and diagnosticity framework (Feldman and Lynch 1988; Lynch 2006). Centola and Macy (2007) argue that for adoption behaviors that are "costly, risky, or controversial, the willingness to participate may require independent affirmation or reinforcement from multiple sources" (p. 703). Because no one has adopted an innovation or product prior to release, prerelease WOM is likely to be riskier to act on than postrelease WOM, which contains first-hand information from individuals who have already adopted the new product. Thus, prerelease WOM can be likened to a more complex contagion than postrelease. In this sense, our work connects complex contagion theory and the diagnosticity framework through explaining and specifying an empirical test of how the level of exposure to pre- and postrelease WOM may be related to adoption.

Exposure to information is dependent upon on the network of connections among individuals (Aral and Walker 2011; 2012; Centola and Macy 2007; Dodds and Watts 2004). In social networks, most people have a few friends and a few people have many friends (Rivera, Soderstrom, and Uzzi 2010). If few people are spreading WOM, chances are it is not coming from the unusual individuals with many contacts but from the individuals with few contacts. As a consequence, WOM is likely to be circulating among contacts in a relatively small number of separate friendship circles of strong ties (Centola and Macy 2007; Valente 2012). However, as the number of people spreading WOM increases, chances rise that the smaller number of highly connected people will be among those spreading WOM (Onnela and Reed-Tsochas 2010). And, when highly connected people spread WOM, they can spread it to their many weak ties throughout the network, who then circulate it among their contacts in their local friendship circles (Valente 2012). Put simply, after a critical mass is achieved, the small number of people with many contacts will spread the messages to many separate friendship circles, which produces multiple exposures and thus enhances social influence. For example, Paluck, Shepherd, and Aronow (2016) found that highly connected students spreading antibullying messages have significantly greater influence in decreasing bullying in middle schools compared to less-connected students sharing the same messages.

The preceding discussion suggests that below a critical value of persons spreading WOM, a relatively small number of persons are likely to experience multiple exposures to WOM, but above the critical value, many persons are likely to experience multiple exposures to WOM (Centola and Macy 2007; Dodds and Watts 2004; Granovetter 1978). We believe this observation, in conjunction with the notions of accessibility and diagnosticity, suggests that the relationship between adoption and pre- and postrelease WOM differ in several predictable ways. First, the relationship between prerelease WOM and adoption can have two distinct regimes, one before reaching and one after reaching a critical mass of persons spreading WOM in the network. In the first regime, any amount of prerelease WOM before the critical value is likely to result in negligible increases in adoption in the population. This outcome arises because only a minority of people in the population are hearing WOM from multiple sources; as such, the majority of the population does not hear WOM at a rate that is likely to meet their accessibility and diagnosticity threshold for adoption. However, after the critical value, the relationship between WOM and adoption is likely to result in significant adoption in the population at all levels of WOM because many people in the population are likely to experience multiple exposures that should facilitate reaching their accessibility and diagnosticity thresholds for adoption.

Second, based on the constructs of accessibility and diagnosticity, such a dual regime is less likely for postrelease WOM. Specifically, as postrelease information should be of greater accessibility and diagnosticity, even one exposure to postrelease WOM could be sufficient to surpass an individual's diagnosticity threshold. Because multiple exposures are not needed, this suggests a linear relationship between the amount of WOM and adoption. No critical value exists; rather, each exposure is likely to prompt an adoption. Thus, comparing the effects of WOM on adoption for the same innovation or product in pre- and postrelease, we expect a critical value dynamic only for prerelease WOM. Formally, we present the three following hypotheses:

H1: A critical value exists that must be met for prerelease WOM to influence innovation adoption. Below this critical value, any level of prerelease WOM has relatively little impact on the level of initial adoption. After WOM is above the critical value, any level of prerelease WOM has a positive effect on adoption.

H2: Small changes around the critical value of prerelease WOM are associated with large differences in adoption.

H3: The effect of postrelease WOM on adoption is independent of a critical value. Postrelease WOM is proportional to adoption at all levels of WOM.

Methods

Data

The movie industry provides a broad basis for theory development and testing (Cattani et al. 2008; Hsu 2006; Sorenson and Waguespack 2006; Zuckerman et al. 2003). Our data includes 309 Hollywood movies released over a two-and-a-half-year period between March 1999 and August 2001. Our tests are based on unique, nonpublic data obtained from a professional survey firm for film production companies and shared with us for research purposes. For each movie, WOM is longitudinally measured in pre- and postrelease phases of adoption life cycle. The survey data records information on respondents' movie-going behavior, movie preferences, and whether they heard WOM about forthcoming and released movies from their family or friends. Respondents were a national random sample chosen through the random digit dialing of over 180,000 respondents. About 300 persons were contacted each day, Monday through Thursday, from March 1999 to August 2001, excluding holidays. The survey had a repeated-survey design; the same items were asked of different respondents on each survey.

A professional telephone interviewer led respondents through the survey. First, respondents were asked to indicate all the movies they knew were playing or forthcoming in the cinema. Second, for all the movies the respondents indicated, the respondents were asked whether friends or family were talking about the movie. Third, respondents were asked questions about their movie-going behavior, such as their favorite genre. Because the data is sold to end users who demand reliability, the data is checked for random sampling across demographic and movie-going groups, and respondents are read pick lists that contain fictitious movie titles to gauge respondents' true recall. We merged our survey data with archival data on movie, studio, star, director, and box office characteristics from the Internet Movie Database (IMDb), and Metacritic.com (Hsu 2006; Sorenson and Waguespack 2006; Zuckerman et al. 2003).

Measures

Our dependent variable is movie adoption. Movie adoption was measured as (1) *opening weekend box office* and (2) *second weekend box office*. Data are from the IMDb and are measured in dollars.

Our criterion variables are pre- and postrelease WOM. Prerelease WOM was operationalized as the percentage of respondents who reported that their friends were talking about a particular movie during the Monday–Thursday prior to its release on opening box office weekend. Postrelease WOM was operationalized as the percentage of respondents who reported that their friends were talking about a particular movie during the Monday–Thursday after opening box office weekend but before the second weekend box office. We note that postrelease WOM is likely to still consist of WOM from those who have not directly seen the movie. However, given we are predicting different functional forms, this limitation appears to make our tests more conservative. To infer the level of pre- or postrelease WOM around the average person in the population, we exploited the random sample's ability to estimate a population mean. Because each respondent was randomly sampled, we aggregated the percentage of respondents reporting they heard WOM into a percentage-level variable for that survey and movie. For example, if 20 percent of the sample of people surveyed on a particular day said they had heard WOM about a specific movie, we operationalized the level of WOM for that movie on that day at 20 percent.

We controlled for a number of factors known to influence movie consumption (Basuroy, Chatterjee, and Ravid 2003; Eliashberg and Shugan 1997; Liu 2006; Sorenson and Waguespack 2006).

Screens. The number of screens a movie is shown on affects the number of tickets that can be sold. This variable also serves as a proxy for advertising because advertising budgets are designed to fill the available seats (Elberse and Eliashberg

2003; Sorenson and Waguespack 2006). We measured this variable as the count of the number of screens on which the movie played as reported in IMDb.

Critics' reviews. Critics affect film attendance (Eliashberg and Shugan 1997; Zuckerman et al. 2003). Critics' reviews were operationalized by Metacritic.com as a weighted average of all the scores assigned by individual critics to each movie. The scores ranged from 0 to 100, with higher scores representing better reviews. Well-known critics (e.g., Roger Ebert) and influential publications were more highly weighted than local reviews (see Metacritic.com for methodological details).

Percent avid. Avid moviegoers more frequently consume movies and by definition have lower thresholds for attending any movie. To control for avidity, we coded a respondent who saw at least one movie a month as an avid (De Vany 2004). The proportion of avids was aggregated from the survey responses in the same way as WOM to form a measure of percent avid.

Holiday release. Films released during holidays experience greater overall demand for movie tickets and advertising. We coded a movie's release date as reported on IMDb for whether or not it was released during a peak movie-going weekend (1 = yes; 0 otherwise).

Movie budget. We measured movie budget as the total production costs in dollars, which subsumes the costs of the movie including salaries, studio time, props, and advertising (Sorenson and Waguespack 2006). Although a line item breakdown of a movie's budget would be ideal to control for the exact level of advertising expenditures, advertising expenditures for movies are not publicly available (Elberse and Eliashberg 2003). Nevertheless, previous work has shown that a movie's production costs provides a reasonable and widely-used proxy measure for advertising expenses (Elberse and Eliashberg 2003; Gopinath et al. 2013; Joshi and Mao 2012; Lui 2006). In addition, we use number of screens and holiday release as further proxy measures (Sorenson and Waguespack 2006) as reported from IMDb.

Star power. The name recognition of the actors (i.e., a bankable star) can affect a movie's box office. We use the methodology of Basuroy et al. (2003) to assess star power by how many top fifteen–grossing films in the previous five years starred one of the top three billed actors in a film. If one star had been in a single top-grossing film, another star had been in three top-grossing films, and the third star had been in no top-grossing films, Star Power equaled 4. Alternative operationalizations, such as assigning star power points for top ten or top twenty–grossing films, produced similar results.

Genre. We controlled for the type of movie with an indicator variable using the standard categories of Action/Adventure, Comedies, Dramas, Horror, Sci-Fi, and Family.

Rating. We controlled for the movie's rating with an indicator variable using the standard categories of G, PG, PG-13, or R.

Lagged number of prior adopters. Prior work operationalized social influence in terms of the number of prior adopters (Cialdini and Goldstein 2004). The number of prior adopters for the second weekend box office was defined as opening weekend box office. By definition, there is no count of prior adopters for prerelease. Descriptive statistics and correlations can be found in the online supplement, appendix 1.

Statistical Model

We used ordinary least squares (OLS) regression and a spline methodology to test for changes in the relationship between WOM and box office at different levels of WOM. Prerelease WOM was measured the week prior to opening weekend box office, and postrelease WOM was measured between opening weekend box office and second weekend box office. The spline method has three steps. (1) Because theory does not specify a critical value or position of a critical value, we adopted a conservative method, which segmented WOM's observed range into equidistant length splines at 5 percentile increments (Long and Freese 2001). (2) For each cut-point, we determined whether the estimated slope before and after the cut-point were statistically different from each other by computing the difference between the slope before the cut point (i.e., slope 1) and the slope after the cut point. Statistically significant different slopes (i.e., slope difference) indicate that a critical value is present at which the strength of the relationship between WOM and adoption changes. (3) To determine which critical value, if any, provides the best fit relative to other critical values or a null relationship of a simple linear model, we used the Bayesian information criterion (BIC) statistic (Kuha 2004). Robust standard errors were used to control for nonhomogeneity in the residuals. Variance inflation factor (VIF) statistics had values <3.0, for which values of 10.0 or more indicate multicollinearity.

Results

Table 1 presents 8 regressions (models 1–8) of opening weekend box office on prerelease WOM levels and control variables. Model 1 is the control variable–only model. Model 2 is the control variable model plus prerelease WOM without a spline segmentation. Our first finding indicates that WOM is positively and significantly related to the level of initial adoption. Highlighting the explanatory power of prerelease WOM on opening box office weekend, model 2 shows that prerelease WOM is positive and significant, and the R-squared is 28 percentage points (0.72–0.44) greater than the baseline model (model 1).

Our second finding indicates that prerelease WOM is associated with a critical value around which the relationship between prerelease WOM and adoption changes. Prerelease WOM had a smaller effect on adoption until a critical value was reached, after which point increases in the level of WOM were associated with

Table 1: Prerelease WOM and first week product adoption.

	Linear Models		Threshold Piece-wise Linear Models					
	Model 1	Model 2	Model 3 35th percentile	Model 4 40th percentile	Model 5 45th percentile	Model 6 55th percentile	Model 7 65th percentile	Model 8 70th percentile
Prerelease WOM		94.940†						
		(6.962)						
Prerelease WOM: Slope 1			39.159*	39.186†	26.726*	34.888†	37.346†	37.310†
			(17.060)	(14.621)	(13.411)	(11.135)	(8.937)	(8.772)
Prerelease WOM: Slope difference			78.423†	81.093†	94.729†	94.073†	98.588†	99.322†
			(18.994)	(17.058)	(16.180)	(14.817)	(15.633)	(16.495)
Screen (log)	6.138†	1.559*	2.750†	2.820†	2.827†	2.846†	2.946†	2.945†
	(1.273)	(0.791)	(1.012)	(1.031)	(1.053)	(1.028)	(1.066)	(1.065)
Budget (sqrt)	22.70†	9.322†	8.317†	8.459†	8.496†	8.512†	8.850†	8.809†
	(3.324)	(2.636)	(2.600)	(2.609)	(2.617)	(2.616)	(2.616)	(2.596)
Critics' reviews	0.187†	0.127†	0.131†	0.134†	0.135†	0.142†	0.144†	0.144†
	(0.037)	(0.024)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Avidity	−13.128	−12.427*	−13.440†	−13.554†	−13.569†	−14.118†	−13.838†	−13.949†
	(8.449)	(5.255)	(5.145)	(5.151)	(5.168)	(5.226)	(5.202)	(5.155)
Holiday release	0.856	0.286	0.171	0.127	0.193	0.334	0.535	0.530
	(1.651)	(1.427)	(1.362)	(1.350)	(1.361)	(1.358)	(1.373)	(1.369)
Star power	0.616	0.171	0.080	0.123	0.113	0.105	0.138	0.145
	(0.483)	(0.447)	(0.436)	(0.436)	(0.436)	(0.432)	(0.429)	(0.433)
Genre	–	–	–	–	–	–	–	–
Rating	–	–	–	–	–	–	–	–
Spline intercept			−3.521†	−3.271†	−1.818*	−2.382*	−0.761	−0.133
			(1.023)	(0.976)	(1.046)	(1.182)	(1.464)	(1.594)
Constant	−45.213†	−16.386†	−17.594*	−18.514*	−17.481*	−18.365*	−19.962*	−19.878*
	(11.430)	(6.864)	(8.245)	(8.285)	(8.478)	(8.188)	(8.518)	(8.515)
BIC′			23.8	27.5	26.7	31.4	34.8	34.8
R-squared	0.44	0.72	0.75	0.75	0.75	0.76	0.76	0.76

Note: 309 observations; robust standard errors in parentheses; VIF statistics showed there was no multicollinearity bias in the specification (VIF between 3.2 and 5.5 across all models). The categorical controls are not shown for simplicity; these data can be found in the online supplement.
†$p < 0.01$; * $p < 0.05$ (two-tailed test of significance)

significant increases in the level of adoption. Models 3–8 represent these findings as a series of splines. Each model creates a spline for a different percentile of WOM over the observed range of WOM, which was between its $35^{th}$and 70^{th} percentile. (Note the percentiles do NOT correspond to the simple percentage of people hearing WOM. In prerelease, for example, the 35^{th} and 65^{th} percentiles correspond to 10 percent and 21 percent of the persons hearing WOM, respectively.) Consistent with hypothesis 1, models 3–8 indicate that a spline model statistically significantly fits the data better than does a linear model. The spline coefficients for *prerelease WOM: slope 1* and *prerelease WOM: slope difference* are jointly and statistically significant for spline models 7 and 8. On average, the effect of prerelease WOM on consumption is almost four times stronger once it exceeds the critical value ([WOM: slope difference + WOM: slope 1] ÷ WOM: slope 1). The BIC statistic of piecewise model was 34 (Table 1, model 7), which provides "strong" evidence that the piecewise model is a better fit than the baseline linear model (Long and Freese 2001). The BIC statistic indicates that the best fit is the 65^{th} percentile; beyond the 65^{th} percentile, there are no additional increases in fit.

Our third finding is that after the critical value is reached, the association between prerelease WOM and adoption intensifies, as shown by the statistically significant value of *prerelease WOM: slope difference*. Small changes in the level of prerelease information around the critical value can tip the system from one regime to the other. The large value of *prerelease WOM: slope difference* substantiates the change in slope that occurs after the critical point. Numerically, model 7 suggests that after the critical value, each one-unit increase in prerelease WOM (units are in 1 percent point increments from 1–100) results in a gain of $1.3 million at the box office. Before the critical value, each one-unit increase in WOM only results in gains of $0.3 million.

Figure 1a plots these relationships. On the x axis is the level of prerelease WOM and on the y axis is the opening box office weekend. Each scatter point on the plot represents a different movie. The plot also indicates that the critical value for this set of movies was approximately at the level of 21 percent WOM in the system. Before this point, each increase in WOM has a small, positive effect on the growth of adopters, but after that critical value, each increase in the percentage of persons spreading WOM is associated with a greater increase in the number of adopters.

Our fourth finding is that distinctive WOM dynamics occur for prerelease and postrelease for the same set of products. The relationship between postrelease WOM and adoption does not display a critical value; rather, the relationship between postrelease WOM and adoption is similar at all levels of WOM. Table 2 shows the effects of regressing second weekend box office on our control variables, as well as opening box office and prerelease WOM. The table of effects indicates that a simple linear model (Table 2, model 2) provides as good a fit to the data as any spline specification (Table 2, models 3–8). All models in Table 2 indicate a positive and significant association between postrelease WOM and second weekend box office. Moreover, the BIC statistic comparing the linear model with the spline models consistently produced a negative BIC statistic, a strong indication that there is no critical value of WOM in postrelease, supporting hypothesis 3. Figure 1c plots these relationships and shows the second weekend box office for the same set of movies

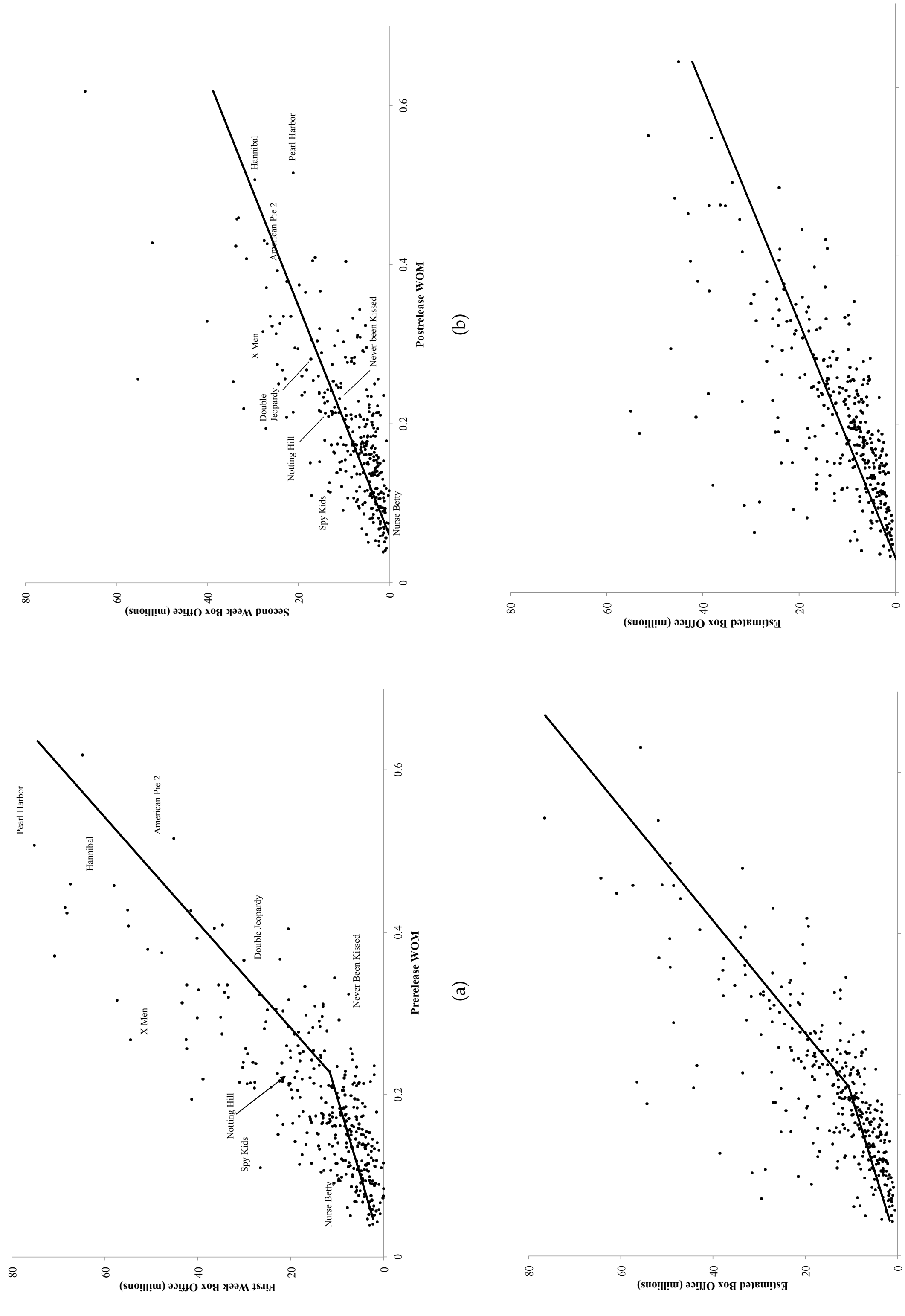


Figure 1: Data distributions for WOM versus adoption. (a) Prerelease WOM empirical results, (b) postrelease WOM empirical results, (c) prerelease WOM simulation results, (d) postrelease WOM simulation results.

as shown in Figure 1a. The plots indicate that the relationship between postrelease WOM and second weekend box office is linear, consistent with hypothesis 3.

Computational Findings

Our empirical tests regressed adoption rates on various levels of pre- and postrelease WOM across different movies and controlled for time-varying covariates. However, a limitation of the empirical data is that it does not allow us to measure a person's infectiousness nor the network structure directly because our person-level observations are randomly sampled nationally, which benefits statistical generalization but does not furnish a direct measure of the friendship network. To address these limitations, we used the above theory to specify agent-based simulations that complement the empirical analyses. The simulations provide a confirmatory analysis of the mechanisms underlying the empirical data and offer tests for the fit and plausibility of alternative mechanisms.

If our proposed micro-framework regarding accessibility and diagnosticity holds, we should find that: (1) the observed functional forms are related to different levels of exposure to WOM in prerelease and postrelease stages of adoption, (2) a critical value exists for prerelease WOM but not postrelease WOM, and (3) the observed critical value and the estimated critical value from the simulation are in agreement. The simulations use a social network structure approximated from an actual, typical social network based on the National Longitudinal Study of Adolescent Health (Add Health). These data have been used extensively for the same purpose we use it here (Fowler and Christakis 2008).[2] Consistent with our empirical analysis, the computational model does not analyze the adoption curve of one product over time but rather the average adoption of multiple movies exhibiting common exposure, informational, and network characteristics.

Our simulation model has three steps. First, we "seed" the network with a certain number of persons who can spread WOM. In the prerelease model, the seed levels were assigned by drawing one observation b_i from a distribution b of "WOM" (the subscript i denotes the ith movie to adopt), which was taken from the survey data for *prerelease WOM*. In the postrelease model, a person who has seen the movie in the prerelease WOM model (i.e., an adopter) can spread WOM.

Second, we assign each person who can spread WOM a probability of spreading it to one of their contacts in their network. In prerelease, a person can spread WOM to a contact with probability t_i, a uniform random distribution between 0.01 and 0.05. This means the expected number of contacts a person spreads WOM to is t_i times the number of contacts he or she has. In postrelease, each person who has seen the movie can spread WOM with probability r_i. We assigned a constant $r_i =$ 0.15, the probability that an adopter spreads WOM to a contact. t_i and r_i were based on research that reported a person's likelihood of spreading WOM about a product before and after its release (Banerjee, et al. 2013; Goldenberg, Libai, Muller, 2001).

Third, adoption of a movie is calculated. In our hypothesized prerelease model, a person goes to a movie after they have heard WOM from two or more network contacts. In our hypothesized postrelease model, any person who has not seen the

Table 2: Postrelease WOM and second week product adoption.

	Linear Models		Threshold Piece-wise Linear Models					
	Model 1	Model 2	Model 3 35th percentile	Model 4 40th percentile	Model 5 45th percentile	Model 6 55th percentile	Model 7 65th percentile	Model 8 70th percentile
Postrelease WOM		$26.092^{\dagger}$						
		(7.965)						
Postrelease WOM: Slope 1			20.884	24.459	25.914^{*}	22.552^{*}	20.287^{*}	22.027^{*}
			(14.866)	(13.764)	(12.443)	(10.782)	(9.815)	(9.073)
Postrelease WOM: Slope difference			6.833	4.293	4.243	7.669	7.880	6.103
			(14.023)	(12.671)	(11.122)	(9.705)	(8.984)	(8.807)
Prerelease WOM		−12.747	−13.168	−13.322	−13.491	−13.531	−13.265	−13.640
		(7.893)	(7.958)	(7.962)	(7.960)	(7.965)	(7.977)	(7.978)
Box office performance	$0.554^{\dagger}$	$0.460^{\dagger}$	$0.452^{\dagger}$	$0.449^{\dagger}$	$0.444^{\dagger}$	$0.443^{\dagger}$	$0.447^{\dagger}$	$0.447^{\dagger}$
(lag)	(0.024)	(0.035)	(0.038)	(0.039)	(0.040)	(0.040)	(0.040)	(0.040)
Screen (log)	0.368	−0.367	−0.196	−0.199	−0.173	−0.118	−0.115	−0.164
	(0.728)	(0.757)	(0.820)	(0.819)	(0.816)	(0.814)	(0.812)	(0.810)
Budget (sqrt)	−1.685	−0.642	−0.717	−0.652	−0.583	−0.647	−0.752	−0.674
	(1.493)	(1.502)	(1.522)	(1.517)	(1.518)	(1.515)	(1.519)	(1.509)
Critics' reviews	$0.044^{\dagger}$	0.037^{*}	0.038^{*}	0.039^{*}	0.040^{*}	0.040^{*}	0.039^{*}	0.040^{*}
	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.016)	(0.016)
Avidity	−2.126	−3.190	−3.215	−3.251	−3.240	−3.318	−3.233	−3.208
	(4.069)	(4.021)	(4.035)	(4.033)	(4.030)	(4.037)	(4.033)	(4.037)
Holiday release	$2.038^{\dagger}$	$2.022^{\dagger}$	$2.029^{\dagger}$					
	(0.621)	(0.615)	(0.619)	(0.619)	(0.617)	(0.617)	(0.617)	(0.617)
Star power	0.239	0.225	0.223	0.225	0.238	0.230	0.224	0.224
	(0.194)	(0.190)	(0.191)	(0.191)	(0.192)	(0.191)	(0.191)	(0.191)
Genre	–	–	–	–	–	–	–	–
Rating	–	–	–	–	–	–	–	–
Spline intercept			−0.007	−0.343	−0.549	−0.126	0.539	0.570
			(0.891)	(0.902)	(0.863)	(0.840)	(0.841)	(0.866)
Constant	−4.892	0.474	−0.178	−0.615	−0.983	−0.966	−0.747	−0.514
	(6.043)	(6.015)	(6.252)	(6.232)	(6.249)	(6.256)	(6.265)	(6.275)
BIC′			−10.9	−10.8	−10.4	−10.5	−10.1	−10.3
R-squared	0.81	0.82	0.82	0.82	0.82	0.82	0.82	0.82

Note: 285 observations; robust standard errors in parentheses; VIF statistics showed there was no multicollinearity bias in the specification (VIF between 4.1 and 4.9 across all models). The categorical controls are not shown for simplicity; these data can be found in the online supplement.
†$p < 0.01$; * $p < 0.05$ (two-tailed test of significance)

movie but who has heard WOM from at least one contact postrelease goes to the movie.

In all WOM models, we assume that a fraction of the population goes to the movie because of idiosyncratic factors that are constant in pre- and postrelease (Gopinath, et al. 2013; Valente 2012) using an error term e_i drawn from a log normal distribution (to avoid negative values) with mean = 0.0025 and variance = 0.00004. In each model, we add up all of the people who have gone to a movie to calculate the total adoption. To estimate the level of adoption from box office sales, we assume a potential movie audience of 300 million people and a ticket cost of $6 each, the average of 1999–2001 ticket prices in the United States (see online supplement, appendix 2, for further details and code).

Robustness Checks

We included tests of alternative mechanisms from the literature (e.g., Centola and Macy, 2007; Goldenberg et al. 2001).

Alternative A. In prerelease, the adoption decision rule changes from the hypothesized relationship to hearing WOM from one or more contacts. This model reflects more standard adoption rules in which pre- and postrelease WOM both act as simple contagions with higher levels of accessibility and diagnosticity.

Alternative B. In postrelease, the adoption decision rule changes from the hypothesized relationship to hearing WOM from two or more contacts. This model reflects a more complex contagion with a higher threshold for accessibility and diagnosticity prior to adoption in both pre- and postrelease stages.

Alternative C. In pre- and postrelease, the adoption decision rules change from the hypothesized relationships to hearing WOM from three or more, four or more, five or more, or a random number of contacts, or from 10 percent, 25 percent, 50 percent, 75 percent, and 100 percent of their contacts. These models test for differences in adoption thresholds.

Alternative D. In the hypothesized models, the number of contacts (i.e., degree) of individuals in the network varies per the empirical distributions of degree found in the Add Health data (range 1 to 10 connections). Here, we change the size of individual networks so degree is fixed for all individuals in the network at two, four, six, or eight connections and follows the hypothesized decision rules.

Results

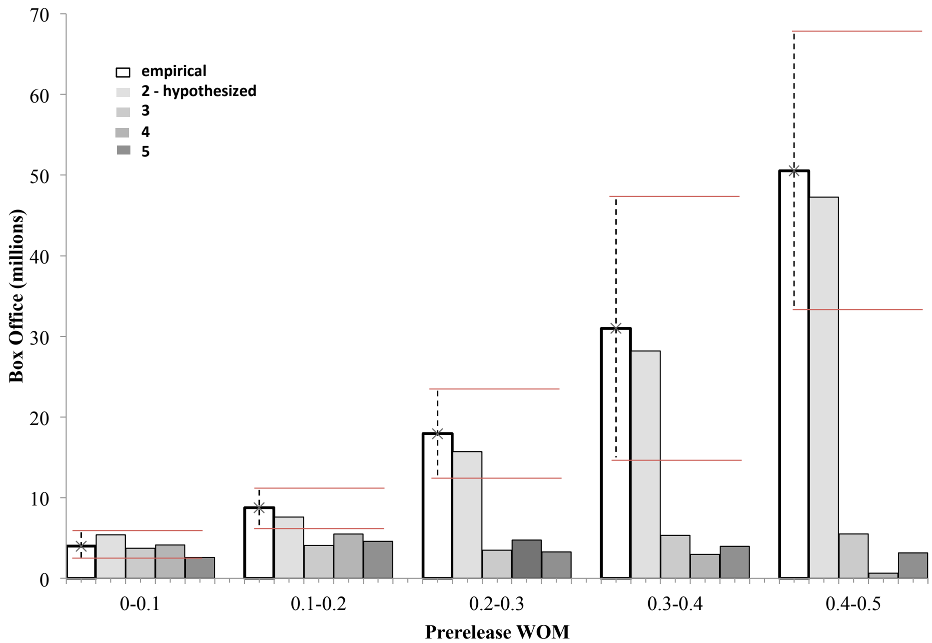
Figure 1 displays scatter plots of the visual agreement between the observed and simulation data for prerelease (left panel; Figure 1a, 1c) and postrelease (right panel; Figure 1b, 1d), respectively. Consistent with our framework and regression analyses, the simulations' results closely mirror the same functional relationship found in the empirical data. The simulations estimated a weak relationship between the level of prerelease WOM and adoption between the values of ∼5 percent to ∼21 percent WOM. After a critical level of prerelease WOM, the simulation shows that each increase in prerelease WOM is associated with large increases in adoption. The pattern of weak and then strong effects before and after the critical value, as well as the critical value itself, correspond closely to the empirical results. By contrast, postrelease WOM does not display the same effects. Postrelease WOM is proportionally associated with adoption, both empirically and in the simulation. These results offer confirmatory support to the findings of the empirical analysis.

Alternative models A–D further support our hypothesized model. Across all models, formal tests indicated that the hypothesized model fit the observed data the best. Simulation results are displayed in Figures 2 and 3. Figure 2 shows that the hypothesized threshold of two persons in prerelease (Figure 2a) and one person in postrelease (Figure 2b) fits the data better than other specifications. For example, alternative model A for prerelease overestimated opening box office adoption by more than 200 percent. Figure 3 shows that the critical network threshold is robust to changes in the size of a person's network. The best fit is for 4 degrees for prerelease (Figure 3a), which corresponds to the average size of a person's network in the Add Health network data; postrelease results (Figure 3b) are less conclusive but generally consistent with our hypothesized model.

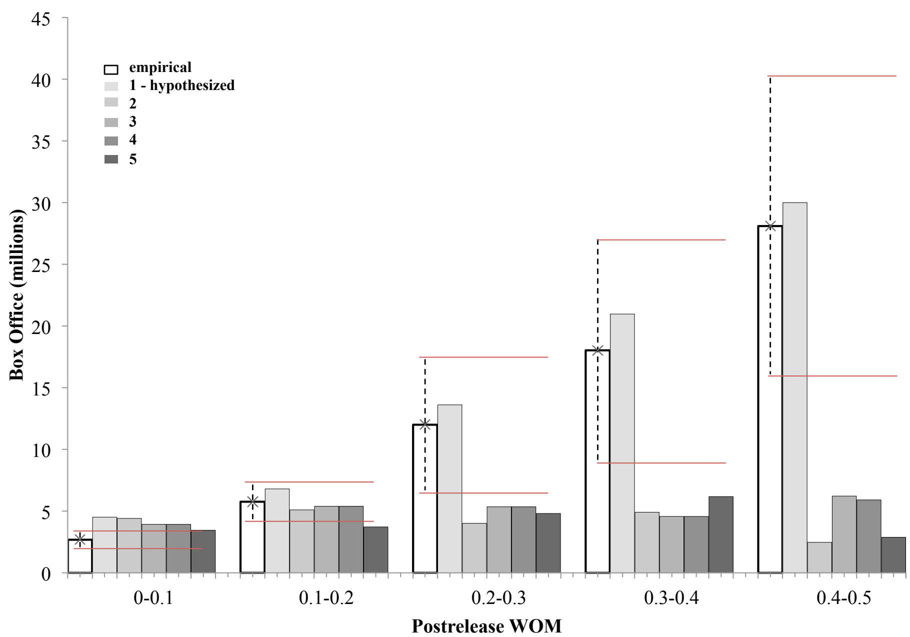
Formal tests bore out these results. We took the mean and the variance of the empirical data at 10 percent intervals of WOM and compared those observed values with the values generated by each alternative model specification. Specifically, we evaluated the fit of all models using the χ^2 test, which measures the sum of squared errors between the model and observed values for each of the bins, both for the means and the variances. We fitted the data to a Landau distribution, which accounts for the long tail of box-office returns that skew toward lower levels in each bin (Landau 1944). Table 3 displays the results of these robustness checks. The hypothesized model fits the prerelease data with a χ^2 of p = 96 percent and postrelease of p = 88 percent. The model that uses a constant degree of 4 also agrees well with prerelease data χ^2 of p = 94 percent but poorly in postrelease of p = 23 percent. These alternative models further support a prerelease individual threshold for adoption of hearing WOM from two or more contacts. The next best fit for a postrelease alternative model was alternative C (random distribution of individual thresholds with mean threshold of 1) with p = 55 percent, which suggests that in postrelease there may be more variation in individual thresholds, with some individuals still wanting to hear from two or more individuals before adopting, but this does not represent the adoption behavior as well as our hypothesized model. These findings indicate that the mechanisms outlined in our framework offer a plausible explanation for how micro behaviors of spreading and hearing pre- and postrelease social influence within networks can generate the observed macro patterns of adoption.

Discussion

As noted at the outset of this article, WOM appears to be of increasing interest to both academics and practitioners. However, prior research has not systematically

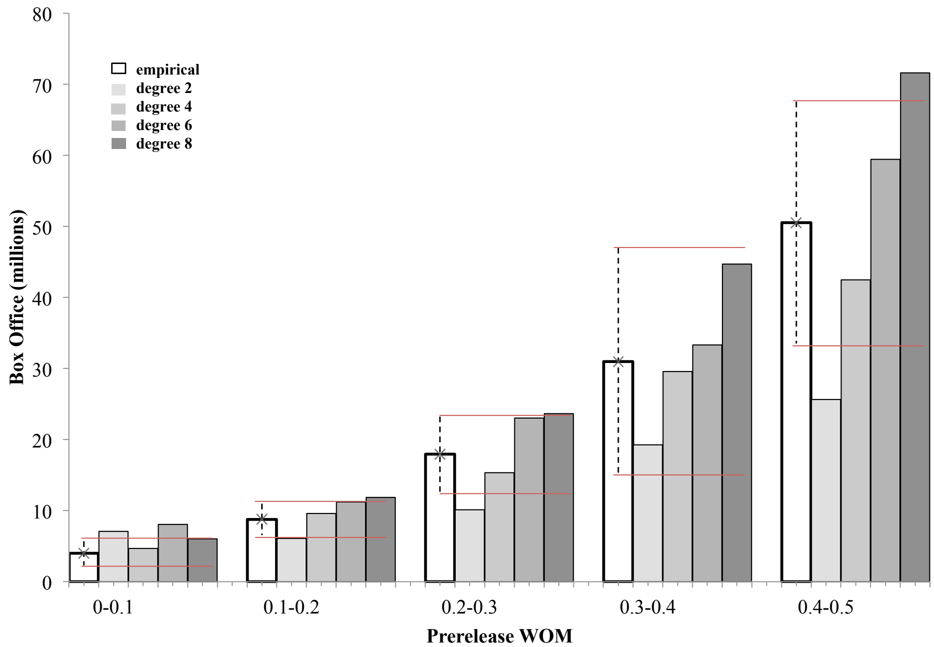


(a)

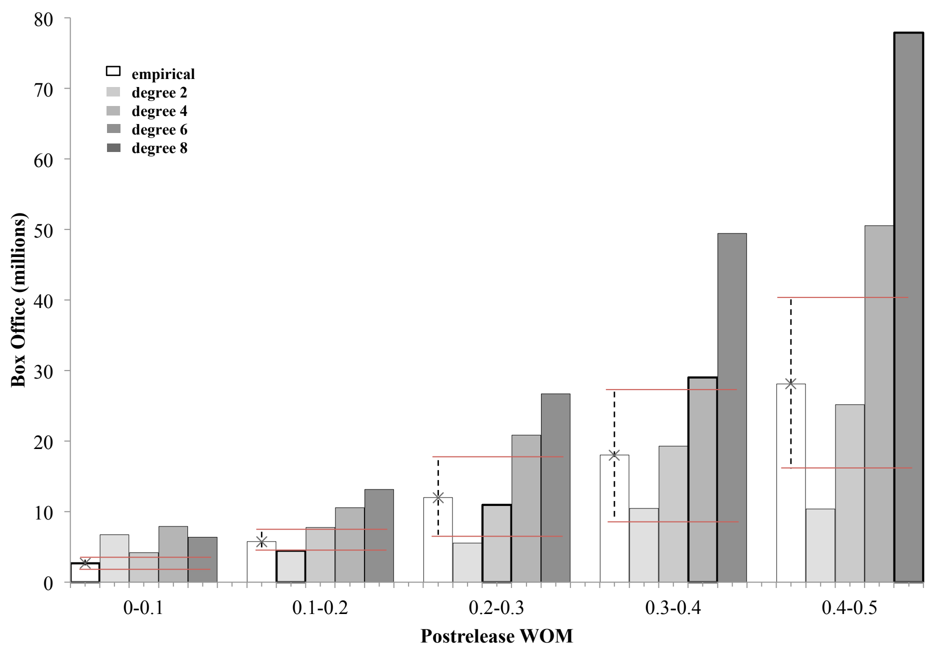


(b)

Figure 2: (a) Opening weekend box office: empirical results compared to simulation outcomes for varying thresholds. (b) 2nd weekend box office: empirical results compared to simulation outcomes for varying thresholds. Note: The vertical lines represent the 1-sigma uncertainty in the empirical data within that range of WOM.



(a)



(b)

Figure 3: (a) Opening weekend box office: empirical results compared to simulation outcomes for varying individual network sizes. (b) 2nd weekend box office: empirical results compared to simulation outcomes for varying individual network sizes. Note: The vertical lines represent the 1-sigma uncertainty in the empirical data within that range of WOM.

Table 3: Simulation models overview.

Model Condition: Simulation Mechanisms		Qualitative Comparison to Empirical Data	Simulation Fit to Empirical Data: Probability of Fit for χ^2 Prerelease:	Postrelease:
***Hypothesized Model*: Test proposed mechanisms**				
Hypothesized Mechanisms	Prerelease: Threshold = 2 or more Postrelease: Threshold = 1 or more	Consistent with empirical data	96%	88%
***Alternative A*: Test baseline with threshold of 1 in both pre- and postrelease**				
1+	Pre- and postrelease: Threshold = 1 or more	Overestimating adoption in prerelease	<5%	88%
***Alternative B*: Test baseline with threshold of 2 in both pre- and postrelease**				
2+	Pre- and postrelease: Threshold = 2 or more	Underestimating adoption in postrelease	96%	<10%
***Alternative C*: Test robustness to individual thresholds as number of contacts and percent of contacts**				
3+	Pre- and postrelease: Threshold = 3 or more	Underestimating adoption in pre- and postrelease	<5%	<5%
4+	Pre- and postrelease: Threshold = 4 or more	Underestimating adoption in pre- and postrelease	<5%	<5%
5+	Pre- and postrelease: Threshold = 5 or more	Underestimating adoption in pre- and postrelease	<5%	<5%
Random distribution of individual threshold	Prerelease: Mean threshold = 2, postrelease: Mean threshold = 1	Overestimating adoption in prerelease	<5%	55%
10%+	Pre- and postrelease: Threshold = 10% of contacts	Overestimating adoption for prerelease Overestimating adoption for low levels of WOM in postrelease	<5%	<5%
25%+	Pre- and postrelease: Threshold = 25% of contacts	Overestimating adoption for prerelease Underestimating adoption for higher levels of WOM in postrelease	<5%	<5%

Table 3 continued.

Model Condition: Simulation Mechanisms		Qualitative Comparison to Empirical Data	Simulation Fit to Empirical Data: Probability of Fit for χ^2 Prerelease:	Postrelease:
50%+	Pre- and postrelease: Threshold = 50% of contacts	Overestimating adoption for prerelease Underestimating adoption for higher levels of WOM in postrelease	<5%	<5%
75%+	Pre- and postrelease: Threshold = 75% of contacts	Overestimating adoption for prerelease Underestimating adoption in postrelease	<5%	<5%
100%	Pre- and postrelease: Threshold = 100% of contacts	Overestimating adoption for low levels of WOM in prerelease Underestimating adoption in postrelease	<5%	<5%
***Alternative D*: Sensitivity Analysis of Individual Network Size**				
Degree of 2	Prerelease: Threshold = 2 or more Postrelease: Threshold = 1 or more	Underestimating adoption in pre- and postrelease	<10%	<5%
Degree of 4	Prerelease: Threshold = 2 or more Postrelease: Threshold = 1 or more	Consistent with empirical data	94%	23%
Degree of 6	Prerelease: Threshold = 2 or more Postrelease: Threshold = 1 or more	Overestimating adoption in pre- and postrelease	37%	<5%
Degree of 8	Prerelease: Threshold = 2 or more Postrelease: Threshold = 1 or more	Overestimating adoption in pre- and postrelease	22%	<5%

compared pre- and postrelease WOM to their social influence. In this article, we tackled this issue using large-scale, real-world empirical data on movie adoption accompanied by an agent-based model. Our results demonstrate that life cycle stage matters: pre- versus postrelease WOM follow distinctive patterns of potential theoretical and practical importance. Theoretically, we introduce the notion of a functional form difference between pre- and postrelease WOM and adoption. For prerelease WOM, until a critical value of WOM is reached, only a small, positive relationship between social influence and adoption is present. However, after this critical value of WOM is reached, every increase in WOM correlates with a significant and large increase in adoption. In contrast, for postrelease WOM, the relationship between WOM and adoption follows a single linear functional form. These patterns were supported by time-series data and agent-based models. Together, these findings suggest the importance of distinguishing and studying pre- versus postrelease WOM with respect to social influence and adoption.

We draw upon an accessibility–diagnosticity framework to explain these functional forms and adoption patterns. The framework focuses on how differences in information and the transfer of information in a network are associated with socially induced adoption. We reasoned that prerelease WOM is based on speculation, hearsay, and other secondhand information that does not appear to significantly affect adoption until sufficient repeated exposure increases the accessibility and diagnosticity of the information. This level of exposure is obtained when potential adopters have the information echoed throughout their network by multiple contacts, which occurs when a sufficient number of highly connected persons in a social network relay prerelease WOM across otherwise disconnected social network clusters. By contrast, because postrelease WOM is more likely to be based on firsthand and direct experience, a single exposure can be sufficient to provide the required accessibility and diagnosticity to prompt adoption.

We suggest prerelease WOM acts as a more complex contagion than postrelease WOM because of differences in accessibility and diagnosticity across a product's life cycle. Our work complements and extends that of Centola and Macy (2007). Using simulations, Centola and Macy found that complex contagions saturate a network more slowly over time than simple contagions. We extend this work by looking at a snapshot of adoption levels for many different products (movies) at one time (either pre- or postrelease). We find a critical point for the influence of a complex contagion (prerelease WOM) on adoption but a linear relationship for a simple contagion (postrelease WOM). Further, our empirical analysis suggests that a contagion as "simple" as WOM can change across a product's life cycle stages as it moves from complex to simple. Future research should explore how the role of weak ties may change over time for product adoption as the complexity of contagion changes.

We also advanced theory by emphasizing the importance of studying interactions between individual and network thresholds. Prior models have investigated the implications of different individual thresholds on adoption (Dodds and Watts 2004; Granovetter 1978). By contrast, we emphasized the predictive value of a global network–level threshold. Unless this global network reaches a certain threshold of prerelease social influence, negligible changes exist in adoption behavior by consumers. Furthermore, we found a key link: a global network threshold occurred when individual thresholds for adoption were responsive to exposures or greater WOM. Future research might turn to examine how individual-level thresholds influence this global threshold.

The importance of prerelease social influence has a number of potential implications for management research. Consumer trends highlight continued growth in social influence as processes for generating and sharing information about products continue to expand via interpersonal and social media (Aral and Walker 2011). The present work suggests that managers should move beyond questions of how social influence spreads and seek to understand how influence patterns differ based on the life cycle of an innovation or product: pre- versus postrelease stages. Indeed, were managers to rely only on relationships or observations of postrelease social influence, they may be poorly equipped to make decisions that involve prerelease marketing efforts. Improvement in practice may further occur if future research investigates a broader range of products to identify how critical values vary across product categories and how sensitive the critical value is to change in the level of prerelease social influence before and after the critical value.

On a related point, our research suggests the possibility of different interventions as a function of pre- versus postrelease of a product. Prior to a product's release, marketers might focus on encouraging communications among a smaller number of diverse consumers to increase the chance that multiple sources of influence are enacted in the network to foster initial levels of adoption. However, in postrelease, marketers might focus more heavily on getting people to hear about one person's experience with the product, as that one experience may be enough to foster adoption. In addition, during the prerelease phase, failure to have the required level of social influence may also indicate that release should be postponed until prerelease social influence reaches the desired value.

Our study uses survey data on face-to-face WOM, which remains a central form of consumer behavior (Bond et al. 2012; Keller and Fay 2012). However, the data are older and censor most of the smallest-budget movies released during that timeframe. Therefore, generalization to current conditions should be done with caution. This limitation recognized, a benefit of the timing for the survey is that it is before the advent of social media sites and therefore likely captured interpersonal WOM. Currently, Facebook and other social media channels complement traditional face-to-face WOM (Aral and Walker 2011; De Bruyn and Lilien 2008). This introduces a new question with respect to how social influence, as measured by WOM, may have changed over time as people hear about products via face-to-face and social media WOM. We suspect that the accessibility, diagnosticity, and complexity of WOM often varies for a phone call compared to a FaceBook post, for example. Future research should explore how the different channels of pre- versus postrelease social influence affect each other as well as consumption behavior.

In all cases, a broader and more complete understanding of social influence is acquired by understanding how it operates in different stages of an innovation's life cycle.

Notes

1 The real name was, of course, the iPad.

2 Add Health's initial wave of the study utilized a sampling design that resulted in a nationally representative sample that included participation from 145 middle, junior high, and high schools; from those schools, 90,118 students completed a 45-minute questionnaire. Each school becomes a full network within the overall Add Health network. In these networks, the number of outward nominations is restricted to 10 because of the procedure used by Add Health. 90.0 percent of subjects named fewer than the maximum, indicating that the degree of each person's network is probably not truncated by the instrument. The average number of friends of a person is 3.8 (SD = 3.7).

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Sara B. Soderstrom: Organizational Studies and Program in the Environment, University of Michigan.
E-mail: capasb@umich.edu.

Brian Uzzi: Management and Organizations, Kellogg School of Management, Northwestern University.
E-mail: uzzi@kellogg.northwestern.edu.

Derek D. Rucker: Marketing, Kellogg School of Management, Northwestern University.
E-mail: d-rucker@kellogg.northwestern.edu.

James H. Fowler: Political Science, University of California, San Diego.
E-mail: fowler@ucsd.edu.

Daniel Diermeier: Provost, The University of Chicago.
E-mail: ddiermeier@uchicago.edu.