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SEBASTIANO A. DELRE, THIJS L.J. BROEKHUIZEN, and TAMMO H.A. BIJMOLT*

Consumers frequently consume hedonic products together with other consumers and derive value from this shared experience. This article investigates the impact of shared consumption, a type of social influence that determines the enjoyment of joint experiences, in the context of a typical hedonic product: movies. The authors argue that this type of influence has important consequences for the diffusion curves of hedonic goods that are consumed together and the effectiveness of advertising in generating launch and postlaunch sales. An empirically validated agent-based model simulates the U.S. motion picture market, with new movies launching, competing, and exiting. The agent-based model serves as a means to demonstrate the essential role of shared consumption for explaining movie life cycles and tests how advertising expenditures accelerate and/or acquire movies' demand in markets with varying levels of shared consumption. The results provide key theoretical insights for the new product diffusion of hedonic products and help managers predict the financial consequences of their strategic decisions.

Keywords: shared consumption, social influence, advertising, motion picture market, agent-based models

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The Effects of Shared Consumption on Product Life Cycles and Advertising Effectiveness: The Case of the Motion Picture Market

Many hedonic consumption activities—such as playing video games; watching movies; visiting a restaurant; or attending concerts, sport matches, or musical performances—are usually

shared with other people. The act of experiencing hedonic activities together provides consumers with additional enjoyment by fulfilling their social need for bonding. Consumers may even refrain from engaging in hedonic activities when doing them alone because they anticipate negative inferences from others (Ratner and Hamilton 2015). Shared consumption affects consumers' decisions through the mere presence of affiliates because this presence affects the level of enjoyment they achieve from their joint experience (Raghunathan and Corfman 2006). Such social influence differs from the more commonly researched form of social influence that represents how consumers adjust their judgments in response to others' purchase decisions (Chen, Wang, and Xie 2011; Deutsch and Gerard 1955). Despite its importance in shaping purchase decisions in multiple hedonic shopping contexts, as well as in postpurchase decision contexts (e.g., car-, house-, office-sharing services), shared

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consumption has received relatively little attention in the marketing literature (Bagozzi 2000; Barsade 2002). Whereas the traditional social influences of word of mouth (WOM) and observational learning are imposed by adopters, shared consumption is instigated by potential adopters that can consume the good together with the focal actor. It is beneficial to stimulate the two types of social influence because they both have converging effects, but their impact on the diffusion of hedonic goods might be distinct. While WOM and observational learning create additional demand in the weeks after launch (Dellarocas, Zhang, and Awad 2007), shared consumption might create immediate converging effects at release because consumers can easily find companions to join. However, because markets consist of a finite pool of consumers, this instant success may come at a cost: it accelerates the decline in later stages owing to the depletion of suitable companions.

We investigate how the importance that consumers attach to shared consumption affects the life cycles of new product launches in the context of a typical hedonic product: movies. Shared consumption is particularly common in the motion picture market and strongly determines movie choices (Hennig-Thurau, Marchand, and Marx 2012; Weinberg 2005). A large-scale German field study (Filmförderungsanstalt [FFA] 2011) demonstrates the importance of such shared experiences: the top reason consumers provided for visiting a movie is “the movie’s theme and story” (43.7% of respondents), followed by “doing something with others” (23.6%). Furthermore, more than 90% of movie visits include friends or relatives, with an average group size of 2.3 people.

Previous research has indicated that external influence (i.e., how strongly moviegoers are affected by advertising campaigns) and internal influence (i.e., how strongly moviegoers imitate the behavior of others) affect box office sales and movies’ life cycles (Ainslie, Drèze, and Zufryden 2005; Basuroy, Desai, and Talukdar 2006; Hennig-Thurau, Houston, and Sridhar 2006), though no research has addressed the role of shared consumption (i.e., how strongly moviegoers are affected by the mere presence of others while watching a movie together). We model a market in which moviegoers select movies on the basis of internal influences, external influences, and shared consumption influences and find support for the crucial role of shared consumption in the motion picture market and its considerable impact on movies’ life cycles and advertising effectiveness. Shared consumption influence should determine the shape of movies’ diffusion (in that higher levels of shared consumption lead to stronger openings and faster decays) as well as the relationship between prerelease advertising campaigns and launch/postlaunch box office sales.

Documenting how social influences affect new products’ life cycles is not straightforward, because their impact on market-level outcomes is complex. We adopt agent-based modeling, a computational method used increasingly to explain complex marketing phenomena (Goldenberg, Libai, and Muller 2010; Libai, Muller, and Peres 2013; Rand and Rust 2011; Trusov, Rand, and Joshi 2013). With our agent-based model (ABM), we simulate the U.S. theatrical motion picture market with new movie releases that launch in the market, compete for moviegoers, and eventually complete their life cycles and exit. As an empirical validation, we use a

vast amount of movie data from the U.S. motion picture industry, including data on new movies’ releases, ad expenditures, and box office sales, as well as statistics on how moviegoers attend movies in groups.

The simulation results demonstrate that by incorporating shared consumption influence into moviegoers’ decision making, we can more realistically simulate new product life cycles in motion picture markets. We provide robustness checks for our ABM and also test alternative explanations, confirming the unique and important role of shared consumption. Thus, our study shows that a largely ignored type of social influence, shared consumption, helps explain the typical product life cycles of hedonic goods such as movies.

Our ABM also demonstrates how the importance consumers attach to shared consumption moderates the effectiveness of advertising in generating launch and postlaunch sales. Inspired by work from Libai, Muller, and Peres (2013), we establish a baseline model to depict how an increase in prerelease advertising expenditures leads to an acquisition effect (i.e., more people visiting as a result of increased advertising) and an acceleration effect (i.e., people move their visit from the postlaunch to the launch period in response to increased advertising). Next, we take advantage of ABM’s capability to explore what-if scenarios by simulating the effects of different prerelease advertising campaigns in markets with varying levels of shared consumption.

We obtain three key results. First, moviegoers, on average, attach more importance to shared consumption than to internal and external influences, and thus shared consumption heavily affects the life cycles of new hedonic products. In contrast with previous studies that have identified the internal influence effect as a strong determinant of movie success, our results indicate that this effect is relatively weak, and consumers attach more importance to another kind of social influence—namely, shared consumption. Second, increasing advertising expenditures leads to a negligible acceleration, but a strong acquisition, of demand at both launch and postlaunch. Despite the demand increase, the additional investment in advertising expenditures is not recouped, which supports previous evidence that studio producers overspend on advertising (Elberse and Anand 2007; Joshi and Hanssens 2009). Third, the importance consumers attach to shared consumption considerably strengthens the acquisition effect of advertising at launch but weakens it at postlaunch.

SHARED CONSUMPTION AND MOVIES’ LIFE CYCLES

Marketing research has moved beyond individual preference models and to model the preferences of groups of people (Hartmann 2010; Hennig-Thurau, Marchand, and Marx 2012) to demonstrate that “the decisions and judgments of individuals in a group are dependent upon the decisions and judgments of other group members such that choice or opinion shifts are induced” (Ariely and Levav 2000, p. 279). Although hedonic experiences may be enjoyed alone, pleasure increases when they are undertaken together (Raghunathan and Corfman 2006). Despite its importance and frequency, very few studies have investigated the social influence that consumers impose on one another by consuming a hedonic good together (Bagozzi 2000; Barsade 2002), and no research has addressed how

shared consumption may affect the life cycles of movies or other hedonic goods.

Movies' life cycles do not follow a standard bell-shaped curve but often display rapid diffusion with fast decays (Eliashberg, Elberse, and Leenders 2006; Jedidi, Krider, and Weinberg 1998). Two typical diffusion types exist in the motion picture industry: blockbuster and sleeper-type movies (Ainslie, Drèze and Zufryden 2005; Sawhney and Eliashberg 1996). Blockbuster movies, such as *Marvel's The Avengers*, *Avatar*, or *Alice in Wonderland*, enter the market with massive box office sales and display an exponentially decaying sales pattern in the postlaunch period. Sleeper movies, such as *Mandela: Long Walk to Freedom* or *The Blair Witch Project*, lack strong quality signals and instead launch with low box office revenues, build sales gradually, and eventually decline. Sawhney and Eliashberg (1996) propose a parsimonious analytical model, BOXMOD, to formalize and estimate these two typical movie patterns. Its parsimony and ability to fit different kinds of movies' life cycles suggest that BOXMOD corresponds to the Bass (1969) model for nondurable experience goods. Several empirical studies have used BOXMOD to link the diffusion types to market success (e.g., cumulative box office sales) and confirm that top-grossing movies often display exponential decay patterns (Ainslie, Drèze, and Zufryden 2005; Elberse and Anand 2007; Eliashberg et al. 2009; Jedidi, Krider, and Weinberg 1998), thereby suggesting that top-grossing movies launch with very high box office sales and decay quickly after launch.¹

One may argue that this decaying pattern of big, top-grossing movies is the result of external influence, whereas small movies experience sales increases in the weeks after launch because of internal influences. Following this line of reasoning, top-grossing movies decay rapidly because studios have built a large pent-up demand by allocating their huge advertising budget entirely before the movie's launch (Elberse and Anand 2007), which quickly disappears after a successful release. In contrast, smaller movies, which usually cannot rely heavily on external influence, increase their sales after launch because of positive WOM. Although these effects are certainly at work, we conjecture that external and internal influences do not fully explain this peculiar characteristic of movie life cycles. Instead, shared consumption crucially helps explain why top-grossing movies decay quickly and small movies increase sales after launch.

Shared consumption experiences are more likely to occur during the launch period, when moviegoers can easily find affiliates to join them. In subsequent weeks, it becomes more difficult to find companions who have not yet seen the movie and want to go see it (Hennig-Thurau et al. 2007; Weinberg 2005). Therefore, regarding the availability of friends, relatives, and acquaintances with whom to visit movies, shared consumption favors top-grossing movies at their launch because no one has seen them yet, and they suffer after launch because the high attendance in the opening week makes it more difficult for moviegoers to find

companions in postlaunch weeks. This effect integrates the pent-up effect of advertising and explains why top-grossing movies decay quickly. In contrast, smaller movies benefit after launch, in the sense that because their launch is limited, it is still easy to find companions in the postlaunch period. This effect integrates the WOM effect and explains why small movies can increase their sales after launch. Shared consumption therefore better explains movie life cycles—in particular, the relationship between movies' market size and their decay. Thus, we introduce a general first hypothesis:

H₁: Accounting for shared consumption influence in moviegoers' decision making leads to more realistic movie life cycles by capturing the relationship between movies' market size and their decay.

As a preliminary check of our general hypothesis, we investigate how the life cycles of different genres of movies decay over time. We expect that shared consumption is more likely to occur for genres with target audiences that watch movies in large groups (teens and young adults). We estimate the decay of movie life cycles of different genres and find that, indeed, large-group genres such as horror, action, and thriller decay faster than small-group genres such as romance and drama. In the Web Appendix, we provide further details about the diffusion model used for the estimation and report detailed estimation results of the genres included in the analysis.

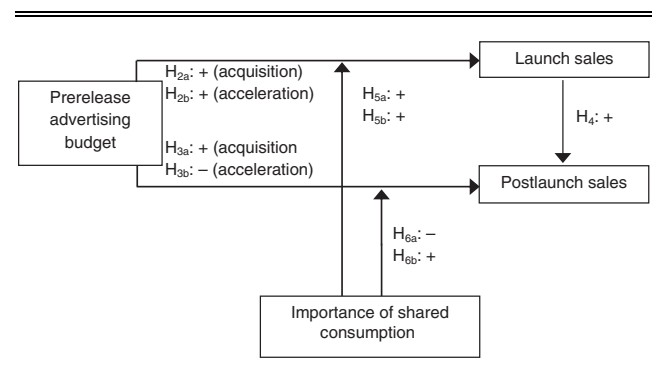
SHARED CONSUMPTION INFLUENCE AND ADVERTISING EFFECTIVENESS

We also investigate how the importance that moviegoers attach to shared consumption determines the effectiveness of advertising in generating launch and postlaunch sales. Our research model (Figure 1) formalizes a baseline model to show how an increase in prerelease advertising expenditures affects launch and postlaunch sales; Figure 1 also introduces the overall importance that consumers attach to shared consumption as a moderator of these relationships.

Impact of Prerelease Advertising on Launch and Postlaunch Sales

Many empirical studies have documented the positive impact of prerelease advertising expenditures on box office

Figure 1
RESEARCH MODEL



¹This peculiar characteristic also appears in other hedonic markets, such as the video games industry. The most successful video games (e.g., *Call of Duty*, *Grand Theft Auto V*) launch on specific release dates and sell extremely well during the opening week, with sales declining very quickly in subsequent weeks.

sales (Ainslie, Drèze, and Zufryden 2005; Basuroy, Desai, and Talukdar 2006; Elberse and Eliashberg 2003; Hennig-Thurau, Houston, and Sridhar 2006). They often distinguish between advertising effects on opening versus cumulative box office revenues, because an increase in opening-week revenues does not always equate with greater total box office sales (Gemser, Van Oostrum, and Leenders 2007). Higher pre-release advertising expenditures may lead existing consumers simply to advance their visit from the postlaunch to the launch (acceleration of demand), or it could attract additional visitors (acquisition of demand). Differentiating acceleration from acquisition effects is therefore fundamental to understanding how advertising affects launch and postlaunch sales (Libai, Muller, and Peres 2013).

A larger advertising budget implies greater signaling properties (Gemser, Van Oostrum, and Leenders 2007) and should convince more people to see the movie (Elberse and Anand 2007). Assuming these informative and persuasive effects, we expect that higher pre-release advertising expenditures increase awareness of and preference for the movie at release, creating both acceleration and acquisition effects. Thus, we hypothesize,

H₂: An increase in pre-release advertising expenditures affects launch box office sales positively as a result of (a) an acquisition effect and (b) an acceleration effect.

Higher advertising budgets should also convince more people to visit the movie after its release. Even though advertising effects decay over time (Assmus, Farley, and Lehmann 1984), pre-release advertising effects tend to persist for a few weeks after release. This carryover effect indicates that not every consumer is instantly exposed to or persuaded by advertising (Elberse and Anand 2007). Higher advertising expenditures may attract more consumers to visit the movie even after its release, though advertising concomitantly might reduce the number of postlaunch consumers, who will have advanced their visit to the launch week. Therefore,

H₃: An increase in pre-release ad expenditures affects postlaunch box office sales (a) positively through an acquisition effect and (b) negatively through an acceleration effect.²

Opening-week box office sales also affect consumers' choices in subsequent weeks through sales-driven WOM (Ainslie, Drèze, and Zufryden 2005; Elberse and Eliashberg 2003). Diffusion literature has denoted this contagious, social imitative effect as an internal influence effect (Bass 1969; Van den Bulte and Joshi 2007). Consumers learn from other consumers' opinions and purchase decisions and make decisions in congruence with their social environment (Chen, Wang, and Xie 2011). An increase in pre-release advertising can indirectly increase postlaunch sales by stimulating imitative social influences through WOM and observational learning. We hypothesize,

H₄: An increase in pre-release advertising expenditures indirectly increases postlaunch box office sales through higher launch box office sales.

Moderating Effects of Shared Consumption

Increasing advertising expenditures should acquire and accelerate consumers at the movie's launch as a result of

stronger informative and persuasive effects. If consumers attach great value to seeing movies together, the advertising effects at launch may become stronger because other consumers have been affected also, and so it is easier to find and convince other group members to visit the movie collectively. Therefore, we hypothesize that the pre-release advertising effect on launch sales grows stronger through shared consumption influence.

H₅: The more importance consumers attach to shared consumption strengthens (a) the acquisition effect and (b) the acceleration effect of pre-release advertising expenditures on launch box office sales.

As we have discussed, we expect that in markets that place high importance on shared consumption, greater pre-release advertising steers consumers to watch the movie jointly at launch. Consumers have more difficulty finding companions in the postlaunch period, so the acquisition of demand generated by higher advertising expenditures is weaker in markets that place higher importance on shared consumption. We hypothesize,

H₆: The more importance consumers attach to shared consumption (a) weakens the acquisition effect and (b) strengthens the acceleration effect of pre-release advertising expenditures on postlaunch box office sales.

THE AGENT-BASED MODEL

As useful tools to analyze and understand complex market dynamics, ABMs are particularly suitable for studying aggregate dynamics that originate from interactions among individual agents (Delre et al. 2007; Goldenberg, Libai, and Muller 2010; Krider and Weinberg 1997; Peres, Muller, and Mahajan 2010). We use Rand and Rust's (2011) guidelines to explain the appropriateness of the ABM for our research, describe the design of our ABM, and provide an empirical validation.

Appropriateness of the ABM as a Research Method

We chose the ABM because of its ability to mimic the dynamics of social behaviors at the individual level and link them with market-level outcomes, as well as its ability to run an experimental setup to assess how marketing instruments' effectiveness varies under different market conditions. Our ABM fulfills the necessary requirement of time dynamics, in that it simulates how advertising and social influences generate movies' box office sales over time. It involves the decisions of numerous, heterogeneous, adaptive consumers who decide, at each time step, which movie to visit, and it collects these individual decisions at the aggregate level of movie life cycles. Moreover, ABMs also enable us to test in an experimental setting how changing parameters (i.e., shared consumption influence) and marketing instruments (advertising budgets), which are difficult to change or control for in reality, influence macro-level outcomes. Agent-based models can thus serve as a means to explore what-if scenarios that simulate different market conditions or use of market instruments and disentangle temporal acquisition and acceleration effects.

We acknowledge that a simultaneous equation model (SEM) can also reveal the effects of advertising and WOM on movie life cycles (Ainslie, Drèze, and Zufryden 2005; Elberse and Eliashberg 2003; Karniouchina 2011) and, in principle, describe the effects of shared consumption. Although such a model can account for many effects that

²Note that H_{2b} and H_{3b} refer to the same effect because the acceleration effect is defined as the increase in launch sales at the expense of postlaunch sales.

take place while movie life cycles unfold as well as control for factors such as production budgets, number of screens, reviews, and stars, an SEM cannot address how individual behaviors lead to movies' life cycles, nor can it create what-if scenarios or differentiate acquisition and acceleration effects (Libai, Muller, and Peres 2013).

Model Design

The ABM simulates the U.S. cinema market for one year, using N_AGENTS as the number of moviegoers and N_MOVIES to represent the number of movies released in one year. A simulation step t of the ABM corresponds to one week in the real market, and $NEW_ENTRIES_t$ represents the fraction of N_MOVIES entering the market per week. We model the probability that agent i visits a movie at time step t as follows:

$$(1) \quad ATTENDANCE_{it} = \frac{F_i}{WEEKS} \times SEASONALITY_t,$$

where F_i is the visiting frequency of agent i , $WEEKS$ is the number of weeks in a year, and $SEASONALITY_t$ is the seasonality effect in week t . Thus, at each time step t , each agent decides to attend a movie with probability $ATTENDANCE_{it}$. Then, the probability that agent i visits movie j at time step t is

$$(2) \quad P(\text{agent } i \text{ visits movie } j \text{ at time step } t | i \text{ has not visited } j \text{ yet})$$

$$= \frac{\exp(A_{ijt})}{\sum_{m=1}^{M_t} \exp(A_{imt})},$$

where A_{ijt} is the attraction of agent i to movie j at time step t , and M_t is the set of movies available at time step t . Similar to other ABMs of new product diffusion (e.g., Goldenberg, Libai, and Muller 2002; Goldenberg et al. 2007; Libai, Muller, and Peres 2005), we model movies' diffusions through the individual probability to adopt. In addition, we use a logit formulation to account for competing diffusions. This formulation assumes that moviegoers watch movies in theaters only once during the movie life cycle, which corresponds with industry norms (Hennig-Thurau et al. 2007; Weinberg 2005).

The individual attraction of agent i for movie j at time step t depends on three components, as indicated in Equation 3: (1) internal influence (WOM and observational learning), (2) external influence (advertising), and (3) shared consumption influence. The input parameters β_1 , β_2 , and β_3 determine the average importance consumers attach to these three components, respectively.

$$(3) \quad A_{ijt} = \underbrace{(\beta_1 \times x_{jt})}_{\text{Internal influence}} + \underbrace{(\beta_2 \times y_{jt})}_{\text{External influence}} + \underbrace{(\beta_3 \times z_{ijt})}_{\text{Shared consumption influence}}.$$

The internal influence x_{jt} is based on the imitation effect, as imposed by adopters. In our formalization, we do not explicitly model how consumers interact at the micro level but assume that internal influence increases when more agents visit movie j at the previous time step ($VISITS_{jt-1}$). Although diffusion studies for consumer durables have used cumulative demand to infer the level of internal influence, studies in the motion picture industry have convincingly demonstrated

that the effect is best reflected by the number of recent adopters, because internal influences are localized in time, as moviegoers talk about movies soon after watching them (Dellarocas, Zhang, and Awad 2007), and these messages also "perish" quickly in subsequent weeks (Elberse and Eliashberg 2003; Karniouchina 2011). Therefore,

$$(4) \quad x_{jt} = \frac{VISITS_{jt-1}}{N_AGENTS}.$$

The external influence component y_{jt} derives from advertising. We opt for a dynamic formalization in which external influence depends on prerelease advertising expenditures when the movie launches and then decays over time. The formalization assumes that the advertising budget is spent completely in the prelaunch campaign (Elberse and Anand 2007). At the time step of the movie release T_j , external influence is determined by the prerelease advertising expenditures of movie j AD_BUDGET_j relative to the average movie ad expenditures $\overline{AD_BUDGET}$ (Equation 5) as well as by ω , which is a parameter that determines the strength of the advertising messages (Hanssens, Parsons, and Schultz 2001; Lilien, Rangaswamy, and De Bruyn 2007).³ After the movie release, the external influence depends on δ , which formalizes the decaying effect of advertising messages over time (Dellarocas, Zhang, and Awad 2007; Lilien, Rangaswamy, and De Bruyn 2007). Therefore,

$$(5) \quad y_{jt} = \delta^{t-T_j} \times \exp\left(-\omega \times \frac{AD_BUDGET_j}{\overline{AD_BUDGET}}\right).$$

Finally, little empirical evidence exists about how consumers decide to consume a product together. In reality, shared consumption influence can take many forms, such as sending movies' links to friends, discussing movie releases, and inviting friends to see a movie. We decide to not model the specific forms of shared consumption and opt for a parsimonious formalization that refers to the social influence of potential consumers who have not yet adopted. Assuming that agent i wants to go to the cinema at time step t with g_i companions, we model shared consumption influence z_{ijt} as the probability that none of his or her g_i companions have seen movie j already. In the case that agent i wants to visit the cinema alone ($g_i = 0$), we set shared consumption influence to 0. Thus,

$$(6) \quad z_{ijt} = \begin{cases} \text{if } g_i \geq 1, \text{ then } \left(1 - \frac{\sum_{k=T_j}^{t-1} VISITS_{jk}}{N_AGENTS}\right)^{g_i} \\ \text{otherwise, } 0 \end{cases}$$

where

$$1 - \frac{\sum_{k=T_j}^{t-1} VISITS_{jk}}{N_AGENTS}$$

is the overall proportion of agents who have not visited movie j at time t . The attraction derived from shared consumption

³Note that in our formalization, when the ω parameter increases, the strength of the advertising messages decreases.

decreases when there are fewer other agents available because it is more difficult to find companions with whom to visit the movie. Moreover, the probability that all companions have not yet seen the movie decreases with g_i , because the more companions agent i wants to include in the shared consumption, the more likely it is that some companion has already seen movie j and will steer the group's visit toward another movie. To understand the intuition behind this formalization, consider the following example: John wants to visit a newly released movie, but he would not like to go alone. The chance that John can visit the movie with some of his friends is highest at launch because, if he decides to visit the movie at a later date, it is more likely that his friends will have already seen it. This likelihood increases more quickly when John wants to include more friends in the shared consumption because it is probable that at least one of them will have seen that movie and may try to direct the group's choice toward other, more recently released movies.

This formalization contains three important assumptions. First, it does not involve any process of group formation or group decision, such that it ignores potential power and preference differences (Arora and Allenby 1999). We do not model why and how agents group together to visit a movie but rather model the attraction that agent i experiences toward movie j , assuming (s)he wants to visit it with g_i companions. Second, we assume that when a movie is first released, its shared consumption influence peaks and equals 1 because none of the g_i companions have seen the movie. In subsequent weeks, the shared consumption influence decreases as more agents see the movie, and it decreases more quickly if agent i wants to visit the movie with more companions. Thus, the formalization depends crucially on the reasonable assumption that each agent visits a movie only once during its theatrical life cycle (Hennig-Thurau et al. 2007; Weinberg 2005). Third, we acknowledge that our formalization assumes that shared consumption influence is never negative but always increases the level of enjoyment of a movie, though empirical research has indicated that shared experiences can be negative if there is incongruity in agents' opinions of the experience (Raghunathan and Corfman 2006).

Finally, to make the three components directly comparable and to allow for straightforward interpretations of the β_1 , β_2 , and β_3 values, we standardize x_{jt} , y_{jt} , and z_{ijt} across movies at each time step. In this way, by setting $\beta_1 = .6$, $\beta_2 = .3$, and $\beta_3 = .1$, for example, we simulate a market in which the average effect of internal influence, β_1 , is twice as strong as the effect of external influence, β_2 , and six times as strong as the effect of shared consumption, β_3 .

Validation

We follow Rand and Rust's (2011) recommendation to support ABMs with strong empirical validation to demonstrate how well the ABM corresponds to reality. They distinguish between micro-face, macro-face, empirical input, and empirical output validation. The first two forms ensure that the micro-mechanisms of the agents and the macro-patterns of the model correspond "on face" to the real world. Empirical input and output validations confirm that the real data being added to the model are accurate and that the output of the ABM corresponds with these real data.

In the following sections, we empirically validate our ABM with a vast amount of information about U.S. movies

released between 2000 and 2010. In Table 1, we summarize the parameters of our ABM, their interpretations, their values, and how we validate them.

Yearly releases, weekly entries, and movies' life cycle length. From 2000 until 2010, an average of 521 movies were released each year in the U.S. market, so we set $N_MOVIES = 521$. For $NEW_ENTRIES_t$, or the number of newly released movies per week, we use actual average weekly releases in the U.S. market (e.g., three releases in week 1, six releases in week 2, etc.). In our ABM, a new entry competes against other new releases and existing movies that have not yet exited the market. We assume that movies' life cycles last for 15 weeks, such that they exit 15 time steps after their release ($MOVIE_LENGTH = 15$). This rule reflects the U.S. data, which show that movies obtain 98% of their box office sales within the first 15 weeks of their life cycles (www.boxofficemojo.com). In the Web Appendix, we provide detailed information about the number of U.S. movies released each year by week and life cycle length.

Seasonality effect and visiting frequency. In our ABM, $ATTENDANCE_{it}$, the probability that agent i is randomly selected to visit a movie at time step t , depends on the typical seasonal effects $SEASONALITY_t$ of the motion picture market (Einav 2007) and on the visiting frequency F_i (Equation 1). We use the total weekly revenues of the real market to determine $SEASONALITY_t$. If real attendance peaks, we set $SEASONALITY_t = 1$ (in the real market, that typically happens during Christmas or at Thanksgiving). However, if in week 37, the real attendance is only 65% of the peak, we set $SEASONALITY_t = .65$ (www.boxofficemojo.com).

Then, to account for consumer heterogeneity in visiting frequency, we model agents' visiting frequency according to real demographic attendance (Motion Picture Association of America [MPAA] 2010). In reality, moviegoers are segmented into nonvisitors (32%), infrequent visitors (10%), occasional visitors (47%), and frequent visitors (11%). We divide the ABM population accordingly and set F_i such that the percentage of the total visits of each segment in the ABM corresponds to the percentage of the total sales in reality. For detailed statistics on the segments and their visiting frequencies, see the Web Appendix.

External influence. When movie j enters the theaters at time step T_j , its external influence depends on its advertising budget AD_BUDGET_j . We opt for an S-shaped response function (Equation 5) that provides macro-face validity for the relation between the advertising budget and the external influence at launch (Lilien, Rangaswamy, and De Bruyn 2007). To empirically validate AD_BUDGET_j , we use real weekly advertising expenditures for a total of 3,601 movies introduced in the U.S. market between 2000 and 2010, and we randomly draw AD_BUDGET_j from a normal distribution with the mean and variance of the real advertising expenditures of the week movie j was released (www.kantarmedia.com). Finally, we validate the strength and the decay of advertising messages, ω and δ . We use the total advertising budgets of the movies in our database, match them with the weekly box office sales of the corresponding movies, and estimate ω and δ for each movie. Our estimation procedure converges for more than 95% of the movies in our database. On average, we find that $\omega = 2.38$ (SD = .88) and $\delta = .54$ (SD = .10) and use these mean values in our ABM. These values of ω and δ also are

Table 1
ABM PARAMETERS

Parameter	Description	Values	Validation
N_AGENTS	Number of agents	50,000	Sensitivity analysis
N_MOVIES	Number of movies released per year	521	Empirical input validation
WEEKS	Number of weeks per year	52	Empirical input validation
NEW_ENTRIES _t	Number of new entries at week t	Min = 3 (week 1); Max = 14 (week 38)	Empirical input validation
SEASONALITY _t	Seasonality effect at week t	Min = .3 (week 37) Max = 1 (week 52)	Empirical input validation
F _i	Visiting frequency of agent i (i.e., how many movies [s]he visits per year)	Min = 1 Max = 23	Empirical input validation
MOVIE_LENGTH	Number of weeks of a movie life cycle	15	Empirical input validation
AD_BUDGET _j	Advertising budget of movie j	Min = \$0, Max = \$60.8 million, AD_BUDGET = \$11.7 million	Empirical input validation
ω	Strength of advertising messages	M = 2.38, SD = .88	Macro-face validation and empirical output validation
δ	Retention rate of advertising messages	M = .54, SD = .10	Macro-face validation and empirical output validation
g _i	Number companions with whom agent i wants to visit movies	9.3% alone, 43.7% in couples, 20.2% in groups of three, 13.3% in groups of four, and 13.5% in groups of five or more	Empirical input validation
β ₁	Weight for internal influence	[0, 1]	Sensitivity analysis
β ₂	Weight for external influence	[0, 1]	Sensitivity analysis
β ₃	Weight for shared consumption influence	[0, 1]	Sensitivity analysis

closely in line with other empirical studies (Assmus, Farley, and Lehmann 1984; Hanssens, Parsons, and Schultz 2001). If we interpret external influence in terms of informative advertisement and awareness, these values imply that 30% of the market is aware of a movie with an average advertising budget and that, in one week, moviegoers retain 54% of the advertising messages they receive. We provide further details about the advertising data and the estimation of ω and δ in the Web Appendix.

Shared consumption influence. In our ABM, the shared consumption influence for a given movie depends on how many agents are still available and with how many companions agent i wants to visit the movie (g_i). We use overall statistics on group sizes for visiting movies to validate g_i (FFA 2011). In particular, we use these field data to assess the distribution of group visits. On average, from 2007 to 2012, 9.3% of the tickets sold were single visits, 43.7% involved couples, 20.2% were groups of three, 13.3% were groups of four, and 13.5% involved groups with five or more consumers. The distribution of group visits remained stable, with no significant changes across the five-year span. We use this distribution to assign g_i values to each agent.

Verification

Verifying an ABM consists of ensuring that the simulation model does what it is supposed to do and that the implemented model corresponds to the conceptual model. Rand and Rust (2011) indicate three ways to verify an ABM: through documentation, programmatic testing, and test cases. The documentation of our ABM provides the MATLAB code, the pseudo-code, and the input files for the empirical validation. We provide code and pseudo-code in

the Web Appendix.⁴ As for the programmatic tests, we engineered a series of checks to ensure that the simulation run does not produce abnormal behaviors. We provide two of them in the MATLAB code. Finally, we also simulate extreme cases to ensure that corner cases replicate intuitive predictions. For example, we verify what happens if a movie launches with an extraordinarily high advertising budget in a market with a high value of β_2 , and as expected, we find that almost all agents visit this movie.

RESULTS

Study 1: Sensitivity Analysis of Internal, External, and Shared Consumption Influence

In this study, we perform a sensitivity analysis to investigate how the output of our ABM varies when we alter the importance that consumers attach to internal, external, and shared consumption influences (respectively, β_1 , β_2 , and β_3). This analysis demonstrates how the levels of internal, external, and shared consumption influence affect the life cycles of the movies and which levels of each influence best mimic the actual motion picture market. We adopted the following procedure:

1. We employed two distinctive market indicators that sharply define the empirical characteristics of movie life cycles in the real market;
2. We ran simulation scenarios with different parameter values for β_1 , β_2 , and β_3 ; and
3. In each simulation scenario, we computed the two indicators and compare them with the values of the real market.

⁴The files for the empirical validation are available on request from the first author.

Market indicator 1: movie life cycle shapes and market size.

The first indicator is based on BOXMOD (Sawhney and Eliashberg 1996) and synthesizes, in a unique measure, the relationship between the shapes of movie life cycles and their market size. BOXMOD is a powerful model that can accurately fit movies' diffusion curves in isolation. It consists of only three parameters: N indicates the size of the market demand, λ determines the time to decide ($= 1/\lambda$), and γ determines the time to act ($= 1/\gamma$). Sawhney and Eliashberg (1996) apply BOXMOD to a set of U.S.-released movies and find that the N and λ estimates relate positively, such that top-grossing movies (i.e., movies with higher N) decay faster (high λ estimates). As we have mentioned, such a relation between movies' market size and their exponential decay pattern is a well-documented, distinctive characteristic of the motion picture market (Ainslie, Drèze, and Zufryden 2005; Elberse and Anand 2007; Eliashberg et al. 2009; Jedidi, Krider, and Weinberg 1998). To corroborate these findings, we also fit BOXMOD to the 1,650 movie life cycles in our database. We calculate the partial correlation between N and λ estimates while controlling for the third BOXMOD estimate, γ , and find a significant positive correlation of .28 ($p < .01$). This association between movies' market size and their life cycle is robust and persistent in the U.S. market. Positive values also result when we do not control for the third estimate γ and when we compute the market indicator for each year separately. Thus, we use this partial correlation coefficient as our first market indicator to capture this distinctive feature of the real market. When fitting BOXMOD to the movies generated with our ABM, we should obtain a market indicator that corresponds to the value found in reality (.28).

Market indicator 2: movies' opening sales. This indicator reflects the relative contribution of movies' launch sales to their cumulative box office sales and follows extant research that distinguishes between opening and overall success (Dellarocas, Zhang, and Awad 2007; Gemser, Van Oostrum, and Leenders 2007). We used the life cycles in our data set to compute the percentage of cumulative box office sales obtained in the first week. On average, 36% of the cumulative sales are generated in the opening week. As with the first indicator, the percentage of opening sales of movies simulated with the ABM should correspond with this real value.

In the Web Appendix, we include additional details about the BOXMOD's parameters and their estimation and report the values of the two market indicators for each year from 2000 until 2010. In combination, these two market indicators enable us to identify levels of β_1 , β_2 , and β_3 that generate realistic simulation scenarios.

Simulations runs. We ran a factorial experimental design with different values for the internal, external, and shared consumption influences (β_1 , β_2 , and β_3). Because we are interested in the relative weights of these three components, without loss of generality, we constrain $\beta_1 + \beta_2 + \beta_3 = 1$ and investigate the following parameter values: $\beta_1 = \{.1, .2, .3, .4, .5, .6, .7, .8\}$, $\beta_2 = \{.1, .2, .3, .4, .5, .6, .7, .8\}$, and $\beta_3 = \{.1, .2, .3, .4, .5, .6, .7, .8\}$, obtaining 36 combinations in total. In addition, to test the robustness of our results against a wider range of the space of the ABM parameters, we simulate three values for the strength of advertising, represented by the parameter ω , and three values for advertising decay, represented by the parameter δ (i.e.,

$\omega = \{2.38, \pm 1 \text{ SD} = .88\}$, $\delta = \{.54, \pm 1 \text{ SD} = .10\}$). Note that these values for ω and δ derive from the empirical validation. The remaining parameters of the ABM are set at their default values, as indicated in Table 1. Finally, to ensure stability and convergence of the two market indicators, we rerun each scenario 60 times, because the market indicator values converge after approximately 30 runs but become very stable after 60 repetitions. Thus, in total we obtain 19,440 ($36 \times 3 \times 3 \times 60$) simulation runs. In the Web Appendix, we provide a detailed list of the simulation scenarios and the convergence analysis of the two market indicators.

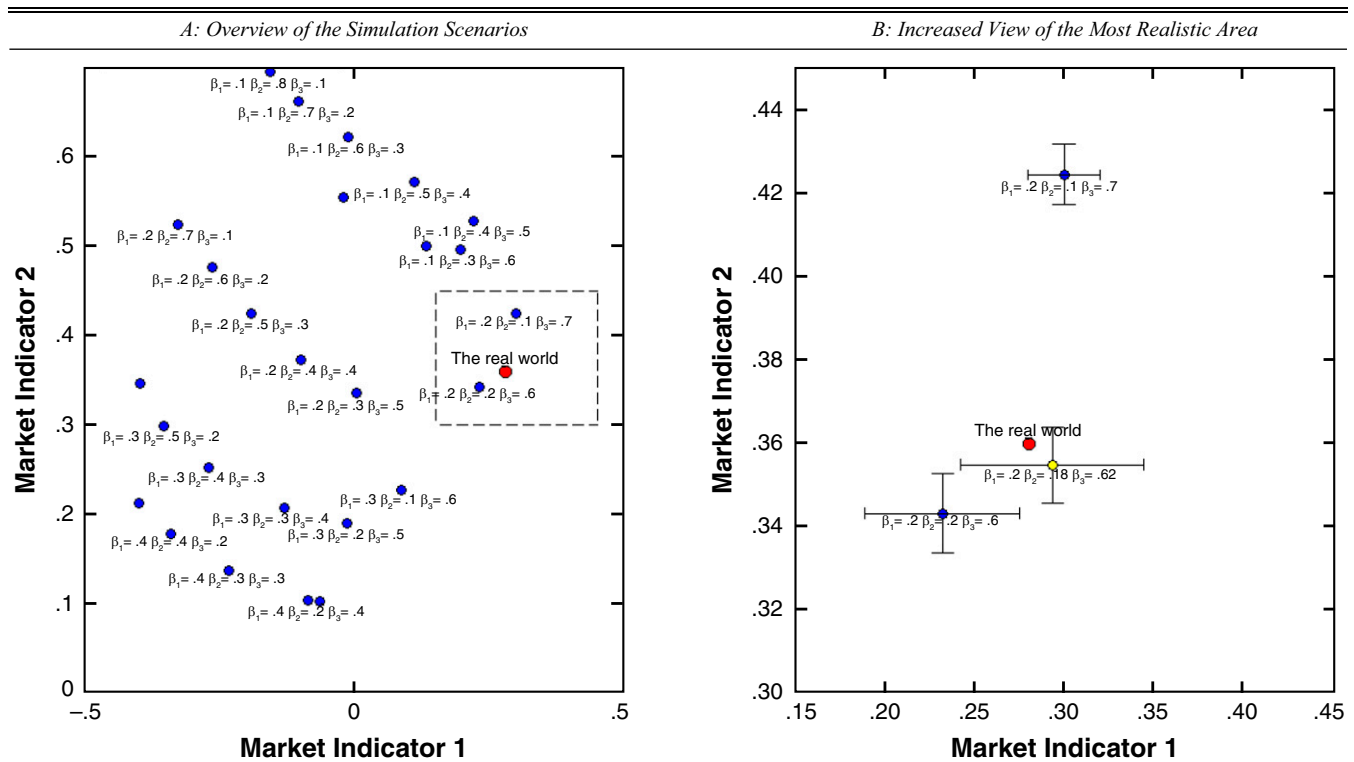
Figure 2 illustrates the output of this simulation experiment by plotting the values of the two market indicators for the real market (red dot) and the output of the simulation scenarios for different values of β_1 , β_2 , and β_3 (blue dots), reporting the average of the 60 runs, with $\omega = 2.38$ and $\delta = .54$. Note that the values of the real-market indicators are computed using the top 150 movies of the annual ranking. Thus, because our ABM simulates the market for one year, we also compute the output of each simulation scenario using the top 150 movies. Figure 2, Panel A, shows that when β_1 (internal influence) equals .1, simulation scenarios are unrealistic because both market indicators are too high (top-left corner). However, when β_1 is greater than or equal to .3, the scenarios are also unrealistic, because both market indicators are too low (bottom-left corner). The simulation scenarios that yield market indicator values that closely match those of the real world are for $\beta_1 = .2$; in particular, the two most realistic scenarios are those in which internal and external influence are low compared with shared consumption influence: $\beta_1 = .2$, $\beta_2 = .1$, $\beta_3 = .7$, and $\beta_1 = .2$, $\beta_2 = .2$, $\beta_3 = .6$. Furthermore, Panel A illustrates that realistically high values for the first market indicator are very difficult to attain. This indicator, which captures the association between movies' market sizes and the decay of their life cycles, is a true differentiator between realistic and unrealistic scenarios. When β_3 (shared consumption influence) is below .5, the first market indicator is always negative, indicating that a high level of shared consumption is thus necessary to attain realistic positive values for this indicator.

Panel B depicts an enlarged view of the dotted area in Panel A and also shows the standard deviations for the two market indicators (horizontal and vertical error bars). Because neither of the two most realistic scenarios we have mentioned include the real world within their confidence regions, we investigate additional simulation scenarios with finer-grained values for β_1 , β_2 , and β_3 and find that the most realistic scenario is for the following weights of internal, external, and shared consumption influence: $\beta_1 = .20$, $\beta_2 = .18$, and $\beta_3 = .62$ (yellow dot in Panel B).

Although these results are not based on an optimization procedure and cannot provide a definitive answer as to how much importance consumers attach to internal, external, and shared consumption influences in the motion picture market, they offer initial support to our first general hypothesis that shared consumption influence plays an essential role in the motion picture industry. In addition, they show that including a substantial influence of shared consumption on moviegoers' decision making leads to a more realistic simulation of the U.S. cinema market.

To further understand the effects of internal, external, and shared consumption influences on movie life cycles and

Figure 2
THE REAL-WORLD AND SIMULATION SCENARIOS



Notes: Panel A offers an overview of the output of the simulation scenarios (blue dots) against the real world (red dot). Panel B zooms in on the most realistic area (circumscribed by the dashed lines in Panel A) and includes an additional scenario's output (yellow dot), which is the most realistic simulation scenario after fine-tuning the weights β_1 , β_2 , and β_3 .

to test the robustness of our results, we regress the two market indicators against the parameters of our experimental design. Because β_1 , β_2 , and β_3 values are constrained to sum to 1, without loss of generality we consider the relative importance that internal, external, and shared consumption influences have to each other, (i.e., β_1/β_2 , β_1/β_3 , and β_2/β_3). Columns 3 and 4 of Table 2 present the results of this sensitivity analysis. We find that the first market indicator is most strongly influenced by the ratio between internal and shared consumption influence (β_1/β_3). The distinctive correlation of the motion picture

market between the market size of the movies and their decay decreases when, ceteris paribus, consumers attach more importance to internal influence. For higher levels of internal influence (β_1), movies, on average, attract more visitors during postlaunch because agents more strongly copy each other. Top-grossing movies strongly benefit from herding behaviors, prolong their life cycles through imitative behaviors, and thus do not display a fast decay. However, when consumers attach more importance to shared consumption influence (β_3), the opposite happens: after launch, big movies decay quickly because agents face

Table 2
SENSITIVITY ANALYSIS

Description	Regression 1	Regression 2	Regression 3
	DV: Market Indicator 1	DV: Market Indicator 2	DV: MSE
β_1/β_2 Importance of internal relative to external influence	.10**	-.38**	-.11**
β_1/β_3 Importance of internal relative to shared consumption influence	-.64**	-.70**	.52**
β_2/β_3 Importance of external relative to shared consumption influence	-.11**	.66**	.25**
ω Strength of advertising messages	-.27**	-.04*	.30**
δ Retention rate of advertising messages	.03**	-.25**	.03**
Adj. R ²	.60**	.81**	.62**

* $p < .05$.

** $p < .01$.

Notes: DV = dependent variable. MSE = mean squared error when fitting the simulated movies using BOXMOD. Standardized regression coefficients are displayed.

difficulty in finding companions to visit a movie with because so many have already seen the movie at launch. Accordingly, small movies are favored and do not decay rapidly, because not many moviegoers have seen the movie at launch.

Not surprisingly, we find that the second market indicator is most strongly influenced by internal and external influences. The percentage of opening sales decreases for markets with higher levels of internal influence because, in these circumstances, moviegoers strongly copy the behavior of other moviegoers, an occurrence that favors postlaunch rather than launch box office sales. The second market indicator increases when external influence becomes more important because the effects of the marketing campaigns are stronger at launch than at postlaunch. Contrarily, the impact of shared consumption influence on the second market indicator is rather weak. In this case, shared consumption influence plays a dual role. On the one hand, higher levels of shared consumption influence steer people toward the opening launch because it is easier for moviegoers to find companions, thereby increasing the indicator. On the other hand, higher levels of shared consumption influence enable movies with small openings to gain in postlaunch periods, which reduces the second market indicator.

Finally, our results provide additional indications of the effects of the strength and retention of advertising messages (ω and δ). Because the standardized coefficients of these effects are quite low with respect to the other effects described previously, we can first conclude that the results of our ABM are rather robust and are primarily affected by internal, external, and shared consumption influences (β_1 , β_2 , and β_3). Second, we find that when the ω parameter increases and prerelease advertising campaigns are weaker, they do not succeed in creating big launches (the second market indicator decreases), and top-grossing movies decay more slowly (the first market indicator also decreases). Moreover, we find that when advertising messages are retained longer (δ increases), movies attain more sales at postlaunch than at launch (the second market indicator decreases).

Our sensitivity analysis has demonstrated that shared consumption influence is essential in explaining the critical association between the decay of movie life cycles and market size. However, one may question whether such a positive correlation between the estimates emerges at the cost of a weaker fit between movie life cycles and BOXMOD. To exclude such a possibility, for each simulation scenario, we collect goodness-of-fit measures to study how well BOXMOD adhered to the life cycles of the simulated movies in each scenario. Then, we compute the average mean squared error (MSE) of the movies in each scenario and regress it against the parameters of the ABM (Table 2, last column). We find that the weights attributed to internal and external influences relative to shared consumption influence (i.e., β_1/β_3 and β_2/β_3) matter most in determining the MSE, with higher levels of shared consumption influence corresponding to a lower MSE. This result again confirms that shared consumption influence is essential in simulating realistic life cycles, as we formulate in H_1 . To demonstrate that shared consumption influence not only leads to more realistic market indicator values but also meaningfully improves the fit of the movie life cycles, we provide a simple example in Figure 3. We compare the real-life cycle patterns of a top-grossing movie (ranked 1st in

2001) and a small movie (ranked 150th in 2001) with those obtained in a realistic and an unrealistic simulation scenario. When comparing the life cycles of the same-ranked movies of our simulations using unrealistically low ($\beta_1 = .4$, $\beta_2 = .5$, $\beta_3 = .1$) and realistic ($\beta_1 = .2$, $\beta_2 = .2$, $\beta_3 = .6$) values of shared consumption, we observe that higher levels of shared consumption help more accurately explain the fast decaying pattern of top-grossing movies and the slower decay of small movies, which again supports H_1 .

Study 2: Advertising Effectiveness and the Moderating Influence of Shared Consumption

In the second study, we test H_2 – H_6 . For the tests of H_2 – H_4 , for each movie j , we create a new scenario by increasing movie j 's advertising budget (AD_BUDGET $_j$) by 25%. Thus, we create a new what-if scenario, in which we can simulate how a given movie would have performed, ceteris paribus, with a larger advertising budget and can assess how prerelease advertising affects launch and post-launch box office sales.

Following Libai, Muller, and Peres (2013), we also investigate how an increase in prerelease advertising induces an acceleration or acquisition effect on box office sales. In particular, we consider four outcome measures: acceleration of demand, acquisition of demand at launch, direct acquisition of demand at postlaunch, and indirect acquisition of demand at postlaunch. The Web Appendix provides a detailed example of how we compute these acceleration and acquisition effects. To test the moderating effects of shared consumption influence on the relationships between prerelease advertising and box office sales, as predicted in H_5 and H_6 , we analyze how the four outcome measures vary when the level of shared consumption influence changes.

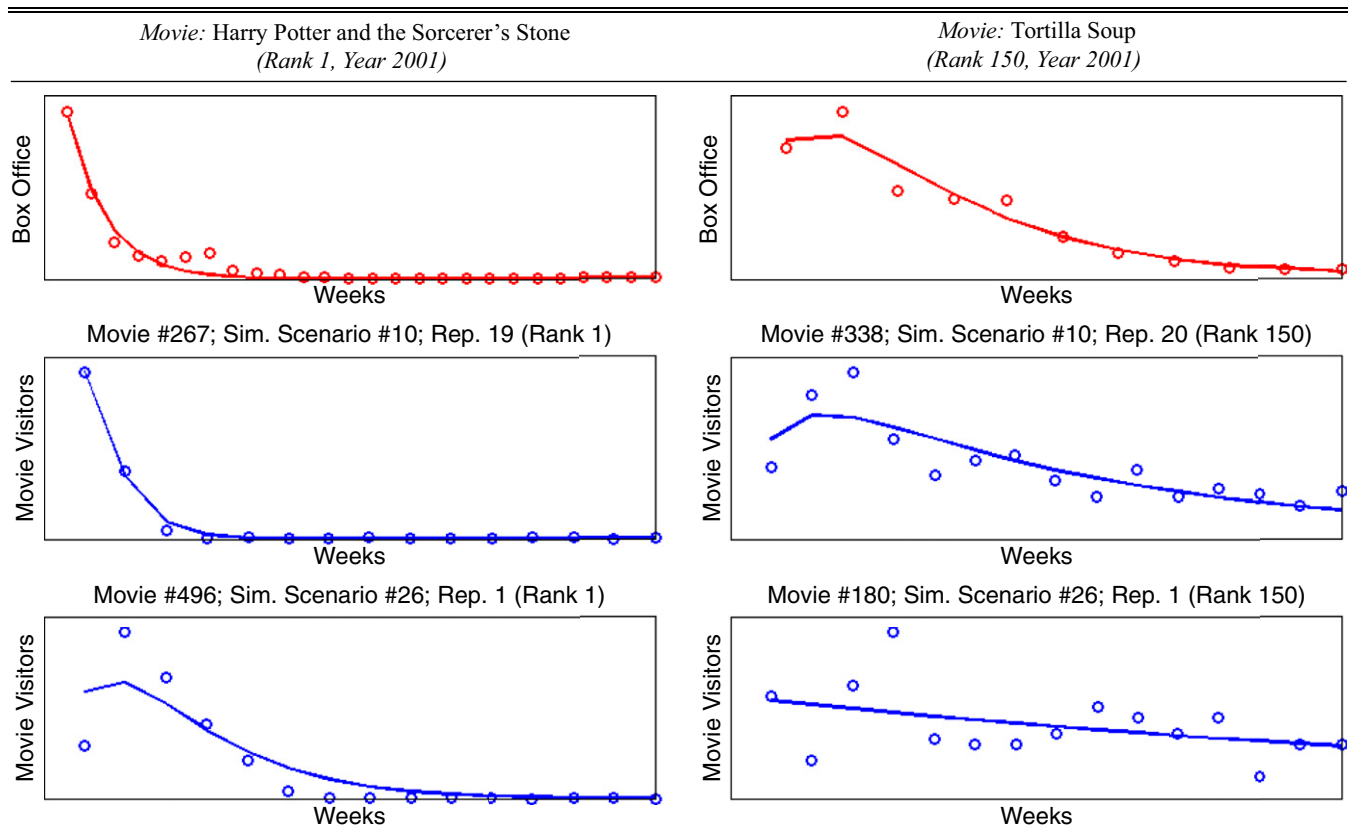
We set the levels of internal and external influence to realistic values ($\beta_1 = .2$ and $\beta_2 = .18$) and vary shared consumption within a realistic range ($\beta_3 = \{.52, .62, .72\}$) to replicate the most realistic scenario identified in Study 1. Then, for each of the top 150 movies, we create a distinctive what-if scenario in which we increase each movie's advertising expenditures. All other ABM parameters take their default levels, obtained from the empirical validation (Table 1). Thus, in total for this experiment, we obtain 450 (3×150) scenarios.

Effects of prerelease advertising on launch and postlaunch box office sales. Table 3 displays the effects of advertising on launch and postlaunch sales for the low and high advertising conditions and contains the decomposed results needed to test H_2 – H_4 . On average, when a movie increases its advertising expenditures by 25%, it obtains an acquisition of demand at launch of 24.40 visitors ($p < .01$; support for H_{2a}), an acceleration of demand of .16 visitors ($p < .01$; support for H_{2b} and H_{3b}), a direct acquisition of demand at postlaunch of 3.31 visitors ($p < .01$; support for H_{3a}), and an indirect effect of -1.66 visitors (no support for H_4 , because the observed effect is negative rather than positive).

We use these results to assess the financial consequences of such an increase in advertising expenditures. First, we determine whether current levels of advertising are (sub)optimal in the motion picture industry. Using the real advertising expenditures of our database, we observe that the average movie spends about \$11.7 million on advertising. In our

Figure 3

MOVIES' LIFE CYCLES IN THE REAL WORLD AND IN TWO SIMULATION SCENARIOS WITH LOW AND HIGH LEVELS OF SHARED CONSUMPTION INFLUENCE



Notes: The red plots show the life cycles of the first and the last movies of the top-ranked 150 movies' yearly box office ranking of 2001. The blue plots in the middle display the life cycles of the first and last movies in a realistic simulation scenario (i.e., simulation scenario #10 with $\beta_1 = .2$, $\beta_2 = .2$, and $\beta_3 = .6$). The blue plots at the bottom display the life cycles of the first and last movies in an unrealistic simulation scenario (i.e., simulation scenario #26 with $\beta_1 = .4$, $\beta_2 = .5$, and $\beta_3 = .1$).

ABM, we increased the advertising budget by 25%, which corresponds to an increase of \$2.93 million. The additional demand created for an average movie is 26.05 (24.40 + 3.31 - 1.66) agents. By relating the annual number of visitors in our ABM (189,757 total visits in the most realistic scenario) to that of the real market (1.43 billion visits; MPAA 2012) and assuming an average ticket price of \$6.50 (for 2000–2010), we determine that the 25% additional investment in advertising expenditures generates an increase in cumulative box office sales of \$1.27 million—much less than the \$2.93 million spent. This result aligns with previous

work that has shown that the returns of advertising for the average movie are negative (Elberse and Anand 2007; Joshi and Hanssens 2009). Moreover, considering that the lion's share of advertising costs is carried by the studio producers, but approximately 50% of ticket sales are shared with the exhibitor (Eliashberg, Elberse, and Leenders 2006), we anticipate that losses are even more pronounced in reality.

Second, although an increase in advertising expenditures leads to a significant acceleration of demand, the effect is very limited in size (.16 agents), especially compared with the acquisition effects at launch and postlaunch. Third, we

Table 3
EFFECTS OF AN INCREASE IN PRERELEASE ADVERTISING EXPENDITURES ON LAUNCH AND POSTLAUNCH SALES

Visitors at Launch	Visitors at Postlaunch	Acquisition at Launch: H_{2a}	Acceleration: H_{2b} and H_{3b}	Acquisition at Postlaunch (Direct): H_{3a}	Acquisition at Postlaunch (Indirect): H_4	Net Demand Effect
Low ad: 153.28	Low ad: 296.80	24.40** (1.29)	.16* (.06)	3.31** (1.01)	-1.66** (.40)	26.05** (1.45)
High ad: 177.84	High ad: 298.29					
Hypothesis testing		Accepted	Accepted	Accepted	Rejected	

* $p < .05$.

** $p < .01$.

Notes: Numbers refer to the average number of visitors gained by each movie with a 25% increase in advertising expenditures. Standard errors of the mean are in parentheses. Significance is based on whether the mean difference significantly differs from zero, using one-sample t-tests.

note the negative sign of the indirect acquisition at post-launch, which indicates that an increase in advertising expenditures determines a decrease in the indirect acquisition at postlaunch. Greater investments in advertising could generate higher box office sales at launch, which in turn should create more sales at postlaunch (H_4). Yet our results show that additional advertising does not generate this contagious effect and indirectly decreases sales at postlaunch. This can be explained by the high importance consumers attach to shared consumption. Because the importance of shared consumption is so high, the higher launch sales induced by additional advertising expenditures do not lead to more imitative behavior but actually make it more difficult to find companions after launch and thereby reduce postlaunch sales indirectly. In this sense, the high importance of shared consumption may cause movies' investments in advertising campaigns to cannibalize the fruitful, endogenous effect of imitative behavior.

Moderating effects of shared consumption. Table 4 shows how advertising effectiveness changes when consumers attach more or less importance to shared consumption influence. Thus, in addition to displaying the number of visitors at launch and postlaunch and the decomposed measures of acceleration and acquisition, as in Table 3, Table 4 provides detailed information for the three levels of shared consumption ($\beta_3 = \{.52, .62, .72\}$). As predicted in H_{5a} and H_{6a} , we find that if moviegoers attach more importance to shared consumption, the acquisition effect at launch becomes stronger, whereas the acquisition effect at postlaunch weakens. In particular, the 25% increase in advertising expenditures yields 17.30 additional visits at launch when shared consumption is low ($\beta_3 = .52$) but acquires 31.85 additional visits at launch when shared consumption is high ($\beta_3 = .72$). Conversely, when shared consumption is low, we obtain a positive postlaunch acquisition of 9.35 visitors, but when shared consumption increases, the postlaunch acquisition decreases and even becomes negative (-3.01 visits; $\beta_3 = .72$).

To confirm the interaction effect between ad expenditures and shared consumption, we run a repeated-measures analysis of variance model with within-movie contrasts (low vs. high ad expenditures) and between-movies effects

(150 movies for each level of shared consumption). Table 5 reports a positive direct effect of advertising at launch but not at postlaunch; positive direct effect of shared consumption at both launch and postlaunch; but, more importantly, significant interaction effects between ad expenditures and shared consumption at launch and postlaunch. As hypothesized, we observe a positive interaction effect at launch and a negative interaction effect at postlaunch. This noteworthy result offers insights into how advertising works during life cycles of hedonic products such as movies: advertising effects interact with the way consumers experience—or expect to experience—movies with others, with substantial impact on the pattern of movie life cycles. As we discuss in the “Discussion and Implications” section, this result provides theoretical insights and relevant managerial implications.

Finally, regarding our hypotheses on the acceleration effects, we reject H_{5b} and H_{6b} because the acceleration of demand does not increase significantly with higher levels of shared consumption. An increase in advertising expenditures results in a modest acceleration effect, independent of whether moviegoers attach high or low importance to shared consumption.

Ruling Out Alternative Explanations

Naturally, our conclusions derive from the analysis of our ABM—a model that is a simplified representation of reality and that makes several assumptions. If certain assumptions of our ABM were to be changed, our conclusions could change as well. To address this concern and ascertain the important role of shared consumption, we introduce a series of extensions of the model that invoke different assumptions and study alternative potential explanations. Although the testing of alternative explanations may provide new insights that demand further exploration, the main goal is not to investigate the alternative explanations in detail but to gain more confidence in the robustness of our results.

We proceed as follows: We introduce several modifications to the ABM and exclude shared consumption influence from the agents' decision making (setting $\beta_3 = 0$). Then, we run the modified ABM to test whether these model's extensions offer valid alternative explanations for

Table 4

MODERATING EFFECTS OF SHARED CONSUMPTION INFLUENCE ON THE RELATIONSHIP BETWEEN PRERELEASE ADVERTISING AND LAUNCH AND POSTLAUNCH SALES

	Visitors at Launch	Visitors at Postlaunch	Acquisition at Launch: H_{5a}	Acceleration: H_{5b} and H_{6b}	Acquisition at Postlaunch (Direct Effect): H_{6a}	Acquisition at Postlaunch (Indirect Effect)	Net Demand Effect
$\beta_3 = .52$	Low ad: 110.43	Low ad: 337.51	17.30 (1.25)	.23 (.09)	9.35 (1.57)	-1.88 (.68)	24.80 (2.21)
	High ad: 127.96	High ad: 344.75					
$\beta_3 = .62$	Low ad: 153.13	Low ad: 295.51	24.05 (2.12)	.05 (.11)	3.59 (1.73)	-2.52 (.68)	25.12 (2.59)
	High ad: 177.23	High ad: 296.54					
$\beta_3 = .72$	Low ad: 196.28	Low ad: 257.37	31.85 (2.87)	.19 (.12)	-3.01 (1.81)	-.59 (.71)	28.25 (2.69)
	High ad: 228.23	High ad: 253.57					
F-value			11.13**	.83	13.09**	2.02	.58
Hypothesis testing			Accepted	Rejected	Accepted		

* $p < .05$.

** $p < .01$.

Notes: Numbers refer to the average number of agents gained by each movie with a 25% increase in advertising expenditures. Analyses of variance show the (in) equality of means across the levels of β_3 , based on $F(2, 447)$ values.

Table 5
EFFECTS OF PRERELEASE ADVERTISING (ADS) AND SHARED CONSUMPTION INFLUENCE (SCI) ON LAUNCH AND POSTLAUNCH SALES

		Launch	Postlaunch
Between-movies effects	SCI	Positive effect 28.39** (.11)	Negative effect 93.19** (.29)
Within-movie contrasts	Ads	Positive effect 374.99** (.47)	Insignificant 1.80 (.00)
Within-movie contrasts	Ads × SCI	Positive effect 10.95** (.05)	Negative effect 8.33** (.04)

* $p < .05$.

** $p < .01$.

Notes: Numbers refer to the F-values derived from a general linear model with repeated measures. Partial eta-squares of effect size are in parentheses.

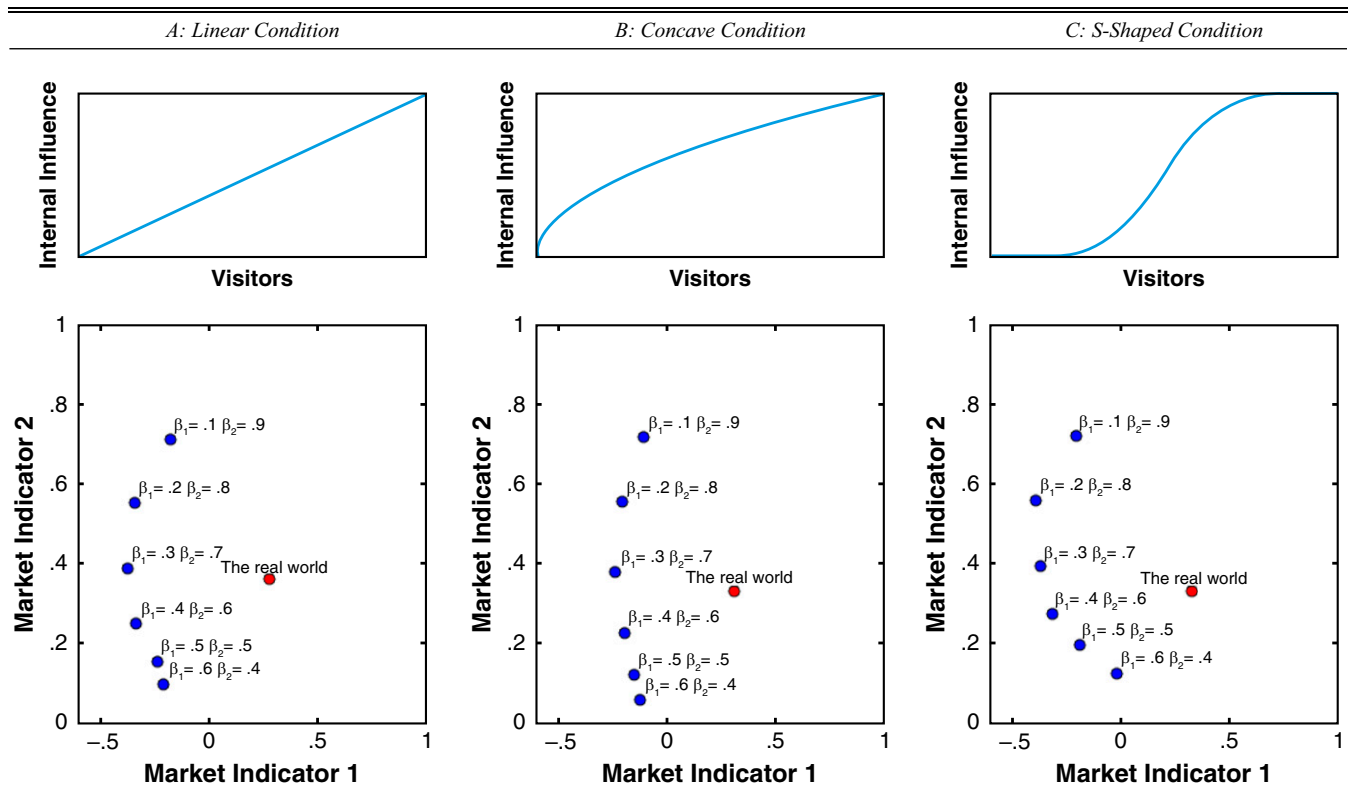
the crucial role of shared consumption. We focus on our first general hypothesis (H_1) and investigate whether, with such extensions and without shared consumption, our ABM generates realistic scenarios. We find that although the model's modifications result in different outcomes, the overall results of these extensions do not succeed in generating realistic scenarios. In particular, we provide substantial evidence that these modifications do not suffice to allow for the distinctive positive association between movies' market size and their fast decay, leading us to support the hypothesized contribution of shared consumption.

Nonlinear functional forms of internal influence. The way we model internal influence (Equation 4) assumes that the movie's attraction depends *linearly* on how many agents have visited that movie in the previous week. Although this assumption follows from previous formalizations of movies' life cycles (Dellarocas, Zhang, and Awad 2007; Elberse and Eliashberg 2003), we acknowledge that a different functional form may affect the shape of the movie life cycles and, thus, may have a significant impact on our market indicators. One may argue that the internal influence is a concave function that increases with the number of previous visitors, or that it follows an S-shaped function, which at first is convex and then concave (Watts and Dodds 2007).

Thus, we run a simulation experiment with three alternative conditions for internal influence—linear, nonlinear concave, and nonlinear S-shaped (Figure 4, Panels A–C)—with nine simulation scenarios in which shared consumption influence is excluded ($\beta_3 = 0$) and β_1 and β_2 vary from .1 to .9 and are constrained to sum to 1 (i.e., scenario 1: $\beta_1 = .1$ and $\beta_2 = .9$; scenario 2: $\beta_1 = .2$ and $\beta_2 = .8$, etc.). As before, we set all other parameters of the ABM at their default values, as in Table 1, and rerun each scenario 60 times. The specification of the functional forms is provided in the Web Appendix, and Figure 4 displays the results. Panel A displays the output of the ABM with the linear internal influence condition, Panel B shows the output of the concave condition, and Panel C shows the output of the S-shaped condition. In the absence of shared consumption,

Figure 4

EXPLORING THE IMPACT OF DIFFERENT FUNCTIONAL FORMS OF INTERNAL INFLUENCE ON THE TWO MARKET INDICATORS



Notes: In Panel A, internal influence is modeled linearly; in Panel B, internal influence is modeled with a concave function; and in Panel C, internal influence follows an S-shaped form.

we do not obtain any simulation scenario with realistic values for both market indicators. In all scenarios, without shared consumption, the first market indicator is negative (or close to zero), indicating highly unrealistic markets in which top-grossing movies do not decay rapidly as in the real U.S. market. Moreover, these results indicate that differences between linear and nonlinear functional forms are not substantial. With respect to the linear condition, the nonlinear formulations affect the performance of the different movies because the concave function improves performance of small movies and the S-shaped function punishes top-grossing movies. However, the results indicate that changing the functional form for the effect of internal influence does not account for the strong positive relationship between movies' market size and their decay.

As an additional check, we also modify the assumption that internal influence depends solely on the number of people who visited the movie at the previous time step, as opposed to when it depends on the cumulative visits of all previous weeks. Also in this case, results confirm that in the absence of shared consumption, the first market indicator is never positive. In the Web Appendix, we provide further details on such modification of the internal influence formalization and how it does not suffice to generate realistic scenarios. In summary, these results provide evidence of how, in our ABM, the effects of internal and shared consumption influences are very distinct in nature and result in substantially different outcomes on the life cycles of the motion picture market.

Network effects. Several studies have demonstrated that network structures that connect consumers and their degree distribution affect the spread of new products (Delre et al. 2010; Goldenberg, Libai, and Muller 2010; Watts and Dodds 2007). For example, the degree distribution of consumers' contacts may affect not only the strength of internal influence but also the penetration patterns of new products (Dover, Goldenberg, and Shapira 2012). The questions of (1) how different network structures may influence the shape of movie life cycles and (2) how networks of moviegoers decide together which movie to visit are interesting ones, but they are beyond the scope of this article. Nevertheless, one may question whether our main results remain the same when introducing a realistic network structure that connects moviegoers. Thus, to strengthen the robustness of our main contribution, we examine whether and how our results change if moviegoers are linked in networks and their decisions are affected by a limited set of local contacts.

To explore the influence agents' social connectedness on internal influence, we introduce a scale-free network structure in our ABM such that each agent i is connected to other moviegoers, CONTACTS_i . We opt for scale-free networks because they mimic both offline networks (Caldarelli 2007; Liljeros et al. 2001) and online social media, such as Facebook (Ugander et al. 2011), on which people have direct links to other people and can share opinions with one another. In these public arenas, members largely differ in terms of their contribution and visibility, as a few members establish many contacts, whereas the large majority have few links. This feature is captured by the power law degree distribution of scale-free networks, which covers a wide range of contacts per agents, from highly connected "influentials" to people with few contacts. We

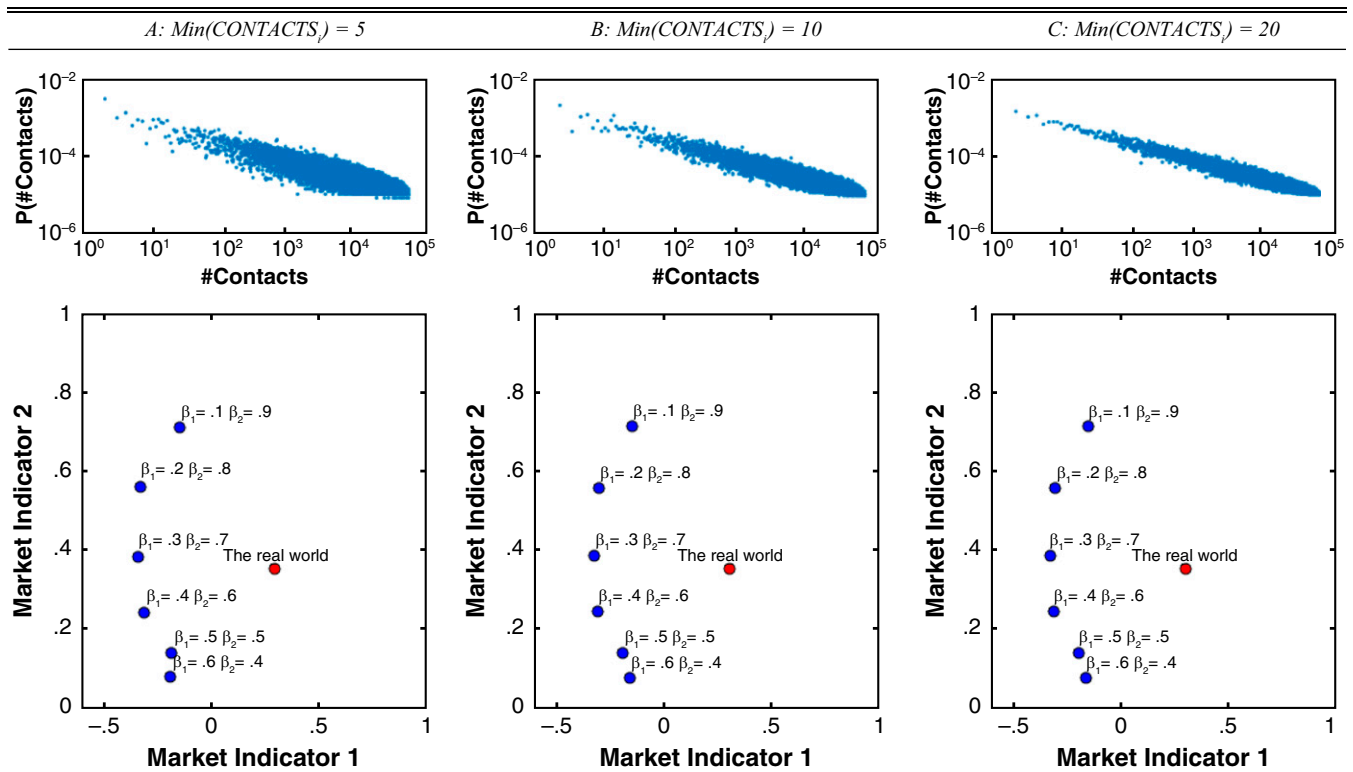
test the effects of scale-free network structures of different densities, varying the minimum number of contacts that each agent has with other moviegoers ($\text{Min}[\text{CONTACTS}_i]$) and considering three cases in which each moviegoer has at least 5, 10, and 20 contacts. In Figure 5, Panels A, B, and C, we illustrate the degree distributions of the three networks. In the Web Appendix, we provide a detailed description of how we generate the three scale-free networks, additional descriptive statistics on their structures, and how the local influence of direct contacts integrates the effect of internal influence. As in the previous model's modification, we run a simulation experiment with $\beta_3 = 0$ and the weights of β_1 and β_2 varying from .1 to .9; we set all other parameters of the ABM as before.

Figure 5 shows the results of the nine scenarios simulated for the three network structures, while in the Web Appendix we regress the two market indicators against the relative weight between internal and external influences β_1/β_2 and the minimum number of contacts per agent, $\text{Min}(\text{CONTACTS}_i)$. In this way, we assess the impact of network structures on the two market indicators as well as whether this model's extension offers an alternative explanation for the crucial role of shared consumption. Figure 5 shows that in all three cases, in the absence of shared consumption, scale-free networks with different densities of contacts do not generate realistic scenarios, because we observe negative associations for the first market indicator. In addition, the regression results presented in the Web Appendix provide evidence that the number of contacts agents have in their local network does not significantly affect the two market indicators, again providing assurance as to the robustness of our results.

Although these findings confirm that our results do not drastically change when internal influence works not only globally but also through a limited set of local contacts, we recognize the limits of this robustness check. For example, we do not consider how clustered the network is or how quickly WOM spreads across contacts, nor do we investigate how local contacts affect joint decisions and shared consumption. Obviously, all these aspects depend on the network's characteristics and can alter the way moviegoers decide on and consume movies together. In this regard, we note that shared consumption influence is a form of direct network effect (Peres, Muller, and Mahajan 2010), as it affects the product's attractiveness through the presence of others who adopt the same product at the same time and place. As such, the process through which shared consumption unfolds likely depends on how moviegoers are connected and how strong their relationships are. In the next section, we invite further research on group decision making to investigate this issue.

Homophily. Although our ABM introduces agent heterogeneity in many aspects—such as visiting frequency (F_i); the number of companions with whom agent i wants to visit a movie (g_i); and, when adding a network structure, the number of individual contacts (CONTACTS_i)—it does not account for homophily. Homophily, the tendency for people to have friends with similar tastes and preferences, has been widely reported in many studies. Although there is very little evidence on how homophily affects global diffusion (Golub and Jackson 2012), research has shown that homophily may confound the effects of WOM on

Figure 5
EXPLORING THE IMPACT OF DIFFERENT NETWORK STRUCTURES ON THE TWO MARKET INDICATORS



Notes: Panels A, B, and C display the degree distribution and corresponding simulation outputs of the three scale-free networks with $\text{Min}(\text{CONTACTS}_i) = 5$, $\text{Min}(\text{CONTACTS}_i) = 10$, and $\text{Min}(\text{CONTACTS}_i) = 20$, respectively.

individual adoption behaviors (Aral and Walker 2012) and overestimate social influence in adoption decisions (Aral, Muchnik, and Sundararajan 2009).

As for the contribution of our study, one may argue that homophily may steer friends to see the same movie not because they want to experience the movie together or because they want to copy the behavior of moviegoers that have already seen the movie but because they have overlapping tastes. However, although it makes intuitive sense that homophily can alter the shared consumption influence, it is not initially clear how the effect of shared consumption may change. In homophilious networks, connected agents share similar characteristics such that they are interested in similar movies. On the one hand, this similarity among connected agents may favor joint consumptions because friends can more easily coordinate their decisions toward the same movie. On the other hand, more similarity may also hamper joint consumption because if a consumer is interested in a given movie, it is also more likely that friends with similar preferences may have already visited that movie.

Accounting for homophily in our model may alter not only the effect of shared consumption but also the contagion effect of internal influence. Homophily generally increases the speed of adoption within friends' networks because friends are more likely to trust and accept messages from similar others. Nitzan and Libai (2011) reveal this effect in explaining consumers' churn decisions as they find that consumers are more strongly affected by prior

churns of friends who are more similar to them. Risselada, Verhoef, and Bijmolt (2014) also account for homophily by considering the similarities among contacts when studying consumers' individual adoption and find that homophily increases the individual hazard of consumers' adopting smartphones. However, these studies focus on individual decisions and cannot infer what happens to global diffusion, as homophily implies both that more similarities exist *within* groups of contacts and that more dissimilarities exist *across* groups (i.e., a greater dissimilarity among unconnected agents). Similar dynamics may pertain to contagion effects among moviegoers, in the sense that more homophilious networks may promote imitation within local groups of similar friends but may also slow the diffusion across dissimilar groups. Following these lines of reasoning, we conclude that whether homophily favors or hampers global diffusion is certainly a worthwhile, relevant open research question. Together with internal and shared consumption influences, homophily may play a role in shaping movie life cycles, but its effects are difficult to project.

We explore the effects of homophily in the Web Appendix. We include the option of having homophilious networks in our ABM, simulate different levels of homophily, and explore their effects on the two market indicators. We study whether different levels of homophily in the population of moviegoers affect the attraction derived from internal and shared consumption influences, x_{ijt} and z_{ijt} , of their selected movies, and then we investigate

whether these deviations determine significant changes in the market (i.e., in our two aggregate market indicators). Although the formalization of homophilious networks into our ABM involves some limitations that we thoroughly describe in the Web Appendix, we derive noteworthy results that we discuss briefly here. We find that in more homophilious networks, the attraction derived from shared consumption influence increases, whereas the attraction obtained from internal influence does not significantly change. We also find that these changes are rather limited in size (see the Web Appendix). In line with the previous tests, homophily does not seem to generate the typical positive relation between movie market size and the decay of movies' life cycles (see the Web Appendix). At the same time, because these tests report significant effects, they invite future studies to assess how homophily influences the way consumers decide and, thus, affects aggregate diffusion dynamics.

In summary, we have investigated whether alternative explanations may re-create the positive association between movies' market size and their fast decay, which we attribute to shared consumption influence. Because we examine each alternative explanation in isolation, it is still possible that although no single alternative explanation can account for this effect, multiple alternative explanations together can do so. Although this may be possible in such models, we believe this is not probable, because it is difficult to hypothesize why such an interaction could generate this effect in the market. Thus, we conclude that the exploration of the alternative explanations strengthens our confidence that shared consumption is an essential driver for this association.

DISCUSSION AND IMPLICATIONS

Key Theoretical Implications

This study uses an ABM to simulate the competition of the motion picture market. Our results imply relevant theoretical insights that contribute to the literature in several ways. First, they suggest that shared consumption influence is essential for explaining the life cycles of such hedonic products as well as the temporal effects of advertising on sales. In reality, we find a persistent positive relation between movies' market size and how fast their life cycles decay. Only when introducing the shared consumption influence in the moviegoers' decision making do we obtain such a relationship in the movies' life cycles. According to our ABM simulation results, the importance that moviegoers attach to shared consumption is stronger than the weight they attach to external and internal influences. This result is novel because it is the first to document the crucial role of shared consumption influence in the motion picture industry.

Second, although our results confirm that both internal and external influences still have relevant effects on the shape of the diffusion life cycle and that both are needed to model movies realistically, they suggest that these well-documented effects are quite limited in size. As for the effects of external influence, we find that advertising expenditures help create strong launches and acquire demand at launch but that their effects quickly wear off. The limited impact of advertising is in line with previous works in this

industry (Elberse and Anand 2007; Joshi and Hanssens 2009). In this regard, our study shows that an increase in advertising mainly results in an acquisition of demand rather than acceleration of demand. Similar to the findings of Libai, Muller, and Peres (2013), which show that firms' investments in seeding marketing campaigns generate success through market expansion, rather than acceleration, we show that the same results hold for movies' prerelease advertising campaigns. Moreover, our results indicate a notable interaction effect between shared consumption and advertising: the differences between the acquisition of demand at launch versus postlaunch become more pronounced when consumers attach greater importance to shared consumption. This result offers insight into how advertising works during movie life cycles: advertising effects interact with the way consumers experience—or expect to experience—movies with others.

Third, our findings help increase understanding of the dynamics of social influences that affect the diffusion of new hedonic products such as movies. Indeed, previous studies have shown that internal influence, such as WOM, affects box office success and that its effect may vary throughout the movie's life cycle (Chintagunta, Gopinath, and Venkataraman 2010; Liu 2006; Norris, Foutz, and Kolarici 2012). For example, Liu (2006) finds that WOM activities during prerelease and opening weeks stimulate opening week box office sales, with a particularly strong influence at launch that decays rapidly thereafter. Norris, Foutz, and Kolarici (2012) find that advertising expenditures, in synergy with WOM, are more effective in driving demand in the earlier theatrical stage of movie releases than in a later video rental stage. Using Godes and Mayzlin's (2009) distinction between consumer-generated WOM and firm-generated WOM, we argue that the WOM measured in Liu (2006) and in the theatrical stage of Norris, Foutz, and Kolarici (2012) is not traditional, consumer-generated WOM provided by adopters but, rather, firm-generated WOM created through heavy advertising. By showing that the interaction between shared consumption and strong prerelease advertising campaigns can steer consumers to visit a movie together, particularly at launch, we offer a possible explanation for findings that social influences affect box office sales at launch rather than postlaunch. That is, the interaction effect between advertising and shared consumption influence persuades many visitors to visit a movie together at launch, when advertising campaigns peak and all friends are potential companions. In turn, more movie discussions and higher sales likely occur at launch and quickly perish in the subsequent weeks. In this regard, Karniouchina (2011) correctly denotes consumer-to-consumer discussions on online movie portals (e.g., Yahoo Movies) as movie buzz. Her results show that higher advertising budgets increase movie buzz and that movie buzz affects box office sales at launch, in line with our interpretation of online consumer-to-consumer discussions as firm-generated WOM. Following this line of reasoning, the recent theoretical identification of different types of WOM by Lovett, Peres, and Shachar (2013) seems extremely relevant for clarifying various forms of consumer-to-consumer discussions, as well as their dynamics, relations with advertising, and effects on the diffusion of new products.

Fourth, this study contributes to the ABM literature by showing a possible way to develop and empirically validate ABMs in a market with new products launching, competing, and exiting. We show how to embed complex social dynamics in a parsimonious ABM and assess the influence of social influences, such as shared consumption influence, on competitive diffusion cycles.

Managerial Implications

Our results suggest several relevant managerial implications. Our finding that moviegoers attribute high importance to shared consumption influence suggests that exhibitors should organize theme nights to cater to the needs of specific social groups (e.g., women's nights, children's parties, midnight releases), offer specific marketing promotions to stimulate group visits (e.g., second ticket for free), and facilitate group movie selection and planning through social media (e.g., using Facebook to find companions). In addition, advertising through social media in early stages of the life cycle will stimulate shared consumption and, thus, box office revenues. However, in the postlaunch stage, promotional activities and the provision of social media tools or apps that facilitate group visits could counterbalance the difficulty to find companions, help sustain postlaunch sales, and attract consumers who otherwise would attend newly released movies.

Our results also provide suggestions for exhibitors on how to allocate the number of screens in their theaters. We find that box office sales of movies of larger market size decay faster. However, when substituting the box office sales with the weekly number of screens, the positive relationship between movies' market size and their decay disappears (see the Web Appendix). This indicates that cinema exhibitors do not take this important aspect of the market into account. Krider et al. (2005) study the lead-lag relationship between distribution (number of screens) and demand (box office sales) in the motion picture industry and show that for 90% of movies, box office sales lead screen allocation. Exhibitors could improve the allocation of their screens by identifying movies whose box office sales may decay very quickly from the effect of shared consumption and possibly reallocate the screens to other movies.

Our contribution provides noteworthy implications for studio producers, too. First, in search of higher box office sales, studio producers advertise their movies heavily prior to release to stimulate moviegoers to visit movies together at launch. This study provides a justification for this strategy to promote group visits because the motion picture industry is characterized by short product life cycles, for which product quality is difficult to assess up front, products are available in abundance, and purchase enhances social bonding (Hennig-Thurau, Marchand, and Marx 2012). Our findings indicate that because consumers attach high importance to shared consumption, studios are right to advertise heavily prior to release to recoup their huge investments quickly and capitalize on shared consumption.

Second, studio producers and exhibitors use sliding-scale agreements, in which a studio's shares are highest (approximately 60%–80%) in the first week and decline (50%) in the following weeks (Eliashberg, Elberse, and Leenders 2006). Therefore, on average, studios benefit from shared consumption influences more than exhibitors

because group visits are easier to encourage at launch than at postlaunch. Consequently, we believe studios should investigate possible ways to leverage on these consumers' needs. Similar to product designs that stimulate WOM (Aral and Walker 2012), studio producers may also create movies with certain characteristics that stimulate group visits. As preliminary evidence, we found that horror, action, and thriller movies, on average, decay faster than movies of other genres, possibly because moviegoers like to visit them in large groups and it is easier to set up such large group visits when movies are released. Studio producers and exhibitors should be aware of these differences and exploit them. For example, studio producers may intensify pre-release advertising to facilitate group visits at launch for specific movie genres that appeal to large group sizes, while cinema exhibitors need to allocate and combine different genres to optimize screen allocation.

Third, even though heavy prerelease advertising can create strong launch sale effects, our results also indicate that, on average, studios overspend on advertising campaigns. Advertising may seem effective, especially in generating acquisition effects at launch, but the high importance consumers attach to seeing movies together creates a counterproductive effect that severely weakens the acquisition effect at postlaunch. Film studios, therefore, should reconsider their prerelease advertising expenditures in their sole pursuit of launch success and should better acknowledge the negative causes of low sales at postlaunch, when consumers have more difficulty finding companions with whom to share the consumption experience.

Research Limitations and Further Research

We highlight three main limitations of our research. First, our focus is on the motion picture industry, which is a peculiar industry, characterized by a high frequency of shared consumption, heavy prerelease advertising, prefixed supply and prices, relatively short product life cycles, and nonrepeat purchases. Although we believe our findings provide important implications to other hedonic products (e.g., video games, music albums, books, events, concerts, art exhibitions, trade shows) that can be consumed together, spread rapidly, are not repurchased, and often launch with strong prerelease advertising campaigns, additional studies should assess how shared consumption influences shape the life cycles of other hedonic products and whether similar acquisition and acceleration effects arise.

Second, to model shared consumption influence, we make some important assumptions about how movie visitors decide which movies to see and how shared consumption affects their decisions. We did not model how and in which form shared consumption takes place but instead modeled its influence probabilistically for reasons of parsimony. Further research on group decision making can specify how groups form, how consumers discuss and jointly decide which movie to visit, whether certain consumers have a larger impact on group decisions and thereby on sales, and the effects of consumers visiting different movies repeatedly with the same group's composition (e.g., couples of significant others). Moreover, our study models the impact of shared consumption on the aggregate market outcomes; we do not model the actual group sizes of single movies and cannot establish how shared consumption

predicts the success of individual movies. With the increasing availability of data on groups of friends (from, e.g., Facebook, WhatsApp) and on actual purchases of movies' group visits (FFA 2011), further research can measure this effect and study how shared consumption varies throughout the movie life cycle and simultaneously determine which consumers most strongly influence the diffusion; moreover, it can incorporate shared consumption influence into new product diffusion models, such as the Bass model and BOXMED, and estimate it using box office sales data. Beyond the main effect of advertising effectiveness and interaction effects with shared consumption, future studies can also investigate interaction effects of shared consumption influences with other movie characteristics, such as genre, the presence of famous stars and directors, or motion picture rating. As we have mentioned, initial evidence on genre data (see the Web Appendix) suggests that shared consumption differs across genres, and genres that appeal to larger group sizes decay faster than those that appeal to smaller group sizes. Such genre differences may exist for other effects such as internal and external influence.

Third, we model the importance of internal, external, and shared consumption influences as constant over time and introduce visitors' heterogeneity on only a few aspects of their decision making. Further research can explore whether shared consumption influence may vary over time (e.g., it may be particularly strong during Christmas or Valentine's Day), how customers' tastes are distributed, and how they relate to internal, external, and shared consumption influences.

Fourth, in our ABM, the number of visits per year does not depend on industry-level advertising, which results in a zero-sum game: increased demand for one movie comes at the expense of another. In the United States, movie visits have been relatively stable for at least a decade (MPAA 2007, 2012), so this assumption appears realistic. Still, extraordinary events pushed by very high investments, such as the releases of *Marvel's The Avengers* or *Avatar* in 3D, may shift visitors' tendencies to choose certain movies (Elberse 2013). We also acknowledge that studio producers could learn about the effectiveness of advertising and strategically react and adjust the level and timing of their advertising. Moving away from a fixed potential to a dynamic potential can have significant implications for temporal advertising effects. Further research could expand our current ABM to incorporate more complex behaviors on both the demand and supply sides, including consumers' utility optimization, responses to viral marketing or referral reward programs, and dynamic competitive reactions. Although a great deal of work is still needed to understand the precise mechanisms and effects of shared consumption on the diffusion curves and ultimate success of hedonic products, we hope this study constitutes a first step toward this goal.

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