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Competitive strategies in the motion picture industry: An ABM to study investment decisions

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Abstract: We study a parsimonious competition setting whereby two studio producers launch their movies simultaneously. They compete deciding about the positioning of their movies, as they can position close to or far from the mainstream, and investing in advertising and in quality. We study our competitive setting with an analytical model and solve it using a standard game-theoretical technique. Next, we use an agent-based model (ABM) to relax several assumptions of the analytical model and investigate more realistic market situations, such as symmetric as well as asymmetric positioning, competitions among big and/or small studios, settings with more than two competitors, and studios that use weighted and evolving decision rules. Our results explain interesting dynamics behind the scenes of the competition. They indicate the drivers of studios' behaviors and shed light on some important aspects of their strategic competition. In this sense, our results offer relevant theoretical and practical implications.

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Competitive strategies in the motion picture industry: An ABM to study investment decisions

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1 Introduction

Many experience goods, such as movies, video games, books, CDs, concerts, and sporting events, enter the market, have a very short life cycle, and exit. Competing firms launch them regularly, often on a weekly basis. Their success depends on how much buzz their advertising campaigns create before their products enter the market (Karniouchina, 2011; Liu, 2006), but also on how much firms have invested in their products' quality (Kopalle & Lehmann, 2006). Both decisions are critical to win the competition, because future sales depend not just on advertising but also on the judgments of the consumers who actually experience the quality of the products and create word of mouth (Bass, 1969; Mahajan, Muller, & Kerin, 1984).

We consider a parsimonious, strategic competition setting for experience goods in which firms compete for the same target, launch their products at the same time, and decide how much to invest in advertising and quality. Several features distinguish our model from existing literature. First, we design our model to apply to the motion picture industry. Most marketing literature that refers to this industry focuses on the effects of advertising on sales and profits (Ainslie, Dréze, & Zufryden, 2005; Basuroy, Desai, & Talukdar, 2006; Elberse & Anand, 2007; Elberse & Eliashberg, 2003; Hennig-Thurau, Houston, & Sridhar, 2006; Joshi & Hanssens, 2009; Prag & Casavant, 1994; Zufryden, 1996). Yet few studies investigate how studio producers compete strategically. In this paper we investigate which investment strategies studios should use, and how their decisions impact studios' profits.

Second, we link studios' budget decisions to the positioning of competing movies in the market. Studios can position their movies close to or far from the mainstream. When movies approach the mainstream, they aim at the mass market or the average preferences of the target segment, whereas when they move away from the mainstream, they focus on customer niches with more extreme preferences (Gemser, Van Oostrum, & Leenders, 2007; Zuckerman & Kim, 2003). Thus, our model also provides information about launching more or less mainstream movies.

Third, we take advantage of a stimulating method of analysis that exploits the interplay between analytical modeling and agent-based modeling (Rand & Rust, 2011). We begin by studying a duopolistic competitive setting with an analytical model and solve it using a standard game-theoretical technique. Next, we use an agent-based model (ABM) to relax several assumptions of the game-theoretical model and investigate more realistic market situations. In our ABM, studios decide how much to invest in advertising and in quality using two simple and realistic decision rules: a *repeat/imitate rule* in which a studio repeats its decision if it performed better than the competitor or copies the decision of the competitor if it performed worse; and a *trend rule* in which studios simply follow recent profitable trends. In this way, we use the analytical model to achieve generalizability and the ABM to investigate interesting extensions of the model that more realistically adhere to the motion picture industry. Specifically, our ABM allows us to study symmetric as well as asymmetric positioning, competitions among big and/or small studios, settings with more than two competitors, and a number of more realistic features of the market.

With these advances, we obtain several interesting results. First, focusing on two major studios positioning their movies equidistant from the mainstream, we find that strategies based on the trend rule are the most profitable. However, this occurs only with symmetric positioning. When studios do not position their movies equidistant from the mainstream and use different rules, the dynamics of the competition change substantially. We find that if a studio uses the trend rule, the competitor can obtain high profits using the repeat/imitate rule as well. This makes the competition very critical because if both studios use the repeat/imitate rule in an attempt to beat each other, they end up with significantly lower profits. Second, when simulating competitions between big and small studios, we find that the major studio should use the repeat/imitate rule, invest substantial budgets, and position very close to the mainstream; whereas the small studio should take some distance from the mainstream only if it reduces its investment considerably by using the trend rule. Third, we conduct several robustness checks and an additional study in which we simulate a market with more than two studios that use weighted and evolving decision rules. In all these cases our results contribute to explaining why competition in this industry is very tough and profits are so low.

2 Competition in the motion picture industry

2.1 Head-to-head competition

We begin by modeling competition between two film studio producers that release their movies at the same time—that is, head-to-head (Krider & Weinberg, 1998). Head-to-head competition occurs very often in reality, especially during high-demand periods (e.g., the Christmas season, pre-award periods), when powerful studios engage in fierce competition in the launch of their movies (Epstein, 2010, Krider & Weinberg, 1998).

In our model, two studios ($i = 1, 2$) produce and simultaneously release their movies after making choices about two strategic variables: how much to invest in advertising the new movie a_i, and how much to invest in making a good movie b_i. Similar to Krider and Weinberg (1998), we model competition between the two movies in a share attraction framework: When the studio allocates its money, it presumes that more prelaunch advertising increases its share of voice and lures more consumers to see its movie (Bell, Keeney & Little, 1975; Jones, 1990; Schroer, 1990). Furthermore, the studio assumes that investing more in making the movie will increase its quality (Kopalle & Lehmann, 2006). We illustrate this competitive setting from the point of view of studio $i = 1$ in Figure 1.

Figure 1 about here.

We collapse the movie life cycle into two periods, such that consumers attend Movie 1 at either its launch or at its post-launch. In our shared attraction framework, at launch, consumers are more attracted to Movie 1 if they have been exposed to more pre-launch advertising of Movie 1 than Movie 2—that is, when a_1 is greater and a_2 is smaller. We let q_1^L indicate viewership of Movie 1 at launch. In the post-launch period, consumers' attraction to Movie 1 depends on word-of-mouth effect, WOM_1. In line with extant literature on innovation diffusion and word of mouth in the motion picture industry, we anticipate that WOM_1 depends on two factors: its volume, or the number of consumers who have experienced the movie at launch (q_1^L), and its valence, which the studio can increase by investing more in quality and producing higher-quality products that invoke better judgments from experienced consumers (Bass, 1969; Godes & Mayzlin, 2009; Liu, 2006; Neelamegham & Chintagunta 1999; Peres, Muller, & Mahajan, 2010). In turn, WOM_1's volume and valence determine viewership of Movie 1 in the post-launch period, which we indicate with q_1^{PL}.

2.2 Movie positioning

Borrowing from extant marketing studies on strategic competition and location models (Hotelling, 1929; Hauser, 1988; Moorthy, 1988; Vandenbosch & Weinberg, 1995) that formalize consumers' preferences as tastes on the horizontal dimension (Desai, 2001; Liu, Putler, & Weinberg, 2004), we model two studios that face a target segment of N consumers with heterogeneous preferences $\theta_j \sim U_{[0,1]}$ and position movies of type P_i for the same target segment, as in Figure 2. Their movies can be close to or far from the mainstream, such that more mainstream movies aim at the mass market and less mainstream movies focus on the edges of the market (Gemser, Van Oostrum, & Leenders, 2007; Zuckerman & Kim, 2003). This distinction is very common in the motion picture market, and our location model adequately captures it: Movies located toward the center of the target segment are more mainstream because they are closer to the average preference of the market, whereas movies that are near the edges are less mainstream products that meet more extreme preferences.

Graphs A and B show symmetric competition by movies equidistant from the average consumer, such that $P_1 = 0.5 - d$ and $P_2 = 0.5 + d$, where d indicates how distant the two movies are from the mainstream. When d decreases, the two major studios move toward the mainstream, and their movies become more similar. Obviously, studios are attracted to the center of the target segment, because from that location they can more easily meet the preferences of consumers; it is where a monopolistic studio ideally would locate. However, when approaching the mainstream, the two competing studios exacerbate competition because their movies become more similar and attract the same consumers.

Graph C instead illustrates an asymmetric competition with one studio that dominates the center of the target segment and launches a typical mainstream movie that meets the average preferences of the target segment, and another studio that launches a less mainstream movie aimed at more extreme preferences.

Figure 2 about here

Our formalization is based on the idea that mainstream movies are closer to the average preference of the market. We acknowledge that this is not the only way of modeling the mainstream. One may think of alternative formalizations of the mainstream concept using a location model a la Hotelling. For example, one may think of a mainstream movie as a segment, instead of a point, that covers a bigger part of the market and attracts more preferences. In Appendix C we propose a formalization in this direction and then in the discussion section we address its implications.

2.3 Moviegoers' behavior and studios' profits

We consider a market with N consumers. We define the attraction of a consumer j to studio i's movie at launch as $A_{ij}^{L} = U_{ij}^{L} - \gamma$, where U_{ij}^{L} is the utility of seeing movie i at launch and $\gamma \geq 0$ is the outside good, or utility derived from other leisure activities. At launch, consumer j sees the movie with the highest positive attraction. If the attractions of both movies are negative, consumer j prefers the outside good and does not see any movie. Then, at post-launch, consumer j considers only the movies not seen at launch. It is attracted to studio i's movie by $A_{ij}^{PL} = U_{ij}^{PL} - \gamma$, where U_{ij}^{PL} indicates the utility of seeing movie i at post-launch. Note that in this formalization, consumer j cannot see the same movie at launch and at post-launch. We model the utilities as follows:

$$U_{ij}^{L} = \frac{\sqrt{a_i}}{c + \mid \theta_j - P_i \mid}, \tag{1}$$

$$U_{ij}^{PL} = \frac{WOM_i}{c + \mid \theta_j - P_i \mid}, \text{ and} \tag{2}$$

$$WOM_i = \delta \; q_i^L \; \bar{Q}_i, \tag{3}$$

where $|\theta_j - P_i|$ indicates the distance between the consumer's preference θ_j and the movie's type P_i, that is, how well the movie released by studio i matches the tastes of consumer j. The quantity $c > 0$ is a parameter that restricts utilities to finite values, as in discrete choice models (Chintagunta, 2002). This parameter reflects the practical constraints of the movie's consumption, such as the distance to the theater, its comfort, and so forth. In Equation 1, we assume decreasing returns to advertising expenditures (Assmus, Farley, & Lehmann, 1984; Simon & Arndt, 1980). In Equations 2 and 3, we define post-launch utility and word of mouth. We specify that WOM_i consists of volume, valence, and persuasiveness (Neelamegham & Chintagunta, 1999). Volume equals viewership at launch q_i^L, and valence is a quality indicator that depends on the average valuation of consumers who have experienced movie i, $\bar{Q}_i$. Assuming that the valuation Q_i^j of consumer j for movie i is an iid variable with $Q_i^j = \sqrt{b_i} + \varepsilon_i^j$ and $E(\varepsilon_i^j) = 0$, such that $\bar{Q}_i = \sqrt{b_i}$, we capture the idea that studios, when deciding to invest in making the movie, expect to increase quality and the valence of word of mouth by increasing their investment in quality. Also for quality investment, we assume decreasing returns. Finally, persuasiveness, measured by δ, specifies how much word of mouth affects utilities, such that it indicates the strength of word of mouth in the cinema market.

Because q_i^L refers to viewership at launch (i.e., how many consumers see movie i at its launch) and q_i^{PL} indicates viewership at post-launch (i.e., how many consumers see movie i at its post-launch), we can indicate cumulative viewership as $q_i^{CUM} = q_i^L + q_i^{PL}$. In the motion picture industry, total viewership is a clear indicator of the theatrical success of the movie because the ticket price is fixed across movies. Thus, the cumulative viewership q_i^{CUM} is a suitable measure of box office revenues. We measure studio i's performance as the difference between cumulative viewership and total budget investments. We call this measure π_i because it indicates the profit of studio i:

$$\pi_i = q_i^{CUM} - (a_i + b_i). \tag{4}$$

In Appendix A we provide a numerical example that describes how the budget choices a_i

and b_i result in studios' profits π_i.

2.4 Assumptions

As with every model, our parsimonious competition setting requires several simplifying assumptions. In our formalization, we assume head-to-head competition, fixed total demand, and no repeated consumption. These assumptions are common in prior literature and supported in the real market. Head-to-head competition is frequent (Epstein, 2010); especially in periods of high demand, big studios launch their new movies on exactly the same day (in the United States usually a Friday). In Appendix E we provide empirical evidence for the conceptual framework of head-to-head competition. Fixed total demand is also a plausible assumption. More rarely, some movies are so popular and well-advertised that that they increase primary demand (e.g., *Titanic*, *Harry Potter and the Sorcerer's Stone*, *Avatar*), most of the time, studios rely on previous years' statistics to estimate total demand and plan their budget investments (Epstein, 2010). We also assume no repeated consumption, in that if a consumer has seen a movie at launch, he or she will not see the same movie again in the post-launch period. Although some revisits are possible in reality, it seems reasonable to consider them rare cases, at least for the theatrical lifecycle of a movie (Hennig-Thurau et al. 2007; Weinberg, 2005).

Another important set of assumptions for our parsimonious competition setting pertains to the strategic variables and their effects on viewership, as described in Figure 1. First, in our model, attendance at post-launch is affected by advertising only through word of mouth. This implies a certain stylization of the advertising effect, however, many studies on the motion picture market have found that advertising effects are seen mainly at launch because ad expenditures are concentrated right before the release (Elberse & Anand, 2007) and decrease very rapidly after launch (Ainslie, Dréze & Zufryden, 2005; Dellarocas, Zhang, & Awad, 2007; Elberse & Elaishberg, 2003; Zufryden, 1996). Moreover, Chen, Chen & Weinberg (2013) found that first-stage performance—that is, attendance in the opening week—has a much stronger effect on subsequent attendance than advertising. This empirical evidence supports our model specification and confirms that most of the advertising effect drains away at launch.

Second, we predict that on average and all things being equal, more money spent to make a movie leads to higher quality (Prag & Casavant, 1994). Other studies rely on several indicators of quality, such as reviews, experts' or popular judgments, and production budgets (Hennig-Thurau, Houston, & Sridhar, 2006; Holbrook, 1999, 2005; Holbrook & Addis, 2008). Of course, some movies with high investments turn out to be flops, and other movies produced with a very low budget are very successful. However, before shooting the movie, when studios must allocate money to make it, success is difficult to forecast. It therefore seems reasonable to predict that when studios decide how to allocate their money, they assume that the more they invest in the production, the higher the quality of the final product should be. Whether they spend their money efficiently and obtain a good or bad movie is not formalized in our competitive setting.

Third, the effects of the investment in quality accrue not at launch but only during the post-launch period, through word of mouth. In our formalization, money spent in producing the movie should enhance the real quality of the movie. Because movies are mainly experience goods, which must be consumed before their real quality can be observed (Darby & Karni, 1973), we assume that quality is not disclosed at launch. Only at a later stage, when real quality is public and experienced consumers can also communicate it to other consumers, does quality affect viewership. This assumption matches Godes and Mayzlin's (2009) theoretical formalization of word of mouth, in that the real quality communicated by experienced consumers in our model refers to consumer-created word of mouth.

3 The analytical benchmark

In this section, we explicitly solve our parsimonious competition setting using standard game-theoretical techniques. Employing a symmetric Nash equilibrium as our solution concept, we derive a closed-form, analytical solution for the equilibrium values of advertising and quality investments, a^e and b^e, as well as the corresponding profits π^e. If we define $x = \left(\frac{\delta N^2}{4\gamma}\right)^2$, we can prove the following:

Proposition 1 *There exists a symmetric Nash equilibrium (SNE), whereby advertising investment is $a^e = (c + d)\,x$, and quality investment is $b^e = x$. The studios obtain equilibrium profits $\pi^e = (1 - c - d)\,x + N\left(\frac{1}{2} - c - d\right)$.*

The proof is provided in Appendix B.

Our analytical benchmark provides initial results as the closed-form solution explicitly indicates the relationship between the parameters of the model and studios' investments and profits. For example, the investment in quality (b^e) is higher as the market is larger (N) and as the utility of other leisure activities (γ) is smaller. In that case, it makes sense to attract people to the cinema by investing in movie quality. Furthermore, our analytical benchmark indicates that when the distance of the movies from the mainstream (d) increases, the advertising investments of the two studios increase, but their quality investments remain constant and their profits decrease. This is an interesting result because it indicates that when movies are more distant from the mainstream, they invest more in advertising to attract the preferences of the mainstream, but this extra investment is ineffective; it only exacerbates the fierce pre-launch advertising battle of the two competing studios, and it results in lower profits.

This closed-form solution represents a general and solid analytical benchmark, which represents a hypothetical world in which the studios are fully rational. However, to solve the theoretical-game, we are forced to make additional stringent assumptions. For example, to facilitate our calculations, we must impose symmetrical positioning and equal investments in advertising and quality. In the next section we propose an ABM that can relax many of these additional assumptions and test interesting extensions of our model.

4 The ABM

In our ABM, a single time step of the simulation run reflects the entire competitive setting of Figure 1. That is, at time step t, two studios ($i = 1, 2$) produce and advertise their movies, making investment decisions about a_{it} and b_{it}, release their movies simultaneously, gather their viewership in two periods—at launch q_{it}^{L} and post-launch q_{it}^{PL}—and finally exit the market. At time step $t + 1$, the entire competitive setting repeats again. The two studios update their investments in advertising and quality, a_{it+1} and b_{it+1}, release them head-to-head, obtain new viewership, and again exit the market.

With respect to the game-theoretical model, we formalize the utilities of the consumers and the profit function as in Equations $1-4$ and simply add a time dimension as follows:

$$U_{ijt}^{L} = \frac{\sqrt{a_{it}}}{c + \mid \theta_j - P_i \mid}, \tag{5}$$

$$U_{ijt}^{PL} = \frac{WOM_{it}}{c + \mid \theta_j - P_i \mid}, \tag{6}$$

$$WOM_{it} = \delta \; q_{it}^{L} \; \bar{Q}_{it}, \tag{7}$$

$$\pi_{it} = q_{it}^{CUM} - (a_{it} + b_{it}). \tag{8}$$

4.1 Studios' decision rules

Competition is considered a key element of marketing strategy and the dominant opinion is that competitor-orientation is indispensable for success (Clark & Montgomery, 1997). Day and Reibstein (1997) qualify the failure to anticipate competitors' moves as a major strategic error. Furthermore, Montgomery, Moore, and Urbany (2005) show that managers actually think a lot about competitors' past and current behavior. However, there is also another school of competition, maintaining that it is better to ignore competition altogether and focus on a company's own strengths. For example, based on laboratory and field studies, Armstrong and Collopy (1996) conclude that the use of competitor-oriented objectives is detrimental to profitability. Moreover, the *Blue Ocean Strategy* by Kim and Mauborgne (2004) is in the same spirit: Companies should not be pre-occupied with competition, but should concentrate on developing their own market space.

In our ABM, we have represented these two views on competition in two different decision rules: (i) *the repeat/imitate rule* and (ii) the *trend rule*. Both are simple quantitative behavioral rules to update budget investments in advertising and quality. They are based on empirical regularities and the well-established behavioral theory of the firm (Greve, 2003a; March & Simon, 1958), and represent plausible rules of thumb that managers, marketers, and practitioners use when making and advertising new movies (Vogel, 2011; Wierenga, 2011). The repeat/imitate rule is competitor-oriented, whereas the trend rule totally ignores the competitor's behavior.

The repeat/imitate rule. Repetition and imitation have a long tradition in competitive industries (Di Maggio & Powell, 1983; Schumpeter, 1942). Repetition enjoys empirical support as firms often prefer to myopically repeat their behavior, especially if their performance does not fall below a certain level (Hannan & Freeman, 1984; Manns & March, 1978). Imitation is one of the most common heuristics for modeling myopic decision making (Greve, 2003b; Lux, 1995; Rivkin, 2000; Salganik, Dodds & Watts, 2006), and it also enjoys empirical support in relation to many strategic interactions (Camerer, 2003; Greve, 2003b; Schnaars, 2002). With this rule, the focal studio i updates its advertising and quality investments by comparing its own profit against the profit of the competitor $(-i)$. The focal studio repeats its investments in advertising and in quality if it earns more than or the same as the competitor, and copies the competitor's investments otherwise:

$$a_{it} = \begin{cases} \text{if } \pi_{it-1} \geq \pi_{-it-1} \text{ then } a_{it-1}; \\ \text{otherwise } a_{it-1}\left(1 - \frac{a_{it-1} - a_{-it-1}}{N}\right). \end{cases} \tag{5}$$

$$b_{it} = \begin{cases} \text{if } \pi_{it-1} \geq \pi_{-it-1} \text{ then } b_{it-1}; \\ \text{otherwise } b_{it-1}\left(1 - \frac{b_{it-1} - b_{-it-1}}{N}\right). \end{cases} \tag{6}$$

In Appendix D, we provide a numerical example for this rule.

The trend rule. According to the trend rule, firms follow recent profitable trends (Brock, Lakonishok, & LeBaron, 1992; de Bondt & Thaler, 1985; Hannan & Freeman, 1984; Jegadeesh & Titman, 1993; Manns & March, 1978). Such myopic behavior often arises in investors' decisions (Brock, Lakonishok, & LeBaron, 1992; de Bondt & Thaler, 1985; Jegadeesh & Titman, 1993) and has been modeled to simulate financial markets (Barberis, Shleifer, & Vishny, 1998; Hommes, 2001). Therefore, when using the trend rule, the focal studio i keeps increasing (decreasing) investments if it enjoyed positive profit growth, whereas it switches and changes its behavior if it encountered negative profit:

$$a_{it} = \begin{cases} \text{if } \pi_{it-1} > \pi_{it-2} \text{ then } a_{it-1}\left(1+\frac{a_{it-1}-a_{it-2}}{a_{it-2}}\right); \\ \text{if } \pi_{it-1} < \pi_{it-2} \text{ then } a_{it-1}\left(1-\frac{a_{it-1}-a_{it-2}}{a_{it-2}}\right); \\ \text{if } \pi_{it-1} = \pi_{it-2} \text{ then } a_{it-1}. \end{cases} \quad (7)$$

$$b_{it} = \begin{cases} \text{if } \pi_{it-1} > \pi_{it-2} \text{ then } b_{it-1}\left(1+\frac{b_{it-1}-b_{it-2}}{b_{it-2}}\right); \\ \text{if } \pi_{it-1} < \pi_{it-2} \text{ then } b_{it-1}\left(1-\frac{b_{it-1}-b_{it-2}}{b_{it-2}}\right); \\ \text{if } \pi_{it-1} = \pi_{it-2} \text{ then } b_{it-1}. \end{cases} \quad (8)$$

Thus, if at time step $t-1$ a studio increases its advertising budget ($\frac{a_{it-1}-a_{it-2}}{a_{it-2}} > 0$) and the movie brings positive profit growth ($\pi_{it-1} > \pi_{it-2}$), the studio continues to increase its advertising at time step t. However, if the increase in advertising investment induces negative growth ($\pi_{it-1} < \pi_{it-2}$), in the next time step t, the studio decreases its advertising budget. The same patterns hold for quality investment. We provide a numerical example in Appendix D for the trend rule as well.

4.2 The design choices of the ABM, validation and verification

Rand and Rust (2011) delineate rigorous guidelines for building and using ABMs. They recommend describing the design choices of the ABM and offering precise indications for how to validate and verify ABMs. We provide a description of how we have followed these guidelines in Appendix E. Below, in Table 1 we summarize the parameters of the ABM, including their default values and their rationales.

Table 1 about here.

Our ABM is now ready to run. In our experiments, we re-ran each scenario with 100 stochastic simulation runs, in which only the consumers' preferences θ_j and the initial budgets a_{i1} and b_{i1} are drawn randomly from the following distributions: $\theta_j \sim U_{[0,1]}$, $a_{i1} \sim U_{[1,N]}$, and $b_{i1} \sim U_{[1,N]}$. Each run keeps track of the evolving means for profit $\overline{\pi}_{it}$, and stops at $T = 10,000$, or alternatively when the evolving mean of the profits of the two studios converge (i.e., $|\overline{\pi}_{iT} - \overline{\pi}_{iT-1}| < \varepsilon$ with $\varepsilon = 0.0001$).

5 Simulations

5.1 Study 1: Symmetric positioning

In this study we use our ABM to simulate a competition between two studios that use the simple decision rules described above. As we are interested in symmetric positioning, we impose that the two studios position their movies equidistant from the mainstream, with Studio 1 on the left of the target segment, and Studio 2 on the right, i.e., $P_1 = \frac{1}{2} - d$ and $P_2 = \frac{1}{2} + d$ (see Figure 2). To preserve symmetry, we also impose that the two studios use the same decision rule. Thus, in this first simulation experiment, we simulate only two scenarios: in Scenario A both studios use the repeat/imitate rule, whereas in Scenario B both studios use the trend rule.[1] The ABM parameters are set at their default values, as

[1] We note that having two studios that use the same decision rule does not necessarily imply that they decide on identical investment allocations. In principle, this may invalidate the comparison between the analytical model and the ABM because the analytical benchmark does impose identical investment allocations. However, that's not the case. As our results show, although the two studios may invest differently at each time step of the simulation run, when they use the same decision rules, their investments and their profits always converge toward similar values.

indicated in Table 1.

Results are presented in Table 2. As results do not qualitatively differ between studios, for exposition reasons, we report the results of Studio 1. The trend rule (Scenario B) is clearly the most efficient decision rule. It also outperforms the analytical benchmark. In this scenario both studios invest very low budgets but earn high profits, whereas in Scenario A, when they use the repeat/imitate rule, they invest a lot but earn negative profits. Figure 3 provides a further description of what happens in these scenarios, offering the dynamics of their typical runs, i.e., how profit π_{it}, investments a_{it} and b_{it}, and viewership q_{it}^{CUM} vary during the simulation run. When using the trend rule, the two studios focus only on their own profit, they do not copy each other and do not escalate their investments in an attempt to profit more than the competitor. Instead, following profitable trends, both studios lower their investments in advertising and in quality. As the two studios lower investments together, they calm competition, do not lose competitive power against each other, and maintain their viewership. Thus, they both obtain high profits. In contrast, when both studios use the repeat/imitate rule, they escalate their investment, aiming to earn more than the competitor, but the result is negative profit.

Table 2 about here.

Figure 3 about here.

In this study we also investigate what happens when studios vary the positioning of their movies, launching more- or less mainstream movies. We conduct another simulation experiment by investigating five different levels of symmetrical positioning, $d = (.05, .15, .25, .35, .45)$, and rerunning Scenarios A and B for each level of d. The other parameters of the ABM are set as before. Recall that, as illustrated in Figure 2, when the value of d is small, the two studios approach the center of the target segment and launch more mainstream movies. Figure 4 displays the results. Interestingly, we find that when both studios use the trend rule, their investments are very low and the level of d does not significantly affect their high profits, which are permanently above 40. In contrast, when both studios use the repeat/imitate rule, their investments are much higher and their profits are much lower, and significantly dependent on how close the movies are to the mainstream. For low levels of d, i.e., when movies are close to the mainstream, the studios' profits are positive, whereas they become negative when $d \geq .25$. This result confirms the insight of the analytical benchmark, which suggests that studios profit more when they launch more mainstream movies. However, it also indicates that such a relationship holds only if both studios use the repeat/imitate rule and invest in large budgets. In contrast, if studios use the trend rule, they calm competition and do not necessarily have to launch mainstream movies.

Figure 4 about here.

5.2 Study 2: Asymmetric positioning

Head-to-head duels between big film studio producers are very common in the motion picture industry. Abundant anecdotal evidence exists about head-to-head competition between very similar movies. Examples include *Sherlock Holmes: A Game of Shadows* against *Mission: Impossible - Ghost Protocol* (both movies are action and adventure) or *The Muppets* against *Arthur Christmas* (comedies for children and families). Such empirical evidence supports the idea that symmetric positioning on the same target segment exists and is relevant. However, just as often studios release quite different movies. In many cases a studio releases a typical mainstream movie whereas a competitor competes head-to-head with a less mainstream movie. Recent examples are *Fantastic Four* (action and adventure) against *The Gift (2015)* (mystery and thriller) or *The Man From U.N.C.L.E.* (action) against *Straight Outta Compton* (biography and music).

In this second study we use our ABM to relax the assumption of symmetric positioning. We no longer force studios to position equidistant from the mainstream and instead allow them to use the positioning of their movies as a third strategic variable. We modify our ABM such that the studios do not only decide on advertising and quality investments, a_i and b_i, but also on how to position their movies, P_i. We extend the repeat/imitation rule and the trend rule such that studios can also update P_i. In Appendix F we formally describe the updating of P_i, which follows the same rationale as for a_i and b_i. The idea is that studios can decide to produce more- or less mainstream movies, repeating their previous choices or copying from the competitor; or alternatively they can follow recent profitable positioning trends.

In contrast to the previous study, in which both studios used the same decision rule, in this study, we also relax the other element of symmetry, i.e., competing studios do not necessarily use the same decision rules. Thus, in this study we investigate four scenarios: in Scenario A both studios use the repeat/imitate rule; in Scenario B they both use the trend rule; in Scenario C Studio 1 uses the repeat/imitate rule and Studio 2 uses the trend rule;

and in Scenario D Studio 1 uses the trend rule and Studio 2 uses the repeat/imitate rule. The other parameters of the ABM are set at their default values.

The results of the simulations are reported in Table 3. Again, results do not qualitatively differ between the two studios and for exposition purposes, we refer to Studio 1 only. As in the previous study, in Scenario B Studio 1 obtains high profits because both studios ignore each other, reduce costs, and calm competition without losing viewership. However, quite interestingly, we find that in Scenario C the profits of Studio 1 are also high. Although the investments are much higher than in Scenario B, the profits are rather similar and not statistically different, i.e., 48.01 and 42.13 ($F = 2.64$; $p = .11$). These results indicate that the trend rule is very profitable when both studios use it together (Scenario B), but they also suggest that if the competitor uses the trend rule, using the repeat/imitate rule is also profitable (Scenario C). Thus, the trend rule is not necessarily the most profitable decision rule to use. Moreover, Table 3 also indicates that the trend rule can be even less beneficial than the repeat/imitate rule. If the competitor uses the repeat/imitate rule (Scenarios A and D), then Studio 1 earns more when using the repeat/imitate rule than the trend rule. In this case, comparing Scenarios A and D, we find that the profits of Studio 1 are statistically different: 7.60 and $-.82$, respectively ($F = 9.1$; $p = .003$).

These results provide initial indications about the stability of these rules. Even though the two studios may see high profits using the trend rule, such a scenario does not necessarily seem stable because, at any time, one of the two studios could switch to the repeat/imitate rule and earn similar profits. In this study we have simulated scenarios in which studios keep using the same decision rule during the entire simulation run. However, in Study 4, we will simulate a more realistic market in which studios can change their decision rules during the simulation run and we will derive further indications of how profitable and stable these rules are in the real market.

In this second study, the studios can also use positioning as a strategic variable. Thus, we obtain indications of how closely the two studios approach the mainstream in the different scenarios. Recall that in our ABM, Studio 1 moves on the left side of the target segment, i.e., $P_{1t} = \left[0, \frac{1}{2}\right]$, and Studio 2 on the right side, i.e., $P_{2t} = \left[\frac{1}{2}, 1\right]$. Thus, the movies' distances from the mainstream $d_{it} = \left|\frac{1}{2} - P_{it}\right|$ can vary from 0 to $\frac{1}{2}$. The results reported in Table 3 indicate that when the studios use the repeat/imitate rule, they end up positioning very close to the mainstream; whereas when they play the trend rule, they are rather distant from the mainstream. This result is in line with the previous study as it confirms that when both studios use the repeat/imitate rule, they tend to invest large budgets and should position their movies close to the mainstream. In contrast, if a studio uses the trend rule, then it lowers the investments and does not need to move toward the mainstream.

Table 3 about here.

5.3 Study 3: Major and independent studios

In Study 2 we investigated head-to-head competition with studios positioning their movies asymmetrically. In that study, we simulated competitions between big film studio producers that can decide freely how much to invest in their movies. However, in the real motion picture industry, mini-majors and independent labels also produce and release movies for the same market but with substantially smaller budgets (Ainslie, Dréze, & Zufryden, 2005; Gemser, Van Oostrum, & Leenders, 2007; Zuckerman & Kim, 2003). While big majors such as Warner Bros. and Universal can invest in very big projects whose budgets can be more than $200 million (Elberse, 2013), independent studios face significant budget constraints and must produce movies with rather small budgets, often less than $10 million. Interestingly, major Hollywood studios often have two separate divisions for big and small productions. For example, Universal Pictures runs a subsidiary division, Focus Features, dedicated to independent movies. The same goes for the 20th Century Fox with Fox Searchlight Pictures, Warner Bros with New Line Cinema, and Sony with Sony Pictures Classics.[2] Thus, in the motion picture industry head-to-head competitions are not always between big majors, but can also involve small studios that face significant budget constraints. The real market offers abundant support for this kind of competition as well. Examples are *Mission: Impossible - Rogue Nation* (produced by Paramount) against *Vacation* (New Line) or *Inside Out* (Buena Vista) against *Dope* (Open Road Films).

In this third study, we modify our ABM to relax the assumption of unlimited budgets. We now distinguish between small and big studios, with small studios facing budget constraints and big studios having the ability to invest unlimited budgets. At each time step, while big studios invest exactly as before (Equations $5-8$), if the investment of a small studio i overtakes a given budget's cap (i.e., $a_{it} + b_{it} > MAX$), the studio adjusts its investment in

[2] For detailed descriptions of major studios, independent film producers, their histories, and their actual relationships, see http://en.wikipedia.org/wiki/Independent_film and https://en.wikipedia.org/wiki/Major_film_studio.

$\widehat{a}_{it}$ and $\widehat{b}_{it}$ as follows:

$$\widehat{a}_{it} = \frac{MAX \cdot a_{it}}{a_{it} + b_{it}} \tag{9}$$

$$\widehat{b}_{it} = \frac{MAX \cdot b_{it}}{a_{it} + b_{it}} \tag{10}$$

Notice that such a simple formalization does not hurt the rationale of the decision rules and preserves the proportions of studios' investments in advertising and quality. As for the positioning, as in Study 2, the studios can also decide how to position their movies using P_i.

5.3.1 A big major against a small studio

Our ABM is now ready to simulate head-to-head competitions between small and big studios. We simulate the same four scenarios as in the previous study and, without loss of generality, we let Studio 1 be the small studio and Studio 2 be the big studio. The ABM parameters are set at their default values. Moreover, we set $MAX = N/4$, which represents quite a strong budget constraint as it confines the studios' investments to a limit that is four times less than the total demand of the target segment (N). Later, in the next section, we show how results change in the case of less stringent constraints, i.e., medium ($MAX = N/2$) and weak ($MAX = N$) constraints.

We report the results of this study in Table 4. First, we compare Table 4 with Table 3 to study how a head-to-head competition against a small studio differs with respect to one against another big studio. Results show that these two competitions are very different. We observe that when competing against a small studio, the most profitable scenarios for the big studio are A and D (37.38 and 48.82, respectively). Conversely, when a big studio competes against another big studio, the most profitable scenarios are B and C (42.13 and

48.01, respectively).

Second, focusing on the profits of the big studio, we derive another relevant insight: The big studio should always use the repeat/imitate rule, independent of what the small studio does. If the small studio uses the repeat/imitate rule (Scenarios A and C), the big studio earns 37.38 when using the repeat/imitate rule (Scenario A) and only 2.55 when using the trend rule (Scenario C). But if the small studio uses the repeat/imitate rule (Scenarios B and D), the big studio should again use the repeat/imitate rule (48.82 in Scenario B) instead of the trend rule (2.55 in Scenario D). We conclude that the repeat/imitate rule is always more profitable for the big studio. When using this rule, the major studio has rather high expenditures for advertising and quality (about 40 in total), and it easily conquers most of the target segment because the small studio has strong budget constraints and its competitive power is limited.

Third, as for the small studio, results indicate that there are no precise indications of which decision rule it should use. If the big studio uses the repeat/imitate rule (Scenarios A and D), then the small studio earns very low profits (9.00 in Scenario A and 5.63 in Scenario D), and it does not have a precise indication of the most profitable rule as these profits are not statistically different ($F = 1.36$, $p = .25$). On the other hand, if the big studio uses the trend rule (Scenarios B and C), then the small studio earns high profits (64.95 and 71.98, respectively), but again profits are rather similar ($F = 4.83$, $p = .03$).

Finally, concerning positioning, these results confirm previous results as both the big and the small studios position their movies rather close to the mainstream when they use the repeat/imitate rule and invest larger budgets, whereas they locate away from the mainstream only when they can reduce their investments using the trend rule.

Table 4 about here.

To summarize, the results of this study indicate that in head-to-head competitions between big and small studios, the major studio should lead the market and using a competitor-oriented strategy such as the repeat/imitate rule. The big studio should invest substantial budgets in advertising and in quality, and position very close to the mainstream. On the other hand, the small studio has limited options due to its budget constraints and its profit largely depends on the decision of the big studio. It should take some distance from the mainstream only if it reduces its investment considerably by using the trend rule.

5.3.2 Sensitivity to budget constraints

Before moving to the next study, in this section we test how our results change in the case of less-stringent budget constraints, and then in the next section we also provide additional details about several robustness checks we have conducted on our ABM. To study how our results change when varying the budget constraints, we have simulated them at three different levels: strong ($MAX = N/4$), medium ($MAX = N/2$), and weak ($MAX = N$). Notice that when the budget constraints of the small studio become less stringent, we move from a very uneven competition between a big studio that can invest an unlimited budget and a small studio that launches very small productions, to a more balanced competition in which the small studio almost becomes a big studio, facing only mild budget limitations. In this sense, this new simulation experiment is a sensitivity analysis that studies the cases in between Study 2 and Study 3.

Figure 5 illustrates the results. Concerning the small studio, we observe that Scenarios B and C remain much more profitable than Scenarios A and D when the budget constraints of the small studio become less stringent. This confirms that its profits largely depend on the decisions of the big studio. Moreover, we observe that, except for Scenario A, the small studio gains more when it faces stronger budget constraints. This is an interesting result as it supports the idea of imposing strict budget constraints to produce smaller and more profitable productions. In the discussion section we elaborate more on this and examine direct managerial implications.

Concerning the big studio, we observe that its profits also change when the small competitor faces different levels of budget constraints. The profits of the big studio decrease in Scenarios A, C, and D. This is due to the fact that the major studio faces a more fierce competition because the minor competitor can invest more. Only in Scenario B do the profits of the big studio increase. This is in line with the results of Study 2, in which we found that Scenario B was profitable because the two competing studios significantly reduced costs using the trend rule.

Figure 5 about here.

5.3.3 Additional robustness checks

To reinforce the strength of our results, in this section, we illustrate additional robustness checks that we have conducted on our ABM. We have investigated alternative formalizations to model the budget constraints of the small studio. Instead of having a unique budget cap (MAX) for the investments of the small studio, we have tried distinct caps for advertising and quality to mimic a situation in which the investments in advertising and quality are unrelated. We have found that with this alternative formalization as well the small studio has no strong indications of which decision rule to use and its profits largely depend on the actions of the big studio.

We have also tested alternative formalizations for the positioning of the big and small studios. For example, we have tested a market in which the big studio uses fixed positioning on the mainstream $P_{2t} = \frac{1}{2}$, while the small studio moves on the left side as before, $P_{1t} = \left[0, \frac{1}{2}\right]$. The rationale for this formalization is that big studios always launch movies for the average audience because that is the simplest way to address the entire target segment. We have found that in this case as well results do not qualitatively change.

Finally, as the output of our studies consist of the average outcomes of 100 simulation runs, to strenghten our results, here we provide evidence that the averages of the runs are indeed robust outcomes. In Appendix G we study the running means of the 100 simulation runs of the four scenarios simulated in Study 2, confirming that average results are very robust, i.e., 100 simulation runs are more than enough to guarantee convergence. An analogous check was performed with the scenarios of Study 3 and we obtained similar evidence.

5.4 Study 4: A market with studios using weighted and evolving decision rules

The two decision rules of our ABM are simple, plausible, and relevant heuristics that studios use when deciding on their investments. In the previous studies we investigated their profitability and derived interesting insights about their use in a competitive setting. However, as in any model's formalization, they represent a simplified version of the decision-making. To compare their profitability and understand their dynamics, we have imposed that the two studios use either one of the two, and cannot switch between them. But in reality, studios often change their strategies. In this last study we implement an evolutionary approach to investigate a market where studios can use weighted decision rules that change during the simulation run. Such an approach is very common in ABMs and it has been used to simulate realistic market dynamics (Palmer et al. 1994; Midgley, Marks, & Cooper, 1997).

In our case, using an evolutionary approach makes our ABM more realistic as it replicates a situation in which the studios do not use the same decision rule for the entire simulation run but instead use a weighted mix of the two rules that can change in time. Moreover, such a modification allows us to understand in more detail the competing dynamics among studios. For example, our previous results suggest that the trend rule can be very profitable but only in a scenario in which two competing studios use it together. It is very interesting to study whether such a scenario would be stable in an evolutionary setting.

To implement the evolutionary approach, we first extend the competition to more than two studios. We maintain the same competition setting with head-to-head competitions but, instead of simulating a market in which two studios repeatedly compete against each other at each time step, now many studios can participate. At each time step, two different studios are randomly selected and compete against each other in the same competition setting as before. This modification of the ABM makes our simulations more realistic because in the real market several big and small studios exist and, most of the time, head-to-head competitions are between different studios.

Second, instead of using either the repeat/imitate or the trend rule, studios now can use weighted decision rules—that is, a mix of the repeat/imitate rule and the trend rule. We define weighted decision rules as probability vectors:

$$\sigma_i = \left[\sigma_i \left(repeat/imitate\right),\ \sigma_i \left(trend\right)\right], \tag{11}$$

where $\sigma_i \left(repeat/imitate\right)$ is the probability that studio i uses the repeat/imitate rule and $\sigma_i \left(trend\right)$ is the probability that it uses the trend rule. For example, if studio i uses a weighted decision rule $\sigma_i = [87\%, 13\%]$, it uses the repeat/imitate rule with probability 0.87 and the trend rule with probability 0.13.

5.4.1 Weighted decision rules: profitability

We start by simulating a competition with twelve studios: six big studios without budget constraints (Studios $1-6$) and six small studios (Studios $7-12$) with budget constraints. These studios use different weighted rules as indicated in Table 5 (second column). In order to obtain a first indication of their profitability, we do not let weighted rules evolve yet; instead, in this first simulation experiment we simply study how the different weighted decision rules perform. The ABM runs for $T = 10,000$ time steps, the ABM's parameters are set at their default values, and, as in Study 3, we initially set $MAX = N/4$ to investigate the case of strong budget constraints and then we also check the case of less stringent budget constraints, i.e., medium ($MAX = N/2$) and weak ($MAX = N$). In Table 5 we display results for $MAX = N/4$, and in Figure 6 we show how the profits change when small studios have different budget constraints.

Table 5 about here.

Figure 6 about here.

Table 5 reports the profit of small and big studios that use different weighted decision rules. On average, both small and big studios profit more with the repeat/imitate rule than with the trend rule. The previous studies indicated that the trend rule may be profitable because it can help in calming fierce competition and curbing studios' investments without losing viewership. However, at the same time, the trend rule may also be quite unprofitable because if competitors do not follow the same trend, the studio may not invest sufficiently and thus may lose a significant part of the target segment against them. In this case, it turns out that using a weighted decision rule with high probability for the trend rule is rather unprofitable because many competitiors use the repeat/imitate rule and keep investing large budgets. Thus, studios that often use the trend rule lose viewership against these competitors and profit less.

Table 5 also shows that both small and big studios tend to position their movies toward the mainstream when they use the repeat/imitate rule. In contrast, when they use the trend rule, they lower their investments and do not necessarily position their movies close to the mainstream, which is in line with our previous results.

Figure 6 illustrates how the profits of the twelve studios change when the small studios face different budget constraints. Interestingly, we notice that small studios earn less when they face weak budget constraints, confirming that imposing strong budget constraints can be beneficial. Moreover, we find not only that small studios earn less when they have no budget limitations, but big studios also suffer. This result confirms that when more studios produce and launch big productions, then competition becomes more fierce and profits decrease for all studios. Finally, we also observe that the repeat/imitate rule is on average more profitable than the trend rule at any level of budget constraint, which again confirms the insight illustrated above.

5.4.2 Weighted decision rules: evolution

Now we also investigate what happens when studios modify the weights of their decision rule during the simulation. The simulation evolves for $G = 10$ generations, with each generation running for $T = 10,000$ time steps. Thus, in total the simulation runs for $T * G = 100,000$ time steps. At the beginning of a new generation, big and small studios modify their weighted decision rules. We indicate the weighted decision rules of big and small studios at generation g with $\sigma\_big_i^g$ and $\sigma\_small_i^g$, respectively. Studios modify them as follows:

$$\sigma\_big_i^g = \frac{\sigma\_big_i^{g-1} + \sigma\_big_{best\_big}^{g-1}}{2}, \tag{11}$$

$$\sigma\_small_i^g = \frac{\sigma\_small_i^{g-1} + \sigma\_small_{best\_small}^{g-1}}{2}, \tag{12}$$

where $\sigma\_big^{g-1}_{best\_big}$ and $\sigma\_small^{g-1}_{best\_small}$ are the weighted decision rules of the most successful studios in the previous generation, i.e., the big and small studios with the highest profits $\overline{\pi}^{g-1}_{iT}$ at generation $g-1$. As before, we simulate a market with twelve studios, Studios $1-6$ are big studios and Studios $7-12$ are small studios with budget constraints. They begin the simulation using the same weighted decision rules indicated in Table 5 (second column). The ABM's parameters are set at their default values and we again consider the case of strong ($MAX = N/4$), medium ($MAX = N/2$), and weak ($MAX = N$) budget constraints.

In Table 6 we report the profits, investments, and positioning of the studios at the end of the evolution, i.e., last generation $g = 10$, in the case of $MAX = N/4$. First, these results show that when implementing an evolutionary approach, at the end of the evolution, neither big nor small studios are significantly different, indicating that big and small studios converge toward similar strategies. Then, we also observe that big studios invest significantly more than small studios and that thus such an effort results in higher profits. As for positioning, we find that all studios tend to approach the mainstream, but big studios slightly more than small studios. Overall, these results confirm the insights of the previous experiments, in that big studios dominate the market by investing large budgets, positioning permanently on the mainstream, and earning more than small studios.

Figure 7 illustrates how the studios evolve and converge across generations. The graphs on the left side show the evolution of the weights of the decision rules, whereas the graphs on the right side plot studios' profits. Then, the graphs above, in the middle, and below refer to strong, medium, and weak budget constraints, respectively. With regard to the evolution of the weights of the decision rules, we observe that when big studios compete against small studios with strong or medium budget constraints, at the end of the evolution, all studios converge toward a weighted decision rule that uses the repeat/imitate rule much more than the trend rule. Big studios converge toward $\sigma\_big = [95\%,\ 5\%]$ in the case of strong budget constraints and $\sigma\_big = [83\%,\ 17\%]$ in the case of medium constraints. Small studios instead converge toward $\sigma\_small = [67\%,\ 33\%]$ and $\sigma\_small = [63\%,\ 37\%]$, respectively. Although the repeat/imitate rule exacerbates the competition by pushing studios toward higher investments, both big and small studios use this rule because it is the most profitable option. Their profits are not very high, though. In Study 3 we have found that a big studio that uses the repeat/imitate rule against a small studio earns a profit of about 40, whereas now at the end of the evolution profits are quite a bit lower, i.e., about 30. This is due to the fact that in this more realistic setting, big studios do not always compete against small studios but against other big studios as well. When they compete against small studios they reap rather high profits, but when they compete against other big studios their profits are significantly lower.

As for the profits of small studios, we observe that when they face strong or medium budget constraints they earn significantly less than big studios. This is not surprising as the success of their projects largely depends on the actions of the big studios, which mainly use the repeat/imitate rule. However, we notice that their profits are not excessively low. Specifically, we find that they earn more when they are forced to constrain their investments within strong budget limitations, which again supports the idea that budget constraints can indeed be useful tools. In this regard, we observe that on average all studios profit more when small studios are constrained to strong budget limitations whereas when small studios are subject to less stringent budget constraints, then the differences between big and small studios shrink, the competition becomes more fierce, and on average studios earn less.

Finally, we notice that when small studios face weak budget constraints—meaning that they can compete with almost similar budgets against big studios—all studios use the trend rule more than the repeat/imitate rule. Big studios converge toward $\sigma\_big = [30\%,\ 70\%]$ and small studios toward $\sigma\_small = [22\%,\ 78\%]$. In the case of weak budget constraints, small studios became almost big studios and they also can launch big productions. Then, in this case the trend rule becomes more profitable and is used more often. This is due to the fact that competitions between big studios are less fierce than competitions between a big and a small studio. However, further investigation into the output of these simulation experiments shows that although the studios use the trend rule much more, their investments are still high, being very similar to the cases of strong and medium budget constraints. Thus, even if studios use the trend rule more often, this is not enough to substantially reduce investments and increase profits.

Overall, these results describe a very competitive market in which studios tend to invest large budgets using a competitor-oriented strategy such as the repeat/imitate rule. They use this rule in an attempt to beat competitors but they end up earning very little profits.

Table 6 about here.

Figure 7 about here.

6 Discussion

In this paper, we formalize a strategic competition setting for the launch of new movies. Our setting reflects the head-to-head competition among studios that advertise their upcoming movies during pre-launch campaigns (Elberse & Anand, 2007). In reality studios use a variety of decision rules and adopt more sophisticated budget strategies than we used in our ABM. However, our results explain interesting dynamics behind the scenes of the competition, in the sense that they indicate the drivers of studios' behaviors and shed light on some important aspects of their strategic competition. In this sense, our results offer relevant theoretical and practical implications. In this section we describe the impact of our contribution, the limitations of our work, and possible future research.

6.1 Strategic launches

Our results indicate that competing big studios would profit more if they used myopic strategies that ignore the competitor and attenuate their fierce competition, such as those based on the trend rule (Study 1). However, this is not a stable situation because major studios have an incentive to use the repeat/imitate rule (Study 2). Interestingly, however, if all studios use the repeat/imitate rule, profits are very low (Studies 2 and 4).

First, these results contribute to explaining why competition in this industry is very tough and profits are so low. Many studies have suggested that the motion picture industry is a very risky industry, with the expected profit of the average movie even being negative

(Eliashberg, Elberse, & Leenders, 2006). In the motion picture industry, studios are well aware of their competitors' projects. They plan to launch their best productions in the weeks of high demand (Epstein, 2010), and know that very likely they will compete head-to-head against their direct competitors. In this context, studios are strongly tempted to invest larger budgets in an attempt to gain market share from the direct competitor and to launch ever-more expensive productions.

Second, our results integrate recent analysis that advocates the so-called *blockbuster strategy* (Elberse, 2013). This strategy consists of concentrating all a studio's investments in one or a few productions of very high quality, rather than spreading these budgets more evenly across other projects; the idea is to enter the market with a huge advertising campaign that creates a massive event and hopefully a commercial success—i.e., a blockbuster. Our result explains the underlying dynamics of the blockbuster strategy, as it indicates why studios are so tempted to increase their investments. This is especially advantageous when competing studios have insufficient means to do the same. In fact, our simulations indicate that big studios that use a strategy of large investments (repeat/imitate rule) earn more when they compete against small producers than against big, direct competitors that can also invest very large budgets. We discuss this more in detail in the next section, where we review the differences between big and small studios.

Third, our results suggest that profitable launches are not only productions of large investment. Our results indicate a few situations in which small productions can also be profitable. For example, in Studies 3 and 4, we show how small studios can efficiently use budget constraints to launch movies that result in higher returns.

6.2 Major and independent studios

The motion picture industry has received lot of attention in the recent marketing literature. However, only a few works have taken competition into account (Ainslie, Dréze & Zufryden, 2005; Elberse & Eliashberg, 2003), and those that have analyzed competition only at the level of the movies. Not much has been done on competition among studio producers. To our knowledge, this is the first work that investigates how studios compete. In this industry it is well-known that six major studios dominate the global market in terms of market share. These are Columbia (Sony), Disney (Buena Vista), Paramount, Fox, Universal, and Warner Bros. The six major studios are contrasted with a number of smaller production companies that are known as independents or *indies*. While big majors usually invest in very big projects, independent studios face significant budget constraints and produce movies with rather small budgets.

First, our results indicate that head-to-head competitions among big majors are rather different than head-to-head competitions that include big and small studios. When a big studio competes against other majors, it profits more when all studios use budget strategies, like the trend rule, that reduce overall investments. However, that is a rather difficult situation to achieve because studios can easily use alternative strategies (such as the repeat/imitate rule) that boost investments without decreasing profits. Moreover, our results indicate that when big studios compete against small competitors, the majors have even stronger incentives to use the repeat/imitate rule, which means launching big productions. Overall, this result testifies to the difficulties that big studios have when competing in very open markets, like the motion picture market, where the studios know about what their competitors are doing, and are constantly tempted to win the competition with higher investments.

Second, with regard to the small studios, we find that overall budget constraints have a positive effect on profits. Without such limits, small studios are inclined to spend too much. Budget caps prevent small studios from investing too much and are particularly useful when both studios use the repeat/imitate rule, i.e., when they have the tendency to one-up each other with spending on quality and advertising. Interestingly, in our last study we have found that big studios obtain larger profits than small studios. However, if we consider the average ROI of their projects, we find that the small productions of the minor studios are more proofitable than the large projects of the big majors. This result partially contradicts the blockbuster strategy (Elberse, 2013) and is very much in line with what we observe in reality, with big studios creating separate and independent studios with the goal of creating small productions.

6.3 To mainstream or not to mainstream?

Our ABM and its simulation results offer critical managerial suggestions about which kinds of movies to produce and how to launch them. When major studios compete head-to-head for the same target segment, they profit more if they launch mainstream movies. When producing and launching more mainstream movies, major studios fuel competition by making their movies more similar and trying to appeal to similar consumers, but they also benefit because they approach the mass market and effectively match the preferences of the target segment.

We find that on average moving toward the average taste of the market is like playing a safe position, which studios tend to do especially when they invest large budgets (repeat/imitate rule). Conversely, studios can explore positions away from the mainstream when they invest less. For example, we find that studios take some distance from the mainstream when they use the trend rule or when they face strong budget constraints that force them toward small productions. These results are in line with common intuition as big productions are usually movies that aim to appeal to everyone. However, they also indicate that other strategies are practical as well, confirming that smaller productions that earn substantial profits are not uncommon in the motion picture market. Usually these are small and innovative productions that are quite distant from the mainstream.

In this regard, we acknowledge that how we model a movie's positioning is not the only way one could formalize the mainstream concept. We used a standard Hotelling model, with the positioning corresponding to a point on the line of possible preferences. But one may think about alternative formalization as well. For example, one may study the case of when studios do not choose a point on the target segment, but instead stretch their positioning to cover a bigger part of the segment. Such a formalization represents an alternative way to model the mainstream concept because it allows the analysis of movies with wider appeal. For example, it can capture the idea of groups of customers that have different preferences but equally enjoy the movie, or movies with specific features that equally appeal to different costumers. Moreover, such an alternative formalization represents an interesting modification of the Hotelling model that could be used in other contexts as well. In Appendix C we examine such an alternative. We obtain results that are very similar to the baseline model, thus providing additional support for our finding.

6.4 Additional methodological insights

Our work provides interesting methodological insights for the use of ABMs in marketing. We offer a practical example of how to exploit the interplay between an ABM and a game-theoretical benchmark. The use of ABMs together with analytical models is definitely not novel. Relevant examples are Brown et al. (2004), and Libai, Muller, and Peres (2005). These works use both formal analysis and ABMs to investigate interesting extensions of the analytical model and strengthen their results. Rand and Rust (2011) point out that the results of analytical modeling, unlike the results of ABM, are generalizable. On the other hand, analytical modeling often builds in restrictive assumptions, while ABM can relax many of these assumptions and build a more complex and realistic model. In our case, using the analytical model allowed us to obtain a significant benchmark and achieve generalizability, whereas the ABM helped us investigate interesting extensions of the model that more realistically adhere to the motion picture industry.

So far in marketing, ABMs have most often been applied to model diffusion of innovations. However, according to Rand and Rust (2011), there are several other marketing research areas with potential for agent-based modeling that should be explored further. In this paper, we use our ABM to investigate competition. In general, competing firms do not provide information about their strategies. Neither is it easy to derive that information from aggregate statistics. With our ABM methodology, we turn the analysis around, starting with plausible decision rules and then deriving their implications for studios' investments and profits. We find that very simple but realistic decision rules, such as the repeat/imitate rule and the trend rule, can generate interesting insights. For example, we show how easily studios escalate their investments in an attempt to win the competition, and how such a tendency pushes studios to position their movies closer to the mainstream.

Finally, we also highlight how the interplay between the ABM and the analytical benchmark can facilitate analyses and partially validate the ABM. Usually, when running simulations, an ABM modeler cannot investigate the entire parameter space because computational resources are invariably limited. Determining the appropriate ranges of the parameters is an empirical question: The right range is the most realistic one. We used the equilibrium conditions of the analytical benchmark to align the analytical benchmark and the ABM, and to guide the validation of our ABM (Appendix E). These equilibrium conditions specified realistic relationships among some parameters of the model (i.e., γ, N, δ, c, and d), so we ensured realistic movie lifecycle patterns and validated a relevant part of our ABM.

6.5 Limitations and future research

Our competition setting reflects solid theoretical assumptions from new product diffusion and word-of-mouth literature (Bass, 1969; Godes & Mayzlin, 2009; Mahajan, Muller, & Kerin, 1984; Neelamegham & Chintagunta, 1999; Peres, Muller, & Mahajan, 2010). As is true of any abstract setting, it does not account for some other important aspects. Before concluding this analysis, it is important point out the limitations of this study and suggest a few possible extensions that pertain to our model.

First, our competition setting refers to experience products with short life cycles that are heavily influenced by pre-launch marketing campaigns. Many experience goods, including movies, also can display longer life cycles, especially across various technological iterations (e.g., DVD market, TV rights, merchandising; Hennig-Thurau, Houston, & Heitjans, 2009), sequential releases in different markets (Elberse & Eliashberg, 2003; Lehmann & Weinberg, 2000), and potential reinvigoration through advertising. We cannot represent these phenomena because we assume all advertising spending takes place right before the launch (Elberse & Anand, 2007).

Second, we limited our analysis to a very simple model. Krider and Weinberg (1998) similarly opt for a parsimonious model with a duopolistic competition in which the studios choose only the release time of their movies. Also, when specifying the behavioral decision rules used by the studios, we rely mainly on the behavioral theory of the firm (Greve, 2003a). However, these rules do not represent a complete set of firm actions. Because the focus of our research is budget competition and realistic budget decisions, we limited our formalization to endogenize the budget-related strategic variables of the studios. Further research should identify other characteristics that mark more extended competition. Possible extensions of our model might consider other aspects of studios' decision-making (e.g., when studios are not risk-neutral; when movies are released sequentially rather than simultaneously; or when the investment decisions on advertising and quality do not derive from a central division but from different offices that decide at different times). Moreover, future research could investigate the demand side, e.g., how market dynamics change when consumers' preferences are not uniformly distributed, or when including negative word-of-mouth. These various extensions can help clarify firms' choices of business strategy even further. The ABM methodology offers a promising tool for further advances in this direction, though.

Finally, our work opens up future empirical investigation of the motion picture industry. While most of the marketing literature on this industry has mainly studied the box office at the level of movies, we have focused on the level of studios. Although our ABM is partially validated with a micro-face validation, still much is needed to empirically ground our setting into the real motion picture industry. As mentioned above, ultimately, the validation of our ABM should involve empirical support for its formalization and assumptions, and should also calibrate the ABM's parameters on the basis of the real behaviors of moviegoers and studio producers. This empirical validation was beyond the scope of this article though, in that our main purpose was to study the effects of the ABM's decision rules and compare them with the analytical benchmark. In the future, other works could use advertising data and quality instruments to test our competition setting empirically. Moreover, additional field evidence could be gathered about how the managers of real studios decide how much to invest in their productions and thus complement our ABM with additional decision rules.

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Appendix A

Numerical example of moviegoers' behavior and studios' profits. Assume a cinema market in which $\gamma = 0$, $N = 20$, $c = 1$, $\delta = \frac{1}{10}$, and studios position their movies at the extremes of the target segment: $P_1 = 0$ and $P_2 = 1$. Next assume that the two studios spend equally on advertising and on quality, e.g. $a_1 = a_2 = 4$ and $b_1 = b_2 = 9$. Consider the behavior of consumer $j = 1$, whose taste is on the left side of the target segment, such as $\theta_1 = 0.25$. At launch, his attraction to Movie 1 is $A^L_{11} = \frac{\sqrt{4}}{1+|0.25-0|} - 0 = 1.6$ and attraction to Movie 2 is $A^L_{21} = \frac{\sqrt{4}}{1+|0.75-1|} - 0 = 1.14$. So, he will visit Movie 1 at launch. It follows that for these values of the cinema market and for these advertising investments of the two studios, at launch all consumers on the left side of the target segment will visit Movie 1 and all consumers on the right side of the target segment will visit Movie 2. Thus, half of the consumers visit Movie 1 and the other half visit Movie 2, such that $q^L_1 = q^L_2 = 10$. Now consider Consumer 1's behavior at post-launch. He has already seen Movie 1 at launch, so he will not consider that movie at post-launch. His attraction to Movie 2 is $A^{PL}_{21} = \frac{\frac{1}{10}\cdot\sqrt{9}\cdot 10}{1+|0.75-1|} - 0 = 1.71$. So, Consumer 1 will visit Movie 2 at post-launch. It follows that at post-launch, all consumers on the left side of the target segment will visit Movie 2 and all consumers on the right side of the target segment will visit Movie 1. Then, post-launch viewerships will be $q^{PL}_1 = q^{PL}_2 = 10$, and cumulative viewerships $q^{CUM}_1 = q^{CUM}_2 = 10 + 10 = 20$. Finally, profits immediately derive from viewerships: $\pi_{1t} = \pi_{2t} = 20 - (4 + 9) = 7$.

Appendix B

Proof. Consider the game version of the model described in Section 2 (Equations $1-4$). In this simple, two-period game, launch is the first period, and post-launch is the second. From Equation 1, we determine the type of consumer θ^L who is indifferent about seeing the two movies at launch,

$$\theta^L = \frac{\sqrt{a_1}\,(c+P_2) - \sqrt{a_2}(c-P_1)}{\sqrt{a_1}+\sqrt{a_2}}, \tag{B1}$$

such that all consumers whose preferences are to the left of θ^L see Movie 1, and all those whose preferences are to the right see Movie 2. Therefore,

$$(q_1^L, q_2^L) = (N\theta^L, N(1-\theta^L)). \tag{B2}$$

From Equation 2, we also know the type of consumer θ_1^{PL} that has not seen Movie 1 at launch and who is indifferent about seeing or not seeing it at post-launch,

$$\theta_1^{PL} = \frac{\delta N \theta^L \sqrt{b_1} - \gamma(c-P_1)}{\gamma}. \tag{B3}$$

Equivalently, for Movie 2 we have

$$\theta_2^{PL} = \frac{\delta N \left(1-\theta^L\right)\sqrt{b_2} - \gamma(c-P_2)}{\gamma}, \tag{B4}$$

such that the cumulative viewership for Movies 1 and 2 are

$$(q_1^{CUM}, q_2^{CUM}) = (q_1^L + q_1^{PL}, q_2^L + q_2^{PL}) = (N\theta_1^{PL}), N(1-\theta_2^{PL})). \tag{B5}$$

Now consider the problem faced by Studio 1. According to Equations $B1$, $B3$, and $B5$, Studio 1's profit function can be rewritten as

$$\max_{a_1, b_1} \quad N\frac{\left[\delta N\sqrt{b_1}\left(\frac{\sqrt{a_1}(c+P_2)-\sqrt{a_2}(c-P_1)}{\sqrt{a_1}+\sqrt{a_2}}\right) - \gamma(c-P_1)\right]}{\gamma} - (a_1+b_1). \tag{B6}$$

Studio 1 thus chooses a_1 and b_1 to maximize its profits. The first-order conditions are:

$$a_1 : \delta N^2 \sqrt{b_1} \left(\frac{\frac{1}{2}\frac{1}{\sqrt{a_1}}\gamma\,(c+P_2)\left(\sqrt{a_1}+\sqrt{a_2}\right) - \frac{1}{2}\frac{1}{\sqrt{a_1}}\gamma\left[\sqrt{a_1}\,(c+P_2) - \sqrt{a_2}(c-P_1)\right]}{\gamma^2\left(\sqrt{a_1}+\sqrt{a_2}\right)^2} \right) = 1, \tag{B7}$$

and

$$b_1 : \delta N^2 \left[\frac{\sqrt{a_1}\,(c+P_2) - \sqrt{a_2}(c-P_1)}{\gamma\left(\sqrt{a_1}+\sqrt{a_2}\right)} \right] \frac{1}{2}\frac{1}{\sqrt{b_1}} = 1. \tag{B8}$$

Equations $B7$ and $B8$ implicitly define the best response functions for Studio 1. Because we focus on a symmetric model, we impose $a_1 = a_2 = a^e$, $b_1 = b_2 = b^e$. Solving Equations $B7$ and $B8$, we obtain

$$a^e = (c+d)\left(\frac{\delta N^2}{4\gamma}\right)^2, \text{ and} \tag{B9}$$

$$b^e = \left(\frac{\delta N^2}{4\gamma}\right)^2. \tag{B10}$$

In turn, we obtain

$$\theta^L = \frac{1}{2}, \tag{B11}$$

$$\theta_1^{PL} = \frac{N^3\delta^2}{8\gamma^2} - \left(c+d-\frac{1}{2}\right), \tag{B12}$$

$$\theta_2^{PL} = \frac{N^3\delta^2}{8\gamma^2} - \left(c+d+\frac{1}{2}\right), \text{ and} \tag{B13}$$

the equilibrium profits

$$\pi^e = (1-c-d)\left(\frac{\delta N^2}{4\gamma}\right)^2 + N\left(\frac{1}{2} - c - d\right). \tag{B14}$$

As a last step, we specify the conditions of the equilibrium and therefore issue the following corollary. ■

Corollary 1 *The SNE in Proposition 1 exists when the following conditions and the corresponding restrictions over the parameters are satisfied:*

CONDITION 1. Full coverage of the market occurs at launch (period 1). To obtain full market coverage at launch we impose that, if $d \leqslant \frac{1}{4}$*, the consumer with preference* θ_0 *visits Movie* 1*. Otherwise, the consumer with preference* $\theta_{\frac{1}{2}}$ *visits Movie* 1*.*

$$\begin{cases} \frac{\sqrt{a^e}}{c+|\theta_0-P_1|} > \gamma \Rightarrow \frac{\sqrt{(c+d)x}}{c+|\theta_0-P_1|} > \gamma \Rightarrow \delta > \frac{4\gamma^2\left(c+\frac{1}{2}-d\right)}{N^2\sqrt{c+d}}, \text{ if } d \leqslant \frac{1}{4} \\ \frac{\sqrt{a^e}}{c+|\theta_{\frac{1}{2}}-P_1|} > \gamma \Rightarrow \frac{\sqrt{(c+d)x}}{c+|\theta_{\frac{1}{2}}-P_1|} > \gamma \Rightarrow \delta > \frac{4\gamma^2\sqrt{c+d}}{N^2}, \text{ if } d > \frac{1}{4}. \end{cases} \tag{B15}$$

CONDITION 2. There exist at least some consumers who attend movies at post-launch (period 2). Because $\theta^L = \frac{1}{2}$ *(Equation* $B11$*) and we have imposed full market coverage at launch, we can conclude that at launch all consumers with preferences* $\theta_i < \frac{1}{2}$ *visit Movie* 1*, and all consumers with preferences* $\theta_i < \frac{1}{2}$ *visit Movie* 2*. As* θ_1^{PL} *has not seen Movie* 1 *at launch and is indifferent about seeing or not seeing it at post-launch, to obtain positive viewership at post-launch, we can impose* $\theta_1^{PL} > \frac{1}{2}$*. Then we have*

$$\theta_1^{PL} > \frac{1}{2} \Rightarrow \frac{\delta N \theta_1^L \sqrt{x} - \gamma(c - P_1)}{\gamma} > \frac{1}{2} \Rightarrow \delta > \sqrt{\frac{8\gamma^2(c+d)}{N^3}}. \tag{B16}$$

CONDITION 3. At the end of the post-launch (period 2), not all consumers have seen all movies. Following the same line of reasoning as in condition 2, we impose $\theta_1^{PL} \leq 1$*. Then we obtain*

$$\theta_1^{PL} \leq 1 \Rightarrow \frac{\delta N \theta_1^L \sqrt{x} - \gamma(c - P_1)}{\gamma} \leq 1 \Rightarrow \delta \leq \sqrt{\frac{8\gamma^2(c+d+\frac{1}{2})}{N^3}}. \tag{B17}$$

Appendix C

In this Appendix we propose an alternative formalization of the movie's positioning. Rather than assuming that movies correspond to points on the Hotelling line, we allow for the possibility that studios launch movies that cover an entire portion of the target segment. Such an alternative formalization captures the idea that a movie with a larger segment is more mainstream because it covers more market preferences and thus appeals to more moviegoers. Obviously studios compete by deciding the length of their segment and incur additional costs when launching movies that cover longer segments. Here we aim to provide a simple extension along this line of reasoning, avoiding the technicalities of a full-fledged analysis, which is beyond the scope of the current paper. We consider a simple case in which studios release movies anchored at the extremes of the segment, in 0 and 1, and decide how much to stretch from these two extremes toward the center of the Hotelling line. Figure C1 provides a graphical representation.

Figure C1 about here.

Let $\Gamma_1 = [0, P_1] \subseteq [0, 1]$ be the segment of Movie 1, and $\Gamma_2 = [P_2, 1] \subseteq [0, 1]$ the segment of Movie 2. By enlarging the segment a movie becomes more appealing to the population of moviegoers according to the following reasoning: all the consumers whose type θ lies in the segment of characteristics Γ_i obtain the greatest utility from movie i; if instead the type θ is not in the segment Γ_i, its utility decreases according to the distance between the consumer's type and the closest characteristic of the movie in the segment Γ_i. Formally speaking, define the distance between θ_j and movie i's segment of characteristics as

$$d_{ij} = \begin{cases} 0, & \text{if } \theta \in \Gamma_i; \\ \mid \theta_j - P_i \mid, & \text{if } \theta \notin \Gamma_i. \end{cases} \tag{C1}$$

The distance d_{ij} affects the attraction of movie i at launch, and similarly to our baseline model, consumer j visits the movie with the highest positive attraction, provided that it obtains a utility that is bigger than the outside good. Then, at post-launch, consumer j decides whether to visit the other movie or not. All the other elements of the model are unchanged, therefore we can model the utilities as follows:

$$U_{ij}^{L} = \frac{\sqrt{a_i}}{c + d_{ij}}, \tag{C2}$$

$$U_{ij}^{PL} = \frac{WOM_i}{c + d_{ij}} = \frac{\delta\ q_i^L\ \bar{Q}_i}{c + d_{ij}}. \tag{C3}$$

Finally, assuming that there is an increasing cost to having a longer segment of characteristics, we measure, for example, Studio 1's performance as the difference between the cumulative viewership and the total investments, with

$$\pi_1 = q_1^{CUM} - (a_1 + b_1 + C(P_1)), \tag{C4}$$

$C' > 0$, $C'' > 0$. To make the comparison with the baseline model, consider the case of when the movies' characteristics do not overlap, such that $P_1 < P_2$. From Equation $C2$, we can determine the type of consumer θ^L who is indifferent about seeing the two movies at launch,

$$\theta^L = \frac{\sqrt{a_1}\,(c + P_2) - \sqrt{a_2}(c - P_1)}{\sqrt{a_1} + \sqrt{a_2}}, \tag{C5}$$

such that all consumers whose preferences are to the left of θ^L see Movie 1, and all those whose preferences are to the right see Movie 2. Therefore, as in the baseline model,

$$(q_1^L, q_2^L) = (N\theta^L, N(1-\theta^L)). \tag{C6}$$

From Equation $C3$, we also know the type of consumer θ_1^{PL} who has not seen Movie 1 at launch and who is indifferent about seeing or not seeing it at post-launch,

$$\theta_1^{PL} = \frac{\delta N \theta^L \sqrt{b_1} - \gamma(c - P_1)}{\gamma}, \tag{C7}$$

such that the cumulative viewership for Movie 1 is

$$q_1^{CUM} = q_1^L + q_1^{PL} = N\theta_1^{PL}. \tag{C8}$$

Now consider the problem faced by Studio 1. If we assume that the studio incurs greater costs when increasing the size of the segment Γ_1, according to Equations $C4$, $C5$, and $C7$, its profits can be rewritten as

$$N\frac{\left[\delta N\sqrt{b_1}\left(\frac{\sqrt{a_1}(c+P_2)-\sqrt{a_2}(c-P_1)}{\sqrt{a_1}+\sqrt{a_2}}\right) - \gamma(c-P_1)\right]}{\gamma} - (a_1 + b_1 + C(P_1)), \tag{C9}$$

and Studio 2's profits will correspond to a similar expression. Thus, in the simple case in which the studios position their movies at the extremes and then compete choosing segments, we obtain a setting that is very similar to the baseline model. If we assume that the studios choose not only their budgets, but also the length of the segment of their movies, when maximizing its profits Studio 1 chooses a_1 and b_1 according to Equations $B7$ and $B8$, whereas P_1 is

$$P_1 : N\frac{\left[\delta N\sqrt{b_1}\frac{\sqrt{a_2}}{\sqrt{a_1}+\sqrt{a_2}} + \gamma\right]}{\gamma} = C'(P_1). \tag{C10}$$

After imposing symmetry, we get

$$P_1 : N\frac{\left[\delta N\left(\frac{\delta N^2}{4\gamma}\right)\frac{1}{2}+\gamma\right]}{\gamma} = C'(P_1) = N + 2\left(\frac{\delta N^2}{4\gamma}\right)^2 = N + 2x = C'(P_1). \qquad (C11)$$

Finally, considering the case of quadratic costs, $C(P_1) = \lambda(P_1)^2$, being $\lambda > 0$ a parameter that determines the costs of producing a more mainstream movie, we get the closed-form solution

$$P^e = \frac{N + 2x}{2\lambda}. \qquad (C12)$$

Example. It is possible to provide conditions such that, in equilibrium, the two studios offer movies for totally distinct segments, $\Gamma_1 \cap \Gamma_2 = \varnothing$ (see Figure C1). This would be the case if

$$P^e = \frac{N + 2x}{2\lambda} = \frac{N + 2\left(\frac{\delta N^2}{4\gamma}\right)^2}{2\lambda} < \frac{1}{2}. \qquad (C13)$$

Using the same numerical values of Table 1 and assuming that $\lambda = 150$, Studio 1 would choose a value

$$P^e = \frac{100 + 2\left(\frac{\frac{\sqrt{6}}{100^3}100^2}{4}\right)^2}{300} = \frac{1}{3} + \frac{1}{4 \cdot 100^3} < \frac{1}{2}. \qquad (C14)$$

Here we conveniently set $\lambda = 150$ to obtain a numerical solution that is consistent with the setting of the other parameters. Eventually, as with the other parameters of the model, also λ should be empirically validated.

First, we note that in this setting the close-form solutions are very similar to the baseline model, as the values of a^e and b^e do not change. Moreover, we are able to obtain a close-form solution for the positioning that intuitively makes sense: P^e depends positively on N and δ

(studios make a more mainstream movie when the target segment is larger and the word-of-mouth effect is stronger), and negatively on γ (studios make a less mainstream movie when the other means of leisure and the cost of making a more mainstream movie increase). Because this new setting represents an alternative way to model the mainstream concept and its results are very similar to the baseline model, we conclude that these results provide additional support for our finding.

Second, we highlight the difficulties that this new formalization entailed, both analytically and with the ABM. Analytically, the more general case of when the studios choose the length of the segments Γ_1 and Γ_2 without starting from the extremes of the Hotelling segment implies a much greater computational cost. For example, just focusing on the derivation of the demand functions at launch, we should account for the following different cases for the consumer's type θ: $\theta \in \Gamma_1 \cap \Gamma_2$; $\theta \in \Gamma_1$ and $\theta \notin \Gamma_2$; $\theta \in \Gamma_2$ and $\theta \notin \Gamma_1$; $\theta \notin \Gamma_1 \cup \Gamma_2$. Considering then the derivation of the demand in the post-launch corresponding to the different cases of the demand at launch, the general analysis when studios compete using segments would generate a large number of cases to be studied, each case leading to different equilibria. On the other hand, concerning the ABM, this formalization is certainly easier to implement. However, this formalization must assume a cost structure (λ) that is inherently difficult to validate. It is reasonable to assume that a movie that covers a larger portion of the Hotelling line has higher costs. But such a cost would be difficult to validate empirically. A movie that covers a larger portion of the Hotelling line indicates a movie that, paying a higher cost, meets more preferences. A movie can aim at meeting a large base of preferences by covering more genres, or by proposing a story-plot for different people, etc. In principle, these costs may be measurable, but their identification could be rather difficult.

Appendix D

Numerical example for the repeat/imitate rule. According to Equation 5, the focal studio repeats its investments in advertising and in quality if it earns more than or the same as the competitor, and copies the competitor otherwise. When it copies the competitor it increases the investment if the competitor invests more, and it decreases it if the competitor invests less. Assume a cinema market in which $N = 100$. At time step $t-1$ Studio 1 invested $a_{1t-1} = 40$ in advertising and $b_{1t-1} = 40$ in quality, obtaining profits $\pi_{1t-1} = 12$, whereas Studio 2 invested $a_{1t-1} = 45$ and $b_{1t-1} = 30$ obtaining $\pi_{2t-1} = 15$. How do the two studios change their budget investments at the next time step t when using the repeat/imitation rule? As Studio 2 profited more than Studio 1, it repeats its budget choices such that $a_{2t} = a_{2t-1} = 40$ and $b_{2t} = b_{2t-1} = 30$. In contrast, as Studio 1 profited less, it copies Studio 2, decreasing its investment in advertising and increasing its investment in quality as follows: $a_{1t} = 45\left(1 - \frac{45-40}{100}\right) = 42.75$ and $b_{1t} = 30\left(1 - \frac{30-40}{100}\right) = 33$. In this example, Studio 1 observes that it is faring worse than its competitor. While Studio 2 repeats its budget choices, Studio 1 imitates decreasing investment in advertising and increasing quality.

Numerical example for the trend rule. Assume that at time step $t-2$, Studio 1 invested $a_{1t-2} = 5$ and $b_{1t-2} = 10$, gaining $\pi_{1t-2} = 7$ and that at time step $t-1$, it increased both advertising and quality to $a_{1t-1} = 6$ and $b_{1t-1} = 11$, resulting in less profit, $\pi_{1t-1} = 6$. How much does it increase or decrease its budget investment in the next time step t when using the trend rule? As profits decreased, $\pi_{1t-1} < \pi_{1t-2}$, substituting in Equations 7 and 8, we obtain $a_{1t} = 6\left(1 - \frac{6-5}{5}\right) = 4.8$ and $b_{1t} = 11\left(1 - \frac{11-10}{10}\right) = 9.9$. This means that at time step t, Studio 1 decides to decrease advertising investment by 20% and quality investment by 10%. In this example, Studio 1 observes that in the previous time step it obtained lower profits after increasing investment in advertising and quality. Then, it decides to switch the trend and decrease investments in both advertising and quality.

Appendix E

In this appendix we first provide empirical evidence for the conceptual framework of head-to-head competition. Then, we offer detailed justification for the design choices of the ABM, and a validation for the setting of the ABM's parameters. Finally we include a section about the ABM's verification.

Empirical evidence of head-to-head competition. As mentioned above, head-to-head competition is very common in the motion picture industry (Epstein, 2010; Krider & Weinberg, 1998). To empirically support our duopolistic competition setting, we collect data on movies' releases in the North American market. Our data include the yearly top 150 motion pictures in terms of sales released in the U.S./Canadian market, from 1999 to 2011.[3] We focus on the release date. Figure E1 reports how many times (i) no movies released; (ii) a movie released alone; (iii) two movies launched on the same date and competed head-to-head; (iv) three movies released on the same date; and (v) more than three movies released on the same date.[4] These frequencies show that when studios release their movies, a head-to-head competition is the most common setting, confirming that head-to-head competition is extremely common in the motion picture industry. Obviously, a studio does not always compete against the same competitor. Head-to-head competitions are among the six big majors (Columbia, Disney, Paramount, 20th Century Fox, Universal, and Warner Bros.), so

[3] These data effectively cover almost the entire market by accounting for more than 95% of total box office sales. Source: www.boxofficemojo.com.

[4] In the North American motion picture market, almost all movies release on Friday. These statistics include releases from major studios, mini-majors, and independent labels. For a classification of the studio producers in North America, see https://en.wikipedia.org/wiki/Major_film_studio.

they indeed rematch often. In Study 4, we also take this aspect into account, simulating a market with more than two competitors.

Figure E1 about here.

The design choices of our ABM. We have prepared a summary that describes the design choices of our ABM based on the Rand and Rust (2011) guidelines. In Table E1, we illustrate the scope of the model, the types of agents in the simulation, their properties and behaviors, the environment, input and output of the ABM, and finally we present a short description of the order of the events in the time step of the simulation run.

Table E1 about here.

Validation. In this section we summarize how we validate our ABM and the initialization of the ABM's parameters. Rand and Rust (2011) define validation as the process of determining how well the implemented model corresponds to reality, and distinguish among micro-face, macro-face, empirical input, and empirical output validation. Micro- and macro-face validations ensure that the micro mechanisms of the agents and the macro patterns of the model correspond "on their face" to the real world. Empirical input and output validations use real data to validate the ABM. The empirical input validation ensures that the data being put into the ABM are accurate and correspond to the real world, whereas the empirical output validation confirms that the output of the implemented model corresponds to the real world. Ultimately, the validation of our ABM should involve empirical support for its formalization and assumptions, and should also calibrate the ABM's parameters on the basis of the real behaviors of moviegoers and studio producers. This empirical validation is beyond the scope of this article, though, in that our main purpose is to study the effects of the ABM's decision rules and compare them with the analytical benchmark. Nevertheless, in order to demonstrate that our ABM is properly grounded in the real market of the motion picture industry, we have provided empirical evidence for the head-to-head competition framework in the previous section and in this section we set the ABM parameters based on a micro-face validation.

We choose the following default values: $\gamma = 1$, $N = 100$, $\theta_j \sim U_{[0,1]}$, $c = 0.25$, $d = 0.25$, and $\delta = \sqrt{\frac{6}{100^3}}$. Although this setting is not totally empirically driven, we maintain that these values realistically reflect the motion picture market and represent a solid validation of our ABM. The parameters γ, N, θ_j, c, d, and δ are micro-face validated, as their values correspond in a meaningful way to the characteristics of the real market (Rand & Rust, 2011).

Without loss of generality, we set $\gamma = 1$, assuming that the attraction of other means of leisure is constant and does not vary in time. Then, to exclude unjustified holes in the distribution of consumers' preferences, we set $N = 100$ and $\theta_j \sim U_{[0,1]}$. We use a uniform distribution to refer to the most general case where consumers' preferences for movie types are equally likely. The parameter c is set at 0.25, which corresponds to the middle point between the maximum utility (i.e., the consumer's preference perfectly matches the closest movie type, $|\theta_j - P_i| = 0$) and the minimum utility (i.e., the consumer's preference is furthest from the closest movie type, $|\theta_j - P_i| = 0.5$). Also the distance of the movies from the mainstream is initially set to its middle point, $d = 0.25$, between the minimum, where both studios locate exactly in the mainstream ($d = 0$, i.e. $P_1 = P_2 = 0.5$), and the maximum, where the studios locate their movies at the extremes of the target segment ($d = 0.5$, i.e. $P_1 = 0$ and $P_2 = 1$).

Finally, we set $\delta = \sqrt{\frac{6}{100^3}}$. To set this parameter we use the cross-validation technique. Cross-validation is a kind of empirical output validation that compares one model against another model that has already been validated (Rand & Rust, 2011). In our case, we use the three equilibrium conditions of the fully rational benchmark that are realistic and, given the parameters' values of above, constrain δ to fall between $\sqrt{\frac{8}{100^3}}$ and $\sqrt{\frac{4}{100^3}}$. The three conditions of the fully rational benchmark ensure that in equilibrium, three realistic macro patterns are satisfied: (a) the target segment is fully covered at launch (condition 1), (b) there exist some consumers who visit the movie in the post-launch (condition 2), and (c) at the end of the post-launch not all consumers have seen all movies (condition 3). Constraining the value of δ such that the three equilibrium conditions are satisfied provides a macro-face validation because these three conditions are well in line with extant evidence about movies' life cycles: (a) peaks of demand are usually well-captured by the launch of new movies (Epstein, 2010); (b) viewership decays quite rapidly after launch, but post-launch viewership determines a relevant part of total sales (Elberse & Eliashberg, 2003; Jedidi, Krider, & Weinberg, 1998; Lehmann & Weinberg, 2000); and (c) consumers who choose among the newly released movies do not necessarily visit the others in the post-launch period.

Verification. To ensure that the ABM does what it is supposed to do and that the implemented model corresponds to the conceptual model, we verify our ABM based on the Rand and Rust (2011) guidelines. We use three different tools: (i) documentation, (ii) programmatic testing, and (iii) test cases. The documentation of our ABM provides the MATLAB code and an input file. These are available on request from the corresponding author. As for the programmatic tests, we programmed several check tests to guarantee that the simulation run does not generate unexpected outputs. Finally, we simulate a few extreme test cases to ensure that the ABM replicates easy and intuitive predictions. For instance, we verify what happens if two studios launch movies with exactly the same advertising and quality investments and symmetrical positioning. As expected, we find that market shares are similar.

Appendix F

In this appendix we illustrate how to relax the assumption of symmetric positioning. We extend the two decision rules such that studios also decide on how to position their movies P_i. The updating of P_i follows the same rationale as for a_i and b_i. Studios decide to launch more- or less mainstream movies by repeating their previous choices or copying from their competitor; alternatively, they can follow recent profitable positioning trends. Here below we present the formal updating for P_i.

The repeat/imitate rule. Studio i updates its positioning by comparing its own profit against the competitor's profit:

$$P_{it} = \begin{cases} \text{if } \pi_{it-1} \geq \pi_{-it-1} \text{ or } P_{it-1} = P_{-it-1} \text{ then } P_{it-1}; \\ \text{if } \pi_{it-1} < \pi_{-it-1} \text{ and } \left|\frac{1}{2} - P_{it-1}\right| > \left|\frac{1}{2} - P_{-it-1}\right| \text{ then } i \text{ moves toward the mainstream;} \\ \text{if } \pi_{it-1} < \pi_{-it-1} \text{ and } \left|\frac{1}{2} - P_{it-1}\right| < \left|\frac{1}{2} - P_{-it-1}\right| \text{ then } i \text{ moves away from the mainstream.} \end{cases} \tag{F32}$$

Studio 1 moves towards the mainstream by $P_{1t} = P_{1t-1} + \omega\left(\frac{1}{2} - P_{1t-1}\right)$, and away from the mainstream by $P_{1t} = P_{1t-1} - \omega P_{1t-1}$. Instead, Studio 2 moves toward the mainstream by $P_{2t-1} - \omega\left(P_{2t-1} - \frac{1}{2}\right)$, and away from the mainstream by $P_{2t-1} + \omega\left(1 - P_{2t-1}\right)$. Here ω is a parameter that determines how much the studios change P_i from time step $t-1$ to time step t. In our simulations, ω is a random number drawn from a uniform distribution: $\omega \sim U_{[0,1]}$. To understand the rationale behind this rule, recall that in our ABM Studio 1 moves on the left side of the target segment, i.e., $P_{1t} = [0,\ 0.5]$, and Studio 2 on the right side, i.e., $P_{2t} = [0.5,\ 1]$, and consider the following example: Assume that at time step $t-1$, $P_{1t-1} = 0.4$, $P_{2t-1} = 0.9$, and $\pi_{it-1} < \pi_{2t-1}$. This means that at time step $t-1$, the movie of Studio 1 is more mainstream and less profitable than the movie of Studio 2. Thus, at time step t, Studio 1 copies Studio 2 and moves away from the mainstream. Assuming that $\omega = 0.3$, $P_{1t} = P_{1t-1} - \omega P_{1t-1} = 0.4 - 0.3 * 0.4 = 0.28$. In contrast, as the movie of Studio 2 is more profitable than the movie of Studio 1, Studio 2 simply repeats its previous movement: $P_{2t} = P_{2t-1} = 0.9$.

The trend rule. Studio i decides its positioning as follows:

$$P_{it} = \begin{cases} \text{if } \pi_{it-1} = \pi_{it-2} \text{ or } P_{it-1} = P_{it-2} \text{ then } P_{it-1}; \\ \text{if } \pi_{it-1} > \pi_{it-2} \text{ and } \left|\frac{1}{2} - P_{it-1}\right| > \left|\frac{1}{2} - P_{it-2}\right| \text{ then } i \text{ moves away from the mainstream;} \\ \text{if } \pi_{it-1} > \pi_{it-2} \text{ and } \left|\frac{1}{2} - P_{it-1}\right| < \left|\frac{1}{2} - P_{it-2}\right| \text{ then } i \text{ moves toward the mainstream;} \\ \text{if } \pi_{it-1} < \pi_{it-2} \text{ and } \left|\frac{1}{2} - P_{it-1}\right| > \left|\frac{1}{2} - P_{it-2}\right| \text{ then } i \text{ moves toward the mainstream;} \\ \text{if } \pi_{it-1} < \pi_{it-2} \text{ and } \left|\frac{1}{2} - P_{it-1}\right| < \left|\frac{1}{2} - P_{it-2}\right| \text{ then } i \text{ moves away from the mainstream.} \end{cases} \tag{F33}$$

The movements of the two studios toward and away from the mainstream are the same: Studio 1 moves toward the mainstream by $P_{1t} = P_{1t-1} + \omega\left(\frac{1}{2} - P_{1t-1}\right)$, and away from the mainstream by $P_{1t} = P_{1t-1} - \omega P_{1t-1}$. Instead, Studio 2 moves toward the mainstream by $P_{2t-1} - \omega\left(P_{2t-1} - \frac{1}{2}\right)$, and away from the mainstream by $P_{2t-1} + \omega\left(1 - P_{2t-1}\right)$.

Appendix G

In this last appendix, we study the running means of a studio's profits to provide evidence that average results indeed reflect convergence. This is important because in all our studies we replicated each simulation scenario for 100 runs. Moreover, results indicate that the outputs of different runs can be rather different. For example, in Studies 2 and 3 (Table 3 and Table 4), especially when the studios use the trend rule, we observe that standard deviations can be rather high, indicating that single runs can differ a lot. The plots of Figure G1 display the running means of the small and big studios' profits in the four scenarios of Study 3. They confirm that average results are very robust, i.e., 100 simulation runs are more than enough to guarantee convergence. We have also conducted additional checks on the running means of the studios' investments in advertising and quality and obtained similar indications.

Figure G1 about here.

Table

Table 1. The parameters of the ABM

Parameter	Name	Default value	Validation (Rand and Rust, 2011)	Rationale
N	Number of consumers	100	Micro-face validation	We simulate a sufficiently high number of consumers to obtain enough variety in consumers' preferences.
θ_j	Consumers' preferences	$U_{[0,1]}$	Micro-face validation	We refer to the most general case where consumers' preferences for movie types are equally likely.
γ	Other means of leisure, i.e. outside good	1	Micro-face validation	We normalize it to 1 assuming other means of leisure do not vary in time. No loss of generality.
c	Practical constrains of movie consumption	.25	Micro-face validation	We refer to the general case where the practical constraints of the movie fruition lays in the middle between the highest and the lowest utility the agent can obtain from the fruition of a movie.
d	Movie's differentiation	.25	Micro-face validation and sensitivity analysis	With symmetric positioning the two competing studios launch movies that are equidistant from the average consumer, i.e. P_1=0.5-d and P_2=0.5+d. Setting d=.25 we study the middle case. Then, varying d, we study the case of more- or less-mainstream movies (Study 1). Finally, in Studies 2, 3 and 4 we study asymmetric positioning.
δ	WOM's persuasiveness	$\sqrt{\frac{6}{100^3}}$	Empirical output validation (cross-validation)	We validate this value based on the three equilibrium conditions of the analytical benchmark.

Notes: In Appendix E we provide a more detailed description of the setting of the ABM's parameters.

Table

Table 2. Symmetric competition

		Profit	Investment in advertising	Investment in quality
Analytical benchmark		18.75	18.75	37.50
Scenario A	Both studios use the repeat or imitate rule	-9.61 (27.36)	44.43 (25.91)	35.51 (21.38)
Scenario B	Both studios use the trend rule	40.31 (30.80)	3.56 (3.89)	6.31 (13.69)
F statistics		146.83*	243.35*	132.24*

Notes: Profit is $\bar{\pi}_{1T}$, investment in advertising is $\bar{a}_{1T}$, and investment in quality is $\bar{b}_{1T}$,; F statistics refer to ANOVA tests comparing the means of the 100 simulation runs among scenarios; SD are in parenthesis; *p<.01.

Table

Table 3. Asymmetric competition

		Profit	Investment in advertising	Investment in quality	Distance from mainstream
Scenario A	Both studios use the repeat or imitate rule	7.60 (27.41)	41.12 (22.97)	29.22 (13.01)	0.08 (0.05)
Scenario B	Both studios use the trend rule	42.13 (30.48)	2.92 (3.93)	3.83 (12.76)	0.24 (0.18)
Scenario C	Studio 1 uses the repeat or imitate rule whereas Studio 2 uses the trend rule	48.01 (19.41)	30.25 (15.60)	19.67 (13.58)	0.14 (0.14)
Scenario D	Studio 1 uses the trend rule whereas Studio 2 uses the repeat or imitate rule	-0.82 (5.35)	1.52 (3.14)	1.16 (0.35)	0.25 (0.24)
F statistics		114.40*	197.50*	137.10*	24.09*

Notes: Profit is $\bar{\pi}_{1T}$, investment in advertising is $\bar{a}_{1T}$, investment in quality is $\bar{b}_{1T}$, and distance from mainstream is $\bar{d}_{1T} = |1/2 - \bar{P}_{1T}|$; F statistics refer to ANOVA tests comparing the means of the 100 simulation runs among scenarios; SD are in parenthesis; *p<.01.

Table

Table 4. Head-to-head competition between a small and a big studio

		Profit (small studio)	Investment in advertising (small studio)	Investment in quality (small studio)	Distance from mainstream (small studio)	Profit (big studio)	Investment in advertising (big studio)	Investment in quality (big studio)	Distance from mainstream (big studio)
Scenario A	Both the small and the big studio use the repeat or imitate rule	9.00 (23.18)	13.65 (6.37)	10.88 (6.58)	0.13 (0.06)	37.38 (16.26)	21.47 (8.89)	19.18 (15.30)	0.09 (0.06)
Scenario B	Both the small and the big studio use the trend rule	64.95 (25.54)	6.42 (6.06)	7.62 (7.48)	0.16 (0.16)	15.93 (31.59)	3.96 (10.85)	5.18 (23.57)	0.19 (0.20)
Scenario C	The small studio uses the repeat or imitate rule and the big studio uses the trend rule	71.98 (17.83)	12.20 (6.97)	8.32 (6.59)	0.11 (0.11)	2.55 (10.14)	4.06 (12.00)	3.90 (13.11)	0.23 (0.23)
Scenario D	The small studio uses the trend rule and the big studio uses the repeat or imitate rule	5.63 (17.23)	7.00 (7.14)	4.62 (5.14)	0.17 (0.19)	48.82 (19.09)	23.87 (13.36)	16.34 (10.22)	0.09 (0.10)
F statistics		270.78*	30.04*	15.68*	4.46*	100.35*	90.17*	22.47*	20.43*

Notes: Results refer to a competition in which small studios face strong budget constraints, i.e., $MAX = N/4$; profit is $\bar{\pi}_{iT}$, investment in advertising is $\bar{a}_{iT}$, investment in quality is $\bar{b}_{iT}$, and distance from mainstream is $\bar{d}_{iT} = |1/2 - \bar{P}_{iT}|$; F statistics refer to ANOVA tests comparing the means of the 100 simulation runs among scenarios; SD are in parenthesis; *p<.01.

Table

Table 5. Competition with more than two studios and weighted decision rules

		Profit	Investment in advertising	Investment in quality	Positioning
Big studios	Studio 1 using [0%, 100%]	1.67 (7.23)	9.85 (25.56)	2.65 (6.32)	0.22 (0.18)
	Studio 2 using [20%, 80%]	18.05 (13.39)	14.68 (12.19)	5.04 (5.34)	0.19 (0.08)
	Studio 3 using [40%, 60%]	29.10 (9.79)	30.21 (9.75)	9.20 (7.74)	0.10 (0.05)
	Studio 4 using [60%, 40%]	30.65 (9.09)	33.88 (10.86)	10.09 (8.03)	0.09 (0.03)
	Studio 5 using [80%, 20%]	31.26 (8.86)	34.88 (12.00)	10.47 (8.12)	0.08 (0.03)
	Studio 6 using [100%, 0%]	32.40 (9.77)	35.58 (12.09)	10.64 (8.20)	0.07 (0.03)
F statistics		149.49*	58.86*	20.07*	56.29*
Small studios	Studio 7 using [0%, 100%]	14.24 (10.76)	9.32 (9.37)	1.66 (1.87)	0.21 (0.14)
	Studio 8 using [20%, 80%]	20.58 (10.44)	14.77 (9.44)	2.56 (2.15)	0.19 (0.06)
	Studio 9 using [40%, 60%]	27.52 (5.10)	20.02 (3.51)	3.47 (3.12)	0.14 (0.03)
	Studio 10 using [60%, 40%]	26.72 (5.05)	20.36 (3.34)	3.54 (3.41)	0.13 (0.02)
	Studio 11 using [80%, 20%]	27.15 (4.62)	20.46 (3.27)	3.61 (3.50)	0.12 (0.02)
	Studio 12 using [100%, 0%]	27.55 (4.56)	20.53 (3.23)	3.63 (3.56)	0.11 (0.02)
F statistics		56.25*	70.05*	7.17*	41.40*

Notes: Results refer to a competition in which small studios face strong budget constraints, i.e., $MAX = N/4$; profit is $\bar{\pi}_{iT}$, investment in advertising is $\bar{a}_{iT}$, investment in quality is $\bar{b}_{iT}$, and distance from mainstream is $\bar{d}_{iT} = |1/2 - \bar{P}_{iT}|$; F statistics refer to ANOVA tests comparing the means of the 100 simulation runs among big or small studios; SD are in parenthesis; *p<.01.

Table

Table 6. Competition with weighted decision rules that evolve

		Profit	Investment in advertising	Investment in quality	Positioning
Big studios	Studio 1 starting the evolution with [0%, 100%]	25.42 (10.56)	34.44 (10.14)	17.63 (8.16)	.07 (.03)
	Studio 2 starting the evolution with [20%, 80%]	24.67 (9.82)	34.59 (10.85)	17.63 (8.07)	.08 (.03)
	Studio 3 starting the evolution with [40%, 60%]	25.10 (10.22)	34.33 (10.53)	17.58 (8.13)	.08 (.03)
	Studio 4 starting the evolution with [60%, 40%]	26.27 (10.42)	34.73 (9.96)	17.62 (7.96)	.07 (.03)
	Studio 5 starting the evolution with [80%, 20%]	26.13 (9.80)	34.80 (10.14)	17.60 (8.08)	.07 (.03)
	Studio 6 starting the evolution with [100%, 0%]	25.52 (9.67)	34.59 (10.21)	17.53 (7.88)	.07 (.03)
F statistics		.36	.03	.04	.57
Small studios	Studio 7 starting the evolution with [0%, 100%]	9.83 (5.29)	19.04 (3.86)	5.30 (4.17)	.13 (.02)
	Studio 8 starting the evolution with [20%, 80%]	9.73 (5.40)	19.01 (3.88)	5.30 (4.15)	.14 (.02)
	Studio 9 starting the evolution with [40%, 60%]	9.91 (5.37)	19.04 (3.87)	5.30 (4.17)	.13 (.02)
	Studio 10 starting the evolution with [60%, 40%]	10.18 (5.34)	19.03 (3.87)	5.28 (4.15)	.13 (.02)
	Studio 11 starting the evolution with [80%, 20%]	10.12 (5.39)	19.04 (3.87)	5.29 (4.18)	.13 (.02)
	Studio 12 starting the evolution with [100%, 0%]	10.24 (5.44)	19.03 (3.87)	5.27 (4.15)	.13 (.02)
F statistics		.15	.00	.00	.14

Notes: Results refer to a competition in which small studios face strong budget constraints, i.e., $MAX = N/4$; profit is $\bar{\pi}_{iT}$, investment in advertising is $\bar{a}_{iT}$, investment in quality is $\bar{b}_{iT}$, and distance from mainstream is $\bar{d}_{iT} = |1/2 - \bar{P}_{iT}|$, at the end of last generation, i.e., *g=10*; F statistics refer to ANOVA tests comparing the means of the 100 simulation runs among big or small studios; SD are in parenthesis; *p<.01.

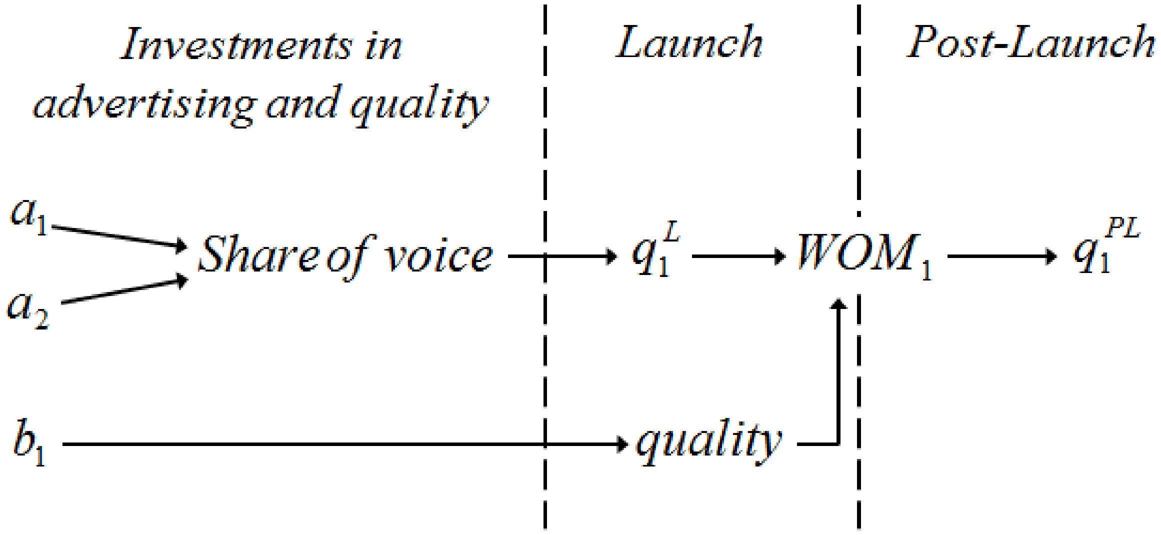
Table

Table E1. Design choices

Scope of the model	What aspects of the complex system under examination will be described in the model?	The scope of this ABM is to study how competing studio producers invest in advertising and in quality when launching new movies. Our focus is on studios' profit, which depends on studios' investments and on movies' viewership. Viewership of a movie consists of two parts: viewership at launch and at post-launch.
Agents	What agent types exist in the model?	In this ABM there are two types of agents: • The studios that produce and launch new movies; • The consumers who make decisions about movie attendance.
Properties	What properties does each agent have?	In this ABM the agents have the following properties: • Studios have three decision variables: investment in advertising, investment in quality, and the positioning of the movie with respect to consumers' preferences for the target segment. Studios may or may not have budget constraints. This defines them as small or major studios, respectively. • Consumers are characterized by their preferences on the target segment.
Behaviors	What behaviors/actions does each agent possess?	In this ABM the agents have the following behaviors: • Studios use decision rules, which determine how they set the value for their decision variables. In this ABM, there are two decision rules—the repeat and imitate rule and the trend rule. • Consumers decide which movie to attend or not to attend any movie.
Environment	What external forces act on each agent, including other agents and the external environment?	In this ABM, the environment consists of three parameters: • The utility derived from alternative leisure activities (outside good). • The practical constraints of the movie's consumption. • WOM's persuasiveness, i.e. the strength of word-of-mouth in the cinema market. These parameters are micro- and macro-face validated and remain constant during the simulation run.
Input and Output	What inputs to the model exist? What outputs can be collected from the model?	The input of this ABM consists of the different decision rules assigned to the studios. In cases of competitions with small studios, the input is also the strength of their budgets' constraints (weak, medium or strong). The output consists of the studios' profits, their investments in advertising and quality, and the positioning of their movies.
Time Step	What is the order of events in the model?	At each time step, studios produce and advertise their movies, making investment decisions on advertising and quality. Then they release their movies simultaneously, gather their viewership in two periods (launch and post-launch), and finally the two movies exit the market.

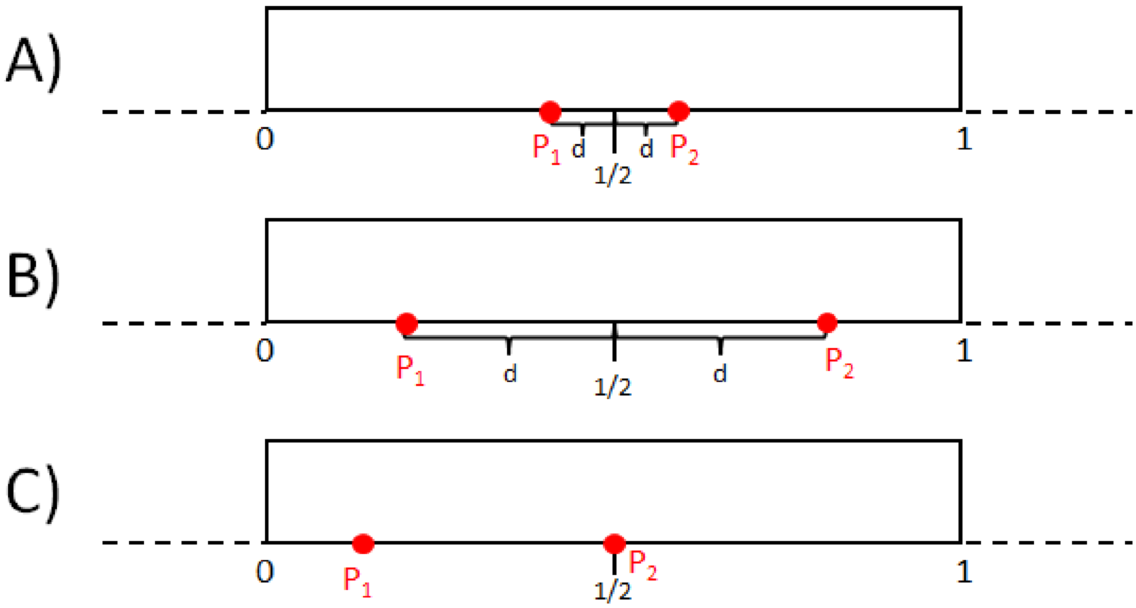
Figure

Figure 1. The competition setting



Figure

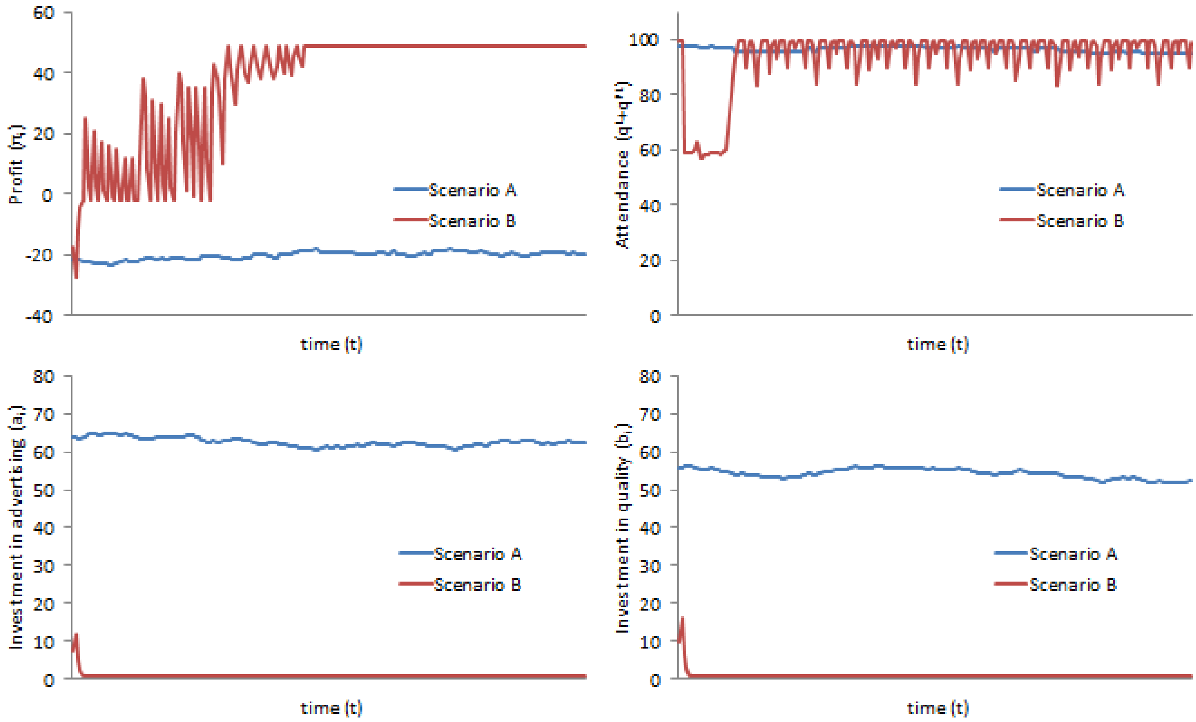
Figure 2. Symmetric and asymmetric positioning



Notes: Graphs A and B depict symmetric competitions. In Graph A, P_1 and P_2 are close to the mainstream and movies' differentiation d is small, whereas in Graph B they are far from the mainstream and movies' differentiation d is large. Graph C illustrates an asymmetric competition with a mainstream movie in the center of the target segment (P_2) and a less mainstream movie that locates at the left extreme (P_1).

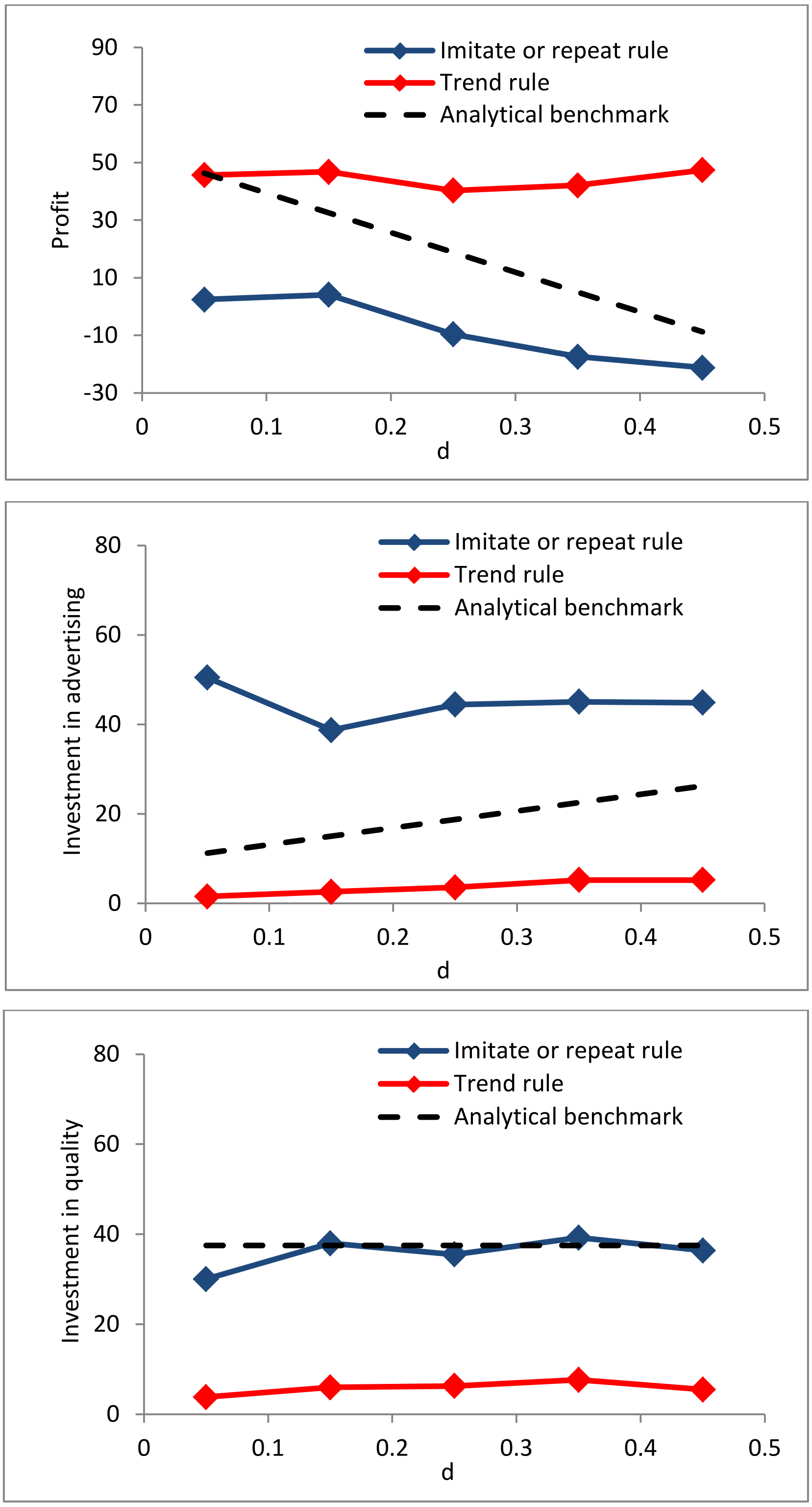
Figure

Figure 3. Typical runs of Scenarios A and B in Study 1



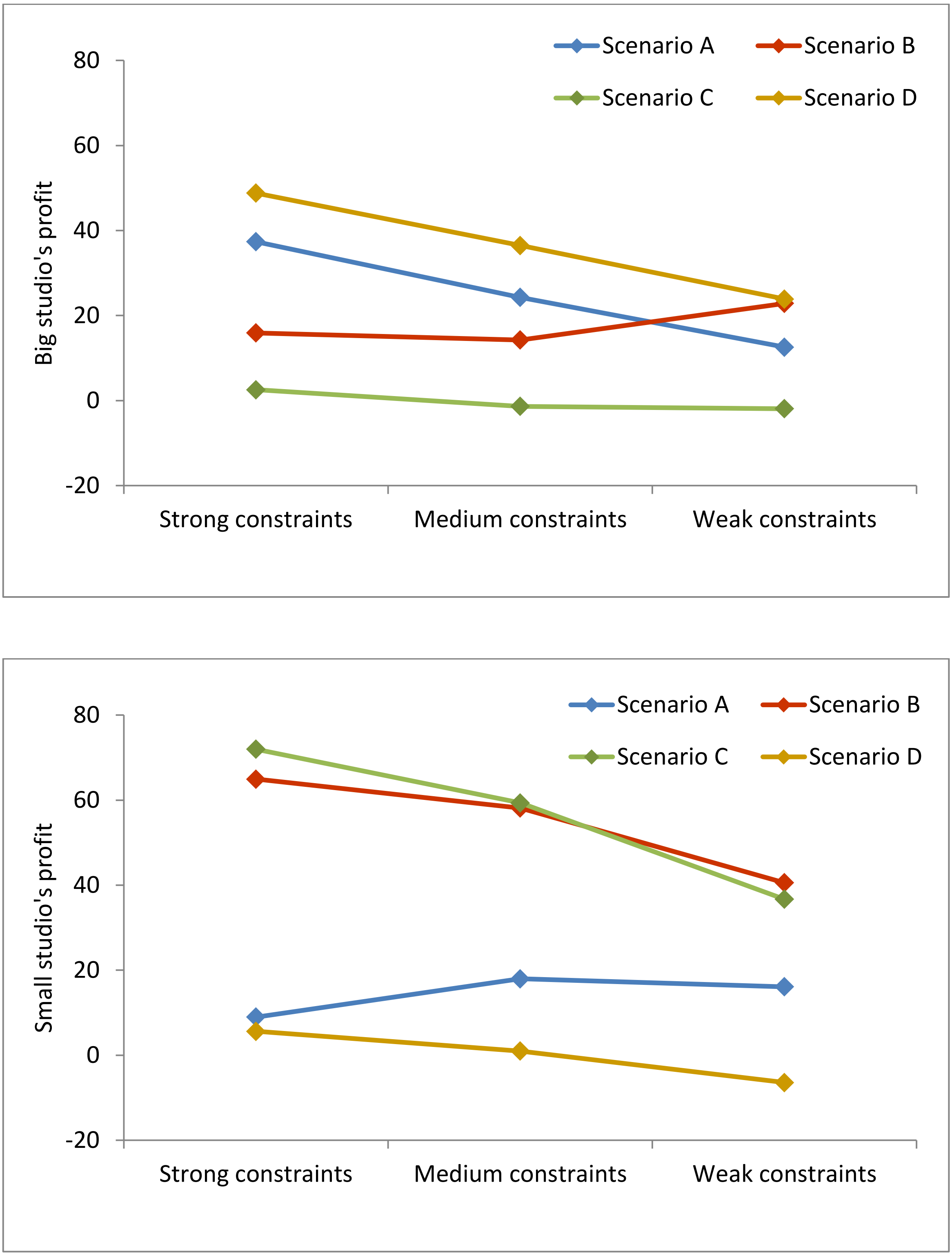
Figure

Figure 4. Symmetric scenarios with different levels of differentiation



Figure

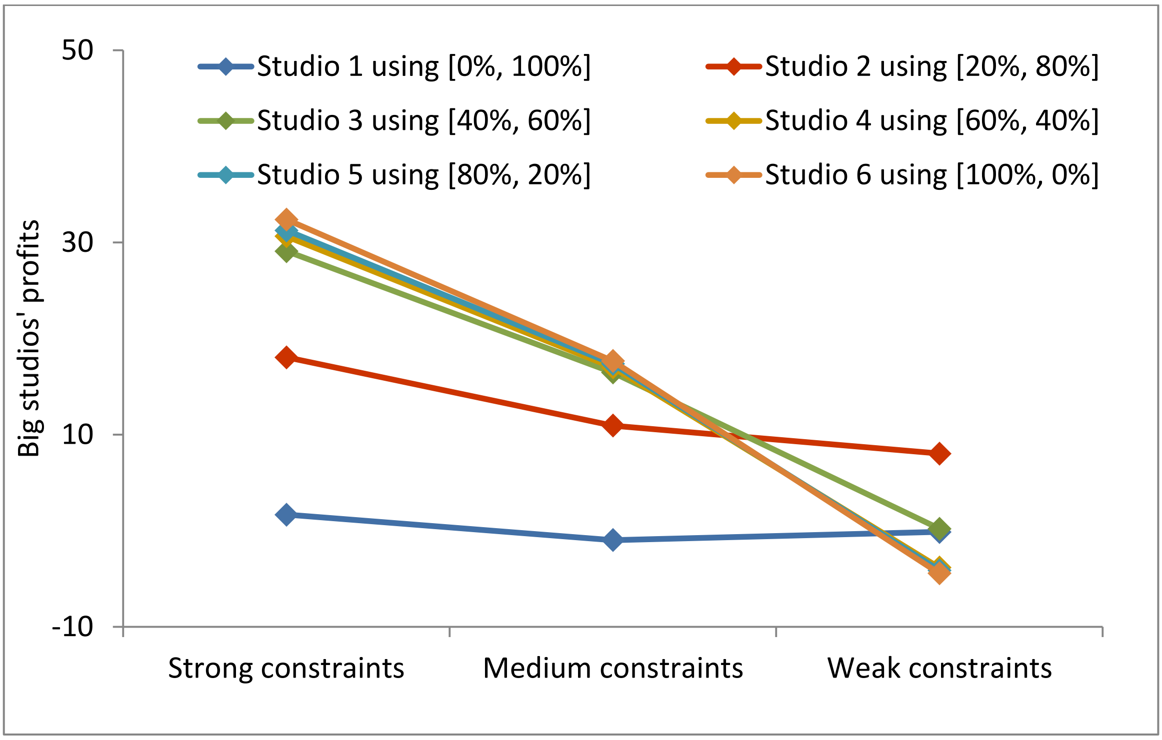
Figure 5. Competition between a small and a big studio

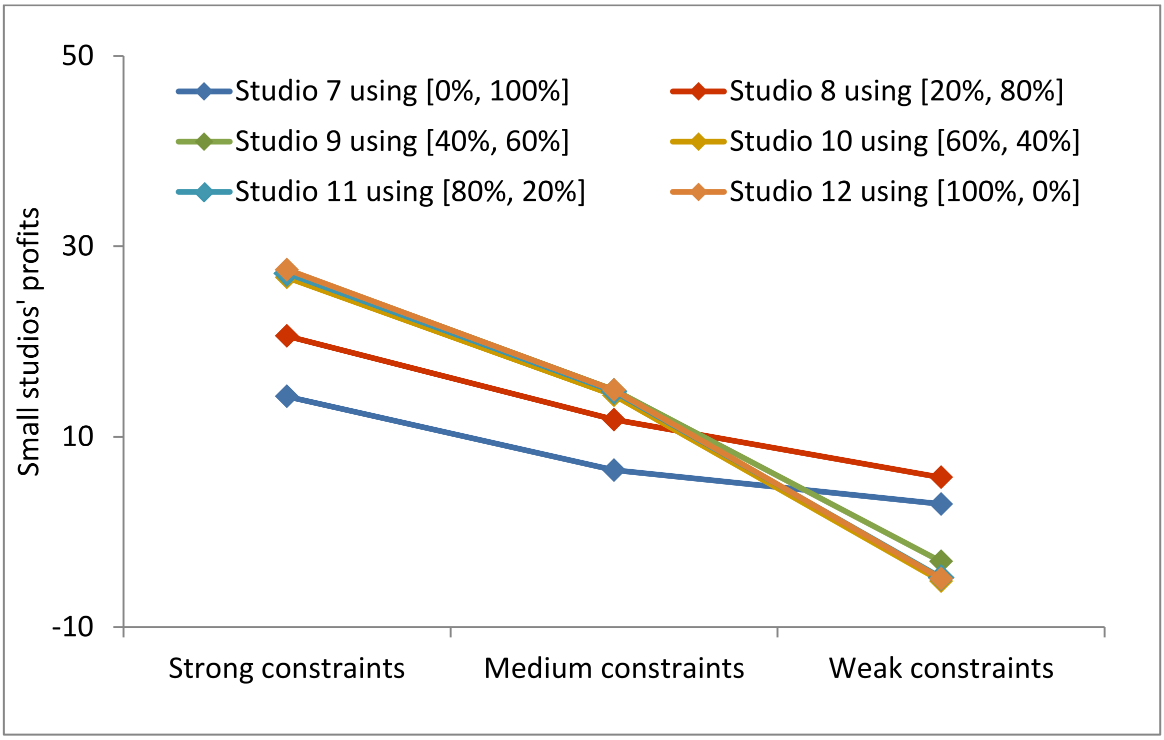


Notes: Studio 1 is the small studio while Studio 2 is the big studio. Scenario A: Both studios use the repeat or imitate rule; Scenario B: Both studios use the trend rule; Scenario C: Studio 1 uses the repeat or imitate rule and Studio 2 uses the trend rule; Scenario D: Studio 1 uses the trend rule and Studio 2 uses the repeat or imitate rule. Weak constraints: $MAX = N$; medium constraints: $MAX = N/2$; strong constraints: $MAX = N/4$.

Figure

Figure 6. A market with studios using weighted decision rules

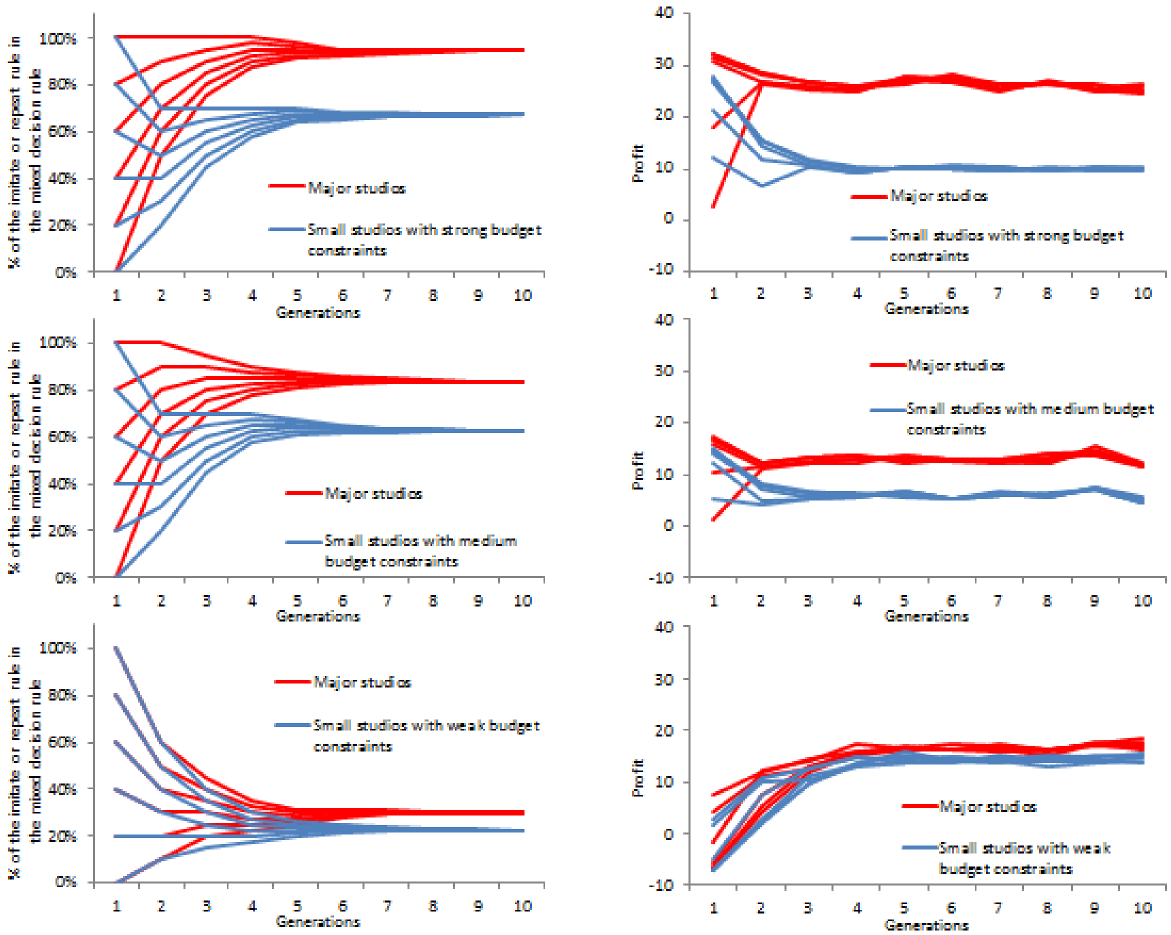




Notes: Weak constraints: $MAX = N$; medium constraints: $MAX = N/2$; strong constraints: $MAX = N/4$.

Figure

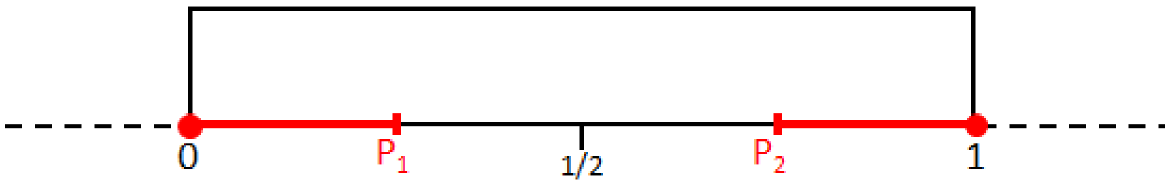
Figure 7. A market with weighted and evolving decision rules



Notes: Weak constraints: $MAX = N$; medium constraints: $MAX = N/2$; strong constraints: $MAX = N/4$.

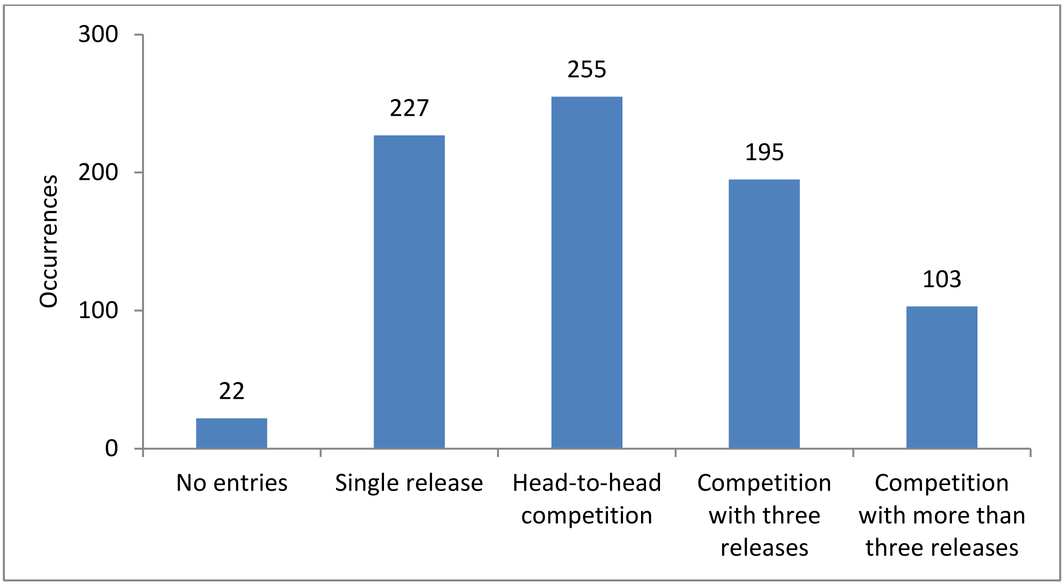
Figure

Figure C1. An alternative formalization of movie positioning



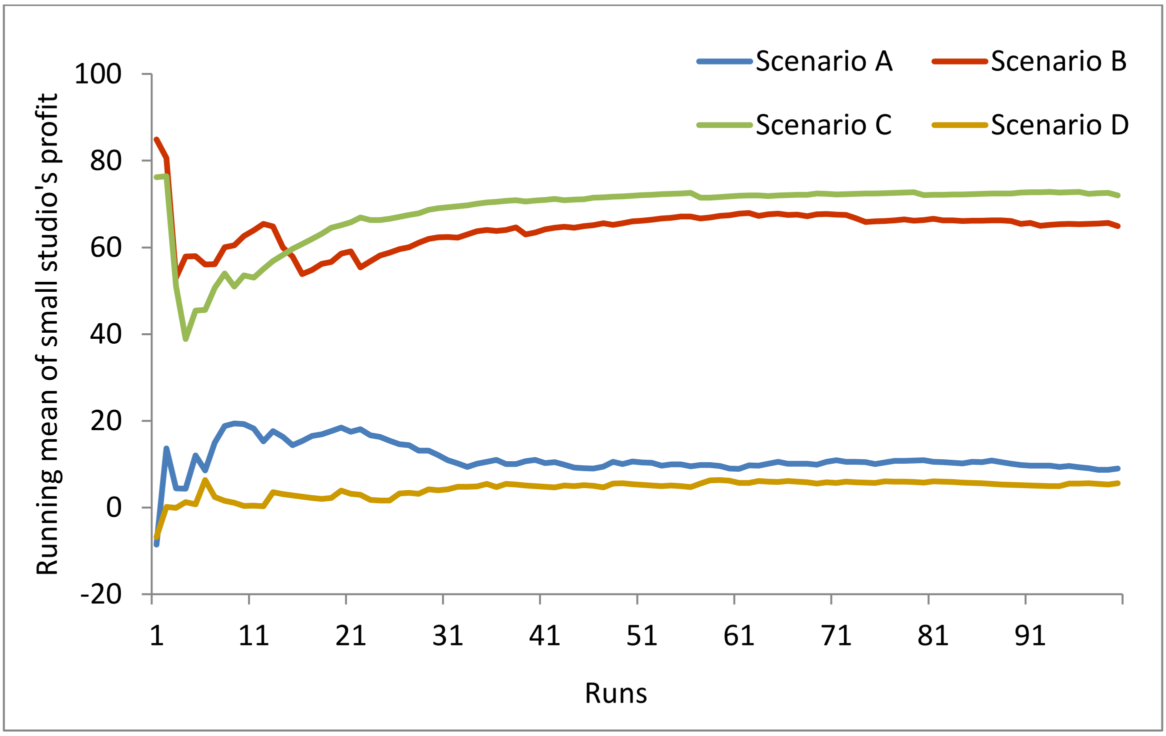
Figure

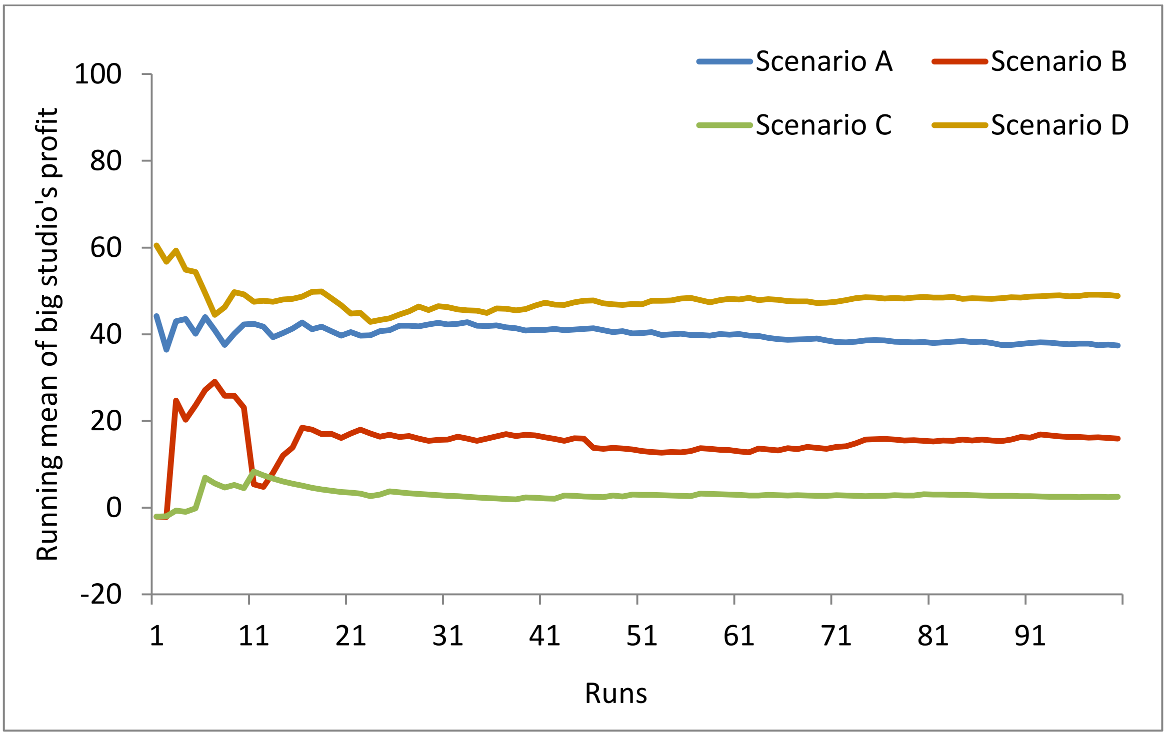
Figure E1. Movies' releases in the U.S./Canadian motion picture industry



Figure

Figure G1. Convergence: Running means of studios' profits





Notes: Scenario A: Both studios use the repeat or imitate rule; Scenario B: Both studios use the trend rule; Scenario C: Studio 1 uses the repeat or imitate rule and Studio 2 uses the trend rule; Scenario D: Studio 1 uses the trend rule and Studio 2 uses the repeat or imitate rule.