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Empirical generalizations of demand and supply dynamics for movies

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ABSTRACT

High financial risks in production and marketing, the hedonic nature of products, and the global cultural relevance of movies have encouraged a substantial number of researchers to analyze the success drivers of movies. This research provides empirical generalizations in managing the supply and demand of motion pictures. Prior empirical research either ignored the endogeneity of box office and screen allocation or was based on selective samples, ignoring the large amount of smaller movies released to the market. Using two large and unique samples of all movies released in two major movie markets, the US (2000–2010; n = 2098) and Germany (2002–2010; n = 1360), we extend prior research and present empirical generalizations and new fields of research.

1. Introduction

In 2010, the movie *Avatar* broke all box office records and grossed more than $2.78 billion worldwide within a few weeks. The movie was an exceptional success for the motion picture industry. Each movie is an innovation requiring specific management attention. In addition, the substantial costs to produce the initial first copy of the movie (Avatar was budgeted at $237 million) and the high prelease advertising costs (US: $53.14 million and Germany: €1.13 million for the Avatar movie) are both sunk at the time of release, making it a risky business (Eliashberg, Jonker, Sawhney, & Wierenga, 2000). Thus, studio managers face a high financial risk of producing the next gigantic flops, adding to such legendary examples as *The Adventures of Pluto Nash*, *Stealth*, and *Gigli*.

The hedonic nature of movies, their relevance in global culture, the high economic importance of the industry, and the public availability of data have led to a substantial number of academic studies on the success drivers of movies (Eliashberg, Elberse, & Leenders, 2006). Scholars have analyzed the effect of various variables such as star power (Elberse, 2007), academy awards (Deuchert, Adjamah, & Pauly, 2005), word-of-mouth (Liu, 2006), and age restrictions (Leenders & Eliashberg, 2011), on success measures such as box office, number of visitors, and screens. However, the large amount of empirical research has provided conflicting results on the effect of several success drivers. For example, the role of critics has been addressed by several researchers without consistency or generalizable results. While some studies show positive effects of positive reviews and negative effects of negative reviews on sales (e.g., Litman, 1983), we also find studies revealing that even negative reviews lead to higher sales (e.g., King, 2007; Wallace, Seigerman, & Holbrook, 1993) or to positive distribution effects with respect to the number of screens (Elberse & Eliashberg, 2003). Furthermore, some authors find evidence that critics influence sales (e.g., Basuroy, Chatterjee, & Ravid, 2003; Boatwright, Basuroy, & Kamakura, 2007; Kamakura, Basuroy, & Boatwright, 2006; Moon, Bergey, & Iacobucci, 2010), whereas others find that critics (actually) only predict sales and that their influence on sales is rather negligible (Eliashberg & Shugan, 1997). Another field with conflicting results is the star power research. Hennig-Thurau, Völckner, Clement, and Hofmann (2013, Appendix A, p.45) present a literature overview of previous research with respect to star power and identify ten studies that report a positive impact of stars on revenues or admissions. However, they also identify twelve studies that find no empirical support for such an effect (six studies find partial support).

The heterogeneous findings may be a result of various data limitations. Many studies are based on outdated data sets or face a substantial selection bias because the authors sampled only successful movies (e.g., top 25 in Variety or a pre-defined minimum production budget) and ignored the large number of "small" movies that entered the market more or less successfully (e.g., Elberse & Eliashberg, 2003; Ravid, 1999). Furthermore, most research focuses on the US market and thus ignores other international markets. Finally, many studies use only a very limited set of variables.

In this research, we focus on the question of whether prior findings in the motion picture industry can be generalized. The relevance of generalizations has been regularly highlighted in Marketing Science (Albers, 2012; Hanssens, 2009). Especially, Bass (1995) and Ehrenberg

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(1995) emphasized the necessity of empirical research focusing on generalizing prior research findings to provide further insights for new research topics. Additionally, several editors (e.g., Goldenberg & Muller, 2012; Winer, 1998) have highlighted the relevance of replications to investigate the generalizability of earlier research findings.

This research contributes to the literature by generalizing prior empirical findings on the success factors of movies. We rely on the established theoretical and modeling framework of Elberse and Eliashberg (2003), which accounts for the interrelationship in the behavior of audiences and exhibitors. Specifically, their dynamic simultaneous equation models account for the endogeneity of revenues and screens and incorporate the need to determine revenues and screens simultaneously. This endogenous relationship has also been identified by Krider, Li, Liu, and Weinberg (2005) who visualize causal interferences using graphical analysis. They conclude that "the dominant industry pattern is one of movie exhibitors monitoring box office sales and then responding with screen allocation decisions" (Krider et al., 2005, p. 625). While Elberse and Eliashberg (2003) (in the following used as E/E) used a sample of 164 American (co-) productions from 1999 that needed to appear at least once in the US box office top 25, we base our analysis on a much larger database covering the full US and German movie markets. Our sample consists of all 2098 movies released in the US between 2000 and (partially) 2010 and all 1360 movies released in Germany between the summer of 2002 and the spring of 2010. We collected information on all movies released during this period from various sources and abandoned any minimum box office criterion when choosing the movies to avoid selection biases. Thus, our sample represents the general movie market in two major countries. Further, we extend the findings of E/E by adding new, important variables such as sequels, MPAA ratings, US productions, genres, and the highly relevant advertising budget for the German market. We also revise the initially counterintuitive results in E/E's study about the effect of reviews. They find that unfavorable reviews by critics correspond with a higher number of opening screens. This finding is surprising in light of the research findings that address the effects of critics on the box office (e.g., Eliashberg & Shugan, 1997), but can be confirmed and explained by supply dynamics and revenue sharing models as we will show later in this paper. Finally, aside from generalizing the results for the US market, we are able to estimate the model covering the full German market. Thus, we provide a setting that also allows for generalizations across the two major international movie markets.

Our findings contribute to the literature in two ways. (1) The nature of our data allows for replication as well as substantial extension and actualization of prior research. Thus, we provide empirical generalizations of prior US-based research findings. (2) We provide new managerial insights for the German movie market that allow us to compare the empirical findings across two major movie markets to generate further empirical generalizations. Summarizing, our contribution lies in demand as well as supply generalizations that are compared across two countries.

In the next section, we provide an overview of our modeling approach. In Section 3, we discuss our data. The estimation results are presented in Section 4, followed by a discussion in Section 5. We conclude with generalizations and avenues for future research.

2. Model

The value chain in the movie business is full of dependencies and conflicting interests (Hennig-Thurau, Henning, Sattler, Eggers, & Houston, 2007). Effectively, two parties are involved in the initial stage of the sequential release strategy (theatrical release) of a movie. Managers of studios and cinemas negotiate with each other, each attempting to enforce favorable conditions (Eliashberg, Swami, Weinberg, & Wierenga, 2001). To analyze the behavior of both parties, our model follows E/E and uses two interdependent equations that cover audience demand (demand equation) and screen allocation by cinemas (supply equation).

Research on the diffusion of movies has shown that demand for the majority of movies reaches its maximum during the first week of release (Ainslie, Drèze, & Zufryden, 2005; Sawhney & Eliashberg, 1996). In particular, first weekend box office results serve as an indicator for the movie's total success (Joshi & Hanssens, 2009). Thus, the industry is release-driven and the market players focus on the first week (Karniouchina, 2011). Consequently, we model the dynamics of supply and demand determinants over time and explicitly differentiate the first week from the following weeks using separate equations. The dynamic interests of the two parties are a result of changing profit margins of distributors and cinemas over time. The expected number of visitors, or at least the distributor's estimate, is best reflected in the number of opening screens, which needs to be determined before release (Eliashberg, Hegie, Ho, Huisman, Miller, et al., 2009). Based on the number of expected visitors, the distributor provides the relevant number of copies to be distributed to the cinemas.

Assuming that a specific market potential of consumers wants to see a movie, declining profit margins over time imply that strong demand for a movie right after release is favorable for the distributor. In contrast, the cinema earns a higher margin if consumers attend the movie in later weeks. Thus, it can be assumed that the distributor will always attempt to collect as many screens as possible for the first weeks, and cinemas will attempt to shift their capacities to later weeks to maximize profits. Therefore, consistent with E/E, we account for the endogeneity of the number of screens when estimating revenues, and we assume that in each week, the errors in the supply and demand equations may be correlated. We also choose a log–log formulation to directly retrieve elasticities that allow us to better compare our results to previous research.

2.1. Model for the US market—week $t = 1$

Eq. (1) provides the model for the demand (measured in box office) for movie i in week $t = 1$.

$$\begin{aligned} REVENUES_{it} = {} & e^{\beta_0} \cdot SCREENS_{it}^{\beta_1} \cdot STAR_i^{\beta_2} \cdot DIRECTOR_i^{\beta_3} \cdot AD\_EXP_i^{\beta_4} \cdot REVIEWS_i^{\beta_5} \\ & \cdot COMP\_SCR\_REV_{it}^{\beta_6} \cdot SEASON_{it}^{\beta_7} \cdot e^{\beta_8 \cdot SEQUEL_i} \cdot e^{\beta_9 \cdot US_i} \cdot MPAA_i^{\beta_{10}} \\ & \cdot e^{\beta_{11} \cdot CHILDREN_i} \cdot e^{\beta_{12} \cdot ACTION_i} \cdot e^{\beta_{13} \cdot DOCUMENTARY_i} \cdot e^{\beta_{14} \cdot HORROR_i} \\ & \cdot e^{\beta_{15} \cdot COMEDY_i} \cdot e^{\beta_{16} \cdot OTHER_i} \cdot e^{\varepsilon_{Rit}} \end{aligned} \tag{1}$$

Revenues are driven by the number of screens allocated to movie i in week $t = 1$ and a set of time-invariant variables (star power, director power, advertising, critical acclaim, sequel, US production, MPAA rating, and genre variables) and time-variant variables (competition and an index variable to measure season). We provide details on the measurement of the variables in Section 3. The error term for the revenue equation is denoted as ε_{Rit}.

We model the supply of screens for movie i in week $t = 1$ as shown in Eq. (2).

$$\begin{aligned} SCREENS_{it} = {} & e^{\alpha_0} \cdot REVENUES_{it}^{**\alpha_1} \cdot BUDGET_i^{\alpha_2} \cdot STAR_i^{\alpha_3} \cdot DIRECTOR_i^{\alpha_4} \cdot AD\_EXP_i^{\alpha_5} \\ & \cdot REVIEWS_i^{\alpha_6} \cdot e^{\alpha_7 \cdot DISTR\_MAJOR_i} \cdot COMP\_SCR\_NEW_{it}^{\alpha_8} \\ & \cdot COMP\_SCR\_ONG_{it}^{\alpha_9} \cdot e^{\alpha_{10} \cdot SEQUEL_i} \cdot e^{\alpha_{11} \cdot US_i} \cdot MPAA_i^{\alpha_{12}} \cdot e^{\alpha_{13} \cdot CHILDREN_i} \\ & \cdot e^{\alpha_{14} \cdot ACTION_i} \cdot e^{\alpha_{15} \cdot DOCUMENTARY_i} \cdot e^{\alpha_{16} \cdot HORROR_i} \cdot e^{\alpha_{17} \cdot COMEDY_i} \\ & \cdot e^{\alpha_{18} \cdot OTHER_i} \cdot e^{\varepsilon_{Sit}} \end{aligned} \tag{2}$$

The number of screens allocated to movie i in week $t = 1$ is a function of its expected revenues ($REVENUES_{it}^{**}$), the time-invariant production budget, the distributor's market power, two time-variant competition variables that cover the competition for screen space from new releases and ongoing movies, and, finally, the same variables as listed in Eq. (1), except that we exclude the season variable in the screen equation because of fixed capacities. We include budget only in the screen supply model because cinema operators usually know the movie budget and use it for evaluating the success potential of the movie. In contrast, the average moviegoer is not aware of the production budget of a movie. The error term for the supply equation is denoted as ε_{Sit}. We model the expected revenues by relying on prerelease interest for the movie on