Box-Office Demand:
The Importance of Being #1

Luís Cabral
New York University and *CEPR*

Gabriel Natividad
New York University

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Abstract. We propose a theoretical framework to understand the effect on a movie's eventual theatrical success of leading the box office during the opening weekend. We consider two possible channels: a positive shock to the utility from watching the movie and a greater awareness of the movie's existence. We derive a series of testable predictions, which we test on U.S. box office data. The results suggest that being #1 in sales during the opening weekend has an economically and statistically significant effect on the movie total demand; and that the primary channel for this effect is through the greater awareness induced by being #1.

Keywords: movie demand; consideration sets; ordinal effects; informative and persuasive advertising.

JEL Classification: L82

Cabral: W R Berkley Term Professor of Economics, Stern School of Business, New York University; SP-SP Research Fellow; and Research Fellow, CEPR (London); luis.cabral@nyu.edu. Natividad: Stern School of Business, New York University. Email: gnativid@stern.nyu.edu.

1. Introduction

How easy is it to predict movie demand? In reference to this question, screenwriter William Goldman once famously quipped that “nobody knows anything” (Goldman, 1983). One thing industry participants do know, however: winning the first competitive battle at the box office — the very first weekend of a film’s theatrical life — can be a strong predictor of a movie’s eventual success.

In this paper, we propose a theoretical framework to understand the relation between leading the box office during a film’s opening weekend and the film’s subsequent economic success. We consider two possible channels. A first one is that being anointed as box office winner implies a positive shock to the consumer utility for watching that movie: for example, being #1 might work as a coordination device for moviegoers with a strong social consumption motivation, that is, moviegoers who want to watch the movies that others watch. A second effect is that some moviegoers are “inattentive,” so that and their consideration set places a disproportionate weight on #1 movies. In other words, being #1 increases awareness of a movie’s existence.

The two channels we consider parallel the classical persuasion-information dichotomy of the effects of advertising on demand. We derive theoretical results that allow us to identify the presence of both effects jointly and of information-mediated effects in particular. One possible test is that that being #1 increases the slope of the regression of box office revenue on movie quality. A second one is that increased consumer exposure to media promotion of films (by their actors and directors) negatively impacts the joint effect of being #1 and movie quality on total box office revenue (in other words, media exposure is a substitute for the awareness effect of being #1).

We test these predictions using U.S. box office data. Controlling for all variables that we are able to control for — including in particular movie quality and a variety of fixed effects — our results suggest that being #1 has an economically and statistically significant effect on a movie’s eventual performance. On average, being #1 is associated with an increase of $40 to 50 million to a movie’s total box office sales. Considering that the mean total sales of our 1,380 #1 movies is $93 million, this is a very large number indeed. Moreover, our regressions are consistent with the effect of being #1 appearing in interaction with the movie’s quality; that is, being #1 is more beneficial for movies of higher quality. This result is consistent with the theoretical prediction that being #1 affects box office revenues by creating greater awareness of the movie’s existence. Further evidence of this information effect is given by our finding that, for movies that were widely featured in the media prior to release, the effect of being #1 is smaller.

Our paper relates to a literature that focuses on estimating the demand for movies (Eliashberg and Shugan, 1997; Sawhney and Eliashberg, 1996; Elberse and Anand, 2007; Elberse, 2007; Moul, 2007; Einav, 2007; Natividad, 2012). Particularly relevant for our research is the work by Moretti (2011), who suggests that the opening weekend matters for a movie’s subsequent performance through peer consumer effects triggered by either positive or negative initial surprises. To the best of our knowledge, ours is the first paper to specifically address the effect of being #1 in the box office on a movie’s eventual success. Moreover, we show that the effect of a #1 ranking remains significant even when we consider the effect of opening weekend Moretti-like surprises.

Regarding the effect of ordinal rankings, our paper is related to the work by Sorensen

(2007), who finds that appearing on the *New York Times* best-seller book list leads to a modest increase in sales for the average book. Similarly, Carare (2012) finds a positive impact of being among the the top 25 apps of the Apple store, though app sales data are unavailable and rankings are truncated. By contrast to books and apps, in the movie industry all new releases are ranked, as the number of new films every week is not large. This leads us to focus on the distinct effect of #1 ranking. Our work also differs in that we provide additional evidence regarding the possible channels through which #1 rankings affect demand.[1]

Another related literature studies the impact of a product's exposure on demand. Typically, this literature finds that, when faced with such lists, individuals often show a disproportionate tendency to select options that are placed at the top (Baye et al, 2007; Smith and Brynjolfsson, 2001).

More generally, our paper is related to an extensive economics and marketing literature on the effects of advertising. In economics, one frequently contrasts the persuasive and informative roles of advertising. More recently, this has been analyzed in the context of advertising models of demand that explicitly control for consideration sets (Andrews and Srinivasan, 1995; Bronnenberg and Vanhonacker, 1996; Goeree, 2008; Haan and Moraga-Gonzales, 2011; Horowitz and Louviere, 1995; Siddarth, Bucklin Morrison, 1995). The relation with our research is that one can think of being #1 in the box office as a form of advertising. Given that, the question arises as to whether its effect on demand — which we estimate to be quite significant — occurs through channels similar to persuasive advertising (shocks to consumer utility) or rather through information effects (shocks to the consumers' consideration sets). Our empirical evidence is consistent with information playing an important role, that is, #1 rankings making moviegoers aware of a movie's existence.

The paper is structured as follows. In Section 2 we lay down a theoretical model that features #1 effects through two different channels: utility shock and consumer awareness. We derive a series of theoretical propositions that imply specific empirical predictions. In Section 3, we describe our data. The main empirical results are presented in Section 4. Section 5 concludes the paper.

2. Theoretical framework

As a motivation to our theoretical analysis, we first consider a simple plot of the data, depicted in Figure 1. On the horizontal axis, we measure opening weekend performance, defined as the difference in first weekend box office (in millions of 2009 dollars) between a movie and the second-best movie. Thus, movies with a positive value are box office winners, whereas movies with a negative or zero value are non-box-office winners. Each unit in the horizontal axis is a bin of width equal to one million dollars. The vertical axis, in turn, shows the average total box-office performance of all movies in a given bin after

1. Still regarding ordinal rankings, our work is related to the economics and strategy literature that studies ordinal vs. cardinal measures of success, in particular the importance of being #1 (Lazear and Rosen, 1981; Podolny, 1993; Cabral, 2013). A strand of the strategy literature has employed ordinal ranking methodologies to assess sustained competitive advantage over multi-year periods (Ruefli and Wilson, 1987; Powell and Reinhardt, 2010); by contrast, we focus on the microdynamics of weekly sales that is typical of information goods in competitive markets.

their full theatrical run in the United States. The dashed lines are 95% confidence intervals of third-degree polynomial fits of the opening week performance variable in explaining total box-office performance.

Figure 1 suggests that there is a very small discontinuity at zero; however, there is a considerable shift in the relation's slope at zero. In other words, (a) being #1 during the opening weekend has a positive effect on a movie's eventual performance, though small if the movie barely makes it to #1; and (b) the effect is greater the better a winner does during the opening weekend. We next consider a simple theoretical framework to better understand the possible effects of being #1 on a movie's success.

We consider two possibilities for the effect of being #1, that is, two channels through which being #1 affects theatrical performance. The first channel corresponds to an increase in consumer utility from watching a movie. This could result, for example, from social consumption benefits (e.g., watching a movie that most people will be talking about). In other words, it could be that being #1 during the opening weekend acts as a coordination device for some consumers who care primarily about discussing a movie with other moviegoers. A second possible channel is that topping the box office creates a special awareness for the movie. For example, the movie's title will appear on many headlines and thus enter the consideration set of consumes who would otherwise not know of its existence.

To consider these two possibilities, we propose a model whereby the lifespan of a movie's theatrical run can be divided into two periods, 0 and 1. We think of 0 as opening weekend and 1 as the rest of a movie's theatrical run. We will refer to $t = 0$ consumers as early moviegoers and $t = 1$ consumers as late moviegoers. Each week n new movies are released. For simplicity, we assume that movies are vertically differentiated. Specifically, let $r_i \in \mathbb{R}^+$ be movie i's quality level.[2]

A central feature of our model is that we assume there are two types of consumers: "informed" (type a) and "inattentive" (type b). Fully informed consumers observe $\{r_i\}_{i=1}^n$, whereas inattentive consumers only observe the value of r_i of box office leaders.[3]

Movie demand evolves as follows. At $t = 0$, only informed consumers (type a) watch movies. Each consumer watches each movie if and only if the utility from watching is greater than the outside option. We assume that utility is given by $u_i = r_i$.[4] For simplicity, we assume that each consumer views as many movies as there are values of r that exceed the outside option.[5] Also for simplicity, in what follows we omit the movie index i, with the understanding that our analysis applies to each movie.

At $t = 1$, a fraction $1-\lambda$ of consumers are informed, whereas a fraction λ are inattentive. Informed consumers act as their $t = 0$ counterparts with one difference: their utility from watching a movie is now given by $u = \alpha + r$ if that movie topped the box office during the

2. In our empirical implementation, we will consider various dimensions of horizontal differentiation as well, such as genre.

3. We do not need to determine the reason for consumer inattentiveness. It could be rational (consumers have a high cost of becoming informed), or it could result from some non-optimizing behavior pattern. Also, a more general version of the model could consider a continuum of types, with different probabilities of awareness of a given movie's existence. However, we believe the main qualitative features of the model would remain the same.

4. More generally, we could assume that utility is proportional to movie quality r, and with no additional loss of generality simply assume that utility is given by r. In other words, by an appropriate change of units we make the utility coefficient equal to 1.

5. An extension of our basic framework might consider the problem of selecting one or a number m of movies to watch at $t = 0$.

opening weekend, where we assume $\alpha > 0$. In other words, α measures the positive utility shock created by being #1 during the opening weekend. If the movie is not a top seller, then utility continues to be as before: $u = r$. Also at $t = 1$, a fraction λ of consumers are inattentive. These consumers behave like $t = 1$ informed consumers except that they are only aware of the existence of the #1 movie.

Let q be a movie's eventual total box office sales. Suppose that type k's outside option ξ_k is distributed according to $F_k(\xi_k)$. Let μ be the ratio of late consumers with respect to early consumers. By an appropriate change of units, we assume that the number of early consumers equals 1. Finally, let $\mathbb{1}$ be an indicator variable that equals 1 if the movie was ranked number 1 at $t = 0$, zero otherwise.

It follows from the preceding analysis that a movie's total box office sales are given by

$$q = F_a(r) + \mu \Big((1-\lambda)\, F_a(r + \alpha\, \mathbb{1}) + \mathbb{1}\, \lambda\, F_b(r + \alpha\, \mathbb{1}) \Big) \tag{1}$$

Notice that the indicator variable $\mathbb{1}$ appears three times in (1). Twice it appears as the argument of $F_k(\cdot)$. This represents the utility boosting effect of being number one, an effect that is measured by the parameter α. The third appearance of $\mathbb{1}$ is multiplying $\mu\, \lambda\, F_b(r + \alpha\, \mathbb{1})$. This represents the awareness boosting effect of being number one, the fact that the movie now belongs to the inattentive consumers' consideration set.

We next develop a series of theoretical results which provide us with testable empirical implications from the model.

Proposition 1. *Being #1 has a positive effect on a movie's theatrical performance:*

$$q\,\big|_{\,\mathbb{1}\,=\,1} \;>\; q\,\big|_{\,\mathbb{1}\,=\,0}$$

This is the most basic of our results: we expect that being number 1 implies a boost to a movie's eventual box office performance. A proof may be seen in the Appendix. Regardless of the channel that the #1 effect takes place, we expect the effect to be positive.

Our next two results pertain to the effect of being #1 on the relation between movie quality and movie performance.

Proposition 2. *If most late moviegoers are inattentive, then being #1 increases the sensitivity of theatrical performance with respect to movie quality. Formally, there exists a* $\lambda' \in [0, 1)$ *such that, if* $\lambda > \lambda'$*, then*

$$\frac{\partial\, q}{\partial\, r}\bigg|_{\,\mathbb{1}\,=\,1} \;>\; \frac{\partial\, q}{\partial\, r}\bigg|_{\,\mathbb{1}\,=\,0}$$

Intuitively, if late moviegoers are inattentive, then the primary effect of being #1 is to make late moviegoers aware of the movie's existence. If a movie is not #1, then late moviegoers are not aware of its existence, and the movie's total sales equal its sales during the opening weekend. To the extent that, conditional on awareness, late moviegoers are more likely to watch a movie if it is of higher quality, then being #1 not only increases attendance but also increases the sensitivity of attendance to movie quality.

Notice that the qualifier $\lambda > \lambda'$ is necessary. To see this, consider the extreme case when $\lambda = 0$. Then the only effect of being #1 is to create a utility boost α. If the values of r and $r + \alpha$ belong to the declining region of $f(\cdot)$ (which is reasonable, considering that we are talking about blockbusters), then the utility boost α decreases the sensitivity of q with respect to r. In other words, being #1 makes the movie more of a "must see" regardless of movie quality.

Our next result follows a similar line of reasoning.

Proposition 3. *Suppose that $f_a(r)$ is decreasing in r when $\mathbb{1} = 1$. An increase in the fraction of uninformed consumers, λ, implies an increase in the interaction term being #1 $\times$ movie quality, that is, $\mathbb{1}\, r$:*

$$\frac{d}{d\lambda}\left(\frac{\partial q}{\partial r}\bigg|_{\mathbb{1}=1} - \frac{\partial q}{\partial r}\bigg|_{\mathbb{1}=0} \right) > 0$$

The intuition for Proposition 3 is similar to that of Proposition 2. The greater λ is, the greater the awareness effect of being #1. This effectively increases the sensitivity of a movie's performance to its quality. In other words, a good movie does well at the box office, but a good movie that is #1 during the opening weekend does particularly well. In fact, being #1 implies that many more consumers are aware of its existence; and being good implies that awareness turns into sales.

Propositions 2 and 3 are similar in that both refer to the interaction of a movie's quality and its sales ranking. However, the precise mathematical statement is different. In Proposition 2, we assume λ is high and posit that #1 movies have a higher $\partial q \,/\, \partial r$. That is, Proposition 2 corresponds to a difference in derivatives. By contrast, Proposition 3 corresponds to a derivative of a difference in derivatives: the greater λ is, the greater the difference between the derivatives $\partial q \,/\, \partial r$ between #1 and not #1 movies.

To conclude this section, we illustrate the model's mechanics by generating pseudo-data on its primitives. Suppose that $\lambda = 1$, $\mu = 6$ and that the outside option of type k consumer is normally distributed with parameters $\mu_a = \sigma_a = \sigma_b = 1$ and $\mu_b = 5$. By generating 100 observations of $n = 10$ movies each, we obtain the values in Figure 2. As can be seen, this theoretically-driven pattern is broadly consistent with the empirical features of Figure 1. The similarity between Figures 1 and 2 provides some support for our theoretical model as an explanation for the effect of #1 effects.

Propositions 1, 2 and 3 provide a series of empirical predictions regarding the effect of a #1 ranking. We examine these in the next sections by regressing q on r, $\mathbb{1}$, and a series of covariates. Specifically, testing Proposition 1 corresponds to estimating the effect of $\mathbb{1}$, that is, a dummy variable that is equal to 1 if the movie was #1 at the box office during the opening weekend. In order to test Propositions 2, we consider the interaction variable $\mathbb{1}\, r$. Finally, in order to test 3 we consider the triple interaction between $\mathbb{1}, r$ and a proxy for λ.

3. Data

To investigate the effect of being #1, we assembled a database on the population of feature films released in U.S. theaters between 1 January 1982 and 31 December 2009. Our dataset draws from different sources: *Variety*, the leading industry periodical, and AC Nielsen EDI, a market research provider, report weekly and weekend box office revenue, weekly screens, and other movie characteristics such as genre. Studio System and *Variety* provide distribution company information. IMDb, an online database owned by Amazon.com, contains film- and person-level data not only on each feature film released but also on other appearances of cast members on TV shows and the printed press, recording the exact date of these appearances. Proprietary information on production budgets through 2009 was acquired from Baseline Intelligence, a *New York Times* company; this provider is a well-trusted source used by industry decision-makers.

Our analysis is conducted at the movie level. From the population of all films released in the United States, we drop those that are re-releases of existent films, and we also drop 45 instances in which there was only one film released in a given week, resulting in a total of 9,933 distinct movies. Information on production budget is available for 79% of these films (7,854). We follow Moretti's (2011) procedure to fill in the missing production budget information on the 21% remainder using the industry average, thus keeping all feature films for estimation. Our sample comprises 1,388 distinct weeks, each of which had an average of 7.16 opening films.

Our data sources allow us to construct proxies for movie quality and movie exposure to media and other promotional events. Our first movie quality variable is given by "star power." This has been widely documented as as a signal of quality driving movie sales (Elberse, 2007); in our context, it is operationalized as the sum of box office revenue of films of each team member over the three calendar years prior to film's release, divided by the number of team members; this variable, which we construct based on data from *Variety*, AC Nielsen EDI, and IMDb, is fixed at the moment of release.

A second measure of movie quality is given by average user ratings at IMDb, a proxy that has been used in previous research (e.g., Natividad, 2012). It should be noted that this variable is only available after the film is released, thus requiring the assumption that the average consumer's judgment about the film reflects underlying quality already present at the moment of release.

Regarding media exposure prior to the release of a movie, we consider the sum of all printed press articles, interviews, magazine covers, and magazine pictorials, as well as the sum of all TV show appearances of actors and directors in the four weeks prior to the release of the film; all this information is from IMDb. Alternatively, we measure participation in film festivals prior to the release date, also available from IMDb.

Table 1 provides basic summary statistics of the main variables used in the regressions that follow.

■ **Controls and fixed effects.** Our tests take the form of movie-level regressions of total box office revenue on proxys capturing the main features of our theory, as outlined above. To assuage concerns that the results may be driven by unobserved movie heterogeneity, we introduce the following control variables: the production budget of the film in millions of 2009 dollars, movie genre dummies, movie MPAA rating dummies, movie distribution company fixed effects, and date of release fixed effects. Importantly, while these granular controls and fixed effects do not fully account for potential omitted variables that may carry significant empirical weight, they constitute the broadest set of variables we can think of. To illustrate, an alternative explanation for #1 effects might be that films may choose a particularly attractive week in which their appeal may be heightened; by introducing date-of-release fixed effects, we are effectively comparing each given film with all other films that chose the same week for release, thus narrowing the range of explanations for being #1 effects.

4. Empirical Results

As mentioned in Section 2, if we consider a regression with box office revenues as a dependent variable, Proposition 1 implies that expected value conditional on $\mathbb{1} = 1$ is greater than expected value conditional on $\mathbb{1} = 0$. Proposition 2, in turn, implies a positive value for the interaction coefficient $\mathbb{1}\,r$. Finally, Proposition 3 implies a test of a triple interaction. We report our tests in slightly different order from our theoretical section, given our empirical specification.

■ **Testing Proposition 2.** The two regressions in Table 2 correspond to two possible r variables: star power and movie quality ratings, both described in Section 3. In both cases, the coefficient on $\mathbb{1}\,r$ is positive, as predicted by Proposition 2. The coefficients are statistically significant (p value lower than 1%) and economically significant as well. Computed at mean variable values, the elasticity of box office revenues with respect to star power is 0.5140 for #1 movies but only 0.0644 for non #1 movies. For movie quality ratings, the elasticity increase from 1.0805 to 7.0327.

Alternatively, we can measure economic significance by the product of the estimated coefficient by the ratio of the standard deviations of independent and dependent variable. For star power, we get 0.2495 for #1 movies and 0.0313 for non #1 movies. In other words, an increase of one standard deviation in star power is associated with a 0.2495 standard deviation increase in box office revenues for #1 movies, but only a 0.0313 standard deviation increase in box office revenues for non #1 movies. For movie quality ratings, the numbers are 0.6141 and 0.0943.

In sum, the results are consistent with Proposition 2, both in terms of coefficient sign and statistical significance. Moreover, the effects seem economically meaningful.

■ **Testing Proposition 1.** Regarding Proposition 1, the results from the star power independent variable in Table 2 are clearly consistent with theory: both the coefficient on $\mathbb{1}$ and the coefficient on $\mathbb{1}\,r$ are positive, so that, controlling for quality, being #1 is associated with higher box office revenues. At the mean value of the star power variable, this corresponds to a combined effect of $31.708 + 31.886 \times .313242 = 41.6960$. In other words, controlling for movie quality, being #1 is associated with a $41 million increase in revenues. Regarding the model with movie quality ratings as an independent variable, it is not as clear that Proposition 1 holds. In fact, while the interaction term $\mathbb{1}\,r$ is positive, the coefficient on $\mathbb{1}$ is negative. However, when we account for the full effect of being #1 over the two coefficients of the regression at the mean value of the independent variable movie quality ratings we obtain $-79.376 + 21.402 \times 6.178959 = 52.8661$; that is, controlling for movie quality, being #1 is associated with a $52 million increase in revenues, which is consistent with Proposition 1.

■ **Testing Proposition 3.** Proposition 3 states that, the greater the measure of inattentive consumers (parameter λ), the greater the impact of being #1 through the awareness channel. In order to test this possibility, we consider two alternative proxys for λ: pre-release media exposure and pre-release festivals. Our prediction is that alternative information sources about a movie's existence lead to a decrease in the value of λ and, by Proposition 3, a decrease in the interaction effect $\mathbb{1}\,r$.

As mentioned earlier, Proposition 3 is about the derivative of a difference of derivatives: a triple interaction term between $\mathbb{1}$, r and λ. Since we have two possible measures of r and two possible proxys for λ, we have four possible regressions. The results are displayed in Table 3. Three of the four regressions show the expected negative sign on the triple interaction term of interest, one of which is also statistically significant. The one regression whose coefficient is opposite to Proposition 3's prediction is not statistically significant.

■ **Some robustness tests.** The main purpose of our empirical regressions is to assess whether the implications of the theoretical model presented in Section 2 are borne out in the data; we do not claim to have exogenous variation for a causality test for the effect of being #1. With this caveat, we performed a series of additional regressions to evaluate the robustness of the results in Table 2.

A natural test for the "discontinuous" effect of being #1 is to add to the regressions in Table 2 the corresponding variables for being #2 and #3. In untabulated models, although these variables have coefficients with the same sign as being #1, the coefficient sizes are considerably smaller. Specifically, the model that uses star power as a proxy for r has a coefficient of 35.8 for the interaction of r and being #1; whereas the interaction coefficients for #2 and #3 are 5.7 and 1.5 (the former with a p value lower than 1%, the latter statistically insignificant). As for the model that uses movie quality ratings as a proxy for r, the corresponding coefficients are 23.1, 5.8 and 3.1 (all with p values lower than 1%).

An alternative robustness test is to consider a set of matched observations. Specifically, we consider a subsample made up of each week's #1 film and a matched companion film released in the same week, the nearest neighbor using the Mahalanobis distance based on quality, star power, and production budget (regardless of rank). Alternatively, we restrict to #1 and #2 films when the Mahalanobis distance between these is in the 25th percentile of smallest distance. In both cases, untabulated here for brevity, we still observe a strong effect from being #1.

■ **Positive surprises and rankings.** As mentioned earlier, Moretti (2011) proposes an alternative theory of why the opening weekend is so important for a movie's eventual box office performance: movies subject to positive surprises during the first weekend perform significantly better than movies not subject to positive surprises (or subject to negative surprises). In order to estimate whether the effect of being #1 goes beyond the positive surprise effect, we run a series of regressions that follow Moretti's (2011) specification but add the #1 indicator variable. Specifically, as in Moretti (2011) we construct a proxy for movie surprises using a multivariate regression model, the residual of which leads to a "positive surprise" dummy whenever it is greater than zero.

Table 4 displays the results of regressions where we allow both for positive surprise effects and being #1 effects. The first two regressions show the effect of each factor in isolation. A positive surprise in the first week is associated with an increase in total box office revenues of about $25 million, whereas being #1 is associated with an increase of $82 million. When we allow for the two effects simultaneously (third regression), we note that both are statistically significant. The surprise effect drops by about 50% to around $14 million, whereas the #1 effect remains high ($78, down from $82). These results suggest that being #1 is more important for total movie sales than being subject to a positive surprise. It should be noted that, in a given week, several newly released movies are subject to positive surprises, whereas only one is ranked #1. Moreover, being #1 is an easily observable movie characteristic after the first weekend, whereas a positive surprise requires fitting a multivariate regression model first, in order to obtain an above-zero residual to determine whether the movie is subject to a positive surprise.

Column 4 of Table 4 adds an interaction term that combines the positive surprise dummy and being #1. The results suggest that the interaction term is quite significant, both statistically and economically. In fact, most of the effect of being #1 seems to "require" that the movie be a positive surprise, and vice versa: a substantial portion of the effect of a positive surprise "requires" that the movie be ranked #1. The last regression of Table 4 adds the usual control variables and fixed effects: the production budget of the film in millions of 2009 dollars, movie genre dummies, movie MPAA rating dummies, movie distribution company fixed effects, and date of release fixed effects. The results remain largely unchanged: both being #1 and being subject to a positive surprise positively affect total box office performance.

■ **Summary.** As mentioned earlier, we do not claim to have exogenous variation for a causality test for the effect of being #1. In the above regressions, the #1 indicator variable may be picking up heterogeneity in movie quality not measured by our quality variables star power and movie quality ratings. Having said that, we believe the empirical results provide strong conditional correlations consistent with our theoretical prediction of the effect of leading the box office during the opening weekend, in particular the relative importance of the information channel.

5. Conclusion

Many models of sales dynamics have used the film industry in the United States as an empirical laboratory to understand the impact of product characteristics and firm policies on demand. We propose a theoretical model of movie consumption where #1 rankings imply both utility shocks and increased awareness of a movie's existence. Our empirical results suggest that being #1 at the box office during the opening weekend has an economically and statistically significant effect on a movie's eventual performance, and that this effect is more pronounced the higher the quality of the box office leader. Additional empirical evidence is consistent with an information-mediated effect, that is, the idea that #1 movies are more likely to be in the consideration set of potential moviegoers.

Appendix

Proof of Proposition 1: From (1),

$$q_i\big|_{\mathbb{1}=1} = F_a(r_i) + \mu\, F_b(r_i)$$

whereas

$$q_i\big|_{\mathbb{1}=0} = F_a(r_i)$$

The result then follows from the assumption that $F_b(r_i)$ has full support. ■

Proof of Proposition 2: From (1), we get

$$\frac{\partial q}{\partial r} = f_a(r) + \mu\Big((1-\lambda)\, f_a(r+\alpha\,\mathbb{1}) + \mathbb{1}\,\lambda\, f_b(r+\alpha\,\mathbb{1})\Big)$$

Taking limits as $\lambda \to 1$,

$$\lim_{\lambda\to 1}\frac{\partial q}{\partial r} = f_a(r) + \mu\,\mathbb{1}\, f_b(r+\alpha\,\mathbb{1})$$

It follows that

$$\lim_{\lambda\to 1}\left(\frac{\partial q}{\partial r}\Big|_{\mathbb{1}=1} - \frac{\partial q}{\partial r}\Big|_{\mathbb{1}=0}\right) = \mu\, f_b(r+\alpha) > 0$$

The result follows by continuity at $\lambda = 1$. ■

Proof of Proposition 3: From (1), we get

$$\frac{\partial q}{\partial r} = f_a(r) + \mu\Big((1-\lambda)\, f_a(r+\alpha\,\mathbb{1}) + \mathbb{1}\,\lambda\, f_b(r+\alpha\,\mathbb{1})\Big)$$

Therefore,

$$\begin{aligned}\frac{\partial q}{\partial r}\Big|_{\mathbb{1}=1} - \frac{\partial q}{\partial r}\Big|_{\mathbb{1}=0} &= \bigg(f_a(r) + \mu\Big((1-\lambda)\, f_a(r+\alpha) + \lambda\, f_b(r+\alpha)\Big)\bigg) \\ &\quad -\bigg(f_a(r) + \mu\Big((1-\lambda)\, f_a(r)\Big)\bigg) \\ &= \mu\Big((1-\lambda)\, f_a(r+\alpha) + \lambda\, f_b(r+\alpha) - (1-\lambda)\, f_a(r)\Big)\end{aligned}$$

Therefore,

$$\frac{d}{d\lambda}\left(\frac{\partial q}{\partial r}\Big|_{\mathbb{1}=1} - \frac{\partial q}{\partial r}\Big|_{\mathbb{1}=0}\right) = f_b(r+\alpha) + f_a(r) - f_a(r+\alpha)$$

The result then follows from the assumption that $f_a(r)$ is decreasing in r when $\mathbb{1} = 1$. ■

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Figure 1
Relation between performance advantage at $t = 0$ and eventual performance using box office data.

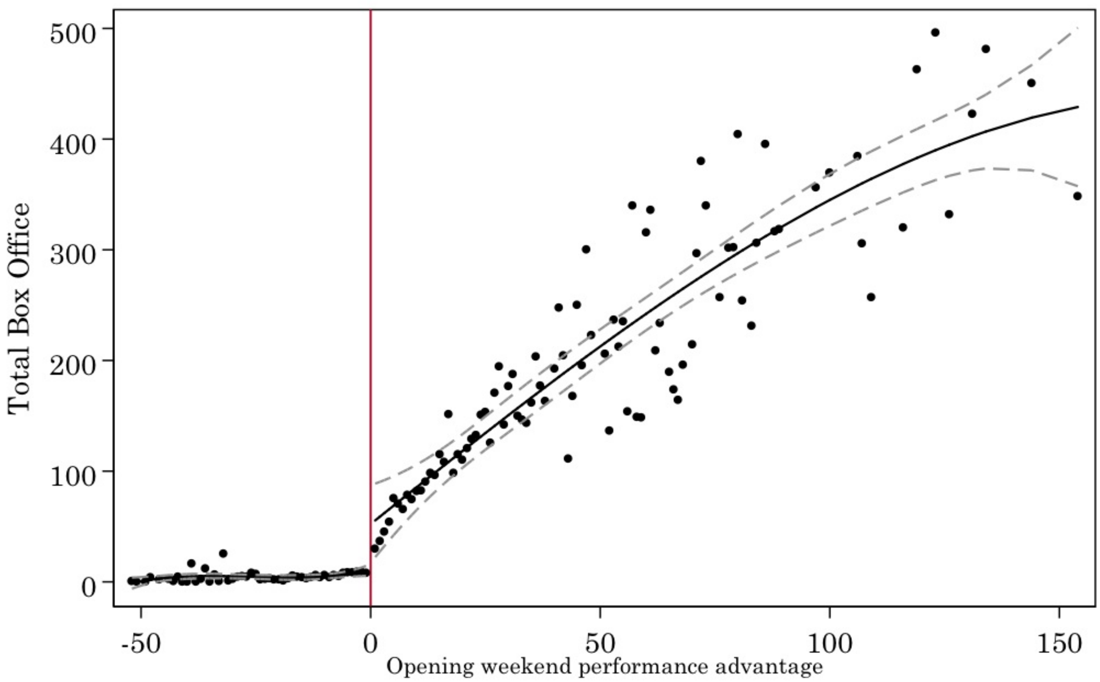

Figure 2
Relation between performance at $t = 0$ and eventual performance using pseudo-data.

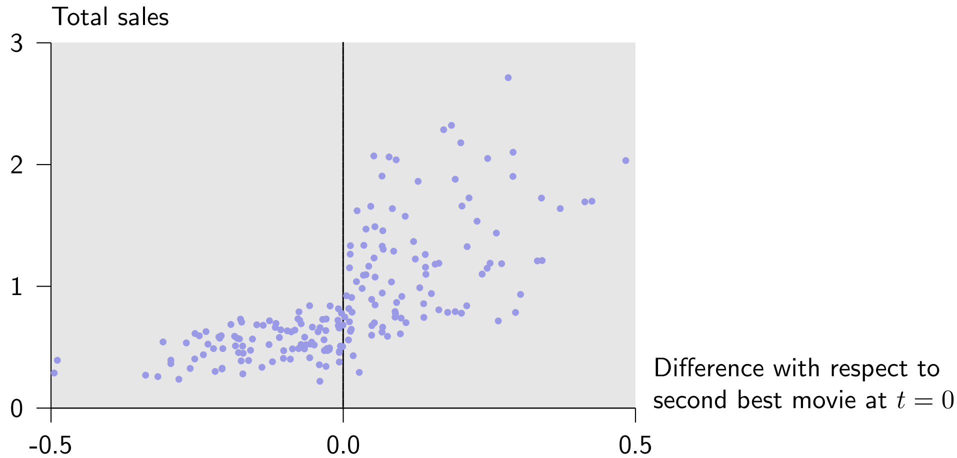

Table 1
Descriptive statistics (movie level)

Variable	Obs	Mean	Std. Dev.	Min	Max
Total box office revenues	9933	22.22	49.71	0.00	802.92
Being #1	9933	0.14	0.35	0	1
Review score	9895	6.18	1.21	1.1	9.8
Star power	9927	0.31	0.34	0	4.63
Media exposure	9927	0.09	0.19	0	2.5
Festival participation	9933	0.98	2.21	0.00	28

Table 2
Being #1 and movie quality

	Dependent Variable: Total Box Office	
Being #1 × Star power	31.886***	
	(7.82)	
Being #1 × Quality rating		21.402***
		(1.93)
Being #1	31.708***	−79.376***
	(4.35)	(10.68)
Star power	4.567**	
	(2.03)	
Quality rating		3.885***
		(0.40)
Controls and Fixed Effects	Yes	Yes
R^2	0.67	0.70
Sample size	9927	9895
N. of clusters (release date)	1388	1388

***, **,* significant at the 1%, 5% and 10% level.
Robust clustered standard errors in parentheses.

Table 3
Movie pre-release information and the effect of being #1

	Dependent Variable: Total Box Office			
Being #1 × Star power	32.640***	32.232***		
	(8.67)	(8.05)		
Being #1 × Quality rating			21.179***	21.867***
			(2.19)	(1.95)
Being #1 × Star power × Pre-media	−59.384***			
	(18.49)			
Being #1 × Star power × Pre-festivals		−15.115		
		(17.23)		
Being #1 × Quality rating × Pre-media			−4.240	
			(8.99)	
Being #1 × Quality rating × Pre-festivals				2.659
				(3.59)
All other interaction terms and levels variables	Yes	Yes	Yes	Yes
Controls and Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.67	0.67	0.70	0.70
Sample size	9927	9927	9893	9895
N. of clusters (release date)	1388	1388	1388	1388

***, **,* significant at the 1%, 5% and 10% level. Robust clustered standard errors in parentheses.

Table 4
Being #1 vs. positive surprises

	Dependent Variable: Total Box Office				
Positive surprise	25.617***		13.744***	7.157***	7.413***
	(0.97)		(0.83)	(0.84)	(0.68)
Being #1		82.479***	78.146***	20.052***	22.936***
		(1.18)	(1.19)	(2.49)	(1.51)
Positive surprise × Being #1				73.940***	68.714***
				(2.81)	(3.25)
Controls and Fixed Effects	No	No	No	No	Yes
R^2	0.07	0.33	0.35	0.39	0.54
Sample size	9933	9933	9933	9933	9933
N. of clusters (release date)					1388

***, **,* significant at the 1%, 5% and 10% level. Robust clustered standard errors in parentheses.