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Information, Blockbusters, and Stars: A Study of the Film Industry*

This article presents two alternative explanations for the role of stars in motion pictures. Either informed insiders signal project quality by hiring an expensive star, or stars capture their expected economic rent. These approaches are tested on a sample of movies produced in the 1990s. Means comparisons suggest that star-studded films bring in higher revenues. However, regressions show that any big budget investment increases revenues. Sequels, highly visible films and "family oriented" ratings also contribute to revenues. A higher return on investment is correlated only with G or PG ratings and marginally with sequels. This is consistent with the "rent capture" hypothesis.

I. Introduction

The purpose of this article is to explore a possible role for stars and other potential informational signals in the movie business. In the first part of this article, I define two alternative economic explanations for the role of stars in motion pictures. These two approaches have different implications regarding stars' pay, movie revenues, and return on investment.

The second part of this article contains an extensive empirical investigation of a sample of movies produced in the 1990s.

In some sense, this analysis applies techniques that are generally used to assess overall firm performance to a discussion of individual projects. There are very few industries in which such a wealth of data concerning individual undertakings is available, and thus the implications of my discussion may transcend the motion picture industry.[1]

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1. There are very few empirical investigations of profitability at a project level, and they often pertain to developing coun-

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II. Project Finance and the Film Industry

Films are essentially projects, similar to a new product line or a new restaurant. However, they possess some unique, important characteristics. They are expensive commodities. The most expensive film in my sample cost $70 million to produce, excluding advertising and distribution expenses. The record to date is held by *Titanic* (released in late 1997), with a price tag exceeding $200 million. The average cost of films has reached $50.4 million in 1995 (see Weinraub 1995).[2] Yet each project is unique. Whereas the essential attributes of most commodities can be easily described and measured, this is not the case for movies. But at each moment in time studios must select projects from among many competing proposals. The exception that proves the rule is the scramble for sequels—if a successful formula is found, it must be tried again.[3] The hype involved in any release of a new film is often heightened by the participation of a major star or by expensive and unusual special effects (examples of movies of the latter type include *Jurassic Park, Volcano, Twister, Titanic,* and many others).

This article investigates two competing hypotheses regarding the role of stars in the movie business. The first hypothesis maintains that stars essentially capture most of their value added. This view can find some support in the institutional background. Until the 1950s, the studio system ruled supreme in Hollywood. A star would sign a long-term contract with a studio. If the star had a successful film and his market value went up, the studio would capture most of the rent. The demise of the studio system made stars essentially free agents, whose salary reflects their market value. Since each star is unique in some sense, one could conjecture that they should be able to capture most of their expected value added.[4]

This "rent capture" hypothesis[5] is supported by significant casual evidence, indicating that stars very quickly adjust their fees to reflect their value. Weinraub (1995) reports that John Travolta, who had

tries. Most theoretical investigations are concerned with optimal investment or capital structure issues; see, e.g., Shah and Thakor (1987), Webb (1991), or Chemmanur and John (1996). Related literature discusses real options; for some recent examples, see Berk, Green, and Naik (1998), Childs, Ott, and Triantis (1998), or a survey by Trigeorgis (1996).

2. Press reports and trade publications propose numerous "average budgets." It is not always clear how each figure is calculated, but my sample seems reasonably representative of the universe of films produced in that period. A figure by the Motion Pictures Association of America (MPAA), the major trade group, reported by S&P for 1996, for instance, is $39.8 million for negative costs and $19.8 million for print and advertising (see *S&P Credit Week* 1997).

3. Later I shall test the role of sequels directly. I thank the referee for suggesting this route.

4 Of course, since the success of the next film is always random, and a star's value is also not always clear ex ante, this can only be true on average.

5. I thank a referee for suggesting this interpretation.

earned only $150,000 for *Pulp Fiction* (a much lower fee than he had commanded earlier in his *Saturday Night Fever* days) increased his fee to $10 million after the success of that film. Alicia Silverstone, who had received $250,000 for *Clueless,* increased her fee for the next film to $5 million. Other examples abound (see Weinraub 1995; Gumbel et al. 1998). A finding of no correlation between star participation and film revenues and/or profitability supports the "rent capture" idea.[6]

The other hypothesis is somewhat more complex and relies on the process by which films are being produced. Studios purchase options on many scripts. Some of these scripts are chosen for development, where additional participants (stars, director) are attached to the project as it progresses. In the process, studio executives learn more about the project. This is where a signaling interpretation may come in. Executives' careers may depend on the success of a film (the average tenure in office for executives in charge of production at large studios had been around 20 years during the 1940s but had declined to 4 years by the 1970s and 1980s [Weinstein 1998, n. 40]). With a significant probability of being fired, a commitment to a star or to expensive special effects can be a high-risk proposition for a risk averse executive. Since it is costly, one can view such commitment in an early stage of the project as a signaling device, by which the executive signals the quality of the project to the studio or to outside financiers. The executive cares about the current effect of the signal because his current compensation is tied to the project he is involved in. He cares about ex post results because his future in the business depends on the success of the project. The signaling process here is thus similar to a simple Ross (1977) type model (but it can be developed into a more complicated set-up, such as John and Williams [1985]; Miller and Rock [1985]; Flannery [1986]; Diamond [1991]; or Ravid and Sarig [1991]). A similar interpretation can apply if a star actor or star director is the initiator of a project (which happens sometimes, e.g., for the film *Forrest Gump*). In this latter case, star participation may signal superior information—in other words, a star will commit to a project because she knows it is of high quality.

Casual evidence seems to support the idea of an in-depth evaluation and gradual attachment of "talent" to the project. This should breed informed insiders who can signal quality. Breese (1992) describes the long screening process a script must endure from submission to acceptance. Lippman (1995) illustrates this notion in the *Wall Street Journal* with a story about a screenplay that had been sold by two newcomers

6. The exact theoretical specification depends on the way the star captures his value. However, empirically, a correlation with both revenues and returns would negate any reasonable interpretation of this approach.

for $1.2 million, but 5 years, four rewrites, and another $1 million in costs after the original sale, it had still not been produced.

The signaling notion is also supported by the fact that stars and directors typically receive a portion of their compensation as percentages of the gross revenue of the film. This setup is consistent with an incentive contract, risk sharing, or a signaling framework (see Weinstein 1998). The institutional background leads one to believe that the latter interpretation may be more likely—reputational effects should keep stars on track even without a specific incentive component in their contract, and the risk sharing interpretation is problematic.[7]

Chisholm (1997) finds that actors are likely to receive share contracts for projects that have a longer production time. This finding can be interpreted in various ways, but it can support the notion that share contracts are more likely if a less transparent project were at stake and if actors were trying to signal quality.[8]

The few studies that have documented the determinants of success in the film industry seem to indicate that stars and other manifestations of recognition are associated with successful movies.[9] Dekom (1992, p. 130) verbalizes this popular notion about stars that can "open" a film in describing Disney's strategy: "The first (strategy) is Disney's technique, which recognizes that once a person is a star, even if his or her fortunes seem to have changed, he or she will be recognized and valued by the public. By uniting an attractive concept, well marketed,

7. Weinstein (1998), in a historical analysis of contracts in the movie industry, believes so, too—in an environment where each project is recontracted, stars cannot afford to fail, and thus it is hard to view gross participation contracts as incentive schemes. The risk-sharing interpretation is problematic since it is not clear which party is more or less risk-averse. This leaves the information story. Further, such a contractual form—i.e., a fixed component plus share participation—agrees with some of the literature on optimal contract design in very uncertain environments (see Ravid and Spiegel 1997).

8. The study by Chisholm (1997) examines the incidence of a share contract vs. a fixed payment contract. A relatively small number of contracts were collected in a painstaking effort for 118 films over 30 years (this represents a very small percentage of the total number of films produced). For some films the information obtained was incomplete. Probit analysis points out that male actors and experienced actors (marginally significant) tend to receive share contracts. There is also a significant correlation between the probability of receiving a share contract and the length of production. Revenue from the previous movie and "previous work-as-a-team" variable are also marginally significant. However, a casual glance at the actors included in the sample reveals that most of them are stars by most definitions. On average, each actor in the sample had two Oscar nominations (maximum: 11) as opposed to about 1.5 per film (i.e., for all cast members) in our more random sample. This selection is because contracts of "lesser" luminaries are usually not reported in the press or in trade publications.

9. There are several studies of the stardom phenomenon, in other words, whether stars are indeed the most talented people in the profession and in some sense "deserve" their fame and fortune or whether they have become stars for other reasons. The classical analysis in this area is by Rosen (1981), followed by a paper by Adler (1985). The empirical evidence is hard to obtain and is somewhat mixed—see, e.g., Hamlen (1991). However, in my case the question is whether stars, who are stars for whatever reason, are hired so as to signal some independent measure of quality.

with a recognizable name (although perhaps from the recent past) Disney has been able to generate considerable grosses.'' Litman (1983) finds that Academy Award nominations or winnings are significantly related to revenues.[10] Litman and Kohl (1989) find that the participation of stars and top directors (classified in a manner similar but not identical to our empirical measures), critical reviews, ratings, and several other variables are significantly related to revenues. However, Academy Award nominations are significant only for the Best Film category, and winning did not seem to affect revenues.

These studies, as well as some sophisticated analyses of success in the business (see Eliashberg and Shugan 1994; Eliashberg and Sawhney 1996), have focused on receipts. The economic measure of success, however, should be profits or returns to investment, which I try to incorporate in this study. Furthermore, in recent years the importance of video and international revenues has increased significantly. This is the first study (to my knowledge) to include such data, reflecting the new reality of the movie business. I also include a comprehensive set of control variables.[11]

In most industries, a discussion of return on investment should be sufficient. However, as noted earlier, the movie industry is very concerned with revenues. This is reflected in reports in the popular press and in some previous empirical studies—in fact, all empirical studies quoted in this article used revenues as the dependent variable and did not try to estimate returns. I will thus also consider revenues as a possible objective in the empirical investigation by looking at the correlation between stars and revenues. This type of test can examine the signaling idea for revenues as well, although the signaling model cannot be empirically disentangled from a simple model proposing that more expensive stars lead to higher revenues. A discussion of revenues will also enable me to better compare my sample and results with other papers.

Finally, I should note that an alternative empirical specification could have included an event study of the announcement effect of hiring a star or of committing to a package of special effects. However, the projects in question, while large, are often not sufficiently significant

10. Smith and Smith (1986) analyze a sample that includes only the most successful films in the 1950s, 1960s, and 1970s. The results (which differ by decade) of running revenues against awards are curious. For instance, winning an award seems to have a negative and significant effect in the 1960s and a positive and significant effect in the 1970s. The Best Actor award variable is insignificant, whereas the Best Actress award variable changes sign from positive in the 1950s to negative in the 1970s. The total number of awards received per film has a positive and significant effect on revenues.

11. *S&P Credit Week* (1997) reports that in 1996 video revenues were the largest component of the average film's revenues. This was not yet the case in my sample period (video revenues have grown about sevenfold between 1986 and 1996); still, the inclusion of video revenues and international theatrical revenues improves the accuracy of my revenue estimate compared to other recent studies.

to warrant discernible changes in stock prices unless the studio is very small. The problem is exacerbated by the fact that studios have been purchased by even larger diversified companies (Sony, for instance). Furthermore, since there is no reporting requirement for decisions concerning individual films, timing may sometimes be hard to gauge. Unfortunately, any study of individual projects can invariably run into such difficulties.

The rest of this article is organized as follows: the next section describes the data. Section IV provides the results. Section V concludes the article.

III. Data and Variables

The data were collected from several sources. I identified a random sample of over 200 films released between late 1991 and early 1993.[12] This sample was pared down because of various missing data to 180 final observations. (For instance, two observations were dropped because of a late release date—as discussed later, late releases may bias the revenue figure downward.) Most testing was performed on 175 films, after eliminating all very low budget films. However, I do report results for the entire sample as well.[13]

Baseline Services in California provided the budget of each film,[14] as well as domestic, international, and video revenues. Specifically, I have domestic box office receipts, whereas international revenues are the shares of domestic distributors in box office receipts overseas. All revenue numbers are current as of the end of 1993. Since revenues tend to taper off rather quickly, and the last movie on the list of 180 was released in February 1993, I am fairly confident that I have a good measure of the revenues for each film.[15] Baseline also provided a list

12. A considerable proportion of the small group of studies that analyze the motion pictures industry focus on the most successful films, say the top 50 or top 100 in *Variety* lists (see, e.g., Smith and Smith 1986; De-Vany and Walls 1997). The current study contains a sample selected completely at random from among the films released in the period in question, and it includes great successes but also miserable failures. Naturally, similar to most studies of project finance, I do not have data on projects that were not completed. However, in the film business, since many of the contracts contain clauses that guarantee payment even if a star is replaced or if a project is not finished, there are considerable incentives to complete any project that had passed some initial screens.

13. This sample covers a significant percentage of films released between late 1991 and early 1993. In 1992 only 150 MPAA-affiliated films were released. The numbers for 1991 and 1993 were 164 and 161, respectively (see Vogel 1994, table 3.2).

14. The trade term for the budget figure provided is "negative cost," or production costs. This does not include gross participation, which is the ex post share of participants in gross revenues. It also does not include guaranteed compensation, which is a guaranteed amount paid out of revenues if revenues exceed this amount. Negative cost also does not include advertising or distribution costs.

15. De-Vany and Walls (1997) describe the inclusion of films in the list of the 50 top grossing films published in *Variety* in the 1980s as a survival process. Twenty-four percent of the 350 films in their sample were at the top 50 list for only 1 week, and just 5% spent more than 14 weeks in the list. Presumably, this also approximates the length of a domestic

of the director and up to eight main cast members. I then consulted several sources so as to characterize the cast members as "stars," "just actors," or unknowns. For the first definition of a "star," I identified all cast members who had won a Best Actor or Best Actress Award (Oscar) in prior years. A dummy variable AWARD denotes films in which at least one actor or the director had won an Academy Award. An alternative measure is NEXT. This dummy variable receives a value of one if any member of the cast had participated in a top-ten-grossing movie in the previous year. These two variables define two alternative sets of "star-studded" films. The measures I have suggested so far are reasonably common in studies of the industry; however, I tried other specifications as well. I collected Best Actor Award nominations for the actors as well as director nominations for each film in the sample. I defined two variables: ANYAWARD and VALAWARD. The first one, ANYAWARD, receives a value of one if one of the actors or the director had been nominated for an award. This increased the number of films in the "star-studded" classification (at least one nomination) to 76 out of 180. A second approach was to measure recognition value. For each of the 76 films in the AWARD category, I summed up the total number of awards and the total number of nominations. This method effectively creates a weight of one for each nomination and doubles the weight of an actual award to two (in other words, if an actress was nominated twice for an award, VALAWARD is two; if she also won in one of these cases, the value goes up to three). Each of the 76 films was thus assigned a numerical value, ranging from 15 (for *Cape Fear,* directed by Martin Scorsese and starring Gregory Peck, Robert Mitchum, Jessica Lange, and Martin Balsam) to 0 (for the films in the sample that had no nominations).[16] These new variables did not perform differently (in terms of sign and statistical significance) from the AWARD and NEXT variables, and hence results are generally not reported (with the exception of table 14).

I also defined another dummy variable, UNKNOWN, which receives a value of one for films in which all cast members did not appear in either of three major references on movies: Walker (1993), Katz (1994), or Maltin (1994). Presumably, if leading cast members are not listed anywhere, the film must be in the opposite end of the star king-

theatrical run. The films in my sample were released between late 1991 and February 1993. Production takes, on average, a year or less. Inflation (measured by the consumer price index) for 1991, 1992, and 1993 was 3.8%, 2.9%, and 2.9%, respectively. Thus the bias introduced by not having data on the time distribution of cash flows is probably not very significant. Further, it is similar in magnitude to biases introduced by any annual flow data on firms, such as operating income.

16. Film journals and other reference sources often carry rankings of stars. However, the rankings, while correlated, tend to be idiosyncratic, where film critics promote their individual choices.

dom. If stars provide significant benefits, these films should be the least profitable or bring in least revenues.

My second dependent variable is the return on investment. Direct profit measures in the film industry are difficult to obtain. The accounting profit of a movie is generally not publicly reported and may be of dubious economic value even if it were to be announced. One of the most glaring recent instances is the film *Forrest Gump*. In spite of revenues in excess of half a billion dollars, the film theoretically failed to make a profit.[17] There are other questionable practices, which may go the other way, in other words, exaggerating low profits. In 1998, FASB (the Financial Accounting Standards Board) started looking into movie accounting with a view toward developing a standardized approach (see Petersen 1998).

Most actors and directors receive, in addition to their salaries, a percentage participation (gross participation) in profits. In recent years, most contracts have reverted from percentages of the net profit to percentages of the gross revenue, which is easier to gauge. Even so, there are quite a few variations—some actors receive points from the first dollar of revenues, others after some revenue figure has been reached (say $30 million), and still others start collecting their share after contractually defined distribution costs have been recouped. At any rate, none of these contracts is contingent on variables that are not reported or cannot be verified by external sources, and at the margin they all involve percentages of revenues.[18] This has two implications: first, it is hard to believe net numbers not trusted even by people who are closely associated with the project. Second, "true" profits are made harder to gauge because of these complex deals.

There are additional issues. Typically, distribution and advertising costs (including fees, shares of exhibitors, costs of theaters, and various other expenses) add significant amounts to negative costs (Vogel 1994; *S&P Credit Week* 1997). The difficulty with including such additional costs, even if the data were available, is that, whereas negative costs end when the film is ready for distribution, advertising can be an ongoing activity. Also, on the revenue side, in today's multimedia world, some sales components may be hard to account for (see Vogel [1994] for some aggregate data). Thus it is difficult to select an appropriate proxy for economic profits. I chose the measure that required fewest assumptions and used (of course) available data—namely, revenues/negative costs, that is, (1 + the return on initial investment). In reality, as mentioned, revenues accruing to the studio or the production com-

17. See also Fee (1998) for a discussion of these issues.

18. Weinstein (1998) points out that if net profits are rigidly defined, they may not be much more subject to manipulation than gross receipts. However, in most cases, studios have more leeway in reaching the net figure than in gross receipts.

pany are a fraction of total revenues (except for international revenue numbers in my data set that exclude exhibitors' shares). Similarly, costs are augmented by advertising and gross participation. However, my measure can be a good approximation under the following assumptions, which I believe to be reasonable. First, I assume that revenues available to the studio or the production company (after exhibitors' cut) are a constant proportion of gross revenues. Since agreements with theaters tend to be standardized, this is not a bad assumption.

On the other side of the equation, one must assume that the actual costs, including advertising and distribution, are a constant proportion (greater than one) of the negative cost. Again, distribution agreements tend to be of similar format across films, which supports this notion. If one accepts these assumptions, then the "true" revenue should be a proportion α of box office receipts, whereas the correct costs would be $(1 + \beta) \times$ (negative costs), where α, β are constants, $\alpha < 1$. Therefore, "true revenue"/"true cost" $= \alpha/(1 + \beta) \times$ (box office receipts/negative costs). In other words, the measure I selected is then (1 + true return on investment) multiplied by a constant. Clearly, this is the best I can do with available data. Because of these limitations, if the ratio I find is greater than one, it does not imply that the film is "profitable." However, if the ratio for film A is greater than the ratio for film B, then film A should be more profitable than film B. This ratio of revenues to costs is the RATE variable.[19] It should also be noted that RATE is not a measure of the accounting profit to the studio or an approximation thereof. It essentially tries to measure if the movie provides a good return on investment.[20]

Another variable that may be of interest is whether or not a film is a sequel. Suppose that there is no quantifiable variable that predicts success; however, there is some elusive component that captures audi-

19. The *Wall Street Journal* (Bannon 1998) discussed the major summer movies of 1998. Twelve out of the 15 movies with budgets below \$100 million had estimated advertising costs of between 67% and 100% of negative costs. The outliers were a "cheap" film (*Bullworth*) that cost \$35 million to produce and carried \$40 million in marketing costs and two mega-films, *Armageddon* with a ratio of 57% and *Lethal Weapon 4* with a ratio of marketing to production costs of 50%. Vogel (1998) provides a table of the evolution of average negative cost as well as the average advertising cost over the years. In the 10 years between 1987 and 1996, advertising costs were on average 39% of negative costs with an SD of only 3%, and there was virtually no trend (recent years have seen an increase in these costs). I might add that, unfortunately, even if I had access to studios books, the advertising expenditure could only be estimated because of what the *New York Times* (Petersen 1998) called the "special effects" use of accounting rules by studios. As mentioned earlier, new FASB rules currently pending approval are supposed to amend the problem. Finally, a crude measure of advertising and distribution costs is probably the number of reviews, which is a variable used in the empirical tests.

20. In an ideal world I might have tried to estimate the value of gross participation for all talent. However, this information is generally a closely guarded secret. Even if available, such contracts are more difficult to price than your run-of-the-mill incentive options since the contingency in the case of movies is on a nontraded asset with a unique risk.

ences' hearts. If a film succeeds, one should then try to reproduce the formula as closely as possible. This implies that sequels should be successful on average. The opposite argument may be that, if indeed success is completely unpredictable, sequels will perform no better than any other film; in fact, they may do worse because they tend to be more expensive as actors capitalize on their earlier achievements.[21] The SEQUEL variable (suggested by a referee) receives a value of one if the movie is a sequel to a previous movie and zero otherwise. I identified 11 such films in my sample.[22]

I use several control variables. The publication *Variety* lists reviews for the first weekend in which a film opens in New York. However, they include national listings as well. I have a measure of the number of reviews (INDEX4) that proxies for the attention the film has received (and possibly the number of screens on which it opened). Reviews are classified by *Variety* as "good," "bad," and "mixed." I use these classifications to come up with several measures of critical review assessment. The variable INDEX1 is the number of good reviews divided by the total number of reviews; INDEX2 is the number of good and mixed reviews divided by the total.

Additionally, since ratings are considered by the industry to be an important issue, I use ratings as dummy variables. For instance, a dummy variable G receives a value of one if the film is rated G and zero otherwise. Note that some films are not rated at all for various reasons, and those receive the default value of zero.

Finally, I looked up each film's release date. In some other studies (see Litman 1983), release dates were used as dummy variables on the theory that, on the one hand, a Christmas release should attract greater audiences and, on the other hand, a release in a low-attendance period should be bad for revenues. However, since there are several peaks and troughs in attendance throughout the year, I use information from Vogel (1994, fig. 2.3) to produce a somewhat more sophisticated measure of seasonality. Vogel constructs a graph that depicts the normalized weekly attendance over the year (based on 1969–84 data). This figure assigns a number between 0 and 1.0 for each date in the year (where Christmas attendance is 1.0 and early December is 0.35 for the high and low points of the year, respectively). I match each release date with this graph and assign a variable that I call RELEASE to account for the seasonal fluctuations.

21. A Harvard case (Luehrman and Teichner 1992) analyzes the problem of valuing sequels. According to the data they collected, sequels on average cost 120% of the negative cost of the original movies, but their revenues (only U.S. theatrical revenues are provided) are only 70% of the revenues of the first film in the series.

22. Sometimes identification was trivial—e.g., *Alien 3*. Sometimes I had to work harder—one film in the sample is a sequel to a movie that was produced in 1985 and had a different title. The movie is called *An American Tail: Fievel Goes West* (1991), which is a sequel to *An American Tail*. Both are animated stories about émigré mice.

TABLE 1 Descriptive Statistics for the Nondummy Variables (N = 175)

Variable	Mean	SD	Maximum	Minimum
INDEX1	.43426	.25391	1.00000	.00000
INDEX2	.67661	.24100	1.00000	.00000
INDEX4	20.9028	9.94390	43.0000	3.00000
BUDGET	15.6791	13.8961	70.0000	1.00000
DOMESTIC	22.0870	32.7949	162.800	.00600
INTER	7.82412	13.0614	69.3000	.00000
VIDEO	10.69708	20.28299	233.7000	.027000
TOTREV	40.60824	60.32909	426.3010	.347000
RATE	2.273892	2.611170	17.05204	.086750
VALAWARD	1.594285	2.69118	15.00000	.000000

NOTE.—For all tables, the variables are described in Appendix A.

IV. Results

Table 1 describes the data for 175 films with budgets exceeding $1 million.[23] The budgets in this sample range up to $70 million. Domestic, video, and international revenues are listed as well. Total revenues range from a low of $347,000 to a high of over $426 million. This variability is perhaps the most significant feature of the sample and of the industry as a whole.

The index variables denote the reviews. On average, positive reviews accounted for almost half of the total (43%), whereas nonnegative (including neutral) reviews constituted over two-thirds (68%). The average number of reviews per film is 20. The range is from 3 to 43.

Seventeen films in the sample feature actors who had top-grossing movies in the previous year (NEXT = 1). For 30 films I could find no references to lead actors in any guide (UNKNOWN = 1). Twenty-six films include actors or directors who had won Academy Awards (AWARD = 1). In 76 of the films, some participant had had an Academy Award nomination or had won an actual award. There were 5 G-rated films, 23 that were rated PG, 41 that were rated PG-13, 87 that were rated R, and the rest were unrated.[24]

Table 2 contains univariate tests comparing AWARD and non-AWARD films. The results are very clear: while the budget, domestic

23. Later I discuss the full sample, including the low-budget films.

24. This distribution is fairly representative of the universe of films. There are 156 MPAA-rated movies: 3.2% are rated G, 14.7% PG, 26.3% PG-13, and 55.7% R. Among the 3,923 rated films produced between 1980 and 1995 that are included in the *Blockbuster Guide to Movies and Videos,* there are 2.0% that are rated G, 24.3% PG, 15.1% PG-13, and 58.5% R. For the more relevant 3-year period of 1991–93, the distribution of the 964 films listed in the Blockbuster guide is even closer to ours: 1.5% are rated G, 15.8% PG, 22.1% PG-13, and 60.7% R. Chi-square tests cannot reject the hypothesis that our sample ratings come from the same distribution as the ratings of the larger sample in the Blockbuster guide. In the 6 years since the data were initially collected (1991–93), some additional films have been rated. See Appendix B for analysis and discussion.

TABLE 2 **Univariate Tests for AWARD (Films in Which at Least One Cast Member Won an Academy Award) and Non-AWARD Films**

	AWARD = 1 (N = 26)		AWARD = 0 (N = 149)		
	Mean	SD	Mean	SD	t-Value
RATE	2.903	2.913	2.164	2.550	1.334
BUDGET	27.538	14.155	13.610	12.813	5.035*
DOMESTIC	42.801	41.194	18.473	29.821	3.609*
INTER	15.324	16.540	6.515	11.948	3.260*
VIDEO	17.505	16.730	9.509	20.660	1.868
TOTREV	75.630	70.041	34.497	56.544	3.298*
INDEX1	.497	.190	.424	.262	1.353
INDEX2	.734	.149	.667	.256	1.295
INDEX4	31.327	8.153	19.302	8.937	6.409*

* Significant at the 5% level.

revenues, and international revenues are significantly higher for films that employ a star, the rate-of-return measures are not significantly different, although the difference is in the "right" direction—that is, "star-studded" films are more profitable. Interestingly, video revenues are not significantly different between the two subsamples, indicating that films in the two categories may not differ that much in video revenues even though their budgets are, on average, more than twice as high.

Table 3 provides an alternative specification for the two subsamples; that is, it compares films with top-grossing stars (NEXT = 1) with the rest of the sample. Again, films with top stars are more expensive, provide more revenues, but are not more profitable according to my measure. Video revenues are higher for films with known actors but, again, not significantly so. The higher revenues for "star-studded"

TABLE 3 **Univariate Tests for Films That Include Actors in Top-Grossing Films the Previous Year (NEXT = 1) versus All Others**

	NEXT = 1 (N = 17)		NEXT = 0 (N = 158)		
	Mean	SD	Mean	SD	t-Value
RATE	2.695	2.934	2.229	2.580	.698
BUDGET	29.971	14.392	14.142	12.977	4.729*
DOMESTIC	41.804	41.043	19.966	31.204	2.654*
INTER	16.941	18.880	6.843	11.948	3.103*
VIDEO	19.228	17.969	9.779	20.355	1.837
TOTREV	77.973	75.014	36.588	57.383	2.737*
AWARD	.588	.507	.101	.303	5.835*
INDEX1	.435	.206	.435	.259	.000
INDEX2	.682	.181	.677	.250	.080
INDEX4	28.471	10.777	20.284	9.365	3.375*

* Significant at the 5% level.

TABLE 4 Univariate Tests of Films with Unknown Casts versus All Other Films

	UNKNOWN = 1 (N = 30)		UNKNOWN = 0 (N = 145)		
	Mean	SD	Mean	SD	t-Value
RATE	1.797	2.541	2.373	2.623	−1.100
BUDGET	5.178	4.901	17.852	14.169	−4.830*
DOMESTIC	4.615	7.228	25.702	34.818	−3.295*
INTER	1.520	2.114	9.128	13.973	−2.969*
VIDEO	2.672	3.560	12.357	21.872	−2.413*
TOTREV	8.808	11.299	47.188	64.171	−3.258*
AWARD	.000	.000	.179	.385	−2.541*
NEXT	.000	.000	.117	.323	−1.979*
INDEX1	.517	2.908	.418	.243	.407
INDEX2	.738	.251	.665	.241	1.490
INDEX4	14.967	7.308	22.345	9.773	−3.911*

* Significant at the 5% level.

films seem to be consistent with the industry concept of "bankable stars," that is, stars who can make money for the studio. Later I demonstrate that this idea may be false.

The critical reviews (INDEX) variables tell an interesting story: films with award-winning participants receive only marginally better reviews (the differences in the INDEX1 and INDEX2 variables are at best marginally significant). There is virtually no difference between reviews of films that employ stars who had a top-ten hit and the rest of the sample. But no matter how star power is measured, star-studded films are much more heavily reviewed—possibly as a result of greater publicity or a wider (more screens) distribution.

Table 4 examines the other end of the spectrum—films in which the actors were not mentioned in any of several leading reference books. Again, while the budget and the revenues are significantly lower for such films, the very high standard deviation does not enable me to establish that profits are statistically different. Interestingly, reviews are better for films that have unknown participants, although not significantly so. Reviewers' attention, however, is significantly lower, as expected. Table 5 provides a univariate comparison for our other specification, namely, separating out films with participants who were either nominated for or received awards. For 76 films the new dummy variable, ANYAWARD, has a value of one. The picture, however, is virtually unchanged, except that now video revenues as well are significantly higher for the "star-studded" subsample. The rates of return are still not significantly different between the two subsamples, and reviews are no better, but, again, reviewers' attention is significantly greater for the "star-studded" films.

TABLE 5 **Univariate Tests for ANYAWARD (Films in Which Cast Members Were Nominated for Academy Awards) versus All Other Films**

	ANYAWARD = 1 (N = 76)		ANYAWARD = 0 (N = 99)		
	Mean	SD	Mean	SD	t-Value
RATE	2.489	2.855	2.108	2.409	.956
BUDGET	22.237	13.936	10.645	11.630	6.339*
DOMESTIC	32.298	41.185	14.248	21.646	4.657*
INTER	12.146	16.500	4.506	8.303	5.052*
VIDEO	16.459	18.807	6.274	7.061	6.897*
TOTREV	60.904	77.956	25.028	35.308	5.334*
INDEX1	.436	.241	.434	.264	.033
INDEX2	.676	.236	.678	.251	.058
INDEX4	24.658	9.934	18.333	8.768	4.636*

* Significant at the 5% level.

Table 6 compares sequels to nonsequels. Sequels have higher budgets and higher revenues than the average film in the sample, but they use fewer stars. Interestingly, they are reviewed less and get worse reviews than the rest of the sample, weakly supporting the notion that sequels sell a formula rather than a unique, quality product. Return on investment is higher, but not significantly so, providing some support for the view that it is hard to quantify what makes a movie tick; however, even with low quality and fewer stars, a sequel still works better than the average film.

The results so far seem not to support any role for stars in either signaling or helping profitability, rejecting a signaling hypothesis.

TABLE 6 **Univariate Tests of Sequels versus All Other Films**

	SEQUEL = 1 (N = 11)		SEQUEL = 0 (N = 164)		
	Mean	SD	Mean	SD	t-Value
RATE	3.689	2.236	2.179	2.613	1.870
BUDGET	26.455	20.587	14.956	13.106	2.705*
DOMESTIC	52.227	55.482	20.065	29.897	3.233*
INTER	19.703	22.259	7.027	11.898	3.197*
VIDEO	21.113	18.177	9.998	20.275	1.770
TOTREV	93.044	90.248	37.091	56.458	3.048
AWARD	.000	.000	.159	.366	−1.431
NEXT	.000	.000	.104	.306	−1.121
RELEASE	.556	.118	.635	.158	−1.636
UNKNOWN	.091	.302	.177	.383	−.728
INDEX1	.334	.231	.441	.254	−1.349
INDEX2	.622	.282	.681	.242	−.775
INDEX4	17.454	10.511	21.323	9.918	−1.248

* Significant at the 5% level.

TABLE 7 **The Domestic Revenue Regression (N = 175)**

Variable	Coefficient	SE	t-Statistic	2-Tailed Significance
C	−3.8073774	.8045552	−4.7322764	.0000
LNBUDGET	1.3492735	.1691444	7.9770514	.0000
AWARD	−.2694808	.3912471	−.6887740	.4920
UNKNOWN	.5363139	.3620966	1.4811351	.1405
NEXT	−.0431328	.4493107	−.0959976	.9236
G	1.3360061	.8430603	1.5847101	.1150
PG	1.3535991	.5202013	2.6020681	.0101
PG13	.4688866	.4770818	.9828223	.3272
R	.3549449	.4370094	.8122133	.4179
INDEX2	.0709012	.6039775	.1173905	.9067
INDEX4	.0679752	.0180777	3.7601600	.0002
RELEASE	.0586542	.7830232	.0749073	.9404
SEQUEL	1.1438608	.5115261	2.2361728	.0267
Statistics:				
R^2		.613320		
Adjusted R^2		.584678		
SE of regression		1.539879		
Log likelihood		−317.1083		
Mean of dependent variable		1.446031		
SD of dependent variable		2.389427		
Sum of squared residuals		384.1386		
F-statistic		21.41263		
prob(F-statistic)		.000000		

NOTE.—The dependent variable is LNDOMES. Independent variables include dummy variables for ratings (G, PG, PG13, R; the default is nonrated films), whether participants had received Academy Awards (AWARD), whether cast members could not be found in standard film references (UNKNOWN), and whether a cast member had participated in a top-grossing film (NEXT). Additional variables include the log of the budget of the film (LNBUDGET), the number of reviews (INDEX4), the percentage of nonnegative reviews (INDEX2), a seasonality variable (RELEASE), and a dummy variable denoting sequels.

However, there seems to be a strong indication that stars do signal (or cause) higher revenues and exposure. This is weakly related to the industry concept of a "bankable star" or a star who can "open" a movie. In other words, star-studded films seem to have significantly higher revenues, whereas films with unknown cast members seem to have significantly lower revenues. Also, sequels seem to be a good idea. These concepts are tested further below.

Subsequent tables provide results of regressions where revenues and profits serve as dependent variables. Tables 7–10 provide revenue regressions, with a breakdown according to the source of revenue. For international, domestic, and video revenues, the most significant variable is the budget—in other words, more expensive films bring in more money. The other significant variables are the number of reviews, that is, the attention the film has received (as noted, this variable may indirectly measure advertising expenses or the number of screens as well). Ratings matter as well; for domestic, video, and total revenues, PG

TABLE 8 The Video Regression (N = 175)

Variable	Coefficient	SE	t-Statistic	2-Tailed Significance
C	−1.3874586	.4574982	−3.0327081	.0028
LNBUDGET	.9457284	.1036397	9.1251540	.0000
AWARD	−.0591275	.2393842	−.2469982	.8052
UNKNOWN	−.2910299	.2219518	−1.3112301	.1916
NEXT	.2790855	.2745635	1.0164696	.3109
G	1.5638631	.5171451	3.0240316	.0029
PG	.7103283	.3153707	2.2523595	.0256
PG13	.2390445	.2902463	.8235918	.4114
R	.0711945	.2648773	.2687831	.7884
INDEX1	−.0426490	.3457541	−.1233506	.9020
INDEX4	.0103442	.0107535	.9619321	.3375
RELEASE	.3366782	.4805477	.7006135	.4845
SEQUEL	.6325177	.3113996	2.0312089	.0439
Statistics:				
R^2		.654020		
Adjusted R^2		.628392		
SE of regression		.941254		
Log likelihood		−230.9653		
Mean of dependent variable		1.444043		
SD of dependent variable		1.544062		
Sum of squared residuals		143.5255		
F-statistic		25.51965		
prob(F-statistic)		.000000		

NOTE.—The dependent variable is LNVID. Independent variables include dummy variables for ratings (G, PG, PG13, R; the default is nonrated films), whether participants had received Academy Awards (AWARD), whether cast members could not be found in standard film references (UNKNOWN), and whether a cast member had participated in a top-grossing film (NEXT). Additional variables include the log of the budget of the film (LNBUDGET), the number of reviews (INDEX4), the percentage of positive reviews (INDEX1), a seasonality variable (RELEASE), and a dummy variable denoting sequels.

ratings are important. For video and total revenues, G ratings will improve sales. The results for international revenues are the most difficult to interpret, with only budget and INDEX4 (the number of reviews) turning out to be significant. One might conjecture that the video market is more concerned with the question of whether the kids are eternally harmed if they accidentally stick the wrong cassette in the VCR, whereas the international theatrical market buys well-received or sometimes ''action'' films, with less regard to their rating.

The interesting feature here is that once I take into account a reasonable variety of independent variables, stars are not correlated with revenues any more (the coefficients are even negative but insignificant). However, big-budget films seem indeed to increase revenues, regardless of the disposition of the big budget—whether it is for star participation, or, for instance, to create expensive special effects. There is a high correlation between budgets and all measures of revenue—73% with domestic and video revenue and 62% with international revenue.

TABLE 9 **The International Revenue Regression (N = 175)**

Variable	Coefficient	SE	t-Statistic	2-Tailed Significance
C	−2.6643092	1.0172154	−2.6192182	.0097
LNBUDGET	1.2297957	.2138527	5.7506677	.0000
AWARD	.4814898	.4946617	.9733718	.3318
UNKNOWN	.7038553	.4578060	1.5374530	.1261
NEXT	−.0636730	.5680726	−.1120861	.9109
G	.7514494	1.0658982	.7049917	.4818
PG	.4783983	.6577010	.7273796	.4680
PG13	−.1095200	.6031842	−.1815697	.8561
R	−.2674686	.5525199	−.4840887	.6290
INDEX2	−.5888299	.7636210	−.7711024	.4418
INDEX4	.0528724	.0228560	2.3132787	.0220
RELEASE	−1.2113537	.9899921	−1.2235993	.2229
SEQUEL	1.1141714	.6467328	1.7227692	.0868
Statistics:				
R^2		.437691		
Adjusted R^2		.396039		
SE of regression		1.946900		
Log likelihood		−358.1518		
Mean of dependent variable		.305644		
SD of dependent variable		2.505181		
Sum of squared residuals		614.0478		
F-statistic		10.50816		
prob(F-statistic)		.000000		

NOTE.—The dependent variable is LNINTER. Independent variables include dummy variables for ratings (G, PG, PG13, R; the default is nonrated films), whether participants had received Academy Awards (AWARD), whether cast members could not be found in standard film references (UNKNOWN), and whether a cast member had participated in a top-grossing film (NEXT). Additional variables include the log of the budget of the film (LNBUDGET), the number of reviews (INDEX4), the percentage of nonnegative reviews (INDEX1), a seasonality variable (RELEASE), and a dummy variable denoting sequels.

These results do not support the view that stars signal revenues, but I cannot reject the "rent-capture" hypothesis.[25] The total revenue regression (table 10) is of course consistent with the parts—total revenues increase if the budget is higher, if the rating is more "family friendly" (G, PG), if the film is a sequel, and if it is heavily reviewed. I should note that I have tried several other specifications, for example, including only NEXT or only AWARD as independent variables, but there was no qualitative difference in the results. I also ran all regressions with different specifications of stars (ANYAWARD, VALAWARD),

25. In order to test further whether stars have an effect on the revenues, I performed a matched-pair test. I matched 20 of the award-winning films with other films in terms of budget, rating, and INDEX4 (the number of reviews) and attempted to see whether there is a significant difference in the revenues. I performed a similar test for 13 films with NEXT = 1 and also for films with unknown cast vs. the rest of the films in the sample. In all cases, the differences between the two subsamples were not statistically significant. Interestingly, movies that have NEXT = 1 had, on average, lower revenues. However, again, the difference was not statistically significant.

TABLE 10 The Total Revenue Regression (N = 175)

Variable	Coefficient	SE	t-Statistic	2-Tailed Significance
C	−1.3678737	.4760825	−2.8731863	.0046
LNBUDGET	1.1144907	.1078497	10.333738	.0000
AWARD	−.1130825	.2491083	−.4539493	.6505
UNKNOWN	.1491674	.2309678	.6458363	.5193
NEXT	.0556393	.2857167	.1947358	.8458
G	1.3330188	.5381523	2.4770291	.0143
PG	1.0410616	.3281816	3.1722124	.0018
PG13	.3358272	.3020365	1.1118761	.2678
R	.2626644	.2756370	.9529361	.3420
INDEX1	.3445801	.3597991	.9577014	.3396
INDEX4	.0326718	.0111903	2.9196396	.0040
RELEASE	.1126997	.5000683	.2253687	.8220
SEQUEL	.8542032	.3240492	2.6360297	.0092
Statistics:				
R^2		.702051		
Adjusted R^2		.679980		
SE of regression		.979489		
Log likelihood		−237.9335		
Mean of dependent variable		2.565284		
SD of dependent variable		1.731456		
Sum of squared residuals		155.4227		
F-statistic		31.80970		
prob(F-statistic)		.000000		

NOTE.—The dependent variable is LNTOTREV. Independent variables include dummy variables for ratings (G, PG, PG13, R; the default is nonrated films), whether participants had received Academy Awards (AWARD), whether cast members could not be found in standard film references (UNKNOWN), and whether a cast member had participated in a top-grossing film (NEXT). Additional variables include the log of the budget of the film (LNBUDGET), the number of reviews (INDEX4), the percentage of nonnegative reviews (INDEX1), a seasonality variable (RELEASE), and a dummy variable denoting sequels.

but that did not affect the outcome. In all regressions, sequels bring in more revenues, which seems to support the idea that although one cannot specify a formula ex ante, once it is found it may work again.

Since stars in general are expensive, it may be that budget proxies to some extent for star power. This would lend support to the signaling hypothesis; in other words, expensive stars, as proxied by a big budget, may indeed signal high revenues or contribute directly to revenues. Since I do not have direct information about star salaries and compensation packages ("one of the best-kept secrets in Hollywood," according to Gumbel et al. [1998]), this must remain a possibility. However, in addition to the low correlation of our measures of star power with budget, there is some anecdotal evidence supporting the view that star participation may not be directly correlated with high budgets. In fact, the cost of the most expensive films in history often reflected special effects and expensive sets. The most recent example is *Titanic,* which reportedly cost over $200 million. According to the *New York*

Times, the star of the film, Leonardo di Caprio, was paid "a mere" \$2.5 million. The *Wall Street Journal* (Gumbel et al. 1998) estimates that costar Kate Winslet received less than \$1 million. Gloria Stuart, nominated for Best Supporting Actress, received only \$300,000, and the director James Cameron waived his fee altogether for (significant) gross participation. In other words, all actors put together received probably less than \$10 million upfront out of a budget of \$200 million. Since this is the most expensive film in history, this casual evidence has some importance.[26] An opposite example in our sample is the star-studded film *Glengarry Glen Ross,* with Al Pacino, Jack Lemmon, Alec Baldwin, and others, written by David Mamet. It cost only \$20 million to produce (probably with significant gross participation).

Gumbel et al. (1998) provide further insight as to the relative cost of stars. Top stars, such as Jack Nicholson or Dustin Hoffman, make about \$15 million per film (female leads make less). Other well-known actors (say, Anthony Hopkins or Robin Williams) take home \$4–\$5 million. This means that a cast including the hottest star in the business and another very well known actor may require less than \$20 million in negative costs. In the period covered by my study, the numbers were even lower.

So far I can conclude that, even though low-budget productions may not be able to afford stars, star-studded films are not necessarily at the other end of the scale. However, even the first part of that statement may not be entirely true. Stars may enter into various participation arrangements in order to take part in low-budget films. For example, according to Gumbel et al. (1998), both Dustin Hoffman for *Wag the Dog* and James Cameron for *Titanic* waived their upfront fees altogether. Jack Nicholson lowered it somewhat for *As Good as It Gets,* which cost \$50 million to make, and so did Anthony Hopkins for *Amistad* and Robin Williams for *Good Will Hunting,* which cost a mere \$14 million dollars (see Gumbel et al. 1998). Of course, lower fees may mean higher participation; however, it also means that a film can be produced for less than \$15 million and still employ a star like Dustin Hoffman. Later I will report some tests related to this notion.

Earlier studies, typically using fewer independent variables and without data on international or video revenues (some are from the prevideo era) obtained mixed results. Litman (1983), with fewer independent variables and a smaller data set, finds that the production budget is an important determinant of revenues, but stars and content seem to matter as well, and so does critical appreciation. Similar results are obtained in Litman and Kohl (1989). However, as noted in their study, the Acad-

26. The two expensive, top-grossing films of 1996, *Twister* and *Independence Day,* provide two additional examples. Both are low on star power and plot and high on special effects. *Jurassic Park* is another illustration of the same phenomenon.

emy Award process is only weakly related to revenues, which is in some agreement with my results. Smith and Smith (1986), who consider a sample of the highest-grossing films up to 1980, come up with the curious finding that in the 1950s and 1960s Academy Awards for Best Actors and Best Films had a negative effect on rentals. I should also note that, if indeed the correct interpretation is that stars receive their marginal value, it is more likely to hold for my data set containing films from the 1990s owing to the demise of the studio system. In 1944, for instance, there were 804 actors under contracts to major studios. This number fell to 164 in 1961 and kept falling. Thus, the earlier the data, the less likely it is that the ''rent-capture'' hypothesis should hold.

In an extensive (but otherwise focused) study of the effect of critical reviews on box office receipts, Eliashberg and Shugan (1994) find that reviewers do not influence the success of a film but are a good predictor of it. While my study cannot distinguish the two, the thrust of my results may be similar. In another study, Eliashberg and Sawhney (1996) measure the effect of early box office receipts on revenues. My study aims at providing an ex ante forecast. Most studies, as noted, have fewer independent variables, which may also account for the different results. Earlier studies have not considered the return on investment, to which I turn next.

Table 11 contains the rate-of-return regressions. The only significant independent variables are the ratings—in other words, G- and PG-rated films seem to do better. This finding may be explained in several ways: first, the potential audiences are nested—for example, everybody can see a G-rated movie; however, most teenagers are excluded from an R-rated movie. Also, the video market for non-family-oriented films may be limited. There are additional indications that I am on the right track with this result. *Variety* periodically publishes a list of the top ''rental champions'' of all time. In the list of the top 10 films of all time (published January 6, 1992), there are eight films rated PG and one film rated G. Although rentals are not the same as grosses, and as the current study demonstrates, neither rentals nor grosses necessarily reflect profitability, this list provides some indication. Furthermore, among the top 100 there are only four films that were released before 1950. A major reason is that the dollar figures are not adjusted for inflation. There was no rating system in place before 1950; however, it is remarkable that three out of the four (*Fantasia, Bambi,* and *Snow White*) carried a G rating in video releases, and the fourth, *Gone with the Wind* was recently rereleased with a G rating. Some recent evidence provides an even more convincing support for the results in table 11. In December 1998 *Variety* published the list of 500 rental champions of all time. I adjusted the figures for inflation somewhat crudely (since the exact time distribution of revenues is not available) using the consumer price index in the year of release. Seven out of the top 10

TABLE 11 The Rate-of-Return Regression (N = 175)

Variable	Coefficient	SE	t-Statistic	2-Tailed Significance
C	−.5462505	1.1388483	−.4796517	.6321
LNBUDGET	.0377177	.2579899	.1461982	.8839
AWARD	.1956128	.5958980	.3282656	.7431
UNKNOWN	.2548779	.5525036	.4613144	.6452
NEXT	.1365797	.6834698	.1998329	.8419
G	5.0920873	1.2873269	3.9555511	.0001
PG	3.1499843	.7850509	4.0124585	.0001
PG13	.7475581	.7225087	1.0346700	.3024
R	.6685193	.6593578	1.0138945	.3121
INDEX1	.9283509	.8606840	1.0786199	.2824
INDEX4	.0383392	.0267687	1.4322397	.1540
RELEASE	.4261174	1.1962252	.3562183	.7221
SEQUEL	1.3570073	.7751657	1.7506028	.0819
Statistics:				
R^2		.250344		
Adjusted R^2		.194814		
SE of regression		2.343060		
Log likelihood		−390.5653		
Mean of dependent variable		2.273892		
SD of dependent variable		2.611171		
Sum of squared residuals		889.3688		
F-statistic		4.508256		
prob(F-statistic)		.000003		

NOTE.—The dependent variable is RATE. Independent variables include dummy variables for ratings (G, PG, PG13, R; the default is nonrated films), whether participants had received Academy Awards (AWARD), whether cast members could not be found in standard film references (UNKNOWN), and whether a cast member had participated in a top-grossing film (NEXT). Additional variables include the log of the budget of the film (LNBUDGET), the number of reviews (INDEX4), the percentage of nonnegative reviews (INDEX1), a seasonality variable (RELEASE), and a dummy variable denoting sequels.

inflation-adjusted champs are rated G (including the four mentioned earlier), and the other three are PG-rated.[27] If the figures are adjusted using average ticket prices, the results are very similar. Note that, given the distribution of ratings, and if success is independent of ratings, the probability of finding any G movies in the top 10 list is rather low. An illustration of the enormous appeal of family movies is *Bambi,* the ''rental champ'' of 1942, which earned more than eight times the amount earned by the runner-up, the six-Academy-Award-winning *Mrs. Miniver,* and 10 times more than third place, *Casablanca.* Further-

27. This is the list of ''rental champions'' of all time, using figures from *Variety* (December 1998). The rentals are in 1998 millions of dollars, rounded to the next million. The adjustment uses Bureau of Labor Statistics consumer price index figures for January of the year of release: (1) *Gone with the Wind* (G; $937), (2) *Snow White* (G; $927), (3) *Star Wars* (PG; $748), (4) *Bambi* (G; $487), (5) *Fantasia* (G; $484), (6) *Pinocchio* (G; $470), (7) *The Sound of Music* (G; $414), (8) *Jaws* (PG; $402), (9) *E.T. the Extra-Terrestrial* (PG; $391), and (10) *101 Dalmatians* (G; $372).

more, it is likely that, if anything, most studies and lists underestimate the revenues of G movies, which are more amenable to ancillary products. For example, *The Lion King,* another very successful recent G movie, cost \$55 million to make in 1994. It took in \$313 million in domestic theaters, \$454 million abroad, and \$520 million in video revenues, but Disney also sold another \$3 billion worth of related merchandise (see Stevens and Grover 1998). Table 11 also shows that stars, or even budgets, are not significantly related to returns. The sequel variable is significant only at the 10% level. Reviewers' attention seems to be positively but not significantly related to return on investment. While care should be taken in interpreting the results, one should note that the explanatory power is good. Thus big budgets may increase revenues, but they do not seem to signal or predict rates of return.[28] Table 11 thus supports the ''rent-capture'' hypothesis rather than the signaling view.[29] The fact that stars do not increase the return on investment but sequels seem to be weakly more profitable supports the view that the industry is run not by knowledgeable insiders who take costly actions to signal to outsiders but by uninformed insiders who guess and often fail in projecting the success of a movie. Stars, who are constantly in the market, are able to capture the best estimate of their ever-changing marginal value. However, there certainly may be a nonquantifiable element that does capture audiences' hearts and pocketbooks, and the best the industry can do is to try and recreate this element in a sequel.

A related interpretation of table 11 reinforces the notion that revenues (empire building, sales maximization) are included in the objective function of decision makers and that it may be signaled by big budgets, whereas profits are either less important or unpredictable, or both.[30]

28. I tried several other combinations of variables, including other review variables, mainly INDEX2 instead of INDEX1. There was no qualitative change. I also altered the specification of the UNKNOWN variable, this time including the director. This of course decreased the number of films for which the variable UNKNOWN had a value of one. However, there was virtually no qualitative change in the profit or revenue regressions or the univariate tests.

29. To be precise, the signaling hypothesis predicts that the sign of star-related variables, namely AWARD or NEXT, should be positive. Hence I may want to consider the one-tailed t-test rather than the two-tailed t-test reported. Generally, the latter test results in higher significance levels. However, even when I computed a one-tailed t-statistic, no additional coefficient became significant in the revenue or rate-of-return equations (some coefficients are negative). The coefficient of ANYAWARD in table 12 (including the small films) becomes more significant, at a better than 10% level.

30. This unpredictability, however, is common in principle to all creative industries and to some extent to other industries as well. It is very hard to predict whether a new toy creation will be the next Barney, or just another stuffed animal (if the reader does not have toddlers at home, I should explain that Barney is a purple dinosaur who has spawned a complete industry, including TV programs, books, and ads). Therefore, the methodology proposed here can be used to analyze other industries as well.

TABLE 12 **The Rate of Return Regression Including Small Films and ANYAWARD (N = 80)**

Variable	Coefficient	SE	t-Statistic	2-Tailed Significance
C	24.466100	20.066829	1.2192310	.2245
LNBUDGET	−28.619559	3.4877912	−8.2056401	.0000
ANYAWARD	11.626220	8.0619062	1.4421180	.1511
UNKNOWN	3.5732958	10.622882	.3363772	.7370
NEXT	11.536452	12.480697	.9243435	.3566
G	54.570068	24.055732	2.2684851	.0246
PG	30.749839	14.445367	2.1286990	.0347
PG13	28.462901	13.000801	2.1893190	.0300
R	25.878054	11.616467	2.2277044	.0272
INDEX1	−36.319857	16.126617	−2.2521684	.0256
INDEX4	1.7507277	.4606050	3.8009307	.0002
RELEASE	−13.630345	23.020937	.5920847	.5546
SEQUEL	17.519313	14.897772	1.1759687	.2413

Statistics:	
R^2	.325257
Adjusted R^2	.276772
SE of regression	45.65710
Log likelihood	−936.4709
Mean of dependent variable	7.259610
SD of dependent variable	53.68721
Sum of squared residuals	348,123.4
F-statistic	6.708466
prob(F-statistic)	.000000

NOTE.—The dependent variable is RATE. Independent variables include dummy variables for ratings (G, PG, PG13, R; the default is nonrated films), whether participants had been nominated for an Academy Award (ANYAWARD), whether cast members could not be found in standard film references (UNKNOWN), and whether a cast member had participated in a top-grossing film (NEXT). Additional variables include the log of the budget of the film (LNBUDGET), the number of reviews (INDEX4), the percentage of nonnegative reviews (INDEX1), a seasonality variable (RELEASE), and a dummy variable denoting sequels.

Finally, I added the five low-budget films. The revenue regression does not change much, except that another rating category becomes marginally significant (see table 13). Sequels are also important for revenues, even more so than for the sample of 175. The return equation, however, has changed dramatically. The most (negatively) significant variable is budget. As can perhaps be expected, once we add successful low-budget films, big budget seems to spell financial failure, on average. This is somewhat misleading of course. However, Weinstein (1998) calculates that the average negative cost in 1995 for films produced by MPA members (who are responsible for all large releases) was \$36.2 million, whereas the average domestic box office receipts were only \$23.5 million. Even without advertising, and not counting the exhibitor profit, large movies may then be a losing proposition.

In this regression all rated films (as opposed to unrated films) contribute to return on investment, but the unexpected transformation is

TABLE 13 The Total Revenue Regression Including Small Budget Films (N = 180)

Variable	Coefficient	SE	t-Statistic	2-Tailed Significance
C	−.4074515	.4922205	−.8277823	.4090
LNBUDGET	.5607678	.0828585	6.7677794	.0000
AWARD	.0160498	.2834129	.0566303	.9549
UNKNOWN	.1081541	.2578389	.4194637	.6754
NEXT	.3146565	.3217440	.9779715	.3295
G	1.9639264	.5838629	3.3636774	.0010
PG	1.2106936	.3518104	3.4413241	.0007
PG13	.5574194	.3170017	1.7584115	.0805
R	.3652622	.2837428	1.2873004	.1998
INDEX1	−.2272955	.3936881	−.5773491	.5645
INDEX4	.0563940	.0115113	4.8990023	.0000
RELEASE	−.0033635	.5616837	−.0059883	.9952
SEQUEL	1.1729983	.3637259	3.2249512	.0015
Statistics:				
R^2		.620478		
Adjusted R^2		.593207		
SE of regression		1.114542		
Log likelihood		−268.1821		
Mean of dependent variable		2.505415		
SD of dependent variable		1.747470		
Sum of squared residuals		207.4480		
F-statistic		22.75228		
prob(F-statistic)		.000000		

NOTE.—The dependent variable is LNTOREV. Independent variables include dummy variables for ratings (G, PG, PG13, R; the default is nonrated films), whether participants had received Academy Awards (AWARD), whether cast members could not be found in standard film references (UNKNOWN), and whether a cast member had participated in a top-grossing film (NEXT). Additional variables include the log of the budget of the film (LNBUDGET), the number of reviews (INDEX4), the percentage of nonnegative reviews (INDEX1), a seasonality variable (RELEASE), and a dummy variable denoting sequels.

in the review variables. Good reviews seem to be negatively related to return on investment. As before, INDEX4, which measures critical attention, seems to be positively, and here also very significantly, related to profits. The sequel variable is still positively, but not significantly, related to returns.

Since three films have extremely low budgets of under $50,000, and two of them made over a million dollars in revenues, I dropped all three and included only two low-budget films in another run (table 14). The results are less extreme, but still the budget coefficient is significantly negative, and G and PG ratings are significantly positive. Reviewers' attention and the sequels variable are also significant in the 5% level.

Thus, when I add to the sample small successful films, the lesson seems to be that indeed, G- and PG-rated films will do better, but small budget is better than big budget, and, as before, critical attention is

TABLE 14 The Rate of Return Regression Including Only Two Small Films and ANYAWARD (N = 177)

Variable	Coefficient	SE	t-Statistic	2-Tailed Significance
C	.1262011	1.2070109	.1045567	.9169
LNBUDGET	−.7268077	.2558502	−2.8407548	.0051
ANYAWARD	.2949189	.4167304	.7076971	.4801
UNKNOWN	.3800146	.6158099	.6170973	.5380
NEXT	.5282033	.7328429	.7207593	.4721
G	6.1875677	1.4195238	4.3589038	.0000
PG	3.7506485	.8479892	4.4229908	.0000
PG13	1.4204555	.7664188	1.8533673	.0656
R	1.2901567	.6899418	1.8699502	.0633
INDEX1	.2472106	.9650555	.2561621	.7981
INDEX4	.0693465	.0281948	2.4595449	.0149
RELEASE	.5725529	1.3419183	.4266675	.6702
SEQUEL	1.6995695	.8704967	1.9524135	.0526
Statistics:				
R^2		.233007		
Adjusted R^2		.176885		
SE of regression		2.654000		
Log likelihood		−417.1651		
Mean of dependent variable		2.388129		
SD of dependent variable		2.925303		
Sum of squared residuals		1,155.170		
F-statistic		4.151834		
prob(F-statistic)		.000011		

NOTE.—The dependent variable is RATE. Independent variables include dummy variables for ratings (G, PG, PG13, R; the default is nonrated films), whether participants had been nominated for an Academy Award (ANYAWARD), whether cast members could not be found in standard film references (UNKNOWN), and whether a cast member had participated in a top-grossing film (NEXT). Additional variables include the log of the budget of the film (LNBUDGET), the number of reviews (INDEX4), the percentage of nonnegative reviews (INDEX1), a seasonality variable (RELEASE), and a dummy variable denoting sequels.

important. However, stars are still not there. An obvious caveat is that the low-budget films in my sample are not necessarily representative of the universe of small films and essentially might have been included in databases because of their success. However, the indication is consistent with the rest of the story, perhaps in a somewhat more dramatic fashion. In conclusion, it is clear that I could not find support for the hypothesis that stars, and perhaps even big budgets, signal quality. The "rent-capture" hypothesis, however, is consistent with my empirical results.

I performed one final test of the signaling notion. As noted, stars sometimes participate in low-budget films, cutting their fees and opting for (presumably) greater gross participation. One can surmise that, if an employee agrees to receive most of his compensation in revenue participation, then she must have some positive inside information. I thus ran revenues and return-on-investment regressions for various subsamples of low-budget films. For films with budgets under $15 million, results were not much different from results reported in the text and thus do not support the signaling view. I then increased the sample to include all films with budgets under $20 million. The variable NEXT, denoting participation of an actor from a previous top grossing film, became somewhat more significant in the rate-of-return regression (significant at the 7% level). For the sample of 180 (including small films), I lost significance in the rate-of-return equation, but NEXT was significant at the 6% level for the revenue regression. The economic interpretation of these results is not clear—there are also examples of stars who cut their fees for failing movies. However, star participation at cut fees in low-budget films may be the closest to a costly signal of inside information.

V. Conclusions

This study considers the film industry practices of hiring stars and engaging in big-budget extravaganzas. I propose two hypotheses: (1) that stars (and perhaps big budgets) signal high returns or at least high revenues, or (2) alternatively, that stars are paid their value (i.e., the "rent-capture" hypothesis). Tests on a sample of close to 200 films seem to show that stars play no role in the financial success of a film. Univariate tests support the industry view that stars increase revenues. However, when I run multiple regressions, including budget figures, budgets seem to take all the significance—in other words, big-budget films may signal high revenues, regardless of the source of spending. Also, attention by reviewers seems to be important to success—the more reviews a film receives, the higher the revenues. Film ratings are important as well, and sequels seem to do better, which is consistent with the view that insiders are not better informed than outsiders. However, when, for whatever elusive reason, a film succeeds, studios attempt to replicate the formula.

Return regressions also cannot reject the "rent-capture" hypothesis. However, the role of budgets sees a dramatic reversal: big budgets do not contribute to profitability. If anything (as table 14 demonstrates), they may contribute to losses. Only G and PG ratings and perhaps sequels or reviewers' attention seem to matter. A final test seems to indicate that star participation in low-budget films may be a weak signal of quality.

Naturally, as in all empirical studies, some caveats are in order. The definition of stars I used is consistent with industry notions and other studies, and I have tried several possible specifications. However, it is still somewhat subjective, as all such definitions must be. Also, return-on-investment calculations are hard to come by in the film industry, and, admittedly, I have a rough proxy. Nevertheless, this study leaves us wondering why the star system is such a cornerstone of Hollywood and why studios keep turning out big-budget films loaded with special effects.

I can offer some tentative ideas. One often hears of films that are produced because a specific star agreed to participate, essentially independent of quality control. Thus a star may be hired simply because the industry faces extreme uncertainty and executives wish to be "covered" in case a project fails. This is close to the rationale for inefficiency of prices used by Froot, Scharfstein, and Stein (1992) or by Keynes, who is quoted in the same article (p. 1462). Keynes had suggested that judges in a beauty contest voted on the basis of their expectation of other judges' vote rather than as a result of any independent judgment on their part. In the context of this article, if everybody is after a given star, signing him or her to a project may be a safe bet for an executive who is concerned about job security. Or perhaps the motive for signing stars on to a project or constructing expensive sets of cities just to destroy them in simulated earthquakes, floods, or alien attacks is even simpler. As noted earlier, executives may care about revenues in addition to or instead of profits, and big budgets seem to predict revenues. This idea is supported by some casual empiricism. Weinraub (1995, p. D11) cites Ron Meyer's (the president of MCA) justification for a recent, three-picture, $60 million deal with Sylvester Stallone: "The major reason for the deal? Mr. Meyer wanted to send a message to Hollywood that Universal was now in the big star action business." However, in the final analysis, perhaps the truth lies with Bill Mechanic, president of 20th Century Fox, who said, in the same article, "The entire business is out of control. There is no rationality for the prices paid" (ibid.).

Appendix A

Definition of Variables

BUDGET is the "negative cost," or production costs of films, not including gross participation.
DOMESTIC is the domestic box office receipts.
INTER is the share of domestic distributors in box office receipts overseas.
VIDEO is video sales revenues.
TOTREV is the sum of revenues from all sources.
RATE is the return on investment measure, total revenues divided by the budget.
G, PG, PG13, and R are dummy variables for ratings. These variables take the value of one if the film is rated G, PG, PG-13, or R, respectively, and zero otherwise.
INDEX1 = positive reviews/total reviews.
INDEX2 = (positive reviews + neutral reviews)/total reviews.
INDEX4 = total number of reviews.

UNKNOWN is a dummy variable receiving a value of one if the lead actors in the film are not found in any of three major guides and encyclopedias of the industry (Walker 1993; Katz 1994; and Maltin 1994).
AWARD is a dummy variable, receiving a value of one if any participant in the film has received an Academy Award.
ANYAWARD is a dummy variable receiving a value of one if any participant in the film has been nominated for an Academy Award.
NEXT is a dummy variable receiving a value of one if any actor participating in the film had participated in the previous year's top-ten grossing films.
SEQUEL is a dummy variable receiving a value of one if the film is a sequel to an earlier movie (not necessarily in our sample).
RELEASE is a variable adjusting for the release date. See the discussion in the text for an exact definition.
VALAWARD adds the number of nominations and actual awards for all cast members in each film.
LN denotes the natural logarithm of a variable.

Appendix B

In mid-1999 I rechecked the ratings of the films in the sample, using the newly available web site of the MPAA. In the 6 years since the collection of the data, a few additional films have been rated, mostly receiving ratings of R or PG-13. This can happen for various reasons, say, for example, a wider release of a foreign film or a video release. As is the case in the investment industry, film distributors are under no obligation to have their product rated. If ratings provide additional information, then it is reasonable to assume that these films, or at least most of them (exact rating dates are not provided), were viewed as unrated at the time my revenue data were collected in 1993. However, if ratings are just a rubber stamp and films are judged by content, then the new classification may be better. This article cannot settle this issue, which is still debated for bonds, although the results below provide some evidence.

Following the assumption that ratings provide information, I left the tables in the text as they were. Nevertheless, I did run all regressions and tests in the article with the new ratings as well. The new results are very similar to the figures reported in the text. In tables B1 and B2, I provide the significant variables for the newly estimated major tables in the text, tables 10 and 11. The same variables are significant as in the text, and the coefficients and *t*-values are similar.

TABLE B1 Total Revenue (Table 10)—Variables That Are Significant at the 5% Level

Variable	Coefficient	2-Tailed Significance
LNBUDGET	1.144	.00
G	1.5	.0136
PG	.6	.0076
INDEX4	.03	.0093
SEQUEL	.827	.0121
Adjusted R^2: .675		

TABLE B2 Rate of Return (Table 11)—Variables That Are Significant at the 10% Level

Variable	Coefficient	2-Tailed Significance
G	4.52	.0023
PG	3.36	.0043
SEQUEL	1.33	.093
Adjusted R^2: .165		

Most other tests yield almost identical results. Naturally, coefficients or levels of significance vary somewhat. There are no changes in the conclusions regarding reviews, sequels, and, most important, stars. Stars are still not correlated with either revenues or return on investment. For example, in the reestimated table 10 (total revenue, table B1) the t-value for AWARD is -0.45 and the t-value for NEXT is 0.22. Similarly, in the rate-of-return table (table B2) the t-value for AWARD is 0.31 and for NEXT is 0.14.

The importance of G-rated films is reaffirmed—in fact, in the total revenue and rate-of-return regressions including small films (tables 12 and 13), ratings besides G lose some significance. Also, in the video regression, PG ratings are not significant at the 5% level, reaffirming the superiority of G films for this format.

References

Adler, M. 1985. Stardom and talent. *American Economic Review* 75 (March): 208–212.

Bannon, L. 1998. A tough summer for big budget movies. *Wall Street Journal,* weekend (September 4).

Berk, J. B.; Green, R. C.; and Naik, V. 1998. Valuation and return dynamics of new ventures. Working paper. Pittsburgh: Carnegie Mellon University, September.

Breese, E. 1992. The story editor. In J. E. Squire (ed.), *The Movie Business Book.* New York: Fireside.

Chemmanur, T. J., and John, K. 1996. Optimal incorporation, structure of debt contracts, and limited-recourse project financing. *Journal of Financial Intermediation* 5, no. 4 (October): 372–408.

Childs, P. D.; Ott, S. H.; and Triantis, A. J. 1998. Capital budgeting for interrelated projects: A real options approach. *Journal of Financial and Quantitative Analysis* 33, no. 3 (September): 305–334.

Chisholm, D. C. 1997. Profit sharing vs. fixed payment contracts: Evidence from the motion pictures industry. *Journal of Law, Economics and Organization* 13, no. 1:169–201.

Dekom, P. J. 1992. Movies, money and madness. In J. E. Squire (ed.), *The Movie Business Book.* New York: Fireside.

De-Vany, A., and Walls, W. D. 1997. The market for motion pictures: Rank, revenue and survival. *Economic Inquiry* 25 (October): 783–97.

Diamond, D. 1991. Debt maturity and liquidity risk. *Quarterly Journal of Economics* 106: 709–37.

Eliashberg, J., and Sawhney, M. S. 1996. A parsimonious model for forecasting gross box-office revenues of motion pictures. *Marketing Science* 15, no. 2:113–31.

Eliashberg, J., and Shugan, S. M. 1994. Motion pictures, critics and commercial box office performance. Working paper. Philadelphia: University of Pennsylvania.

Fee, C. E. 1998. The costs of outside equity control: Evidence from motion picture financing decisions. Working paper. Gainesville: University of Florida.

Fershtman, C., and Judd, K. L. 1987. Equilibrium incentives in oligopoly. *American Economic Review* 77 (December): 927–40.

Flannery, M. 1986. Asymmetric information and risky debt maturity choice. *Journal of Finance* 41 (March): 18–37.

Froot, K. J.; Scharfstein, D. S.; and Stein, J. C. 1992. Herd on the street: Information inefficiencies in the market with short term speculation. *Journal of Finance* 47 (September): 1461–84.

Gumbel, P.; Lippman, J.; Bannon, L.; and Orwall, B. 1998. What is an Oscar worth? *Wall Street Journal* weekend journal (March 20).

Hamlen, W. A. 1991. Superstardom in popular music: Empirical evidence. *Review of Economics and Statistics* 73 (November): 729–33.

John, K., and Williams, J. 1985. Dividends, dilution, and taxes: A signaling equilibrium. *Journal of Finance* 40 (September): 1053–70.

Katz, Ephraim. 1994. *The Film Encyclopedia.* 2d ed. New York: Harper Perennial.

Lippman, J. 1995. Dying hard—how a red-hot script that made a fortune never became a movie. *Wall Street Journal* (June 13).

Litman, B. R. 1983. Predicting the success of theatrical movies: An empirical study. *Journal of Popular Culture* 17 (Spring): 159–75.

Litman, B. R., and Kohl, L. 1989. Predicting financial success of motion pictures: The 80's experience. *Journal of Media Economics* 2 (Fall): 35–49.

Luehrman, T. A., and Teichner, W. A. 1992. *Arundel Partners: The Sequel Project.* Cambridge, Mass., Harvard Business School.

Maltin, Leonard. 1994. *Leonard Maltin's Movie and Video Guide, 1995.* New York: Signet.

Miller, M., and Rock, K. 1985. Dividend policy under asymmetric information. *Journal of Finance* 40 (September): 1031–51.

Petersen, M. 1998. Film industry is confronting likely change in accounting. *New York Times,* Business Day (September 21).

Ravid, S. A., and Sarig, O. 1991. Financial signaling by committing to cash flows. *Journal of Financial and Quantitative Analysis* 26 (June): 165–80.

Ravid, S. A., and Spiegel, M. 1997. Optimal financial contracts for a startup with unlimited operating discretion. *Journal of Financial and Quantitative Analysis* 32 (September): 269–86.

Rosen, S. 1981. The economics of superstars. *American Economic Review* 71 (December): 845–58.

Ross, S. 1977. The determination of financial structure: The incentive signaling approach. *Bell Journal of Economics* 8 (Spring): 23–40.

S&P Credit Week. 1997. Are the cameras ready to roll on securitizing the movies? (September 3).

Shah, S., and Thakor, A. V. 1987. Optimal capital structure and project financing. *Journal of Economic Theory* 42, no. 2 (August): 209–43.

Smith, S. P., and Smith, V. K. 1986. Successful movies: A preliminary empirical analysis. *Applied Economics* 18 (May): 501–7.

Stevens, E. L., and Grover, R. 1998. The entertainment glut. *Businessweek* (February 16).

Trigeorgis, L. 1996. *Real Options: Managerial Flexibility and Strategy in Resource Allocation.* Cambridge, Mass.: MIT Press.

Vogel, H. 1994. *Entertainment Industry Economics.* 3d ed. Cambridge: Cambridge University Press.

Vogel, H. 1998. *Entertainment Industry Economics.* 4th ed. Cambridge: Cambridge University Press.

Walker, John (ed.). 1993. *Halliwell's Filmgoer's and Video Viewer's Companion.* New York: Harper Perennial.

Webb, D. C. 1991. Long-term financial contracts can mitigate the adverse selection problem in project financing. *International Economic Review* 32, no. 2 (May): 305–20.

Weinraub, B. 1995. Skyrocketing star salaries. *New York Times* (September 18).

Weinstein, M. 1998. Profit sharing contracts in Hollywood: Evolution and analysis. *Journal of Legal Studies* 27 (January): 67–112.