Does Hollywood Make Too Many R-Rated Movies? Risk, Stochastic Dominance, and the Illusion of Expectation

Author(s): Arthur De Vany and W. David Walls

Source: *The Journal of Business*, Vol. 75, No. 3 (July 2002), pp. 425-451
Published by: The University of Chicago Press
Stable URL: http://www.jstor.org/stable/10.1086/339890
Accessed: 28-09-2016 15:43 UTC

Arthur De Vany
University of California at Irvine

W. David Walls
University of Calgary

Does Hollywood Make Too Many R-Rated Movies? Risk, Stochastic Dominance, and the Illusion of Expectation*

> When the typical "PG" film generates nearly three times the revenue of the typical "R" bloodbath or shocker, then the industry's insistence on cranking out more than four times as many "R" titles must be seen as an irrational and irresponsible habit. (MEDVED 1992, p. 290)

We estimate the probability distributions of budgets, revenues, returns, and profits to G-, PG-, PG13-, and R-rated movies. The distributions are non-Gaussian and show a self-similar stable Paretian form with nonfinite variance and nonstationary mean. The profit distributions have asymmetric tails, which means that Hollywood could trim its "downside" risk while increasing its "upside" possibilities by shifting production dollars out of R-rated movies into G-, PG-, and PG13-rated movies. Stars who are willing to appear in edgy, counterculture R-rated movies for their prestige value may induce an "illusion of expectation" leading studios to "greenlight" movies that have biased expectations.

I. Introduction

Film writer Michael Medved (1992) has criticized Hollywood's fascination with R-rated movies on both cultural and economic grounds. From the White House to Main Street, many individuals share his view that Hollywood makes too many R-rated movies. His argument goes beyond a cultural and critical judgment; he makes the sophisticated economic argument that Hollywood is missing a profit opportunity by making too many R-rated movies and too few G-rated movies. He accounts for this neglect of profitability as a search

* De Vany acknowledges support from the Private Enterprise Research Center of Texas A&M University. Walls acknowledges support from the Committee on Research and Conference Grants of the University of Hong Kong. We thank the referee for useful criticism.

(*Journal of Business*, 2002, vol. 75, no. 3)

0021-9398/2002/7503-0002$10.00

for prestige bestowed by Hollywood insiders on edgy, counterculture movies. Could the movie portfolio that brings such criticism of Hollywood on the grounds of taste and morals also be costing it money? Could a search for prestige among peers lead Hollywood to neglect its bottom line?

This article shows that Medved is right: there are too many R-rated movies in Hollywood's portfolio. An executive seeking to trim the "down-side" risk and increase the "upside" possibilities in a studio's film portfolio could do so by shifting production dollars out of R-rated movies into G-, PG-, and PG13-rated movies.

Putting tastes and morals aside, even a casual look at the evidence does suggest that there are too many R-rated movies compared with G-, PG-, and PG13-rated movies. More than half of all the movies released in the past decade are R-rated, and only 3% are G-rated. About 20% are PG-rated, and 25% are PG13-rated. Based on the production numbers alone, the R-rated category does seem to be crowded, while the G category is almost empty. Medved's evidence suggests that R-rated movies are less successful than G-rated movies: he showed that R-rated films were less than half as likely as PG-rated releases to reach $25 million in domestic box-office revenue, and the median gross of PG-rated movies was nearly triple the median gross of R-rated pictures, while G-rated pictures earned the highest median gross of all.[1]

But Medved's comparisons do not take budgets or profits into account. More important, they fail to account for risk. Motion pictures are among the riskiest of products; each movie is a "one-off" innovation with highly unpredictable revenues and profits.[2] Unless one accounts for the differing risks among the rating categories, it is impossible to reach a conclusion that R-rated movies are overproduced. For example, the low median or average return on R-rated movies could just reflect lower risk (if they had lower risk). In addition, median revenue will generally differ from expected revenue. Moreover, expected values may be so heavily influenced by a few blockbuster movies as to misstate prospects. Even the use of mean-variance analysis can be misleading (as we shall show) in motion pictures, so one must look to more basic considerations to assess the prospects of motion pictures.

Fundamentally, until it is released, a motion picture is just an unknown, uncertain prospect in the eye of the producer and in the studio's statistical model. Even the conviction that a movie is a "sure thing" is no more than a belief that its probabilities are skewed toward successful outcomes. So, in

1. Ravid (1999) showed that G-rated movies earned higher average profit than R-rated movies.
2. Scherer, Harhoff, and Kukies (2000) show that the profit distribution from technological innovations is highly skewed with a Paretian tail. De Vany and Walls (1996) find the Bose-Einstein process and the stable Paretian distribution to be a good model of motion picture revenue dynamics and outcomes. Sornette and Zajdenweber (1999) explicitly model innovation as an α-stable Lévy motion and show that the innovation and international motion picture data follow the stable Paretian law.

order to compare motion pictures as prospects one must compare their probability distributions.

The objectives of this article are to characterize the uncertainty that movies face by identifying their probability distributions and to bring the right decision tools to the task of evaluating them as economic prospects. This means that the primary task is to get the statistical model right, and when we do that we see that there is little scientific justification for a studio to interfere with the producer's "vision." On the other hand, there is plenty of justification for a studio to be wary of a "pitch" for an R-rated, big-budget movie that a major creative talent is eager to make. There is also more room than the "numbers" might suggest for hunches and intuition that center on the nonquantifiable intangibles of story and character. These points follow from and will be demonstrated in what follows from the nature of the statistics.

The statistics of the movie business are a bit exotic, and much of our work is aimed at characterizing the statistical distributions of the relevant variables. The distribution of motion picture revenues is highly skewed, and the mean is dominated by a few movies in the extreme tail. Hence, its mean is related to its variance. Moreover, the distribution may not have finite moments and so may have neither convergent expected values nor variances (De Vany and Walls 1999). The sample mean is unstable and does not converge to the population mean. The distribution of profits is not symmetric—it has a heavier positive than negative tail—so that conventional portfolio choices that reduce variance for a given expected return are dominated by choices that exploit the asymmetry of the tails.[3] All these points will be established in what follows, and they form a central conclusion of this analysis beyond our conclusions about the stochastic rankings of the ratings.

Once we establish the correct statistical model by estimating the probability distributions for revenues, budgets, returns, and profits in the four Motion Picture Association ratings categories—G, PG, PG13, and R—we then rely on the unambiguous ranking concept of stochastic dominance to investigate Medved's hypothesis. One movie (first-degree) stochastically dominates another if it has a higher probability of exceeding the other's revenues for all possible revenue outcomes. This applies also to budgets, with a reversal of the ranking. With regard to profits, stochastic dominance is more subtle because the distribution has two parts that correspond to profits and losses and the distribution is not symmetrical. Accordingly, we rank the positive and negative parts (tails) of the asymmetrical profit distribution. We show that R-rated movies are dominated by G-, PG-, and PG13-rated movies in all dimensions of revenues, costs, return on production cost, and profits. We also show that there are dramatic differences in risk, budget variability, and profits among the ratings. The arbitrage opportunity that this implies predicts some of the changes that Hollywood has made to its portfolio in the years following

3. The strategy of exploiting the asymmetric tails of the distribution to increase returns and lower large risks was developed by Anderson and Sornette (1999).

our sample period (which ends in 1996). The formation of animation units in several studios, their alliances with computer animation specialists, the increased rate of releases in the animated G-rated category, and the sharp rise in the salaries of animators in the past few years are all evidence that Hollywood detected some of the arbitrage opportunities that we show here.

In Section II, we summarize the production levels, revenue, and returns to movies in each of the ratings categories. In Section III, we discuss the stable Paretian and normal distribution statistical models and show that the stable Paretian model is the right model for the movie business. In Section IV, we discuss the success rates among movie ratings classes. In Section V, we determine the probability distributions of box-office revenues, success rates, returns, and profits and show how R-, G-, PG-, and PG13-rated movies are stochastically ranked with respect to one another. We conclude in Section VI.

II. An Overview of Motion-Picture Production by Ratings

Our sample of data includes 2,015 movies that were released to theaters in North America from 1985 to 1996, inclusive. The data were obtained from ACNielson EDI's historical database. The data were complied from distributor-reported box-office reports of films in theatrical engagements (direct-to-video releases are not included) and estimated production budgets. These data are the standard industry source for published information on the motion pictures and are used by many major industry publications, including *Daily Variety* and *Weekly Variety*. The ACNielson EDI data were augmented by creating a variable indicating whether a "star" was associated with each film. Each actor, producer, or director appearing on *Premier*'s annual listing of the 100 most powerful people in Hollywood or on James Ulmer's list of A and A+ people was considered to be a "star" in our statistical analysis. This definition of star is broader than most since it includes artists on both sides of the camera and includes producers as well. For example, Oliver Stone and Steven Spielberg are included in the list as well as stars in the more conventional sense, like Tom Hanks and Sandra Bullock.

A cross-tabulation of the sample of movies is given in table 1. The table shows the sample of movies disaggregated by year, rating classification, and the presence of a star. From 1985 to 1996 inclusive, Hollywood made 1,057 R-rated movies; just 60 G-rated movies were made during that same period. R-rated movies dominate G-, PG-, and PG13-rated movies and comprise just over half of all the movies made. Of the 2,015 movies in the sample, 326 feature stars either in front of the camera or behind it. R-rated movies accounted for 52% of the 1,689 movies that did not feature a star, and they accounted for 57% of the movies that did feature a star. The 100 stars of the "A-list" appear in, produce, or direct more often in R-rated movies than in movies with any other rating.

The preponderance of stars in R-rated movies is even greater in high-budget

TABLE 1 Tabulation of All Movies by Rating, Star Presence, and Year

	No Star				Star				
Year	G	PG	PG13	R	G	PG	PG13	R	Total
1985	2	20	17	21	0	3	4	4	71
1986	6	28	34	71	0	8	5	8	160
1987	2	42	32	74	0	4	1	18	173
1988	5	45	32	91	0	4	1	18	196
1989	6	36	56	134	0	7	6	14	259
1990	6	25	40	86	0	5	9	17	188
1991	5	27	44	89	0	5	6	18	194
1992	3	25	38	66	1	5	11	18	167
1993	5	34	27	56	0	1	8	13	144
1994	5	21	29	50	0	3	11	15	134
1995	7	17	30	62	1	5	10	24	156
1996	6	24	37	71	0	5	11	19	173
Total	58	344	416	871	2	55	83	186	2,015

movies. Table 2 documents the distribution of stars over ratings categories by budget. As is evident, stars are present in 45% of R-rated movies with large budgets, a much higher percentage than for any other rating or budget classification. By contrast, they appear in only 30% of high-budget PG13-rated movies, 23% of PG-rated movies, and only 10.5% of G-rated movies. In medium- and low-budget films, the distribution of stars is similar between PG- and PG13-rated movies. No stars appeared in the G-rated medium- or low-budget movies, and they appeared predominately in R-rated movies among low-budget movies.[4] It is notable that R-rated films—portrayed by critics as attacks on conventional social values and morals—attract a disproportionately large share of Hollywood's on-screen and behind-the-camera stars, and this is even more true of high-budget R-rated movies.

About half of the G-rated movies in our sample are animated, and half are live action. We will discover later in the article that most of the high-grossing G-rated movies are animated, although live-action G-rated movies also earn very high box-office grosses, with *101 Dalmations* and *Babe* being the sixth and twelfth highest grossing G-rated movies in the sample. The distinction between animated and live-action movies may be important if there are barriers to entry into the production of animated G-rated movies.[5]

Table 3 shows the mean, standard deviation, median, and upper and lower quantiles for revenues, budgets, and returns in our sample of movies disaggregated by rating category. All monetary magnitudes reported in the table, and in the remainder of the article, are in constant 1982–84 U.S. dollars. These data are consistent with Medved's calculations, as we shall show in Section

4. A star may take "scale" to appear in a low budget movie if they feel that they can exhibit their craft in a strong role. These kinds of roles seem to occur in R-rated movies or are seen by the stars to occur there. This is not to be confused with gross or profit participation, which a star would only take in a high-budget movie with good prospects.

5. We will return to this point.

TABLE 2 Percentage of Movies Featuring Stars by Rating and Budget

	Low Budget		Medium Budget		High Budget	
Rating	No Star	Star	No Star	Star	No Star	Star
G	100.00	.00	100.00	.00	89.47	10.53
PG	99.12	.88	89.26	10.74	76.97	23.03
PG13	98.18	1.82	90.76	9.24	70.24	29.76
R	97.17	2.83	89.94	10.06	55.25	44.75

NOTE.—This table reports, in each row, the percentage of movies featuring a "star" for that particular rating and budget category. Low-, medium-, and high-budget categories correspond to the lower, middle, and upper third of the distribution of movies by budget, respectively.

V. But it is essential to evaluate the probability distributions to rank the ratings consistently. We estimate and rank the distributions of revenues, budgets, returns, and profits in Section V.

III. Choosing among Uncertain Movie Projects: Getting the Statistical Model Right

Movies are uncertain prospects. Before a movie is released, only probabilities of outcomes may be known. Even these probabilities may be difficult to ascertain since each movie is unique. When a studio considers a motion picture for its production slate, it is, in effect, evaluating it as a probability distribution over various profit or return outcomes and comparing it to other projects that it might choose to produce. How should an executive decide, among the many projects, which ones to produce? Here we abstract from considerations of story value, character, or originality to focus on the quantifiable economic aspects of the decision. How then should information about the odds of different outcomes be factored into the decision to "green-light" a movie or to choose the movies that will go into a studio's production portfolio?

Since a motion picture will not incur costs until production begins or earn revenues or profits until it is released, the studio executive must form expectations about these highly uncertain elements of a motion picture as an investment. A first cut at formulating this decision might be making an estimate of the expected budget, box-office revenues, and profits given what is known about the movie's "creative elements" such as the screenwriter, director, stars, story line, genre, and rating. This first cut would be very incomplete, however, for the error in forecasting the expectation must be taken into account. Two movies having the same forecasted expected return on investment may have very different risks associated with them.

A more sophisticated approach would be to consider the expectation and risk associated with a motion picture. To do this, one must know the probabilities of the different outcomes that the movie might realize when it is released. This means that one must know how probability is distributed over different outcomes. A budget, box-office, return, or profit outcome for a movie is a random variable X that has a probability distribution $\Pr(X \leq z) = F(X \leq z)$. A movie's prospects are given by the probability distributions of

TABLE 3 **Box-Office Revenues, Budgets, and Returns**

Rating	Twenty-Fifth Percentile	Fiftieth Percentile	Seventy-Fifth Percentile	Mean	SD
The revenue distribution:					
G	2,574,743	1.01e + 07	2.28e + 07	2.58e + 07	3.99e + 07
PG	1,566,304	1.12e + 07	2.88e + 07	2.15e + 07	3.00e + 07
PG13	1,922,510	8,439,733	2.39e + 07	1.96e + 07	3.15e + 07
R	814,088.6	5,171,729	1.58e + 07	1.35e + 07	2.11e + 07
Total	1,169,457	6,943,376	2.06e + 07	1.70e + 07	2.68e + 07
The budget distribution:					
G	4,917,709	9,510,306	1.47e + 07	1.19e + 07	9,617,613
PG	5,287,010	1.10e + 07	1.71e + 07	1.28e + 07	9,625,494
PG13	6,324,666	1.13e + 07	1.70e + 07	1.39e + 07	1.14e + 07
R	3,776,435	7,285,343	1.41e + 07	1.05e + 07	9,797,142
Total	4,399,749	9,096,816	1.56e + 07	1.18e + 07	1.03e + 07
The returns distribution:					
G	.4009847	1.245965	2.381497	2.152229	3.46846
PG	.25854	.8924453	2.153059	1.662702	2.23019
PG13	.2193686	.6822007	1.786988	1.390128	2.20324
R	.1832344	.6636797	1.669723	2.142445	16.16777
Total	.2040572	.7273786	1.789731	1.861434	11.8195

NOTE.—All monetary magnitudes reported in constant 1982–84 dollars. Gross returns are defined as revenue/budget. Since rentals are about half of box-office gross, an approximate rate of return to the studio is 0.5 × (gross return) − 1. The break-even gross return is two. Revenue is domestic theatrical revenue only and does not include foreign theatrical revenues or other revenue sources.

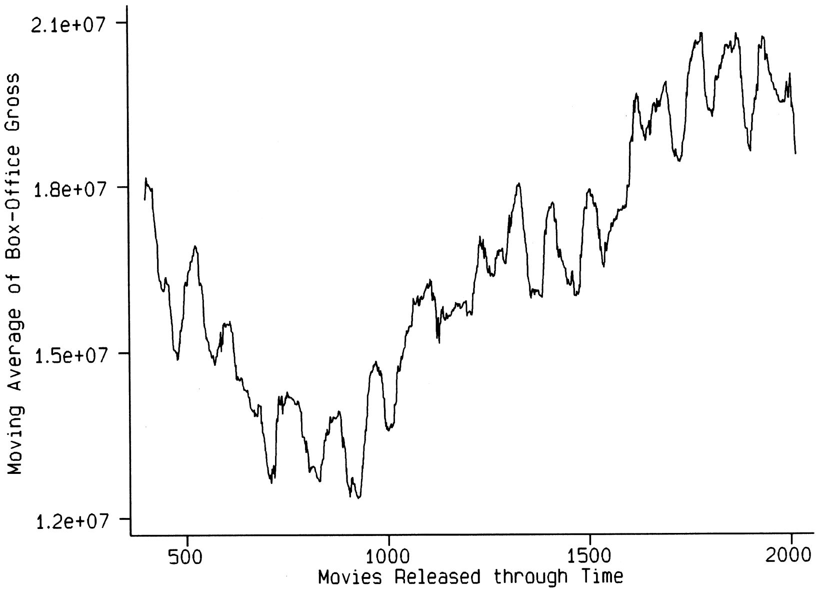

FIG. 1.—Moving average gross over number of films

its budget, revenues, and return on investment, all of which are random variables.

To make informed decisions, the studio must get the statistical model of these random variables right. This is where the first critical error is often made. A studio might assume that the probability distribution is a normal (or lognormal) distribution and might use estimates of the mean and variance (or standard deviation) from past movies to form an estimate of the expectation and risk (variance or standard deviation) of a movie's prospects. Using the mean and standard deviation estimated from a sample of movies that have been produced and released, a financial analyst might forecast expected revenues, say, as the mean and use the standard deviation to describe the error of the forecast.

As we show below, the normal (or lognormal) distribution model is the wrong model for the movie business. In the movies the average is unstable and does not converge to a stationary value over the course of time. The variance of outcomes increases with the size of the sample. These points are dramatically indicated by figures 1 and 2, which show the average and variance of box-office revenues as the number of movies released increases over time. Both series are volatile and self-similar (segments of the graphs look like the whole graph).[6] Since the average rises and falls randomly and often quite

6. De Vany and Lee (2000) verify that the revenue increments are an α-stable Lévy motion whose increments scale as $\delta t^{1/\alpha}$. The process is dense with discontinuities, as McCulloch (1996) shows is true of an α-stable Lévy motion. The discontinuities are quite evident in the figure even though the series shown is a time-expanding average rather than the raw increments.

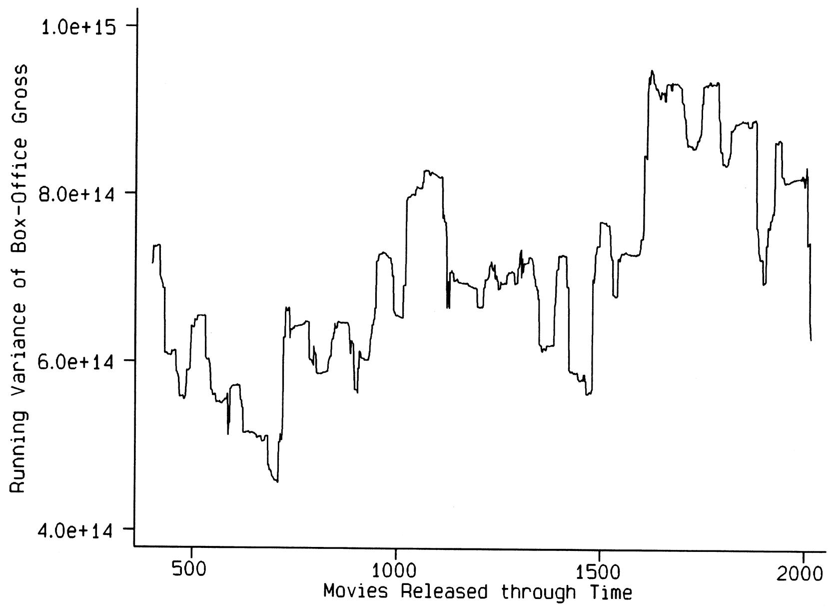

FIG. 2.—Moving average variance about the mean over number of films

dramatically as the number of movies in the sample increases, an average calculated from a given sample of movies will be a poor forecast of the average in the future. Because the average is unstable, it is a poor estimator of the expected next event. The average is also a poor forecast of the most probable future outcome. This is because the average is not the most probable outcome. The average is dominated by rare, extreme outcomes and is quite far above the most probable outcome. Because extreme outcomes dominate the average, the expectation will differ from the average, and it need not even exist mathematically. The variance is unstable as well; it grows with the number of movies included in the sample. The variance may be unbounded and need not have a finite value (and usually does not).

All these points follow from the nature of the probability distributions that describe the movie business. We shall briefly describe the features of the statistical models that capture the movie business and show that the stable Paretian model is the right model. The stable Paretian model was proposed by Mandelbrot (1963*a* 1963*b*, 1967) for economic data and by Fama (1963, 1965) for returns to financial assets.[7] The estimates of the parameters of the

7. De Vany and Walls (1996) show that the statistical dynamics of box-office revenues converge asymptotically to a Pareto distribution, and they (De Vany and Walls 1999) demonstrate that the stable Paretian model is consistent with box-office revenue data. De Vany and Lee (2000) perform a battery of diagnostic tests on motion picture data that strongly supports the stable Paretian model.

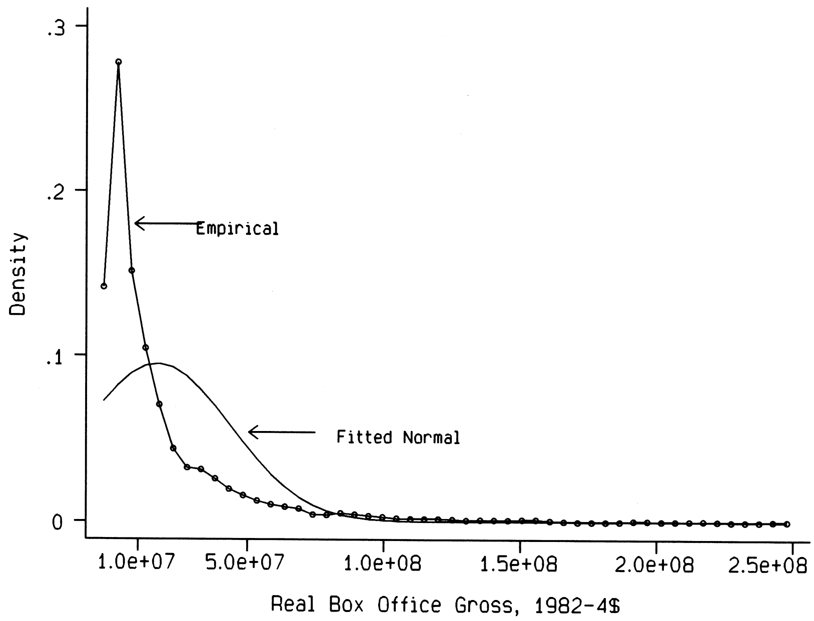

FIG. 3.—Normal and stable Paretian distributions of revenue

stable Paretian model are presented below. Here we focus on the contrast between the stable Paretian model and the normal distribution model.[8]

Consider the probability distributions shown in figures 3 and 4. In these figures, the probability density function of box-office revenues and the logarithm of box-office revenues of all movies in the sample are estimated and overlaid with a normal distribution. The probability distribution is highly skewed and is not symmetrical. Most of the probability mass is placed on the most frequent, low-revenue outcomes. These low outcomes far exceed the frequency predicted by the normal distribution. The correct model has a long, thick tail to the right, showing that the probability of extremely high revenues exceeds what is predicted by the normal distribution model. The mean revenue is much higher than the most probable revenue, which is where the density function reaches its highest level. This is different from a normal distribution where the most probable outcome (the peak of the probability density curve) equals the mean.

The stable Paretian model implies that, in the upper tail, the probability density function converges to a Pareto distribution. Figure 5 shows the Paretian property of the upper tail. In this figure we are looking at the highest grossing movies and ranking from high (a value of one) to low. Hence, we are looking

8. We are not asserting that studios use the normal or lognormal distributions; the normal (or lognormal) distribution model is a useful and familiar base case against which to contrast the stable Paretian model.

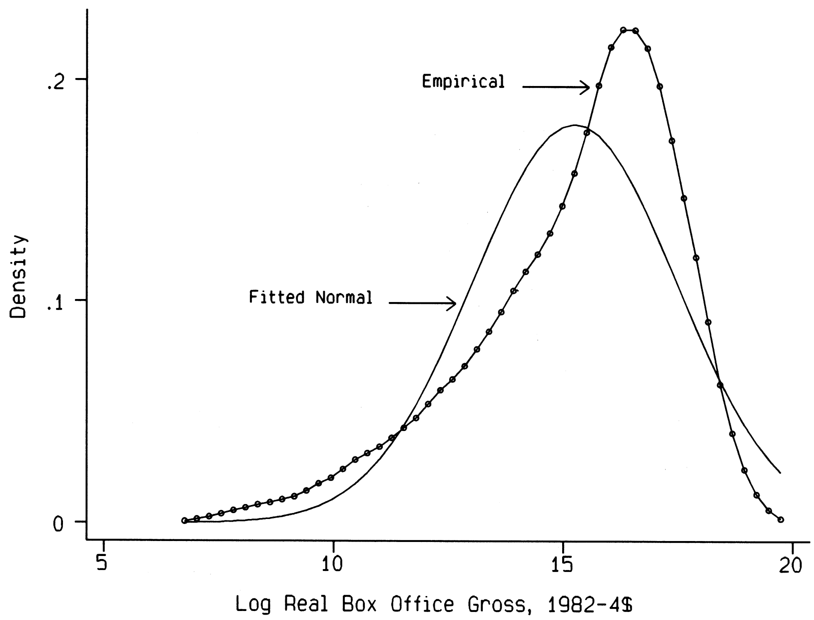

FIG. 4.—LogNormal and stable Paretian distributions of revenue

at the upper tail of the probability distribution, but through the lens of its extreme outcomes. The figure shows that the dominant share of the box-office revenues is taken by the high-ranking movies so the tails of the distributions are where the important events are located. The central part of the distribution is relatively unimportant relative to the tails. The approximate linearity of the graph at the higher ranks (upper tail) is a signature of a stable Paretian distribution. The significance of the Paretian upper tail property is that a few extreme outcomes dominate total and average revenue and that these extreme outcomes are more probable than the normal distribution model would predict. The heavy tails and the dense probability mass on low outcomes of the stable Paretian model are most important features of the movie business.

IV. Ranking by Success Rates

Based on the foregoing discussion, it is clear that one must compare whole probability distributions rather than averages or expectations and their variance. A simple first test of which movies are better prospects, then, may rely on simple calculations of the probabilities of outcomes. If movie A has a higher probability of "success" than movie B, then A is weakly preferred to B. By using different measures of success we can rank movie prospects in each rating class.

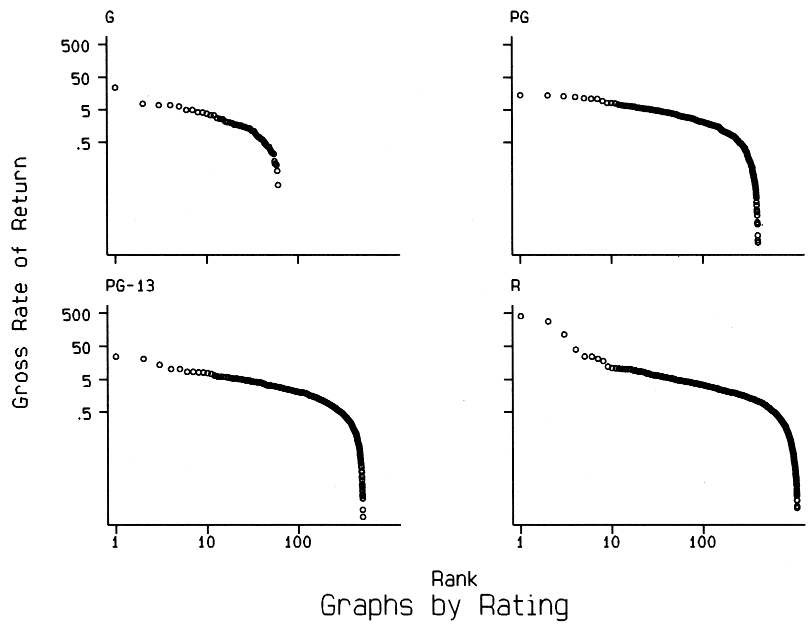

FIG. 5.—Rank Pareto distribution of revenue

A. Box-Office Revenue Success Rates

In table 4, we tabulate the number of movies that earned cumulative box-office revenues in excess of $50 million; we term these movies "revenue hits." The number of R-rated movies that are box-office revenue hits is 68, while there are far fewer revenue hits in the other rating classifications: only eight G-rated movies are hits. A χ^2 test indicates that we cannot reject the null hypothesis that the revenue hits in each rating category are independent of the year of theatrical exhibition. In other words, this relationship appears to be independent of the year of release.

However, the number of hits for each rating class should be scaled by the number of movies made in each rating classification each year. Success rates are a more representative measure of revenue earning power than is the number of high-grossing films. Table 5 displays the proportion of films in each rating classification, by year, that were revenue hits. The success rate for R-rated movies is just 6%, whereas 13% of G- and PG-rated movies are hits and 10% of PG13-rated movies are hits. The box-office success rates for all non-R-rated movies (G-, PG-, and PG13-rated) are twice the rate for that of R-rated movies.

B. Return on Production Cost Success Rates

Table 6 displays a tabulation of movies by year and rating classification that had box-office revenues in excess of three times the production budget; we

TABLE 4 Tabulation of Revenue Hits: Tabulation of Movies with Box-Office Gross > $50 Million

	Year												
Rating	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	Total
G	0	0	0	0	1	0	1	1	0	1	2	2	8
PG	6	3	2	5	8	6	4	3	2	4	5	3	51
PG13	2	4	3	2	6	5	6	2	4	5	5	5	49
R	1	4	8	6	5	6	7	11	5	5	4	6	68
Total	9	11	13	13	20	17	18	17	11	15	16	16	176

NOTE.—To make expected cell frequencies not less than five, we grouped years into six 2-year categories and deleted the G rating. The resulting $\chi^2(10) = 10.622$, with a marginal significance level of 0.388.

refer to these films as "returns hits." Here again, we are using a point on the distribution of outcomes to calculate probability. The table shows that there are about twice as many R-rated returns hits as PG- and PG13-rated returns hits, and about 10 times as many R-rated hits as G-rated hits. The composition of hits across rating classes is independent of the year of theatrical exhibition according to the standard χ^2 statistical test for independence of rows and columns.

To calculate the success rate of returns hits, we must control for the number of films released each year in each rating class. In table 7, we show the success rates for the ratings. Overall, 20% of G-rated films are returns hits in terms of their rate of return on the production budget.[9] The proportion of returns hits is 16% in PG-, 12% in PG13-, and 11% in R-rated films.

These tabulations of rates of box-office and returns hits make clear that the G- PG-, and PG13-rated films had a higher proportion of hits than did R-rated movies, both at the box office and in returns on production dollars. The number of R-rated successes is high because more of these movies are made (and that may blind decision makers who do not pay attention to the odds), but the success rate of R-rated movies is much less than the success rates of G-, PG-, and PG13-rated movies.

V. Ranking by Stochastic Dominance

The foregoing comparison is informative, but, by focusing on the probabilities of a fixed outcome rather than the whole probability distribution, it does not use all the available information. A more sophisticated comparison is to use the probability distributions (which include probabilities of all outcomes) to rank movie prospects. The relevant criterion in this case is stochastic dominance.[10] Intuitively, the idea behind the stochastic dominance ranking is that if probability distribution A has less mass on low-value outcomes and more

9. To be sure, if we were to include ancillary products—t-shirt sales, fast-food franchise tie-ins, toys, etc.—the rate of return on G-rated films would dominate the other rating categories by an even greater amount.

10. See Huang and Litzenberger (1988) for a good exposition of stochastic dominance in portfolio theory.

TABLE 5 Success Rate for Revenue Hits: Success Rate for Movies with Box-Office Gross > $50 Million

	Year												
Rating	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	Total
G	0	0	0	0	17	0	20	25	0	20	25	33	13
PG	26	8	4	10	19	20	13	10	6	17	23	10	13
PG13	10	10	9	6	10	10	12	4	11	13	13	10	10
R	4	5	9	6	3	6	7	13	7	8	5	7	6
Total	13	7	8	7	8	9	9	10	8	11	10	9	9

NOTE.—Percentage success rate calculated as 100 times the ratio of table 4 to table 1.

mass on high-value outcomes than probability distribution B, then A is preferred to B. This means that for any outcome z, the probability that movie A will, say, gross more than z is higher than the probability that movie B will gross more than z. When this holds for all values of z, then movie A first-order stochastically dominates movie B. More formally, random variable X first-order stochastically dominates random variable Y if

$$\Pr(x > z) \geq \Pr(Y > z) \quad \text{for all } z. \tag{1}$$

Since $\Pr(X > z) = 1 - F(z)$, where $F(z)$ is the cumulative probability density function, first-order stochastic dominance of distribution $F(z)$ over distribution $G(z)$ can be written in the form

$$F(z) \leq G(z) \quad \text{for all } z. \tag{2}$$

So, $F(z)$ first-order stochastically dominates $G(z)$ if there is less probability of lower outcomes than z under $F(z)$ than under $G(z)$, and this holds for all outcomes z. It can be shown that all expected utility-maximizing decision makers would prefer $F(z)$ to $G(z)$ when $F(z)$ first-order stochastically dominates $G(z)$.[11]

In what follows we focus on characterizing the statistical distributions and stochastically ranking them. We are not analyzing why these distributions might be different or what factors might account for whatever differences that we may find. In this respect, the analysis is comparable to determining the return distribution on common stock in various categories, for example, small-cap or large-cap funds, or real estate versus energy equities. This is a necessary first step in developing an analysis of Hollywood's film portfolio. Individual differences among movies may be great and can be influenced by budgets, release strategies, stars, story, and many other factors. It is this difference within each rating that we capture in the probability distribution, and the question is: Do ratings matter? Do the distributions differ for revenues, costs, returns, and profits? We have previously shown (De Vany and Walls 1999) that ratings, as a group, are statistically significant in revenue outcomes and

11. A weaker form of stochastic dominance is second-order stochastic dominance. We will focus on first-order stochastic dominance as it corresponds to the empirical analysis that follows.

TABLE 6 Tabulation of Returns Hits: Tabulation of Movies with Box-Office Gross/Budget > 3

	Year												
Rating	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	Total
G	0	1	1	2	1	0	2	1	1	1	1	1	12
PG	8	5	4	7	8	6	4	8	7	2	3	3	65
PG13	4	8	13	2	7	2	7	1	3	4	5	4	60
R	7	16	14	16	10	5	8	9	8	8	9	11	121
Total	19	30	32	27	26	13	21	19	19	15	18	19	258

NOTE.—To make expected cell frequencies not less than five, we grouped years into six 2-year categories and deleted the G rating. The resulting $\chi^2(10) = 6.094$, with a marginal significance level of 0.807.

that each rating is also individually significant. This is not true of genre categories; genre is a significant variable, but the individual genre variables are not significant; Simonoff and Sparrow (2000) also find genre as a group to be statistically significant. So, rating does condition the distribution of outcomes, and, as we shall show, there are important differences among rating classes.

A. Revenues

The upper panel of table 3 shows the median, mean, standard deviation, and lower and upper quartiles of box-office revenue in constant 1982–84 U.S. dollars for the movies in our sample. Mean revenues of G-, PG- and PG13-rated movies dominate mean revenues of R-rated movies. The average revenues for movies that are G-rated is \$25.8 million, for movies that are PG-rated is \$21.5 million, and for movies that are PG13-rated is \$19.6 million versus \$13.5 million for R-rated movies. The standard deviations of non-R-rated movie revenues are greater than the standard deviation of R-rated movie revenues, an indication of their long upper tails.

The high degree of rightward skew in the distributions (as implied by the stable Paretian model) can be verified by looking at the revenue percentiles. The percentiles in table 3 indicate that the probability mass of G-rated movies is skewed far to the right. The average revenue exceeds revenue at the seventy-fifth percentile. The other ratings classes do not show this extreme skew, but they are highly skewed to the right nonetheless—their means lie above the median and near the seventy-fifth percentile.

As Mandelbrot (1963*a*) showed, the stable Paretian model implies that the asymptotic distribution function of extreme values is a Pareto distribution. The Pareto cumulative distribution function is

$$\mathrm{Prob}(X > x) = F(x; k,\alpha) = 1 - \left(\frac{k}{x}\right)^{\alpha}, \tag{3}$$

where $x \geq k$ and $k,\ \alpha > 0$.

We have estimated the exponent α of the Pareto distribution by maximum

TABLE 7 Success Rate for Returns Hits: Success Rate for Movies with Box-Office Gross/Budget > 3

	Year												
Rating	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	Total
G	0	17	50	40	17	0	40	25	20	20	13	17	20
PG	35	14	9	14	19	20	13	27	20	8	14	10	16
PG13	19	21	39	6	11	4	14	2	9	10	13	8	12
R	28	20	15	15	7	5	7	11	12	12	10	12	11
Total	27	19	18	14	10	7	11	11	13	11	12	11	13

NOTE.—Percentage success rate calculated as 100 times the ratio of table 6 to table 1.

likelihood for the upper tail of the box-office revenue distribution.[12] The data are well-fitted by the Pareto distribution—Kolmogorov-Smirnov tests do not reject the hypothesis that box-office revenues are Pareto-distributed in the upper tail, above $40 million revenue.[13] The data do not reject the hypothesis that animated and live-action G-rated movies represent draws from the same distribution.[14] But there is some evidence that animated G-rated movies earned more than live action movies.

The estimated values of α for revenues of $k \geq 40$ million are shown by rating class in table 8. The values of α in all ratings but R lie in the interval $1 \leq \alpha \leq 2$. These estimates imply that for every rating class but R, the expected value of box-office revenue is finite, but the variance is infinite! Only the R-rated movies have an α value greater than two, implying that the distribution of R-rated movie revenues has less probability mass at high outcomes and a finite variance (this was shown also by the lower standard deviation over the sample of R-rated movies discussed above). The Pareto revenue distribution of movies in the non-R categories places so much probability on extremely high revenue outcomes that their revenues have infinite variance.

It follows from the estimated values of α that box-office revenues of G-rated movies are more skewed to the right than are revenues in the other ratings categories. That G-rated distribution, therefore, has a higher probability of extremely high revenue outcomes. This follows from the small value of α for the G-rated revenue distribution relative to other movies (probability in the upper tail declines as $x^{-\alpha}$, so the smaller value of α for the G-rated distribution implies that probability declines less rapidly as revenues move

12. The diagnostic tests confirming the stable Paretian model for revenues are contained in De Vany and Lee (2000). See also figs. 1 and 2 above, which show the unstable mean and variance that Mandelbrot 1963*b* identified as salient characteristics of the stable distribution. The log-log linearity of the upper tail, which Mandelbrot shows to be implied by the stable Paretian model, is also visible in fig. 5.

13. Stuart, Ord, and Arnold (1999, ch. 25) contains a discussion of the Kolmogorov-Smirnov test. De Vany and Walls (1999) and Sornette and Zajdenweber (1999) verify the Paretian tail of box-office revenues, and both show it to be stable over time. These authors also reject log normality in favor of the Paretian distribution. De Vany and Walls (1996) formally reject log normality and three-parameter log normality for motion picture revenues.

14. The exact *p*-values for the Kolmogorov-Smirnov test of equality of distribution functions for revenues, profits, and returns are 0.074, 0.198, and 0.173, respectively.

TABLE 8 Estimated Pareto Exponents for Revenues by Rating

Rating	Pareto Exponent	K–S Test *p*-Value
G	1.591	.712
PG	1.814	.252
PG13	1.661	.617
R	2.274	.234

NOTE.—K–S test = Kolmogorov-Smirnov test. The Pareto exponent was estimated by maximum likelihood conditional on a minimum revenue of \$40 million. The K-S test *p*-values reported are for the null hypothesis that the data are consistent with the theoretical Pareto distribution.

into the upper tail of the G-rated distribution). This property provides a direct way to rank the revenue distributions.

From the formula for the Pareto distribution in equation (3), it follows that the random variable having the smallest value of α puts more probability above every revenue outcome exceeding \$40 million. Set $z = \$40$ million. Denote the cumulative probability distributions of revenues of each rating class as $G(z)$, $PG(z)$, $PG13(z)$, and $R(z)$. Then from the α values in table 8, we can succinctly state the relationship as $G(z) \geq PG13(z) \geq PG(z) \geq R(z)$, where $\geq$ denotes first-order stochastic dominance. In words, G-rated movies dominate PG13-rated movies, which in turn dominate PG-rated movies, which in turn dominate R-rated movies.

Using the estimated values of the tail weights, α, we can use the relationship of the expected value to the most probable value for the Pareto distribution to highlight the difference among ratings of the most probable and the expected value. For the Pareto distribution the expectation of revenue conditional on revenue $z \geq \$40$ million may be written as a function of the tail weight α, as

$$E(x|z) = z\left[\frac{\alpha}{(\alpha - 1)}\right], \ \alpha > 1. \tag{4}$$

The ratio $\alpha/(\alpha - 1)$ is the ratio of the expected value to the most probable value of box-office revenue. The most probable value is the peak of the probability density function for each distribution. Since we used a common value of \$40 million for the estimates, this is the most probable outcome for box-office revenue in each rating. Then the multiple by which the expected value exceeds the most probable value is a direct way to rank the revenue distributions among the ratings. Using the estimated values of α, the ratios of the expected to the most probable value of box-office revenues for G-, PG13-, PG-, and R-rated movies, respectively, are 2.69, 2.51, 2.22, and 1.78. R-rated movies rank last.

One question that we have not addressed is that, in our sample, most of the observations in the upper tail of the revenue distribution are animated movies. This raises a natural question: Is it possible to arbitrage between animated and live-action movies? Is Disney the sole reason for the success of animated G-rated movies? If so, then it may not be possible for other studios to exploit the arbitrage opportunity indicated by these results. To explore this issue we estimated the Pareto exponent for animated G-rated films and for all G-rated movies. The animated G-rated movie Pareto exponent is 1.531. For all G-rated movies, the Pareto exponent is 1.591.[15] These estimates suggest that the upper tail of the distribution for animated G-rated movies contains slightly more probability than the upper tail for live-action G-rated movies. This may be one reason we have seen Warner Brothers and DreamWorks, along with Pixar and others, entering the animated G-rated movie segment. Animator salaries have escalated in the past few years, and there has been a move to produce more computer-animated films. Thus, the industry has behaved in a way implied by the results to capture the superior returns in animated G-rated movies.

But, it is important to remember the difference between the empirical and the theoretical distributions at work here. Even though the live-action G-rated movies are dominated by animated G-rated movies in the sample, it still remains true that, given the form of the probability distribution, the probability that a live-action G-rated or PG-rated movie will earn revenues that exceed an animated G-rated movie is positive and not negligible. The ability of the Paretian model to predict "out-of-sample" events is one of its strengths.[16]

B. Production Budgets

Production budgets also face a kind of uncertainty. Each movie has a planned budget, but anecdotal evidence indicates that many, if not most, movies go over budget. There is always a risk that a movie will exceed its planned budget, and there are examples where they go far over budget: *Heaven's Gate*, *Titanic*, and *Cleopatra*. There is no way in our data to judge how the actual production budget compares with the intended budget, but we can still learn something of the variability of budgets by examining the distribution of production budgets. Some of this variability is intended, but some is unintended and is the result of a movie going over the intended budget. Consequently, the variability that we can measure consists of an intended part and an unintended part. By holding rating constant, we control to some extent for the intended part. And by comparing the variability relative to the average we also control for some (unknown) portion of the intended variation.

The middle panel of table 3 presents the statistics on production budgets; this does not include print or advertising costs. The statistics reveal that R-rated movies are generally cheaper to make than G-rated movies. The average budget of an R-rated movie is $10.5 million, whereas the average budgets of a G-, PG-, and PG13-rated movie are $11.9, $12.8, and $13.9 million, re-

15. We have to group the sample into all G-rated movies and animated G-rated movies because we do not have enough observations on live-action G-rated movies whose box-office gross exceeds $40 million to estimate the Pareto exponent for live-action G-movies group separately.

16. The record opening week revenues earned by *The Grinch*, which opened on screens in late 2000, provides another example that G- or PG-rated movies need not be animated to land in the extreme upper tail of the distribution of revenue outcomes.

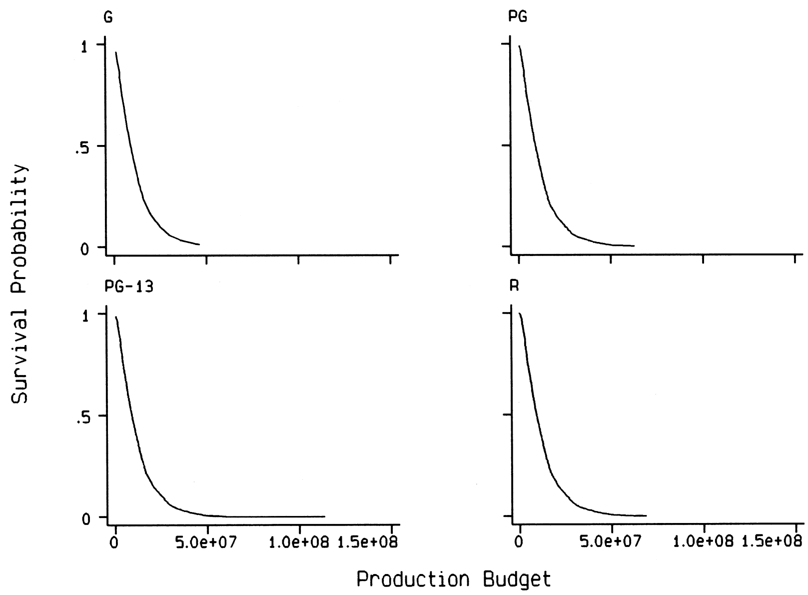

FIG. 6.—Survival probabilities of budgets by rating

spectively. PG13-rated movies were the most expensive movies during our time frame, and the highest-budget movie (*Waterworld*) also was PG13-rated.

The budgets corresponding to the twenty-fifth and fiftieth percentiles of the R-rated production budgets are less than the budgets associated with these percentiles in the other rating categories. By the seventy-fifth percentile of R-rated movies, however, budgets are nearly equal to G-rated movie budgets. One reason for this is accounted for by the fact that more stars appear in R-rated than in G-rated movies. High-budget R-rated movies are also more likely to feature expensive special effects. On the other hand, PG-rated movies have the smallest standard deviation of budget and, by far, the lowest ratio of standard deviation to average budget, followed by G-, PG13-, and R-rated movies. This suggests that G-rated movie budgets are easier to control than high-budget star movies.

A picture of the stochastic dominance rankings of movie ratings by budget can be gotten from figure 6. Note that we are now ranking in terms of "unfavorable" events, so it is desirable to have a low probability that a given budget level will be exceeded. Consequently, the inequality in equation (1) is reversed. In figure 6, the so-called survival probability is shown; this is the probability that a movie will exceed each budget level. The survival probability is plotted in the figure for each rating class. Except for the very low-budget R-rated movies, G-rated movies are the least expensive to make. This is illustrated in the figure by the fact that the probability that a G-rated movie budget will exceed the amount on the horizontal axis lies below the probabilities that the budgets of other movies will exceed these amounts. The exception to this rule is the very low-budget R-rated movies.

The PG13-rated movies are more expensive and have more variable budgets than other movies, with the exception of high-budget R-rated movies. The survival probability of PG13-rated movies is above the others until the R-rated movies cross over the other curves at a budget just below $60 million. With the exception of one PG13-rated movie, R-rated movies become the most expensive movies to make in the above $50 million budget category. The low average budget for R-rated movies primarily results from the large number of low-budget movies with this rating. As R-rated movies move into the upper budget tier they become more expensive than other movies, and their budgets become more variable. This seems to reflect a fact we have already mentioned: high-budget, R-rated films feature a disproportionate number of stars and special effects. In the upper budget categories R-rated movies are first-order stochastically dominated by G-, PG-, and PG13-rated movies.

C. *Rates of Return*

We now examine rates of return because it is the rate of return that drives investment. We take as a measure of the rate of return the ratio of box-office revenue to production budget in each class. This measure is shown in the bottom panel of table 3. G- and R-rated movies have nearly equal average rates of return. G-rated movies on average earned box-office revenues 2.15 times their production cost; R-rated movies earned 2.14 times their production cost. The PG- and PG13-rated movies have average ratios of revenues to costs of 1.66 and 1.39.

Note how the quantile values compare among movies. At the twenty-fifth, fiftieth, and seventy-fifth percentiles, the return is greater in G-, PG-, and PG13- than in R-rated movies. This means that for every level of return but the very highest returns, the returns to all other ratings categories dominate the returns to R-rated movies. A few extreme returns in the R-rated category pull the average return in this category to near equality with the return in G-rated movies and above the average return in the other categories. The large differences in the standard deviations reflect this dominance in the R category of a few extremely high returns. R-rated movies have a standard deviation of returns that is about five times that of G-rated movies and about eight times that of PG-rated and PG13-rated movies.

R-rated movies are stochastically dominated by non-R-rated movies in the gross rate of return up to the seventy-fifth percentile of the high-grossing movies. Well beyond this point, the R-rated probability distribution crosses the PG-rated and PG13-rated distributions but is almost everywhere dominated by the G-rated distribution. This situation is depicted graphically in figure 7, in which we plot the empirical cumulative distribution functions of the gross rate of return of each rating category. Only a tiny fraction of R-rated movies

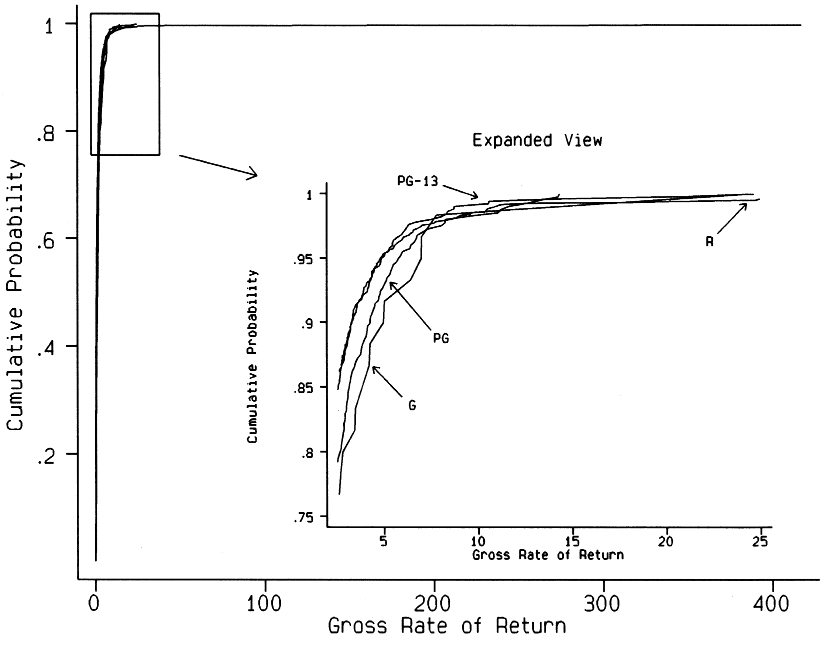

FIG. 7.—Empirical distribution of return by rating

make rates of return higher than non-R-rated movies, but this handful of movies earn such high rates of return that they pull the mean R-movie return above PG-rated and PG13-rated movies but not above the G-rated movies.

R-rated movies account for virtually all of the gross rates of return in excess of 25. But these high returns are concentrated in low-budget movies, and the total profit associated with these movies is small. The distribution functions for G- and PG-rated films lie substantially below the distribution functions for PG13- and R-rated movies, up to a gross rate of return of about seven. There is, therefore, a higher probability that G-rated and PG-rated movies will earn a gross rate of return greater than seven compared with R-rated and PG13-rated movies.

We estimated the probability distributions of returns in each ratings class.[17] In each case, the return distribution is a Pareto distribution. The estimated parameter values are given in table 9 for all movies. The extreme values of return are overwhelmingly earned by low-budget movies.

These low-budget movies, however, earn small aggregate profits and make a negligible contribution to Hollywood's bottom line. To look at returns for

17. We also estimated the Pareto exponent for returns on animated G-rated movies and obtained a point estimate of 1.294, which is smaller than the estimate of 1.357 for all G-rated movies. These estimates suggest that the upper tail of the distribution for animated G-rated movies contains slightly more probability than the upper tail of the distribution for live-action G-rated movies.

TABLE 9 Estimated Pareto Exponents for Returns by Rating

Rating	Pareto Exponent	K–S Test *p*-Value
G	1.357	.495
PG	1.559	.165
PG13	1.787	.620
R	1.480	.838

NOTE.—K–S test = Kolmogorov-Smirnov test. The Pareto exponent was estimated by maximum likelihood conditional on a minimum value of two. The K-S test *p*-values reported are for the null hypothesis that the data are consistent with the theoretical Pareto distribution.

films that do contribute large absolute profits, we estimated the α parameters in the rating classes for movies that grossed more than $40 million. These are reported in table 10. Since all the estimates are in $1 \leq \alpha \leq 2$, the mean is finite and the variance is infinite for all ratings.

Applying first-order stochastic dominance to these values is equivalent to ranking the distributions according to their α values, where a distribution with a lower α dominates one with a higher value. Using the values from table 10 we obtain the returns ranking $G(z) \geq PG(z) \geq PG13(z) \geq R(z)$. The fitted Pareto distributions are plotted in figure 8 for each rating category of movie. This figure makes clear that G-, PG-, and PG13-rated movies stochastically dominate the R-rated movies over the range of outcomes that makes the most important contribution to profits in the industry.

D. Profits and Losses

We measure profits as one-half of theatrical revenues minus production cost. This is an approximation to "real" profits, which are known only to the producer. One-half of theatrical revenues approximates rentals that are paid to the distributor. Certain costs are excluded, such as print, advertising, and distribution costs. North American theatrical revenues do not include world revenues.[18] Domestic revenues averaged about 40% of total world revenue from all sources during the time period of our sample.[19] Nor do our revenue figures include video, television, or ancillary revenues. So, the "profits" we are able to measure with accuracy do not conform to the total profit of a movie. Nonetheless, the profit measure is a good approximation to the North American profitability of a movie. The importance is threefold: (1) the North American theatrical market is the "launching point" for the markets that follow; (2) it is of interest to know the relative profitability of the North American theatrical market to the other markets; and (3) the data are more reliable and

18. World revenues are reported in a less complete fashion but are known also to follow the Pareto distribution (Walls 1997; Sornette and Zajdenweber 1999; Ghosh 2000) and to be correlated with North American revenues.

19. A personal communication from Louis Wilde with De Vany (1997) indicates that the foreign and other market "windows" are as chaotic (meaning that they probably follow an α-stable process) as our results indicate the domestic market to be.

TABLE 10 Estimated Pareto Exponents for Returns by Rating for High-Grossing Films

Rating	Pareto Exponent	K–S Test *p*-Value
G	1.241	.128
PG	1.331	.194
PG13	1.322	.306
R	1.406	.214

NOTE.—K–S test = Kolmogorov-Smirnov test. The Pareto exponent was estimated by maximum likelihood conditional on a minimum value of two for return and $40 million for box-office gross. The K-S test *p*-values reported are for the null hypothesis that the data are consistent with the theoretical Pareto distribution.

more movies are reported, which permits us to identify more accurately the correct statistical model (which can then be tested on the other "windows" as in Walls [1997]; Sornette and Zajdenweber [1999]; Ghosh [2000]).

In tables 11 and 12, we estimate the Pareto exponent α for the upper and lower tails of the profit distribution.[20] In the positive tail of the profits distribution, low α is good because it means there is more probability mass (tail weight) on extreme profits. Consequently, one can stochastically rank the profit tails from low to high α. PG13-rated movies have the lowest positive tail α, followed by G-, PG-, and then R-rated movies.[21] It is important to note that positive profits have a finite mean and an infinite variance because $1 \leq \alpha \leq 2$. The infinite variance of profits implies there is no natural upper bound on how much profit a movie might earn.[22] In the positive profits tail, R-rated movies are stochastically dominated by other movies.

In the negative tail of profits (the positive tail of losses), large α is good because then there is less probability mass on the extreme losses. So, in this tail, stochastic dominance is ordered from high to low values of α. We see in table 12 that the Pareto exponent for losses is largest for G-rated movies, followed by PG-rated, R-rated, and PG13-rated movies. Thus, in the loss tail, R-rated movies are dominated by G-rated and PG-rated movies and dominate only PG13-rated movies. One PG13-rated movie, *Waterworld*, is responsible for the dominance of the R over the PG13 category. Note that all of the α values in the loss tail are greater than two, implying that both the mean and variance of losses are finite. Losses are bounded below, but positive profits

20. Estimation of the upper tail is straightforward. For the lower tail, we estimated the exponent for losses, i.e., the upper tail of the distribution of losses (negative profits).

21. We also estimated the Pareto exponent for profits on animated G-rated movies and obtained a point estimate of 1.192, which is smaller than the estimate of 1.354 for all G-rated movies. These estimates suggest that the upper tail of the distribution for animated G-rated movies contains more probability than the upper tail of the distribution for live-action G-rated movies. It also indicates that animated G-rated movies stochastically dominate all categories except PG13.

22. The model, therefore, predicts that extremely profitable movies are not unlikely, as they would be were the profit distribution normal. Even though the model is estimated before *Titanic*, it indicates that movies like it and even movies exceeding it occur with nonnegligible probability. De Vany and Walls (2000*a*) study the distribution of profits in more detail using the general stable distribution.

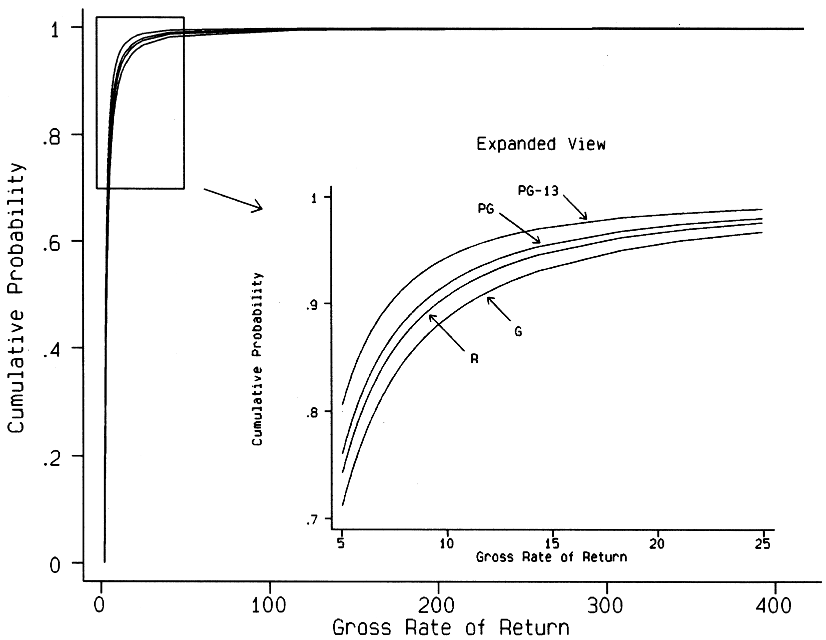

FIG. 8.—Fitted Pareto distribution of return by rating

are not. The lower bound on losses is determined by budget spending since you cannot lose more than you spend. There is no upper bound on profits since there is no natural limit to what a movie can earn in box-office revenues (De Vany and Walls 1996).

R-rated movies have the lowest tail mass (high α) on positive profits and the second-largest tail mass (low α) on losses. Because losses are finite, this indicates that R-rated movies are stochastically dominated in profits by movies in all the other ratings categories.

For those R-rated movies with high budgets (there are 295 in the sample), the estimated Pareto exponent for profits is 1.479 and for losses is 1.914. The α values for high-budget R-rated movies imply the distributions are asymmetric in the tails. Profits have infinite variance and losses are near the borderline of finite-infinite variance. Aggregating high-budget R-rated movies with and without stars, however, hides an important difference in the distribution of profits. The positive tail α for high-budget R-rated star movies is 1.589, while the negative tail α value is 1.666; the tails are nearly symmetric. The positive tail α for high-budget R-rated movies without a star is 1.398, while the negative tail α value is 2.232; the tails are not symmetric. An R-rated high-budget movie without a star has less probability mass in the loss tail (with a finite variance there) and more mass in the profit tail (with infinite variance there) than an R-rated high-budget movie with a star. The conclusion

TABLE 11 **Estimated Pareto Exponents for Profits**

Rating	Pareto Exponent	K–S Test *p*-Value
G	1.354	.728
PG	1.431	.391
PG13	1.118	.087
R	1.606	.301

NOTE.—K–S test = Kolmogorov-Smirnov test. The Pareto exponent was estimated by maximum likelihood conditional on a minimum value of $10 million for profits. The K-S test *p*-values reported are for the null hypothesis that the data are consistent with the theoretical Pareto distribution.

is that putting a star in a high-budget R-rated project gives a thinner tail for positive profits (with a finite variance) and gives a thicker tail (with infinite variance) on losses.[23]

VI. Conclusion

A. *Are There Too Many R-Rated Movies?*

The evidence shows convincingly that Hollywood makes too many R-rated movies. Why would Hollywood make too many R-rated movies? Medved argued that there is a strong need for approval among Hollywood producers, executives, and stars. In the struggle between art and commerce, he argues, commerce has taken a back seat as artists, producers, and even executives attempt to earn insider praise and esteem by making movies that are “audacious, artistic, and unusual”; these figures show “a disposition to dislike any piece of work that too obviously panders to the public” (Medved 1992, p. 306).

Our results come tantalizingly close to confirming Medved’s hypothesis that R-rated movies bring the most prestige in Hollywood. If a star champions a “prestige” R-rated movie, his or her “bankability” may get it approved and produced. Putting a star in a movie does increase the size of its opening, which puts a floor on its box-office revenues (De Vany and Walls 2000*b*). But a high-budget, R-rated, star movie raises the studio’s odds of suffering large losses and lowers its chances of making large profits. A studio that accepts this inferior prospect is trading profit for prestige and a “big” opening or does not understand the unfavorable odds.

B. *Getting the Statistical Model Right*

The distributions of motion picture revenues, budgets, returns, and profits follow the stable Paretian model. Estimates of the revenue, returns, and profit distributions show that they are highly skewed and may have infinite variance.

23. For high-budget, R-rated movies this is another confirmation of Ravid’s (1999) conclusion that stars do not increase the profitability of films; in fact, stars do worse than that—they decrease the probability of positive profits and increase the probability of losses.

TABLE 12 Estimated Pareto Exponents for Losses

Rating	Pareto Exponent	K–S Test *p*-Value
G	2.598	.516
PG	2.288	.289
PG13	2.105	.158
R	2.167	.123

NOTE.—K–S Test = Kolmogorov-Smirnov test. The Pareto exponent was estimated by maximum likelihood conditional on a minimum value of $10 million for losses. The K-S test *p*-values reported are for the null hypothesis that the data are consistent with the theoretical Pareto distribution.

A few "blockbuster" outliers in the upper tail influence the mean, and the distributions are not symmetrical. There is no representative or "exemplar" movie, nor is there a natural revenue or profit. The most probable outcome is located at the peak of the distribution near the lowest values and is well below the mean. Outcomes diverge over the space of possibilities rather than converging on an average, and the probabilities of extreme outcomes are not negligible. It is, therefore, an illusion to believe that accurate predictions of revenues or profits can be made. This conclusion echoes William Goldman's famous statement that "nobody knows anything" (Goldman 1983).

C. *There Are Some Answers*

Nobody loves a prophet whose message is "There is no answer." Moreover, few in Hollywood will love the message of this article. But there are some answers that follow from this research if one asks the right questions. The important questions have to do with probabilities and with getting the statistical model right before making decisions. One must give up the quest for accurate forecasts and learn to live with the probabilities. With the underpinning of a correct statistical model, tools like stochastic dominance, value-at-risk, and extreme event analysis can be used to improve decisions.

Once the hard work of pinning down the distributions is done, we can give fairly straightforward answers to important questions. For example, we have shown that the asymmetry of the profit distributions among ratings implies that a studio seeking to trim "down-side" risk and increase "upside" possibilities can do so by shifting production dollars out of R-rated movies into G-, PG-, and PG13-rated movies. It can also be shown that the studio's value-at-risk increases with the number of R-rated movies that it makes. One could also use the stable Paretian models estimated here to estimate the probabilities of extreme events like a bankruptcy. A strong advantage of the stable Paretian model is that it can be used to make out-of-sample predictions. Thus, one could estimate the odds that some yet-to-be-made movie will gross more than *Titanic* or four times what it grossed. The probabilities of events larger than the highest values in the sample do not vanish in the stable Paretian model the way that they do in the normal or log-normal model, so one can use the model to estimate the probabilities of events that are larger than any that have occurred.

The stable Paretian model teaches that a belief that one can make accurate predictions of revenues or profits, even if a star is in a movie, is an illusion. In the decision to produce, release, book, or appear in a movie, no one can afford to ignore those elements that cannot be quantified—like story and character—because those that can be quantified predict so little and so often mislead.

References

Anderson, J. V., and Sornette, D. 1999. Have your cake and eat it too: Increasing returns while lowering large risks. Working paper. Los Angeles: University of California, Los Angeles, Institute for Geophysics and Planetary Physics.

De Vany, A. S., and Lee, C. 2000. Motion pictures and the stable Paretian hypothesis. IMBS working paper. Irvine: University of California, Irvine.

De Vany, A. S., and Walls, W. D. 1996. Bose-Einstein dynamics and adaptive contracting in the motion picture industry. *Economic Journal* 439 (November): 1493–1514.

De Vany, A. S., and Walls, W. D. 1999. Uncertainty in the movie industry: Does star power reduce the terror of the box office? *Journal of Cultural Economics* 23 (November): 285–318.

De Vany, A. S., and Walls, W. D. 2000*a*. Motion picture profits: How can they be so elusive and yet so large? IMBS working paper. Irvine: University of California, Irvine.

De Vany, A. S., and Walls, W. D. 2000*b*. Private information, demand cascades and the blockbuster strategy. IMBS working paper. Irvine: University of California, Irvine.

Fama, E. 1963. Mandelbrot and the stable Paretian hypothesis. *Journal of Business* 36 (October): 420–29.

Fama, E. 1965. The behavior of stock market prices. *Journal of Business* 38 (January): 34–105.

Ghosh, A. 2000. The size distribution of international box office revenues and the stable Paretian hypothesis. Working paper. Irvine: University of California, Irvine, Economics Department.

Goldman, W. 1983. *Adventures in the Film Trade*. New York: Warner.

Huang, C. F., and Litzenberger, R. H. 1988. *Foundations for Financial Economics*. New York: North Holland.

Mandelbrot, B. 1963*a*. New methods in statistical economics. *Journal of Political Economy* 71 (October): 421–40.

Mandelbrot, B. 1963*b*. The variation of certain speculative prices. *Journal of Business* 36 (October): 394–419.

Mandelbrot, B. 1967. The variation of some other speculative prices. *Journal of Business* 40 (October): 393–413.

McCulloch, J. H. 1996. Financial applications of stable distributions. In G. S. Maddala and C. R. Rao (eds.), *Statistical Methods in Finance*. New York: North Holland.

Medved, M. 1992. *Hollywood vs. America: Popular Culture and the War on Traditional Values*. New York: HarperCollins.

Ravid, S. A. 1999. Information, blockbusters, and stars: A study of the film industry. *Journal of Business* 72 (October): 463–86.

Scherer, F. M.; Harhoff, D.; and Kukies, J. 2000. Uncertainty and the size distribution of rewards from innovation. *Evolutionary Economics* 10 (January): 175–200.

Simonoff, J. S., and Sparrow, I. R. 2000. Predicting movie grosses: Winners and losers, blockbusters and sleepers. *Chance* 13 (Summer): 15–24.

Sornette, D., and Zajdenweber, D. 1999. The economic return of research: The Pareto law and its implications. *European Physical Journal B* 8:653–64.

Stuart, A.; Ord, J. K.; and Arnold, S. 1999. *Kendall's Advanced Theory of Statistics*. Vol. 2A. 6th ed. London: Arnold.

Walls, W. D. 1997. Increasing returns to information: Evidence from the Hong Kong movie market. *Applied Economics Letters* 4 (May): 187–90.