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Managerial Objectives, the R-Rating Puzzle, and the Production of Violent Films*

We analyze project choice in the motion picture industry and find evidence consistent with revenue maximization and excessive hedging. We find that movies that are very violent or feature sex and violence do not provide excess returns, but they increase revenues, particularly in the international market. Further, they tend to lose money less often and their returns are more predictable, even though there are never mega-hits. This evidence is consistent with studies of other industries, and it partially explains the "R-rating puzzle," that is, the preponderance of R-rated films although most studies find that G- and PG-rated films perform better.

I. Introduction and Theoretical Background

The purpose of this article is threefold. First, we provide project-based evidence consistent with risk averse and revenue maximizing behavior on the part of executives in charge of large projects. Second, we partially explain the "R-rated puzzle" that has come up in several recent empirical papers on the motion picture industry. Third, we shed some light on the economic motivation behind violent entertainment. The latter topic has been in the forefront of government and media policy discussions for a while.

Violence, sex, and gore are abundant in films. The high popularity of some of these movies, such as *Lethal Weapon, Scream,* and *I Know What You Did Last Summer,* has turned them into franchises. Since movies are a big business, it seems that violence (in films)

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must pay. However, recent studies seem to show the opposite. Ravid (1999) shows that having an R rating does not have a significant impact on the rate of return on film projects or even on various movie-related revenue streams. In fact, the only characteristics that seem to produce excess returns are a G or a PG rating and, to some extent, a sequel status. This superior performance of family films is supported also by evidence in De Vany and Walls (2002). De Vany and Walls (2002) study U.S. theatrical revenues of a large number of films. They find, using a variety of statistical measures, that the production of R-rated films is not a good idea. For example, R-rated films are less often "revenue hits" than any other category. Returns on R-rated films are stochastically dominated by non-R-rated films up to the seventy-fifth percentile and by G-rated movies almost everywhere. Thus they conclude that "Hollywood produces too many R-rated films" (Devany and Walls 2002, p. 449). Simonoff and Sparrow (2000) analyze the statistical properties of the domestic revenue stream of a smaller number of films released in the period 1997–98. They come to similar conclusions, that is, that G-rated films and, in particular, animated films, significantly contribute to revenues. R-rated films do not increase revenues. Fee (2002) describes the choice between independent fiancing and studio financing. He also uses only domestic revenues, and his sample period is not very different from Ravid's (1999). The focus is different, but Fee (2002) does run a regression where the dependent variable is the domestic rate of return (his table 6). Fee's most significant independent variable in that regression is a G rating. Ravid and Sunder (2003), in a study that focuses on directors' careers and that spans a very different sample, also find that G ratings enhance returns.

In spite of this evidence, the percentage of G-rated films (the "best" category by all studies) released every year has remained less than 5%. On the other hand, the percentage of R-rated films among the U.S. releases has been high and has been increasing further, from about 65% of the total in 1995 to about 69% of all films released in 2001 (http://www.mpaa.org). Many of these R-rated films are violent fare. This creates a puzzle—why do profit-maximizing studios turn out violent and steamy fare rather than G- or PG-rated films?[1] The analysis in this article suggests that looking at R-rated films in the aggregate may not be the best way of approaching and explaining the actual decision-making process of executives in charge of film projects. Rather, one should consider subsets of R-rated films that may have different characteristics. R-rated films range from adventures, to steamy love stories, to sci-fi, and to very violent action films. In order to take this into account, some papers categorize films by genre. However, genres present difficult problems—the characterizations tend to be subjective, and quite a few films defy easy classification (see Ravid [1999] for a further discussion of this). For example, a

1. It seems that Hollywood is slowly getting the message. By late 2001 and early 2002, the number of very visible family projects had increased. Bing and Dunkley (2002) dedicate a lead article in *Variety* to that trend, concluding that "Hollywood has found its inner child" (p. 1).

movie like *Titanic* can be a love story, an action adventure, or perhaps a historical film. If we consider the issue from the perspective of a decision maker who seeks to condition his choice on an ex ante characteristic, genres may present difficult measurement problems.

In this article, we focus on easier to observe, clear-cut themes, such as sex and violence, which are much more likely to be used as ex ante conditioning mechanisms. We find that the production of films with themes of violence and sex does not necessarily "make sense" from a value maximization point of view. However, consistent with a large literature in finance and economics, we can show that it may be consistent with managers' excessive hedging behavior and with revenue maximization.

Agency theory, going back to Jensen and Meckling (1976), Holmstrom (1979), and many other related papers, suggests that, if the objective function of the agent is different from that of the principal, one may observe behavior that deviates from value maximization (unless it is not too costly to eliminate all such deviations with the proper use of incentives). In particular, many papers, going back to Baumol (1958), have described revenue maximization as a possible goal for firm managers. For example, Fershtman and Judd (1987) model a case where owners who are interested in profit maximization may find it optimal to include sales maximization in the agent's objective function in an oligopoly setting. The general idea is that, if one of the two firms modeled maximizes sales, then the other is better off increasing output rather than keeping output low.[2] Zabojnik (1998) develops this idea further.

Other studies have sought to justify and document what is seemingly another deviation from profit or value maximization, namely, corporate hedging and risk shifting behavior. In general, investors should not want firms to hedge risks, which shareholders can usually hedge better on their own by portfolio choices and in various derivative markets; in particular, managers should not hedge their own production,[3] which has the added disadvantage of negating all effort incentives. However, sometimes market frictions can make hedging an optimal policy for an individual business entity. A well-known paper by Froot, Scharfstein, and Stein (1993) justifies hedging as a way of avoiding costly external financing. Thus, hedging enables the firm to take advantage of profitable investment opportunities. Smith and Stulz (1985) identify and

2. Kedia (2002) finds empirical support for the idea that top management compensation is related to sales maximization in an oligopoly setting.

3. This can be easily understood by the following extreme example. Suppose that two firms produce the same product and that their revenue can be either \$50 or \$150, with equal probabilities. Suppose further that the revenue streams are perfectly negatively correlated. The firm can pay an insurance company to guarantee \$100 in all states by paying the \$50 in the good state to cover the \$50 shortfall in the bad state. Suppose that the insurance company charges \$3. Then investors are guaranteed \$97. However, it should be obvious that, just by buying the two stocks, investors can guarantee \$100 × 2 in all states on their own, without paying the \$3. Or, of course, they can just buy treasuries. Thus, as long as investors can create portfolios relatively cheaply, firms should not hedge. The other important issue is incentives. Clearly, if the outcome is guaranteed regardless of managerial effort, managers will not put in any effort. Whatever for? This does not apply to hedging input exposure, which is exogenous to the firm.

model three such frictions, namely, taxes, bankruptcy costs, and managerial risk aversion. The latter motivation can arise also when managers have too much of their wealth invested in their own companies. Amihud and Lev (1981) suggest that managers diversify their own risky position via conglomerate mergers. DeMarzo and Duffie (1995) focus on another possible set-up that can lead managers to take too little risk, namely, the presence of asymmetric information coupled with career concerns. If a manager knows that he will be judged on performance alone and his efforts will remain unobservable, he may be tempted to overhedge. In fact, consistent with our empirical work, DeMarzo and Duffie (1995) show that, when managers cannot hedge effectively, they may choose inferior projects that are less risky (propositions 10, 11).[4] This points out an important issue for our purposes. Managers can lower the risk stemming from production uncertainty in two ways. One is by using hedging instruments (such as derivatives), and the other is by the suboptimal choice of projects. Whereas the former may be observable (see empirical work below), the latter is much more difficult to monitor (who can tell which projects the manager might have taken?). The advantage of our data set is that it contains project data, and further, one may reasonably argue that, in the motion picture industry, there is a very large supply of projects of all types and so the observed outcome is because of choices rather than availability—for each film produced, there are thousands of screenplays, pitches, and ideas that are rejected.

Empirical studies, in particular a study by Tufano (1996) of the gold-mining industry, seem to show that corporate officers do engage in hedging their own product. Tufano (1996) finds that almost all firms in the gold mining industry employ some form of hedging in gold-derivative markets. He detects no correlation between hedging and measures of bankruptcy costs. However, he does find a significant relationship between hedging measures and proxies for risk exposure of executives. Tufano (1996) also tests several other theories. He cannot find support for the theory in Froot et al. (1993). However, Haushalter (2000), who studies the hedging behavior of oil and gas producers, does find a correlation between leverage-related variables and the fraction of production hedged, which he interprets as supporting the financial contracting cost hypothesis. There is little support in his study for tax proxies and mixed support for managerial risk aversion proxies, mainly, the structure of compensation. A study of the mutual funds industry by Chevalier and Ellison (1997) also discovers seemingly suboptimal risk management in response to incentives that has little to do with timing and age of the fund (see also Jin [2002], where performance is tied, theoretically and empirically, to different types of risks faced by managers).[5]

4. John and John (1993) describe seemingly reasonable managerial objective functions that can lead to suboptimal behavior on the part of managers (along the lines described here) if the firm carries some leverage.

5. Lim and Wang (2003) suggest that there may be a trade-off between corporate diversification and hedging as risk management mechanisms.

All of these studies and several others use firm-level data, and their analysis is at the CEO or CFO level. They generally document hedging behavior and not project choice. The motion picture industry provides a unique opportunity to study project choice, which, as we argued above, may be an easier way to lower risk and increase sales. Further, it seems that the particular characteristics of this industry are likely to encourage seemingly suboptimal behavior on the part of managers, along the lines described in the literature. In particular, film studios have a collection of projects, which are difficult to hedge individually and as a group. The motion picture industry is characterized by extreme uncertainty (see De Vany and Walls 1999).[6] There is no job security and, in practice, executive turnover has been accelerating (see Weinstein 1998). In view of this, and of the previous discussion, it seems almost impossible, or perhaps equivalently, excessively costly, to provide risk-averse executives with the incentives to avoid suboptimal choice of projects as risk management, à la DeMarzo and Duffie (1995). It is important to note that, since the number of screenplays available exceeds the number of films actually produced by a factor of several hundreds, it would also be correct to assume that you can choose any type of project that you want at any point in time. This is much less so for projects that involve anything but intellectual property.

We can expect to find evidence for sales maximization in the motion picture industry for two reasons. First, the large studios indeed form an oligopoly and, as such, share the market in a way that may be close to a Fershtman and Judd (1987)–type environment. Industry concerns with market shares and huge advertisements touting significant revenue milestones (see any issue of *Variety*) seem to support this view. Further, the revenue information of films is publicly available, as most newspapers, magazines, and television news routinely report weekly movie grosses. However, profit calculations are not publicly transparent, and Hollywood accounting is notorious. Thus, an executive who is fired will find it much easier to substantiate a record of high-revenue projects rather than one of high-profit projects. Second, since executives decide on a project but do not necessarily buy the inputs (other people typically negotiate cast salaries and buy other inputs), one can always claim that the project was "good" but that it just was not budgeted right. All of these elements seem to point to suboptimal (from the shareholders' point of view) risk reduction and revenue maximization as possible decision criteria. In the rest of this article, we will consider violent entertainment from the perspective of managerial objective functions. The findings may also help to explain the R-rating puzzle and to provide an economic backdrop to the violent entertainment debate.

The remainder of the article is organized as follows. In Section II, we

6. An illustrative example is the film *Titanic*, the highest grossing (in nominal terms) film of all times. Several months before the end of the project, with its budget exploding, Fox felt that the risk was too high. It sold Paramount a significant stake in the film in return for $65 million toward the budget. In retrospect, it was one of the best investments in the history of motion pictures for Paramount and the worst opportunity loss for Fox.

provide a summary of the policy debate regarding violent movies. We also discuss briefly what we know about violence in the media so as to explain where our study fits in empirically. In Section III, we describe the data and the methodology. In Section IV, we discuss the results in detail, and in Section V, we conclude.

II. Policy Issues and Research

Violence is ubiquitous in today's movies. Shootings, beatings, and massacres are portrayed in graphic detail on the screen. Film directors like Quentin Tarantino (*Reservoir Dogs* [1992] and *Pulp Fiction* [1995]) and Oliver Stone (*Natural Born Killers* [1995] and *U-Turn* [1998]), although highly controversial, have come to enjoy popular acclaim through their carefully crafted images of gore and violence on the screen. Several violent films have developed into franchises, such as the *Amityville Horror* series, *Lethal Weapon*, and *Scream*.

Recently, and in particular after the Columbine high school massacre in 1999, there have been legislative initiatives to curb violence on the screen. The most sweeping attempt was a proposal by Representative Henry Hyde to make it a crime punishable by up to 5 years in prison to sell, distribute, or lend violent movies, TV programs, video cassettes, books, or internet material to children. In spite of spirited speeches on the floor of the house, the proposal was soundly defeated by a margin of 282 to 146 in June 1999 (Rosenbaum 1999).

It is not clear whether it is the generous campaign contributions of the entertainment industry, the firm belief in the first amendment, or the lack of belief in the efficacy of censorship that caused such a defeat. However, the topic has not left the front burner—it has resurfaced in many industry forums. In a press conference in March 2000, President Clinton expressed renewed concern over violence in the media and proposed a unified rating system (Boliek 2000). In September 2000, at the height of the presidential elections campaign, the Federal Trade Commission (FTC) released a report claiming that violent entertainment is marketed to young audiences. It concluded: "Of the 44 movies rated R for violence . . . 80% were targeted for children under 17" (Federal Trade Commission 2000). This was followed by hearings in Congress, wide press coverage, and pledges from industry to stop marketing violent movies to underage viewers (see Lyman 2000; and McClintock 2000). In the wake of the terrorist attacks on the World Trade Center in September 2001, some of the planned violent fare was postponed, in particular, movies whose topic was terrorism. However, other violent films (e.g., *Thirteen Ghosts* or *Training Day*) were released, and in early 2002, one of the delayed films, *Collateral Damage*, was also released. It seems that not much can derail violent entertainment.

Whereas the motion picture industry has agreed to limit the marketing of violent entertainment to minors, it has always defended making such movies in the first place. Executives and other industry professionals have proposed several counterarguments to requests to tame down the violent content of films. We summarize some of these in appendix C.

The bulk of the research on violent entertainment, including television and movies, has focused on sociological and psychological issues. Researchers ask why people choose to watch violent movies and why and how people respond to violence in particular ways (see, e.g., Hill 1997; Goldstein 1998; Potter 1999). Very few studies have explored the economic implications of violent entertainment. One of the most comprehensive studies on violence in television programming is Hamilton (1998). Hamilton argues that violent television programs may be attractive to some target audiences but that, in the process, they expose innocent viewers, and in particular children, to this violence. Thus, according to Hamilton, television networks with violent programs may increase their viewership and profits but they impose a negative externality on society. Earlier, Clark and Blankenburg (1972) analyze prime-time programs on three commercial networks from 1956 to 1969. They find no correlation between ratings and violence. However, they do find a strong correlation ($r = .49$) between ratings of violent programs in one year and the number of highly violent programs in the following year. Gerbner (1994) compares average Nielsen ratings for violent and nonviolent shows from 1988 to 1993 and finds that nonviolent shows in general have a higher mean rating (11.1–13.8).

Mainstream economic literature has often discussed the economics of crime and violence, but it has left aside the issue of violent entertainment. The common context in the economic literature is that of optimal criminal behavior and law enforcement. This strand of literature goes back to Becker (1968) and Stigler (1970) and includes many recent contributions, such as Donohue and Levitt (1998), Glaeser and Glendon (1998), and Anderson (1999). However, to our knowledge, there has been no economic study of violence in the motion picture industry. As noted. in an earlier study, Ravid (1999) shows that G and PG ratings are virtually the only significant determinants of return on investment in films. De Vany and Walls (2002, p. 449), also show, using a different framework and a different data base, that “Hollywood produces too many R-rated films,” and they conclude that shifting resources to PG and PG-13 films will trim the loss tail of the revenue distribution and expand the profit tale. This is supported in Simonoff and Sparrow (2000) and Fee (2002).

In this study, we try to understand whether the production of violent entertainment in spite of political opposition is driven by economic motives, and if so, by which motives. We first test whether violent films provide a higher rate of return than other types of films. We then investigate whether or not violent entertainment is less risky and whether it increases revenues, in accordance with possible managerial objective functions, as outlined above. In the process, we establish where demand for violent films originates, which should frame the legal debate—very different laws apply to video sales, to theatrical presentations, and, naturally, to sales outside of the United States.

III. Data and Variables

Many of the data in this article are based on sources identified in Ravid (1999). Ravid (1999) selected a random sample of over 200 films released between late 1991 and early 1993. This sample was pared down to 180 final observations because of various missing data. However, we confine our tests to 175 films, eliminating five very low budget films.

Baseline Services in California provided the budget (negative cost) of each film as well as the domestic, international, and video revenues. Very few papers have ventured beyond U.S. theatrical revenues (for an exception, see Ravid 1999). Considering all sources of income is important for the current analysis because it provides a more comprehensive profit picture and also because we want to test the impact of violence on each source of revenue separately. Our data thus contain domestic box office receipts as well as a proxy for international revenues, namely, the share of domestic distributors in box office receipts overseas. We also have video revenues. The sum of all these revenues is our total revenue variable. All revenue numbers are current as of the end of 1993. Our proxy for return on investment is total revenue divided by budgets. This measure does not directly reflect profitability to the studio, but, under reasonable assumptions, it serves as a good proxy (see Ravid [1999] for an extensive discussion of the issues regarding this choice). In addition, we collected opening-weekend revenue. These data were collected separately from various issues of *Variety* magazine. Advertising expenses (AD) were separately collected from various issues of *Leading National Advertisers* (1991–93).

Ravid (1999) finds that ratings are very important determinants of revenues and return on investment. All ratings are used as dummy variables. For instance, a dummy variable G receives a value of one if the film is rated G and zero otherwise. The default is unrated films. Since the empirical goal of this article is to isolate and examine the specific impact of violent or very violent films on revenues and return on investment, we first need to define violent films. We consider only R-rated films—under the assumption that, if a film does not qualify for an R rating, it is probably not too violent. We then read the description provided by the Motion Pictures Association of America (MPAA) in determining the rating. We divide the R-rated films into several categories. The first group contains all films that were described by MPAA as containing violence. We exclude a few films that were rated R for other reasons but that contained “brief” violent scenes. This group (VIOLENT) is further subdivided into “very violent” films (VV)—namely, films for which the MPAA description contains a qualifying adjective, such as “graphic” or “extreme” violence. A second group (V) complements the first group and includes films that are rated R for violent content but that are not “very violent.” The nonviolent R-rated films are included in a third group (RNOTV). In our tests, we sometimes group all violent films together, and, at other times, we separate the “merely” violent films from the very violent films. We then split the R-rated films into films that had significant sexual content (SEX) versus all other R's (RNOSEX). These are cases where the MPAA description contains words such as "explicit sexual content" or "sensuality." A small subset was named STSEX. It contains films with "strong" or "graphic" sexual content. We also define an interactive variable for films that feature both sex and violence (SEXV).

We feel that this classification method, while imperfect, has the advantage of being the most objective possible. The MPAA ratings are comparative descriptions handed out by a board that watches hundreds of films. The MPAA is thus in the best position to provide a reasonably consistent classification. Other possible definitions are probably more subjective.

We use several additional control variables. Star power can, in principle, significantly affect box office revenues.[7] To this end, for each film, Baseline Services provided a list of the director and up to eight main cast members. We then consulted several sources in order to characterize the cast members as "stars, "'just' actors," or "unknowns." For the first definition of a "star," we 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 leading member of the cast had participated in a top-10-grossing movie in the previous year. These two variables define two alternative sets of "star-studded" films. The measures that we have suggested so far are reasonably common in studies of the movie industry. However, we try other specifications as well. We collected Best Actor/Actress award nominations as well as director nominations for each film in the sample. Two variables were defined—ANYAWARD and VALAWARD. The first one, ANYAWARD, receives a value of one if one of the film's actors/actresses 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 175. The second variable, VALAWARD, measures recognition value. For each of the 76 films in the AWARD category, we summed up the total number of awards and the total number of nominations. This method effectively creates a weight of 1 for each nomination and doubles the weight of an actual award to 2. (In other words, if, say, two actresses in the cast had been nominated for an academy award, VALAWARD is 2. If one of them won in one of these cases, the value goes up to 3.) Each of the 76 films was thus assigned a numerical value, ranging from 15 (for *Cape Fear*, directed by Martin Scorcese and starring Robert DeNiro, Nick Nolte, Jessica Lange, and Juliette Lewis) to 0 for the films that had no nominations. These new variables did not perform differently (in terms of sign and statistical significance) than the

7. In Ravid (1999), however, star power did not end up being a significant determinant of either revenues or return on investment. For a seminal investigation of the concept of stardom, see Rosen (1981) and and dynamic model by MacDonald (1988).

AWARD and NEXT variables, and hence we generally do not report those results.

We also consider another dummy variable, UNKNOWN. This variable receives a value of 1 for films in which all cast members did not appear in either of three major references on movies: Walker (1993), Katz (1994), or Maltin (1995). Presumably, if leading cast members are not listed anywhere, the film must be in the opposite end of the star kingdom. If the stars provide significant benefits, “unknown” films should bring in the least in revenues.

Another variable that may be of interest is whether or not a film is a sequel. While sequels tend to be more expensive and to bring in lower revenues than the original film, they may still outperform the average film if they can capitalize on a successful formula. Ravid (1999) supports this view. The SEQUEL variable receives a value of one if the movie is a sequel to a previous movie and zero otherwise. We identified 11 such films in our sample.

We use several additional variables. The publication *Variety* lists reviews for the first weekend in which a film opens in New York. Although reviews are provided for other cities, the “New York” reviews are usually the first to appear, contain the largest number of reviews, and include national listings as well (such as broadcast network reviews or national magazines). Thus we use the New York reviews in our analysis. The total number of reviews, TOTREVIEW, tends to be significant—it probably proxies for the attention a film has received. Variety classifies reviews as “pro,” “con,” and “mixed.” We use these classifications to come up with measures of the quality of critical reviews: POSREVIEW is the ratio of number of “pro” reviews divided by the number of total reviews, while MIXREVIEW is the ratio of nonnegative reviews (i.e., good plus mixed) divided by the number of total reviews.

Finally, we looked up each film’s release date. In some other studies (Litman 1983; Chisholm 2000), release dates were used as dummy variables on the theory that a Christmas release should attract greater audiences, while, 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, we use information from Vogel (2001, fig. 2.4) to produce a somewhat more sophisticated measure of seasonality. Vogel constructs a graph that depicts normalized weekly attendance over the year (based on 1969–84 data). This figure assigns a number between 0 and 1.00 for each date in the year (where Christmas attendance is 1.00 and early December is 0.35 for high and low points of the year, respectively). We match each release date with this graph and assign a variable that we call RELEASE to account for seasonal fluctuations.[8]

8. See a later discussion of robustness checks where we use a dummy specification, similar to the earlier studies, to account for release dates. This does not change the qualitative outcome. A more interesting issue is the question of competition. However, if we assume optimal adjustment of screens during the run, we can argue that competition (net of a release date variable) will have more of an effect on the pattern of weekly revenues, rather than on the aggregate. Further,

TABLE 1 **Descriptive Statistics of the Nondummy Variables**

Variable	Mean	Median	SD	Maximum	Minimum
BUDGET	15.68	12.00	13.90	70.00	1.00
DOMREV	22.09	7.30	32.80	162.80	.01
OPENWKREV	4.02	.76	6.23	45.69	.00
INTLREV	7.82	1.71	13.06	69.30	.00
VIDREV	10.70	5.27	20.28	233.70	.03
RATE	2.27	1.29	2.61	17.05	.08
TOTREV	40.60	17.50	60.33	426.30	.35
AD	4.12	3.51	3.93	15.04	.04
POSREVIEW	.43	.44	.25	1.00	.00
TOTREVIEW	20.90	19.00	9.94	43.00	3.00

Note.—BUDGET, AD, and the revenues (DOMREV, INTLREV, VIDREV, and TOTREV) are in millions of dollars.

IV. Results

Table 1 describes the data for 175 movies. The film with the highest budget in this sample is *Batman Returns* ($70 million). *Batman Returns* also turns out to be the movie that recorded the highest first-week box office revenue—$69.30 million. On average, positive reviews (POSREVIEW) account for almost half of the total (43%) number of reviews, whereas nonnegative (including mixed) reviews make up 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 a top-grossing movie the previous year (NEXT = 1). For 30 films, we 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 an academy award nomination or had won an actual award (ANYAWARD = 1). The sample has six films that were rate G, 25 rated PG, 44 rated PG13, and 94 rated R. The rest of the films were unrated. Of the R-rated films, 47 are violent (VIOLENT), and among those, 17 are very violent (VV), while the other 30 are violent (V) but not "very violent." There are 38 films with a nonzero sex (SEX) dummy, and 17 films contain both sex and violence (SEXV).

Table 2 contains our first set of tests. It shows that very violent films have significantly higher opening-weekend revenues compared to other R-rated films. The budget, domestic revenues, video revenues, rate of return, total revenues, and advertisement outlays are generally higher for very violent films than for other R-rated films, but the *t*-values are low. However, the number of total reviews for very violent films is significantly lower, and these reviews are also worse. A similar picture obtains when we compare very violent films to all other films in the sample (table 3).

Table 4 contains the most striking set of univariate tests. It compares all

there are several studies that focus on this issue—see Einav (2003) and Eliashberg and Elberse (2003), as well as Filson (2003), who present related work.

TABLE 2 **Univariate Tests for Very Violent Films versus Other R-Rated Films**

	VV = 1 (*n* = 17)			VV = 0 (*n* = 77)			
Variable	Mean	Median	SD	Mean	Median	SD	*t*-Value
BUDGET	16.073	12.000	14.954	14.030	10.000	12.732	.580
DOMREV	22.941	11.501	28.558	16.632	2.000	27.926	.840
OPENWK	6.012	4.424	6.599	2.898	.165	5.431	1.945*
INTLREV	10.825	5.568	13.705	5.972	.897	12.029	1.468
VIDREV	9.303	5.100	9.429	7.207	3.840	7.841	.961
RATE	2.201	1.903	1.694	1.802	1.043	2.011	.760
TOTREV	43.070	20.074	50.168	29.812	8.677	46.154	1.055
AD	3.800	3.211	3.623	3.538	1.067	4.238	.222
POSREVIEW	.301	.214	.290	.459	.476	.228	−2.452**
TOTREVIEW	13.058	12.000	8.377	22.766	22.000	9.373	−3.934**

NOTE.–BUDGET, AD, and the revenues (DOMREV, INTLREV, VIDREV, and TOTREV) are in millions of dollars.
* Significant at the .05 level.
** Significant at the .01 level.

violent films to other R-rated films. Violent films have significantly higher revenues in all categories. Their budgets are higher, but, in spite of that, the rate of return on these projects is significantly higher as well. The picture changes when we compare violent films to all other films (table 5). There the statistical significance basically disappears, except that opening-week revenues are significantly higher for violent films. In other words, the implication so far seems to be that if one were to make an R-rated film, one should make it violent, but one should not make an R-rated film in the first place.

We can already suggest some insights into how perceptions may be formed. Violent films open well, and if we compare them only to R-rated films, they perform better in every category. Even very violent films seem to open better and to have higher revenues than other R-rated films.

Tables 6 and 7 show that, surprisingly, there is not much action in the films

TABLE 3 **Univariate Tests for Very Violent Films versus All Other Films**

	VV = 1 (*n* = 17)			VV = 0 (*n* = 158)			
Variable	Mean	Median	SD	Mean	Median	SD	*t*-Value
BUDGET	16.073	12.000	14.954	15.636	12.250	13.827	.123
DOMREV	22.941	11.501	28.558	21.995	7.113	33.298	.113
OPENWK	6.012	4.424	6.599	3.824	.449	6.182	1.297
INTLREV	10.825	5.568	13.705	7.501	1.684	12.994	.997
VIDREV	9.303	5.100	9.429	10.847	5.328	21.134	−.297
RATE	2.201	1.903	1.694	2.281	1.277	2.695	−.120
TOTREV	43.070	20.074	50.168	40.343	17.229	61.453	.177
AD	3.800	3.211	3.623	4.155	3.549	3.969	−.332
POSREVIEW	.301	.214	.290	.448	.449	.246	−2.301**
TOTREVIEW	13.058	12.000	8.377	21.746	21.000	9.749	−3.534**

NOTE.—BUDGET, AD, and the revenues (DOMREV, INTLREV, VIDREV, and TOTREV) are in millions of dollars.
** Significant at the .01 level.

TABLE 4 Univariate Tests for Violent Films versus Other R-Rated Films

	VIOLENT = 1 (n = 47)			VIOLENT = 0 (n = 47)			
Variable	Mean	Median	SD	Mean	Median	SD	t-Value
BUDGET	17.949	13.576	13.825	10.851	6.000	11.402	2.716**
DOMREV	26.946	12.500	33.379	8.600	1.459	17.264	3.347**
OPENWK	5.820	4.051	6.987	1.103	.069	2.600	4.191**
INTLREV	9.800	1.800	14.906	3.900	.778	8.458	2.360**
VIDREV	10.644	8.400	9.046	4.528	2.280	5.734	3.915**
RATE	2.264	1.836	2.147	1.484	.933	1.675	1.964*
TOTREV	47.391	20.635	55.462	17.029	5.772	30.018	3.301**
AD	5.066	4.398	4.304	1.995	.314	3.260	3.644**
POSREVIEW	.387	.381	.260	.474	.500	.226	−1.732+
TOTREVIEW	19.914	18.100	10.759	22.106	23.000	8.937	−1.074

NOTE.—BUDGET, AD, and the revenues (DOMREV, INTLREV, VIDREV, and TOTREV) are in millions of dollars.
+ Significant at the .10 level.
* Significant at the .05 level.
** Significant at the .01 level.

that combine sex and violence. In other words, it seems that these films are not significantly different from the rest of the sample. Tables 8 and 9 compare all films with sexual content to other films. Films that combine sex and violence are cheaper to make and have lower international revenues than other R-rated films, but the comparison with all films in the sample (table 9) is even more striking. Films with just sexual content have significantly lower revenues in all categories, but since their budgets are significantly lower as well, the rate of return comparison is not significant.

In summary, it seems that, while violence contributes to a film's financial standing, sex does not. Naturally, our sample does not contain XXX-rated movies, which are generally released exclusively to video, but rather is made up of "legitimate" films with sexual content.

TABLE 5 Univariate Tests for Violent Films versus All Other Films

	VIOLENT = 1 (n = 47)			VIOLENT = 0 (n = 128)			
Variable	Mean	Median	SD	Mean	Median	SD	t-Value
BUDGET	17.949	13.576	13.825	14.845	11.800	13.882	1.312
DOMREV	26.946	12.500	33.379	20.302	5.407	32.527	1.189
OPENWK	5.820	4.051	6.987	3.371	.314	5.828	2.230*
INTLREV	9.800	1.800	14.906	7.098	1.702	12.299	1.214
VIDREV	10.644	8.400	9.046	10.716	4.500	23.108	−.021
RATE	2.264	1.836	2.147	2.277	1.284	2.769	−.028
TOTREV	47.391	20.635	55.462	38.117	16.050	62.041	.901
AD	5.066	4.398	4.304	3.754	3.263	3.728	1.874+
POSREVIEW	.387	.381	.260	.451	.464	.250	−1.494
TOTREVIEW	19.914	18.100	10.759	21.265	20.500	9.646	−.796

NOTE.—BUDGET, AD, and the revenues (DOMREV, INTLREV, VIDREV, and TOTREV) are in millions of dollars.
+ Significant at the .10 level.
* Significant at the .05 level.

TABLE 6 **Univariate Tests for Films that Combine Sex and Violence versus R-Rated Films**

	SEXV = 1 (n = 17)			SEXV = 0 (n = 77)			
Variable	Mean	Median	SD	Mean	Median	SD	t-Value
BUDGET	16.939	15.000	11.083	13.839	8.000	13.503	.882
DOMREV	24.176	12.500	27.034	16.360	1.800	28.174	1.042
OPENWK	4.427	3.192	5.020	3.211	.191	5.889	.765
INTLREV	6.809	1.800	11.336	6.858	1.196	12.708	−.015
VIDREV	10.795	8.400	7.322	6.878	3.047	8.179	1.819^{+}
RATE	2.373	1.836	1.749	1.764	1.096	1.991	1.165
TOTREV	41.781	20.074	43.669	30.097	7.011	47.003	.929
AD	4.731	3.426	4.142	3.291	.781	4.086	1.292
POSREVIEW	.336	.375	.208	.451	.467	.251	−1.753^{+}
TOTREVIEW	20.117	21.000	11.252	21.207	19.000	9.645	−.409

NOTE.—BUDGET, AD, and the revenues (DOMREV, INTLREV, VIDREV, and TOTREV) are in millions of dollars.

$^{+}$ Significant at the .10 level.

Subsequent tables contain regressions in which various sources of revenues and the rate of return serve as dependent variables. This analysis will show whether the perceptions we have identified so far have a sound basis in economic reality when other control variables are taken into account as well. As noted, we consider the following two splits of R-rated films. The first split creates three dummies—very violent films (VV), the rest of the violent films (V), and the rest of the R-rated films (RNOTV). The second split generates two dummies—an interactive variable for films that contained both sex and violence (SEXV) versus the rest of the R films (RNOSEXV). We also split the R's into violent films versus all other R's, films with sexual content versus all other R's, and films with strong sexual content versus all R's.

These latter splits (violent vs. nonviolent films, films with sexual content vs. films without sexual content) do not provide interesting results. Therefore,

TABLE 7 **Univariate Tests for Films that Combine Sex and Violence versus All Other Films**

	SEXV = 1 (n = 17)			SEXV = 0 (n = 158)			
Variable	Mean	Median	SD	Mean	Median	SD	t-Value
BUDGET	16.939	15.000	11.083	15.543	12.000	14.188	.393
DOMREV	24.176	12.500	27.034	21.862	6.760	33.420	.276
OPENWK	4.427	3.192	5.020	3.985	.440	6.367	.268
INTLREV	6.809	1.800	11.336	7.933	1.702	13.260	−.336
VIDREV	10.795	8.400	7.322	10.686	4.593	21.224	.021
RATE	2.373	1.836	1.749	2.263	1.291	2.691	.165
TOTREV	41.781	20.074	43.669	40.482	17.018	61.961	.084
AD	4.731	3.426	4.142	4.045	3.549	3.909	.678
POSREVIEW	.336	.375	.208	.444	.449	.256	−1.675
TOTREVIEW	20.117	21.000	11.252	20.987	19.000	9.829	−.342

NOTE.—BUDGET, AD, and the revenues (DOMREV, INTLREV, VIDREV, and TOTREV) are in millions of dollars.

TABLE 8 **Univariate Tests for Films with Sexual Content versus R-Rated Films**

	SEX = 1 (*n* = 38)			SEX = 0 (*n* = 56)			
Variable	Mean	Median	SD	Mean	Median	SD	*t*-Value
BUDGET	11.512	7.500	10.907	16.359	12.000	14.157	−1.781+
DOMREV	12.348	1.900	20.830	21.454	5.930	31.606	−1.560
OPENWK	2.281	.130	4.230	4.249	.930	6.506	−1.591
INTLREV	4.136	1.005	8.523	8.691	1.422	14.252	−1.765+
VIDREV	6.039	3.570	6.593	8.636	4.450	8.939	−1.529
RATE	1.967	1.358	2.006	1.811	1.112	1.935	.378
TOTREV	22.525	8.003	34.453	38.782	16.870	53.036	−1.665
AD	2.399	.781	3.377	4.495	3.549	4.421	−2.364*
POSREVIEW	.391	.395	.232	.457	.465	.254	−1.286
TOTREVIEW	20.473	21.000	9.078	21.375	19.000	10.483	−.431

NOTE.—BUDGET, AD, and the revenues (DOMREV, INTLREV, VIDREV, and TOTREV) are in millions of dollars.
+ Significant at the .10 level.
* Significant at the .05 level.

we report in table 10 only one regression for each split, namely, the total revenue (including domestic, international, and video revenues) regression. The coefficients of the control variables in table 10 are consistent with later results, that is, the sequel variable, G and PG ratings, total number of reviews (proxy for critical attention), and, first and foremost, budget, tend to be significant determinants of revenues. However, the sex dummy variable does not perform very well (no pun intended), and the standard error is rather large in the total revenue regression (presented here),[9] in the all component regression, and in the rate of return regression. We also ran regressions with the strong sex dummy versus all other R's, but that dummy was not significant

TABLE 9 **Univariate Tests for Films with Sexual Content versus All Other Films**

	SEX = 1 (*n* = 38)			SEX = 0 (*n* = 137)			
Variable	Mean	Median	SD	Mean	Median	SD	*t*-Value
BUDGET	11.512	7.500	10.907	16.834	13.000	24.788	−2.11*
DOMREV	12.348	1.900	20.830	24.788	9.330	34.987	−2.09*
OPENWK	2.281	.130	4.230	4.537	2.449	6.632	−1.93*
INTLREV	4.136	1.005	8.523	8.846	1.800	13.915	−1.98*
VIDREV	6.039	3.570	6.593	11.988	6.444	22.511	−1.607
RATE	1.967	1.358	2.006	2.358	1.298	2.755	−.817
TOTREV	22.525	8.003	34.453	45.623	20.635	64.937	−2.11*
AD	2.399	.781	3.377	4.646	4.498	3.945	−3.088**
POSREVIEW	.391	.395	.232	.446	.448	.259	−1.185
TOTREVIEW	20.473	21.000	9.078	21.021	19.000	10.199	−.300

NOTE.—BUDGET, AD, and the revenues (DOMREV, INTLREV, VIDREV, and TOTREV) are in millions of dollars.
* Significant at the .05 level.
** Significant at the .01 level.

9. For a discussion of the presentation of the coefficients and standard errors, see n. 10 below and app. B.

TABLE 10 Regression Results: The Determinants of Film Revenues When Films Are Classified According to Sexual and Violent Content, Respectively

Variable	Total Revenue Regression (1)	Total Revenue Regression (2)
How R is split	SEX & RNOSEX	VIOLENT & RNOTV
CONSTANT	−1.655	−1.585
	(.593)	(.590)
	[.519]	[.512]
LNBUDGET	1.182	1.075
	(.114)	(.112)
	[.106]	[.106]
AWARD		−.061
		(.251)
		[.255]
UNKNOWN	.069	.066
	(.233)	(.229
	[.257]	[.265]
NEXT	.021	−.004
	(.274)	(.287)
	[.273]	[.291]
G	1.517	1.608
	(.604)	(.599)
	[.549]	[.543]
PG	1.245	1.345
	(.482)	(.475)
	[.433]	[.44]
PG13	.592	.695
	(.464)	(.460)
	[.349]	[.355]
POSREVIEW	.404	.331
	(.371)	(.364)
	[.394]	[.389]
TOTREVIEW	.029	.034
	(.011)	(.011)
	[.011]	[.011]
SEQUEL	.801	.812
	(.327)	(.323)
	[.348]	[.34]
RELEASE	.072	.009
	(.504)	(.499
	[.535]	[.52]
SEX	.624	
	(.464)	
	[.345]	
RNOSEX	.566	
	(.456)	
	[.320]	
VIOLENT		.870
		(.459)
		[.361]
RNOTV		.427
		(.452)
		[.326]

TABLE 10 ***(Continued)***

Variable	Total Revenue Regression (1)	Total Revenue Regression (2)
ANYAWARD	−.188	
	(.179)	
	[.185]	
R^2	.699	.705
Adjusted R^2	.674	.681
F-value	28.79	29.59

NOTE.—The dependent variable in both regressions is the log (TOTREV). Independent variables include log (BUDGET), dummies for ratings (G, PG, PG13; default is unrated films), whether participants had been nominated for an Oscar (ANYAWARD) or received an Oscar (AWARD), whether cast members could not be found in standard film references (UNKNOWN), whether a film is a sequel or not (SEQUEL), and whether a cast member had participated in previous year's top-10-grossing films (NEXT). Additional variables include the total number of reviews (TOTREVIEW), the percentage of positive reviews (POSREVIEW), a seasonality variable (RELEASE), and dummies for sexual content (SEX), R-rated but no sexual content (RNOSEX), violent content (VIOLENT), and R-rated but not violent (RNOTV). Standard errors are in parentheses. Davidson-MacKinnon-White errors are reported in the brackets.

in any regression either. We will keep these conclusions in mind when we discuss the sex and violence dummy later on. The violence variable is only marginally significant at best; in fact, the best regression is the total revenue regression presented here, which features a 6% significance level. The coefficient also tends to be small relative to G and PG coefficients, which are highly significant. The conclusion so far is that, whereas means tests seem to imply that violent films do well and sex films perform poorly, when we consider other determinants of revenues and returns, these results do not hold water. Revenues for violent films are only marginally higher than for other films but, still, family films tend to perform best. When we further split the R's, as suggested above, the results are much more interesting. First we focus on returns, which are, of course, the correct measure of economic success, and then we consider revenues.[10]

A. The Rate of Return Regression Results

Table 11 shows that violent films, very violent films, and films with sex and violence do not have a high rate of return. The OLS equation shows that, at

10. All of the equations passed the White's (1980) general test for the presence of heteroskedasticity except the RATE equation. We first tried the White correction, but that equation failed some other tests. Hence, we corrected for heteroskedasticity using a weighted least squares procedure, where the weight used was the percentage of positive reviews (POSREVIEW) for a logarithmic transformation of RATE. With this correction for heteroskedasticity, the equation passed the White's Test, the Breusch-Pagan Test, and the Cook-Weisberg Test. We are grateful to Rob Engle, Shailendra Gajanan, Darius Palia, Nagesh Revankar, and Robert Whitelaw for discussions on these issues. We report the OLS results and the White adjusted errors, as well as the corrected equations, where the coefficients are harder to interpret. For all the revenue equations, we report two sets of results—one based on White's heteroskedasticity consistent errors and the other without that correction, which again, was not necessarily warranted. Furthermore, the White correction works best for large samples. Hence, we corrected the errors using the Davidson-Mckinnon procedure (see Green 2000, chap. 12). Fortunately, although the standard errors differ, most of our qualitative results are unchanged.

TABLE 11 Regression Results: Rate of Return and Domestic Revenues When Films Are Classified as Very Violent, Films Containing Sex versus All Other Films

	Rate Regression (1)		Rate Regression (2)		Domestic Revenue Regression (3)	
Variable	VV & V & RNOTV	SEXV & RNOSEXV	VV & V & RNOTV	SEXV & RNOSEXV	VV & V & RNOTV	SEXV & RNOSEXV
CONSTANT	−.649	−.147			−4.589	−4.526
	(1.437)	(1.504)	.497*	.544*	(.904)	(.918)
	[1.126]	[1.166]	(.135)	(.138)	[.823]	[.836]
LNBUDGET	−.002	−.001			1.439	1.441
	(.269)	(.272)	−.009*	.021*	(.176)	(.169)
	[.225]	[.24]	(.028)	(.025)	[.17]	[.178]
AWARD	.276					−.212
	(.578)		−.009*	−.014*		(.390)
	[.692]		(.085)	(.085)		[.352]
UNKNOWN	−.065	−.025			.281	.324
	(.556)	(.566)	.020*	.048*	(.353)	(.357)
	[.613]	[.601]	(.071)	(.070)	[.422]	[.406]
NEXT						−.006
						(.442
G	4.733	4.667			1.744	1.555
	(.145)	(1.458)	.346*	.288*	(.917)	(.929)
	[2.535]	[2.594]	(.192)	(.192)	[.755]	[.79]
PG	3.449	3.256			1.660	1.720
	(1.154)	(1.166)	.355*	.325*	(.732)	(.738)
	[.993]	[.976]	(.155)	(.156)	[.672]	[.675]
PG13	1.116	.902			.892	.888
	(1.116)	(1.121)	.196*	.168*	(.705)	(.714)
	[.594]	[.554]	(.149)	(.150)	[.546]	[.555]
POSREVIEW	.934	.063			1.136	1.198
	(.883)	(.934)	−.078†	−.122†	(.558)	(.565)
	[.862]	[.902]	(.166)	(.162)	[.592]	[.614]
TOTREVIEW	.040	.051			.056	.048
	(.028)	(.027)	.010*	.008*	(.017)	(.017)
	[.026]	[.027]	(.003)	(.003)	[.016]	[.016]

SEQUEL	1.257	1.331			.946	1.168
	(.793)	(.788)	.362*	.375*	(.498)	(.503)
	[1.047]	[.962]	(.113)	(.108)	[.534]	[.535]
RELEASE	.050	−.163			.246	.095
	(1.20)	(1.203)	−.114*	−.103*	(.758)	(.777)
	[1.201]	[1.217]	(.147)	(.143)	[.778]	[.808]
VV	1.717				1.537	
	(1.213)		.187*		(.767)	
	[.728]		(.152)		[.691]	
V	1.472				.973	
	(1.151)		.227*		(.727	
	[.676]		(.150)		[.581]	
RNOTV	.679				.407	
	(1.096)		.040*		(.693)	
	[.557]		(.145)		[.499]	
SEXV		1.508				1.476
		(1.212)		.197*		(.774)
		[.632]		(.149)		[.597]
RNOSEXV		.802				.675
		(1.087)		.080*		(.690)
		[.491]		(.145)		[.51]
ANYAWARD		−.022			−.390	
		(.432)			(.271)	
		[.389]			[.279]	
R^2	.235	.220	.343	.325	.636	.626
Adjusted	.174	.163	.286	.271	.606	.596
F-value	3.82	3.82	5.99	6.03	21.64	20.75

Note.—The dependent variable in 1 is RATE, and in 3 it is log (DOMREV). Independent variables include log (BUDGET), dummies for ratings (G, PG, PG13; default is unrated films), whether participants had been nominated for an Oscar (ANYAWARD) or received an Oscar (AWARD), whether cast members could not be found in standard film references (UNKNOWN), whether a film is a sequel or not (SEQUEL), and whether a cast member had participated in the previous year's top-10-grossing films (NEXT). Additional variables include the total number of reviews (TOTREVIEW), the percentage of positive reviews (POSREVIEW), a seasonality variable (RELEASE), and dummies for very violent content (VV), violent content (V), R-rated but not violent (RNOTV), both sexual and violent content (SEXV), and R-rated but neither sexual nor violent content (RNOTV). The regression in 2 is a transformation of 1, where the weight used is POSREVIEW. The dependent variable in 2 is log (RATE/POSREVIEW). Standard errors are in parentheses. Davidson-MacKinnon-White errors are reported in the brackets.

* The corresponding variable has been transformed through division by POSREVIEW.

† The variable is (1/POSREVIEW).

the 5% level, only two variables have a significant impact on the rate of return, namely, G and PG ratings. This is consistent with earlier results obtained by Ravid (1999). This equation has a heteroskedasticity problem, as noted earlier. The White (with the Davidson Mac-Kinnon adjustment) correction lowers the standard deviation of the very violent and sex and violent films (because their variances are indeed lower). As a result, the significance level increases. On the other hand, as noted, the adjusted equation still fails other tests, and when we run a weighted least squares regression, which is more "correct" in a sense, the resulting equations are qualitatively similar to the OLS results. In this latter equation, sequel status and critical attention become significant. The very violent or sex and violence dummies are mostly insignificant. However, in all rate regressions, the coefficients for very violent films and sex- and violence-laden films are lower than the coefficients for G- and PG-rated films. This presents us with the puzzle discussed earlier—if violent films make less money, why are they made, and why are so few family films being produced? In the analysis below we will try to shed light on this by showing that violent entertainment may gross more and also may be less risky.

B. The Domestic Revenue Regression Results

Although U.S. theatrical revenue now brings in less than 20% of the total revenue of U.S. films, it is still a major focus of discussion, and it is the most visible sign of success. It is also the most easily monitored variable, as compared to video and foreign receipts, and thus it is important to individual executives. Table 11 presents the two specifications of the domestic revenue regression.[11] In both, the budget is significant, as in Ravid (1999), indicating again that more expensive films also bring in more revenues (but not necessarily a higher return). Other variables with varying levels of significance are G and PG ratings, sequel status, and total reviews. Positive reviews also seem to increase domestic revenues. The dummy for very violent content is also significant at the 5% level, and the coefficient is only slightly below that of G and PG ratings, indicating that a very violent classification is worth less, but not much less, than a G or PG rating in the domestic market. The sex and violence dummy is somewhat less significant, and it has a coefficient comparable to that of the VV dummy. This is particularly interesting when we note that films with sexual content alone do not outperform other films at all. However, it supports the view that, if you would like to increase revenues in the most visible of all markets—the domestic market—very violent movies or films that combine sex and violence bring in significant revenues. The variables AWARD or ANYAWARD are negative but not significant. That is,

11. As noted earlier, all equations below passed the White test. Therefore, strictly speaking, one need not modify the OLS equations, and, again, strictly speaking, modification may present errors. We do provide the White-Davidson-MacKinnon adjustment, but, in general, we place more weight on variables that are significant in both specifications.

you do not need a star to succeed. One is reminded of the endless and successful series such as *Friday the Thirteenth* or *Murder on Elm Street*—they were very violent films, with many sequels, and they featured actors who, in general, could not be classified as stars.

We tried a few other specifications, for example, including only NEXT or only AWARD as independent variables, but there was no qualitative difference in the results. We also ran regressions with different specifications for the stars (ANYAWARD or VALAWARD) and for reviews, but that did not affect the outcome. We can conclude that just being a violent film may not be enough; however, having very violent content or violence with some sexual content, everything else equal, seems to have a significant positive effect on domestic revenues.

C. The International Revenue Regression Results

The international revenue regression is perhaps the most interesting of all. Overall, international revenue is a growing percentage of total revenues for Hollywood. As found in Ravid (1999), this is the most difficult piece of the pie to explain. International revenues may change for various reasons, and there are probably country-specific issues that are not captured in the regressions. It is therefore economically significant that, next to the budget, the very violent dummy has the strongest impact on international revenues (table 12). Further, the coefficient is high—that is, a very violent designation buys studios a lot of revenues. Nonviolent R-rated films, RNOTV, or violent, V, movies have no significant impact on international revenues. Sexual content is only significant in one specification (table 12), but the coefficient is lower than that of very violent films. The star variable, AWARD, is not significant either. Again, we tried a few other specifications, but they did not affect the outcome. Thus, it seems that very violent films sell well internationally, everything else equal.

This, of course, makes sense. Whereas comedies or even films with sexual content are culture-dependent, violence transcends cultural barriers. In a review of the recent Sylvester Stallone movie *Get Carter* (which according to MPAA includes scenes of ultra violence), Elvis Mitchell wrote in the *New York Times* (October 7, 2000, available at http://www.NYTimes.com): "It is so minimally plotted that not only does it lack a subtext or context, but it also may be the world's first movie without even a text." Similarly, the Arnold Schwartzenager movie *End of Days* (1999), which, by our classification, would fit at the extreme end of the very violent category, made only $67 million in the United States, but overseas revenues were $135 million (see Diorio 2000). The international success of very violent movies also has very important policy implications, since, if the most significant profit center for very violent films is the foreign market, domestic legislation will be less effective in that regard.

D. *The Video Revenue Regression Results*

Videos, on the other hand, are in the realm of family entertainment. As is evident from table 12, the violent or very violent dummies have no significant impact on video revenues, and a similar fate awaits the sex and violence dummy. Only high budgets, G ratings, and a sequel status significantly enhance video revenues. It is interesting that having unknown actors negatively affects a film's revenues.

The insignificant impact of violent movies on video revenues is perhaps not difficult to interpret. Since videos are often rented for family viewing, parents or guardians who rent videos may want to avoid violent films. The same reasoning can explain why sequels and G ratings contribute to video revenues. Neither the percentage of positive reviews nor the total number of reviews is an important determinant of video revenues. Videos come out many months after the original films debut in theaters. By that time, the impact of any review is swamped by word of mouth. Here, too, we tried a few other specifications, for example, including only NEXT or only AWARD as independent variables, but there was no qualitative difference in the results. We also ran regressions with different specifications for the stars (ANYAWARD or VALAWARD), but that did not affect the outcome. We should note that, in the years that have elapsed since the close of our sample in 1993, video income has captured a more significant share of revenues (from about a quarter on average in our sample to more than half in the early twenty-first century). Furthermore, consistent with our ideas, several studios have been issuing sequels to popular movies such as *The Lion King* or *The Little Mermaid* directly to video. This is because G-rated films and sequels sell well, particularly in video, and a theatrical run is very costly. While video revenues have been gaining in importance, in our sample period, video revenue numbers were much less widely available than they are today, and they have been mired in arcane contractual agreements. Therefore, the fact that violent fare does not do as well in video may not have been that important in terms of revenue maximization.

E. *The Total Revenue Regression Results*

From the analysis we have provided so far, it should be clear that the impact of violent content on total revenue will depend on the relative shares of domestic, international, and video revenues in the mix and may change over time as the revenue mix shifts. Table 12 presents the total revenue regression for our sample. Total revenues are affected significantly by the budget, indicating that more expensive films bring in larger total revenues. The G and PG ratings are very important, reflecting their impact on domestic revenues and video returns. Other significant variables include the total number of reviews and the sequel dummy. However, very violent films also significantly (5%) increase total revenues, as do films that combine sex and violence. The coefficients and the significance of these two dummies are higher than the coefficient and the significance of the violence dummy in table 12. We thus have captured the impact of the most important subset of violent movies.

Obviously, the significant effect of very violent films reflects mainly increased international sales, as well as, to some extent, the increase in domestic revenues. However, one should note that, whereas both family friendly ratings and very violent or sex and violent classifications increase revenues, family films increase revenues more—the coefficients are much higher. Finally, the variable AWARD is not significant. Positive reviews have no significant impact either. We can then conclude that an executive who considers revenue maximization as part of his objective function can choose ex ante very violent projects or projects that feature sex and violence.

We tried, as usual, a few other specifications, for example, including only NEXT or only AWARD as independent variable, but there was no qualitative difference in the results. We also ran regressions with different specifications for the stars (ANYAWARD or VALAWARD), but that did not affect the outcome.

F. Additional Tests and the Opening Weekend Revenue Regression Results

In an additional set of tests, we wanted to find out if violent films open better because that may be consistent with our view that visible revenue maximization is the goal of the game. Opening-weekend regressions, however, are fraught with econometric problems because revenues depend to some extent on the number of screens of the opening, whereas the number of screens, in turn, may be endogenous because expected revenue will determine the number of screens a company selects. We present just two simple regressions (table 12) that do not include the number of screens (this would be correct if the same variables determine both revenues and the number of screens, that is, if we have a reduced form equation). In general, we find that violent and very violent films open well. It is interesting that, when we run regressions where the dependent variable is the revenue per screen (including the number of screens on the right-hand side—these regressions are not reported here), no violence-related dummy is significant. This specification thus provides further support to the revenue maximization hypothesis.

G. Some Other Robustness Checks and Specifications

We tried several other specifications. In all of the above regressions, we introduced interactive variables, including AWARD*VV, ANYAWARD*VV, and VALAWARD*VV. However, none of these interaction terms produced any significant effect on any of the dependent variables. The regressions remained virtually unchanged. We also tried to add to the costs the ad expenditures to the negative cost and thus specify a different rate of return (you cannot run ad expenditures as a separate variable because it is highly correlated with the budget variable). There was no qualitative change in any of the results.

TABLE 12 Regression Results: International Reveunues, Total Revenues, and Opening Weekend Revenues When Films Are Classified as Very Violent, Containing Sex and Violence versus All Others

	International Revenue Regression (1)		Video Revenue Regression (2)		Total Revenue Regression (3)		Opening Weekend Revenue Regression (4)	
Variable	VV & V & RNOTV	SEXV & RNOSEXV	VV & V & RNOTV	SEXV & RNOSEXV	VV & V & RNOTV	SEXV & RNOSEXV	VV &V & RNOTV	SEXV & RNOSEXV
CONSTANT	−4.536	−4.161	−1.138	−1.137	−1.653	−1.579	−5.177	−5.169
	(1.156)	(1.178)	(.570)	(.563)	(.592)	(.587)	(1.056)	(1.084)
	[.830]	[.83]	[.505]	[.498]	[.526]	[.513]	[.965]	[.994]
LNBUDGET	1.344	1.300	.901	.914	1.073	1.141	1.533	1.708
	(.216)	(.217)	(.108)	(.104)	(.112)	(.113)	(.199)	(.196)
	[.220]	[.177]	[.105]	[.106]	[.105]	[.112]	[.216]	[.208]
AWARD	.382	.538	.009	.018	−.098		−.868	−.778
	(.465)	(.500)	(.242)	(.239)	(.251)		(.428)	(.417)
	[.363]	[.422]	[.235]	[.223]	[.252]		[.463]	[.491]
UNKNOWN	.750	.704	−.416	−.443	.066	.017	.374	.372
	(.447)	(.458)	(.220)	(.219)	(.229)	(.231)	(.412)	(.428)
	[.405]	[.404]	[.305]	[.297]	[.268]	[.256]	[.416]	[.40]
NEXT		−.072	.186	.267	.073	.038	.266	
		(.569)	(.278)	(.272)	(.289)	(.271)	(.498)	
		[.479]	[.213]	[.204]	[.29]	[.275]	[.553]	
G	1.508	1.508	1.376	1.334	1.622	1.562	1.517	1.207
	(1.170)	(1.192)	(.577)	(.570)	(.599)	(.597)	(1.049)	(1.077)
	[.981]	[.974]	[.592]	[.583]	[.544]	[.542]	[.904]	[.919]
PG	1.524	1.598	.618	.595	1.336	1.266	2.239	2.122
	(.928)	(.947)	(.457)	(.453)	(.475)	(.476)	(.852)	(.877)
	[.607]	[.587]	[.454]	[.453]	[.445]	[.430]	[.720]	[.718]
PG13	.910	1.015	.146	.131	.646	.623	1.208	1.086
	(.898)	(.917)	(.443)	(.438)	(.460)	(.459)	(.828)	(.852)
	[.573]	[.553]	[.378]	[.378]	[.363]	[.347]	[.637]	[.637]
POSREVIEW	.571	.553	−.098	−.202	.341	.425	−1.248	−1.083
	(.710)	(.725)	(.350)	(.346)	(.363)	(.364)	(.649)	(.670)
	[.636]	[.634]	[.332]	[.328]	[.383]	[.396]	[.696]	[.738]

TOTREVIEW	.044	.033	.012	.010	.037	.031	.047	.031
	(.022)	(.022)	(.011)	(.010)	(.012)	(.011)	(.202)	(.020)
	[.021]	[.019]	[.012]	[.012]	[.012]	[.011]	[.018]	[.018]
SEQUEL	.682	1.058	.633	.684	.742	.845	1.361	1.539
	(.638)	(.646)	(.316)	(.309)	(.328)	(.324)	(.552)	(.556)
	[.555]	[.558]	[.298]	[.266]	[.351]	[.338]	[.573]	[.519]
RELEASE	−.976	−1.225	.208	.184	.054	.005	−1.416	−1.489
	(.965)	(.997)	(.482)	(.477)	(.500)	(.499)	(.849)	(.867)
	[.769]	[.879]	[.454]	[.462]	[.517]	[.523]	[.997]	[1.01]
VV	2.000		.137		1.110		2.221	
	(.976)		(.481)		(.499)		(.903)	
	[.616]		[.486]		[.420]		[.705]	
V	.268		.281		.723		1.685	
	(.926)		(.457)		(.474)		(.849)	
	[.831]		[.404]		[.392]		[.702]	
RNOTV	.888		−.204		.413		.559	
	(.882)		(.434)		(.451)		(.813)	
	[.549]		[.404]		[.334]		[.965]	
SEXV		1.364		.529		1.038		1.710
		(.993)		(.475)		(.496)		(.914)
		[.604]		[.401]		[.364]		[.76]
RNOSEXV		.861		−.127		.502		.997
		(.885)		(.423)		(.444)		(.827)
		[.522]		[.498]		[.310]		[.598]
ANYAWARD						−.205		
						(.177)		
						[.181]		
R^2	.463	.439	.659	.662	.707	.706	.650	.623
Adjusted R^2	.419	.394	.629	.635	.682	.682	.616	.592
F-value	10.68	9.72	22.10	24.34	27.67	29.77	19.27	20.26

NOTE.—The dependent variable in 1 is log (INTLREV); in 2 it is log (VIDREV), in 3 it is log (TOTREV), and in 4 it is log (OPENWK). Independent variables include log (BUDGET), dummies for ratings (G, PG, PG13; default is unrated films), whether participants had been nominated for an Oscar (ANYAWARD) or received an Oscar (AWARD), whether cast members could not be found in standard film references (UNKNOWN), whether a film is a sequel or not (SEQUEL), and whether a cast member had participated in previous year's top-10-grossing films (NEXT). Additional variables include the total number of reviews (TOTREVIEW), the percentage of positive reviews (POSREVIEW), a seasonality variable (RELEASE), and dummies for very violent content (VV), violent content (V), R-rated but not violent (RNOTV), both sexual and violent content (SEXV), and R-rated but neither sexual nor violent content (RNOTV). Standard errors are in parentheses. Davidson-MacKinnon-White errors are reported in the brackets.

We also substituted for our continuous release date measure the Litman (1998) and Chisholm (2000) release dummy variable that measures "holiday" versus "nonholiday" periods. The resulting regressions did not produce any appreciable change in the coefficients, and therefore they are not presented here.

So far we have established a possible revenue maximization motive for the production of violent entertainment. In other words, very violent films or films that feature sex and violence may be produced because they provide significantly higher revenues, everything else equal. In the next section, we consider possible risk management (hedging) motives.

H. Risk-Related Tests

A comprehensive measure of risk at a project level is difficult to pinpoint. However, we tried several tests to find out whether very violent films are less risky choices. The first test considers whether or not very violent or violent films "break even" more often, that is, whether their rate of return on these films tends to be higher than one more often.[12]

Among the 175 films in the sample, 59.4% have a rate of return that is greater than one. This percentage is lower for all R-rated films, where only 56.4% "break even," which is consistent with all previous work. Table 13 shows that films with sexual content do not fare much better, with a "break even" percentage of 58%. Violent films as a whole break even less often than other films. On the other hand, fully 77% of the very violent films, as well as 71% of the films with sex and violence (SEXV), feature a rate of return higher than one. For G films, this percentage is 83%, but the number of G films in our sample is naturally small. Table 13 provides *Z*-tests that show that, indeed, very violent films are significantly "less risky" in that sense. Similarly, sequels are less risky as well.

The second set of tests examines the distribution of returns by deciles. Table 14 (see also fig. 1) shows how various types of films are distributed in different return on investment (ROI) deciles. Whereas the distribution of the rate of return for violent films as a whole seems to be similar to that of all films, very violent films are much "safer." About 71% of these films are in the sixth to ninth deciles, whereas only 23% of these movies are in the lowest four deciles. For films that contain both sex and violence, the picture is similar but somewhat less appealing—71% of these films are in the fifth through ninth deciles. No film of this category is in the lowest decile, whereas the percentage for the bottom four is 29%. No film that is very violent or that features sex and violence is in the uppermost decile either. In other words, films that are very violent or that feature sex and violence tend to cluster in the middle deciles. Figure 1 provides a graphic description of our findings.

Finally, we use an *F*-test to consider the hypothesis that the variances of very

12. Naturally, our rate of return variable is only a proxy, and therefore, if a film has a rate of return greater than one, it does not necessarily mean that the studio actually made money. However, this proxy provides comparability across observations.

TABLE 13 Proportion of Films That Break Even

Film Content (1)	Proportion of Films in (1) That Break Even (2)	Proportion of Other R-Rated Films (= 94 − n in [1]) That Break Even (3)	Proportion of All Other Films (=175 − n in [1]) That Break Even (4)	Z-Value: (2) vs. (3)(5)	Z-Value: (2) vs. (4) (6)
SEX (n = 38)	.580	.554	.599	.28	.22
SEXV (n = 17)	.705	.532	.582	1.33^{+}	1.01
VV (n = 17)	.765	.519	.578	1.81*	1.36*
V (n = 30)	.383	.745	.672	−3.56**	−2.49**
SEQUEL (n = 11)	.909	N.A.	.573	N.A.	2.20**

$^{+}$ Significant at the .10 level.
* Significant at the .05 level.
** Significant at the .01 level.

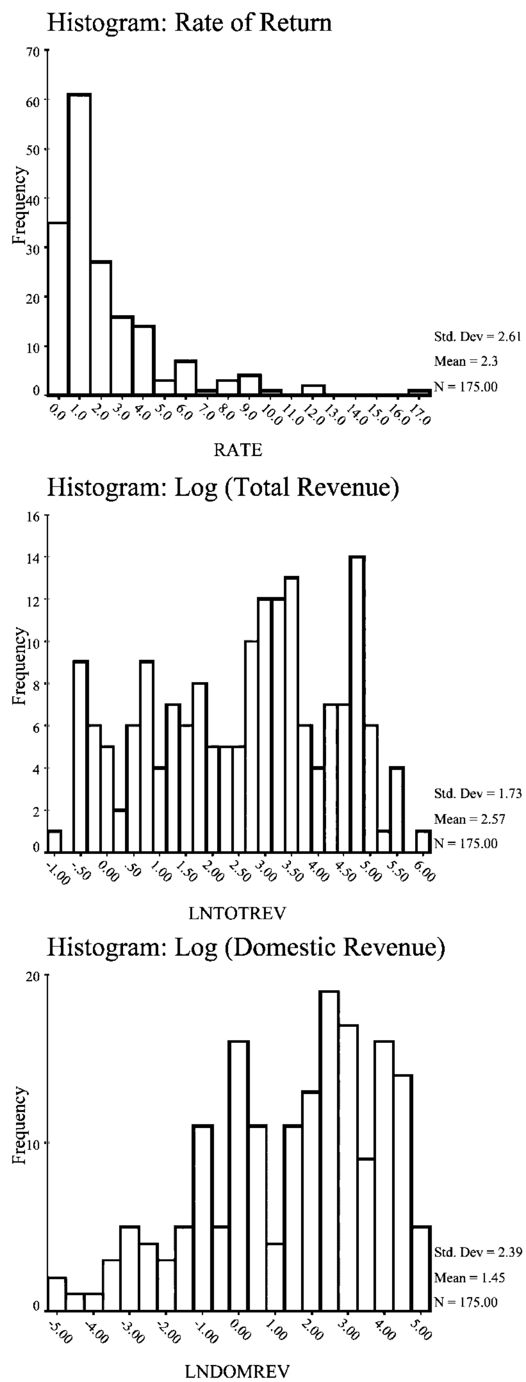

FIG. 1.—Distributions of revenues and rate of return

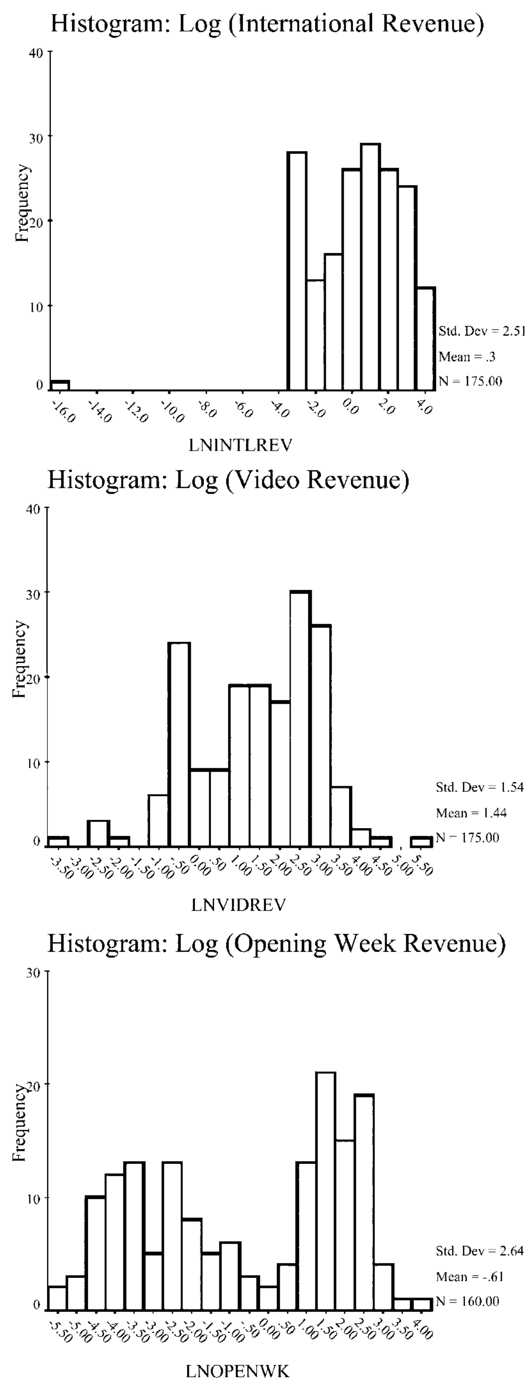

FIG. 1 (*Continued*)

TABLE 14 Percentages of Different Types of Films in Various Return on Investment (ROI) Deciles

ROI Deciles	ROI Range	VV	SEXV	VIOLENT	SEQUEL
Tenth decile	5.79 – 17.05	0	0	.04	.27
Ninth decile	3.53 – 5.74	.18	.29	.15	.27
Eighth decile	2.56 – 3.52	.06	.12	.13	.18
Seventh decile	1.89 – 2.33	.35	.06	.17	.18
Sixth decile	1.30 – 1.85	.12	.12	.06	.09
Fifth decile	1.00 – 1.29	.06	.12	.11	0
Fourth decile	.70 – .98	0	.06	.13	0
Third decile	.50 – .69	.12	.18	.09	0
Second decile	.34 – .49	0	.06	.04	0
First decile	.09 – .29	.12	0	.09	0

violent films and films with sex and violence are smaller. The results are presented in table 15. This table shows again that very violent films and films that contain sex and violence have significantly lower variances than other films, as do violent films.[13]

I. Sequels

We left a discussion of sequels until the end. A sequel designation can be a very easy characteristic to observe. However, as noted earlier, it would be impossible to produce a large number of sequels, even if one came to the conclusion that sequels are indeed a very good idea. You need the rights to a successful film, complete with at least partial cast participation, and, of course, the successful film for which you own rights, must be "sequelable." This implies a dearth of such possibilities. However, examining the data above, the pattern for sequels is almost identical to that of violent films, with some slight differences. Table 11 shows that sequels are at best marginally profitable. However, tables 11 and 12 show that sequel status significantly contributes to domestic revenues, video revenues. and total revenues. Sequels also open very well.

Similarly, in table 13, we see that sequels tend to break even much more often than other films. Table 14 reinforces this impression—there are no sequels in the lower deciles of returns. However, there is no significant difference between the variances of sequels and the variances of other films.

V. Discussion and Conclusions

The portrayal of violence in the media in general and in the movies in particular has been a constant source of public debate. The discussions in the media and in the political arena have primarily focused on moral and ethical issues. Academic research on the portrayal of violence often focuses on sociological

13. De Vany and Walls (2002) find that R-rated films in general are cheaper to produce and are stochastically dominated by other categories. However, they do note that, at the upper deciles of the distribution, R-rated films tend to be more expensive—this probably includes our very violent, effect-laden movies.

TABLE 15 Results of *F*-Tests for the Variances of Films in Various Categories

	VV (n = 17)		VIOLENT (n = 47)		SEXV (n = 17)		SEX (n = 38)		SEQUEL (n = 11)
	Other R (77)	All Films (158)	Other R (47)	All Films (128)	Other R (77)	All Films (158)	Other R (56)	All Films (137)	All Films (164)
Variances in ROI	4.04/2.87 = 1.41	7.29/2.87 = 2.52*	2.81/4.62 = .61	7.67/4.62 = 1.66*	3.96/3.06 = 1.29	7.24/3.06 = 2.36*	3.76/4.02 = .93	7.59/4.02 = 1.88^{+}	6.81/5.01 = 1.36

$^{+}$ Significant at the .10 level.
* Significant at the .05 level.

and psychological aspects. The current article contributes to the debate by focusing on the economic issues at hand. In particular, our results support the view that the production of violent and, in particular, very violent movies is consistent with suboptimal risk choices and revenue maximization motives by studio executives. This is similar to studies of other industries where executives are exposed to significant risks.

Our first important empirical finding is that much of the economic "action" is either in the movies that portray graphic violence or in movies that include both sex and violence. Such films, however, do not provide a higher rate of return than other types of movies. On the other hand, they increase revenues significantly. In the domestic market, very violent films or films that have both sex and violence produce higher revenues. In the international market very violent films sell very well, but in the video market family fare does better. We also find that very violent films tend to open much better than other films. When we sum it all up, in the total revenue regression, very violent films and films that contain both sex and violence provide significantly higher revenues. This makes production of such films consistent with revenue (sales) maximization objectives. It is important to note, however, that the coefficients of G and PG ratings, which also increase revenues, are higher; in other words, one will have more revenues than the base case (unrated) or than the average film in the sample if one produces a violent film, but one will do even better if one produces a family friendly feature (which also increases the rate of return on investment).

We then provide several tests that show that very violent films and films that feature sex and violence are less "risky" in several important ways—they lose money less often, their returns are concentrated in the middle deciles, and their variances are lower. These findings are consistent with a risk management (hedging) managerial objective. Other studies, with a different focus, offer additional evidence consistent with this view of the decision-making process in the motion picture industry. Basuroy, Chatterjee, and Ravid (2003) show that stars and big budgets help films that receive predominantly negative reviews but that they have no effect on films that receive predominantly positive reviews. In a similar vein, Einav (2003) documents a seemingly suboptimal clustering of release dates of films that may be the result of an attempt to herd.

Appendix A

Definition of Variables Used in All Tables

BUDGET is the "negative cost" or production costs of films, not including gross participation.

DOMREV are box office receipts for domestic revenues.

VIDREV are video sales revenues.

INTLREV is the share of domestic distributors in box office receipts overseas.

OPENWK are the revenues for the opening week.

TOTREV is the sum of all revenues, as defined above.

G, PG, PG13, and R are dummy variables for ratings. These variables take the value of one if the film is rated G, PG, PG13, or R, respectively, and zero otherwise.

VIOLENT is a dummy variable for films with violent content.

VV is a dummy variable for R-rated films that were defined by MPAA as having scenes of extreme or graphic or ultra violence.

V is a dummy for R-rated films with violent content, neither very violent nor containing extreme violence. V+VV are all the violent films.

RNOTV are the rest of the R films, that is, ones that are neither V nor VV.

SEX is a dummy variable receiving a value of one if the MPAA description includes words such as sexual content, sensuality, or similar.

RNOSEX is a dummy variable that takes the value of one if the film is rated R but is not SEX.

SEXV is a dummy variable receiving a value of one if SEX = 1 and VIOLENT = 1, that is, if it contains both sex and violence.

RNOSEXV is a dummy variable that takes the value of one if the film is rated R but is not SEXV.

POSREVIEW is positive reviews/total number of reviews.

MIXREVIEW is (positive reviews + neutral reviews)/total number of reviews.

TOTREVIEW is 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.

AWARD is a dummy variable, receiving a value of one if any participant in the film had received an academy award.

ANYAWARD is a dummy variable receiving a value of one if any participant in the film had 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-10-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 release date. See the discussion in the text for an exact definition.

Ln denotes the natural logarithm of a variable.

AD is advertisement expenditure.

Appendix B

Additional Statistical Analysis

In the text, we provided some robustness tests and, in particular, heteroskedasticity adjustments, for our regressions. In this appendix, we briefly describe some additional statistical analysis we performed on our data to prove robustness.

Since most data are not normally distributed, we first document the moments of the distributions of various variables and also chart histograms to illustrate them. It seems that total revenues are most evenly distributed and that the rate distribution is most skewed. When we compare the distribution of total revenues to the distribution of the various revenue components, it becomes clear that adding sources of revenues tends to even out the distribution; that is, films that are less successful domestically may do well in video or internationally, and vice versa. This observation is reinforced when we calculate the moments (see app. table B1). We obtain large values for kurtosis only for rate and international revenues, indicating long tails and a few extreme observations. For the rate distribution, the median is very different from the mean, and the distribution is skewed. In the case of international revenues, as we also see in the histogram, the long tail is negative; on the other hand, the rate distribution has a long positive tail.

We first examined the impact of extreme and influential observations by using the criteria outlined in Belsley, Kuh, and Welsch (1980). We computed RSTUDENT, COVRATIO, DFFITS, DFBETA, and the *h* metrics. We classified an observation as influential if two or more of the computed metrics exceeded the cutoff values suggested by Belsley et al. (1980). After deleting these observations from the sample, we reestimated all of the models. This procedure did not lead to any appreciable change in the results for the total revenue and international revenue equations.

Other regressions changed. However, the main "culprits" were the G-rated films, which were generally, as argued above, very successful. Dropping these observations as outliers would defeat the purpose of the analysis.

In order to tackle the issue from a different angle, we ran robust regressions (Rousseeuw and Leroy 1987). Robust regressions perform an initial screening based on Cook's distance to eliminate gross outliers. Then the procedure calculates starting values and then performs, as suggested by Li (1985), Huber iterations followed by biweight iterations. The results of the robust regressions were generally consistent with those of the OLS regressions and were omitted from the presentation in the text.

Next we tested for multicollinearity, employing Belsley et al. (1980) collinearity diagnostics. Both the condition index and VARPROP were below the cutoffs suggested by Belsley et al. (1980) for all the regression equations, indicating virtually no multicollinearity problem.

All the equations passed White's (1980) general test for the presence of heteroskedasticity, except the RATE equation. We employed the White adjustment for that equation, but the resulting equation still failed some tests. Therefore we further corrected for heteroskedasticity using a weighted least squares procedure, where the weight used was the percentage of positive reviews (POSREVIEW) for a logarithmic transformation of RATE. With this correction for heteroskedasticity, the equation passed the White's Test, the Breusch-Pagan Test, and the Cook-Weisberg Test. Thus, we report the OLS results and the White's adjusted errors, as well as the weighted least squares equations, where the coefficients are harder to interpret.

For all the revenue equations, we report two sets of results—one based on White's heteroskedasticity consistent errors and the other without that correction, which again, was not necessarily warranted, since the equations did pass the White tests for heteroskedasticity. It may even introduce some errors. Furthermore, the White correction

TABLE B1 Mean, Median, Mode, Skewness, and Kurtosis Measures

	Rate	Ln Totrev	Ln Domrev	Ln Intlrev	Ln Vidrev	Ln Openwk
Mean	2.27	2.56	1.45	.31	1.44	−.62
Median	1.30	2.86	1.98	.54	1.66	−.29
Mode	.23	−.39	−.92	−3.10	−.51	−5.37
Skewness	2.42	−.23	−.62	−1.66	−.52	−.19
Kurtosis	7.57	−.97	−.38	9.05	−.04	−1.51

works best for large samples; hence, we corrected the errors using the Davidson-Mckinnon procedure (see Green 2000, chap. 12). Although the standard errors differ, most of our qualitative results are the same. Most of this information is repeated in note 10.

Appendix C

Reasons Given for Violent Entertainment

The main reasoning on the part of the entertainment industry has been to claim that violence is part of life. Baldwin and Lewis (1972) report that several of the producers of prime time network television they interviewed claimed that it would be "a fantasy" to pretend that violence did not exist. In other words, violence exists on screen and in the media because violence exists in life.

Second, the industry argues that most drama is based on conflict and that violence is a tool for conflict. In their study, Baldwin and Lewis (1972) quote one producer as saying "Violence and drama are almost synonymous" (p. 303). They quote another producer as saying: "Good drama is based on conflict which erupts in violent emotion" (p. 303). Hamilton's (1998) findings, however, do not seem to support this view. Hamilton analyzes movies shown on 32 television channels during a 12-month period. Of the 5,030 movies that had violent content, only 2.8% received a four-star rating, the highest quality rating, by critics.

Third, industry representatives have often argued that violence can be used responsibly by showing its negative side. For example, portrayals of child abuse and racism help raise the viewers' awareness of these issues. However, the National Television Violence Study (1998) analyzed 9,000 television programs and reported that, in only 4% of the violent programs, did characters display remorse for the use of violence.

Fourth, industry officials have also held that fictional violence does not harm viewers, even children. In other words, viewers should know the distinction between real and fictional violence, a point that was put forth by viewers as well. Baldwin and Lewis (1972) provide the following quote: "My kids know the violence they see on Gunsmoke is make-believe and what they see on a newscast is real" (pp. 342–43). All of of these arguments are highly controversial, and it is beyond the scope of this article to properly debate them. However, we should also note that there is an extensive body of psychological and sociological research suggesting that viewing violent movies is often deemed to be a pleasurable activity.[14]

14. Some of the reasons offered are the following: *Catharsis*: This is the purging of tragic feeling on the part of the viewer. Violence on screen may purge the viewers' anxiety and fears, releasing pent up emotions (Potter 1999). *Violent movies test viewers*: In some focus group studies, audiences said that realistic portrayals of violence challenged them (Hill 1997). *Viewing violence is a social activity*: The media hype and peer pressure that surround some of the violent movies may make watching them a social activity. Often viewers do not watch violent movies alone but instead do so in the company of friends. Hill (1997) quotes a focus group participant as saying "How can you go to a dinner party if you haven't seen *Pulp Fiction*?" (p. 23). *Real violence is raw and brutal and not entertaining*: Consumers of violent movies do not find real violence entertaining. Watching movies is a safe way for understanding violence without having to experience the real thing. *Fictional violence is entertaining*: Some movies are thought to be more entertaining than others, depending on the representation of violence. *There is pleasure from arousal*: Zillman (1998) argues that people simply want to experience the pleasure of

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arousal. He argues that "there can be little doubt, then, that righteous violence, however brutal, but justified by the ends, will prompt gloriously intense euphoric reactions the more it is preceded by patently unjust and similarly brutal violence" (Zillman 1998, p. 208).

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