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

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Abstract

We analyze project choice in the motion pictures industry and find evidence consistent with revenue maximization and excessive hedging. We focus on the production of violent films and films that feature sex and violence. We find that such movies 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. Our findings are consistent with studies of other industries, and they also partially explain the “R-rating puzzle” that is, the fact that most films produced are R-rated in spite of much evidence suggesting that G and PG rated films perform better.

1. Introduction and theoretical background

The purpose of this paper is three-fold. 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" which 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*, *I Know What You Did Last Summer*, and several others, has turned them into franchises. Since movies are a big business, it seems that violence (in films) must pay. However, recent studies seem to show the opposite. Ravid (1999) shows that 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 75th percentile and by G rated movies almost everywhere. Thus they conclude: "Hollywood produces too many R-rated films". Simonoff and Sparrow (2000) analyze the statistical properties of the domestic revenue stream of a smaller number of films released in 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 and studio financing. He also uses only domestic revenues, and his sample period is not very different from Ravid (1999). The focus is different, but Fee (2002) does run a regression where the dependent variable is the domestic rate of return (table 6). His most significant independent variable in that regression is a G- rating. John Ravid and Sunder (2003), in a study which focuses on directors' careers and 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 five percent. 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 sixty-five percent of the total in 1995 to about sixty nine percent of all films released in 2001 (www.mpaa.org). Many of these 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.[2] The analysis in this paper 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 sub-sets of R-rated films, which 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 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 paper, 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), and 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[3]. Zabojnik (1998) develops this idea further.

Other studies have sought to justify and document another seeming 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, and in particular, managers should not hedge their own production[4], which has the added disadvantage of negating all effort incentives. However, sometimes market frictions can make hedging an optimal policy for an

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[2] It seems that Hollywood is slowly getting the message. In late 2001 and early 2002 the number of very visible family projects has increased. Bing and Dunley (2002) dedicate a lead article in Variety to that trend, concluding that "Hollywood has found its inner child".

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

[4] This can be easily understood by the following extreme example. Suppose that two firms produce the same product, and 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 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 x 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.

individual business entity. A well-known paper by Froot et al. (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 model three such frictions, namely, taxes, bankruptcy costs, and managerial risk aversion. This latter motivation can arise also when managers have too much of their wealth invested in their own companies. DeMarzo and Duffie (1995) focus on another possible set-up, which 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 over hedge. In fact, consistent with our empirical work, DeMarzo and Duffie (1995) show that when managers cannot hedge effectively, they may choose inferior projects, which are less risky (propositions 10, 11)[5]. This points out an important issue for our purposes. Managers can lower the risk stemming from production uncertainly in two ways. One is by using hedging instruments (such as derivatives) and the other is by the sub-optimal 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 project of all types, so that 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

[5] John and John (1993) describe seemingly reasonable managerial objective functions, which can lead to sub –optimal behavior on the part of managers (along the lines described here) if the firm carries some

exposure of executives. Tufano (1996) also tests several other theories. He cannot find support for the theory in Froot et al. (1993). However, Houshalter (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 sub-optimal risk management in response to incentives, which have 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)[6].

All 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 sub-optimal behavior on the part of managers, along the lines described in the literature. In particular, film studios are a collection of projects, which are difficult to hedge individually and as a group. The motion pictures industry is characterized by extreme uncertainty[7] (see De Vany and Walls 1999). 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 sub-optimal

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leverage.

[6] Lim and Wang (2001) suggest that there may be a trade-off between corporate diversification and hedging as risk management mechanisms.

[7] 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 dollars 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.

choice of projects as risk management, a-la DeMarzo and Duffie (1995). Importantly, 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, 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 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", it was just not budgeted right. All of these elements seem to point to sub-optimal (from shareholders point of view) risk reduction and revenue maximization as possible decision criteria. In the rest of the paper, we will consider violent entertainment from the perspective of managerial objective functions. The findings may also help explain the R-rating puzzle, and provide an economic backdrop to the violent entertainment debate.

The remainder of the paper is organized as follows. In the next section, we 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 3 we describe the data and the methodology. In section 4, we discuss the results in detail. Section 5 concludes.

2. 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) though 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 of 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 of 2000, in the height of the presidential elections campaign, the 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" (FTC report, 2000). This was followed by hearings in Congress, wide press coverage, and by pledges from industry to stop marketing violent movies to under-age viewers (see McClintock 2000, and Lyman 2000). In the wake of the terrorist attacks on the World Trade Center in September of 2001, some of the planned violent fare was postponed, and in particular, movies whose topic was terrorism. However, other violent films (such as *Thirteen Ghosts*, or *Training Day*) were released, and in early 2002 one of the delayed films, *Collateral Damage* was released too. It seems that not much can derail violent entertainment.

Whereas industry has agreed to limit 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 counter-arguments to requests to tame down the violent content of films. We summarize some of them in an appendix.

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, for example, Goldstein 1998; Hill 1997; 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 by Hamilton (1998). He argues that violent television programs may be attractive to some target audiences, but in the process, expose innocent viewers, and in particular children, to this violence. Thus, according to Hamilton (1998), 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 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 Glaeser and Glendon (1998), Anderson (1999) and Donohue and Levitt (1998). 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), 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 will 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, 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 the United States

3. Data and Variables

Much of the data in this paper is 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 5 very low budget films.

Baseline services in California provided the budget (negative cost) of each film, as well as 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 contains 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. This data was collected separately from various issues of *Variety* magazine. Advertising expenses were separately collected from various issues of *Leading National Advertisers* (1991-1993).

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 1 if the film is rated G and zero otherwise. The default is unrated films. Since the empirical goal of this paper 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 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 contained “brief” violent scenes. This group (VIOLENT) is further sub-divided 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 rated R for violent content, but are not “very violent”. The non-violent R-rated films are contained in a third group (RNOTV). In our tests, we sometimes group all violent films together, and at other times 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) vs. all other R’s (RNOSEX). These are cases where the MPAA description contains words such as “explicit sexual content” or “sensuality”. A small sub-set was named “STSEX”. It contains films with “strong” or “graphic” sexual content. We also define an interactive variable for films, which feature both sex and violence (SEXV).

We feel that this classification method, while imperfect, has the advantage of being the most objective possible. MPAA ratings are comparative descriptions handed out by a board that watches hundreds of films. 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 impact box office revenues[8]. To this end, for each film, Baseline provided a list of the director, and up to 8 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-ten 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 actor/actress or 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, which had no nominations. These new variables did not perform differently (in terms of sign and statistical significance) than the AWARD and NEXT variables, and hence are generally not reported.

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: Katz (1994) Maltin (1995) or Walker (1993). 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 least 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 bring in lower revenues than the original film, they may

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[8] In Ravid (1999), however, star power did not end up being a significant determinant of either revenues or return on investment.

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 1 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. MIXREVIEW is the ratio of non-negative 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, and on the other hand, a release in a low attendance period should be bad for revenues. However, since there are several peaks and troughs in attendance throughout the year, we use information from Vogel (2001 figure 2.4) to produce a somewhat more sophisticated measure of seasonality. Vogel constructs a graph, which depicts normalized weekly attendance over the year (based upon 1969-1984 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 which we call RELEASE to account for seasonal fluctuations[9].

[9] 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

4. Results

Table 1 below describes the data for 175 movies. The film with the highest budget in this sample is Batman Returns (70 million dollars). Batman Returns also turns out to be the movie that recorded the highest first week's box-office revenue - 69.30 million dollars. On average, positive reviews (POSREVIEW) account for almost half of the total (43%) number of reviews, whereas non-negative (including mixed) reviews comprise 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 6 G rated films, 25 that were rated PG, 44 that were rated PG13, and 94 R rated films. The rest of the films were un-rated. Out 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 non-zero 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, the rate of return, total revenues, and advertisement outlays are generally higher for very violent films than for other R-rated films, but *t*-values are low. However, the number of total reviews for very violent films is significantly lower and these

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 variables) will have more of an effect on the pattern of weekly revenues, rather than on the aggregate. Further, there are several studies which focus on this issue-see Einav (2002) and Eliashberg and Elberse (2002) as well as Filson et al.(2002) who present related work.

reviews are also worse. A similar picture obtains when we compare very violent films to all other films in the sample (table 2b).

Table 3a contains the most striking set of univariate tests. It compares all 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 3b). 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.

Table 4 shows that, surprisingly, there is not much action in the films that combine sex and violence. Table 5 compares all films with sexual content to other films. These films are cheaper to make and have lower international revenues than other R rated films, but the comparison with all films in the sample (table 5b) is more even 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 "legitimate" films with sexual content.

Subsequent tables contain regressions, where 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) vs. the rest of the R films (RNOSEXV). We also split the R’s into violent films vs. all other R’s, films with sexual content vs. all other R’s and films with strong sexual content vs. all R’s.

These latter splits (violent vs. non-violent films, or films with sexual content vs. films without sexual content) do not provide interesting results. Therefore, we report in Tables 6a 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 6a 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[10] (presented here), in all component regression and in the rate of return regression. We also ran regressions with the strong sex dummy vs. all other R's, but that dummy was not significant 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

[10] For a discussion of the presentation of the coefficients and standard errors see footnote 11 below and the statistical appendix.

much more interesting. First we focus on returns, which are of course the correct measure of economic success, and then we consider revenues[11].

The Rate of return Regression Results

Tables 6b show that violent, very violent films or films with sex and violence do not have a high rate of return. The OLS equation shows that at 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.

[11] All 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, Chapter 12). Fortunately, although the standard errors differ, most of our qualitative results are unchanged.

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, compared to video and foreign receipts, and thus is important to individual executives. Table 6b presents the two specifications of the domestic revenue regression[12]. 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 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, you do not need a star to succeed. One is reminded of the endless and successful series such as Friday the 13th or Murder on Elm St.- very violent films, with many sequels, which 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

[12] As noted earlier, all equations below passed the White test. Hence, 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.

regressions with different specifications for the stars (ANYAWARD or VALAWARD), and for reviews, but that did not affect the outcome. We can conclude that being just a violent film may not be enough, but very violent content, or violence with some sexual content, everything else equal, seem to have a significant positive effect on domestic revenues.

The International Revenue Regression Results

The international revenue regression is perhaps the most interesting. 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 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 6c). Further, the coefficient is high – that is, a very violent designation buys studios a lot of revenues. Non-violent R rated films, RNOTV, or violent, V, movies have no significant impact on international revenues. Sexual content is only significant in one specification (table 6c), 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): "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 Schwartznager movie *End of Days* (1999) which, by our classification, would fit at the extreme end of the very violent category, made only 67 million dollars in the U.S., but overseas revenues were 135 million dollars (see Diorio 2000).

The international success of very violent movies has also 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.

The Video Revenue Regression Results

Videos, on the other hand, are the realm of family entertainment. 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 or a sequel status significantly enhance video revenues. Interestingly, unknown actors negatively affect 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 21st century). Furthermore, consistent with our ideas, several studios have been issuing sequels to popular movies, such as Lion King or 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.

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 thus might change over time, as the revenue mix shifts. Table 6c 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. 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, and so 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 6c. 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.

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 6c), which 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. Interestingly, 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.

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, VALAWARD*VV, etc. 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.

We also substituted for our continuous release date measure the Chisholm (2000) and Litman (1998) release dummy variable, which measures “Holiday” vs. “Non Holiday” periods.

The resulting regressions did not produce any appreciable change in the coefficients and therefore 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.

Risk –Related tests

A comprehensive measure of risk at a project level is difficult to pin-point. 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.[13]

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", consistent with all previous work. Table 7 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 7 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 8a (see also figure 1) shows how various types of films are distributed in different 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 6-9th 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 5th through 9th 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 upper most 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 violent films and films with sex and violence are smaller. The results are presented in table 8b. This table shows again that very violent films and films that contains sex and violence have significantly lower variances than other films, and so do violent films[14].

Sequels

We left a discussion of sequels to 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 6b shows that sequels are at best marginally profitable. However, tables 6b and 6c show that sequel status significantly contributes to domestic revenues, video revenues and total revenues. They also open very well.

[13] Naturally, our rate of return variable is only a proxy, and therefore, if a film has a rate of return greater than 1 it does not necessarily mean that the studio actually made money. However, this proxy provides comparability across observations.

[14] De Vany and Walls (2002) find that R rated films in general are cheaper to produce and they 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 includes most probably our very violent, effect laden movies.

Similarly, in table 7 we see that sequels tend to break even much more often than other films. Table 8a 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**.**

5. 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 and psychological aspects. The current paper 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 sub-optimal risk choices and revenue maximization motives by studio executives. This is similar to studies of other industries where executives are exposed to signficant 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 increase 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 picutres industry. Basuroy Chatterjee and Ravid (2003) show that stars and big budgets help films that receive predominantly negative reviews, but have no effect on films that receive predominantly positive reviews. In a similar vein, Einav (2002) documents a seemingly sub-optimal clustering of release dates of films which may be the result of an attempt to herd.

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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, whereas INTLREV are the share of domestic distributors in box office receipts overseas.
VIDREV are video sales revenues.
INTLREV 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, R are dummy variables for ratings. These variables take the value of 1 if the film is rated G, PG, PG13 or R respectively and 0 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, but neither very violent nor containing extreme violence. V+VV are all the violent films.
RNOTV is the rest of the R films, i.e. ones that are not either V or 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 1 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, i.e., containing both sex and violence.
RNOSEXV is a dummy variable that takes the value of 1 if the film is rated R but is not SEXV.
POSREVIEW = positive reviews / total number of reviews.
MIXREVIEW = (positive reviews + neutral reviews) / total number of reviews
TOTREVIEW = total number of reviews.
UNKNOWN is a dummy variable receiving a value of 1 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 1 if any participant in the film had received an academy award.
ANYAWARD is a dummy variable receiving a value of 1 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 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 discussion in the text for an exact definition.
LN denotes the natural logarithm of a variable.

Appendix B

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 is 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, which are less successful domestically, may do well in video or internationally and vice versa. This observation is reinforced when we calculate the moments (see appendix table A below). 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, and 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 the 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, Kuh and Welsch (1980). After deleting these observations from the sample, we re-estimated the all the models. This procedure did not lead to any appreciable change in the results for the Total Revenue and the 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 bi-weight 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 multi-collinearity, employing Belsley, Kuh and Welsch (1980) collinearity diagnostics. Both the condition index and VARPROP were below the cutoffs suggested by Belsley, Kuh and Welsch (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. Hence 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 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 works best for large samples, hence we corrected the errors using the Davidson-Mckinnon procedure (see Green 2000, Chapter 12). Though the standard errors differ, most of our qualitative results are the same. Most of this information is repeated in footnote 11.

Appendix Table A: Mean, Median, Mode, Skewness, and Kurtosis Measures

	Rate	LnTotrev	LnDomrev	LnIntlrev	LnVidrev	LnOpenwk
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

Appendix C: The 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 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 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 twelve-month period. Of the 5030 movies that had violent content, only 2.8% received a four star rating, the highest quality ratings 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 9000 television programs and reported that in only 4% of the violent programs, characters displayed 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" (p. 342-343). All of these arguments are highly controversial, and it is beyond the scope of this paper 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[15].

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[15] . Some of the reasons offered are:

Catharsis i.e. 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).

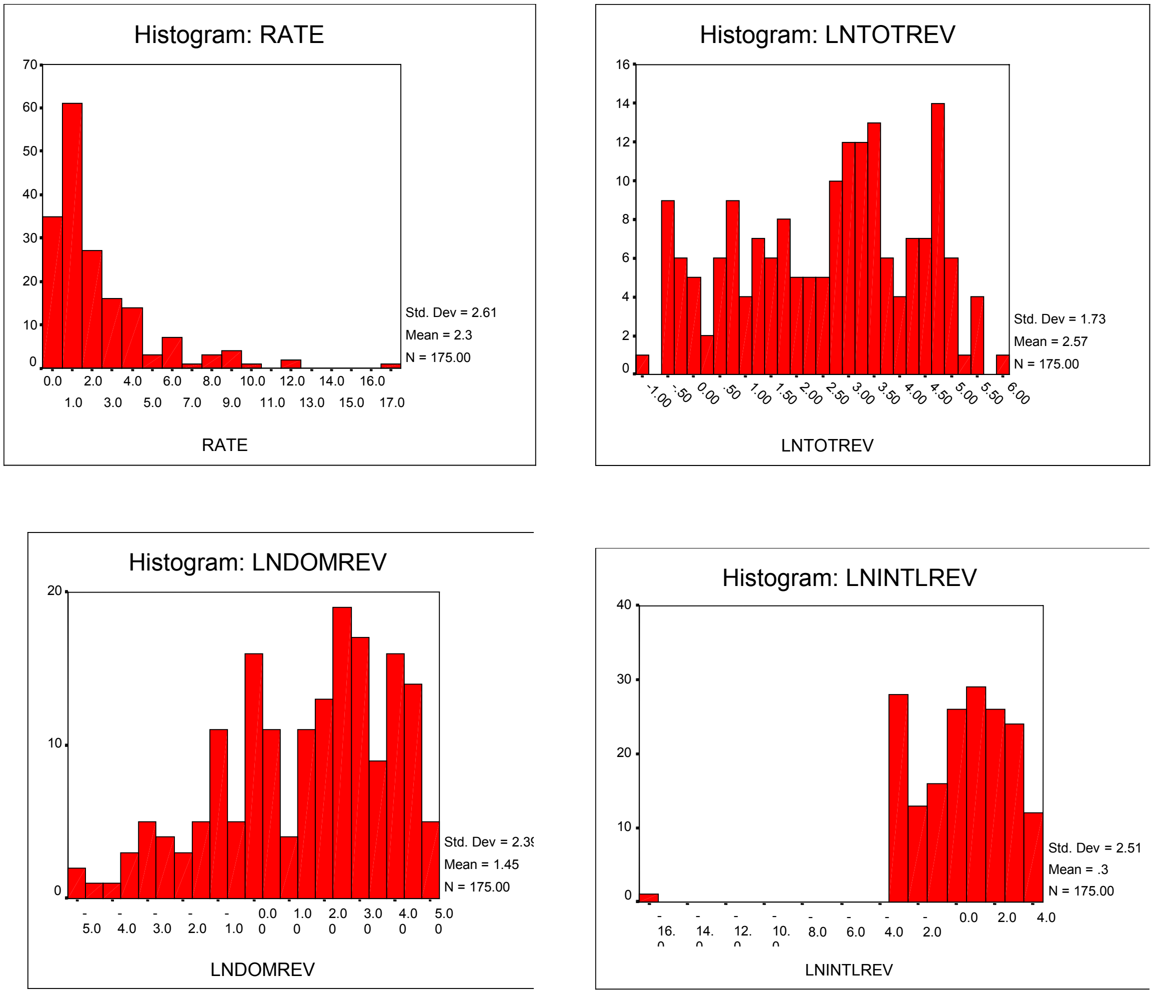
Viewing violence is a social activity. The media hype and peer pressure that surround some of the violent movies may make watching them a social activity. Often viewers do not watch violent movies alone, but do so in the company of friends. Hill (1997) quotes a focus group participant as saying "How can you go to a dinner party if you haven't seen Pulp Fiction?" (p. 23).

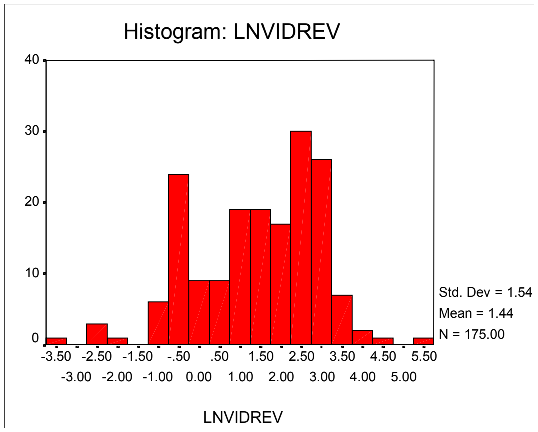
Real violence is raw and brutal and not entertaining. Consumers of violent movies do not find real violence entertaining. Watching movies is a safe way for understanding violence without having to experience the real thing.

Fictional violence is entertaining. Some movies are thought to be more entertaining than others depending on the representation of violence.

Pleasure of arousal. Zillman (1998) argues that people simply want to experience the pleasure of 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).

Figure 1: Distributions of revenues and rate of return




Histogram: LNVIDREV
40
30
20
10
0
-3.50 -2.50 -1.50 -.50 .50 1.50 2.50 3.50 4.50 5.50
-3.00 -2.00 -1.00 0.00 1.00 2.00 3.00 4.00 5.00
Std. Dev = 1.54
Mean = 1.44
N = 175.00
LNVIDREV

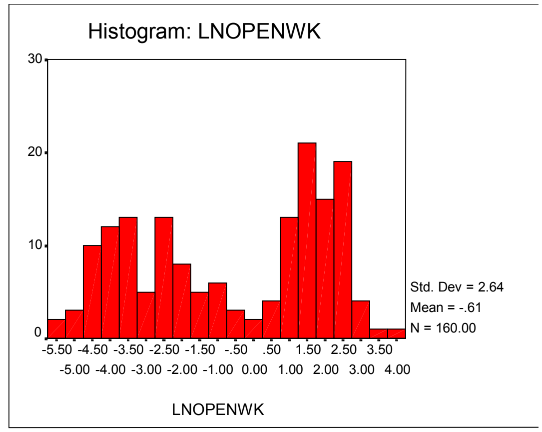

Histogram: LNOPENWK
30
20
10
0
-5.50 -4.50 -3.50 -2.50 -1.50 -.50 .50 1.50 2.50 3.50
-5.00 -4.00 -3.00 -2.00 -1.00 0.00 1.00 2.00 3.00 4.00
Std. Dev = 2.64
Mean = -.61
N = 160.00
LNOPENWK

TABLE 1: Descriptive Statistics of the Non-Dummy Variables (n=175)

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	0.01
OPENWKREV	4.02	0.76	6.23	45.69	0.00
INTLREV	7.82	1.71	13.06	69.30	0.00
VIDREV	10.70	5.27	20.28	233.70	0.03
RATE	2.27	1.29	2.61	17.05	0.08
TOTREV	40.60	17.50	60.33	426.30	0.35
AD	4.12	3.51	3.93	15.04	0.04
POSREVIEW	0.43	0.44	0.25	1.00	0.00
TOTREVIEW	20.90	19.00	9.94	43.00	3.00

Budget, Ad, and the Revenues are in Millions of dollars

TABLE 2a: Univariate Tests for Very Violent Films versus Other R Rated Films (n=94)

	VERYVIOLENT=1 (n=17)			VERYVIOLENT=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***

Budget, Ad, and the Revenues are in Millions of dollars
*** significant at .01 level; ** significant at .05 level; * significant at .10 level

TABLE 2b: Univariate Tests for Very Violent Films versus All Other Films (n=175)

	VERYVIOLENT=1 (n=17)			VERYVIOLENT=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***

Budget, Ad, and the Revenues are in Millions of dollars
*** significant at .01 level; ** significant at .05 level; * significant at .10 level

TABLE 3a: Univariate Tests for Violent Films versus Other R Rated Films (n=94).

	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

Budget, Ad, and the Revenues are in Millions of dollars.
*** significant at .01 level; ** significant at .05 level; * significant at .10 level

TABLE 3b: Univariate Tests for Violent Films versus All Other Films (n=175)

	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

Budget, Ad, and the Revenues are in Millions of dollars
*** significant at .01 level; ** significant at .05 level; * significant at .10 level

TABLE 4a: Univariate Tests for Films that Combine Sex and Violence versus R Rated Films (n=94)

	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

Budget, Ad, and the Revenues are in Millions of dollars
*** significant at .01 level; ** significant at .05 level; * significant at .10 level

TABLE 4b: Univariate Tests for Films that Combine Sex and Violence versus All Other Films (n=175)

	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

Budget, Ad, and the Revenues are in Millions of dollars.
*** significant at .01 level; ** significant at .05 level; * significant at .10 level

TABLE 5a: Univariate Tests for Films with Sexual Content versus R Rated Films (n=94)

	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

Budget, Ad, and the Revenues are in Millions of dollars
*** significant at .01 level; ** significant at .05 level; * significant at .10 level

TABLE 5b: Univariate Tests for films with Sexual Content versus All Other Films (n=175)

	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

Budget, Ad, and the Revenues are in Millions of dollars
***significant at .01 level; ** significant at .05 level; * significant at .10 level

Table 6a: Regression Results

Variable	**Total Revenue Regression (1)**	**Total Revenue Regression (2)**
How R is Split	SEX & RNOSEX	VIOLENT & RNOTV
CONSTANT	-1.655 (.593) [.519]	-1.585 (.590) [.512]
LNBUDGET	1.182 (.114) [.106]	1.075 (.112) [.106]
AWARD		-.061 (.251) [.255]
UNKNOWN	.069 (.233) [.257]	.066 (.229) [.265]
NEXT	.021 (.274) [.273]	-.004 (.287) [.291]
G	1.517 (.604) [.549]	1.608 (.599) [.543]
PG	1.245 (.482) [.433]	1.345 (.475) [.44]
PG13	.592 (.464) [.349]	.695 (.460) [.355]
POSREVIEW	.404 (.371) [.394]	.331 (.364) [.389]
TOTREVIEW	.029 (.011) [.011]	.034 (.011) [.011]
SEQUEL	.801 (.327) [.348]	.812 (.323) [.34]
RELEASE	.072 (.504) [.535]	.009 (.499) [.52]
SEX	.624 (.464) [.345]	
RNOSEX	.566 (.456) [.320]	
VIOLENT		.870 (.459) [.361]
RNOTV		.427 (.452) [.326]
ANYAWARD	-.188 (.179) [.185]	
R-Sq	.699	.705
Adj. R-Sq.	.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-ten grossing films (NEXT). Additional variables include the total number of reviews (TOTREVIEW), 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.

Table 6b: Regression Results

Variable	**Rate Regression (1)**		**Rate Regression (2)**		**Domestic Revenue Regression (3)**	
How R is Split	VV & V & RNOTV	SEXV & RNOSEXV	VV & V & RNOTV	SEXV & RNOSEXV	VV & V & RNOTV	SEXV & RNOSEXV
CONSTANT	-.649 (1.437) [1.126]	-.147 (1.504) [1.166]	.497+ (.135)	.544+ (.138)	-4.589 (.904) [.823]	-4.526 (.918) [.836]
LNBUDGET	-.002 (.269) [.225]	-.001 (.272) [.24]	-.009+ (.028)	.021+ (.025)	1.439 (.176) [.17]	1.441 (.169) [.178]
AWARD	.276 (.578) [.692]		-.009+ (.085)	-.014+ (.085)		-.212 (.390) [.352]
UNKNOWN	-.065 (.556) [.613]	-.025 (.566) [.601]	.020+ (.071)	.048+ (.070)	.281 (.353) [.422]	.324 (.357) [.406]
NEXT						-.006 (.442
G	4.733 (.145) [2.535]	4.667 (1.458) [2.594]	.346+ (.192)	.288+ (.192)	1.744 (.917) [.755]	1.555 (.929) [.79]
PG	3.449 (1.154) [.993]	3.256 (1.166) [.976]	.355+ (.155)	.325+ (.156)	1.660 (.732) [.672]	1.720 (.738) [.675]
PG13	1.116 (1.116) [.594]	.902 (1.121) [.554]	.196+ (.149)	.168+ (.150)	.892 (.705) [.546]	.888 (.714) [.555]
POSREVIEW	.934 (.883) [.862]	.063 (.934) [.902]	-.078++ (.166)	-.122++ (.162)	1.136 (.558) [.592]	1.198 (.565) [.614]
TOTREVIEW	.040 (.028) [.026]	.051 (.027) [.027]	.010+ (.003)	.008+ (.003)	.056 (.017) [.016]	.048 (.017) [.016]
SEQUEL	1.257 (.793) [1.047]	1.331 (.788) [.962]	.362+ (.113)	.375+ (.108)	.946 (.498) [.534]	1.168 (.503) [.535]
RELEASE	.050 (1.20) [1.201]	-.163 (1.203) [1.217]	-.114+ (.147)	-.103+ (.143)	.246 (.758) [.778]	.095 (.777) [.808]
VV	1.717 (1.213) [.728]		.187+ (.152)		1.537 (.767) [.691]	
V	1.472 (1.151) [.676]		.227+ (.150)		.973 (.727) [.581]	
RNOTV	.679 (1.096) [.557]		.040+ (.145)		.407 (.693) [.499]	
SEXV		1.508 (1.212) [.632]		.197+ (.149)		1.476 (.774) [.597]
RNOSEXV		.802 (1.087) [.491]		.080+ (.145)		.675 (.690) [.51]
ANYAWARD		-.022 (.432) [.389]			-.390 (.271) [.279]	
R-Sq	.235	.220	.343	.325	.636	.626
Adj. R-Sq.	.174	.163	.286	.271	.606	.596
F-value	3.82	3.82	5.99	6.03	21.64	20.75

The dependent variable in (1) is RATE, and in (3) 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 previous year's top-ten grossing films (NEXT). Additional variables include the total number of reviews (TOTREVIEW), 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).
+ The corresponding variable has been transformed through division by POSREVIEW.
++ The variable is (1/POSREVIEW)
Standard errors are in parentheses. Davidson-MacKinnon-White errors are reported in the brackets.

Table 6c: Regression Results

Variable	International Revenue Regression (1)		Video Revenue Regression (2)		Total Revenue Regression (3)		Opening Weekend Revenue Regression (3)	
How R is Split	VV & V & RNOTV	SEXV & RNOSEXV	VV & V & RNOTV	SEXV & RNOSEXV	VV & V & RNOTV	SEXV & RNOSEXV	VV &V & RNOTV	SEXV & RNOSEXV
CONSTANT	-4.536 (1.156) [.830]	-4.161 (1.178) [.83]	-1.138 (.570) [.505]	-1.137 (.563) [.498]	-1.653 (.592) [.526]	-1.579 (.587) [.513]	-5.177 (1.056) [.965]	-5.169 (1.084) [.994]
LNBUDGET	1.344 (.216) [.220]	1.300 (.217) [.177]	.901 (.108) [.105]	.914 (.104) [.106]	1.073 (.112) [.105]	1.141 (.113) [.112]	1.533 (.199) [.216]	1.708 (.196) [.208]
AWARD	.382 (.465) [.363]	.538 (.500) [.422]	.009 (.242) [.235]	.018 (.239) [.223]	-.098 (.251) [.252]		-.868 (.428) [.463]	-.778 (.417) [.491]
UNKNOWN	.750 (.447) [.405]	.704 (.458) [.404]	-.416 (.220) [.305]	-.443 (.219) [.297]	.066 (.229) [.268]	.017 (.231) [.256]	.374 (.412) [.416]	.372 (.428) [.40]
NEXT		-.072 (.569) [.479]	.186 (.278) [.213]	.267 (.272) [.204]	.073 (.289) [.29]	.038 (.271) [.275]	.266 (.498) [.553]	
G	1.508 (1.170) [.981]	1.508 (1.192) [.974]	1.376 (.577) [.592]	1.334 (.570) [.583]	1.622 (.599) [.544]	1.562 (.597) [.542]	1.517 (1.049) [.904]	1.207 (1.077) [.919]
PG	1.524 (.928) [.607]	1.598 (.947) [.587]	.618 (.457) [.454]	.595 (.453) [.453]	1.336 (.475) [.445]	1.266 (.476) [.430]	2.239 (.852) [.720]	2.122 (.877) [.718]
PG13	.910 (.898) [.573]	1.015 (.917) [.553]	.146 (.443) [.378]	.131 (.438) [.378]	.646 (.460) [.363]	.623 (.459) [.347]	1.208 (.828) [.637]	1.086 (.852) [.637]
POSREVIEW	.571 (.710) [.636]	.553 (.725) [.634]	-.098 (.350) [.332]	-.202 (.346) [.328]	.341 (.363) [.383]	.425 (.364) [.396]	-1.248 (..649) [.696]	-1.083 (.670) [.738]
TOTREVIEW	.044 (.022) [.021]	.033 (.022) [.019]	.012 (.011) [.012]	.010 (.010) [.012]	.037 (.012) [.012]	.031 (.011) [.011]	.047 (.202) [.018]	.031 (.020) [.018]
SEQUEL	.682 (.638) [.555]	1.058 (.646) [.558]	.633 (.316) [.298]	.684 (.309) [.266]	.742 (.328) [.351]	.845 (.324) [.338]	1.361 (.552) [.573]	1.539 (.556) [.519]
RELEASE	-.976 (.965) [.769]	-1.225 (.997) [.879]	.208 (.482) [.454]	.184 (.477) [.462]	.054 (.500) [.517]	.005 (.499) [.523]	-1.416 (.849) [.997]	-1.489 (.867) [1.01]
VV	2.000 (.976) [.616]		.137 (.481) [.486]		1.110 (.499) [.420]		2.221 (.903) [.705]	
V	.268 (.926) [.831]		.281 (.457) [.404]		.723 (.474) [.392]		1.685 (.849) [.702]	
RNOTV	.888 (.882) [.549]		-.204 (.434) [.404]		.413 (.451) [.334]		.559 (.813) [.965]	
SEXV		1.364 (.993) [.604]		.529 (.475) [.401]		1.038 (.496) [.364]		1.710 (.914) [.76]
RNOSEXV		.861 (.885) [.522]		-.127 (.423) [.498]		.502 (.444) [.310]		.997 (.827) [.598]
ANYAWARD						-.205 (.177) [.181]		
R-Sq	.463	.439	.659	.662	.707	.706	.650	.623
Adj. R-Sq.	.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

The dependent variable in (1) is log (INTLREV), in (2) is log (VIDREV), in (3) is log (TOTREV), and in (4) 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-ten grossing films (NEXT). Additional variables include the total number of reviews (TOTREVIEW), 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.

Table 7. Proportion of films that "Break-Even"

Film Content (1)	Proportion of films in (1) breaking-even (2)	Proportion of Other R-rated Films (= 94 - # in (1)) Breaking-even (3)	Proportion of All Other Films (=175 - # in (1)) Breaking-even (4)	Z-value: (2) vs. (3) (5)	Z-value: (2) vs. (4) (6)
SEX (n=38)	0.580	0.554	0.599	.28	.22
SEXV (n=17)	0.705	0.532	0.582	1.33*	1.01
VV (n=17)	0.765	0.519	0.578	1.81**	1.36*
V (n=30)	0.383	0.745	0.672	-3.56***	-2.49***
SEQUEL (n=11)	0.909	N/A	0.573	N/A	2.20***

***Significant at .01 level; **Significant at .05 level; *Significant at .10 level.

Table 8a. The Percentages of Different Types of Films In Various ROI Deciles

ROI Deciles	ROI Range	VV	SEXV	VIOLENT	SEQUEL
10th Decile	5.79 – 17.05	0	0	0.04	0.27
9th Decile	3.53 – 5.74	0.18	0.29	0.15	0.27
8th Decile	2.56 - 3.52	0.06	0.12	0.13	0.18
7th Decile	1.89 – 2.33	0.35	0.06	0.17	0.18
6th Decile	1.30 – 1.85	0.12	0.12	0.06	0.09
5th Decile	1.00 - 1.29	0.06	0.12	0.11	0
4th Decile	.70 - .98	0	0.06	0.13	0
3rd Decile	.50 - .69	0.12	0.18	0.09	0
2nd Decile	.34 - .49	0	0.06	0.04	0
1st Decile	.09 - .29	0.12	0	0.09	0

Table 8b. Results of F-tests for the variances of films in various categories.

Variances in	**VV (n=17)**		**VIOLENT (n=47)**		**SEXV (n=17)**		**SEX (n=38)**		**SEQUEL (n=11)**
	Other R (77) $F_{.05, 76, 16} = 2.06$	All Films (158) $F_{.05, 157, 16} = 2.01$	Other R (47) $F_{.05, 46, 46} = 1.69$	All Films (128) $F_{.05, 127, 46} = 1.45$	Other R (77) $F_{.05, 76, 16} = 2.06$	All Films (158) $F_{.05, 157, 16} = 2.01$	Other R (56) $F_{.05, 55, 37} = 1.64$	All Films (137) $F_{.05, 136, 37} = 1.51$	All Films (164) $F_{.05, 10, 163} = 1.81$
ROI	4.04/2.87 = 1.41 ns	7.29/2.87 = 2.52**	2.81/4.62 = .61 ns	7.67/4.62 = 1.66**	3.96/3.06 = 1.29 ns	7.24/3.06 = 2.36**	3.76/4.02 = .93 ns	7.59/4.02 =1.88*	6.81/5.01 =1.36

***Significant at .01 level; **Significant at .05 level; *Significant at .10 level; ns=Not Significant