

The Market for Motion Pictures:
Rank, Revenue, and Survival*

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Abstract

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Every motion picture is an innovation that competes for theater screens and audiences during its brief life against a changing array of imperfect substitutes. We analyze a large sample of motion pictures as an evolving rank tournament of survival and death. The results of a survival analysis indicate that the failure rate of motion pictures is time-dependent, and that survival time is strongly related to the number of initial bookings. Weekly box office revenue is highly convex in rank and thus is consistent with Rosen's (1981) superstar phenomenon. Our empirical results also have implications for the licensing arrangements between motion picture distributors and exhibitors which have been severely restricted as a result of U.S. court decisions (the Paramount Decrees).

JEL Classification: D2, L1, L8

1 Introduction

On any given day in every major city there may from 50 to 100 motion pictures playing on theater screens. Each is unique and its producer hopes it will catch that bit of magic that lights up the screen and the box office. Yet, few achieve this feat and most lead lives that are unpredictable and brief. Each film competes for screens and audiences during its brief life against a changing array of imperfect and equally unique substitutes. How is one to understand this market? Is there any sense in which this market could be called competitive and how is it organized? What institutions and contracts are adapted to this market environment and how do they shape the results?

We seek to answer some these questions by examining the relationship between contractual practices and motion picture hazard and survival distributions. Our modeling is based on a large sample of motion picture revenues and theater bookings during their theatrical runs. Our detailed sample of motion picture lifetimes is a rare look at this fascinating industry whose unusual and complex features challenge economic theory in interesting ways. As Smith and Smith observe, “Given the interesting characteristics of movies as ideal examples of differentiated products and of the institutional arrangements governing their production and distribution, such increased data availability would make this an exceptionally attractive area for applied micro-economic research” (Smith and Smith, 1986, p. 506).

Much of the empirical work on the motion picture industry has focused on the attributes of successful movies. Smith and Smith (1986) examined the impact of Oscar awards on the cumulative rentals of movies released from the 1950s through the 1970s. In more recent work, Nelson et al. (undated) have quantified the value of an Oscar award on movie revenues using a large panel of data and an event study methodology. In a somewhat broader empirical study, Prag and Cassavant (1994) examined the determinants of movie revenues and marketing expenditures and found that marketing expenditures and quality are important determinants of a film’s success, and that production cost, star actors and awards are positively related to marketing expenses.

In the present paper, we want to account for the dynamic patterns in the data. Because each film is unique and plays in its own way, its life as a commercial product in the theatrical market is hazardous. Indeed most motion pictures have short and unpredictable lives that because audiences must discover what they like and films compete against an ever-changing cast of competitors. For these reasons it is productive to use evolutionary models of survival and death to model the data.¹ We model competition among films in the theatrical market as an evolving rank tournament of survival.²

Motion pictures live and die in the box office tournament as they are challenged during their run by a randomly evolving cast of new competitors. The challengers come from films previously released and from newly released films. The contending films are ranked by film-goers and those with high rank survive and are carried over to the next week. Low ranked films fail and are replaced by new contenders.

These attributes of the motion picture market contribute to increasing returns and give the box office revenue distribution the distinctive convex shape of a tournament prize distribution.³ The leading products command a disproportionate share of the market and they have longer runs. Even then, a film's rank in the tournament is ephemeral and its life unpredictable. "In fact, of any 10 major theatrical films produced, on the average 6 or 7 are unprofitable, and 1 will break even" (Vogel, 1990, p. 29).

2 The Motion Picture Exhibition Market

Once a film is produced, it is distributed to theaters who "exhibit" it for audiences. The distributor chooses a release pattern—the number and location

¹See Alchian (1950), Nelson (1977) and especially Day (1975) for a discussion of evolutionary models.

²The theatrical release usually precedes the video market, and we are modeling only the theatrical stage. The video and foreign markets yield about as much revenue now as the theatrical market, though these revenues depend on a successful theatrical run. Consequently, the total revenue of a motion picture will usually exceed the theatrical revenue we are here modeling.

³Fixed costs with information feedback and limited outlets create "superstars" or "hits" as in Rosen's (1981) model. As this market is organized sequentially, increasing returns come through a lengthening of product life for successful films; the adaptive run is the primary mechanism for capturing hit revenues.

of theaters in which the film is “booked” or licensed to play. Distributors also choose a date at which to release their films for exhibition, looking for high demand periods and seeking to avoid playing against films that are strong substitutes. Distributors time some films for release during Easter and Christmas because they are high demand periods; films also vie for screens during the period preceding the Academy Awards. But, release timing is difficult because finishing a production and editing and preparing copies for release is highly uncertain.

The number of theaters and their locations for the initial release are based on the distributor’s *a priori* estimate of demand. The size of the initial release determines the number of “prints” or copies that are needed for distribution to each of the theaters. The number of viewers who are able to see the film is limited by the availability of seats in the theaters booked in the release. The Motion Picture Antitrust Decrees of the late 1940s limit the distributor’s release strategies significantly. All the signatories, the major theater owning studios during the 1940s, were made to divest themselves of their theaters. Until very recently, no distributors owned theaters. In addition, the decisions leading to the Decrees found illegal certain contracting practices that can limit a distributor’s release strategies: generally, long term contracts, franchises, or repeated licensing between a distributor and a theater are illegal under the antitrust laws.

Most distributors use an auction process to license films to theaters, following the advice of their lawyers who interpret the court rulings to say that an auction of individual licenses, one theater at a time, is the approved method. They send out bid letters announcing the tentative date the film is available to be played and the suggested terms the distributor is seeking. Theaters bid or respond indicating a willingness to negotiate a license and one or several of them are selected, depending on the distributor’s release plans. If the film plays better than expected and fills all these seats, there is an economy of scale up to the capacity of the system in each week the seats are filled.

Supply adaptation is dynamic. The supply of seats for a successful motion picture is adjusted by expanding the number of weeks the film runs in theaters

where it is booked; the exhibition license includes a “hold-over” clause which specifies a box office revenue in the latter weeks of the contracted run that will cause the run to be extended another week. Lengthening the run conditional on each week’s revenue is a source of increasing returns as the film’s production, print and advertising costs are fixed with respect to changes in the length of run.

Distributors use the information they acquire from box office reports to adjust the release pattern dynamically to match supply to demand. New exhibitors may seek to play the film if it is drawing large audiences and they can be added in accord with contractual commitments to the initial exhibitors and the availability of prints.⁴ Strong demand may even lead the distributor to produce more prints. Supply adjusts dynamically to high demand by adding exhibitors and lengthening runs. The decisions which distributors and exhibitors make during each week of a film’s run rely on information that is widely circulated in daily and weekly trade publications and overnight reports *via* proprietary channels.

A film’s release pattern represents its distributor’s strategy for acquiring the demand information that will guide subsequent decisions. The release also sets the initial supply of engagements. Because of the flexibility which the exhibition license affords to adapt the supply of seats to demand, the industry is able to capture bandwagon effects if word of mouth and other information starts one.⁵ A wide release on many screens draws a large, simultaneous sample in many theaters and cities. A tailored release strategy samples sequentially, starting at a few theaters and using the information from that sample to adjust bookings if the film builds an audience. Following its initial release, decisions to expand engagements or lengthen its run are both centralized and decentralized. The exhibitor uses local information about how the film is playing in his theater to decide how long to play it. This decision is conditioned on the exhibition contract, but it uses local information and the exhibitor’s assessment of how

⁴The contract “clears” an area around the licensing exhibitor of competing showings of the film.

⁵De Vany and Walls (1995) show that the information dynamics of motion pictures can produce bandwagon effects as well as swift death.

much other motion pictures might earn at his theater. Exhibitors in other locations monitor box office information in making their booking decisions if they have not already committed all their screens to other motion pictures.

The contract to exhibit a film usually requires the theater to show it for a minimum number of weeks; 4 weeks is a common minimum, though 6 and 8 week minimums are sometimes used. In addition, the contract contains a hold-over clause that requires the theater to continue exhibiting the film another week if the previous week's box office revenue exceeds a stipulated amount. The contract also clears an area near the theater where the distributor cannot license the film to other theaters.

Exhibitors pay to the film's distributor a weekly rental for the privilege of playing it. The rental usually is some percentage of the exhibitor's box office revenue. The typical arrangement might call for the exhibitor to pay 90 percent of his box office revenue in excess of a fixed amount negotiated as part of the contract; this fixed amount is referred to as the "house nut" in industry parlance. In addition, the rental rate is subject to a minimum percentage of total box office revenue. The minimum rental rate usually declines over the length of the run; a typical arrangement for a four week run might be minimum box office percentages of 70, 70, 60, 60 in the first, second, third and fourth weeks, respectively. Additional weeks beyond the contract period often have a minimum rental rate of 40 percent of total box office revenues. Throughout the run, the 90 percent rental rate will be triggered any time the weekly box office gross exceeds the house nut by a sufficient amount.⁶

The declining rental rate is an incentive to the exhibitor to continue the film even as its box office revenue declines over its run. After it has run for the contracted minimum number of weeks, the film must then gross more than its hold-over figure to continue playing. Or, it must yield the exhibitor higher earnings than the alternative motion pictures available. Thus, the decision to continue the exhibition is placed in the hands of the exhibitor after the contingent hold-over clause no longer is binding.⁷ Whether it is the hold-over

⁶See De Vany and Eckert (1991) for an analysis of motion picture exhibition contracts.

⁷Kenney and Klein (1983) note that the exhibitor may have an incentive to over-search and show that the liquidated damages provision of the block-booking contract often used before it

clause or the exhibitor’s decision to hold a film over, the decision to extend the run at each theater uses local information about how the film is playing at that theater. The temporal and spatial distribution of a film’s engagements is self-organized; it evolves after the opening release in response to the pattern of demand throughout the film’s run, adapting to the audience through contingent contracting and exhibitor decisions that rely on a mixture of global and local information.

3 Evolutionary Survival Tournaments

Each film must earn a critical level of box office revenue to survive. Otherwise, theatrical exhibitors will choose to exhibit another film. The critical level changes as audiences change, films play out their runs, and other films begin their runs. The level of revenue that ensures survival is the amount the film must earn each week to be carried over in theaters to the following week. As we said above, the survival level partly is set by the hold-over amount in the exhibition contract. But, it depends also on what the film earns against the other films competing with it for screens.

Motion pictures can be modeled as if they are competing for the top fifty spots in our data as though they are in a tournament.⁸ Suppose there are $m(t) > 50$ motion pictures competing at time t for these 50 spots. Rank box office revenues at time t from high to low in the m -dimensional vector $r = (r_1(t), r_2(t), \dots, r_m(t))$, where low numerical ranks indicate high box office revenues. Revenue is a random variable which may depend on the motion pictures in the tournament, which change each week. The cutoff revenue which a film must earn to survive from week t to $t+1$ is a random variable $C(t) = r_{50}(t)$. A film i playing at time t survives if its revenue exceeds the critical level, $r_i(t) \geq C(t)$, and it dies otherwise. Every film in the top fifty sample meets this condition by definition. When a motion picture does not meet the condition, it

was outlawed limited search. In the present context, over-searching would mean an exhibitor ends the run prematurely, something that is guarded against, in part, by the minimum run and the hold-over clause.

⁸Our data are *Variety’s Top-50* motion pictures, consisting of the top 50 revenue earning motion pictures playing each week. Hence, without restricting generality, we speak here of 50 slots in the tournament.

dies and falls out of the sample to be replaced by another contender. Generally, a film will move up or down in rank during each week of its run. The length of occupancy time in each rank is a random variable and we place no restrictions on this stochastic process, letting the data determine the statistics of survival in rank. In order to have a long life, a film can achieve high rank and occupy several ranks before death, or it must spend a long time at low rank or ranks. This latter path to a long run seems unlikely and the data confirm this.

A few films will achieve high rank in their first week, but most will not. If a film gains acceptance it may increase its rank over time, but its revenues eventually must fall as it exhausts its potential audience. Over its lifetime, then, a film's rank must eventually decline. As it ages and declines in rank, it becomes vulnerable to newly released pictures and we might expect that its occupancy time in rank becomes more brief; its hazard also should rise.

We should expect a film's rank at birth to be the mean rank, 25.5, and expect its rank at death to be between 26 and 50. These do hold for the sample (see Table 1); mean rank at birth is 25.51 and mean rank at death is 36.02. The median rank at birth is 26 and the median rank at death is 39. Similarly, longer lived films must achieve and sustain high ranks. In the sample, the mean life is 5.71 weeks and the median is 4 weeks. Of 31 films that ran 6 weeks, 28 were at sometime in their run ranked in the Top 10 or higher. Films that achieved a highest rank of 1 during their run had a mean run length of 17.67 weeks. The top ranked film holds its first place position an average of 2.86 weeks, nearly twice as long as films hold second place in the ranking. Mean time in rank declines as rank declines.

4 The *Variety* Data

The data are from *Variety*'s domestic box office sample. The *Variety* sample is a computerized weekly report of domestic film box office performance in major and medium metropolitan market areas. The sample includes the box office revenue, the numbers of theaters and screens showing a film, the number of weeks of the run on any prior release, the rank, and the number of weeks in the current release on the chart of the top fifty grossing movies in the United States.

These data are from a sample of theaters covering approximately 12–15% of the nation’s screens. Summary statistics of the sample are contained in Table 1.

Each film in the sample was tracked from its birth to its death: birth is defined as the inception of a run and death is defined as falling off the *Top-50* chart.⁹ The sample includes 350 unique motion pictures that were listed on *Variety’s Top-50* chart during the interval from May 8, 1985 to January 29, 1986, inclusive. Of these movies, 251 entered for the first time and 99 re-entered after previously falling out of the *Top-50*; the two groups of films are referred to as *New-Entries* and *Re-Entries*, respectively.

The top four grossing movies in our sample accounted for 20.5% of the total box office revenue, and the top eight grossing movies accounted for 28.1% of the total box office revenue. In descending order the eight highest grossing movies in the sample were *Back to the Future*, *Rambo*, *Rocky IV*, *Cocoon*, *The Jewel*, *The Goonies*, *The Colorado*, and *White Knights*. The four lowest grossing movies accounted for only 0.0036% of the total box office revenue, and the eight lowest grossing movies accounted for 0.0082% of the total box office revenue. The highest grossing movie, *Back to the Future*, earned cumulative revenues of \$49.2 million, while the lowest grossing movie, *Matter Of Importance*, earned \$4,615. The mean of box office revenue is \$1,918,261 and its standard deviation is \$4,528,685, more than twice the mean.

In Table 2 we see that half the films that ran just one week opened in the bottom 10 ranks, and half of these were in the bottom 5. The highest rank achieved by 34 films that ran 2 weeks was in the top 5, but 6 of these were in the bottom 5. How can a film rank in the top 5 and last just 2 weeks? It could if it were heavily promoted and widely released but received unfavorable word-of-mouth information after it opened. The longest run by a film whose rank never exceeded the bottom 10 was 5 weeks (two made it).

The highest ranked films live longer and the lowest ranked die sooner. Films that made rank 1 ran at least 9 weeks and at most 30 weeks. The longest running film ran 40 weeks without ever getting into the top 10 ranks. Another feature of

⁹Some of the films in the sample were censored because they remained on the charts after the terminal date of our sample. The survival model estimated in Section 6 explicitly accounts for the censored data.

the market that fits the tournament characterization is that the market renews weekly with new contenders and old survivors. Each new entrant replaces a former contestant, so for each birth there is a death. Figure 1 shows how births and deaths varied over the sample. As few as 3 and as many as 14 films were replaced each week in the sequence of tournaments and the average rate of births/deaths is 7.69 per week. Deaths and births are Poisson distributed.¹⁰ Most films showing in a given week are survivors from prior weeks. The average number of deaths is nearly 8 per week and between 35 and 47 films in the *Top-50* tournament are carry-overs.

The Gods must be Crazy was the longest running film at 40 weeks, but it generated only 0.74% (\$4.98 million) of the total box office revenues. *Back to the Future* was the second longest running film at 30 weeks, and it generated the highest revenue (\$49.2 million) at 7.34% of the total revenue. The third longest running film at 27 weeks was *Kiss of the Spider Woman* with .89% (or only \$5.95 million). The fourth longest running film was *Rambo* with about 5.25% (or \$35.2 million). The fifth longest running film at 21 weeks was *Prizzi's Honor* with 1.56% (\$10.5 million). Films with runs between 5 and 11 weeks generate 50% of the total revenue.

5 The Survival Model

The analysis of duration is important in motion pictures as increasing or shortening the length of the run is the most common way to adjust supply to demand. The other margin of supply adjustment is the number of screens playing a film. So, the time pattern of box office revenue, the number of screens showing it, and the duration from its birth to its death contain most of the information about the interplay of demand and supply.

The theatrical life cycle of a motion picture is a pure birth-death process in a system that is time-dependent. Define the *survival time* of a motion picture as the time interval from birth until death. This time interval is a random variable τ with distribution function $F(t) = \text{Prob}(\tau \leq t)$. The *survivor function* is

¹⁰The hypothesis that Births/Deaths are Poisson distributed could not be rejected using a χ^2 goodness-of-fit test. The marginal significance level was 0.545.

defined as the probability that a movie is still alive at time t and is denoted by $R(t) = 1 - F(t)$.

The probability that a movie alive at time t will fail prior to time τ is the conditional distribution $F(\tau|\tau > t)$. Given that the movie is alive at time t , the probability that it will die between t and $t + dt$ is given by the product $f(\tau|\tau \geq t)dt$. At time ($\tau = t$) the conditional density is a function of t alone and is known as the *hazard rate*, the instantaneous rate of failure for each time t : $h(t) = f(\tau|\tau \geq t) = -\frac{r(t)}{R(t)}$, where $r(t) = R'(t)$ is the density of the survivor function. The hazard rate representation of the survival model has a natural interpretation: it is the probability that a movie will fall from the charts during a time interval given that it is on the charts at the beginning of the interval.

As a function of time the hazard rate may be increasing, decreasing, or constant.¹¹ An increasing hazard would reflect the saturation of demand, while a decreasing hazard would reflect the increased attendance effected by an information cascade. De Vany and Walls (1996, Fig. 1) identify several patterns relating box office revenue, a film's rank in the *Top-50*, and the length of a film's theatrical run that illustrate the various forms of the hazard rate. For example, some films, such as *Back to the Future* open at a high rank and revenue and gradually decline in rank and revenue until falling from the charts. Other films, such as *Pumping Iron*, open at a relatively low rank and build revenue and increase in rank. Other films enter the charts at at low rank and fall rapidly from the charts.

In addition to modeling the shape of the survivor function and the hazard function, it is of interest to model the effects of explanatory variables on these functions. Postulate the survivor function $R(t)$ to depend on a vector of variables z that represents the attributes of a movie's theatrical run. Suppose further that there is a function of the attributes $\psi(z)$ such that the survivor function can be expressed as $R(t; z) = R_0(t\psi(z))$ where $R_0(\cdot)$ refers to the baseline survivor function where $z = 0$ and $\psi(0) = 1$. In this formulation the z

¹¹Note that a constant hazard rate is a necessary and sufficient condition for the survival time to follow an exponential distribution. A constant hazard rate reflects the exponential distribution's lack of memory. When the survival times follow an exponential distribution the probability of failure in an interval (t, τ) depends only on the length of the interval $(\tau - t)$.

variables simply increase or decrease the argument of the survivor function.¹² Cox and Oates (1984) have shown that this survivor model can be rewritten as

$$\log T = E[\log T_0] - \log \psi(z) + \epsilon \quad (1)$$

where ϵ is independent of z . This parameterization is referred to as the accelerated life model and it is estimated in the following section.¹³

¹²The function $\psi(z)$ may take values greater than or less than one corresponding to decreasing or increasing survival times, respectively.

¹³An alternative parameterization is to model the effect of z on the hazard function directly: $h(t; z) = \psi(z)h_0(t)$. This form is referred to as the proportional hazards model. Cox and Oates (1984) have shown that the accelerated life model and the proportional model coincide when survival times follow a Weibull distribution.

6 Empirical Results

6.1 Empirical Survivor Functions

We initially estimate the survivor function using a nonparametric estimator so that we need not make any assumptions about the distribution of survival times. We use the product-limit estimator which is a function of the data only; moreover, it is a maximum likelihood estimator of the survivor function in that it maximizes the general likelihood over the space of all distributions (Kaplan and Meier, 1958). As a purely empirical approach to examining the survival and hazard functions the product-limit estimator can provide only a limited amount of information, but it is useful to employ this method since it is largely immune to heterogeneity and the restrictions imposed by parametric models.¹⁴

Each movie in our sample was observed for a single spell on the *Top-50* charts. However, some movies had previously appeared on the charts (Re-Entries) and other movies made their debut on the charts (New-Entries). We estimated the baseline survivor functions for the groups New-Entries and Re-Entries, and we tested them for equality using the Logrank and Mantel-Haenszel tests.¹⁵ The null hypothesis that the survivor function for New-Entries into the *Top-50* is the same as the survivor function for Re-Entries could not be rejected at conventional significance levels.¹⁶ Thus, we pooled observations on Re-Entries and New-Entries.

Figure 2 plots the product-limit estimate of the survivor function for the entire sample. The estimated survivor function is decreasing and convex, showing that most movies tend to drop out of the *Top-50* soon after birth. A movie has less than a 25% chance of lasting 7 weeks or more in the *Top-50* and less than a 15% chance of lasting 10 weeks or more. A film with “legs,” surviving more than 15 weeks on the charts, is an aberration when compared to the population

¹⁴For example, correcting for heterogeneity in the parametric Weibull model can overparameterize the model and lead to seriously misleading statistical inferences (Heckman and Singer, 1984).

¹⁵See Pagano and Gauvreau (1993) for a discussion of the product-limit estimator and the tests for equality of survivor functions. See Kalbfleisch and Prentice (1980) and Cox and Oates (1984) for more mathematical discussions.

¹⁶The the Logrank test had a marginal significance level of 0.507, and the Mantel-Haenszel test had a marginal significance level of 0.502.

of motion pictures that breaks into the *Top-50*. In interpreting the empirical survivor function it is important to emphasize that the *Variety* data are a national sample, so that movies will generally move between theaters within the nation during their theatrical runs. Rarely would all theaters book a film simultaneously so that a film would fall from the charts when its contracted run ends. Moreover, theaters in different towns will make their own agreements as to minimum length of run and hold-over clauses. Thus the theatrical run would rarely, if ever, wholly be determined by the minimum run specified in the first-run contract and is dependent on box office revenues.

Figure 3 plots the maximum likelihood estimate of the hazard function.¹⁷ The plot indicates increasing time dependence of the hazard rate. Thus it is appropriate to consider theoretical survival distributions which allow for a *non-constant* hazard rate. One such distribution that is often used in practice is the Weibull distribution. When survival times follow a Weibull distribution, the survivor function is

$$R(t) = \exp \left\{ - \left(\frac{t}{\sigma} \right)^\lambda \right\} \quad (2)$$

and this can be written in the log expected time form as

$$\log \{ - \log [R(t)] \} = - \lambda \log(\lambda) + \frac{1}{\sigma} \log(t). \quad (3)$$

In this specification the time-dependence is a parameter to be estimated: when $\sigma = 1$ the hazard rate is time-independent; when $\sigma < 1$ the hazard rate is an increasing function of time; when $\sigma > 1$ the hazard rate is a decreasing function of time. The Weibull model also allows the survival model to be estimated more efficiently since it takes advantage of the actual survival times and not only their ordering.¹⁸

6.2 Estimates of the Survival Model

We now examine how weekly revenue, the release pattern, rank, and time into the run affect expected survival. We are interested in discovering how these

¹⁷See Kalbfleisch and Prentice (1980, pp. 15–28) on the maximum likelihood estimator of the hazard function.

¹⁸We also estimated a Cox proportional hazards model to provide a check on the assumption of a Weibull distribution. The estimated relative risks were nearly the same as those obtained from the proportional hazards parameterization of the Weibull model (De Vany and Walls, 1993).

variables condition a film’s expected life given its history at each point in the run. We estimated the survival model with the vector of explanatory variables including the number of first run bookings, the week’s revenue, the number of weeks the film previously had been in the *Variety’s Top-50* (“release” in Table 3), the film’s rank, and the number of showcases in which the film played in its debut on the charts.¹⁹ Many of the explanatory variables are factors that would cause an exhibitor to continue showing a film either voluntarily or as the result of a contingency in the exhibition contract; for example, high revenues in a given week would trigger the hold-over clause and would be expected, *ceteris paribus*, to increase the life a film. Our inclusion of the number of weeks a film previously had been in the *Top-50* is intended to investigate how this previous exposure altered the play pattern of a film that was re-released. Tracking such films (*ET* is an example) permits inference to be made on the effect of previous exposure. Finally, we controlled for seasonality in movie attendance that might affect the hazard rate by including a set of dummy variables for the movie release dates.

Table 3 reports the estimation results for the censored Weibull regression model. We can statistically reject the hypothesis that the hazard rate is time-independent ($\sigma = 1$) in favor of the alternative that the hazard rate is an increasing function of time ($\sigma < 1$). For the explanatory variables we report the coefficients as $\exp(\beta)$ or time ratios for ease of interpretation: each reported coefficient indicates the multiplicative factor for expected survival time for a one unit change in the regressor. The number of first run screens, revenue, and the number of weeks in which the film previously was in the *Top-50* each increase significantly the survival time of a movie. The effect of weekly revenue was an expected result of the model and is implied also by the “hold-over” clause of the exhibition contract. For a re-released film, the number of weeks it ran in its previous release is a measure of its entertainment value and this value carries over to the subsequent run; this is a strong confirmation of information transmission and memory. That the number of first run engagements might

¹⁹Screens and showcases were very highly correlated, and many observations of screen data were missing, so we used showcases instead to proxy the total number of screens.

increase survival time is evidence that release strategies are reasonably well-designed, for this positive association indicates that films with good prospects are booked in more first run engagements.

Only the number of first runs appears to be *economically* significant, increasing the survival time by 11.3%. The number of showcases, our proxy for the total number of screens playing the film, and the film's numerical rank decrease survival time. After its early weeks, a motion picture begins to lose rank and it becomes more vulnerable to replacement by the exhibitor with another motion picture. If a film is widely released initially, it may die quickly if it dilutes revenues among many theaters. If a film earns low revenue per screen exhibitors will replace it with another with better prospects. Thus, a wide release cannot guarantee high revenues after the early weeks and may lead to a short run. If many exhibitors are willing to show a film, then its revenues will be high in early weeks. But, only films with high revenue potential will be taken by a large number of theaters. Moreover, in order to induce many theaters to take a film, the distributor might have to accept lower terms for it.

6.3 Rank and Revenue

The survival model has shown how each of the attributes of a movie's theatrical run affect the survival time conditional on the other attributes. In this section we quantify the cross-sectional relationship between rank and revenue across movies that were included in the *Top-50*. We examine this relationship in order to demonstrate the convexity of the prize distribution for each week in the survival tournament. It is through a highly convex prize distribution that some films with relatively short lives are able to earn high revenues and some films with relatively long lives earn low revenues.

Figure 4 plots the rank and revenue for the movies in the *Top-50* for the final week of our sample. It is apparent that the prize distribution is highly convex in rank for this week. The plots of revenue versus rank for the other weeks of the sample also looked like rectangular hyperbolas. Thus, we quantified the relationship between weekly revenue and rank by estimating regressions of the following form: $\text{revenue} = \beta_1 + \beta_2 \frac{1}{\text{rank}} + \mu$. This functional form has

the desirable property that the change in revenue with rank declines as rank declines, *i.e.* $\partial(\text{revenue})/\partial(\text{rank})$ varies as rank varies. Moving from rank 2 to 1 may lead to a large decrease in revenue, while moving from 50 to 49 will not. Since $\partial(\text{revenue})/\partial(\text{rank}) = -\beta_2/\text{rank}^2$ and $\partial^2(\text{revenue})/\partial(\text{rank})^2 = \beta_2/r^3$, the payoff distribution is decreasing and convex in (the numerical value of) rank if $\beta_2 > 0$. We included week-specific dummy variables in the estimated equations to allow the distribution of revenue across ranks to shift between weeks; this controls for seasonality or other unobserved changes in movie attendance may occur on a week-to-week basis. We also controlled for heteroscedasticity and the length of run in some of the regressions.

We suspected that when a film earns high revenue (a numerically low rank) the variance in revenue earned would be high, and when a film has a low rank (numerically high) the variance would be low. To test for this form of heteroscedasticity we sorted the data by rank, separated the data into two halves, and applied the Goldfeld-Quandt heteroscedasticity test. We rejected the null hypothesis of homoscedasticity at the 1 percent marginal significance level. We corrected for the heteroscedasticity by weighting the observations by $\sqrt{\text{Rank}}$. Table 4 reports the unweighted OLS regression results and the heteroscedasticity-corrected GLS results of the revenue—revenue relationship.

We found that β_2 was significantly different from zero at the 1% marginal significance level in all of the estimated regressions. Thus, the distribution of prizes is highly convex in the rank. To illustrate this, we calculated the change in the prize from a one step fall in rank from rank 1 through 5 using the estimates shown in column (3) of Table 4. The results of the calculations are shown in Table 5 and they illustrate the implications of the convex prize distribution for a change in rank: Falling from rank 1 to rank 2 decreases weekly box office revenue by about \$2.4 million, while falling from rank 4 to rank 5 decreases box office revenue by only about \$235,000. This highly convex revenue function is consistent with Rosen’s (1981) superstar phenomenon in which small differences in talent are magnified into enormous differences in success.²⁰

²⁰The highly convex revenue distribution could also result with competitors that are homogeneous with respect to talent. See, for example, Adler (1985) and Chung and Cox (1994).

7 Conclusions

Motion pictures lead hazardous lives. The hazard that a film's run will end is high and rising over the run and its expected life is brief. The variance of film revenue is high. Just a few highly ranked films earn nearly all the revenue. The hazard rate varies with time; it is low early in a run and high late in the run. A time-varying hazard implies that audiences have a taste for variety

Long runs do not guarantee success because revenue is highly convex in rank. Many of the longest-lived films in our sample earned a small box office revenue and some of the top-grossing films had relatively short lives. A specialty film may play on only a few screens and it may run a long time if its audience develops slowly and its revenue is not diluted over many screens. A mass appeal film usually will be licensed to many theaters. Because there are many screens, it may play off rapidly because demand is saturated quickly. Its revenue per screen will fall rapidly and exhibitors drop it. Only a few widely released films are so appealing that they have "legs" and run for many weeks. When they do, they become the superstars. A long and broad run is typical of the handful of films that lie at the upper tail of the revenue distribution. Durability is unpredictable because each film meets many challenges from existing and new releases during its theatrical run.

Time-dependent survivor functions incorporate information about revenues, rank, and other characteristics of the film's play from the opening to its last week. Information flows through word-of-mouth transmission among viewers, through advertising, and is disseminated by trade information to exhibitors and distributors. The adaptive run is the primary mechanism for capturing motion picture value and casting out failures. It depends on a mixture of flexible contracting and the use of global and local information that decentralizes decisions to expand or contract exhibitions in response to demand.

Current antitrust decisions and policy with respect to the licensing of films and ownership of theaters by distributors have implications for what sorts of films are produced and how they are exhibited. The courts have required films to be individually licensed, theater by theater, and solely on the merits of

the film and theater. This requirement has stood in the way of ownership, franchising, or other forms of long-term contracting between exhibitors and distributors. It also has been interpreted to restrict multiple-picture licensing. In practice, what this has meant is that it is not possible for a theater to agree with a distributor to exhibit more than one film at a time. No contracts can be made for the whole season of a distributor's releases, nor for any portion of them. This makes it impossible for a theater to be the outlet for a single distributor such as Twentieth Century or New Line Cinema or Buena Vista. Nor is it possible to license a series of films to theaters as a means of financing their production. Moreover, the inability to contract for portfolios of motion pictures restricts the means by which distributors, producers and theaters manage risk and uncertainty.

In general, the licensing restrictions of the Paramount decisions limit the ability of exhibitors to supply funds to finance motion pictures. At one time, when the studios owned their own theaters and when they could contract for many productions with theaters for a period of years, the theaters were among the primary means of financing production. This was labelled "block booking" and halted by the Paramount Decrees. The licensing and ownership restrictions of the Paramount antitrust litigation has made it impossible for exhibitors to finance the production of motion pictures for release in their theaters. As a result, motion picture financing falls almost entirely on the distributors who rely on internally generated funds or the capital market. This, in turn, has probably been a major factor in the emergence of the concept of a "bankable" star whose participation in a project can assure its financing because the star will get it on theater screens where it has an opportunity to earn revenue.

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Table 1: Summary Statistics of *Variety*'s Box Office Sample

Variable	Obs	Min	Max	Median	Mean	Std. Dev.
Rank at Birth	350	1	50	26	25.51	16.19
Rank at Weeks=2	266	1	50	22	23.06	15.49
Rank at Weeks=3	232	1	50	24.5	24.24	15.43
Rank at Weeks=4	191	1	50	21	23.46	14.30
Rank at Weeks=5	173	1	50	24	24.28	13.39
Rank at Death	309	1	50	39	36.02	11.84
Weeks at Rank=1	14	1	12	1.5	2.86	3.03
Weeks at Rank=2	27	1	4	1	1.48	0.75
Weeks at Rank=3	30	1	4	1	1.33	0.71
Weeks at Rank=4	35	1	3	1	1.14	0.43
Weeks at Rank=5	33	1	3	1	1.21	0.60
Weeks in Top-50	309	1	40	4	5.71	5.18
Showcases	2000	1	347	13	53.12	73.25
Cities	2000	1	191	4	7.44	8.08
Weekly Revenue (1,000's)	2000	2.5	10,000	57.5	335.70	685.26

NOTES—The sample contained 350 movies of which 309 were observed to fall from the *Top-50* chart. The remaining 41 movies were censored. Rank at Death and Weeks in *Top-50* were calculated using only the uncensored observations.

Table 2: Distribution of Highest Rank and Length of Run

Length of Run	Number of Films by Highest Rank Achieved					
	All	Rank = 1	Top 5	Top 10	Bottom 10	Bottom 5
1	84	0	1	2	39	22
2	34	0	1	2	7	6
3	41	0	3	6	6	1
4	18	0	3	8	1	0
5	19	0	4	8	2	0
6	31	3	10	15	0	0
7	31	2	12	18	0	0
8	13	0	5	7	0	0
9	14	1	5	8	0	0
10	11	2	7	8	0	0
11	7	0	3	3	0	0
12	10	0	1	1	0	0
13	10	1	4	5	0	0
14	9	1	5	8	0	0
15	3	0	0	2	0	0
16	3	0	1	0	0	0
17	2	0	0	1	0	0
18	2	0	0	0	0	0
19	1	1	1	1	0	0
20	2	0	0	0	0	0
21	1	0	1	1	0	0
22	1	1	1	1	0	0
27	1	0	1	1	0	0
30	1	1	1	1	0	0
40	1	0	0	0	0	0

Table 3: Accelerated Life Model

Censored Weibull Regression Estimates^a
 Controlling for the Date of Release^b

Parameter	Estimate ^c	Standard Error ^d	<i>t</i> -statistic ^e
First Runs	1.113241	0.0365918	3.264
Revenue	1.000165	0.0000603	2.744
Release	1.019550	0.0052376	3.769
Showcase	0.996470	0.0011858	-2.972
Rank	0.973358	0.0067019	-3.922
σ	0.420	0.028	-20.714

Ancillary Statistics

Log Likelihood = -98.322

Model $\chi^2(5) = 118.954$

Pseudo $R^2 = 0.4020$

NOTES—

^a 41 out of the 350 motion pictures were not observed to fall from the Top-50 chart during the sample. The Weibull regression model explicitly accounts for the censored data.

^b A set of week-specific dummy variables was included in the regression equation. The marginal significance level for the set of dummy variables was 1.67 percent.

^c Estimates of explanatory variables are reported as time ratios.

^d Standard errors are conditional on σ .

^e *t*-statistics are for the null hypotheses that the parameters equal unity.

Table 4: Distribution of Box Office Revenue and Rank

INDEPENDENT VARIABLES	COEFFICIENTS			
	(1)	(2)	(3)	(4)
1/(Rank in Top-50)	3,644.86 ^a (53.37)	3,601.98 ^a (53.55)	4,703.30 ^a (64.12)	4,692.78 ^a (63.96)
Weeks in Current Run		-9.40 ^a (1.72)		-2.24 ^a (0.59)
Constant	-89.61 (52.95)	-76.35 (52.62)	-87.87 ^a (18.27)	-85.22 ^a (18.22)
Week-Specific Variables ^b	yes	yes	yes	yes
Observations	2000	2000	2000	2000
R^2	0.70	0.71	0.74	0.74
Estimation Method	OLS	OLS	GLS	GLS
Weighting Factor	—	—	$\sqrt{\text{Rank}}$	$\sqrt{\text{Rank}}$

NOTES—Dependent variable is weekly box office revenue in thousands of dollars. Standard errors are in parentheses.

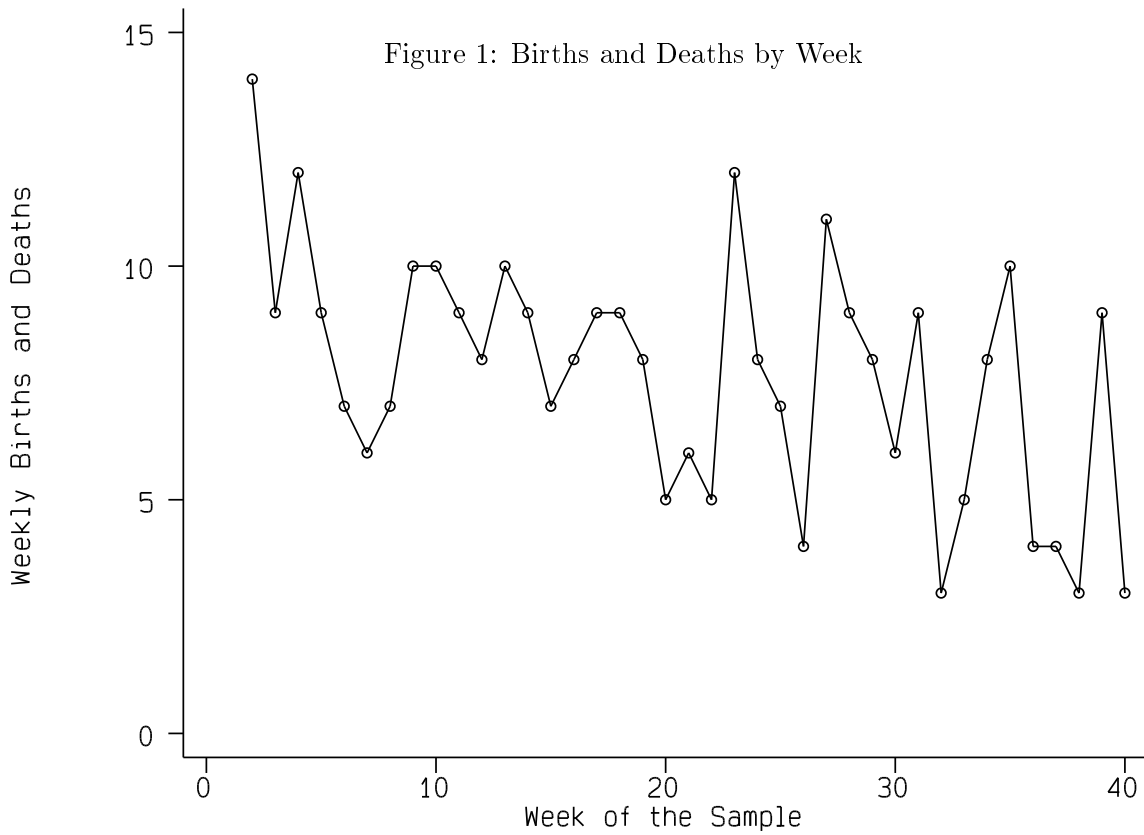
^aIndicates marginal significance level ≤ 1 percent.

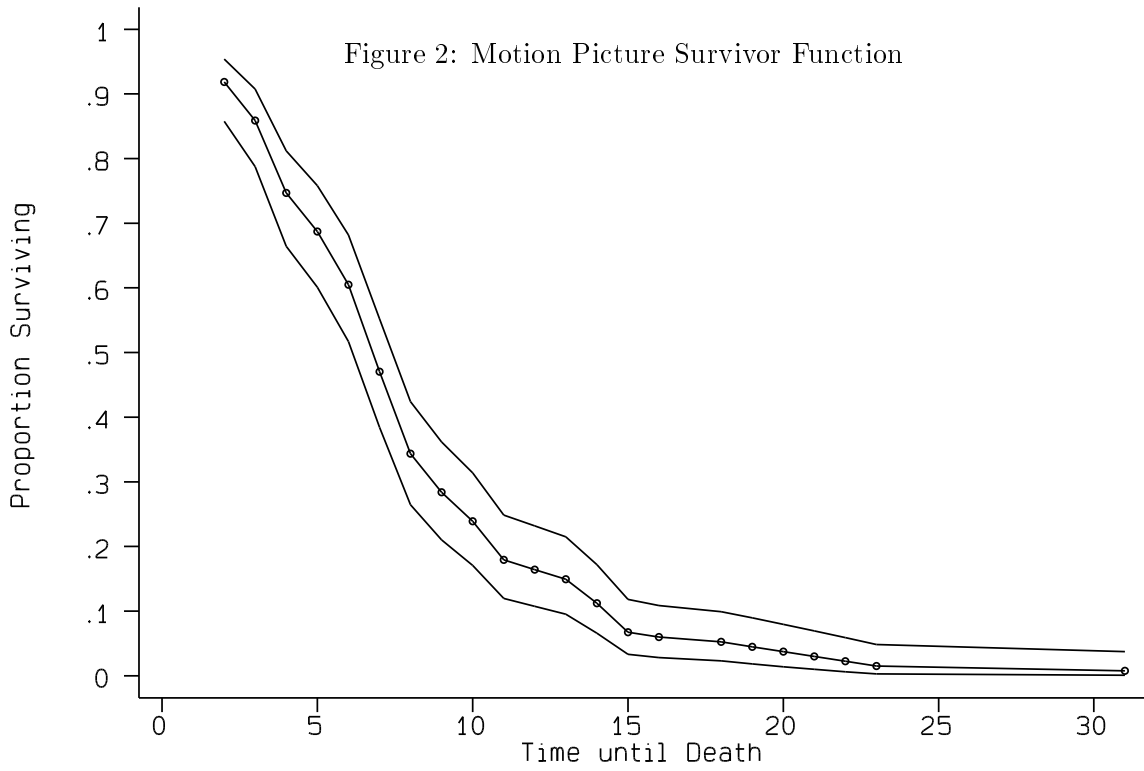
^bDummy variables were included for each week in the sample except the first week. The set of weekly dummy variables was significant at the 5% level in each regression equation.

Table 5: Decline in Revenue with One Unit Decline in Rank

<u>Rank</u>	<u>$\partial\text{Revenue}/\partial\text{Rank}$</u>
1	-\$4,703,300
2	-\$2,351,650
3	-\$1,567,770
4	-\$1,175,820
5	-\$940,660

NOTE—These effects of rank on revenue were calculated from estimated equation (3) in Table 4.





Survivor Function Estimate with 95% Confidence Bands

Figure 3: Motion Picture Hazard Rate Function

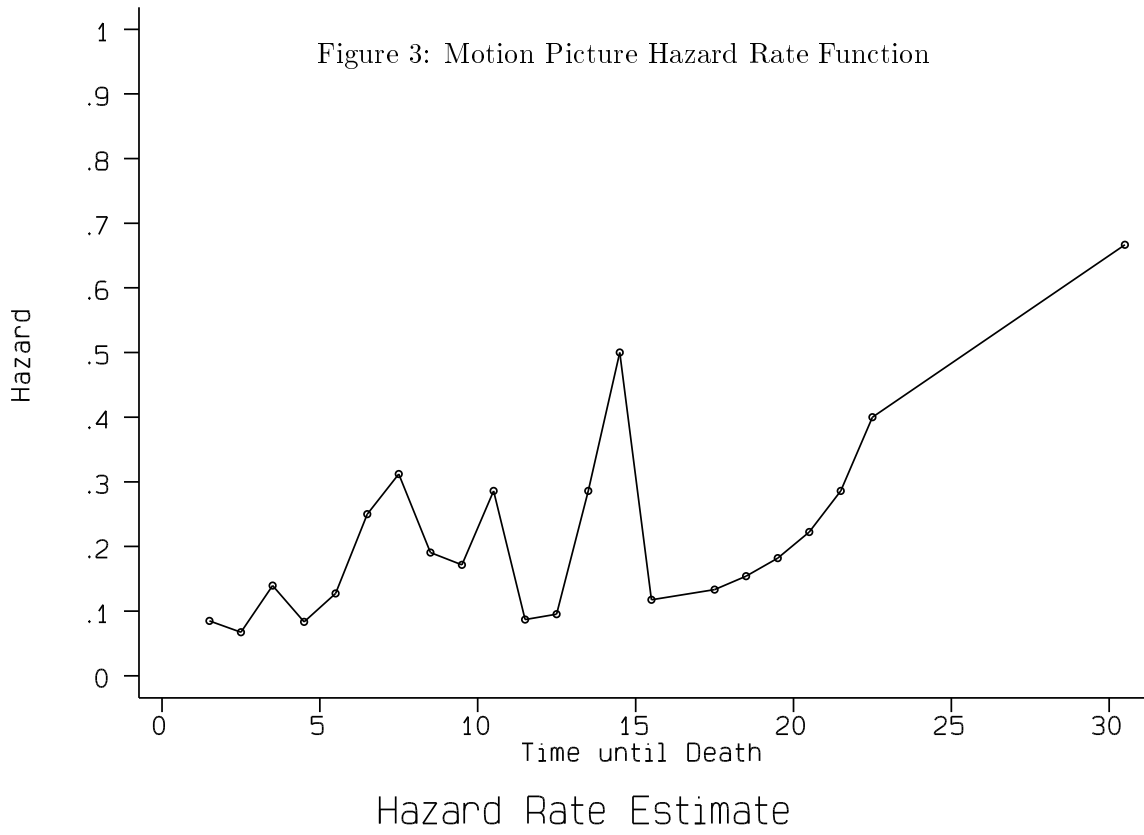


Figure 4: Box Office Revenue and Rank

