

# **Blockbusters: Building Perceptions and Delivering at the Box Office**

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## **Abstract**

*The Hollywood Stock Exchange (HSX) is an on-line market that tracks the perceived value of movie talent and their product: the movies themselves, while they are in development or production. We model the decision rules that drive this market place and estimate the underlying decision parameters by calibrating the evolution of a selected sample of 23 movies released in 2001-2002. Our results show systematic differences in the decision rules followed by the market for the eventual winners (a.k.a. the blockbusters) and the losers at the box office. Regression analysis of combined decision parameters for winners and losers cannot explain the variance in the box office performance. However, segmenting these data between winners and losers provides selective insights about how the aggregate market perceptions evolve.*

## **Key Words**

Movie, Box Office, HSX, Actor, Director

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## **Caveat**

All findings are based on publicly available data from ([www.hsx.com](http://www.hsx.com)). HSX has provided us access more detailed data. However, our analysis does not account for some of the details. To that extent, the findings in this paper are preliminary.

## 1. Introduction

Movies are a multi-billion dollar business. An average of 300 movies are developed and released every year in the US. Developing movies is a very expensive endeavor. For instance, the cost to produce Harry Potter and the Chamber of Secrets, one of last year's blockbusters, was \$120.5 million. Its revenue from the box office was \$255.5 million in the first 10 weeks after release; this amount is expected to triple through post release market sales such as: DVD, rentals, television rights and merchandise. Producing, releasing and launching movies amount to a special case of the new product development (NPD) process. While the development process of conventional products such as automobiles has been studied extensively (Clark and Fujimoto, 1991), the decisions of movie making have generally gone without much analysis within the NPD literature.

The development side of movies is characterized as a risky business with nearly 95% of movie projects getting canceled or failing to return the expected profit. This is primarily because decision-makers, such as studio executives, distributors and merchandisers, are asked to commit millions of dollars towards projects based on the speculated creative abilities of the talent, i.e. actors and a director. The problems are compounded because these decision processes are flooded with scripts and themes that may not be in line with the studio's preferences (Trip 1997). Another uncertainty in the mix is how well a particular movie script/theme will be received. Speculations about talents' abilities are typically gauged based on the perceived public perception. Studio executives attempt to match the right talent with the right script at the right time to maximize the potential at the box office and the after market. The decision making process is clouded by two layers of bias. The first bias originates from the customers' perception and the second originates from the executives' perception of the market place.

In this paper, we argue that studying the evolution of public perceptions can shed light on factors that drive these perceptions during development. We have crafted this argument by exploring a data set from the Hollywood Stock Exchange ([www.hsx.com](http://www.hsx.com)), an information clearing house where visitors buy and sell virtual shares of talent and movies with a currency called the Hollywood Dollar®. Hollywood Dollars are allocated to each new member at no cost because

they are a fictional currency. The company's virtual technology allows an unlimited number of consumers to trade thousands of virtual entertainment securities in a fair and orderly, supply-and-demand-based market. These data are an excellent proxy for the consumers' perception of talent and movies because of this free market environment. We explore the question: are market assessments, and underlying decision rules, of a movie's stock on HSX a good predictor of the movie's box office earnings and return on investment. We defined a decision rule as a numerical composite of the weights that the market puts on different parameters that drive the stock price.

We conduct an aggregate analysis of a data set from a sample of 23 movies (and their associated talent), released over a two-year period, using a simple single feedback loop model to estimate decisions rule parameters. We then conduct regression analysis to statistically explore if the underlying decision making process deals with a dynamic environment while accounting for market feedback effects. The results suggest that, consistent with the findings of other dynamic decision making situations (see Sterman 1989; Kampmann 1992), the HSX market as a whole is a poor predictor of return on investment and box office success. However, when we segment the data into populations of winner and losers, we illustrate that the estimated decision rules can provide selective insights into the biases within the decision making process.

The rest of the paper is organized as follows. We begin by describing the decisions associated with the movie development process and how these decisions reflect the reference modes derived from the HSX market place. This is followed by a short discussion of the literature on estimating decision rules in dynamic markets. We then describe our constructs, model formulation, data collection, and analysis methodology. This is followed by a presentation of the statistical findings. The paper concludes with a discussion of the limitation of our approach, managerial implications of these findings, and possible extensions for this work.

## **2. Decisions Associated within the Movie Making Process**

The movie making process consists of four very distinct stages, with equivalent "phases" and "gates" in the conventional NPD terminology where projects are approved, recycled, or canceled

(Cooper, 1994; Ulrich and Eppinger 2000). These stages are - development, green light, production, and distribution.

## **2.1 Development**

A project in the ‘development’ stage has been typically sourced from books, characters, plays, or simply an idea. It is not uncommon for movie projects to be simply titles at this stage with no script attached. The development process consists of developing a story through numerous iterations on a script. Content for a script will be found through story meetings, research, interviews, and multiple writers rewriting drafts of scripts.

Projects can stay in the development stage for as long as a studio chooses. Studios will, from time to time, sell projects to each other. Some projects are considered to be ‘fast tracked’ which usually means that they are on track for being produced within a few months. Often times, titles, which are fast tracked, have acting talent already associated with them, and script drafts are customized to the particular talent.

Major studios (Disney, Warner Bros., Universal, etc.) will spend millions of dollars developing projects with many of them never reaching the next stage. Development expenses can range from \$100 thousand to \$10 million per movie. Typically, the high development expense films are those that require extensive research (documentaries) or extensive consulting for realism (e.g. Pearl Harbor). Usually about 1 in 10 projects, which are in development, make it past the development gate at the major studios.

## **2.2 Green Light**

The green lighting process at most studios consists of negotiating talent assignment and solidifying the production budget. It is typical for a producer to already be attached to the project by this point either because the producer brought it to the studio, or because a producer was attached during the development stage. The studio then faces a ‘chicken and the egg’ problem where a director will usually accept assignment to a project only if a certain actor/actress is attached, and vice versa (unless of course the project was brought to the studio as a package deal, which is not uncommon). Once the top acting talent, the director, the shoot

schedule, and the budget have been agreed to – the studio chairman will ‘green light’ the project moving it to the production stage. Approximately 1 in 5 projects, that pass through the initial development gate makes it through the green lighting process.

### **2.3 Production**

During production the budget, plan, and schedule developed during the “green light” stage are executed. The production budget consists of ‘above the line’ (ATL) and ‘below the line’ (BTL) expenses. ATL expenses are talent related expenses, which can make up nearly 50% of the total production budget of the film (e.g. *The Sixth Sense*). BTL expenses are the actual shooting related expenses (i.e. set design, travel, craft services, etc.)

Studios are able to accurately predict the shoot schedule of most films, which in turn allows them to accurately determine a release date. Along with the shoot schedule, a studio will take into account their film pipeline (a.k.a. the film slate) and competition so as not to cannibalize their revenues or mismatch the release against other films.

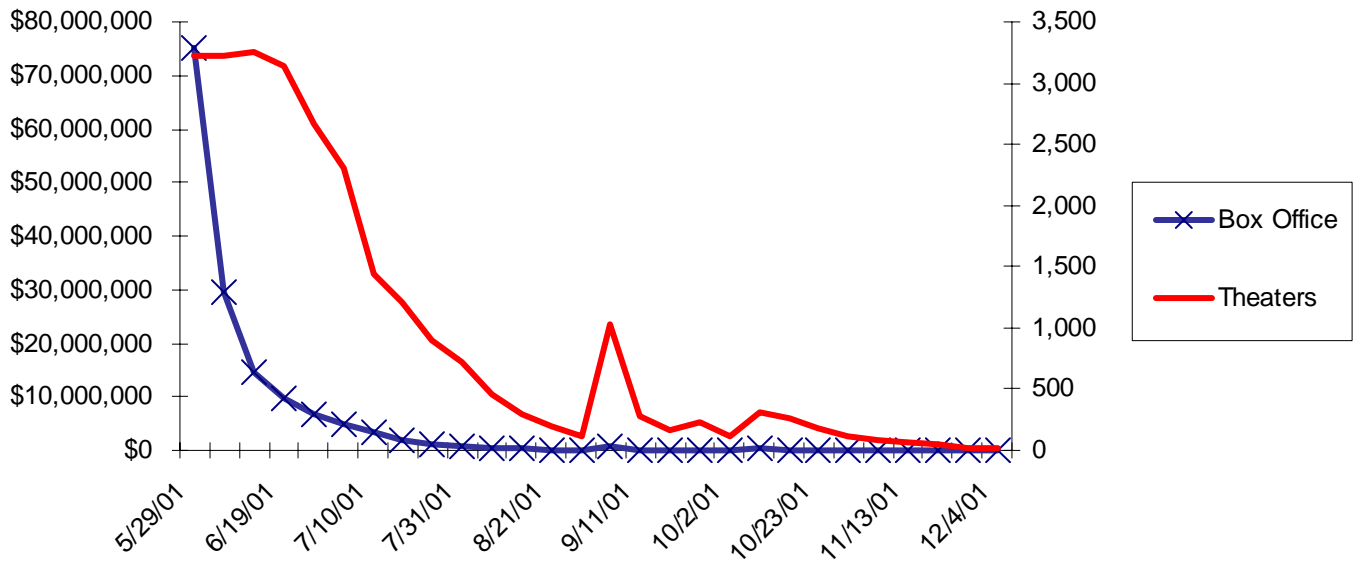
Once a reasonable amount of footage has been shot and a release date has been decided upon, the studio’s marketing group can begin assembling the marketing collateral (i.e. trailers, one-sheets, etc.) and the actual marketing investment. The marketing investment is typically not a function of the production budget of the film, but rather the studio executive’s expectation of the film’s performance at the box office. Trailers are released to the public at this point creating an early awareness of the film. These trailers often serve as the first point of contact with users of HSX and typically cause the most noticeable increase in a movie’s stock price. There is quite a bit of time invested in positioning the movie appropriately in the marketplace since many viewers use this form of marketing as their final decision on seeing the movie.

### **2.4 Distribution**

Figure 1 shows the typical evolution of the cumulative box office revenue and the number of theaters showing the movie. It is important to note that the box office returns evolve rather quickly, in 10 weeks or so, compared with the development cycle that takes more than 100 weeks. In anticipation of the box office run, and concurrent with the marketing group’s

preparation, a studio’s distribution team decides the number of theatrical screens and the delivery schedule. The number of screens is also based on the studio’s expectation of the film. Typical blockbusters are released on about 3,500 screens (Spider-Man reached about 3,800 at its widest point). Eliashberg et al. (2000) have modeled prerelease market evaluation of motion pictures, however their work does not account for a web based perception-tracking systems.

**Pearl Harbor**  
**Weekly Box Office and # of Theaters**



**Figure 1: Box Office Revenue and Theater Coverage for the movie Pearl Harbor**

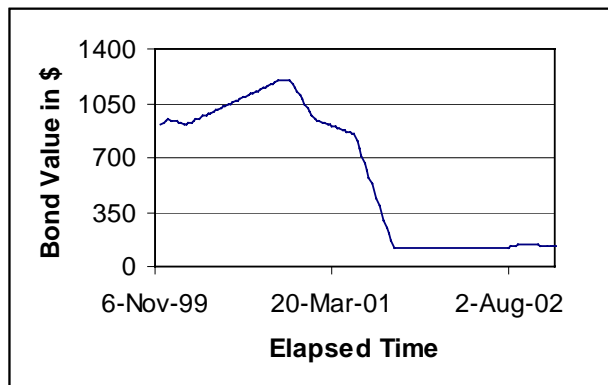
The marketing group also works in conjunction with the film’s producer and director in conducting test screenings. These test screenings are designed to give the marketing team an idea of the demographics that the film appeals to (via analyzing data obtained in audience screenings) and to indicate to the director portions of the film that may need to be changed. It is not uncommon for a movie to make significant amendments to the film at this stage ranging from the downplaying of a character to fundamentally changing portions of the movie. In some isolated cases the release date is changed to match the public’s interests or to preempt competition.

### 3.0 HSX and Decisions of Movie Making

The Hollywood Stock Exchange is an on-line marketplace. It treats Hollywood talent like financial securities and allows for a market price to be determined through active trading. The typical user of HSX is a person who has a fair amount of knowledge about the entertainment industry, reads trade journals such as Variety, and has a socially curious interest in ‘the business.’

Talent (producer, director, actor and writers) bonds are constantly traded without being de-listed unless the talent is no longer active (i.e. retired, deceased, etc). Typically, a talent’s bond rises and falls are directly attributable to their current productions (see Figure 2 for M. Night Shyamalan’s lifetime bond value. In his case there was an IPO on 11/24/99 right after the release of The Sixth Sense. An IPO is an initial public offering, which for HSX means that it is the first time that the stock or bond was available for purchase by investors.

Evolutions of a selected set of movie stocks, some winners and other losers, are the reference modes that we will explore systematically in the second half of this paper.

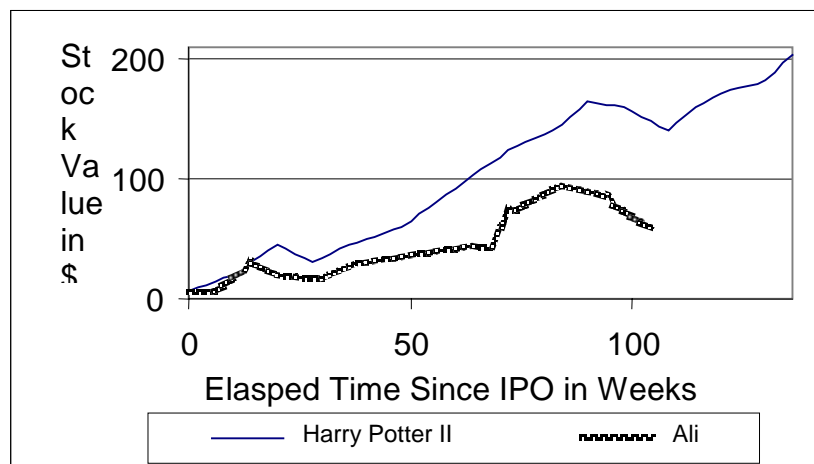


**Figure 2: Lifetime Bond Value for M. Night Shyamalan**

When a movie is first announced, its Stock receives an IPO price and it is available for trading until a few weeks past the release date of the film. During this time users can buy and sell the stock at their own discretion. Figure 3 shows the stocks of “Harry Potter and the Chamber of Secrets” (IPO on 5/01/2000 under the name HPOT2, released on 11/15/2002; Life = 135 weeks)

and “Ali” (IPO on 12/14/1999 and released on 12/25/2001; Life = 104 weeks). Trading is heavy: HPO2 was traded 3,384,340 times over its life. Harry Potter turned out to be a winner at the box office where as Ali was a loser in terms of its box office collections.

As the movie gets closer to completion there is a greater amount of information known about the movie, which in turn would affect the perceptions of HSX users. Preliminary movie trailers are probably the most descriptive information that becomes available causing active buying and selling shortly after trailer releases. Additionally, there are a number of entertainment periodicals, which track movie productions very closely. The Hollywood Reporter has a weekly issue that details changes to active productions throughout the industry. Presumably, with a trained eye, one can see the impact of budget overruns and changes of release dates as being positive or negative for the referenced stock.



**Figure 3: Reference Modes for the Stocks of Harry Potter-II and Ali**  
(Data sets terminate upon theatrical release)

The evolution of stock and the estimated box office revenue is of interest in the equity analysis community as well. Besides the obvious application of the model’s output to determine which movie studio has the most powerful and potentially successful pipeline of products, it can also be used to improve tax and financial reporting procedures. The improvement will come from having better estimates of the lifetime revenues of the movies, which can then be more accurately depreciated, based on incoming revenue (Lesley 1996).



We also view this data as a natural experiment for studying market dynamics. Data on market-based assessments of products while they are under development are rarely available. In many instances, scholars have studied the decision making process underlying such markets by running controlled experiments. There is a rich tradition within the system dynamics literature for estimating aggregate decision rules in controlled settings that simulate either idealized markets (Kampman, 1992) or industrial situations such as Beer Distribution (Sterman 1989), Real Estate (Bakken, 1993) and Service Supply Chains (Anderson and Morrice 2000). Much of this literature illustrates that actors tend to ignore much of the dynamic stimuli, relying on their mental models, and in general perform sub-optimally in such settings.

These data lend themselves to estimation of market decision rule parameters in a manner suggested by Oliva (2003b). In his work, Oliva had used the calibration capability of the system dynamics simulation tools to make optimal estimates of model parameters. Oliva has also argued for the use of Theil Statistics to assess the goodness of fit between the observed and the simulated data. In the following section we build on this methodology to inform our research design and to develop cross-sectional estimates of decision rule parameters within our data set.

#### **4. Research Design**

Our research design seeks to:

- (i) model and estimate the decision rules that guide the evolution of our reference mode, namely the time history of a movie stock from it's IPO to the release;
- (ii) assess, in aggregate, if the estimated decision rule parameters influence the box office and critical performance of these movies

##### **4.1 Modeling the Decision Rule**

We build on the system dynamics tradition (Sterman 2000) by modeling perception as a stock that seeks to reach a target value. The target value is driven by the decision rules for the HSX market place.

$$\begin{aligned} \text{Movie\_Stock}(t+1) = & \text{Movie\_Stock}(t) & (1) \\ & + \{ \text{Target\_Value}(t) - \text{Movie\_Stock}(t) \} / \text{Time to Adjust Perceptions} \end{aligned}$$

$$\text{Target\_Value}(t) = W_1 * \text{Actor}_1(t) + W_2 * \text{Actor}_2(t) + W_3 * \text{Actor}_3(t) + W_d * \text{Director}(t) + W_{ru} * t + W_{cp} * \text{Completion Pressure}(t) \quad (2)$$

Where:

- $W_1, W_2, W_3, W_d, W_{ru}, W_{cp}$  are the unknown parameters within the decision rule. We assume that these parameters are time invariant.
- $\text{Actor}_1(t), \text{Actor}_2(t), \text{Actor}_3(t)$  and  $\text{Director}(t)$  are known parameters for the talent pool's value in the HSX market place
- $t$  is the elapsed (a.k.a. ramp up) time in weeks since the IPO of the movie on HSX
- $\text{Completion Pressure}(t) = 1 / \ln(\text{Release Date} - t)$ ; the Release Date is measured as the elapsed time since the IPO in weeks.

We justify the specification of the decision rule for the target value based both on literature and on anecdotal evidence around practices within the movie industry. Recall from the discussion in sections 1 and 2 that executives in the movie industry put a lot of emphasis on the choice of the talent pool while funding the movies. Also, recall that these data are immediately available as cues to the HSX users through a web-based interface. The choice of variables associated with timing, i.e. elapsed time and completion pressure, has been identified as key drivers for performance in the NPD literature (Ulrich and Eppinger 2000).

#### 4.2 Estimation of Decision Rule Parameters

We follow the procedure suggested by Oliva (2003a) while calibrating the model outcome against the time series for stock performance. The fitted model seeks to minimize the gap between the estimated and the observed time series by selecting the decision parameters:  $W_1, W_2, W_3, W_d, W_{ru}, W_{cp}$  and **Time to Adjust Perceptions**. (see Appendix) The default settings for the input parameters and optimization control parameters during the search are listed in the appendix.

We save the time series for the fitted model and compute Theil statistics for goodness of fit using a free-ware module made available by Oliva (2003b). While accepting the fit, we wish to minimize the bias and maximize the co-variation between the fitted and observed data set.

Indicators of the goodness of fit statistics for the aggregate data are presented in section 5 along with the results.

### 4.3 Decision Parameters and Ex-Post Performance of Movies

Estimated decision rule parameters are regressed against the ex-post performance of the movie at the box office (Box Office) and the associated pay off (Pay Off) taken from [www.baseline.com](http://www.baseline.com).

The regression models are specified as:

$$\text{Box Office} = \alpha_0 + \alpha_1 * W_1 + \alpha_2 * W_2 + \alpha_3 * W_3 + \alpha_4 * W_d + \alpha_5 * W_{ru} + \alpha_6 * W_{cp} + \alpha_7 * \text{Time to Adjust Stock} + \epsilon_{BO} \quad (3)$$

$$\text{Pay Off} = \beta_0 + \beta_1 * W_1 + \beta_2 * W_2 + \beta_3 * W_3 + \beta_4 * W_d + \beta_5 * W_{ru} + \beta_6 * W_{cp} + \beta_7 * \text{Time to Adjust Stock} + \epsilon_{PO} \quad (4)$$

Where:

- Box Office is the earnings (in millions of dollars) from the movie at the box office after 10 weeks of run.
- Pay Off = (4 \* Box Office – Cost)/Costs; The Box Office Earnings have been multiplied by a factor of 4 to reflect the gains from the after market. This 300% mark up a commonly assumed benchmark in the movie industry, it also reflects the idea that earnings from the box office and the after market are correlated. Costs are the reported cost of development and production.
- $\epsilon_{BO}$  and  $\epsilon_{PO}$  are the noise terms.

We have ignored several fixed factors, e.g. timing of release (e.g. the 4th of July weekend effect) and a Studio's portfolio effect in these specifications.

### 4.4 The Data Set

We have collected data on a total of 23 movies released over a two-year window in 2001-2002. The sample includes the top 12 movies that did well in the box office. The rest were selected from a random sampling of the population. In some instances, complete data for lead actors were not available on HSX because these actors were not traded when their movie IPO took place. In such cases, we have used a truncated data set as long as complete data are available for at least half the life cycle of the development; otherwise the movie was eliminated and the next movie from the sample list is included.

We are also in the process of collecting weekly data from HSX's database. For the purpose of this analysis, our time series data capture the break points, with data for the intermediate weeks generated via linear interpolation. Implications of this assumption on the interpretation of results are discussed in section 6.

## 5. Results

We begin this section by presenting the calibration results, i.e. estimates of the decision rule parameters and allied goodness of fit statistics. These are followed by the regression results.

### 5.1 Calibration of Decision Parameters

For the movie Harry Potter and the Chamber of Secrets (HPOT2) the values of estimated parameters are  $W_1 = 0.6$ ;  $W_2 = 0.23$ ;  $W_3 = -0.01$ ;  $W_d = 0.49$ ,  $W_{ru} = -1.08$ ,  $W_{cp} = 543$ . The corresponding Theil statistics are:  $R^2 = 0.9994$ ; Bias = 0.00465; Variation = 0.04828; Covariation = 0.947. Recall that HPOT2 has been deemed as a blockbuster or a "winner," based on its box office returns.

On the other hand, "Ali" is a less successful movie and has been termed a "loser." The values of estimated parameters for Ali are:  $W_1 = 0.0007$ ;  $W_2 = 0.196$ ;  $W_3 = -0.012$ ;  $W_d = -0.12$ ,  $W_{ru} = 0.90$ ,  $W_{cp} = 36$ . The corresponding Theil statistics are:  $R^2 = 0.959$ ; Bias = 0.0019; Variation = 0.127; Covariation = 0.871.

Recall from Figure 3 that both movies start out with relatively similar stock value and growth pattern. However, Ali's stock falters when it reaches close to the release date. This loss is mirrored within the estimated parameters. We interpreted these parameters as follows; in the case of Harry Potter,  $W_{cp}$  drives the HSX stock price higher as the movie nears completion (i.e. the completion pressure increases). On the other hand, for Ali,  $W_{cp}$  does not drive the HSX stock price up. Additionally, it is also interesting to note that the market does not place a premium on the lead talent in Ali (i.e. Will Smith) but places a relatively higher emphasis on the talent pool in Harry Potter. While it is difficult to generalize which parameter will have the largest impact on the overall perception of movie stocks, we have shown that by analyzing the HSX data it is

possible to assess these parameters during movie development, based on the most up to date information. The managerial implications for use of these parameter estimates will be discussed further in Section 6.

We have compiled similar estimates for all the movies in the sample. We present the average values (and the associated standard deviations) for the decision parameters in Table I, separated into two sub-samples: box office winners and losers. Winners and losers are delineated based on box office revenue for the purpose of discerning whether or not “Investors” use two distinct sets of decision rules in valuing movie stocks. The corresponding Theil statistics, in Table II, confirm the low bias and high co-variation in the estimated data set. Again in the manner described above, the aggregate statistics suggest that the completion pressure parameter ( $W_{cp}$ ) for the winners and losers indicate different contributions. Whereas the elapsed time, i.e. the ramp up, parameter ( $W_{ru}$ ) shows comparable contributions.

**Table I: Estimated Decision Rule Parameters**

		Time to Adjust	W 1	W 2	W 3	W d	Wcp	Wru
Box Office Losers (n = 12)	Average	5.395	-0.053	0.155	-0.168	-0.074	-187.105	0.824
	St. Dev.	2.457	0.100	0.403	0.475	0.425	974.808	0.686
Box Office Winners (n = 11)	Average	6.329	0.064	0.008	-0.011	0.005	305.938	0.823
	St. Dev.	1.951	0.185	0.142	0.141	0.186	324.537	1.108

**Table II: Theil Statistics for fit between the simulated and observed Stocks.**

		Sample Size	R <sup>2</sup>	Bias	Variation	Covariation	Mean Abs. % Error
Box Office Losers (n=12)	Average	82.417	0.958	0.002	0.023	0.976	0.083
	St. Dev.	29.516	0.078	0.004	0.037	0.037	0.063
Box Office Winners (n=11)	Average	92.400	0.989	0.002	0.011	0.987	0.061
	St. Dev.	52.846	0.009	0.002	0.014	0.015	0.070

## 5.2 Regression Analysis

We show the aggregate statistics for the dependent variables, i.e. the Box Office earnings and the Pay Off in Table III. We regressed the Box Office earnings against the estimated parameters according to the specification in equation (3). The results are shown in Table IV.

**Table III: Aggregate statistics for the dependent variables**

Aggregate Value	Pay Off	Box Office Earnings	Cost
	Ratio*	in Million \$	in Million \$
Average	5.886	161.130	92.457
Standard Deviation	2.756	81.684	25.646

n = 23

\* More is better

These results indicate that for the overall sample the variance in box office performance cannot be explained by the estimated coefficients in the decision rules. However, the  $R^2$  increases when these data are divided into losers and winner sub-samples.

We also regress the pay off against the decision rule parameters following the specification in equation (4). Recall that the pay off is defined as the ratio of profit and the cost. We illustrate in table V that none of the models are statistically significant. Hence we conclude that payoff expectations cannot be explored using the HSX data. On the other hand, the nearly 71% variance in the “winner” sub-sample is explained by the model shown in equation (3), where as only 18% variation box office performance of the “loser” sample can be explained by this model. The most important conclusion is that the decision rules for the entire population should not be pooled while analyzing the HSX data. This analysis also indicates that  $\alpha_0$  and  $\alpha_3$  are statistically significant coefficients. .

**Table IV: Regression Results with Box Office Earnings as the Dependent Variable**

Symbol	Corresponding Parameter	Winners		Losers		All	
		Coefficient	p	Coefficient	P	Coefficient	p
$\alpha_0$	Intercept	<b>206.84</b>	<b>0.03</b>	14.32	0.82	97.30	0.18
$\alpha_1$	W 1	489.70	0.11	-37.09	0.95	170.34	0.39
$\alpha_2$	W 2	-9.05	0.97	-361.68	0.27	-41.69	0.88
$\alpha_3$	W 3	<b>456.44</b>	<b>0.03</b>	-510.54	0.24	-94.93	0.64
$\alpha_4$	W d	-306.53	0.13	-110.51	0.53	-117.01	0.30
$\alpha_5$	$W_{cp}$	-0.13	0.14	0.14	0.39	0.08	0.22
$\alpha_6$	$W_{ru}$	25.51	0.19	38.29	0.36	4.99	0.83
$\alpha_7$	Time to Adj	2.32	0.73	7.30	0.53	7.82	0.43
N		11		12		23	
Adj. R2		0.718		0.180		-0.067	

**Table V: Regression Results with Pay off as the Dependent Variable**

Symbol	Corresponding Parameter	Winners		Losers		All	
		Coefficient	p	Coefficient	P	Coefficient	p
$\beta_0$	Intercept	3.80	0.73	9.32	<b>0.07</b>	97.30	0.07
$\beta_1$	W 1	-3.30	0.81	26.14	0.26	-41.69	0.91
$\beta_2$	W 2	8.86	0.55	-11.39	0.25	-94.93	0.76
$\beta_3$	W 3	23.00	0.32	-8.56	0.25	-117.01	0.67
$\beta_4$	W d	4.16	0.79	1.48	0.68	0.08	0.59
$\beta_5$	W <sub>cp</sub>	0.00	0.84	0.00	0.54	4.99	0.41
$\beta_6$	W <sub>ru</sub>	1.34	0.39	-1.53	0.35	7.82	0.81
$\beta_7$	Time to Adjust	0.43	0.77	-0.68	0.16	170.34	0.68
N		11		12		23	
Adj. R2		-0.305		0.180		-0.235	

## 6. Discussions

Our results show that it is possible to explore the perception of the market place about a movie, while it is being developed, by estimating the decision rules followed by an interested set of observers on HSX. We have also shown that one basic difference in winners and losers lies in Completion Pressure. Using HSX as a sole source or measure of future box office potential can be misleading. However, using the HSX data in conjunction with other cues can be useful. It might be appropriate to reflect on why HSX data might be correlated with the eventual box office performance and why some of the parameters, such as  $\alpha_0$  and  $\alpha_3$ , are significant for the winners. We speculate that the HSX data and underlying processes are indeed endogenous to the perception of box office success and drive the mindset of the executives to make a movie successful. This occurs because of the long development time (> 100 weeks on average) and the relatively short box office run (~10 weeks). In the rest of this section, we discuss the implications of our findings, their limitations and suggest some extensions that will improve this work.

### 6.1 Limitations

There are some confounding features within our results. It is difficult to explain why  $\alpha_3$  contributes to the success, where as  $\alpha_1$  and  $\alpha_2$  do not? Our choice of assignment of the talent to the slots Actor\_1; Actor\_2 and Actor\_3 is arbitrary. The market may be putting different weights

on actors, but our measurement may confound these signals, and that may be a reason why the intercept ( $\alpha_0$ ) is significant. We also think that our data set is not detailed enough, and thus filters out some of the high frequency (i.e. low time constant) event. This may be a reason why the time to adjust the perception is not a significant contributor to the regression results.

Competition between studios is fierce given the high stakes of the industry. Our model does not capture the following that could be factored in as fixed factors for exploring the decision rules:

Studio Portfolio Effects: A studio's brand value and portfolio can have an impact on the performance of films. For example, the Disney brand name gives parents a level of comfort in knowing that the film will adhere to certain family value standards. A studio's portfolio of movies may speak to their ability to handle the scope of a slate of films during a given year. For example, from a cash standpoint, few studios can afford numerous blockbuster (high budget) films in the same year. Additionally, physical capacity constraints may become an issue from a production standpoint. There may be a particular sound stage which is appropriate for two separate films, but it can only be used by one film at a time, with up to six months of exclusivity.

Film similarity: – On numerous occasions, the movie industry has turned out similar films within a short time frame from each other. This will have an impact on the performance of one or both films as moviegoers tend to have a low tolerance for perceived duplication.

Other factors that could be included in this analysis are the quality of script, awards, talent synergies, actors' extra curricular activities, and limited entertainment wallet.

## **6.2 Implications for Studio Executives**

Typically, users of HSX are reacting to publicly available information such as daily reports from the shoot location and trailers released to theaters, television and the Internet. HSX data does a good job of predicting the box office successes while it does a poor job of predicting box office failures. Having said this, a studio executive would be interested in knowing if their movie is not on this track, because they can take actions, which can impact the public's perception. We have described the decisions made by the executives in section 2.3 that take place beyond the green light phase. For instance, the marketing investment is typically not a function of the production budget of the film, but rather the studio executive's expectation of the film. Currently, some of



this positioning is done using market research. Arguably, HSX like measures would be useful to measure and manage the trending effects, by adjusting the release of trailers and allied collateral.

Aside from the marketing angle, a studio may employ risk reduction strategies while the film is being produced if preliminary perception is negative. These are typically done in two ways:

*Pre-selling* – A studio may find it economical to seek a third party to distribute the film in a particular territory (usually because a 3<sup>rd</sup> party may have a better distribution infrastructure or because the studio has little faith in the film).

*Co-production* – The financial risk of a full-length feature film can be so great, that studios would seek financial partnerships with other studios to reduce their down side risk. If the movie under performs, then the lead studio loses less than if they carried the entire cost of the film. Similarly, their upside is equally reduced.

We note that currently movie production costs are capitalized and amortized based on the percentage of expected revenues that were actually earned in a period of time. It is common practice for the estimate of the ultimate revenue to change on a period to period basis depending on how well the movie is performing. Changing the denominator in the amortization equation can have drastic effects on the financial health of the movie studio. In addition, changing amortization rates sends mixed signals to investors, and raises “red flags” within the IRS. Neither of these effects is beneficial. Applying our model in the pre-release time frame to a studios portfolio could improve both tax and financial reporting methods. The application of a quantified model based on the public’s perception of talent and timing will produce more accurate results than an executive’s perception of the public’s perception. In essence, the model can remove one layer of bias from the existing accounting methods.

### **6.3 Implications in the Post Release Market**

Knowing the estimated box office performance of a movie well before it is released in theaters can allow downstream distribution channels to plan accordingly. The life span of a movie is significantly shorter than in previous generations. For example, the home entertainment release date of a movie typically occurs just days after a movie is pulled from theaters, whereas in the past, it was up to a year after the theatrical run. Theatrical box office is the best indicator of the performance of the movie in all other distribution channels.

Having an understanding of a movie's performance before release could significantly affect the way future movie deals are structured for Hollywood talent. If the talent of a movie has an understanding of the performance of their current film, they can decide to accept or decline their next project based on the anticipated success or failure of the movie.

#### **6.4 Extensions**

Data on the evolution of box office earnings of a typical movie, as shown in Figure 1, indicates that the earnings follow a goal seeking behavior. Such a behavior is typically an outcome of a classic market diffusion model. The decision rule specified in equation 2 can be made endogenous to the market diffusion model. Such a model can then be used to study issues such as the share of distribution channels, ancillary revenue analysis, and theater capacity allocation.

#### **7. Conclusion**

We have applied the system dynamics methodology to a novel class of development scenario, i.e. the development of movies. We model the decision rules that drive this market place and estimate the underlying decision parameters by calibrating the evolution of a selected sample of 23 movies released in 2001-2002. Our results show systematic differences in the decision rules followed by the market for the eventual winners (a.k.a. the blockbusters) and the losers at the box office. Regression analysis of combined decision parameters for eventual winners and losers cannot explain the variance in the box office performance. However, segmenting these data between winners and losers provides interesting insights about how the market perceptions evolve. These simple results have managerial and accounting implications in the movie industry and can be extended for the analysis of the NPD processes in other settings.

#### **Appendix**

##### Default settings for Optimization Process Using Vensim DSS 32 V 4.1

Type of Simulation: Calibration

Payoff Element: Movie Stock| Observed Stock/1

Optimizer: Powell-Random

Type: Linear  
Max Iterations: 1000  
Vector Points: 25  
Absolute Tolerance: 1  
Fractional Tolerance: 0.0003  
Tolerance Multiplier: 21

#### Initialization of Calibration Parameters

$W_1 = 0.014$       $W_2 = 0.01$       $W_3 = 0.03$       $W_d = 0.02$       $W_{ru} = 0.01$       $W_{cp} = 0.01$

Time to Adjust Perceptions: 1 Week

#### Constraint

$0.5 \leq \text{Time to Adjust Perceptions} \leq 7.0$

#### **References**

- Anderson, E.G., and D.J. Morrice (2000). "A Simulation Game for Service-Oriented Supply Chain Management: Does Information Sharing Help Managers with Service Capacity Decisions?" *Production and Operations Management* 9 (1), 44-55.
- Bakken, B. (1993), "Learning and Transfer of Understanding in Dynamic Decision Environments," MIT System Dynamics Group Publication D-4343.
- Clark, K. and T. Fujimoto (1991), *Product Development Performance*. Boston: HBS Press.
- Cooper, R. (1994), "Perspective: Third-generation New product processes," *Journal of Product Innovation Management* 11(1) 3-14.
- Eliashberg, J., Jonker, J., Sawhney, M., Wierenga, B. (2000). "MOVIEMOD: An Implementable Decision-Support System for Prerelease Market Evaluation of Motion Pictures," *Marketing Science*, 19(3), 0226-0243.
- Kampman, C. (1992), "Feedback Complexity, and Market Adjustment: An Experimental Approach," MIT System Dynamics Group Publication D-4304.
- Lesley, E. (1996), "Fatal Subtraction? Hollywood's Creative Accounting Gets a Rewrite," *Businessweek* March 11.
- Oliva, R. (2003a), "Model Calibration as a Testing Strategy for System Dynamics Models," forthcoming *European Journal of Operational Research*.
- Oliva, R. (2003b) "Vensim® Module to Calculate Summary Statistics for Historical Fit," available at <http://www.people.hbs.edu/roliva/research/sd/>
- Sterman, J. (1989), "Modeling Managerial Behavior: Misperception of Feedback in Dynamic Decision making," *Management Science* 35(3), 321-339.
- Sterman, J. (2000), *Business Dynamics: Systems Thinking and Modeling for a Complex World*. New York: Irwin-McGraw Hill.
- Trip, G. (1997), "Turning Rough Takes Summer's Big Hits," *New York Times*, May 5, pD1.
- Ulrich, K. and S. Eppinger (2000), *Product Design and Development*. New York: Irwin-McGraw Hill.
- [www.baseline.com](http://www.baseline.com), ex-post movie facts database.