THE PENNSYLVANIA STATE UNIVERSITY
SCHREYER HONORS COLLEGE

DEPARTMENT OF FINANCE

THE PRODUCER'S DILEMMA:
STRATEGIZING FOR FILM PRODUCERS USING DECISION TREE ANALYSIS

NIKI ARAKELIAN
SPRING 2013

A thesis
submitted in partial fulfillment
of the requirements
for a baccalaureate degree
in Finance
with honors in Finance

Reviewed and approved* by the following:

James Miles
Professor of Finance
Thesis Co-Supervisor and Honors Adviser

Christoph Hinkelmann
Clinical Assistant Professor of Finance
Thesis Co-Supervisor

* Signatures are on file in the Schreyer Honors College.

ABSTRACT

Industry professionals and academics have long searched for a model to predict the profit of movies. Models for accomplishing this objective range from statistical analyses of fundamental variables to film success (such as genre, budget, and star power) to non-traditional forecasting methods of the digital age (such as social media and neural network predictors). The following thesis will use fundamental variables to a film's success, including genre, budget, and release date, and decision tree analysis to predict the real profit of any film before its released. A film producer can use this model to value any decision he makes throughout the entire production of a film. This model can also generate an optimal strategy for a producer even when things do not go according to plan, which happens often in the chaotic film industry.

TABLE OF CONTENTS

INTRODUCTION

This thesis will introduce the Producer's Dilemma. In this scenario, a film producer wants to make a feature-length film and release it in theaters. In order to accomplish this objective, the producer must decide on four crucial aspects of the film (genre, financing, budget, and release season), all of which affect the film's ultimate profits. How can the producer determine which decisions will lead to the highest real profit for his film?

Using decision tree analysis, this producer can identify all possible decisions, the value of each decision, and which decisions will lead to the highest ultimate real profits. In the end, this decision tree analysis will accomplish three crucial goals of finance. It will:

1) Analyze and value all possible decisions the film producer can make
2) Incorporate the time value of money when valuing future decisions
3) Perform all analyses in real terms that are adjusted for inflation.

LITERATURE REVIEW

This review shows the development of film forecasting research from 1989-2013. Especially since the advent of the digital age, the variables and methods used for predicting box office profit have changed.

Litman and Kohl (1989) found that the five major factors to a film's success are actors, characters, story, positive reviewers, and "kudos from industry associations."

Leuhrman and Teichner (1992) introduced a model for pricing real options on film sequels. In the authors' case study, a group of investors considers buying the rights to sequels for a portfolio of feature films. Using real options pricing models, the investors determine a value for the sequels' rights today based on the expected future revenues of the sequels.

Sawhney and Eliashberg (1996) forecasted film revenue based on early box office data. The authors found that box office receipts display "remarkable empirical regularity."

Eliashberg and Shugan (1997) showed that film critics' reviews positively correlate with late and cumulative box office receipts. However, reviews do not have a significant correlation with early box office receipts.

De Vany and Walls (1999) found that box office revenues are asymptotically Pareto-distributed and have infinite variance. The authors argued that it is impossible to attribute the success of a film to causal factors.

Zufryden (2000) found that there was significant positive correlation between six variables (website activity, screens, film rating, film release, production budget, and seasonality) and a film's ticket sales.

Sharda and Delen (2003) classified movies into one of nine categories, ranging from "flop" to "blockbuster," and then used neural networks to predict box office receipts. They argued that neural networks do a much better job of predicting actual performance than other statistical methods proposed in recent studies.

Zuckerman and Kim (2003) showed that the film industry has a fundamental tradeoff. When a movie is positively reviewed by critics who are experienced with major releases and mainstream blockbusters, the film will have an easier time penetrating the mass market, but it will have a more difficult time penetrating the “art-house” market.

Chang and Eyun-Jung (2005) developed a model for forecasting box office receipts based on four categories of independent variables: objective features, brand-related variables, information sources, and distribution-related variables. They found that sequel potential, star power, budget, genre, MPAA rating, release periods, and number of first week screens were significantly related to total box office performance.

Buck (2005) found that a larger film budget tends to lead to higher box office intake and video rental figures, but not to higher return on investment. In addition, Buck found that actors and directors accredited by the Academy of Motion Picture Arts and Sciences do not influence box office receipts, video rental proceeds, or investment returns.

Segal (2005) developed a forecasting model that used genre, run time, release week, star quality, and other publicly available variables to predict overall box office gross.

Suman et al. (2006) studied the correlation between film reviews, budgets, stars, and box office performance. The authors found that negative reviews hurt film performance more than positive reviews help film performance, but that reviews in general have diminishing influence as time goes on. In addition, big budgets and big stars help films that receive mostly negative reviews but do little for films that receive mostly positive reviews.

Liu (2006) found that the volume of word-of-mouth information, such as comments on movie sites like Yahoo! Movies, can be predictive of a film’s success within the first weeks of its run.

Eliashberg et al. (2007) developed techniques for predicting the return on investment of a film based only on textual information available in its script.

Boatwright et al. (2007) found that specific key critics serve as “market gatekeepers” in the film industry and may carry strong influence on box office success.

Elberse (2007) found that stars influence box office receipts. The stronger the cast is, the greater the impact a recruited actor has if he or she comes with a proven track record of success.

Antipov and Pokryshevskaya (2007) argued that the analysis of pooled samples when predicting box office success does not shed light on underlying segmentations in the film industry. The authors recommend developing different movie success models for different segments.

Liu et al. (2007) analyzed the sentiment information contained in blogs to predict box office revenues.

Kurkiewicz (2008) found that a film’s budget and success during its first week of release are accurate predictors of the film’s ultimate gross profits and return on investment.

Chance et al. (2008) used a Bass model to price the option on revenues from a film.

Abel et al. (2010) found that the “characteristic features” and information contained in blogs can be used to predict box office revenue.

Bhosarekar (2010) used Support Vector Machines to predict the Oscar award nominations for Best Screenplay and Best Picture. These awards are closely linked to overall box office revenue. The authors’ prediction model used only the information contained in screenplays, such as types of film scenes.

Gong et al. (2011) developed a model for pricing real options on two major decisions in the film industry; the decisions of how much to spend on marketing and whether or not to make a sequel.

Karniouchina (2011) examined the effectiveness of virtual markets, such as the Hollywood Stock Exchange, at predicting box office revenues. Karniouchina found that, on average, virtual markets overestimate the revenues of films.

Asar and Huberman (2013) used the chatter from Twitter.com to forecast box office revenues. They argued that the rate at which tweets are created can “outperform market-based predictors.”

Chapter 1

The Producer's Dilemma

In the Producer's Dilemma, a producer wants to make a feature-length film and release it in theaters. This producer has four crucial decisions to make before his film can be seen in theaters:

1) Genre Decision – First, the producer must decide on a genre for his film. The film can be any number of standard Hollywood genres. These genres include: action, adventure, animation, biography, comedy, crime, documentary, drama, family, fantasy, history, horror, music, musical, mystery, romance, sci-fi, sport, thriller, war, and western. This decision can only be made after the producer has found and optioned a screenplay. This process is assumed to take 6 months.
2) Financing Decision – Secondly, the producer must decide on how to finance his film. He can choose between independent financing or studio financing. Independent financing is riskier and more difficult to obtain, but it will give the producer more creative freedom on the final product. Studio financing is usually safer and more secure, but the producer will probably have less creative freedom, as he will have to appeal to development, production, and other studio executives for many decisions. The financing decision can only be made after the producer has pitched his movie idea to studios and independent investors around the film industry. This process is assumed to take 6 months.
3) Budget Decision – Thirdly, the producer must decide on a budget for his film. He can choose between big budget (over $100 million in 2013), medium budget ($20 million-$100 million), or small budget (below $20 million). The budget drives all aspects of a

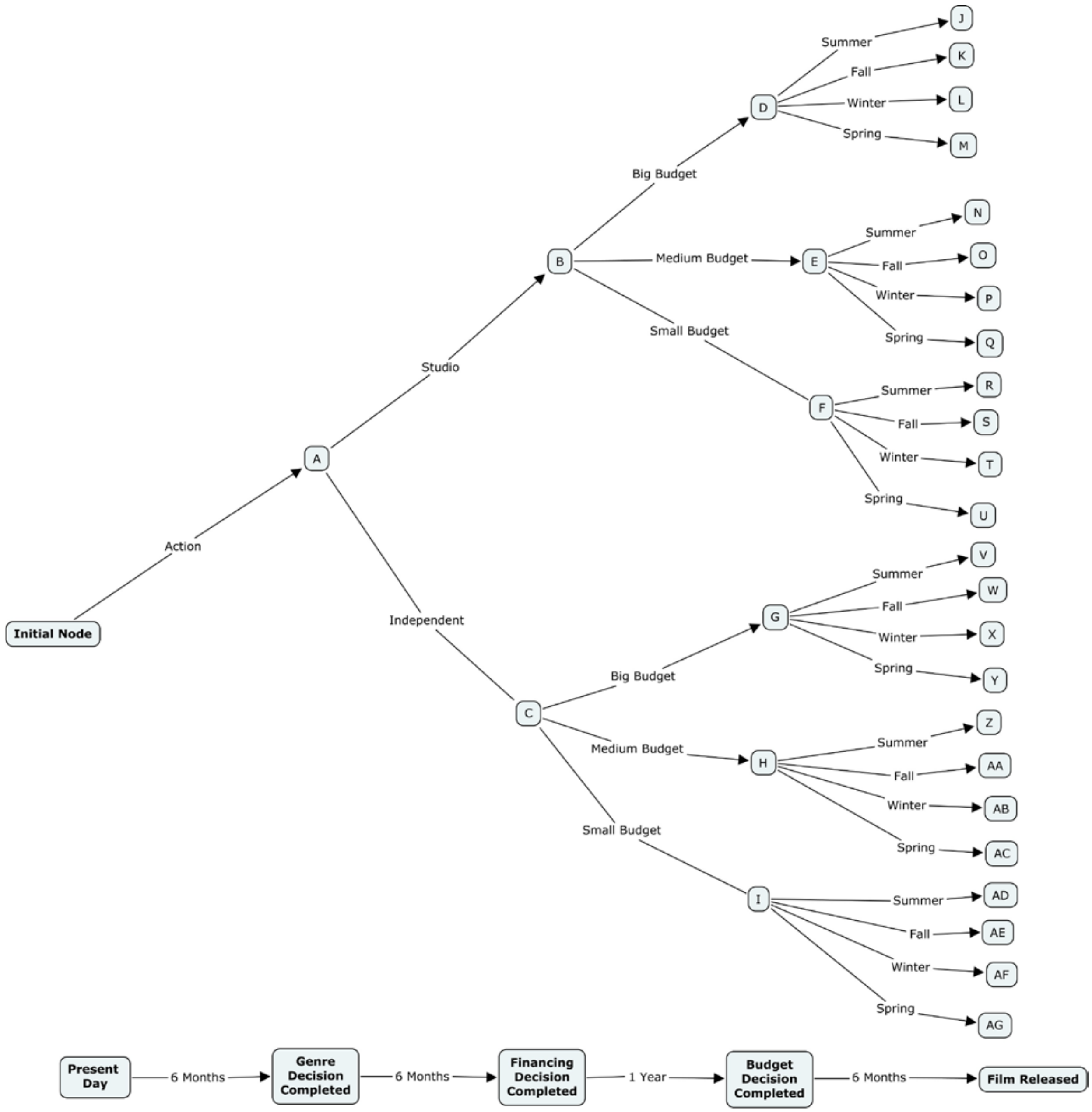
film's business structure, from creative to finances to marketing. If a film has a big budget, we can expect that the film will have top-notch actors, an experienced director, high quality special effects, and a huge marketing plan. The budget decision can only be completed after the entire film has wrapped and accountants can record all costs and overages. This process is assumed to take 1 year.

4) Release Decision – Finally, the producer must decide on a release season for his film. He can release it in the summer, fall, spring, or winter. This decision takes 6 months to be completed as the producer negotiates a release date with distributors.

The Decision Tree

A decision tree can illustrate all of the producer's possible decisions and the value of each decision. The decision tree for this game is very large. The producer chooses from among 21 genres, 2 methods of financing, 3 types of budgets, and 4 seasons of release.

Below is an example of one section of this decision tree. In this case, the producer chose to make an action movie.



In the above tree, each letter (A-AG) corresponds to a decision point, which has a certain value.

The producer begins at the Initial Node in the present day. After 6 months, he chooses a genre for his film project. In the above example, it is assumed that he chose to make an action film. After the genre is locked, the value of the producer's project equals A. After another 6 months, the producer decides on financing. If he chooses studio financing, the value of his project at that point is B. If he chooses independent financing, the value of his project at that point is C.

After one year, the producer has wrapped production and made a decision on the final budget of his film. Based on his previous two decisions, his project could be valued anywhere from D-I. After another 6 months, the producer settles on a release season, and the final value of his project is anywhere from J-AG.

The next challenge was assigning numerical values to each decision point. The model in this study is based on a sample of 1,839 films released from 1939-2012. The final values in the decision tree (J-AG) were calculated by taking the average real profit of the films in this sample that met the letter's criteria. Each film's real profit was calculated using the following formula:

$$\text{Real Profit} = \frac{(\text{Nominal Worldwide Gross Revenue} - \text{Nominal Production Budget})}{\text{Average Ticket Price in Year Film was Released}}$$

For example, the value at J is the average real profit of films that were action, studio, big-budget, summer releases.

The probability that this average real profit would be achieved was also calculated using the sample of 1,839 films. For example, the probability that J's profit will actually be achieved is given by the following formula:

$$P(J) = \frac{\text{\# of action, studio, big-budget films released in the summer}}{\text{\# of action, studio, big-budget films}}$$

Backward induction was then used to assign values for A-I. The values of these decision points equal their expected values discounted to the current period. This analysis assumes a discount rate of 20%, which means that a feature film is slightly riskier than the long-run average return of small-cap firms in the United States.

For example, the value of D is given by the following equation:

$$D = e^{-r\Delta t} (P(J) * J + P(K) * K + P(L) * L + P(M) * M)$$

where r is assumed to be 20% and Δt = .5 or 6 months

This process was repeated for all decision points, in all genres, until every decision point had a numerical value.

Chapter 2

Analysis

Sample

The complete decision tree was constructed using a sample of 1,839 films from 1939-2012. The data for these films, an example of which is in Appendix A, is from the Internet Movie Database (IMDB) and The-Numbers.com. IMDB is an Amazon company that publishes information on the film industry. The-Numbers.com is a film research site by Nash Information Services, LLC. Average ticket prices from 1939-2012 were obtained by IMDB's film information company, BoxOfficeMojo.com.

Importance of Studying Real Figures

All values in the decision tree are in real terms. These values are in total film tickets sold, not US dollars. Therefore, the final values in the decision tree were calculated by averaging real profits.

This decision tree is in real terms because film ticket prices have significantly inflated since 1939. Therefore, nominal analyses of the film industry can distort box office performance. For example, in nominal terms, *Avatar* (2009) made $2.5 billion while *Gone with the Wind* (1939) only made $386 million. *Avatar* appears to be the better-performing film. However, the ultimate goal of any producer is to sell as many tickets as possible above the costs of the film (also in terms of tickets sold). When these figures are converted into real terms, *Gone with the Wind* actually had a real profit that was five times higher than that of *Avatar*, making it the more successful film. In order to avoid distorting box office performance, any long-run analysis of the film industry should be done in real terms.

Real Profit vs. ROI

This analysis will be performed in terms of real profit as opposed to ROI. The major advantages to using real profit are that it takes into account the production costs, revenue, and scale of the film productions. ROI takes into account production costs and revenue, but it fails to take into account scale.

Chapter 3

The Complete Decision Tree

The following pages show the complete decision tree, broken up by genre for ease of reading. For example, the following page shows the decision tree assuming that the producer chose to make an action film. The next page shows the decision tree assuming the producer chose to make an adventure film. The genres chosen are located in the upper left-hand corner of each tree.

The value of the project at each stage is located underneath the decision point's title. For example, after the producer decides to make an action film, his project is worth 18,107,534 tickets sold. To convert this real value to nominal terms, multiply the real value by the current year's average ticket price. For the final outcomes, the standard deviation of the outcome is shown to the right of the decision's value.

How should a producer use the following trees? If a producer knows the genre of his next film project, he can skip to the decision tree for that genre. Then, he will progress through the decision tree on the "path of highest value." The "path of highest value" is the path that yields the highest real profits. For example, if studio financing yields a higher real profit than independent financing, the producer should choose studio financing. Given that decision, if big budget has the highest real profit out of the budget options, he should give his film a big budget.

Although producers should move along this path, they should also keep an eye out for the standard deviation at the end of the tree. If standard deviation is abnormally high, then the producer should caution against using that path, because it will be extremely volatile and risky. For example, the musical genre may yield the highest expected real profit, but it also has abnormally high volatility compared to the other genre decisions. By choosing a war genre, the producer takes a slight hit on expected real profit, but he tremendously reduces the volatility of his film project.

All of the above assumes that the producer has complete freedom in making these decisions. If the producer is locked into a certain decision already, he can drop himself into the decision tree at that decision, and then continue progressing on the "path of highest value." For example, if the producer is locked into producing an adventure movie with a studio, he can start in the adventure tree, choose the studio financing path, and then start assessing the decisions from there forward.

Genre Decision		Financing Decision		Budget Decision		Release Decision	Standard Deviation
Action		Studio		Big		Summer	
18,107,534		20,460,820		39,800,476		35,758,919	34,197,737
						Fall	
						28,615,336	26,121,831
						Winter	
						56,421,891	75,111,532
						Spring	
						43,943,465	36,035,363
				Medium		Summer	
				16,800,792		23,146,108	28,679,484
						Fall	
						6,107,610	12,229,492
						Winter	
						16,977,500	30,938,779
						Spring	
						18,707,401	26,700,028
				Small		Summer	
				3,822,295		1,441,353	3,452,884
						Fall	
						5,337,384	7,426,926
						Winter	
						1,210,616	0
						Spring	
						3,435,699	3,944,357
		Independent		Big		Summer	
		7,119,663		-2,948,266		-9,163,988	0
						Fall	
						0	0
						Winter	
						0	0
						Spring	
						3,267,456	0
				Medium		Summer	
				13,865,091		14,340,803	13,071,897
						Fall	
						10,325,474	25,148,155
						Winter	
						5,599,645	0
						Spring	
						19,525,573	22,214,766
				Small		Summer	
				302,266		0	0
						Fall	
						618,481	540,314
						Winter	
						0	0
						Spring	
						-646,376	0

Adventure	Studio	Big	Summer	
24,181,136	27,314,895	45,820,099	46,835,693	49,189,540
			Fall	
			36,835,982	39,248,537
			Winter	
			53,074,868	70,245,103
			Spring	
			46,775,621	39,318,845
		Medium	Summer	
		25,620,884	29,093,544	41,296,668
			Fall	
			27,661,949	37,058,963
			Winter	
			17,198,955	24,580,271
			Spring	
			27,378,827	33,573,176
		Small	Summer	
		2,232,521	1,574,738	3,447,872
			Fall	
			1,601,630	2,912,002
			Winter	
			9,174,940	0
			Spring	
			3,345,880	3,974,511
	Independent	Big	Summer	
	15,172,226	-2,948,266	-9,163,988	0
			Fall	
			0	0
			Winter	
			0	0
			Spring	
			3,267,456	0
		Medium	Summer	
		24,199,966	11,287,778	14,281,843
			Fall	
			26,411,677	42,722,670
			Winter	
			0	0
			Spring	
			44,495,064	95,577
		Small	Summer	
		15,759,599	14,129,920	0
			Fall	
			22,930,373	42,756,067
			Winter	
			2,207,760	0
			Spring	
			2,258,023	0

Animation		Studio		Big		Summer	
23,678,583		26,692,977		38,935,913		48,687,123	54,260,138
						Fall	
						30,684,938	28,017,095
						Winter	
						25,503,057	17,884,922
						Spring	
						42,737,334	45,196,320
				Medium		Summer	
				30,825,814		24,533,755	34,012,325
						Fall	
						36,242,412	37,713,613
						Winter	
						16,792,961	16,832,132
						Spring	
						48,472,203	42,742,710
				Small		Summer	
				2,223,515		3,513,368	6,782,626
						Fall	
						1,410,718	1,212,549
						Winter	
						2,152,858	5,563,479
						Spring	
						0	0
		Independent		Big		Summer	
		-2,933,709		-9,163,988		-9,163,988	0
						Fall	
						0	0
						Winter	
						0	0
						Spring	
						0	0
				Medium		Summer	
				0		0	0
						Fall	
						0	0
						Winter	
						0	0
						Spring	
						0	0
				Small		Summer	
				1,997,655		0	0
						Fall	
						1,997,655	0
						Winter	
						0	0
						Spring	
						0	0

Biography	Studio	Big	Summer	
8,855,189	10,216,249	20,167,191	12,921,608	9,074,865
			Fall	
			9,482,129	11,631,052
			Winter	
			33,454,677	35,459,953
			Spring	
			31,494,253	0
		Medium	Summer	
		16,002,191	4,992,435	9,277,780
			Fall	
			7,959,586	11,226,871
			Winter	
			14,480,663	22,647,637
			Spring	
			52,059,733	110,564,869
		Small	Summer	
		4,087,699	1,243,446	3,445,899
			Fall	
			6,055,638	13,724,933
			Winter	
			4,320,187	5,648,224
			Spring	
			3,351,661	0
	Independent	Big	Summer	
	3,052,034	0	0	0
			Fall	
			0	0
			Winter	
			0	0
			Spring	
			0	0
		Medium	Summer	
		3,966,992	0	0
			Fall	
			5,290,002	0
			Winter	
			2,643,982	0
			Spring	
			0	0
		Small	Summer	
		3,608,033	-680,924	0
			Fall	
			7,862,378	12,164,834
			Winter	
			0	0
			Spring	
			-611,702	0

Comedy	Studio	Big	Summer	
10,490,366	11,974,344	26,053,587	25,909,368	31,446,996
			Fall	
			23,726,512	24,700,368
			Winter	
			19,611,094	22,522,937
			Spring	
			37,082,861	44,650,072
		Medium	Summer	
		16,132,718	15,373,303	21,440,017
			Fall	
			17,708,597	25,134,962
			Winter	
			15,190,236	18,667,634
			Spring	
			16,396,208	25,669,105
		Small	Summer	
		4,088,522	7,005,308	13,923,950
			Fall	
			3,934,839	6,675,037
			Winter	
			3,607,928	6,238,518
			Spring	
			2,306,845	2,992,394
	Independent	Big	Summer	
	7,934,370	0	0	0
			Fall	
			0	0
			Winter	
			0	0
			Spring	
			0	0
		Medium	Summer	
		15,066,813	21,193,436	26,140,740
			Fall	
			1,909,457	1,721,092
			Winter	
			17,638,466	21,193,804
			Spring	
			12,304,301	21,962,827
		Small	Summer	
		8,197,541	8,822,745	18,359,235
			Fall	
			6,164,821	19,568,830
			Winter	
			4,960,957	3,809,768
			Spring	
			11,206,040	21,913,228

Crime	Studio	Big	Summer	
11,445,083	13,496,930	31,613,047	29,196,804	22,799,128
			Fall	
			33,656,797	24,158,466
			Winter	
			34,772,082	20,964,117
			Spring	
			33,065,866	29,554,284
		Medium	Summer	
		16,287,661	25,397,442	26,696,547
			Fall	
			8,862,976	16,384,728
			Winter	
			22,242,469	32,826,381
			Spring	
			11,972,152	23,622,252
		Small	Summer	
		3,545,771	2,071,400	4,374,706
			Fall	
			5,114,396	7,382,973
			Winter	
			3,191,809	5,210,603
			Spring	
			2,835,246	3,943,763
	Independent	Big	Summer	
	4,602,020	16,076,008	0	0
			Fall	
			0	0
			Winter	
			16,076,008	0
			Spring	
			0	0
		Medium	Summer	
		8,733,420	5,561,047	13,143,812
			Fall	
			-907,978	2,263,362
			Winter	
			7,250,424	8,781,695
			Spring	
			16,252,554	19,257,424
		Small	Summer	
		3,677,587	2,119,497	3,093,831
			Fall	
			5,109,140	14,119,866
			Winter	
			0	0
			Spring	
			2,109,587	2,749,724

Documentary	Studio	Big	Summer	
4,049,160	3,555,814	0	0	0
			Fall	
			0	0
			Winter	
			0	0
			Spring	
			0	0
		Medium	Summer	
		-709,570	0	0
			Fall	
			-709,570	0
			Winter	
			0	0
			Spring	
			0	0
		Small	Summer	
		4,623,689	3,657,926	7,157,533
			Fall	
			6,215,648	7,714,079
			Winter	
			5,995,716	6,863,857
			Spring	
			1,059,971	393,735
	Independent	Big	Summer	
	7,967,749	0	0	0
			Fall	
			0	0
			Winter	
			0	0
			Spring	
			0	0
		Medium	Summer	
		0	0	0
			Fall	
			0	0
			Winter	
			0	0
			Spring	
			0	0
		Small	Summer	
		9,731,629	13,755,182	18,568,985
			Fall	
			2,647,936	0
			Winter	
			0	0
			Spring	
			4,744,665	0

Drama	Studio	Big	Summer	
10,342,418	12,221,030	53,140,788	39,984,086	47,368,877
			Fall	
			12,507,431	16,732,900
			Winter	
			126,352,770	374,175,868
			Spring	
			33,544,378	30,571,860
		Medium	Summer	
		12,334,384	19,223,857	25,681,710
			Fall	
			9,021,366	20,058,390
			Winter	
			12,203,980	19,062,620
			Spring	
			12,204,308	34,697,111
		Small	Summer	
		5,048,844	2,991,246	8,547,956
			Fall	
			4,977,630	14,544,785
			Winter	
			6,486,537	9,735,122
			Spring	
			5,697,329	11,987,560
	Independent	Big	Summer	
	5,773,560	6,790,745	0	0
			Fall	
			0	0
			Winter	
			6,790,745	13,131,345
			Spring	
			0	0
		Medium	Summer	
		18,833,474	17,684,792	30,289,376
			Fall	
			19,740,163	31,951,011
			Winter	
			22,544,620	40,557,500
			Spring	
			13,224,411	17,896,613
		Small	Summer	
		3,329,892	3,362,932	5,188,791
			Fall	
			2,502,854	5,012,924
			Winter	
			2,394,710	3,169,541
			Spring	
			6,189,254	15,409,653

Family	Studio	Big	Summer	
20,361,644	22,722,928	41,527,956	54,490,486	57,514,269
			Fall	
			38,678,626	42,303,257
			Winter	
			23,622,155	30,124,046
			Spring	
			42,236,862	43,771,521
		Medium	Summer	
		23,100,101	15,453,522	23,191,401
			Fall	
			28,671,975	33,463,619
			Winter	
			14,000,161	14,769,585
			Spring	
			37,398,342	58,056,765
		Small	Summer	
		3,956,594	1,783,770	2,723,227
			Fall	
			5,221,330	13,852,436
			Winter	
			5,279,093	2,607,478
			Spring	
			3,267,893	3,298,772
	Independent	Big	Summer	
	9,188,964	0	0	0
			Fall	
			0	0
			Winter	
			0	0
			Spring	
			0	0
		Medium	Summer	
		14,298,372	-833,766	4,916,925
			Fall	
			0	0
			Winter	
			0	0
			Spring	
			44,562,648	0
		Small	Summer	
		1,997,655	0	0
			Fall	
			1,997,655	0
			Winter	
			0	0
			Spring	
			0	0

Fantasy	Studio	Big	Summer	
23,587,118	27,230,304	51,957,672	44,219,054	38,622,254
			Fall	
			45,369,849	52,778,154
			Winter	
			58,097,434	82,204,040
			Spring	
			62,315,677	41,749,130
		Medium	Summer	
		21,445,412	21,545,062	32,529,746
			Fall	
			25,775,354	34,769,907
			Winter	
			13,280,942	16,468,096
			Spring	
			27,455,208	36,204,607
		Small	Summer	
		2,983,026	-14,966	2,256,395
			Fall	
			1,962,947	2,917,350
			Winter	
			4,097,426	5,314,817
			Spring	
			5,195,951	5,274,178
	Independent	Big	Summer	
	1,881,770	-9,163,988	-9,163,988	0
			Fall	
			0	0
			Winter	
			0	0
			Spring	
			0	0
		Medium	Summer	
		4,358,248	13,060,964	14,733,191
			Fall	
			397,040	6,009,636
			Winter	
			0	0
			Spring	
			-383,261	5,411,627
		Small	Summer	
		1,999,340	-75,433	0
			Fall	
			3,815,429	0
			Winter	
			0	0
			Spring	
			2,258,023	0

History	Studio	Big	Summer	
10,141,213	10,388,477	23,799,694	16,497,990	22,653,047
			Fall	
			24,217,614	29,200,215
			Winter	
			48,616,724	34,148,074
			Spring	
			18,881,111	26,047,148
		Medium	Summer	
		10,995,534	32,062,442	49,620,488
			Fall	
			2,499,888	7,190,352
			Winter	
			14,901,360	21,088,650
			Spring	
			4,210,681	7,107,203
		Small	Summer	
		4,656,152	49,978	1,656,787
			Fall	
			9,346,902	19,275,721
			Winter	
			3,367,957	5,290,276
			Spring	
			12,534,877	0
	Independent	Big	Summer	
	20,082,112	6,790,745	0	0
			Fall	
			0	0
			Winter	
			6,790,745	13,131,345
			Spring	
			0	0
		Medium	Summer	
		48,576,373	0	0
			Fall	
			0	0
			Winter	
			48,576,373	64,958,210
			Spring	
			0	0
		Small	Summer	
		18,216,397	34,849,359	0
			Fall	
			1,583,435	0
			Winter	
			0	0
			Spring	
			0	0

Horror	Studio	Big	Summer	
10,164,688	11,574,490	12,978,716	16,275,400	18,062,759
			Fall	
			24,517,255	3,485,614
			Winter	
			-6,801,536	2,734,195
			Spring	
			0	0
		Medium	Summer	
		16,880,544	31,136,695	59,519,389
			Fall	
			10,845,824	12,289,630
			Winter	
			22,131,544	50,686,857
			Spring	
			10,322,211	17,284,221
		Small	Summer	
		8,560,303	5,742,902	3,256,642
			Fall	
			12,007,027	10,683,426
			Winter	
			5,444,468	4,254,353
			Spring	
			2,795,347	3,267,753
	Independent	Big	Summer	
	8,990,907	0	0	0
			Fall	
			0	0
			Winter	
			0	0
			Spring	
			0	0
		Medium	Summer	
		5,898,470	5,621,459	8,504,685
			Fall	
			3,343,377	3,857,080
			Winter	
			0	0
			Spring	
			11,839,688	0
		Small	Summer	
		13,327,208	19,124,574	26,020,280
			Fall	
			11,393,870	11,936,276
			Winter	
			4,141,930	0
			Spring	
			15,990,479	8,511,680

Music		Studio		Big		Summer	
6,849,889		8,207,277		12,821,016		0	0
						Fall	
						21,930,199	33,759,224
						Winter	
						0	0
						Spring	
						-5,397,349	0
				Medium		Summer	
				12,064,528		3,398,429	6,432,746
						Fall	
						15,732,459	28,566,786
						Winter	
						20,436,451	21,056,070
						Spring	
						1,399,172	3,286,214
				Small		Summer	
				7,849,156		7,254,516	15,973,581
						Fall	
						3,427,122	4,486,974
						Winter	
						7,208,290	6,860,273
						Spring	
						17,248,761	25,403,107
		Independent		Big		Summer	
		1,654,683		0		0	0
						Fall	
						0	0
						Winter	
						0	0
						Spring	
						0	0
				Medium		Summer	
				-3,733,032		-3,733,032	0
						Fall	
						0	0
						Winter	
						0	0
						Spring	
						0	0
				Small		Summer	
				2,979,996		0	0
						Fall	
						5,683,275	11,836,118
						Winter	
						720,927	3,740,907
						Spring	
						-611,702	0

Musical		Studio		Big		Summer	
28,106,781		35,199,672		67,903,930		86,224,786	81,982,006
						Fall	
						31,262,218	14,325,505
						Winter	
						0	0
						Spring	
						0	0
				Medium		Summer	
				40,746,415		25,609,887	28,776,353
						Fall	
						40,362,804	48,568,854
						Winter	
						18,163,157	17,251,584
						Spring	
						162,695,135	159,193,119
				Small		Summer	
				30,203,085		87,204,322	107,247,947
						Fall	
						11,630,527	12,817,614
						Winter	
						9,063,404	0
						Spring	
						0	0
		Independent		Big		Summer	
		2,102,100		0		0	0
						Fall	
						0	0
						Winter	
						0	0
						Spring	
						0	0
				Medium		Summer	
				2,973,096		2,643,025	0
						Fall	
						0	0
						Winter	
						3,303,167	0
						Spring	
						0	0
				Small		Summer	
				2,297,031		0	0
						Fall	
						2,297,031	3,695,502
						Winter	
						0	0
						Spring	
						0	0

Mystery	Studio	Big	Summer	
12,302,131	14,313,743	41,348,400	40,661,091	38,572,797
			Fall	
			58,173,965	54,069,428
			Winter	
			20,072,690	23,358,437
			Spring	
			36,122,536	36,975,023
		Medium	Summer	
		13,507,387	24,760,893	32,858,554
			Fall	
			7,814,071	14,128,411
			Winter	
			15,503,880	15,494,018
			Spring	
			6,884,970	6,639,082
		Small	Summer	
		7,923,846	3,563,888	3,391,912
			Fall	
			11,198,343	10,924,088
			Winter	
			7,758,217	12,224,196
			Spring	
			1,909,449	0
	Independent	Big	Summer	
	5,220,006	0	0	0
			Fall	
			0	0
			Winter	
			0	0
			Spring	
			0	0
		Medium	Summer	
		8,446,958	0	0
			Fall	
			8,446,958	3,360,473
			Winter	
			0	0
			Spring	
			0	0
		Small	Summer	
		6,056,927	13,384,304	20,206,671
			Fall	
			969,714	3,550,095
			Winter	
			0	0
			Spring	
			5,030,531	0

Romance	Studio	Big	Summer	
14,513,636	16,800,331	70,711,234	37,051,980	38,097,134
			Fall	
			10,171,063	16,105,231
			Winter	
			170,695,995	463,858,076
			Spring	
			12,883,927	22,882,229
		Medium	Summer	
		17,256,093	20,326,925	27,462,042
			Fall	
			13,977,931	26,209,398
			Winter	
			15,950,455	18,930,463
			Spring	
			18,609,119	40,861,347
		Small	Summer	
		7,412,664	13,675,656	36,521,366
			Fall	
			5,034,474	10,625,016
			Winter	
			6,957,239	8,862,383
			Spring	
			5,954,620	13,888,228
	Independent	Big	Summer	
	6,432,885	0	0	0
			Fall	
			0	0
			Winter	
			0	0
			Spring	
			0	0
		Medium	Summer	
		11,261,623	0	0
			Fall	
			16,108,294	24,623,200
			Winter	
			3,303,167	0
			Spring	
			7,970,844	5,108,573
		Small	Summer	
		7,005,820	2,516,338	3,748,809
			Fall	
			1,552,311	1,923,009
			Winter	
			2,153,536	4,026,416
			Spring	
			18,942,470	28,390,233

Sci-Fi	Studio	Big	Summer	
17,012,882	19,605,195	37,738,897	39,195,829	47,229,874
			Fall	
			17,941,635	19,018,160
			Winter	
			53,827,163	100,646,473
			Spring	
			38,699,015	39,580,734
		Medium	Summer	
		16,966,002	20,141,059	23,089,106
			Fall	
			17,682,202	32,519,184
			Winter	
			10,955,950	11,262,923
			Spring	
			16,629,538	23,644,935
		Small	Summer	
		4,762,251	2,036,658	3,402,258
			Fall	
			4,239,933	6,093,534
			Winter	
			11,048,965	4,300,198
			Spring	
			6,015,995	5,897,662
	Independent	Big	Summer	
	8,058,507	-2,948,266	-9,163,988	0
			Fall	
			0	0
			Winter	
			0	0
			Spring	
			3,267,456	0
		Medium	Summer	
		12,003,409	5,759,140	15,393,380
			Fall	
			1,324,025	11,525,328
			Winter	
			5,599,645	0
			Spring	
			26,297,088	21,234,078
		Small	Summer	
		10,446,233	8,592,750	0
			Fall	
			11,372,975	16,179,686
			Winter	
			0	0
			Spring	
			0	0

Sport	Studio	Big	Summer	
7,341,776	8,398,096	11,831,474	10,807,575	8,691,117
			Fall	
			29,446,541	12,813,124
			Winter	
			-3,766,084	0
			Spring	
			-3,705,507	0
		Medium	Summer	
		9,845,379	12,616,163	18,406,735
			Fall	
			10,650,142	14,417,177
			Winter	
			11,399,433	15,428,776
			Spring	
			3,384,914	7,138,525
		Small	Summer	
		10,916,893	1,199,057	2,809,219
			Fall	
			26,427,553	52,492,708
			Winter	
			7,795,679	4,089,701
			Spring	
			3,351,661	0
	Independent	Big	Summer	
	2,783,906	0	0	0
			Fall	
			0	0
			Winter	
			0	0
			Spring	
			0	0
		Medium	Summer	
		-3,852,414	0	0
			Fall	
			-3,852,414	0
			Winter	
			0	0
			Spring	
			0	0
		Small	Summer	
		5,817,738	7,402,640	10,640,271
			Fall	
			2,647,936	0
			Winter	
			0	0
			Spring	
			0	0

Thriller	Studio	Big	Summer	
12,620,845	14,498,195	33,294,071	35,043,176	34,033,564
			Fall	
			26,859,935	23,081,912
			Winter	
			26,129,404	23,463,576
			Spring	
			39,621,752	35,447,979
		Medium	Summer	
		15,171,998	25,391,093	34,561,333
			Fall	
			8,460,585	15,607,428
			Winter	
			18,111,130	34,584,636
			Spring	
			11,449,836	15,207,835
		Small	Summer	
		4,570,023	1,539,146	3,119,971
			Fall	
			5,694,576	10,578,264
			Winter	
			5,918,009	8,515,302
			Spring	
			3,147,183	4,275,167
	Independent	Big	Summer	
	5,249,750	-5,829,253	-9,163,988	0
			Fall	
			0	0
			Winter	
			-2,494,518	0
			Spring	
			0	0
		Medium	Summer	
		8,295,915	12,368,183	12,051,600
			Fall	
			5,826,738	14,513,695
			Winter	
			9,409,100	5,387,382
			Spring	
			6,878,767	6,653,002
		Small	Summer	
		5,992,734	2,664,661	4,722,361
			Fall	
			7,687,890	15,511,240
			Winter	
			0	0
			Spring	
			7,501,171	3,494,014

War		Studio		Big		Summer	
27,518,151		31,223,187		112,276,950		23,364,314	38,949,558
						Fall	
						21,251,373	24,568,870
						Winter	
						368,073,403	734,490,773
						Spring	
						18,213,594	24,876,399
				Medium		Summer	
				8,836,749		7,822,761	14,527,201
						Fall	
						2,166,679	7,475,921
						Winter	
						16,063,592	22,445,368
						Spring	
						10,695,540	25,455,641
				Small		Summer	
				2,063,610		-245,061	1,154,833
						Fall	
						1,596,580	3,128,348
						Winter	
						3,173,890	5,768,401
						Spring	
						0	0
		Independent		Big		Summer	
		17,229,255		0		0	0
						Fall	
						0	0
						Winter	
						0	0
						Spring	
						0	0
				Medium		Summer	
				16,441,444		0	0
						Fall	
						44,505,967	0
						Winter	
						2,643,982	0
						Spring	
						2,174,384	0
				Small		Summer	
				34,849,359		34,849,359	0
						Fall	
						0	0
						Winter	
						0	0
						Spring	
						0	0

Western	Studio	Big	Summer	
8,276,148	6,375,144	5,869,855	12,983,973	21,311,402
			Fall	
			0	0
			Winter	
			0	0
			Spring	
			534,266	11,003,302
		Medium	Summer	
		9,628,604	1,227,225	8,184,175
			Fall	
			1,828,469	4,938,061
			Winter	
			11,904,598	17,082,699
			Spring	
			20,734,468	21,311,906
		Small	Summer	
		-242,612	-1,313,001	0
			Fall	
			0	0
			Winter	
			0	0
			Spring	
			827,777	0
	Independent	Big	Summer	
	78,429,452	0	0	0
			Fall	
			0	0
			Winter	
			0	0
			Spring	
			0	0
		Medium	Summer	
		95,791,962	0	0
			Fall	
			95,791,962	0
			Winter	
			0	0
			Spring	
			0	0
		Small	Summer	
		0	0	0
			Fall	
			0	0
			Winter	
			0	0
			Spring	
			0	0

Chapter 4

Observations

The decision tree above will value any major decision a producer could face. Producers should jump to the decisions in the tree that most accurately reflect their personal situation in the film industry.

However, the complete decision tree also highlights general patterns to profitability, which producers can use as guidelines.

Season Decision

For big budget, studio-financed films, any release season has huge profit potential. Producers of these films have an extremely high flexibility for choosing time of release. Among the fifty highest values for the season decisions, 70% were for big budget, studio-financed projects, and these projects were almost evenly split among the seasons.

The spring and fall were the most profitable seasons to release independent films, especially independent films with medium-sized budgets. Major flops at the box office were just as likely in any season.

Budget Decision

Among the twenty highest values for budget decisions, 65% went to big budget projects. Over 90% of big budget successes were studio-financed. In other words, big budget studio-financed movies tend to reign king.

However, among the fifty highest values for budget decisions, 50% were for medium budgets, 40% were for big budgets, and only 10% were for small budgets. Two-thirds of medium budget successes came from studio-financed productions. In other words, medium budgets still have very high profit potential, but mostly under studio financing.

Although small budgets have flexible options for financing, these types of films give producers very small chances for success.

Financing Decision

Among the twenty-five highest values for financing decisions, 76% were for projects that chose studio financing, while 24% came from independent projects. A producer maximizes his chances for success by financing his movie through a studio.

Genre Decision

The best choices for genres were (in descending order): war, musical, adventure, animation, and fantasy. Although musical yielded the highest real profit, the genre had an extremely high volatility compared with the other genres. If the producer chooses the war genre instead, the producer may take a slight hit on expected real profit, but the producer also significantly reduces the volatility of his project. The genres that were most likely to flop were (in ascending order): documentary, music, sport, and western.

Implications for the Future of the Film Industry

The above analysis may or may not be indicative of the future of the film industry. The decision tree uses historical box office data to derive a profit-maximizing strategy. However, anything can happen in the future.

If one assumes that the above analysis correlates with profit-maximizing projects, and that film professionals will gravitate toward these projects, then the above analysis may suggest several future trends for the film industry. First, it would suggest that the Hollywood studio system will strengthen in the future. As is the case today, studios will dominate the film industry, and independent film will continue to cater to smaller, niche markets. In the future, big budgets will tend to yield the highest ticket sales, but the market for medium budget films will also be very significant. The market for small budget films will probably shrink.

Finally, studios will focus their efforts around big budget movies that combine the war, adventure, and fantasy genres. These three genres can easily be combined into one film, and they all are highly profitable over the long run. When these genres are combined, they tend to cater to males and females over 13 years old, and often skew toward male audiences. To reach children, studios will strengthen their animation divisions. An animation division kills two birds with one stone. It allows the studio to make youth-oriented animated films, while also providing the studio with a CGI and specials effects factory for its war, fantasy, and adventure films. Finally, to balance its target audience equally between males and females, the studio may occasionally release a musical-based film, which heavily skews toward female audiences.

Chapter 5

Conclusion

The decision tree constructed in this thesis has two key advantages. First, it allows a producer to value all possible decisions throughout the production process. Secondly, that producer can derive an optimal strategy for success no matter where he is on the decision tree. When things do not go according to plan, a producer can drop himself into the tree and continue making profit-maximizing decisions.

For example, suppose that a producer is locked into producing an animated film with a studio. The producer never wanted to be in this position, but due to personal financial reasons, the producer is forced to take the project. The decision tree can still derive an optimal strategy for this scenario. The producer would maximize real profit by giving his film a big budget and releasing it in the summer. Suppose that a producer gets locked into producing a mystery movie, studio-financed, with a small budget. That producer would maximize real profit by releasing the film in the fall.

On the other hand, if the producer has complete freedom for his film project, the decision tree will again reveal an optimal strategy for success. That producer will maximize real profit by making a war film, studio-financed, with a big budget and winter release.

This last scenario is very rare in Hollywood. Breaking through the pearly studio gates and making a big-budget blockbuster is a very difficult task. It takes a lot before a studio is willing to give a producer $200 million to make his next movie. This makes the decision tree all the more important. It allows producers in all different types of situations, with different accesses to resources, to derive an optimal strategy for success.

Possible Extensions of Thesis

Future extensions of this thesis could incorporate additional variables into the analysis. This analysis focused on four critical variables (genre, financing, budget, and release season). There are many other variables to a film's success that might increase the accuracy of this model, such as star power, director momentum, or social media activity.

In addition, extensions of this thesis could utilize a larger, more international sample for study. The sample used included some international films, but many international films were excluded because their home countries do not publicly release financial data on feature films. The model may become more accurate if these films were incorporated into the analysis.

Finally, this model assumes a discount rate that was slightly higher than the long-run average return for small cap firms in the United States. Further research could be done into the appropriate discount rate for feature films, which would improve the accuracy of any box office forecasting model that incorporates the time value of money.

Appendix A

Data Set

All information about the films used in this analysis was taken from publicly available sources at IMDB.com, The-Numbers.com, and BoxOfficeMojo.com. The following page shows an example of the data used in this study.

Film Title	Genre	Financing	Budget	Release Season	Nominal Budget ($000)	Nominal Worldwide Gross Revenue ($000)	Avg. Ticket Price	Real Budget (000 of ticket sales)	Real Worldwide Gross (000 of ticket sales)
…									
Nine (2009)	Drama,Musical,Romance	Studio	Medium	Winter	$80,000	$53,509	$7.50	10,667	7,135
Ninja Assassin (2009)	Action,Crime,Thriller	Studio	Medium	Fall	50,000	61,623	7.50	6,667	8,216
Nixon (1995)	Biography,Drama	Studio	Medium	Winter	45,000	34,668	4.35	10,345	7,970
No Country for Old Men (2007)	Crime,Thriller	Studio	Medium	Fall	25,000	162,985	6.88	3,634	23,690
No Man's Land (2001)	Drama,War	Studio	Small	Winter	1,000	2,684	5.66	177	474
No Reservations (2007)	Comedy,Drama,Romance	Studio	Medium	Summer	28,000	91,666	6.88	4,070	13,324
North Country (2005)	Drama	Studio	Medium	Fall	30,000	25,224	6.41	4,680	3,935
Northfork (2003)	Drama,Fantasy	Independent	Small	Summer	1,900	1,445	6.03	315	240
Not Another Teen Movie (2001)	Comedy	Studio	Medium	Winter	15,000	62,401	5.66	2,650	11,025
Notes on a Scandal (2006)	Drama,Thriller	Studio	Medium	Winter	27,500	49,752	6.55	4,198	7,596
Nothing To Lose (1997)	Action,Adventure,Comedy,Crime	Studio	Medium	Summer	25,000	64,594	4.59	5,447	14,073
Notorious (2009)	Biography,Drama,Music	Studio	Small	Winter	19,000	44,475	7.50	2,533	5,930
Notting Hill (1999)	Comedy,Romance	Studio	Medium	Spring	42,000	363,728	5.08	8,268	71,600
Novocaine (2001)	Comedy,Crime,Drama,Thriller	Independent	Small	Fall	6,000	2,523	5.66	1,060	446
Nowhere to Run (1993)	Action,Drama,Romance	Studio	Medium	Winter	15,000	52,189	4.14	3,623	12,606
Nurse Betty (2000)	Comedy,Crime,Romance,Thriller	Independent	Medium	Fall	24,000	27,732	5.39	4,453	5,145
Ocean's Eleven (2001)	Crime,Thriller	Studio	Big	Winter	85,000	450,729	5.66	15,018	79,634
Ocean's Thirteen (2007)	Crime,Thriller	Studio	Medium	Summer	85,000	311,744	6.88	12,355	45,312
Ocean's Twelve (2004)	Crime,Thriller	Studio	Big	Winter	110,000	362,989	6.21	17,713	58,452
Octopussy (1983)	Action,Adventure,Crime,Thriller	Studio	Medium	Summer	27,500	187,500	3.15	8,730	59,524
Office Space (1999)	Comedy,Crime	Studio	Small	Winter	10,000	12,828	5.08	1,969	2,525
Old School (2003)	Comedy	Studio	Medium	Winter	24,000	86,326	6.03	3,980	14,316
Oliver Twist (2005)	Drama,Family	Studio	Medium	Fall	65,000	26,671	6.41	10,140	4,161
…									

BIBLIOGRAPHY

Abel, F.; Diaz-Aviles, E.; Henze, N.; Krause, D.; Siehndel, P." Analyzing the Blogosphere for Predicting the Success of Music and Movie Products," *Advances in Social Networks Analysis and Mining (ASONAM), 2010 International Conference on Advances in Social Networks Analysis and Mining*, pp.276-280, 9-11 Aug. 2010.

Antipov, E., & Pokryshevskaya, E. (2011). Accounting for latent classes in movie box office modeling. *Journal of Targeting, Measurement and Analysis for Marketing, 19*(1), 3-10. doi: http://dx.doi.org/10.1057/jt.2011.3.

Asar, Sitarum, and Bernardo A. Huberman. "Predicting the Future with Social Media." (2010): n. pag. *Cornell University Library*. Web. 20 Feb. 2013. <http://arxiv.org/abs/1003.5699>.

Basuroy, Suman, Subimal Chatterjee, and S. Abraham Ravid. "How Critical Are Critical Reviews? The Box Office Effects of Film Critics, Star Power, and Budgets." *Journal of Marketing* 67.4 (2003): 103-17. Print.

Bhosarekar, N. S. (2010). *Prediction of Oscar Award Nominations Based on Movie Scripts*. University of Maryland, Baltimore County). *ProQuest Dissertations and Theses*,56. Retrieved from http://search.proquest.com/docview/757888570?accountid=13158. (757888570).

Boatwright, Peter, Suman Basuroy, and Wagner Kamakura. "Reviewing the Reviewers: The Impact of Individual Film Critics on Box Office Performance." *Quantitative Marketing and Economics* 5.4 (2007): 401-25. Print.

Buck, Erin E. *Is the Silver Screen a Golden Opportunity?* Thesis. The Pennsylvania State University, 2005. Print.

Chance, D. M., E. Hillebrand, and J. E. Hilliard. "Pricing an Option on Revenue from an Innovation: An Application to Movie Box Office Revenue." *Management Science*54.5 (2008): 1015-028. Print.

Chang, Byeng-Hee, and Eyun-Jung Ki. "Devising a Practical Model for Predicting Theatrical Movie Success: Focusing on the Experience Good Property." *Journal of Media Economics* 18.4 (2005): 247-69. Print.

De Vany, Arthur, and W. David Walls. "Uncertainty in the Movie Industry: Does Star Power Reduce the Terror of the Box Office?" *Journal of Cultural Economics*23.4 (1999): 285-318. Print.

Elberse, Anita. "The Power of Stars: Do Star Actors Drive the Success of Movies?" *Journal of Marketing* 71.4 (2007): 102-20. Print.

Eliashberg, Jehoshua, and Steven M. Shugan. "Film Critics: Influencers or Predictors?" *Journal of Marketing* 61 (1997): 68-78. Print.

Eliashberg, J., S. K. Hui, and Z. J. Zhang. "From Story Line to Box Office: A New Approach for Green-Lighting Movie Scripts." *Management Science* 53.6 (2007): 881-93. Print.

Gong, James Jianxin, Wim A. Van Der Stede, and S. Mark Young. "Real Options in the Motion Picture Industry: Evidence from Film Marketing and Sequels." *Contemporary Accounting Research* (2011): No. Print.

Karniouchina, Ekaterina V. "Are Virtual Markets Efficient Predictors of New Product Success? The Case of the Hollywood Stock Exchange." *The Journal of Product Innovation Management* 28.4 (2011): 470-84. Print.

Kurkiewicz, Carly. *A Financial Analysis of Movies: Anticipating Box Office Success*. Thesis. The Pennsylvania State University, 2008. Print.

Leuhrman, Timothy, and William Teichner. "Arundel Partners: The Sequel Project." *Harvard Case Studies* (1992): 1-19. Print.

Litman, Barry R., and Linda S. Kohl. "Predicting Financial Success of Motion Pictures: The '80s Experience." *Journal of Media Economics* 2.2 (1989): 35-50. Print.

Liu, Yang, Xiangji Huang, Aijun An, and Xiaohui Yu. "ARSA: A Sentiment-aware Model for Predicting Sales Performance Using Blogs." *SIGIR '07 Proceedings of the 30th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval* (2007): n. pag. Print.

Liu, Yong. "Word-of-Mouth for Movies: Its Dynamics and Impact on Box Office Revenue." *Journal of Marketing* 70.3 (2006): 74-89. Print.

Sawhney, M. S., and J. Eliashberg. "A Parsimonious Model for Forecasting Gross Box-Office Revenues of Motion Pictures." *Marketing Science* 15.2 (1996): 113-31. Print.

Segal, Brad M. *The Business Behind the Art: Finance and the Film Industry*. Thesis. The Pennsylvania State University, 2005. Print.

Sharda, R., and D. Delen. "Predicting Box-office Success of Motion Pictures with Neural Networks." *Expert Systems with Applications* 30.2 (2006): 243-54. Print.

Zuckerman, Ezra W., and Tai-Young Kim. "The Critical Trade-off: Identity Assignment and Box-office Success in the Feature Film Industry." *Industrial and Corporate Change* 12.1 (2003): 27-67. Print.

Zufryden, Fred. "New Film Website Promotion and Box-Office Performance." *Journal of Advertising Research* 40 (2000): 55-64. Print.

(215) 622-8690
nikiarakelian@gmail.com

Niki Arakelian

532 E. College Ave. #3
State College, PA 16801

Participant Media *(Lincoln, The Help, An Inconvenient Truth)* Beverly Hills, CA
Production Assistant, Production Intern May 2012 – August 2012

- Created and pitched $100,000 marketing plan to Board of Directors for marketing feature films to college students (the Board will implement the plan in Fall 2013)
- Directed video production of the Thirst Gala, a $200,000 fundraiser for providing clean drinking water to Africa
- Coordinated casting calls with 26 actors from Upright Citizens Brigade and Groundlings comedic troupes
- Assisted directors and producers on set and edited 3 Participant TV episodes from start to finish
- Marketed upcoming TV series using social media and by contacting celebrity agents, managers, and publicists

NBCUniversal – Syfy Channel Universal City, CA
Development, Production, and Programming Intern January 2012 – May 2012

- Covered desks for Tim Krubsack (Senior Vice President, Development), Lucia Gervino (SVP, Production), Robyn Lattaker-Johnson (VP, Development), Colin Whelan (VP, Development), and Janice Ferrell (Director, Production)
- Pitched my original TV show concept to development executives through a 20-minute presentation and sizzle reel
- Evaluated pilots, rough cuts, treatments, sizzle reels, and pitches, and provided coverage to executives and assistants
- Researched story ideas, potential talent, and TV shows that could compete with Syfy programming
- Participated in weekly network meetings, department meetings, and pitch meetings with senior executives

SA Productions State College, PA
Director, Producer, Writer, Editor September 2010 – Present

- Produced 8-minute film, *Z*, which was nominated for Best Short Film in the International Vegas Cine Fest
- Wrote 9 political op-ed articles for PSU News on election issues, campaign strategies, and climate science
- Directed, produced, wrote, and delivered presentations on dangers of nuclear waste for the PSU Department of Communications and the hydrogen economy myth for the PSU Department of Energy Science
- Directed 3 video commercials in $1,000, 60-hour advertising project for the Athletic Clubs of State College
- Directed, produced, wrote, and edited official video commercial and marketing campaign for the Penn State Golf Teaching and Research Center

Penn State Marketing Association State College, PA
Project Manager, Creative Director September 2010 – December 2011

- Directed, produced, and edited the video production of the American Marketing Association Regional Conference
- Directed, produced, and edited the video production of the annual Kohl's Business Case Competition
- Awarded Project Manager of the Month (400 other students) for directing 2 film projects and 3 commercials
- Awarded Top Associate of the Month twice by the PSMA Board for leadership within the organization

Castro-Utrera Venture Capital State College, PA
Financial Adviser, Website Developer August 2010 – January 2011

- Co-Authored the official business plan for $18,000, student-run venture capital firm in a 120-hour project
- Led development of marketing plan, risk assessment, financial forecasts, and company website
- Pitched the company's business plan through a 25-minute presentation to potential investors and financial advisers

Benefit Concert for Haiti State College, PA
Co-Founder, Producer January 2010 – April 2010

- Co-Founded first Penn State Benefit Concert for Haiti to raise $500 for the United Way Disaster Relief Fund
- Appointed team leader of Production Unit to organize venue setup, sound managers, equipment, and talent
- Directed video production of slideshow to visually depict the earthquake relief efforts and raise awareness

Central Bucks Cable Network Doylestown, PA
Director, Producer, Writer, Editor September 2007 – May 2009

- Directed, produced, wrote, and edited 15 commercials, 3 weekly news broadcasts, and 2 short films for the network
- Directed, produced, wrote, and edited video marketing campaign for Susan G. Komen For The Cure fundraisers
- Awarded the Communications and Video Production Award for leadership and excellence in film production

Pennsylvania State University University Park, PA
B.S. Finance with Honors in Finance Graduate in May 2013

- Student of the Schreyer Honors College and the International Honor Society Beta Gamma Sigma
- Awarded Evan Pugh Scholar Award (top .5% of class) and Academic Excellence Scholarship ($3,500/year)
- Highly proficient with Adobe Premiere, Apple Final Cut Pro, Microsoft Office Suite, and Visual Basic