Ilmenau University of Technology
Institute of Economics

Ilmenau Economics Discussion Papers, Vol. 20, No. 98

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December 2015

Institute of Economics

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http://www.wirtschaft.tu-ilmenau.de

ISSN 0949-3859

Movie success in a genre-specific contest: Evidence from the US film industry

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Abstract: This article examines the economic effect of computer animation movie success by using data from all widely released feature length movies between 2011 and 2014, and all computer animated movies in North America between 1995 and 2014. We show that computer animated movies successfully attract families, parents, children, and teenagers and outperform other major movie genres (e.g., action, comedy or drama). This research sample also provides initial evidence that, counter to industry thinking in the film business, stardom is not directly associated with movie success.

JEL classification: C31 · L10 · L82 · M21

Keywords: Motion pictures economics, Movie genre, Computer animated movies

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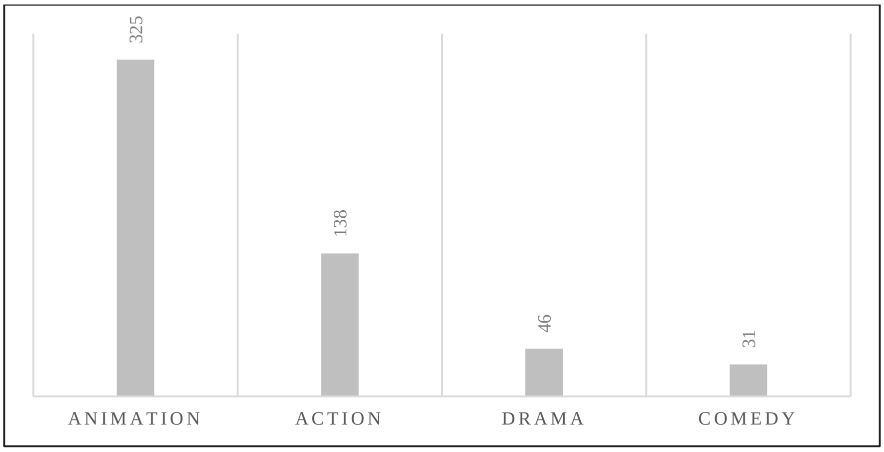
This work was partially supported by the German Research Foundation (DFG) within the Collaborative Research Centre “On-The-Fly Computing” (SFB 901).

Introduction

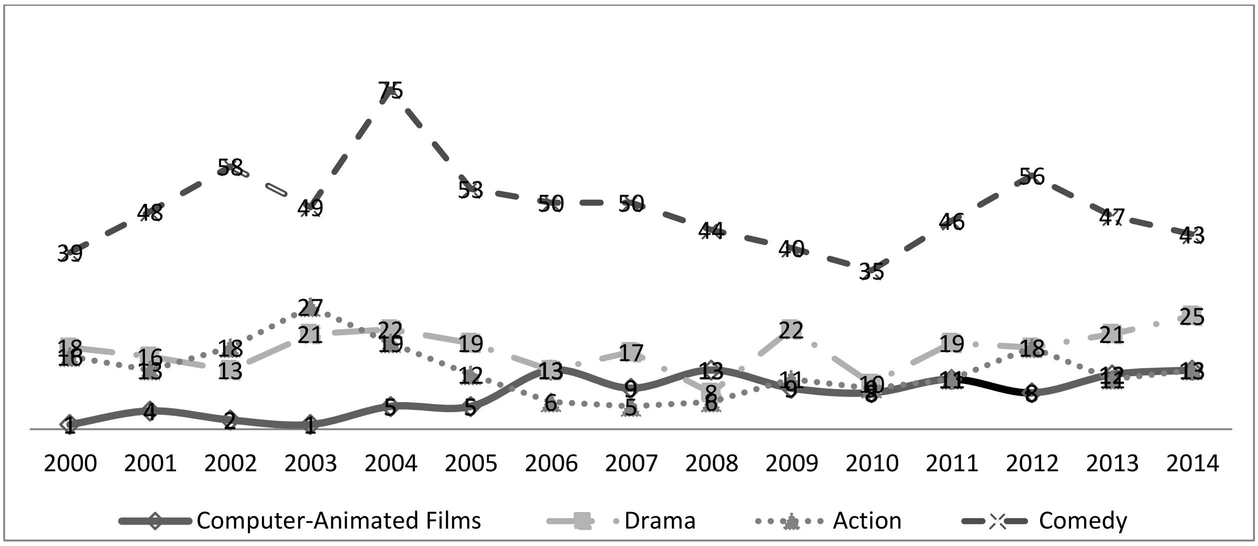
Movie genres represent reputational effects that help consumers to assess the quality of a movie before consumption and to bring their preference and perceptions in line with market offerings (De Silva 1998). With an average profit of 325 million US dollars, computer animated movies head the table of the top-profitable genres in the US cinema market between 2004 and 2013 and thus is placed even ahead of classic blockbuster genres such as action, drama or comedy (see figure 1). Additionally and compared to these three genres, computer animated movies are one of the few genre that show a continuous growth in production and cinema premieres in the last decade (see figure 2). We present an explorative genre-specific analysis and ask the question: 'why computer animations are more successful than other movie genres; why specifically computer animated movies consistently increased productions; and what specific signals of quality characterize the computer animation movie genre?'

Figure 1: Average movie profit by genre between 2004 and 2013 (in million US dollars)



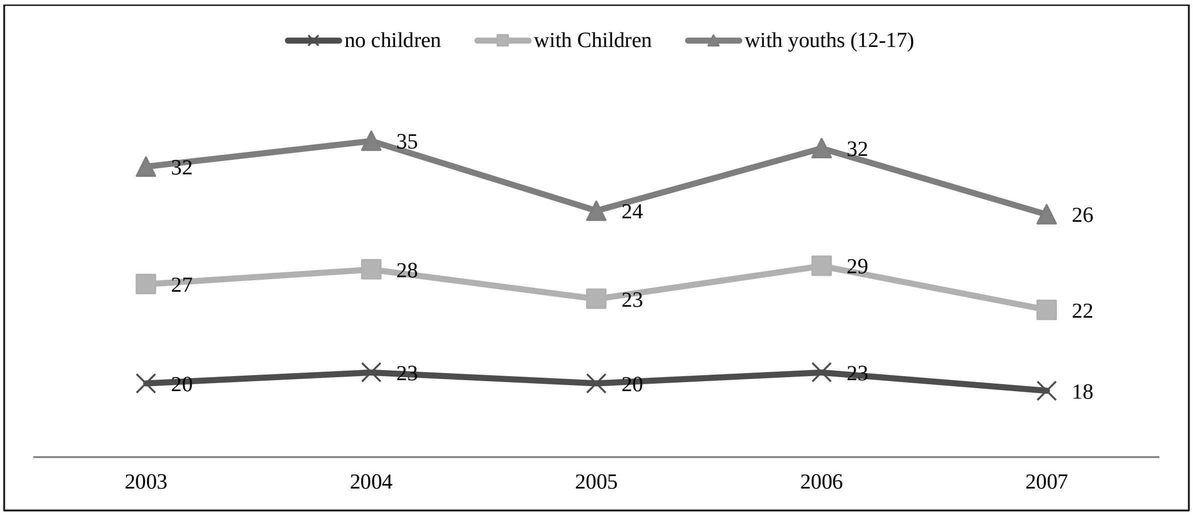
Source: Box office Mojo; Nomura Holdings (statista 2015)

Figure 2: Absolute numbers of cinema premieres from 2000 to 2014



The apparent business strategy for a movie to be successful is to appeal to everyone who goes to the cinema. As illustrated in Figure 3, almost 50 percent of all movie-goers were parents or singles with children or teenager. Computer animations play well with these consumer groups. For children they are easily understandable and entertaining. For teenagers they hold a rebellious potential and for adults they offer subtle meanings and humor. Accordingly, computer animation movies simultaneously appeal children and young people, but also attract adolescents, adults and parents.

Figure 3: Frequent US moviegoers by household composition from 2003 to 2007 in %



Source: MPAA Movie Attendance Study 2007

The movie business literature mainly analyses and quantifies the economic success of American feature films (Eliashberg and Shugan 1997, Nelson et al. 2001, Hand 2002, De Vany 2004, Basuroy et al. 2003, Elberse 2007). In 1983, Litman empirically investigated the influence of movie success mechanisms on market success for 125 movies that had a cinema release between 1972 and 1978 and showed that a film release in one of the categories science fiction and horror will increase distributors' revenue by approximately $5.9 million. Litman and Kohl included fifteen genre categories in their 1989 study that consisted of 697 films that had been released between 1981 and 1986. The results showed a significant influence of the two categories science fiction-fantasy and dramas on total box office. In contrast to the previous study from Litman (1983), the horror genre did not show any significant relationships. Prag and Casavant studied the market appeal of the movie genres romance/family, comedy, action, and drama in their 1994 movie business study of 652 movies released between 1975 and 1984. Only the drama genre showed a significant but negative impact on total box office but the comedy and action genre had significantly higher marketing expenditures. Sawhney and Eliashberg (1996) used the action, comedy, drama, horror, science fiction, and children/animation genre dummies in their movie success analysis of 111 films. Their findings show a faster reception by the customers of the action genre, whereas movies belonging to the drama genre seem to take more time until they receive the attention of moviegoers. Walls (2005) analysed the influence of genres on film returns using a dataset of 1989 movies in total. Walls found no significant influence of any one of the six genre classifications: action, adventure, animation, black comedy, comedy, and documentary.

Based on the findings of these studies, we contend that there is a genre effect that influences consumer behavior and that specifically computer animated movies show a significantly higher number of tickets sold than other movie genres. Although the effect of computer animated movies on box office success is presumable, the costs of producing a complete digital movie also increase significantly and thus require substantial financial investments. As we assume that the production studios want to maximize their profits, we also presume that the marginal costs of making a compute animated movie are exceeded by the marginal revenues generated by computer animated movies. Consequently and in line with studies from Litman (1983), Prag and Casavant (1994), Sawhney and Eliashberg (1996), De Vany (2004), Walls (2005), Einav (2007), Moon et al. (2010) and Treme and Craig (2013) and movie industry economics (Vogel 2011), we study the effect of computer animated movies on two key facets of economic success: (i) the numbers of tickets sold on the opening weekend measured as the opening box office gross, and (ii) the total attendance number measured as the total box office gross. We formulate the following research hypotheses referring to movie genres, computer animated movies and movie success:

H_1: The opening box office revenues generated by computer animated movies are significantly higher compared to other movie genres

H_2: The total box office revenues generated by computer animated movies are significantly higher compared to other movie genres.

I. Data and Model

Our data set consists of two samples. The first sample represents the collection of all new feature length movies given a minimum box office gross of $1 million in North America between 2011 and 2014. It consists of 657 movies characterizing the genres action, animation, comedy, drama, fantasy, foreign, horror, science fiction, thriller, documentary, and musical. In addition, we collected a second sample that represents all 114 widely released computer animated movies in North America between 1995 and 2014. Figures and several variables for explaining the success of moviers are obtained from Box Office Mojo, Internet Movie Database (imdb) and Rotten Tomatoes. Our analytical models reflect the previously stated hypotheses. The genre effects model is stated as follows:

$$\mathrm{lnMovieSuccess_i} = \beta_0 + \beta_1 \mathrm{Genre_i} + \beta_2 \mathrm{MovieCharacteristics_i} + \beta_3 \mathrm{Trend_i} + \varepsilon \quad (1)$$

The dependent variable $\mathrm{MovieSuccess}$ stands for the total revenues of movie i over its life cycle on the one hand and the total revenues of movie i on the opening weekend on the other hand. The Genre vector represents the main effect in finding a genre effect that influences consumer behavior and that computer animated movies perform significantly better than other movie genres. It comprises the genre variables action, animation, comedy, drama, fantasy, foreign, horror, science fiction, thriller, documentary, and musical. The vector $\mathrm{MovieCharacteristics}$ consists of additional movie success drives. To date, the most expensive computer animated movie is Tangled (2010) from Pixar/Disney with overall production costs of $260 million, which represents one of the top 5 most expensive movie productions worldwide behind box office champions like Pirates of the Caribbean 4 (production costs of $387.5 million), Avengers: Age of Ultron (production costs of $279, 9 million) and John Carter (production costs of $263, 5 million). Because there is a positive correlation between production costs and theatrical rentals (see inter alia Litman (1983)), production budget can be seen as a "proxy variable" for the overall technical and artistic quality of a movie. Following the literature (De Vany and Walls (2002) and Ravid (1999)), we also assume a significant relationship between movies revenues and their

MPAA restrictions. For that reason, we include the MPAA ratings G (general audiences), PG (parental guidance suggested) and PG-13 (parents strongly cautioned) as dummy variables in our analysis for explaining a movies success. In order to measure the effect of film critics on $\mathrm{MovieSuccess}$, the rating scores from professional reviewers and audience critics have also been collected as explanatory variables (inter alia Basuroy et al. 2003, Litman and Kohl 1989, Eliashberg and Shugan 1997, Moon et al. 2010, Prag and Casavant 1994, Ravid and Basuroy 2004, Wallace et al. 1993). Another independent variable is a dummy variable for whether the movie is a sequel, prequel or an adaption title, because pre-releases of movies influence the success of movies (Prag and Cassavant (1994)). An actor's reputation effect as well as reputation effects of winning awards in terms of acknowledgment of artistic quality and achievement can be important indicators for the quality of a film. Star actors may attract a bigger audience (Rosen 1981). For instance, De Vany (2004) demonstrate that movies with stars are shown on more screens than those without popular actors. Various researchers (Litman and Kohl 1989, Wallace et al. 1993, Ravid 1999, Elliot and Simmons 2008) have focused their analyses on the influence of actors with ex ante popularity. We generate a variable for star apperance and classified an actor as a star with ex ante popularity by means of the Quigley's Annual List of Box-Office Champions from 1995 to 2014. Against the background of analyzing the relationship between award wins, we collected data from the Academy Awards. Trend represents the temporal point in time when movie i was released, measured as the release quarter of each movie and the release year.

The computer animated model studies the genre specific movies success drivers of the computer animation genre:

$$\mathrm{lnMovieSuccess_i} = \gamma_0 + \gamma_1 \mathrm{MovieCharacteristics_i} + \gamma_2 \mathrm{Trend_i} + \theta \qquad (2)$$

As mentioned before, MovieSuccess also contains the total revenues of movie i over its life cycle and the total revenues of movie i on the opening weekend in our computer animation sample. The vector MovieCharacteristics represents the movie success drives for explaning the success of computer animated movies, namely the production costs of movie i, the MPAA age rating classification (G, PG and PG-13) of movie i, the reviews from professional critics and moviegoers of movie i, brand extension information regarding a sequel, prequel or adaption title, the wins of an Academy Award of movie i and the number of participated major star actors. Trend represents the temporal point in time when movie i was released, measured as the release quarter of each movie and the release year as well.

Table 1 and Table 2 provide the descriptive statistics of both the genre sample and the computer animated data set.

Table 1: Descriptive statistics of the genre sample

Variable	Obs	Mean	Std. Dev.	Min	Max
MOVIE SUCCESS					
(1) Total Gross	657	62.061.102	77.405.621	1.005.800	623.357.910
(2) Opening Gross	657	18.574.996	25.945.536	109	207.438.708
GENRE					
(3) Action	657	0.1903	0.3928	0	1
(4) Computer Animation	657	0.0578	0.2336	0	1
(5) Comedy	657	0.2420	0.4286	0	1
(6) Drama	657	0.2222	0.4161	0	1
(7) Fantasy	657	0.0182	0.1340	0	1
(8) Horror	657	0.0594	0.2365	0	1
(9) Science Fiction	657	0.0639	0.2448	0	1
(10) Thriller	657	0.0776	0.2678	0	1
(11) Documentary	657	0.01370	0.1163	0	1
(12) Musical	657	0.0228	0.1495	0	1
MOVIE CHARACTERISTICS					
(13) Production Budget	657	47.852.253	52.876.108	40000	250.000.000
(14) G	657	0.0152	0.1225	0	1
(15) PG	657	0.1385	0.3457	0	1
(16) PG-13	657	0.4307	0.4955	0	1
(17) Critics Ratings	657	53.3531	28.0253	0	99
(18) Audience Ratings	657	59.0792	19.6921	3	95
(19) Sequel/Prequel	657	0.1674	0.3736	0	1
(20) Adaption	657	0.1766	0.3816	0	1
(21) Oscar Wins	657	0.1355	0.7272	0	11
(22) Star Appearance	657	0.0761	0.2710	0	2
TREND					
(23) Q2	657	0.2359	0.4249	0	1
(24) Q3	657	0.2603	0.4391	0	1
(25) Q4	657	0.2785	0.4486	0	1

Table 2: Descriptive statistics of the computer animation sample

Variable	Obs	Mean	Std. Dev.	Min	Max
MOVIE SUCCESS					
(1) Total Gross	114	128.504.497	100.230.256	4091	441.226.247
(2) Opening Gross	114	33.503.807	25.758.883	4091	121.629.270
MOVIE CHARACTERISTICS					
(3) Production Budget	114	95.405.263	54.698.038	2.000.000	260.000.000
(4) G	114	0.2281	0.4214	0	1
(5) PG	114	0.7193	0.4513	0	1
(6) PG-13	114	0.0263	0.1607	0	1
(7) Critics Ratings	114	61.9035	26.7310	4	100
(8) Audience Ratings	114	66.9561	13.6274	24	92
(9) Sequel/Prequel	114	0.2193	0.4156	0	1
(10) Adaption	114	0.1842	0.3894	0	1
(11) Oscar Wins	114	0.1667	0.4396	0	2
(12) Star Appearance	114	0.1228	0.3555	0	2
TREND					
(13) Q2	114	0.2456	0.4324	0	1
(14) Q3	114	0.2193	0.4156	0	1
(15) Q4	114	0.3596	0.4820	0	1

II. Results

We present our estimations of the total box office gross and the opening box office gross for both the genre and the computer animated sample in Table 3. OLS Regression output from four different model specifications are presented. We also estimated our models by quantile regressions. Our estimations lead to consistent results, which underlines the robustness of our models.

In general, the results from our analytical genre effects model confirm the results by the literature (except Walls (2005)) to the extent that genres show basically a significantly effect on MoviesSuccess. Our results, however, show a strong significantly effect on MovieSuccess. More precisely, all of the ten genres are significantly related to TotalGross and OpeningGross with a positive sign on a three star level (except documentary with a one star level).

When looking at the genre-variable coefficients, there is an important and highly interesting result in the data: the nearly niche product of computer animated movies generates a higher total box office gross in comparison to all other very popular genres like action, comedy and drama, except horror-movies. Accordingly, we completely confirm our first hypothesis that the total box office revenues generated by computer animated movies are significantly higher compared to other movie genres. Regarding our second hypothesis, the computer animation genre is, at least, among the top five genres generating the highest opening box office revenues. The opening box office revenues generated by computer animated movies are significantly higher compared to movie genres: documentary, drama, comedy and thriller. For that reason, we also affirm our second hypothesis with respect to the above mentioned genres. The genre sample also establishes empirical evidence for control vectors such as, inter alia, production costs, MPAA age rating classification, reviews from moviegoers and star popularity.

The first conclusion we can draw from the computer animated analysis is that its MovieSucess significantly depents on the production budget. The level of production budget has a strong positive significant influence on both, the total and opening box office gross. Therefore, production budget can be seen as as a proxy variable for the overall technical and artistic quality of a movie (Litman 1983). Additionally, all non-restrictive MPAA age classifications (G, PG and PG-13) show a strong statistically significant influence on movie success. A one unit increase in production of family friendly movies associates with an average increase in revenues of 6.88%. Related to a mean in additional box revenues in our dataset of $8.8 million, economically this is a significant number.

We also find strong statistically significant influences of reputation effects of sequels (or prequels) on MovieSucess with a positive sign. Accordingly, computer animated sequels bring on reputation effects that positively influence ticket sales by minimizing uncertainties in the decision process of consumers (see also Prag and Cassavant (1994)). Besides, reviews from professional critics play also a positive significant role by explaining the success of computer animated movies. Movie reviews from professional critics have the ability to directly influence consumers' choices because of their reliable expertise. We cannot find a significant effect of professional critics on opening gross. However, winning Academy Awards lead to significant economic effects on both total and opening box office gross. They do not only have a high media marketing impact but also ticket sales promotion effects. Incidentally, we have to consider time-effects and causality here, because prizes are sometimes later awarded than the release of a movie. For that reason, awards could maybe simply act as a proxy for other unobserved variables. In terms of the influence of the released quarter, our computer animated model does not support the results of the literature (Litman (1983), Nelson et al. (2001), Sochay (1994) and Einav (2007)). Movies that are released in the second and fourth quarter, so between April and June and during Thanksgiving and Christmas, show a significantly negative impact on ticket sales and consequently on total revenues and those on the opening weekend. This can be explained by the fact of high competition during these quarters.

Focusing on the impact of star popularity on the opening and the total gross, it is apparent that stardom associates positively but insignificantly with sales in our dataset. This conclusion is important because it shows that the important factor of stardom (strong significant in our genre sample) does not play any significant role by producing a computer animated movie in our sample. Consequently, we cannot affirm the study findings that verify the positive influence of actors with ex ante popularity on box office gross (Litman and Kohl (1989), Wallace, Steigermann and Holbrook (1993)). The star actors' salary costs account for 5.5% of the average production costs of a computer animation movie. Thus, the non-contracting of a star would result to a reduction of production costs of $5.3 million in our sample. An economically significant relationship for movie studios facing increasing competition and decreasing profits.

Furthermore, we cannot find empirical evidence regaring the reviews from moviegoers. This is also a very interesting point, because social and peer group effects generated by the audience seem to be less important for children and families.

Table 3: Genre and computer animation sample estimations

	Genre Sample		Computer Animation Sample	
	(1)	(2)	(3)	(4)
VARIABLES	ln Total Gross	ln Opening Gross	ln Total Gross	ln Opening Gross
GENRE				
Action	1.489***	3.035***		
	(0.272)	(0.524)		
Computer Animation	1.831***	2.925***		
	(0.320)	(0.586)		
Comedy	1.688***	2.826***		
	(0.252)	(0.511)		
Drama	1.115***	2.130***		
	(0.255)	(0.515)		
Fantasy	1.620***	2.931***		
	(0.329)	(0.593)		
Horror	2.019***	4.098***		
	(0.322)	(0.574)		
Science Fiction	1.731***	3.551***		
	(0.351)	(0.604)		
Thriller	1.403***	2.883***		
	(0.291)	(0.563)		
Documentary	1.247***	1.624*		
	(0.440)	(0.942)		
Musical	1.538***	3.551***		
	(0.318)	(0.564)		
Foreign	Reference genre			
MOVIE CHARACTERISTICS				
ln Production Budget	0.531***	0.726***	0.919***	0.836***
	(0.066)	(0.095)	(0.262)	(0.214)
G	-0.057	0.614	7.151***	6.524***
	(0.484)	(0.562)	(0.904)	(0.626)
PG	0.172	0.477**	7.038***	6.559***
	(0.141)	(0.194)	(0.922)	(0.634)
PG-13	0.279***	0.239	6.454***	6.261***
	(0.098)	(0.176)	(1.046)	(0.764)
Critics Ratings	0.001	-0.017***	0.011**	0.007
	(0.002)	(0.004)	(0.005)	(0.005)
Audience Ratings	0.010***	0.010*	0.015	0.014
	(0.003)	(0.005)	(0.013)	(0.011)
Sequel/Prequel	0.528***	0.793***	0.579***	0.660***
	(0.102)	(0.142)	(0.159)	(0.151)
Adaption	0.210**	0.412***	-0.116	-0.104
	(0.102)	(0.154)	(0.190)	(0.172)
Oscar Wins	0.189***	-0.016	0.266*	0.273**
	(0.040)	(0.106)	(0.140)	(0.121)
Star Appearance	0.479***	0.592***	0.055	0.018
	(0.098)	(0.198)	(0.172)	(0.160)
TREND				
Q2	-0.145	-0.291	-0.464*	-0.456**
	(0.127)	(0.206)	(0.250)	(0.213)
Q3	-0.024	-0.099	-0.047	-0.253
	(0.115)	(0.193)	(0.245)	(0.205)
Q4	-0.048	-0.587***	-0.659**	-0.803***
	(0.110)	(0.190)	(0.262)	(0.224)
ZT	0.033	-0.026	-0.059***	-0.053***
	(0.038)	(0.060)	(0.019)	(0.017)
Observations	657	657	114	114
R-squared	0.534	0.503	0.853	0.870

Robust standard errors in parentheses
*** p<0.01. ** p<0.05. * p<0.1

III. Conclusion

Genre-effects have been a major point of economic discussion with respect to genres like action, drama, comedy and horror. In distinction from past studies, we analyze the niche genre of computer animated movies for the first time. First, we analyzed 657 movies given a minimum box office gross of $1 million representing different genres. Second, we conducted an empirical analysis of all widely released computer animated movies. The findings of this study reinforce the hypothesis that movie genres associate strongly with movie success. Especially, computer animated movies show significantly higher box office revenues than other movie genres such as action, drama or comedy.

Furthermore, computer animated movies successfully canvass families, parents, children and teenager. All nonrestrictive age classifications show strong statistically significant influences on movie success with diminishing value of impact of more restrictive ratings. Consequently, movie studios are well-advised to step up efforts of producing family-oriented movies. Economically important is also the fact that our dataset of computer animated movies show no statistically significant relationship of star popularity on neither the total gross nor the opening gross. Consequently, our results are intuitive to a commonly held belief in the value of star actors on the commercial success of animated movies and emphasise the greater importance of computer animated movies in this particular market context.

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