,

Yixuan Wang

Abstract: In this paper I apply the Quantile Regression model that suits for the different contribution of the attributes surrounding different levels of film revenues. The regression coefficients from this model reflects the correlation between the film revenue and the various attributes (production budget, popularity, runtime, vote average and vote count). Th 842( )-22(e)-10(m)28pitril

tre has died various tentil ioflencng fators on fionc l rfom513aenceof

anlysi82(s)423(r)-7(e)12(s)-19pult ss that Q coefficents var arss differentioterlsoffilmrevenue Ths imles 257(t)5(h)] TJETQq0.000008873 0 595.44 841.92 reW* nBT/F1 10.56 Tf1 0 0 1 465.51 11.354 Tm0 g0 G[(a)

implement positive impact on the distribution of financial success for films, while the effect of popularity and vote average depend on the interval of the profitability of the film. Furthermore in the analysis, for the samples used in this paper, traces of economic scale in film industry is not evident as the film revenue increases so long as the square of the budget increases.

1-

Prior researches have comprehensively studied the potential influencing factors of film performance, with similar results. Using film revenue as the key film performance measure (e.g., Raj and Aditya, 2017; Derrick et al., 2014; Ainslie et al., 2005; Walls, 2005), many researchers conclude that promotion spending, number of screens played and viewer satisfaction play a

al., 2005; Walls, 2005; Moon et al., 2010) To be specific, Moon et al. (2010) categorizes film reviewer into general viewer and in-depth viewer. They point out that general viewer give film ratings based on the past ratings and ongoing controversy, whereas in-depth viewer give film ratings based on their watch experiences. Thus, these causes of general viewers and in-depth viewers need to be taken into account when predicting viewer satisfaction, and hence film revenue. Celebrity appeal has equal importance in both success and failure of a movie. (e.g., Raj and Aditya, 2017; Derrick et al., 2014; Walls, 2005) Other influencing factors include high season, vertical integration in the industry, special effects and movie album. (Derrick et al., 2014; Gil, 2009; Walls, 2005)

Most of the literature apply linear regression model to examine the influencing factors of film revenue. (e.g., Raj and Aditya, 2017; Derrick et al., 2014; Moon et al., 2010) In particular, Derrick et al. (2014) establishes a two-stage linear model that examines the influencing factors of the first week revenue and the subsequent week revenue. A proxy variable of the first week revenue is incorporated in the subsequent week revenue model which results in a positive

nation of a market share model

and a demand model, estimated using a Markov Chain Monte Carlo (MCMC) Algorithm.

Derrick et al. (2014). Walls (2005) states that based on the extreme uncertainty and various possibility on film revenue, a stable distribution regression model with infinite variance should be suitable for examining the influencing factors in this case. However, Derrick et al. (2014) refute this by applying the model on the 135 films that were released in 1999. After computing the R^2, p value with corresponding F statistics, MSE, and MAD, it appears to have no evidence of stable distribution regression model.

Current directions of the literature lead to a question on the different contributions of influencing factors on films with different levels of film revenue. To address this problem, this study aims to investigate influencing factors of film revenues with various quantiles, using Quantile Regression method.

-

on a set of explanatory variables. Compared with conventional methods, using QR presents two benefits for this investigation. First and
across quantile levels, which suits our purpose to study the profit formula of films making revenues of different levels. However, conventional methods, e.g., OLS and its variants, assume a constan

problem, suggested by Lee and Li (2012). Such problem always occurs when using conventional models. To address heterogeneity, one tradition way is to first separate the sample and then conducts a comparative analysis on the sub-
problem.

itability, five potential influencing factors for film revenue are included in this QR model. In particular, the budget, popularity, runtime, vote average, and vote count of a film are used as the five explanatory variables, according to Walls (2005). More
greatest focus of film investors.

Hence, the regression model is derived as follows:

response variable. The budget variable directly reflects the quality of casting, production and

result of its marketing strategy, while runtime controls the amount of times the film is played. The vote average and vote count mirrors the depth of the film theme and the quality of the acting.

-

In the previous section, linear regression is applied to examine the overall impact of film revenue on the five explanatory variables (budget, popularity, runtime, average vote and vote count). In fact, in the film industry, these five explanatory variables contribute differently to films at various profitability levels. Literary films, like Cinema Paradiso, attract the audience through its vote on film review platforms. Science Fiction films, such as The Avengers, boost the revenue mainly on their billions of dollars investment. Thus, simply examining the film revenue in linear regression is not able to accurately reflect the contribution of each explanatory

variable to films of all profitability levels. So in this section, I use quantile regression method to further model the film revenue.

In this section, quantile regression is used to measure the impact of film revenue on the five explanatory variables (i.e., budget, popularity, runtime, average vote and vote count). Estimation of the parameter of each explanatory variable across different quantile level is provided in table 1,2,3,4, and 5, with their corresponding plots.

Table 1 The relation between film revenue (REV) and budget based on quantile regression

Notes: 1. * Significance at the 5% level.

** Significance at the 1% level.

2. p-Value refers to the T tests of the QR estimates across various quantiles.

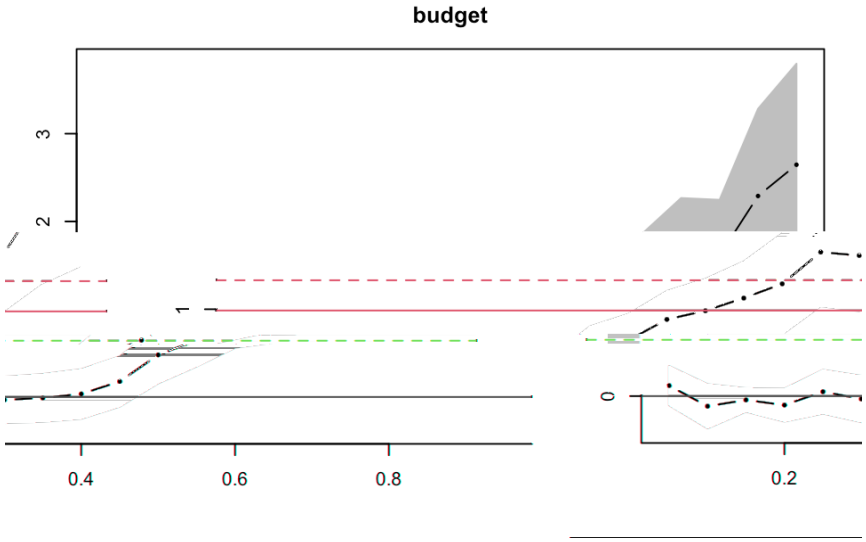

Figure 1. The impact of film revenue on budget along quantile levels of budget.

Based on the information in Table 1 and figure 1, with the improvement of quantile level, there is a significant "J" relationship between film production budget investment and film box office revenue. At the quantile level of 0.05 to 0.15, the contribution margin of box office revenue of film production budget investment is high, the marginal contribution value is 0.5771

to 0.8935, and the highest value is 9 times of the lowest marginal contribution value, reaching 40% of the maximum marginal contribution value. At the quantile level of 0.2 to 0.35, its marginal contribution value fell to the bottom, only between 0.1113 and 0.1484, only one thirtieth of the best marginal contribution value. From the 0.4 quantile level, the marginal contribution value of film production budget investment increased steadily in an exponential curve, from 1.6478 to 3.3074 times.

Table 2 The relation between film revenue (REV) and popularity based on quantile regression

Table 3 The relation between film revenue (REV) and runtime based on quantile regression

Notes: 1. * Significance at the 5% level.

** Significance at the 1% level.

2. p-Value refers to the T tests of the QR estimates across various quantiles.

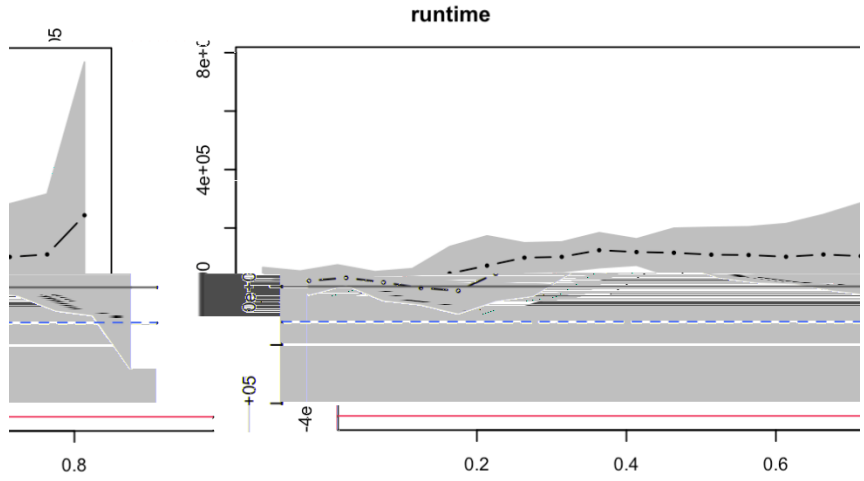

Figure 3. The impact of film revenue on runtime along quantile levels of runtime.

Based on the information in Table 3 and figure 3, the impact of operation time on film box office revenue is only significant at the three quantile level, at the 0.95 confidence level, and the significant quantile level accounts for only 15%. Its marginal contribution value below the 0.5 quantile level is mainly negative, while above the 0.5 quantile level, it is positive, and its marginal contribution value is also stable at about 140000.

Table 4 The relation between film revenue (REV) and Vote Average based on quantile regression.
