Heterogeneity analysis of the role of film box office revenue factors - based on quantile regression analysis

Yixuan Wang[①]

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). The empirical analysis result shows that QR coefficients vary across different intervals of film revenue. This implies that the size of the effect for the influencing factors differ between profitability quantiles of films.

Key Words: film revenues; Quantile Regression model; potential influencing factors; Marginal contribution; U-shaped curve

1.Introduction

Large literature has studied various potential influencing factors on financial performance of motion-pictures, most of them agree that promotion spending, number of screens played and viewer satisfaction play a significant role in a film's success. (e.g., Raj and Aditya, 2017; Derrick et al., 2014; Ainslie et al., 2005; Walls, 2005; Moon et al., 2010) Many of them apply a linear model to examine the effect of the influencing factors. Most recently, 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 relation to a film's success.

Quantile Regression model analyzing the financial performance of motion-pictures returns result of samples from movies with different profitability level under the effects of multiple independent variables: production budget, popularity, runtime, vote average and vote count. In this analysis, I found that the QR estimates vary across different quantiles: budget and vote count

[①] Yixuan Wang, Assistant Research Fellow, University of California, Santa Barbara. Statistics and Data Science, UC Santa Barbara, California, U.S.A.93106

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.

2.Literature review

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 significant role in a film's success. (e.g., Raj and Aditya, 2017; Derrick et al., 2014; Ainslie et 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 relation to a film's success. Ainslie et al. (2005) apply a combination of a market share model and a demand model, estimated using a Markov Chain Monte Carlo (MCMC) Algorithm. Moreover, a debate occurs on the "heavy tails" trait of film data, between Walls (2005) and 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.

3.Empirical model

The empirical model we use to estimate is the quantile regression (QR) of films' profitability on a set of explanatory variables. Compared with conventional methods, using QR presents two benefits for this investigation. First and foremost, QR measure the variation of film's profitability 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 constant impact of the films' revenue across different quantile levels of explanatory variables. Secondly, the QR method uses the entire sample and thus avoids the "truncation of sample" 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-samples, which leads to "truncation of sample" problem.

Based on specific characteristics of films' profitability, 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). Moreover, the revenue of a film represents the film's profitability, which is also the greatest focus of film investors.

Hence, the regression model is derived as follows:

$$\begin{aligned} Revenue_i = \beta_0 + \beta_1(budget)_i + \beta_2(populairty)_i + \beta_3(runtime)_i \\ +\beta_4(vote\ \ average)_i + \beta_5(vote\ \ count)_i + \mu_i \end{aligned} \tag{1}$$

where i indexes individual movies. A film's revenue is on the right side of the model, as the response variable. The budget variable directly reflects the quality of casting, production and promotion, which largely decides audiences' film experience. The variable popularity is the 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.

4. Result and discussion

4.1 the quantile-varying relations between revenue and influencing factors

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

Quantile	Estimate	p-Value	Quantile	Estimate	p-Value
0.05	0.5771	(0.000)**	0.55	1.9117	(0.000) **
0.10	0.8132	(0.000) **	0.60	2.0935	(0.000) **
0.15	0.8935	(0.000) **	0.65	2.2787	(0.000) **
0.20	0.1113	(0.000) **	0.70	2.3497	(0.000) **
0.25	0.1173	(0.000) **	0.75	2.5028	(0.000) **
0.30	0.1347	(0.000) **	0.80	2.5863	(0.000) **
0.35	0.1484	(0.000) **	0.85	2.7389	(0.000) **
0.40	1.6478	(0.000) **	0.90	3.3074	(0.000) **
0.45	1.7867	(0.000) **	0.95	-	(0.000) **
0.50	1.8255	(0.000) **			

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.

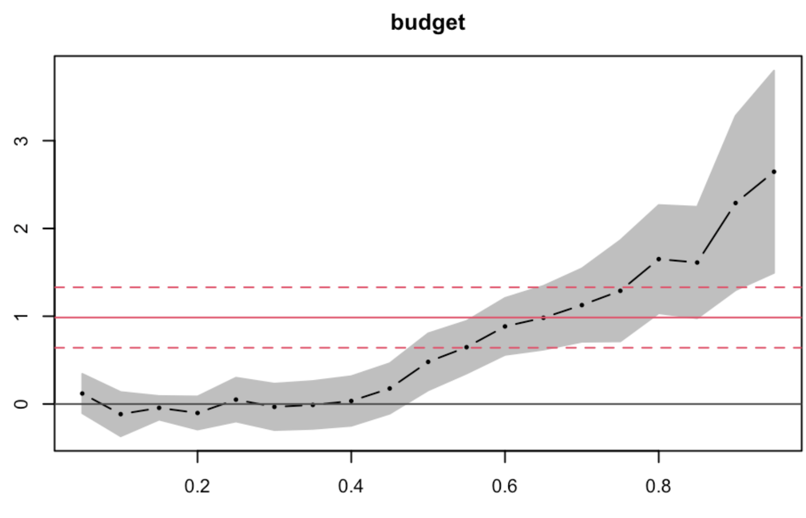

Figure 1. The impact of film revenue on budget along quantile levels of budget.

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

Quantile	Estimate	p-Value	Quantile	Estimate	p-Value
0.05	3.9322×10^4	(0.822)	0.55	9.1934×10^5	(0.030)*
0.10	4.5141×10^4	(0.901)	0.60	1.0562×10^6	(0.002) **
0.15	3.0312×10^5	(0.615)	0.65	9.3585×10^5	(0.000) **
0.20	6.3695×10^5	(0.170)	0.70	8.0395×10^5	(0.000) **
0.25	6.1073×10^5	(0.105)	0.75	6.0014×10^5	(0.000) **
0.30	5.6554×10^5	(0.000) **	0.80	4.2285×10^5	(0.592)
0.35	5.1464×10^5	(0.031) *	0.85	1.1556×10^6	(0.250)
0.40	5.4248×10^5	(0.008) **	0.90	1.0593×10^6	(0.000) **
0.45	5.7286×10^4	(0.144)	0.95	7.0323×10^5	(0.405)
0.50	6.2783×10^4	(0.204)			

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.

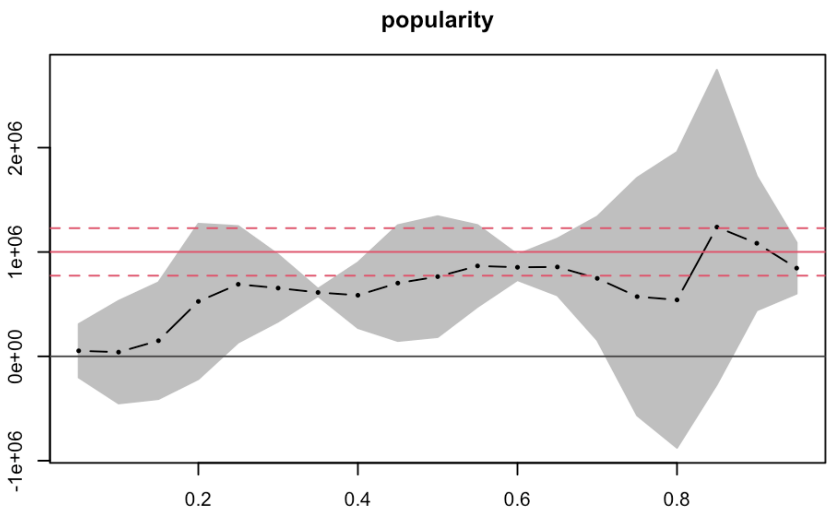

Figure 2. The impact of film revenue on popularity along quantile levels of popularity.

Based on the information in Table 2 and Figure 2, the effect of regional population size on film box office revenue is not significant in the whole sample, but significant at the quantile levels of 0.30, 0.35, 0.4, 0.55, 0.6, 0.65, 0.7, 0.75 and 0.9 and Significance at the 5% and 1% level. Its marginal contribution value fluctuates between 10000 and 100000. The mode is about 60000.

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

Quantile	Estimate	p-Value	Quantile	Estimate	p-Value
0.05	-3.4079×10^4	(0.601)	0.55	1.0393×10^5	(0.000) **
0.10	-7.3600×10^4	(0.053)	0.60	1.4663×10^5	(0.125)
0.15	-9.7722×10^4	(0.047)	0.65	1.3447×10^5	(0.128)
0.20	-1.3390×10^5	(0.001) **	0.70	1.4523×10^5	(0.089)
0.25	-1.4397×10^5	(0.005) **	0.75	1.2143×10^5	(0.061)
0.30	-8.4120×10^4	(0.079)	0.80	1.0582×10^5	(0.232)
0.35	7.8078×10^2	(0.968)	0.85	1.1167×10^5	(0.342)
0.40	-1.3886×10^4	(0.861)	0.90	1.0555×10^5	(0.405)
0.45	2.2896×10^4	(0.736)	0.95	1.4049×10^5	(0.092)
0.50	4.2362×10^4	(0.619)			

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.

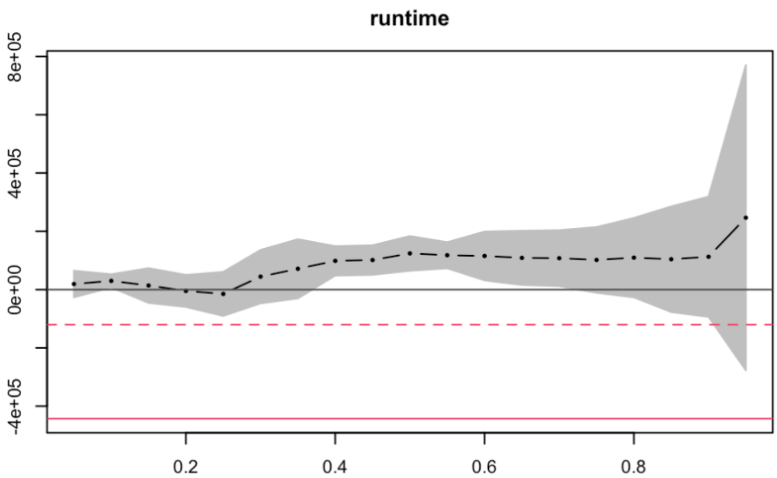

Figure 3. The impact of film revenue on runtime along quantile levels of runtime.

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.

Quantile	Estimate	p-Value	Quantile	Estimate	p-Value
0.05	1.8166×10^6	(0.142)	0.55	-1.1627×10^6	(0.244)
0.10	2.4512×10^6	(0.000) **	0.60	-3.4965×10^5	(0.816)
0.15	1.8594×10^6	(0.078)	0.65	-3.4794×10^5	(0.847)
0.20	2.9571×10^6	(0.000) **	0.70	7.6087×10^4	(0.967)

0.25	7.1936×10^5	(0.467)	0.75	9.8400×10^5	(0.592)
0.30	5.0687×10^5	(0.407)	0.80	7.5989×10^5	(0.705)
0.35	7.5092×10^5	(0.410)	0.85	5.9532×10^5	(0.809)
0.40	7.5104×10^4	(0.961)	0.90	2.0744×10^5	(0.942)
0.45	-1.4471×10^6	(0.262)	0.95	5.976×10^5	(0.927)
0.50	-9.2850×10^5	(0.456)			

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.

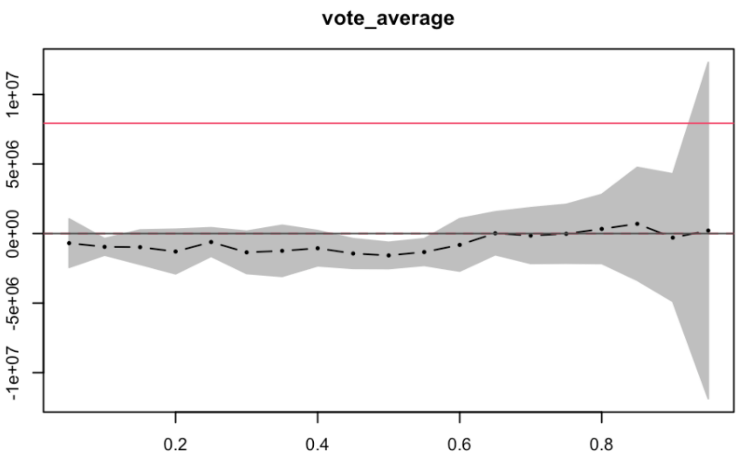

Figure 4. The impact of film revenue on vote average along quantile levels of vote average.

It can be seen from the information in Table 4 and Figure 4 that the marginal contribution of the voting average to the film box office revenue is also significantly positive only at the 5% significant level at the quantile level of 10%, and the marginal contribution of the voting average to the film box office revenue is negative at the middle quantile levels of 0.45, 0.5, 0.55, 0.60 and 0.65, with an action value of 35000-150000; At the other quantile level, the marginal contribution is positive, and its action value is unstable and fluctuates greatly in the quantile range, from 70000 to 1.81 million.

Table 5 The relation between film revenue (REV) and Vote Count based on quantile regression

Quantile	Estimate	p-Value	Quantile	Estimate	p-Value
0.05	1.5029×10^4	(0.000) **	0.55	4.3038×10^4	(0.000) **
0.10	2.3154×10^4	(0.000) **	0.60	4.2126×10^4	(0.000) **
0.15	2.8780×10^4	(0.000) **	0.65	4.3240×10^4	(0.000) **
0.20	3.2293×10^4	(0.000) **	0.70	5.2118×10^4	(0.000) **
0.25	3.3802×10^4	(0.000) **	0.75	5.4742×10^4	(0.000) **
0.30	3.7639×10^4	(0.000) **	0.80	6.2204×10^4	(0.000) **
0.35	3.7974×10^4	(0.000) **	0.85	6.9630×10^4	(0.000) **
0.40	3.7592×10^4	(0.000) **	0.90	7.0977×10^4	(0.000) **
0.45	4.1257×10^4	(0.000) **	0.95	1.0704×10^5	(0.000) **

0.50	4.3186×10^4	(0.000) **

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.

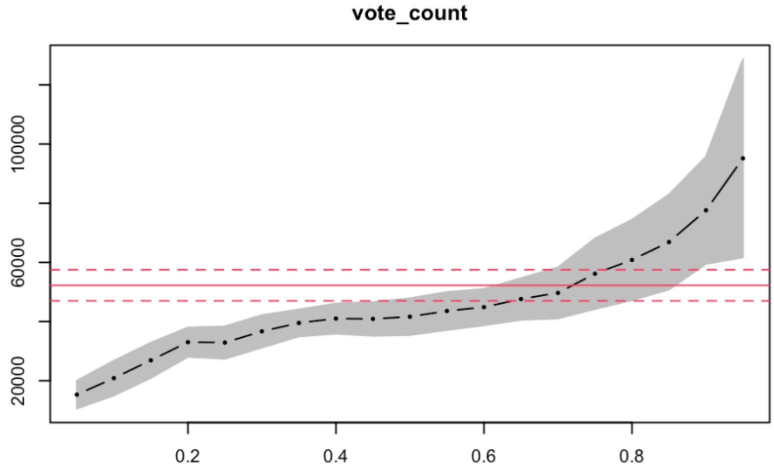

Figure 5. The impact of film revenue on vote count along quantile levels of vote count.

It can be seen from the information in Table 5 and figure 5 that the effect of votes based on Quantile Regression on film revenue (Rev) is a significant positive effect at the 95% confidence level, and with the improvement of quantile level, the marginal contribution value also shows a steady upward trend, from the initial 15000 to 100000.

Table 1,2and 5 show that the QR estimates of the coefficients of film revenue are positive. This implies direct relations between film revenue and budget, popularity and vote count. In other words, with an increase in the budget, popularity and vote count of a film, film revenue is highly likely to encounter an increase. This result corresponds to the quantile-varying pattern in figures 1,2 and 5. Table 3 suggests that the QR estimates of the coefficient is negative in 0.05-0.40 interval, then switches to positive in 0.40-0.95 interval. This shows an inverse relation between film revenue and runtime in 0.05-0.40 quantile, while a direct relation is shown in 0.40-0.95 quantile. Furthermore, table 4 shows negative QR estimates of the coefficients of film revenue in 0.45-0.55 quantile, and positive QR estimates of it in 0.05-0.45 and 0.7-0.95 quantile. The results of table 3 and 4 coincides with their fig. 3 and 4.

In tables 1-5, the QR estimates are non-uniform which vary across various quantiles. To be specific, in tables 1 and 5, the value of the quantile-varying estimates of the coefficient of film revenue on budget and vote count tend to increase as their quantile level increase. Similar quantile-varying pattern only occur in the 0.05-0.20 and 0.80-0.95 quantile level in table 2 and 3. That is to say, within 0.20-0.80 quantile level, the coefficient of film revenue on popularity and runtime make slight increase. While in the 0.05-0.20 and 0.80-0.95 quantile level, major rise in the coefficients can be seen across different quantiles. In table 4, different from other explanatory variables, the quantile-varying pattern of the QR estimates is relatively flat along quantile levels. Moreover, the p-Value of the T tests shown in table 1-5 suggest that the QR estimates of budget, popularity, and vote count are significant at the 5% level.

Apart from the quantile-varying relation, the estimated slope parameter tends to vary with the quantile levels of the explanatory variables. In Table 1,5 and Fig. 1,5, the slope estimate monotonically increases across various quantile levels. This shows that budget and vote count positively affect film revenue. This effect implies that the film revenue is higher (lower) when the film gains higher (lower) budget and vote count. As shown in Table 2,3and Fig. 2,3, the slope estimates experience a large growth in the lowest quantile (i.e., from 0.05 to 0.20 quantile) and the highest quantile (i.e., from 0.80 to 0.95 quantile). From 0.20 to 0.80 quantile, the slope parameters of the explanatory variables (i.e., popularity and runtime) make small variation. As a result, the popularity and the runtime affect the revenue for films making the lowest (i.e., from 0.05 to 0.20 quantile) and the highest profit (i.e., from 0.80 to 0.95 quantile). In other words, for films making the middle level (i.e., from 0.20 to 0.80 quantile) of profit, their popularity and runtime do not have much impact on the film revenue. In Table 4 and Fig. 4, the slope estimates of the explanatory variable (i.e., vote average) is relatively the same throughout different quantile levels. This means that the vote average of a film does not make difference in film revenue.

4.2 The quantile-varying relations between revenue and squares of budget

In section 4.1, we have examined the quantile-varying relations between film revenue and the five explanatory variables. However, one of the greatest concerns of most film investors is the budget of a film. To address this concern, we assume the budget follows the rule of economics scales. Thus in this section, we aim to use quantile regression method to further examine the impact of film revenue on the square value of the budget. Table 6 shows the QR estimates of the parameter of this explanatory variable (i.e., budget square) with its corresponding Fig.6.

Table 6 The relation between film revenue (REV) and the square of budget based on quantile regression

Quantile	Estimate	p-Value	Quantile	Estimate	p-Value
0.05	4.0000×10^{-5}	(0.079)	0.55	9.0000×10^{-5}	(0.000) **
0.10	8.0000×10^{-5}	(0.002) **	0.60	8.0000×10^{-5}	(0.000) **
0.15	9.0000×10^{-5}	(0.000) **	0.65	8.0000×10^{-5}	(0.000) **
0.20	9.0000×10^{-5}	(0.000) **	0.70	8.0000×10^{-5}	(0.000) **
0.25	9.0000×10^{-5}	(0.000) **	0.75	8.0000×10^{-5}	(0.004) **
0.30	1.0000×10^{-4}	(0.000) **	0.80	7.0000×10^{-5}	(0.007) **
0.35	1.0000×10^{-4}	(0.000) **	0.85	8.0000×10^{-5}	(0.000) **
0.40	1.0000×10^{-4}	(0.000) **	0.90	5.0000×10^{-5}	(0.029) **

0.45	1.0000×10^{-4}	(0.000) **	0.95	8.0000×10^{-5}	(0.014) **
0.50	9.0000×10^{-5}	(0.000) **			

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.

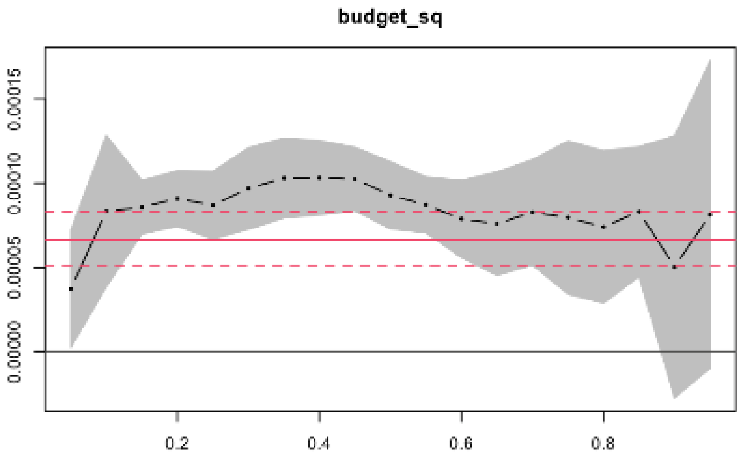

Figure 6. The impact of film revenue on budget square along quantile levels of budget square.

Based on the information in Table 6 and Figure 6, in the quantile regression of further analysis, the square term of film production investment is significant at the 95% confidence level, which further shows that the contribution of film production investment to film box office revenue is positive and negative, but the positive effect is dominant on the whole.

From Table 6, the estimates of the coefficient for the film revenue are mostly significant at the 5% level. What's more, unlike Fig. 2-5, Fig. 6 presents evidence of inverse relation between film revenue and the square of budget in the highest quantile (i.e., from 0.45 to 0.95 quantile). Within the lowest quantile (i.e., from 0.05 to 0.45 quantile), a direct relation between film revenue and the square of budget can be seen.

Table 7 The turning point of film revenue at different quantile levels of budget square

Quantile	Value	Quantile	Value
0.05	-7.2137×10^{3}	0.55	-1.1948×10^{4}
0.10	-5.0825×10^{3}	0.60	-1.3084×10^{4}
0.15	-4.9639×10^{3}	0.65	-1.4241×10^{4}
0.20	-6.1833×10^{2}	0.70	-1.4685×10^{4}
0.25	-6.5167×10^{2}	0.75	-1.7877×10^{4}
0.30	-6.7350×10^{2}	0.80	-1.1616×10^{4}
0.35	-7.420×10^{2}	0.85	-2.7389×10^{4}
0.40	-8.2390×10^{3}	0.90	-2.0671×10^{4}
0.45	-8.9335×10^{3}	0.95	-4.5037×10^{4}
0.50	-1.0141×10^{4}		

Notes: 1. Value refers to the turning point value of film revenue at different quantile levels.

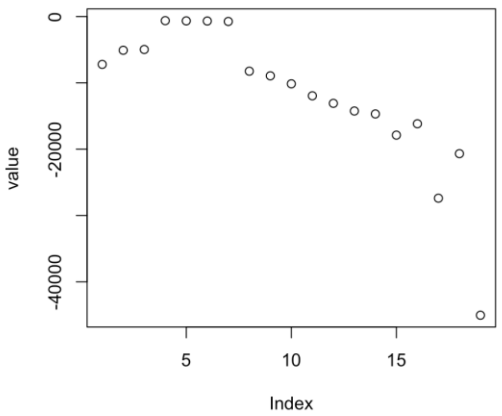

Figure 7. Turning points of film revenue across quantile levels.

Based on the information in Table 7 and Figure 7, the inflection point value of film box office revenue at different quantile levels of film production investment is also unstable, which is basically an inverted U-shaped curve.

In economics scale, the turning point indicates the shift between the economic trend being positive and being negative. (Kazushi) Measuring turning point is important for film investors to evaluate their investment and to maximize their profit. For this purpose, we calculate the turning point of film revenue at various quantile levels, as shown in Table 7.

From Table 7, it is shown that the turning point value of film revenue at various quantiles are negative. However, in Table 7 and Fig. 7, the absolute value of the turning point shows a monotonically increase in the quantile-varying pattern, instead of the inverse U-pattern. This implies that the sample data of the films are still at the economic growth stage. This result suggests that data of various types and time should be added for further investigation into the turning points of film revenue under economics scale.

5. Conclusion

Although film success is always under exposure of uncertain risk, much is known about the influencing factors of films with large revenues, allowing us to measure the quantile-varying relation between revenue and influencing factors. The Quantile Regression model employed in this article is particularly suitable to statistical analysis of the film industries where contribution of attributes differ from films with various profitability. In the analysis, I measure the quantile-varying relations between revenue and influencing factors and further measure the quantile-varying relations between revenue and squares of risk: to be specific, the QR estimates of the coefficients vary across various quantiles, as well as the estimated slope parameter, most of which are statistically significant at the 5% level. To take the influence of the economic scale into account, I calculate the turning point of the film revenue at different profitability, which implies larger range of the types and time of data should be added for further study.

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