

Does increasing movie budget lead to an increase in audience ratings?

Team A3



Meet the Team



Kushal Murthy



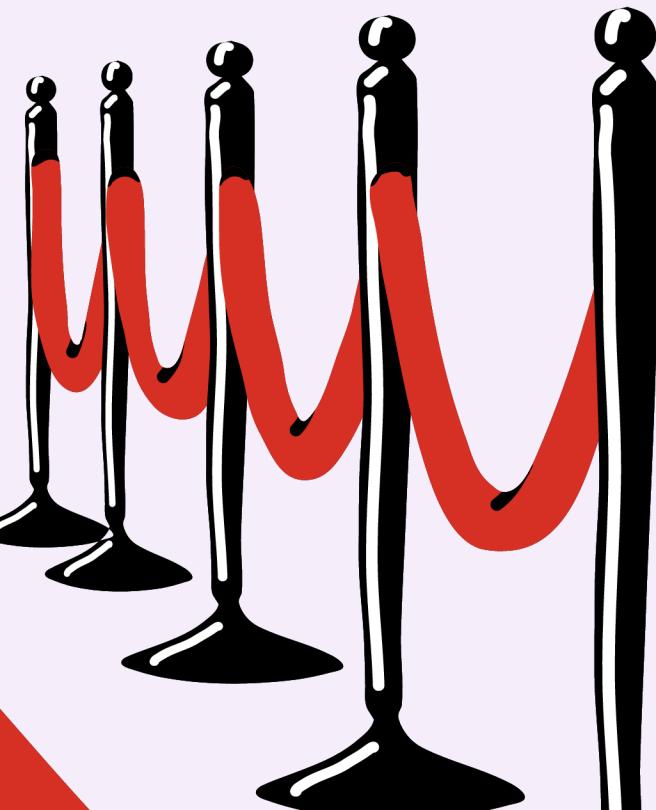
Irene Varsou



Yao Cheng



Steve Feng



Gihyeon Kwon



Theo Bravos



Raymond Moy



Does a Bigger Budget Lead to Better Audience Ratings?

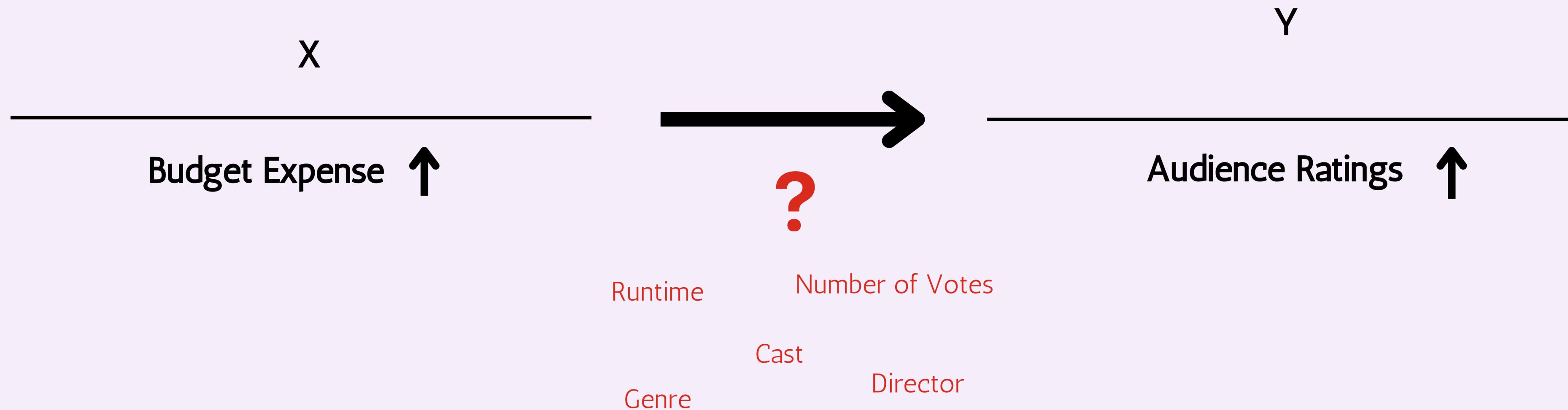
Problem Statement

Studios invest heavily in production, but the relationship between budget and audience ratings remains unclear. Does higher spending directly lead to better reviews, or do factors like genre, runtime, and budget allocation play a bigger role?

Research Questions

- What is the causal relationship between a movie's budget and its audience ratings?
- What additional factors (e.g., genre, cast, marketing) moderate or confound this relationship?

Does a Bigger Budget Lead to Better Audience Ratings?



Why it matters



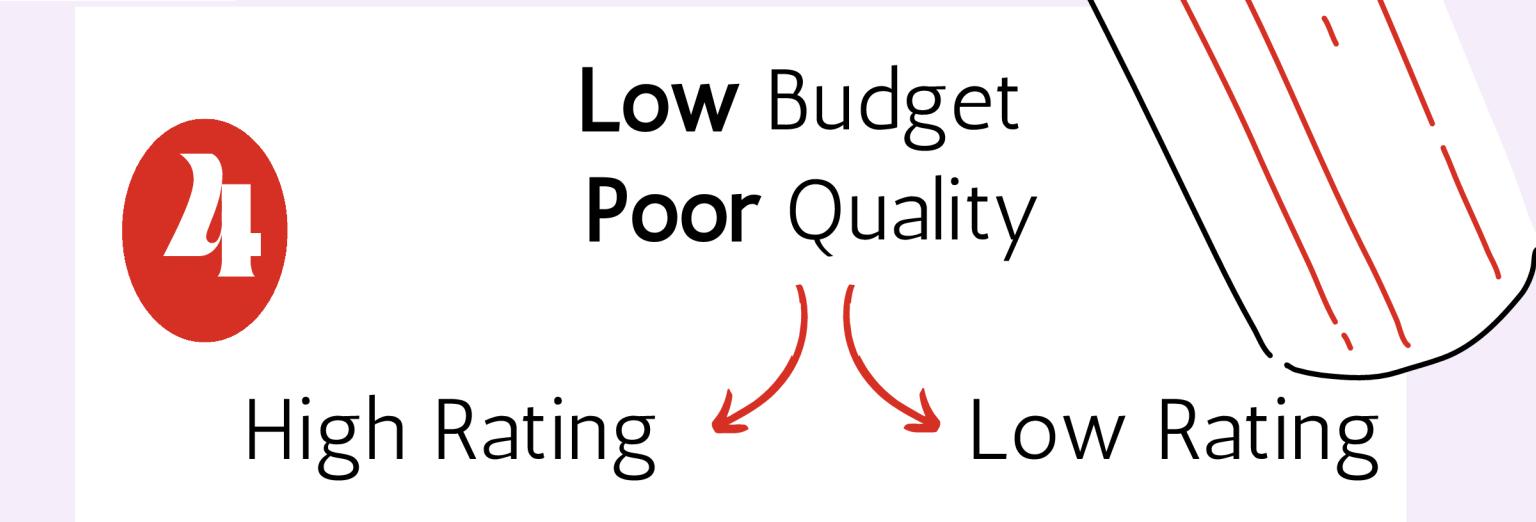
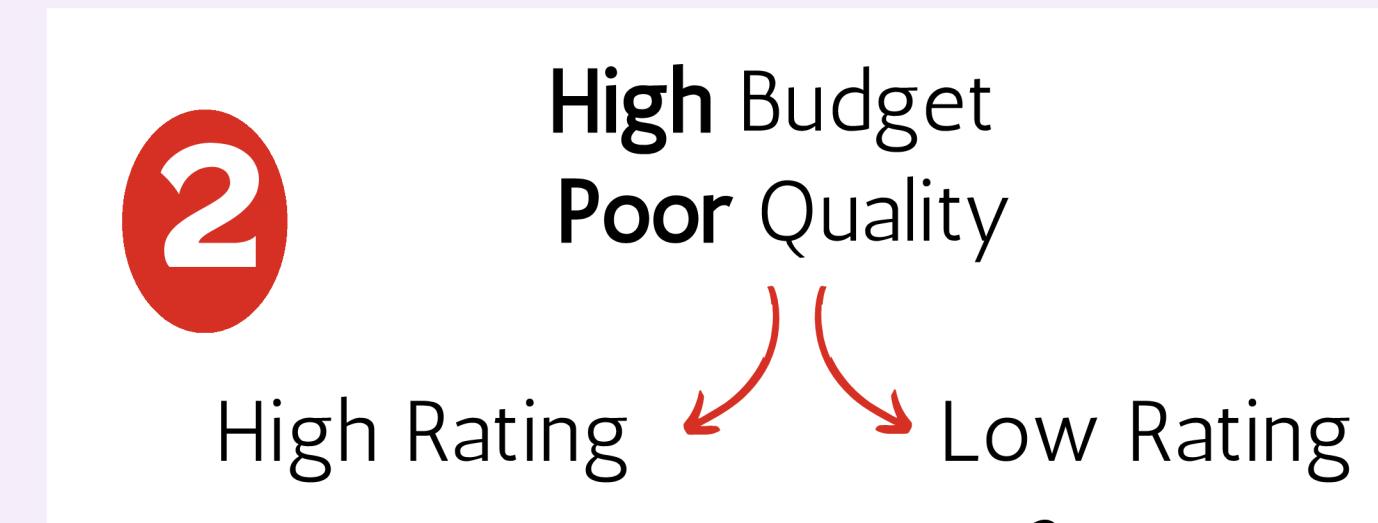
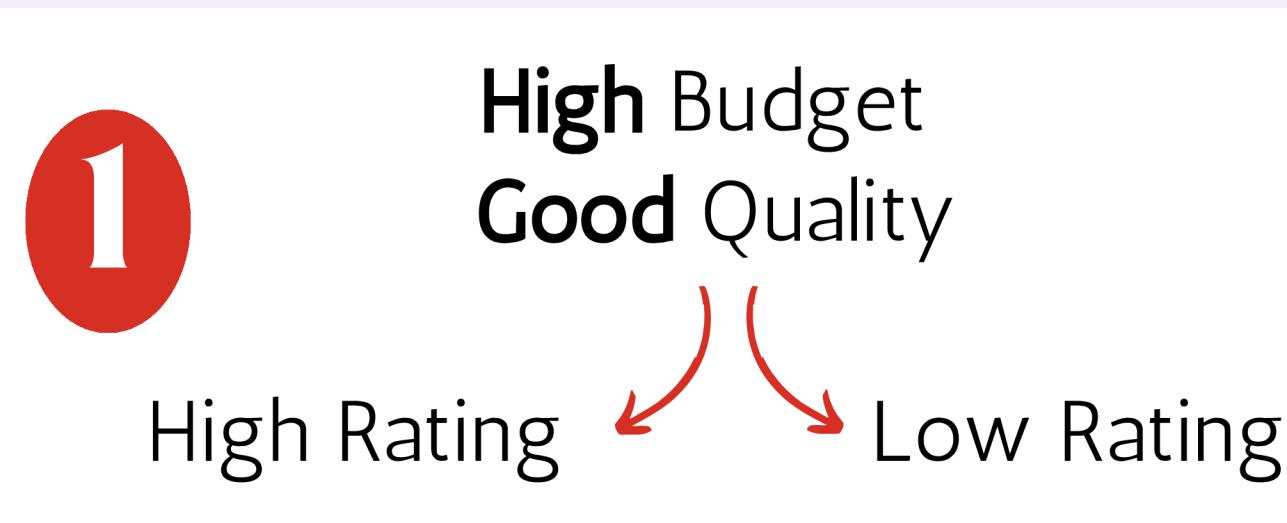
Studios often assume that bigger budgets lead to higher ratings and greater revenue. But is that always the case?

Key Considerations:

- Could overspending result in diminishing returns?
- How can studios strategically allocate resources for success?



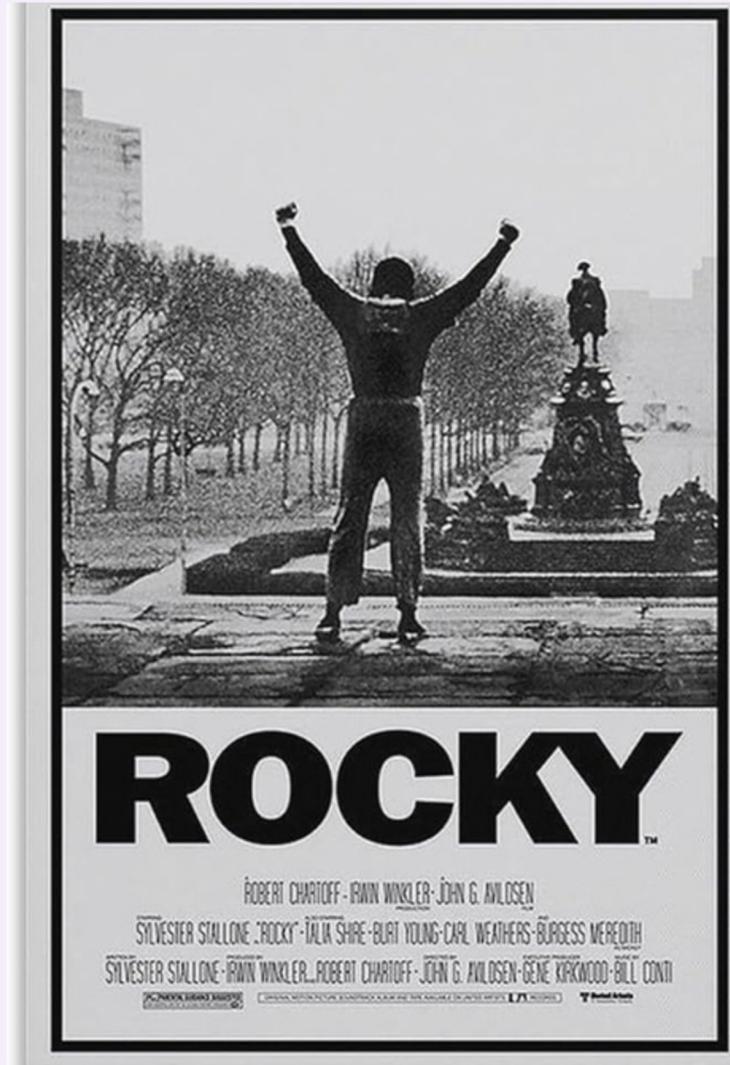
Possible Outcome Scenarios



Examples

Low Budget
High Rating

Budget: 1.1 million USD



93%

Tomatometer

IMDb RATING
★ 8.1/10
654K

High Budget
High Rating

Budget: 356 million USD



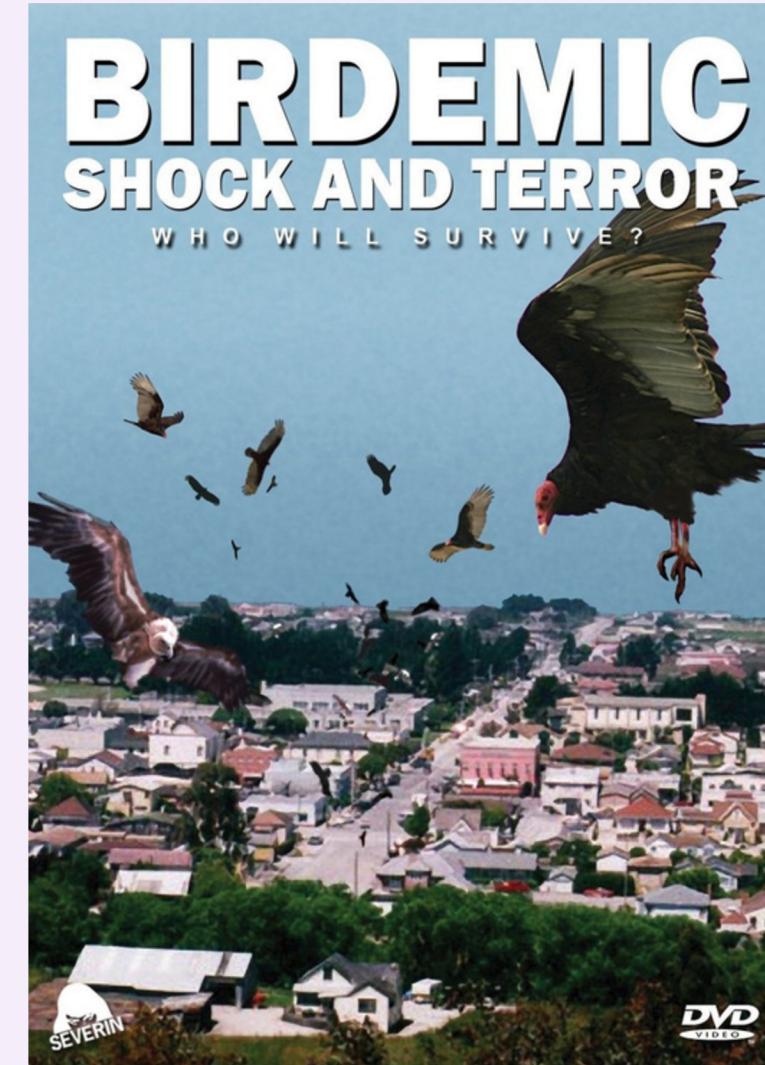
94%

Tomatometer

IMDb RATING
★ 8.4/10
1.3M

Low Budget
Low Rating

Budget: 10,000 USD



19%

Tomatometer

IMDb RATING
★ 1.7/10
26K

High Budget
Low Rating

Budget: 146 million USD



35%

Tomatometer

IMDb RATING
★ 5.2/10
106K



Dataset Overview

Data Source: *TMDB Movies Dataset* (Kaggle) & *IMDB Movies* (IMDB.com)

01

Categorical Variables



- Title
- Original Language
- Original Title
- **Genres**
- Production Companies
- Production Countries

02

Numerical Variables



- ID
- Availability
- **Average Rating**
- **Budget**
- Revenue
- **Release Date**
- **Runtime**
- IMDB ID
- Popularity
- **Number of Votes**
- Year

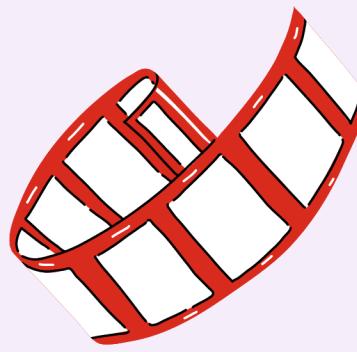
Data Filtering



Date Range: Filtered movie data from 2000 to 2025 for analysis
- Rating websites became increasingly accessible in the digital age



Budget Outliers: Included movies with budgets between \$8,000 and \$300M to filter extreme cases



Average Rating Scale:
Kept movies with an average rating from 1 to 10



Runtime Filter: Only movies with a minimum runtime of 30 minutes were included

Ideal Experiment

Randomized Controlled Trial (RTC) with Control Variables

- Independent Variable (IV): Movie budget allocation
 - Low: < \$5M, Medium: \$5M - \$50M, High: > \$50M
 - Control Group: Low Budget Allocation Films
- Dependent Variable (DV): Audience Ratings (IMDb, Rotten Tomatoes, etc.)

Control Variables

To isolate budget effects, we need identical conditions across groups:

- Cast Quality: Assign actors with similar levels of fame across budgets
- Marketing Spend: Keep marketing budget proportional or fixed
- Genre: Ensure films within each budget group have comparable genres
- Platform Distribution: Ensure all movies get equal exposure (e.g., theatrical + streaming)

Alt: Longitudinal Observational Study

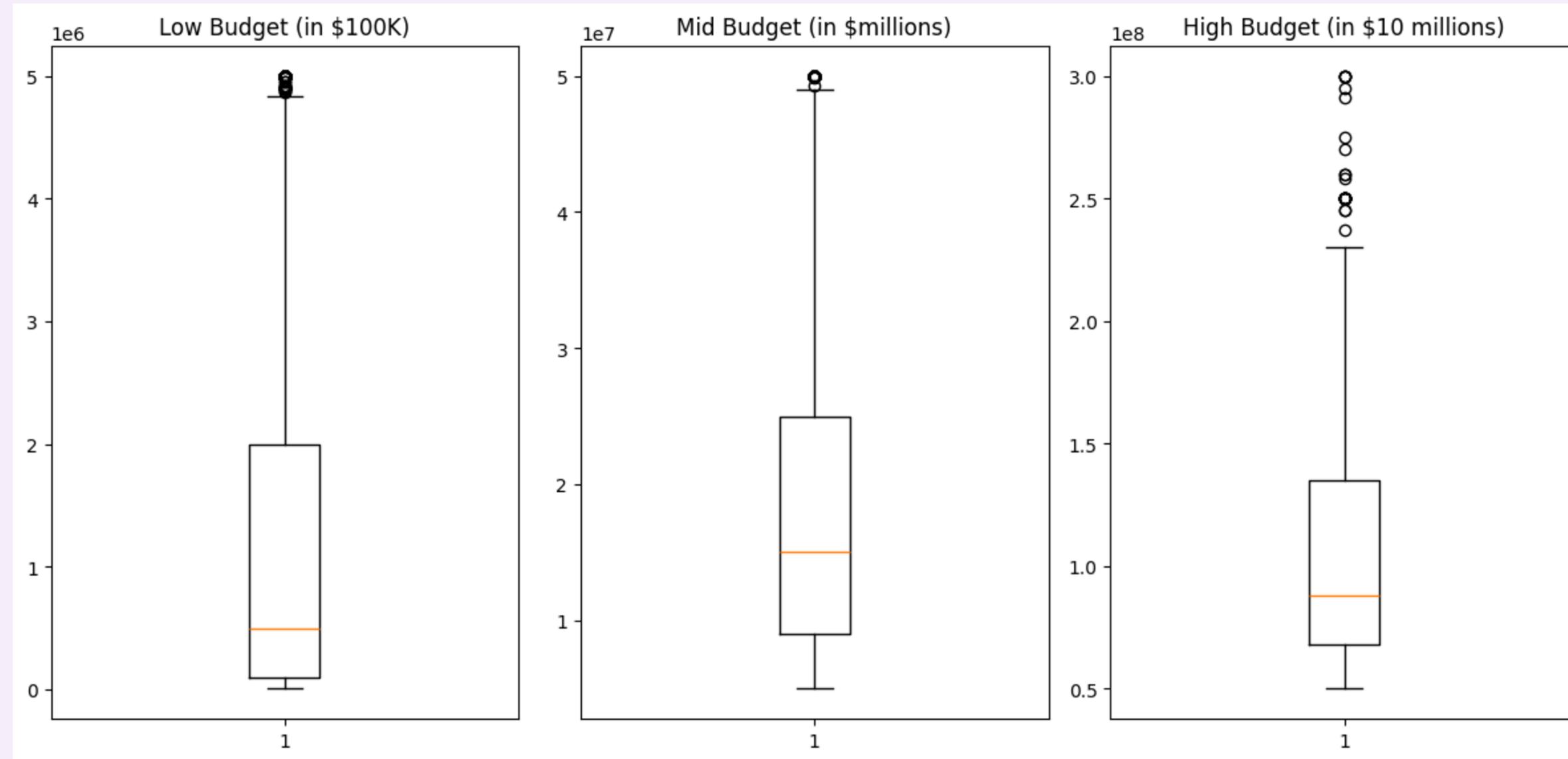
- Difference-in-Differences (DiD): Compare sequels with different budgets (e.g., Marvel films with varying production costs).
- Instrumental Variables (IV): Use external shocks (e.g., tax incentives, pandemic effects) to determine how budget influences ratings

Challenges

Not feasible due to real-world constraints

- Studios do not randomly assign budgets
- Genre, cast, and marketing impact are not present in the current dataset

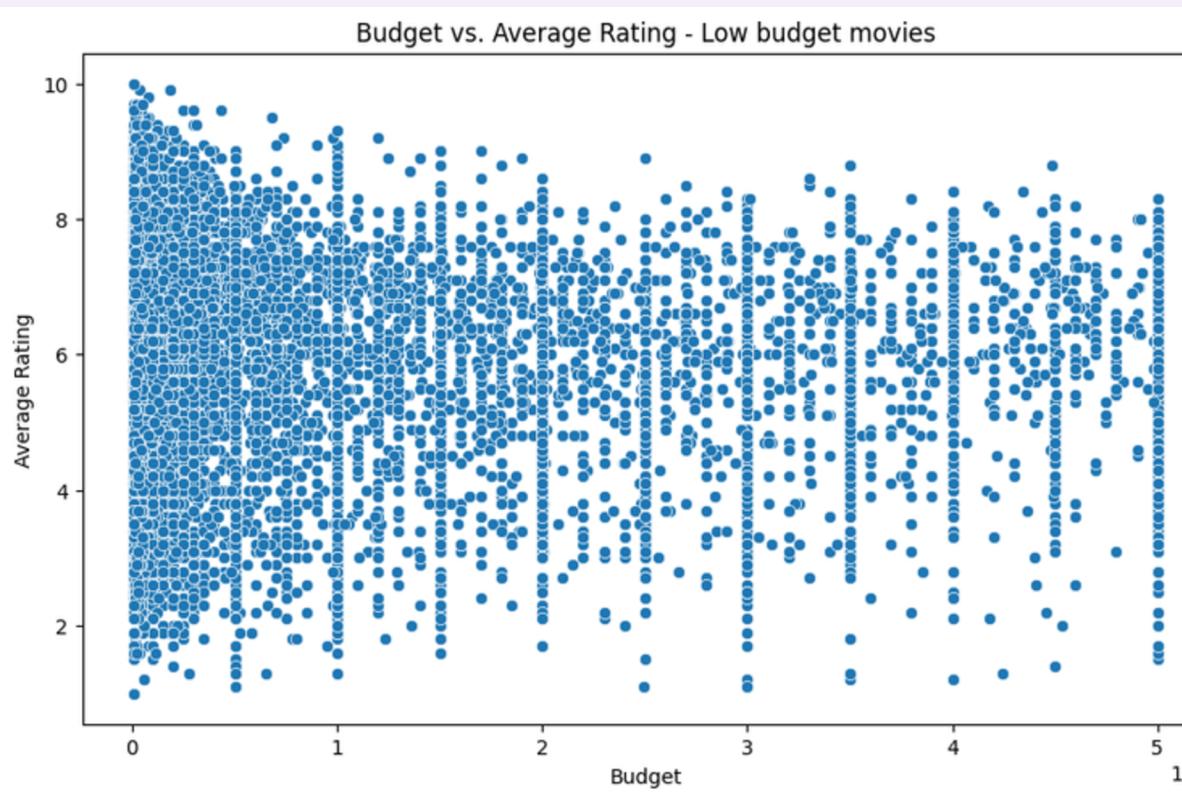
Descriptive Statistics



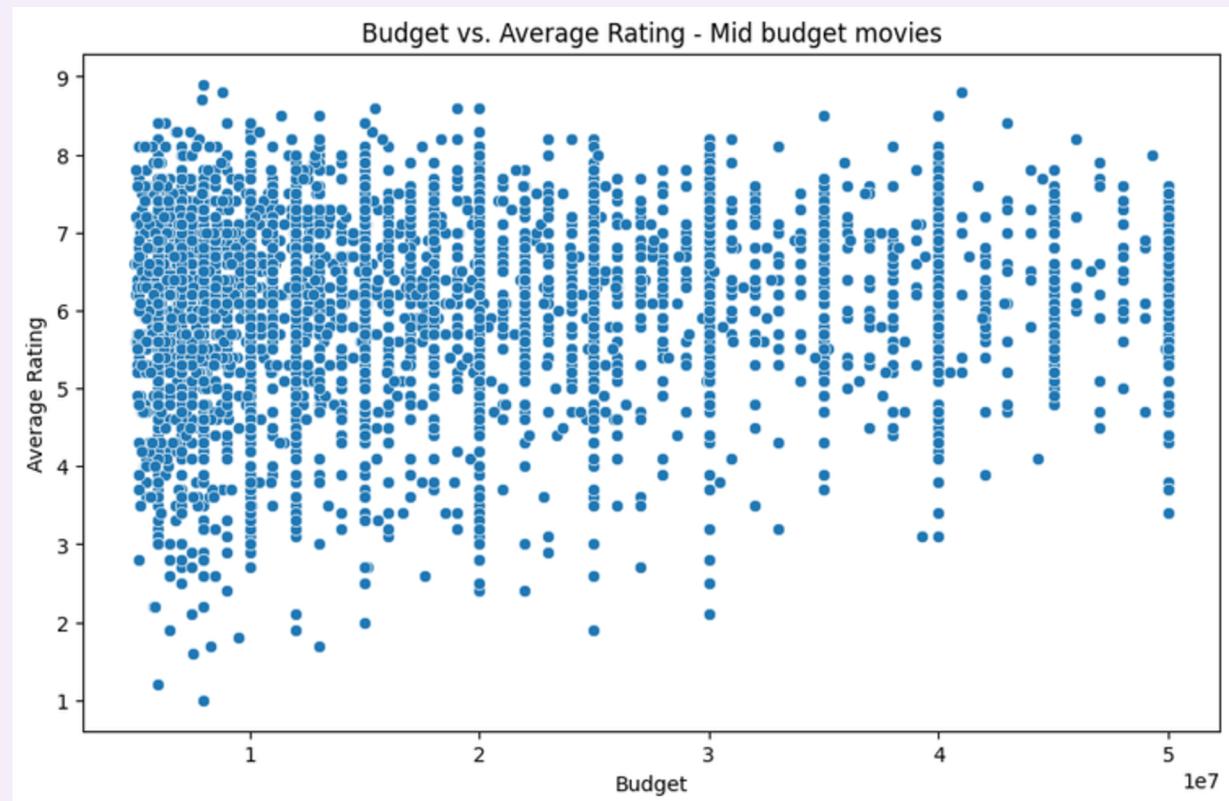
- Low Budget $\leq \$5M$
- Mid Budget between $\$5M$ and $\$50M$
- High Budget $> 50M$
- Movie budgets are right-skewed, with most films having lower budgets and some blockbusters with extremely high budgets

Descriptive Statistics

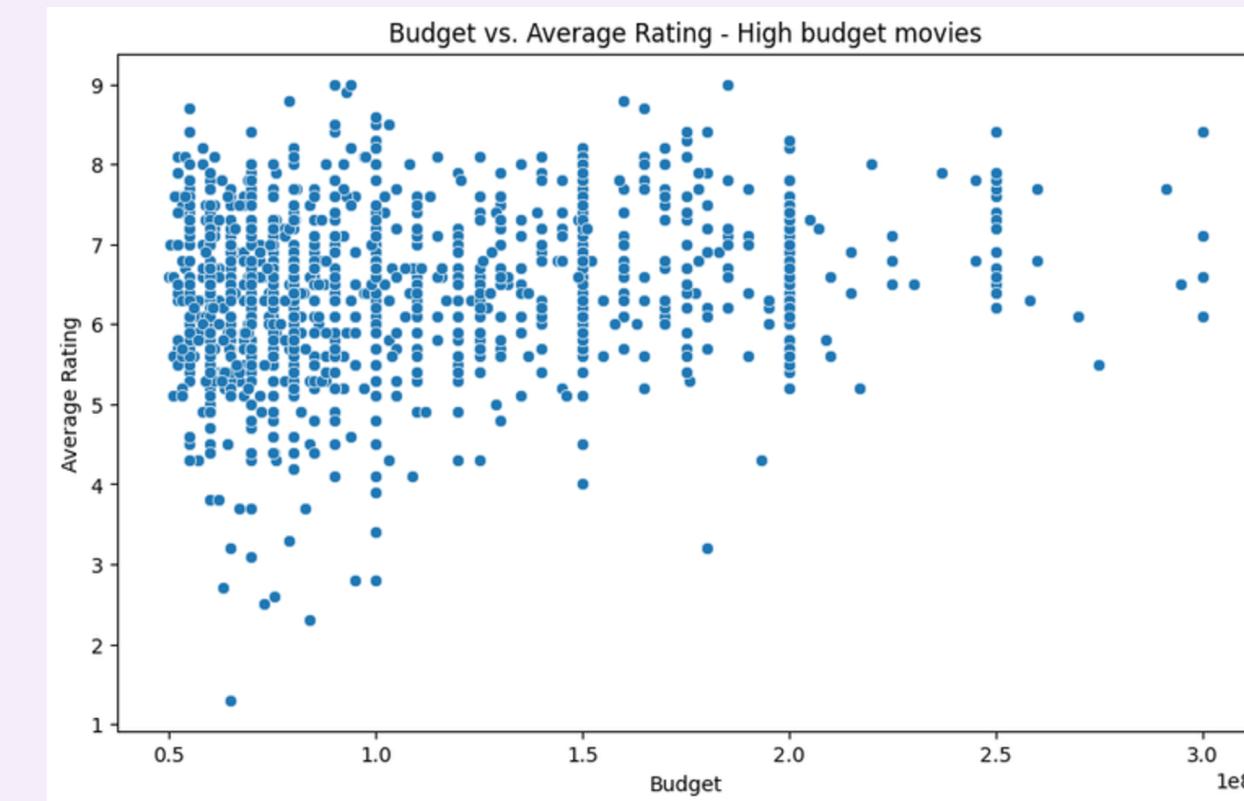
Low Budget Movies



Mid Budget Movies



High Budget Movies

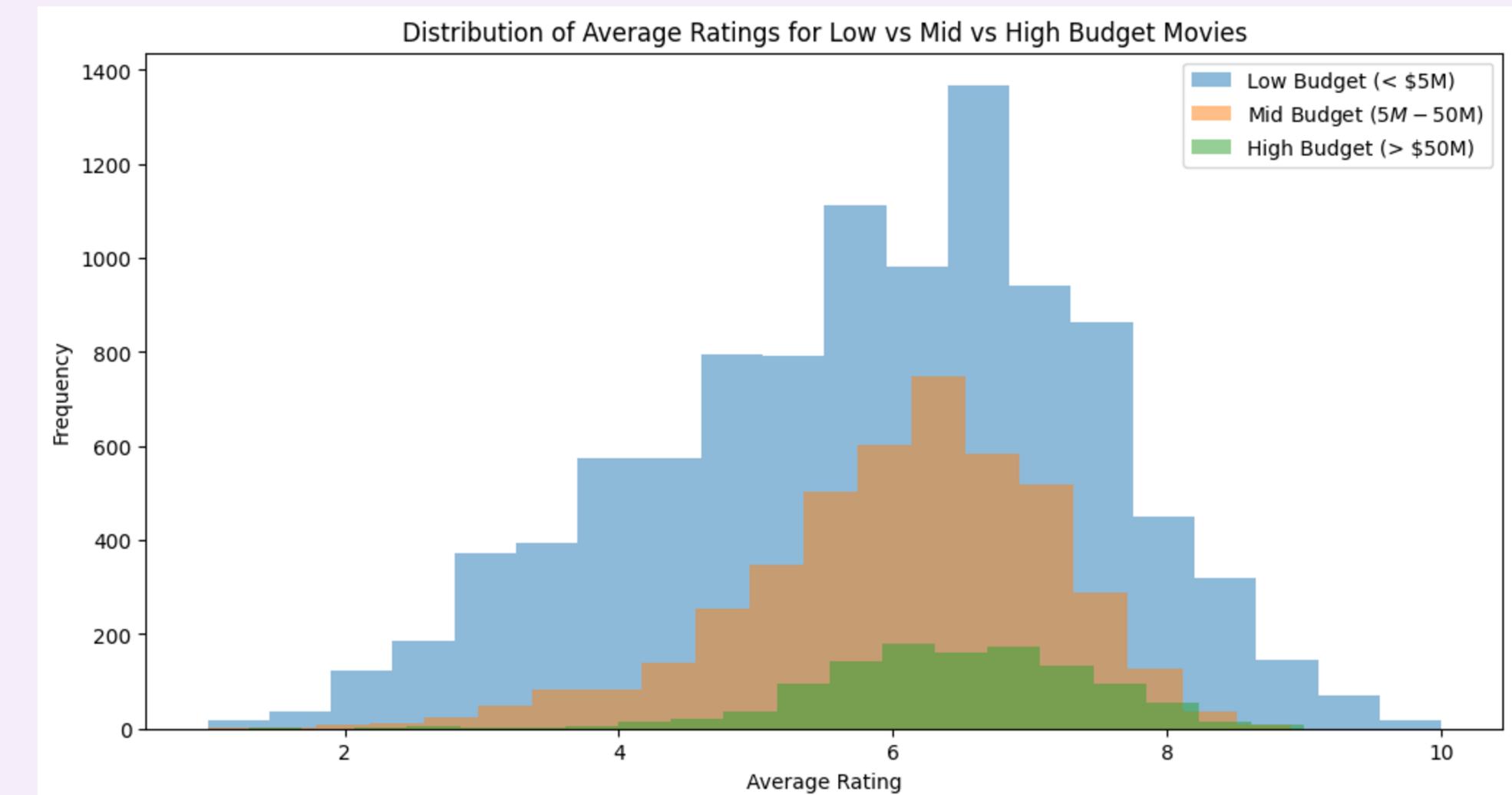
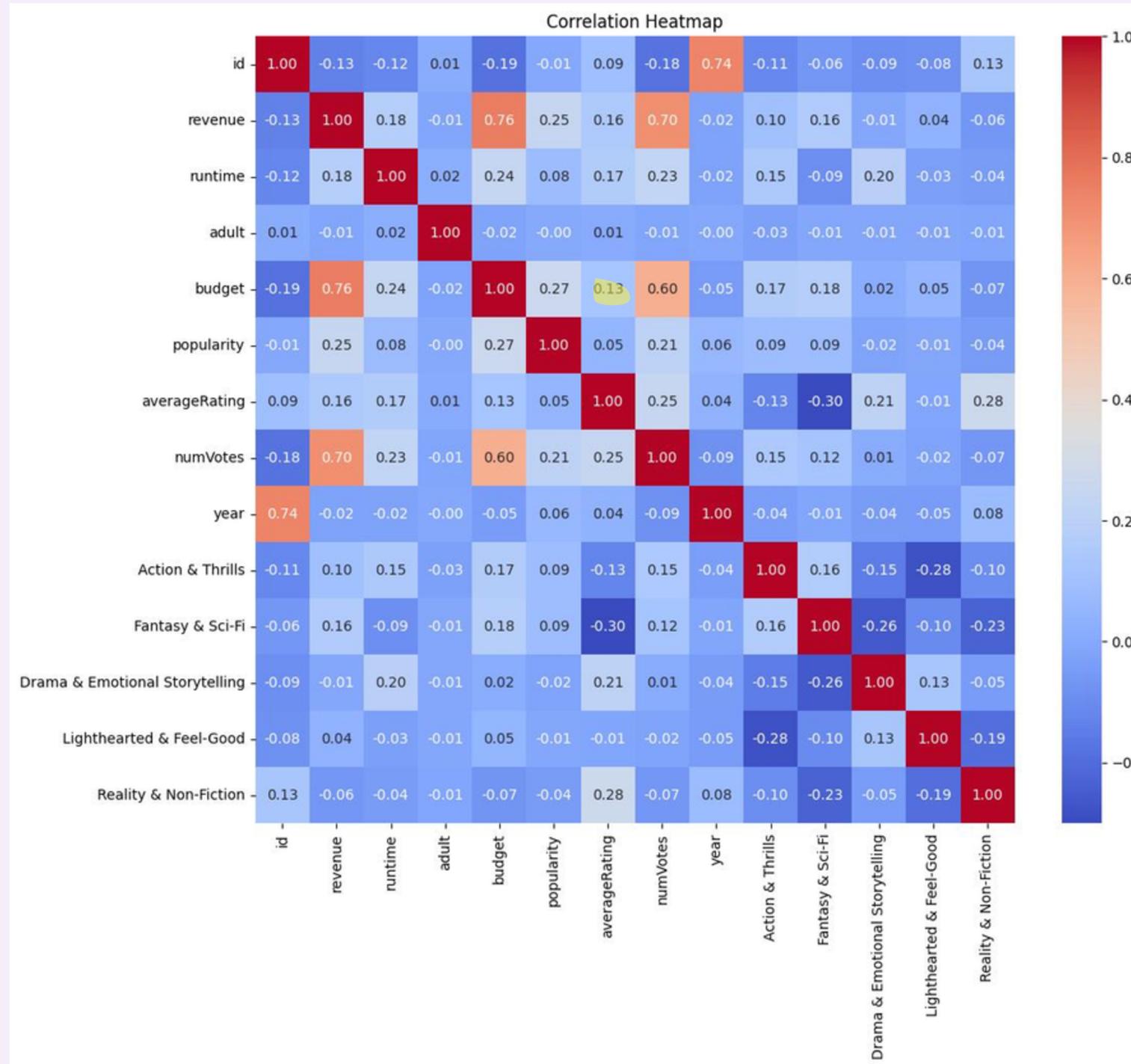


- There is a high concentration of movies with lower budgets and a wide spread in ratings
- Some low-budget movies achieve high ratings, but others receive very low ratings, leading to high variability

- Ratings appear more stable compared to low-budget movies, with a less extreme spread
- There is no strong trend showing that increasing the budget significantly improves ratings

- Most high-budget movies have moderate to high ratings, but there are still some low-rated films
- The budget range is much larger, but ratings appear to plateau—increasing the budget further does not guarantee higher ratings

Descriptive Statistics: Bivariate

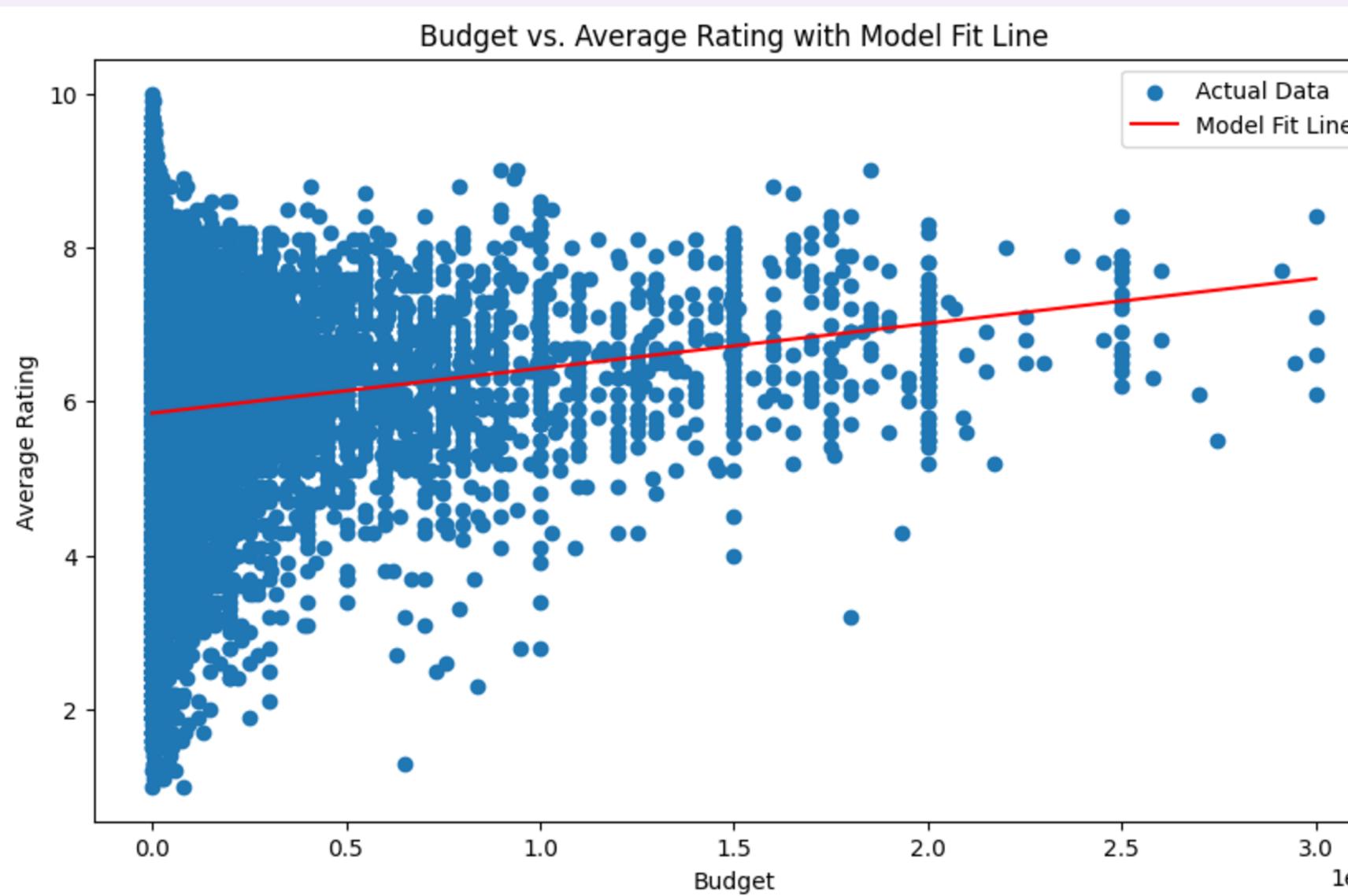


Simple Regression Model

Model



$$\text{Average Rating} = \beta_0 + \beta_1 \times \text{Budget}$$



OLS Regression Results						
Dep. Variable:	averageRating	R-squared:	0.016			
Model:	OLS	Adj. R-squared:	0.016			
Method:	Least Squares	F-statistic:	249.3			
Date:	Thu, 27 Feb 2025	Prob (F-statistic):	9.80e-56			
Time:	07:49:37	Log-Likelihood:	-27902.			
No. Observations:	15692	AIC:	5.581e+04			
Df Residuals:	15690	BIC:	5.582e+04			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	5.8491	0.013	467.644	0.000	5.825	5.874
budget	5.822e-09	3.69e-10	15.790	0.000	5.1e-09	6.55e-09
Omnibus:	400.911	Durbin-Watson:	1.786			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	432.107			
Skew:	-0.406	Prob(JB):	1.48e-94			
Kurtosis:	2.999	Cond. No.	3.71e+07			



Our Approach

To accurately analyze the relationship between budget and audience ratings, we go beyond a simple linear model and consider alternative modeling approaches to capture underlying complexities in the data

- **Multivariate Regression Analysis:** Accounts for potential confounding variables such as number of votes, genre, runtime, year it was released
- **P-value Analysis:** Determines the statistical significance of budget's impact on ratings



Multivariate Regression Model

Null:

Budget has no effect on ratings ($\beta_{\text{Budget}} = 0$)

$$\hat{\text{averageRating}} = \beta_0 + \beta_1 \cdot \text{budget} + \beta_2 \cdot \text{numVotes} + \beta_3 \cdot \text{yearsSinceRelease}$$

Alternative:

Budget has a significant effect on ratings ($\beta_{\text{Budget}} \neq 0$)

$$+ \beta_4 \cdot \text{runtime} + \beta_5 \cdot \text{ActionThrills} + \beta_6 \cdot \text{FantasySciFi} + \beta_7 \cdot \text{DramaEmotional} + \beta_8 \cdot \text{LightheartedFeelGood} + \beta_9 \cdot \text{RealityNonFiction} + \epsilon$$

Low budget group <= \$5m

\$50m <= Mid budget group > \$5m

High budget group > \$50m

OLS Regression Results											
Dep. Variable:	averageRating	R-squared:	0.278								
Model:	OLS	Adj. R-squared:	0.277								
Method:	Least Squares	F-statistic:	432.7								
Date:	Thu, 27 Feb 2025	Prob (F-statistic):	0.00								
Time:	20:09:34	Log-Likelihood:	-17417.								
No. Observations:	10134	AIC:	3.485e+04								
Df Residuals:	10124	BIC:	3.493e+04								
Df Model:	9										
Covariance Type:	nonrobust										
	coef	std err	t	P> t	[0.025	0.975]					
const	5.7114	0.062	92.107	0.000	5.590	5.833					
budget	-6.628e-08	1.01e-08	-6.546	0.000	-8.61e-08	-4.64e-08					
numVotes	8.636e-06	4.4e-07	19.616	0.000	7.77e-06	9.5e-06					
years_since_release	-0.0127	0.002	-5.629	0.000	-0.017	-0.008					
runtime	0.0034	0.001	6.380	0.000	0.002	0.004					
Action & Thrills	-0.3485	0.031	-11.273	0.000	-0.409	-0.288					
Fantasy & Sci-Fi	-0.9765	0.033	-29.980	0.000	-1.040	-0.913					
Drama & Emotional Storytelling	0.4098	0.029	13.902	0.000	0.352	0.468					
Lighthearted & Feel-Good	-0.0464	0.031	-1.497	0.134	-0.107	0.014					
Reality & Non-Fiction	1.1316	0.040	28.265	0.000	1.053	1.210					
Omnibus:	93.764	Durbin-Watson:	1.784								
Prob(Omnibus):	0.000	Jarque-Bera (JB):	97.486								
Skew:	-0.223	Prob(JB):	6.78e-22								
Kurtosis:	3.179	Cond. No.	9.23e+06								

OLS Regression Results											
Dep. Variable:	averageRating	R-squared:	0.336								
Model:	OLS	Adj. R-squared:	0.335								
Method:	Least Squares	F-statistic:	248.0								
Date:	Thu, 27 Feb 2025	Prob (F-statistic):	0.00								
Time:	20:09:34	Log-Likelihood:	-5842.2								
No. Observations:	4416	AIC:	1.170e+04								
Df Residuals:	4406	BIC:	1.177e+04								
Df Model:	9										
Covariance Type:	nonrobust										
	coef	std err	t	P> t	[0.025	0.975]					
const	4.5536	0.090	50.455	0.000	4.377	4.731					
budget	-1.209e-09	1.2e-09	-1.009	0.313	-3.56e-09	1.14e-09					
numVotes	3.716e-06	1.19e-07	31.226	0.000	3.48e-06	3.95e-06					
years_since_release	-0.0041	0.002	-1.821	0.069	-0.009	0.000					
runtime	0.0111	0.001	16.815	0.000	0.010	0.012					
Action & Thrills	-0.1501	0.032	-4.717	0.000	-0.212	-0.088					
Fantasy & Sci-Fi	-0.1829	0.032	-5.758	0.000	-0.245	-0.121					
Drama & Emotional Storytelling	0.4420	0.032	14.022	0.000	0.380	0.504					
Lighthearted & Feel-Good	-0.1296	0.032	-4.055	0.000	-0.192	-0.067					
Reality & Non-Fiction	0.3620	0.048	7.571	0.000	0.268	0.456					
Omnibus:	736.203	Durbin-Watson:	1.724								
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1587.606								
Skew:	-0.977	Prob(JB):	0.00								
Kurtosis:	5.193	Cond. No.	1.49e+08								

OLS Regression Results											
Dep. Variable:	averageRating	R-squared:	0.442								
Model:	OLS	Adj. R-squared:	0.438								
Method:	Least Squares	F-statistic:	99.67								
Date:	Thu, 27 Feb 2025	Prob (F-statistic):	7.74e-137								
Time:	20:09:35	Log-Likelihood:	-1281.5								
No. Observations:	1142	AIC:	2583.								
Df Residuals:	1132	BIC:	2633.								
Df Model:	9										
Covariance Type:	nonrobust										
	coef	std err	t	P> t	[0.025	0.975]					
const	5.7057	0.134	42.572	0.000	5.443	5.969					
budget	-2.228e-10	5.06e-10	-0.441	0.659	-1.21e-09	7.69e-10					
numVotes	2.02e-06	8.13e-08	24.830	0.000	1.86e-06	2.18e-06					
years_since_release	-0.0120	0.003	-3.463	0.001	-0.019	-0.005					
runtime	0.0029	0.001	4.431	0.000	0.002	0.004					
Action & Thrills	-0.1274	0.059	-2.155	0.031	-0.243	-0.011					
Fantasy & Sci-Fi	-0.0686	0.051	-1.353	0.176	-0.168	0.031					
Drama & Emotional Storytelling	0.2573	0.054	4.752	0.000	0.151	0.364					
Lighthearted & Feel-Good	-0.0579	0.059	-0.975	0.330	-0.174	0.059					
Reality & Non-Fiction	0.3984	0.091	4.391	0.000	0.220	0.576					
Omnibus:	294.656	Durbin-Watson:	1.902								
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1086.936								
Skew:	-1.207	Prob(JB):	9.44e-237								
Kurtosis:	7.125	Cond. No.	7.54e+08								

Model Limitations

- **Budget Allocation Uncertainty:** A large portion of a movie's budget goes to marketing rather than production, making our financial impact analysis unclear
- **Star Power:** The model does not account for starring actors, which can significantly impact ratings
- **Review Bombing:** Audience ratings may be skewed due to intentional mass ratings (positive or negative)
- The current regression model assumes **a linear relationship**. However, diminishing returns is a possible factor

Conclusion

- Low-budget films: Reject the null
- Mid-budget films: Fail to reject the null
- High-budget films: Fail to reject the null
- Key takeaway: Simply increasing the budget **does not guarantee** better ratings: strategic allocation matters.
- Next steps:
 - Prioritizing **storytelling** and **production**
 - Allocate budget efficiently between **marketing** and **talent**
 - Conduct deeper **analysis** on **audience** preferences



The End

