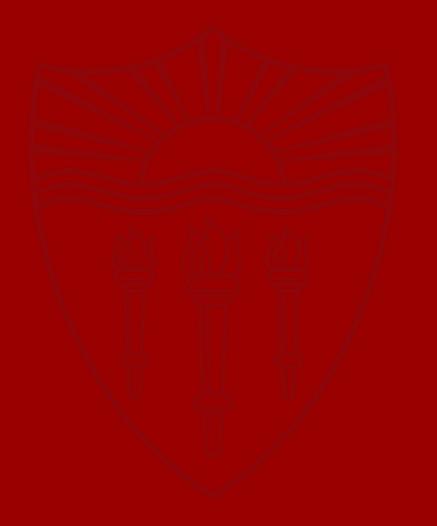


The Effect of Movie Lead's Gender on Movie's Revenue

Xiaoxuan (Hayley) Gu Chaiyapuk (KK) Titinanapun Xinwen (Gabriel) Wu Anyi (Aprill) Zhao Jiaying (Grace) Zheng Yue (Lydia) Zou Nov 29, 2022



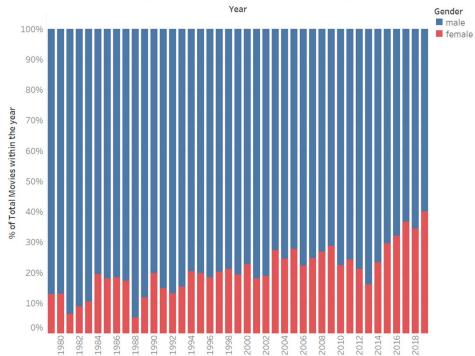
Background





Background

More films have been produced with a female leading role.



% of Total Count_Released_date for each Year. Color shows details about Gender. The data is filtered on Gross Adj, which includes values greater than or equal to 10. Percents are based on each column of each pane of the table.



Hypothesis and Why Using Data?

Hypothesis:

Genders of movie leads have impact on movie revenue.

Why using Data?

- Many factors affecting revenue
- Common perception V.S. Data justification*





Ideal Experiment

Create a series pairs of two movies with the same qualities but different genders of the lead as follow:

- Genres
- Scripts
- Directors
- Two movie leads with same popularity and acting skill
- Constructed in a similar way
- Displayed in the same place







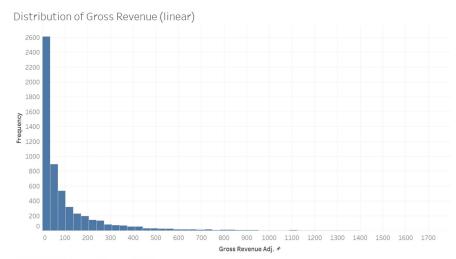
Our Dataset

	Variables	Description		
Dependent Variable	Gross	Revenue of a movie (in million dollars); Adjusted by inflation rate; Revenue lower than 10 millions dollars were removed		
	Gender	Gender of leading character of the movie		
Independent Variable	Budget	Budget of a movie (in million dollars); Adjusted by inflation rate;		
	Year	Releasing year of a movie; 1: 1980, 41: 2020		
	Scores	IMDB score of a movie; range: 0 - 10		
	Rating	Age limits of a movie G and PG; PG-13; R, NC-17 and others		
	Genres	Categories of a movie Adventures, action, comedy, drama movies, and others		

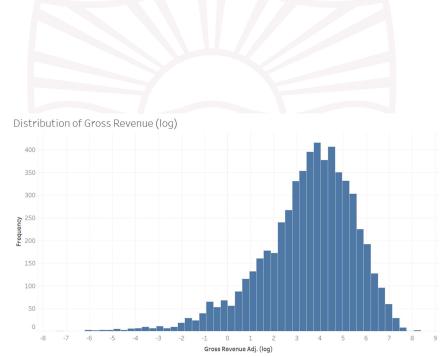


Revenue Distribution:

Highly right-skewed



The trend of count of Gross Adj for Gross Adj (bin).

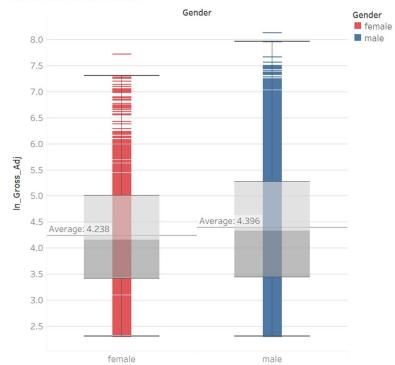


The trend of count of In_Gross_Adj for In_Gross_Adj (bin).



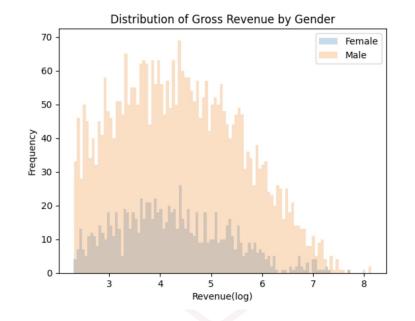
Revenue vs Gender:

Revenue and Gender



Ln_Gross_Adj for each Gender. Color shows details about Gender. The data is filtered on Gross Adj, which includes values greater than or equal to 10.

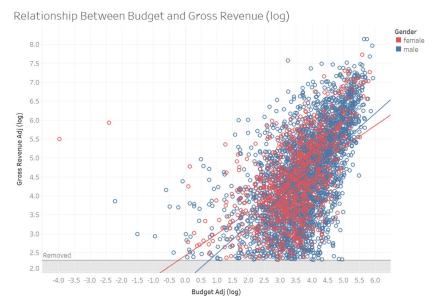
- Males' revenue are higher than
 Females' in general and on average.
- There are less high revenue samples in female-lead movies





Revenue vs Budget:

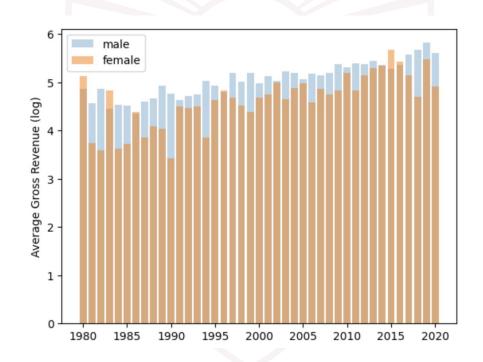
- Positive
- Determine potential



 $Ln_Budget_Adjvs. \\ ln_Gross_Adj. \\ Color shows details about Gender. \\ Details are shown for Name and Released. \\ The data is filtered on Gross Adj. \\ which includes values greater than or equal to 10.$

Revenue vs Year:

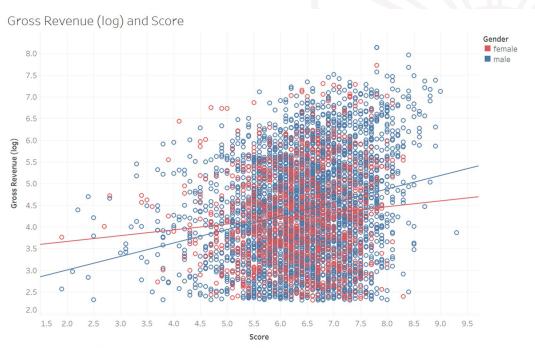
Inflation adjusted





Revenue vs Score:

Quality of a movie

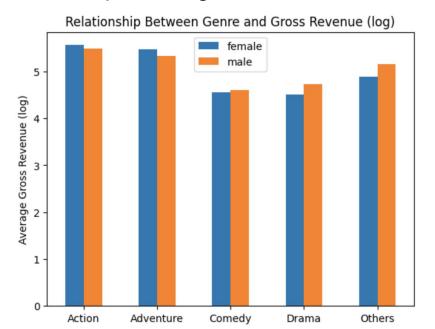


Score vs. In_Gross_Adj. Color shows details about Gender. The data is filtered on Gross Adj, which includes values greater than or equal to 10.



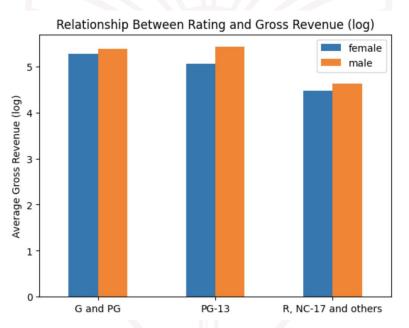
Revenue vs Genre:

Grouped categories



Revenue vs Rating:

Limits targeted audience



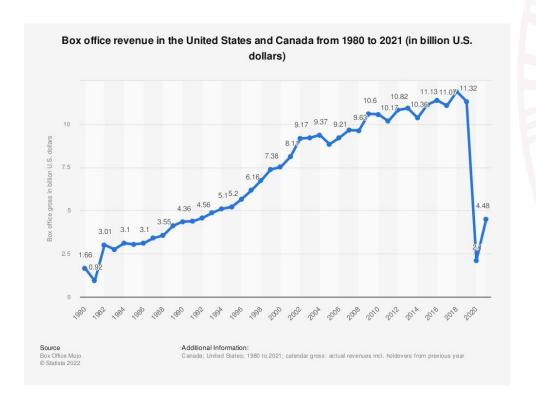
Different average revenues for different categories



Model and Interpretation



Control Variables



- Budget adj: budget of a movie determines its potential (adjusted by inflation)
- Year: movies industry has been growing in the last 40 years
- Scores: measures quality of a movie
 Rating: limits targeted audience of a movie
- Genres: adventures, action, comedy, drama movies have the highest box office revenue in the North America market



OLS Regression Results					
R-squared	0.441	Adj. R-squared	0.440		
F-statistic	340.2	Prob (F-statistic)	0.00		
		Coefficient	P-Value		
Intercept		0.0793	0.536		
Rating[PG-13]		-0.1644	0.000		
Rating[R, NC and Others]		-0.4581	0.000		
Genre[Adventure]		-0.1921	0.003		
Genre[Comedy]		-0.1729	0.000		
Genre[Drama]		-0.3357	0.000		
Genre[Others]		-0.1207	0.004		
ln(Budget)		0.5999	0.000		
Year		0.0163	0.000		
Score		0.3451	0.000		

In(gross) ~ In(budget) + year + score + rating + genre

- Without gender
- Adj. R-squared: 0.440



OLS Regression Results					
R-squared	0.443	Adj. R-squared	0.441		
F-statistic	308.2	Prob (F-statistic)	0.00		
		Coefficient	P-Value		
Intercept		0.1578	0.225		
Gender[Male]		-0.1230	0.001		
Rating[PG-13]		-0.1720	0.000		
Rating[R, NC an	d Others]	-0.4600	0.000		
Genre[Adventure	e]	-0.2002	0.002		
Genre[Comedy]		-0.1897	0.000		
Genre[Drama]		-0.3588	0.000		
Genre[Others]		-0.1346	0.001		
ln(Budget)		0.6054	0.000		
Year		0.0157	0.000		
Score		0.3462	0.000		

In(gross) ~ gender + In(budget) + year + score + rating + genre

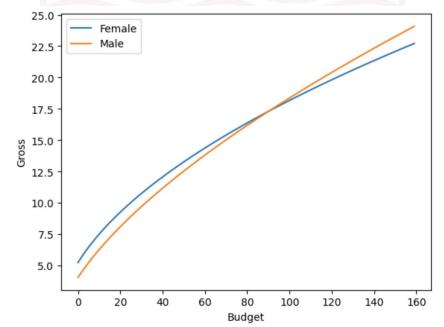
- Gender: coef = -0.1230 (p-value=0.001) $(e^{-0.1230}-1)*100 = -11.57\%$
- Controlling other variables, male-lead movies make 11.57% less revenue compared to female-leads movies
- Adj. R-squared changes little
- The relationships between revenue and control variables are the same



OLS Regression Results					
R-squared	0.444	Adj. R-squared	0.443		
F-statistic	281.8	Prob (F-statistic)	0.00		
		Coefficient	P-Value		
Intercept		0.4576	0.004		
Gender[Male]		-0.5145	0.000		
Gender[Male]*lı	n(Budget)	0.1117	0.002		
Rating[PG-13]		-0.1725	0.000		
Rating[R, NC and Others]		-0.4562	0.000		
Genre[Adventure]		-0.1941	0.003		
Genre[Comedy]		-0.1837	0.000		
Genre[Drama]		-0.3551	0.000		
Genre[Others]		-0.1342	0.001		
ln(Budget)		0.5196	0.000		
Year		0.0154	0.000		
Score		0.3456	0.000		

In(gross) ~ gender + gender * In(budget) + In(budget) + year + score + rating + genre

Gender * In(budget):
 coef = 0.1117 (p-value=0.002)
 = 0.1117% more rev per 1%





OLS Regression Results				
R-squared	0.447	Adj. R-squared	0.446	
F-statistic	261.7	Prob (F-statistic)	0.00	
		Coefficient	P-Value	
Intercept		1.0999	0.000	
Gender[Male]		-1.2699	0.000	
Gender[Male]*so	core	0.1813	0.000	
Rating[PG-13]		-0.1870	0.000	
Rating[R, NC an	d Others]	-0.4754	0.000	
Genre[Adventure]		-0.2072	0.002	
Genre[Comedy]		-0.1944	0.000	
Genre[Drama]		-0.3593	0.000	
Genre[Others]		-0.1430	0.001	
ln(Budget)		0.6030	0.000	
Year		0.0159	0.000	
Score		0.1998	0.000	

In(gross) ~ gender + gender * score + In(budget) + year + score + rating + genre

• Gender: coef = -1.2699 (p-value=0.000) $(e^{-1.2699}-1)*100 = -71.91\%$

- Gender * score: coef = 0.1813 (p-value=0.000) $(e^{0.1813}-1) * 100 = 19.88\%$
- Male will generate more revenue than female when the score is 7 or higher. (percentile 72)

	coef	std err	t	P> t
Intercept	0.0297	0.155	0.192	0.848
<pre>gender[T.male]</pre>	0.0222	0.102	0.219	0.827
rating_adj[T.PG-13]	-0.1706	0.042	-4.050	0.000
rating_adj[T.R, NC-17 and others]	-0.4595	0.041	-11.076	0.000
<pre>genre_adj[T.Adventure]</pre>	-0.2015	0.065	-3.076	0.002
<pre>genre_adj[T.Comedy]</pre>	-0.1864	0.040	-4.636	0.000
genre_adj[T.Drama]	-0.3564	0.048	-7.422	0.000
genre_adj[T.Others]	-0.1316	0.042	-3.152	0.002
<pre>np.log(budget_adj)</pre>	0.6072	0.016	37.109	0.000
year	0.0202	0.003	6.080	0.000
gender[T.male]:year	-0.0056	0.004	-1.524	0.128
score	0.3458	0.016	22.190	0.000

Other Interaction Terms: Insignificant (P-value >0.05)

In(gross) ~ gender + gender * year + In(budget) + year + score + rating + genre

	coef	std err	t	P> t
Intercept	0.1404	0.149	0.945	0.345
gender[T.male]	-0.1115	0.084	-1.326	0.185
rating_adj[T.PG-13]	-0.1738	0.042	-4.122	0.000
rating_adj[T.R, NC-17 and others]	-0.4611	0.042	-11.103	0.000
genre_adj[T.Adventure]	-0.1602	0.166	-0.963	0.336
<pre>genre_adj[T.Comedy]</pre>	-0.1989	0.096	-2.065	0.039
genre_adj[T.Drama]	-0.3951	0.105	-3.760	0.000
genre_adj[T.Others]	-0.0558	0.101	-0.550	0.582
<pre>genre_adj[T.Adventure]:gender[T.male]</pre>	-0.0471	0.179	-0.263	0.793
<pre>genre_adj[T.Comedy]:gender[T.male]</pre>	0.0162	0.104	0.157	0.875
<pre>genre_adj[T.Drama]:gender[T.male]</pre>	0.0565	0.116	0.487	0.626
<pre>genre_adj[T.Others]:gender[T.male]</pre>	-0.0998	0.109	-0.916	0.300
np.log(budget_adj)	0.6066	0.016	37.067	0.000
year	0.0157	0.001	10.827	0.000
score	0.3465	0.016	22.210	0.000

In(gross) ~ gender + gender * genre + In(budget) + year + score + rating + genre





Conclusions and Limitations



Limitations

- We didn't control for these things
 - Effects from people
 - Cast List
 - Director
 - Producer
 - Composer
 - Cinematographer
 - Distributor
 - Movie Title
 - Social Factor (Youtube, Tweets, Wikipedia)

- Score and Budget can be a proxy everything else (e.g. Director, Cast, Producer). However, we do not know the separated effect from each of them.
- We do not have a lot of big name female movies (high-budget & high-score) in comparison to male movies.
- ❖ Big name male movies:
 - Titanic, Avengers, Pirate of the Caribbean, etc.
- Big name female movies:
 - Star Wars 7-9



Conclusions:

- Gender does affect the revenue.
- Controlling all other variables, movies with male leads seem to generate
 11.57% less revenue.
- The slopes for gender with budget and gender with score are significant.
 - Within top 14th percentile budget, male led movies tend to generate more revenue
 - Within top 28th percentile score, male led movies tend to generate more revenue





Thank you

The Effect of Movie Lead's Gender on Movie's Revenue