How much is a Best Picture Oscar Worth? An Analysis on Inflation Adjusted Domestic Box Office Revenues

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Introduction

In this project, we are looking to find an answer to the question: How much is a Best Picture Oscar worth? To answer this question, we collected data and created a theoretical model using metrics from each of the Best Picture Oscar nominees dating back to 1977. We ran an econometric analysis on this data, testing for the effect of several explanatory variables on our dependent variable, the total box office revenue of a movie. Based on the results of these tests, we refined our model and came to several conclusions.

Economic Theory & Our Variables

Our analysis looked for explanatory variables that would have a significant effect on the demand for specific movies, as indicated by the total box office revenue, including different economic conditions, different movie characteristics, movies that appeal to different consumer preferences, and promotions for the movie. Based on these criteria, our explanatory variables are the year of release, the run time, the genre, the IMDb rating, when the movie was released relative to the COVID-19 pandemic, whether or not the movie won the Best Picture Oscar award, and when the movie was released relative to the September 11th attacks.

$$SRF : Y = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + \beta_3 * X_3 + \beta_4 * X_4 + \beta_5 * X_5 + \beta_6 * X_6 + \beta_7 * X_7 + \beta_8 * X_8 + \beta_9 * X_9 + \beta_{10} * X_{10} + \beta_{11} * X_{11} + \beta_{12} * X_{12} + \beta_{13} *$$

Y = Total Box Office Revenue X1 - X5 = Decade of Release X6 = Run Time X8 - X15 = Genre X7 = IMDb Rating X18 = COVID-19 (Dummy Variable) X16 = Award 1 (Dummy Variable) X17 = After 9/11 (Dummy Variable)

Dependent Variable (Y): Total Box Office Revenue The dependent variable in our model is the total box office revenue of each movie, adjusted for inflation. This measure captures the total revenue a movie generates over its run in theaters, providing a good indicator of its commercial success. Adjusting for inflation is important as it allows us to compare movies released in different years consistently.

Explanatory Variable (X1 - X5): Decade of Release The decade of release is included to account for temporal trends in the industry. Various factors, like technological advancements, changing consumer preferences, and cyclical economic conditions can influence box-office revenues over time. By including this variable, we can control for the nature of the industry and any economic trends that might affect movie demand across the decades. This categorical variable included 5 categories, each corresponding to their Beta value. Each decade, beginning from the 1980s and going through the 2020s, was its own category.

Explanatory Variable (X6): Run Time Run time, measured in minutes, captures the duration of a movie. The length of a movie could impact its box-office performance, as it might affect how many screenings a theater can have per day, as well as audience preferences. Some audiences may prefer longer movies for perceived value, while others might favor shorter films due to the convenience or their attention spans.

Explanatory Variable (X8 - X15): Genre Genre is a categorical variable used to capture the market's preferences. Different genres have varying levels of popularity and target different audience segments, which can significantly influence a movie's revenue. Including genre helps control for these differences and allows us to see how specific genres perform relative to others. The genres are, in order of their Beta values: adventure, animation, biography, comedy, crime, drama, family, and horror. Each genre is its own category in this categorical variable.

Explanatory Variable (X7): IMDb Rating The IMDb rating provides a measure of the perceived quality of a movie based on user reviews (preferences). Higher ratings generally indicate a better audience reception and can influence potential viewers' decisions to watch a movie. This variable helps capture the effect of early word-of-mouth and critical reception on a movie's financial success.

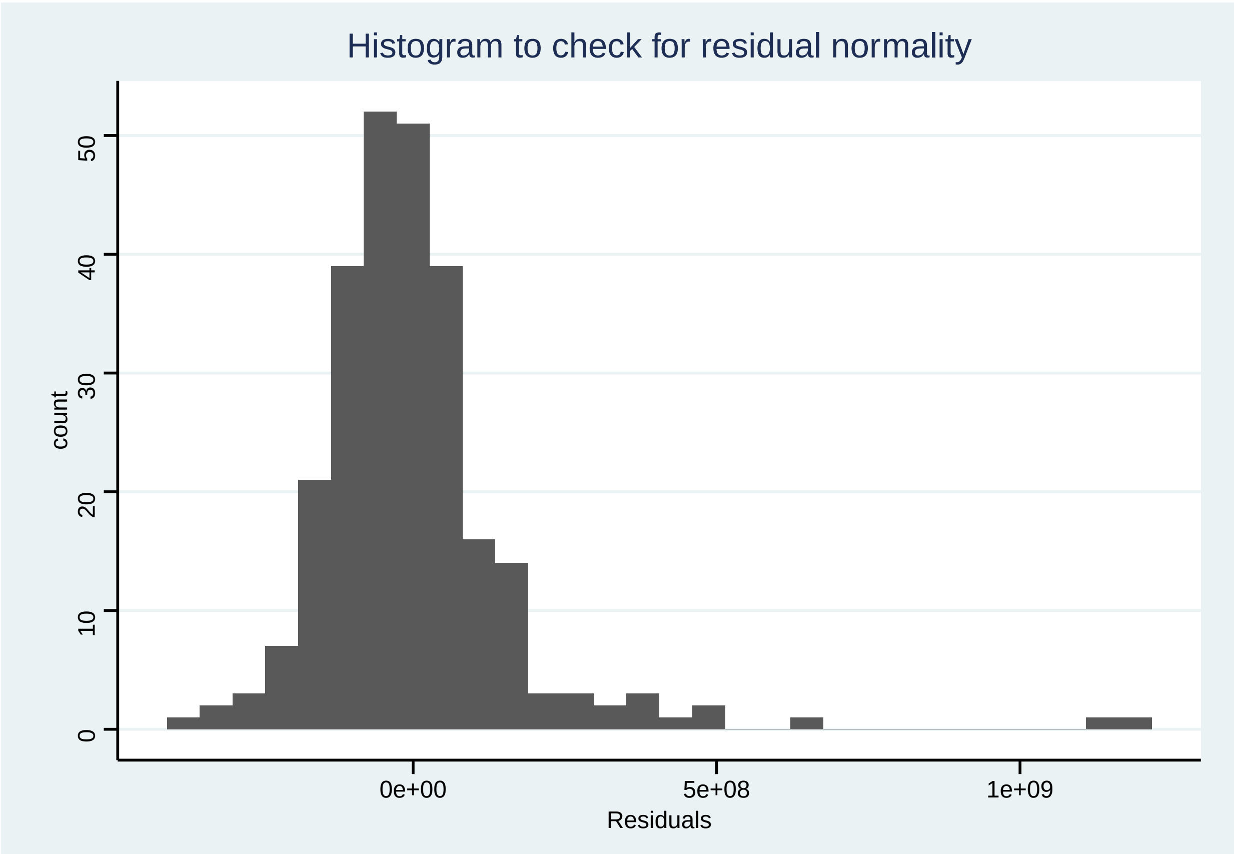
Explanatory Variable (X18): COVID-19 Pandemic (Dummy Variable) This dummy variable was made to account for the COVID-19 Pandemic. We expected that the demand for watching a movie in theaters would decrease as consumers grew wary of the risks of watching a movie in theaters with the pandemic spreading. We coded this Dummy variable to have a value of 1 for movies released after March 2020 and 0 for movies from before then.

Explanatory Variable (X16): Best Picture Oscar - Won or Not (Dummy Variable) This dummy variable indicates whether a movie won the Best Picture Oscar. Winning this prestigious award can significantly boost a movie's visibility and credibility, often leading to increased box-office revenues. By including this variable, we can assess the impact of winning an Oscar on a movie's financial performance and determine if there is a notable difference in revenues for award-winning films.

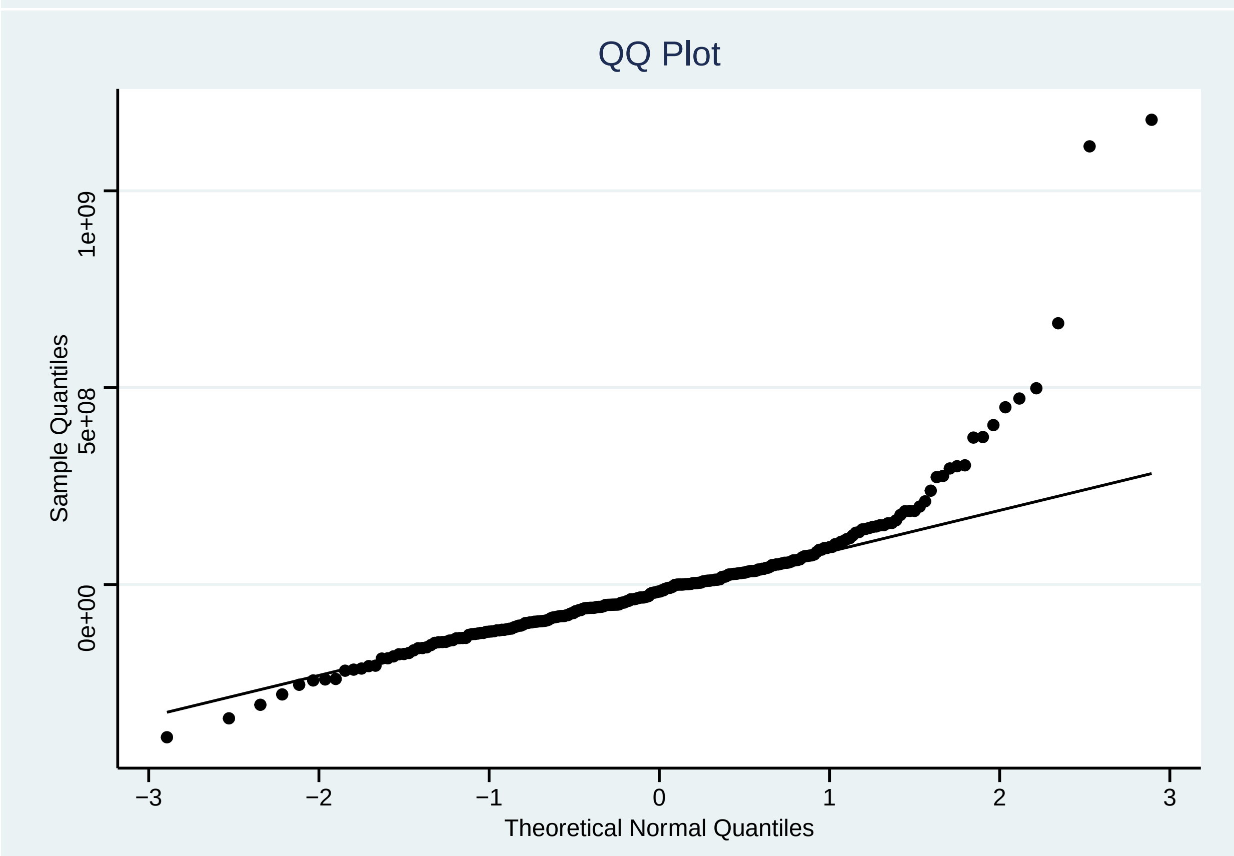
Explanatory Variable (X17): September 11th Attacks (Dummy Variable) This dummy variable indicates when a movie was released relative to the attacks on September 11th, 2001. Because these attacks heavily slowed consumerism for the following years, we anticipate that demand for movies in theaters would have slowed. This variable is coded with a value of 1 for movies released within the 5 years following the attacks, and 0 for all other movies.

Regression Analysis

Our first step in our econometric analysis was to run a regression for our model, including each explanatory variable. We used a histogram to test for the normality of our residuals, which appeared relatively normal with the exception of several values on the right tail. A Q-Q norm test yielded similar results. Because our Shapiro-Wilks test, with a p-value = 2.2 x 10-16 and a W = 0.7861, did not indicate normality, we retested the normality of the residuals without the outliers. Despite our results visually indicating normality, after removing the outliers our Shapiro-Wilks test still did not indicate normality, with a p-value = 4.924 x 10-10 and W = 0.92554.



Histogram to check for residual normality
count
0
10
20
30
40
50
0e+00
5e+08
1e+09
Residuals



QQ Plot
Sample Quantiles
0e+00
5e+08
1e+09
−3
−2
−1
0
1
2
3
Theoretical Normal Quantiles

```
    Shapiro-Wilk normality test

data:  model1$residuals
W = 0.78608, p-value < 2.2e-16
```

```
        28        242         85        161        100          4
 450217215  472421937  498488122  663597755 1112930656 1180413930
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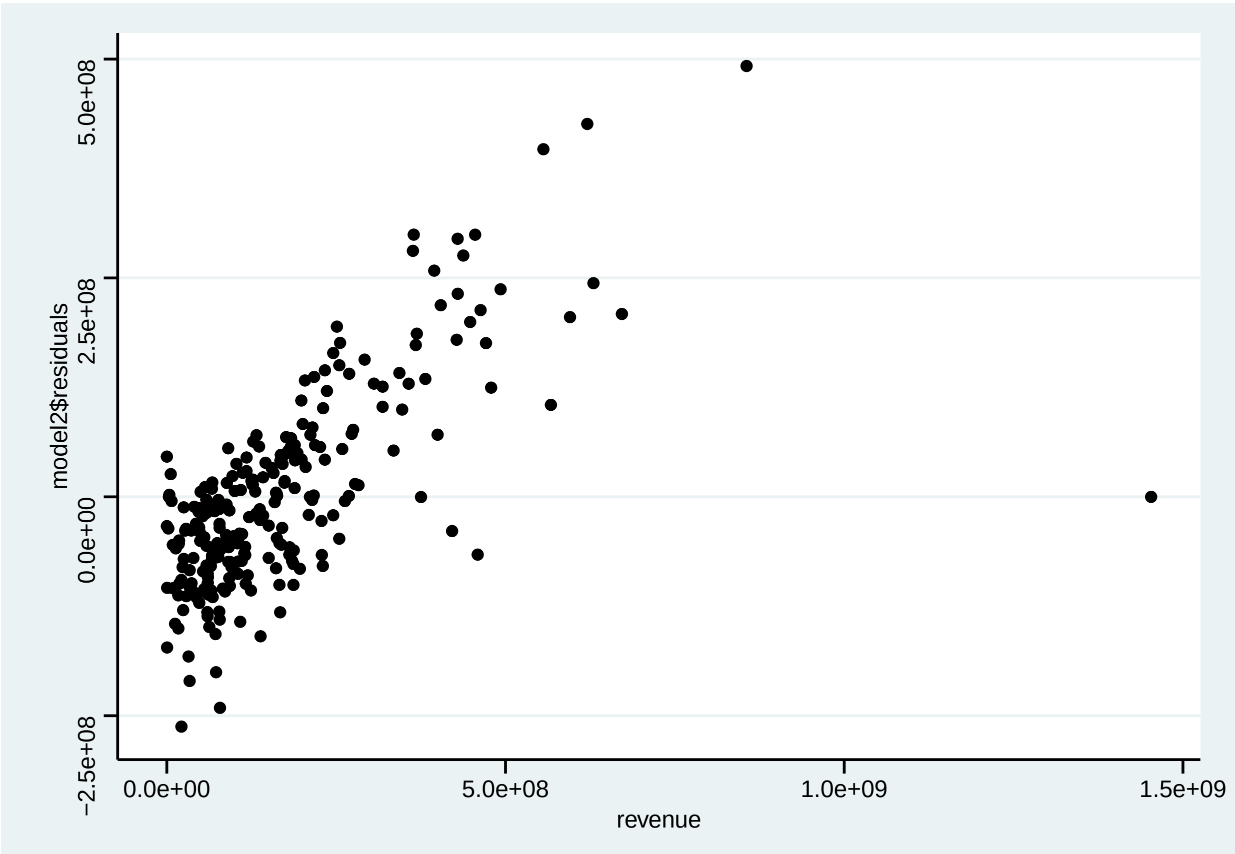


```
    Shapiro-Wilk normality test

data:  model2$residuals
W = 0.92554, p-value = 4.924e-10
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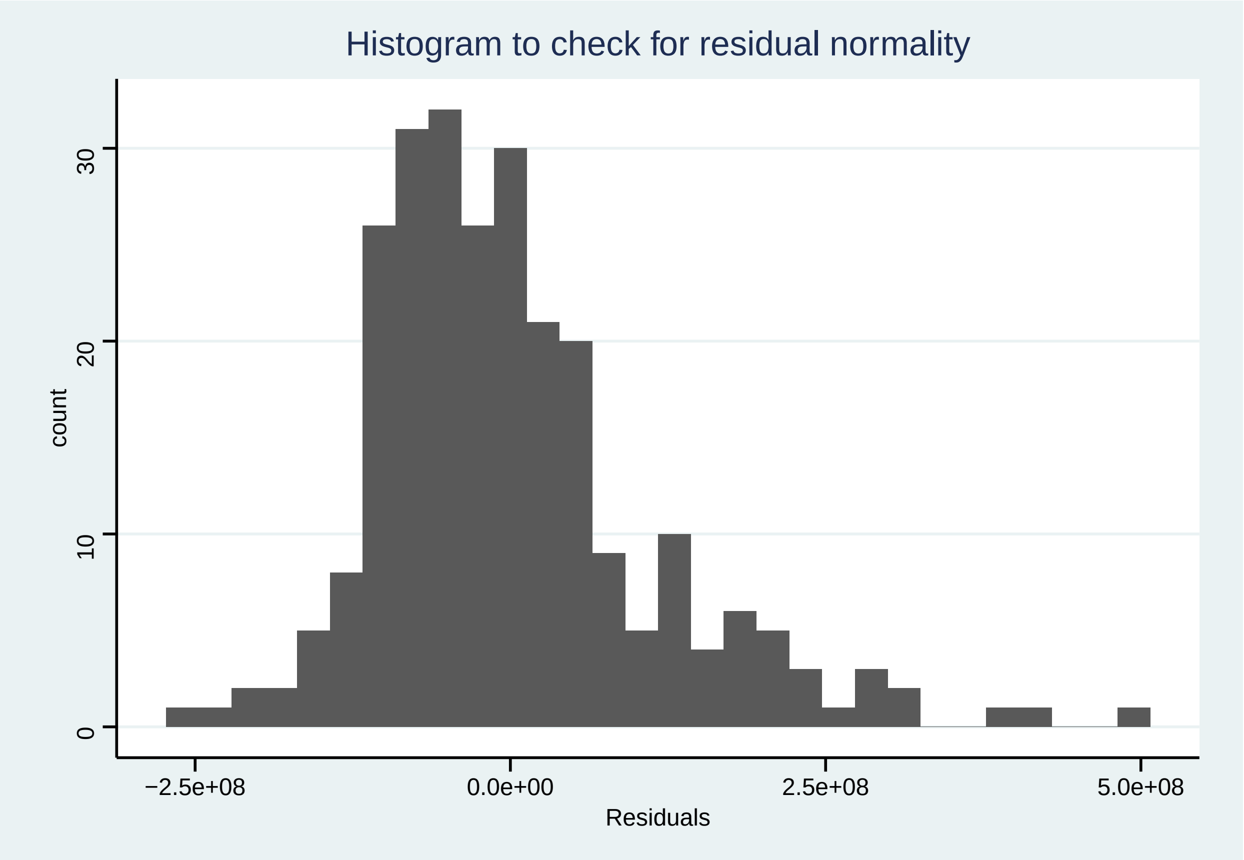
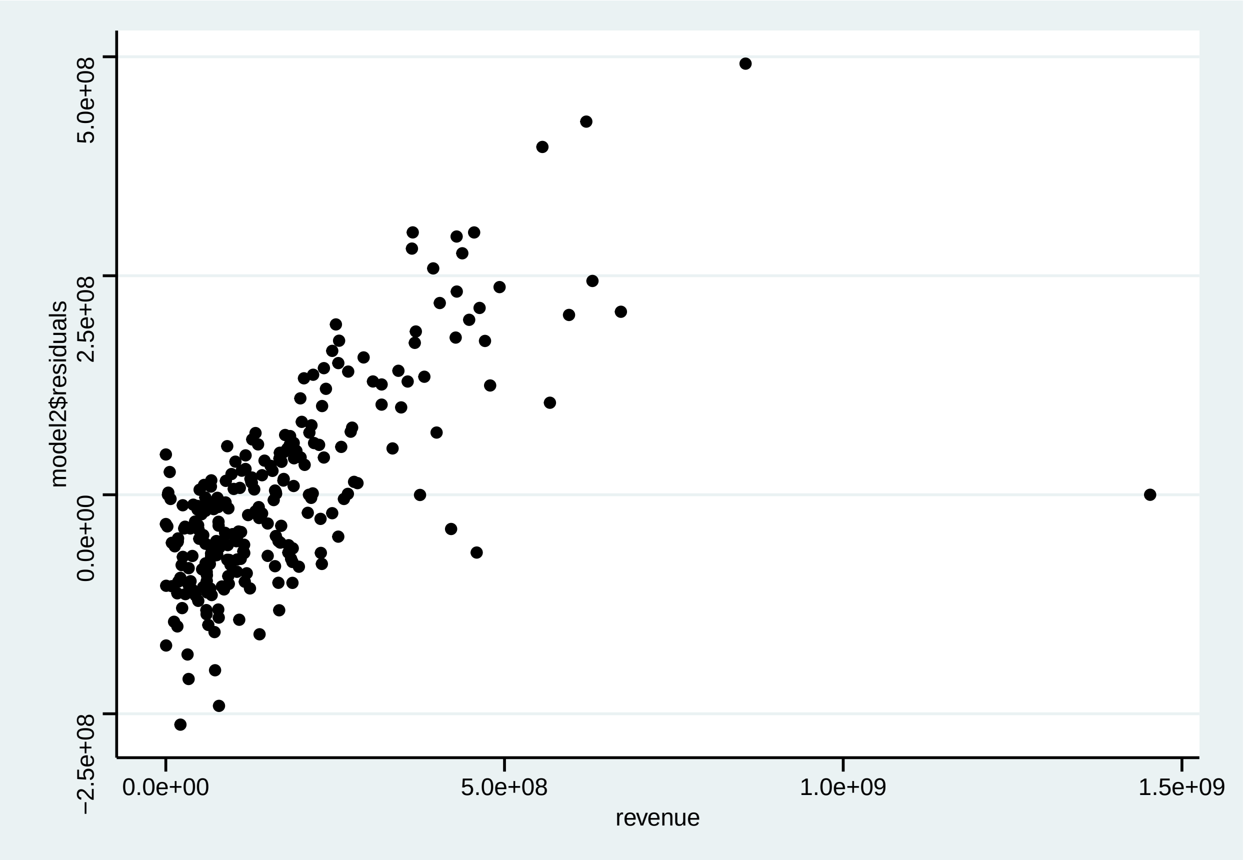

Histogram to check for residual normality
count
30
20
10
0
−2.5e+08
0.0e+00
2.5e+08
5.0e+08
Residuals


model2$residuals
5.0e+08
2.5e+08
0.0e+00
−2.5e+08
0.0e+00
5.0e+08
1.0e+09
1.5e+09
revenue

Ramsey RESET Test

Next, we ran a Ramsey RESET Test to test that the relationship between revenue and IMDb rating and run time (our two quantitative variables) was linear. We used degrees of freedom of 2 and 241 to find our acceptance region of (0, 3.041). Our calculated F-statistic was 0.482, falling within our acceptance region, so we failed to reject the null hypothesis that the relationship between revenue and IMDb rating run time is linear.

F-Tests

Because our COVID-19 variable and our September 11th Attacks variable did not appear to be statistically significant using the quick and dirty rule from our summary, we decided to run an F-test on each of these variables to determine whether they should be included in our final model.

To test for the significance of the September 11th attacks, we used 1 and 244 degrees of freedom at a 5% level of significance, with a critical region of (0,3.888). Using an unrestricted R-squared value of 0.4226 and a restricted R-squared of 0.4225, we calculated an F-statistic of 0.0422584. Because this F-statistic lies in our acceptance region, we fail to reject the null hypothesis that $\theta = 0$ and that there is no difference between the R^2 values of the two models, so we will not include this variable in our model.

To test for the significance of COVID-19, the R-squared value for both our restricted and unrestricted model was 0.4226, meaning that the F-statistic will be 0. With an F-statistic of 0, we will never reject the null hypothesis, and therefore we fail to reject the null hypothesis that $\theta = 0$ and that there is no difference between the R^2 values of the two models, so we will not include this variable in our model.

Heteroscedasticity

We then tested for heteroscedasticity using a Breusch-Pagan-Godfrey test. We chose this test over a Park test because it was a more general test that can be applied to multiple regression models like ours. Because our Breusch-Pagan-Godfrey test concluded that heteroscedasticity was present in our model (df = 16, p = 0.003846). We proceeded to calculate the White-robust standard errors estimates for our explanatory variables. While this doesn't address problems with the inefficiency of those variables, it does allow us to use accurate predicted standard errors so we can proceed with statistical inference. In this case, R, in assuming no heteroscedasticity in our data, underestimated many of our predicted standard errors. For example, R's estimate for the standard error on the decade1980 variable was 51,064,140, whereas the White-corrected standard error estimate was 84,476,057. However, R didn't underestimate all of the estimates, as in our genreHorror variable, R estimated a standard error of 179,404,172 whereas the White-corrected standard error was 78,715,217.

Hypothesis Tests

We ran a T-test on our Award 1 variable to test for whether winning the Best Picture is significant at a 5% level of significance with 243 degrees of freedom. The hypotheses for this test are:

$$H_0 : \beta_{16} = 0$$

$$H_1 : \beta_{16} \neq 0$$

Our estimate for $\beta_1 6$ lies outside of the acceptance region for this test, therefore we reject the null hypothesis that $\beta_1 6 = 0$ and that there is no significant effect on box office revenues after winning best picture. Winning the Best Picture Oscar does have a significant effect on box office revenue.

Autocorrelation

We then performed a Durbin-Watson test, which tests for autocorrelation on our model. Smaller values (close to 0) of the D-statistic signify positive autocorrelation, while larger values (closer to 4) signify negative autocorrelation. After performing our test, we found a D-statistic of 2.1246. Our p-value was 0.71633. We conclude that with a D-statistic close to 2 and a large p-value, we fail to reject the null hypothesis that $\rho = 0$. Therefore we conclude that there is no autocorrelation in our model.

Hypotheses for the Durbin-Watson:

$$H0 : \rho = 0$$

$$H1 : \rho > 0$$

Multicollinearity

To test for multicollinearity, we looked at the VIF values for each of our explanatory variables. If we set our baseline value at 10, as specified in Gujarati and Porter, the only variable that might point to multicollinearity is decade, with a vif value of 14.7. This makes sense; if a movie came out in a specific decade, other decades' values could not be 1 as well. Thinking about the economic context of our study and data, we conclude that dealing with this issue isn't super necessary. We still want to look at the significance of different decades and how they impact inflation adjusted domestic box office revenues. We also don't want to omit the variable and possibly run into omitted variables bias.

Conclusion

Our analysis sought to determine the impact of winning the Best Picture Oscar on a movie's total box office revenue, using a dataset composed of Best Picture Oscar nominees since 1977. We constructed a theoretical model using various explanatory variables and performed multiple regression analyses, along with several tests to ensure the robustness of our findings.

Our regression model identified several significant factors influencing box office revenue, including decade of release, run time, genre, IMDb rating, and whether the movie won the Best Picture Oscar. Despite the non-normal distribution of residuals as indicated by the Shapiro-Wilks test, when outliers were removed our normality plots looked more normal. However, the Shapiro-Wilks test still concluded non-normality. The Ramsey RESET test confirmed the linearity of the relationship between revenue and our quantitative variables, IMDb rating, and run time.

Our hypothesis test concluded that winning the Best Picture Oscar significantly increases box office revenue, as evidenced by the rejection of the null hypothesis for this variable. Following our F-tests, we failed to reject the null hypothesis that the variables for the COVID-19 pandemic and the September 11th attacks did not significantly impact box office revenue, suggesting that there was no significant difference between our restricted and unrestricted models.

We also found no evidence of autocorrelation in our model, further supporting the reliability of our regression results. However, we did find heteroscedasticity, so we used White corrected standard errors to perform further statistical inference. Despite the challenges with the genre variable, we ensured that our model accurately reflected the influence of movie genres on box office performance.

Our econometric analysis confirms that winning the Best Picture Oscar has a positive and significant effect on a movie's box office revenue, highlighting the economic value of this prestigious award.