linear_regression_model

March 8, 2023

1 What did Adam do to AMC?

1.0.1 Let's use data science to find out.

- First we will do a little exploratory analysis and visualizations about earnings.
- We will construct a predictive model to predict the 2023 EOY earnings.
- In addition, two other predictive models will be constructed for comparative analysis.
- We will evaluate, and visualize the AMC float dilution history.
- Finally we will determine whether dilution has ever caused AMC share prices to increase.

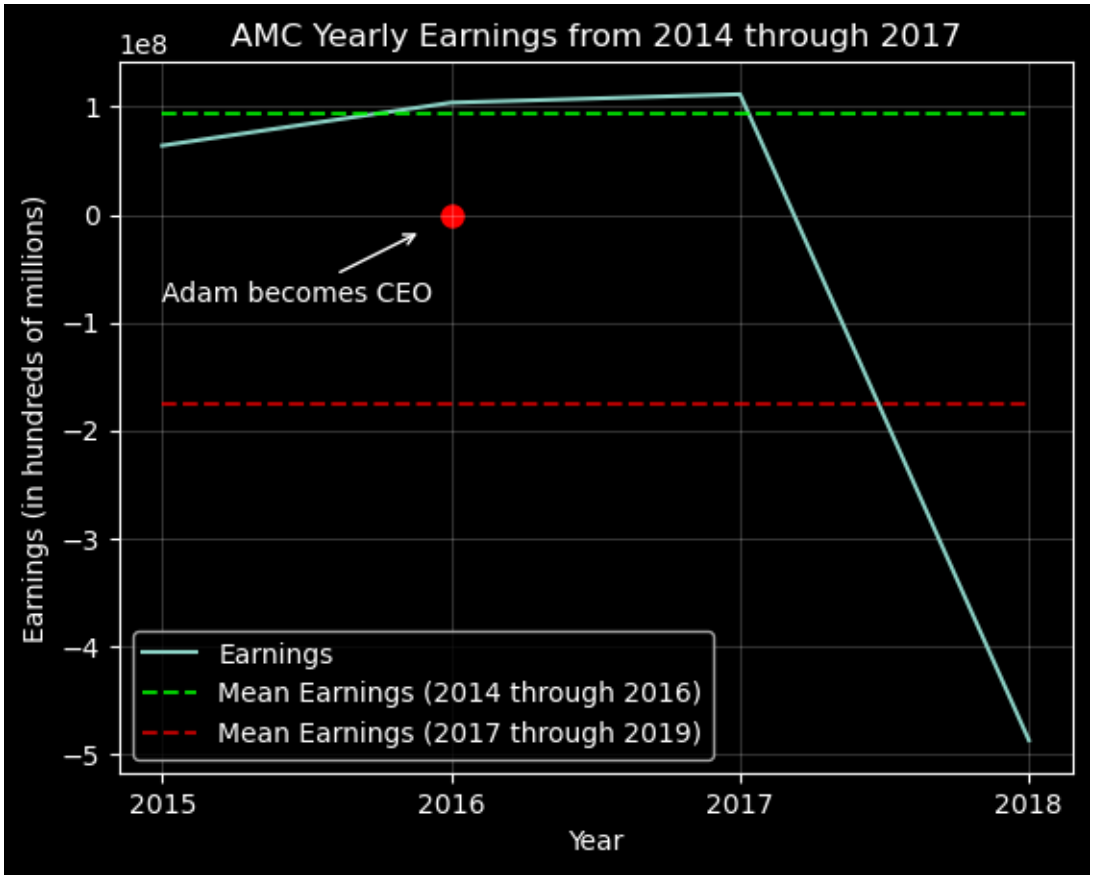
[ ]:
```
# Import statements.

import matplotlib.pyplot as plt
from datetime import datetime
import pandas as pd
import numpy as np
import math

import sys
if sys.path[0] != "scripts": sys.path.insert(0, "scripts")
from scripts.comparative import comparative
from scripts.residuals import presiduals
from scripts.datasets import pdatasets
from scripts.prediction import predict
from scripts.earnings import eplot
from scripts.pfloat import pfloat
from scripts.epies import epies
from scripts.dhist import hplot
from scripts.preg import rplot
from scripts.dbo import dplot

plt.style.use("dark_background")
```

[ ]:
```
# Load the data.
df = pd.read_csv("data/data.csv", index_col = 0)
```

2 Consider AMC Earnings.

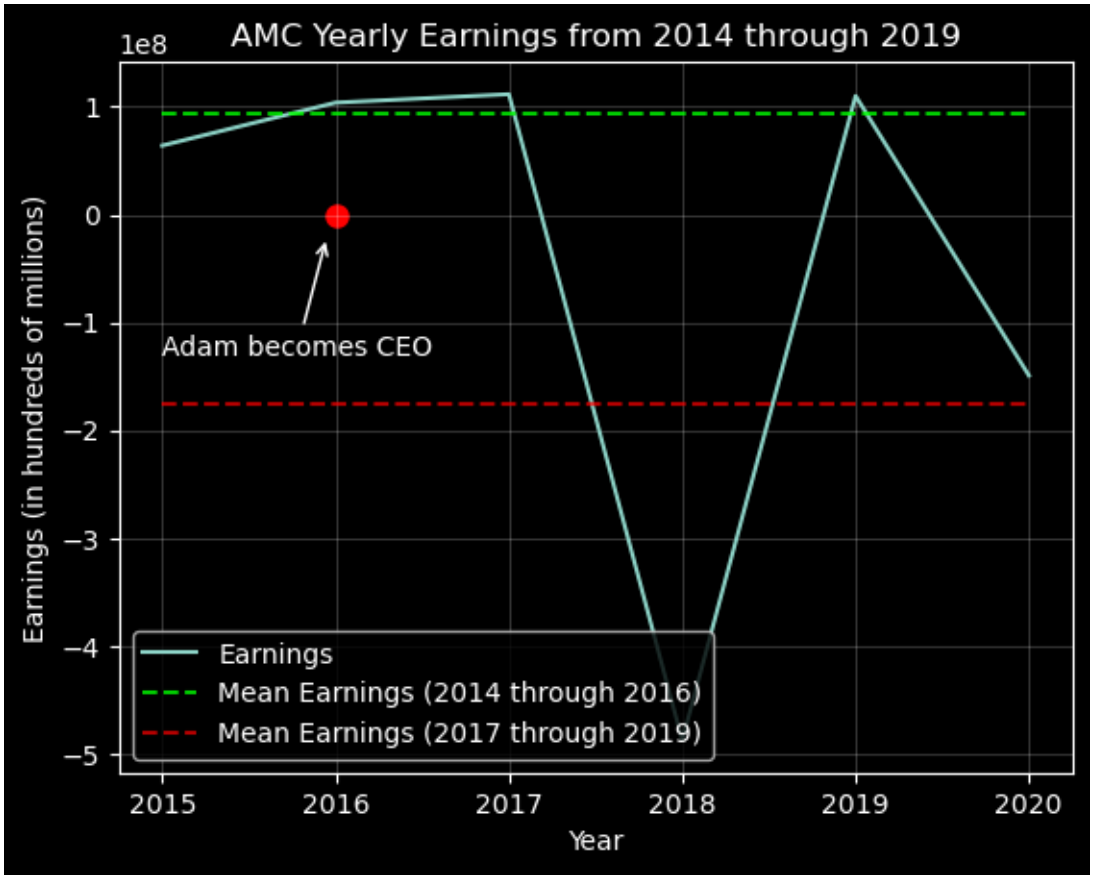
- Adam became CEO in 2016
- Adam purchased Odion in 2017

[ ]:
```
# See: analysis/scripts/earnings.py
eplot(4, 2014, 2017, 2014, -0.8, 2014.9, -0.15, 8, plt, df)
```



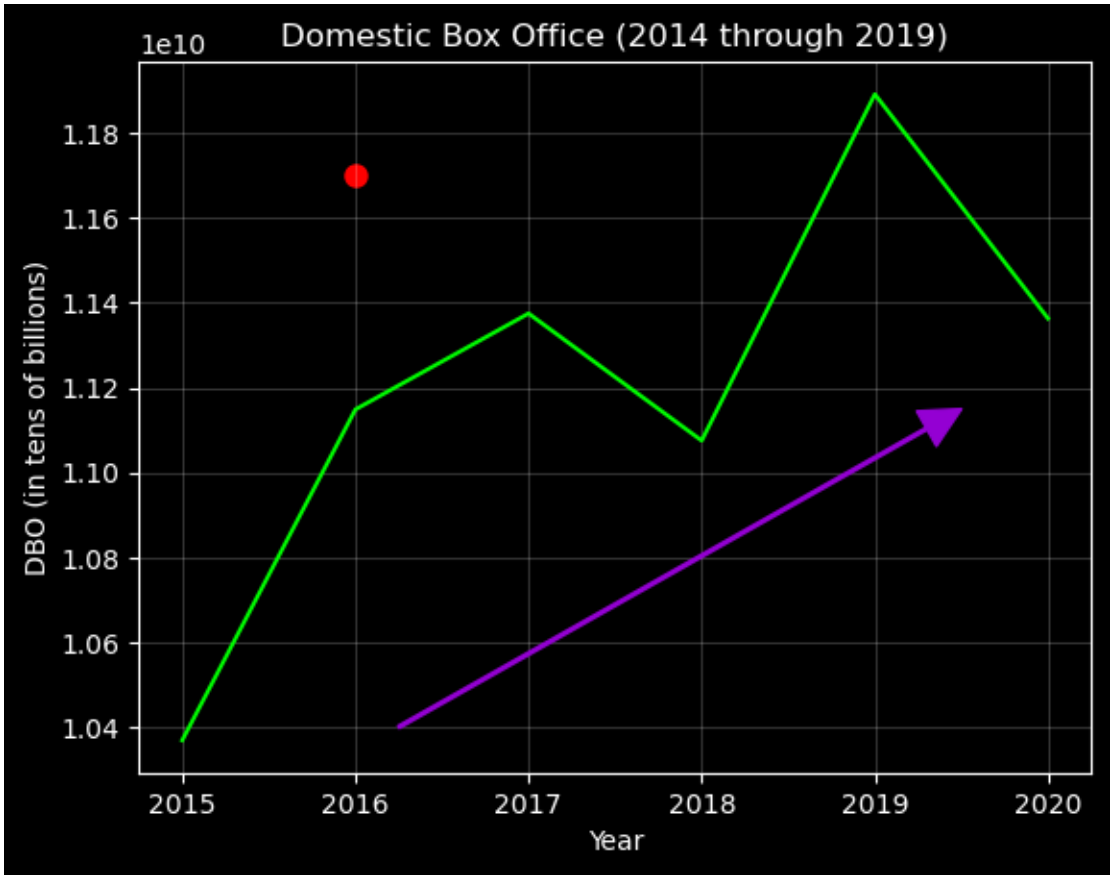
Let's zoom out for some context.

[ ]:
```
# See: analysis/scripts/earnings.py
eplot(6, 2014, 2019, 2014, -1.3, 2014.95, -0.2, 8, plt, df)
```



Compare that to the domestic box office for the same time period.

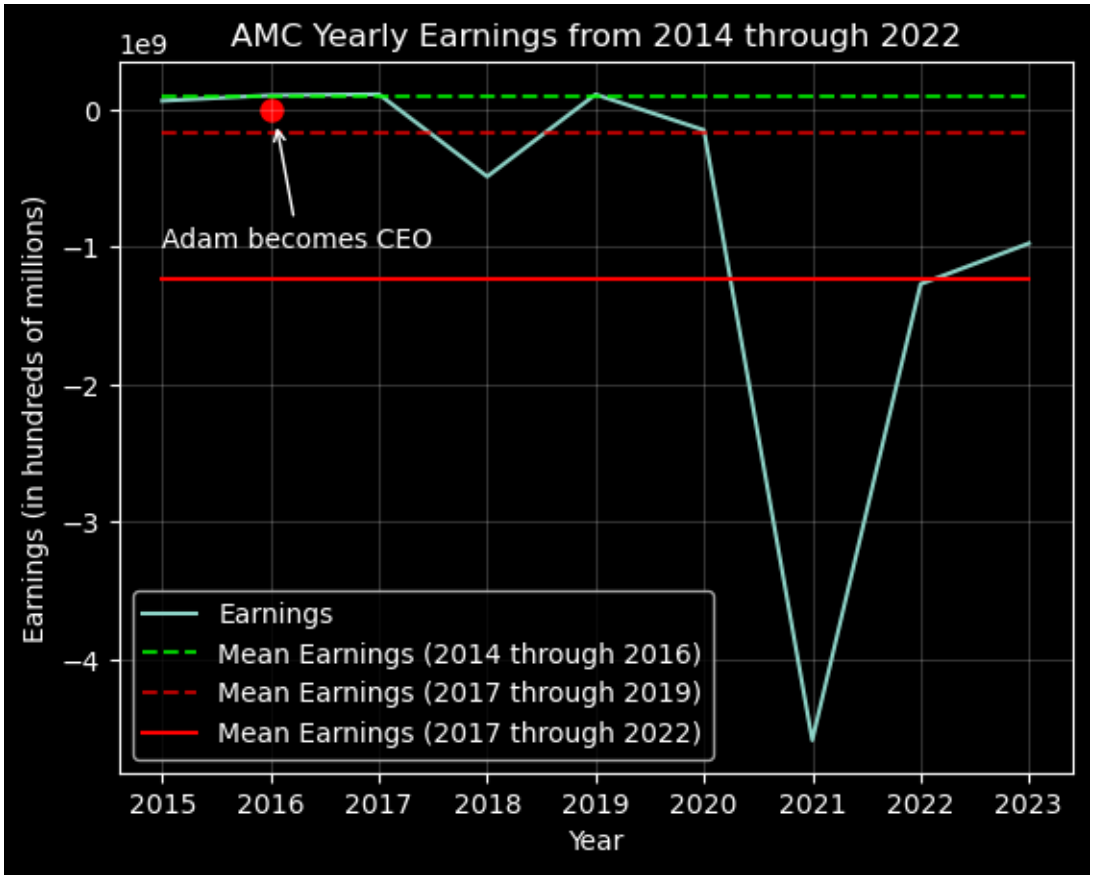
[ ]:
```
# See: analysis/scripts/dbo.py
dplot(plt, df)
```



After the Odion purchase it took domestic box office reaching all time highs in 2019 to push AMC past a net loss and back up just slightly above it's mean net earnings from 2014 through 2017. That can't be good.

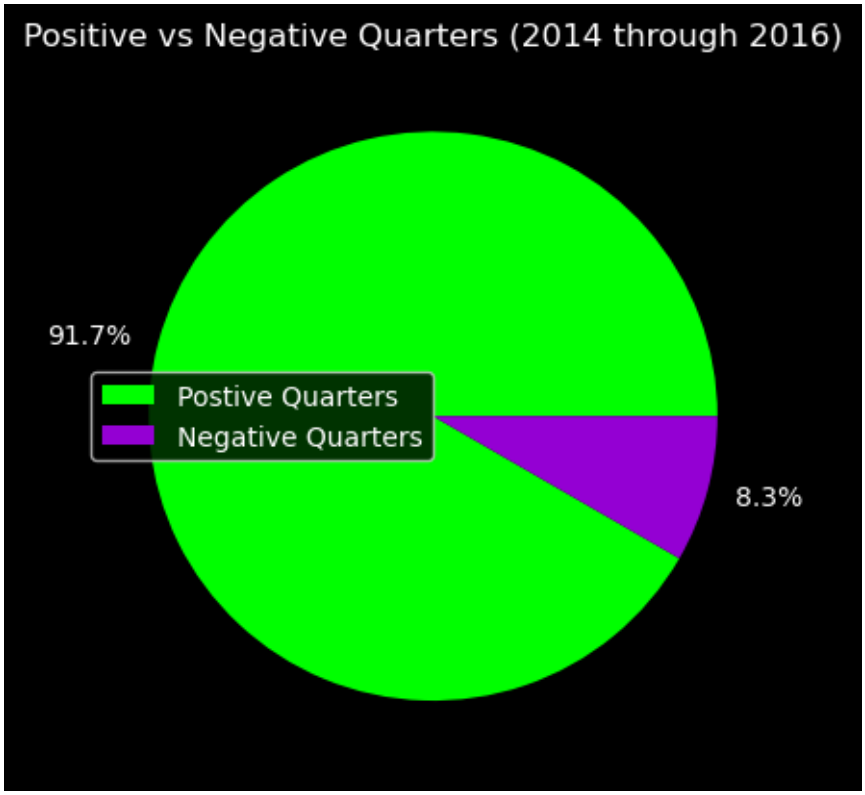
Let's look at earnings for the entire dataset, that is, from 2014 to 2023.

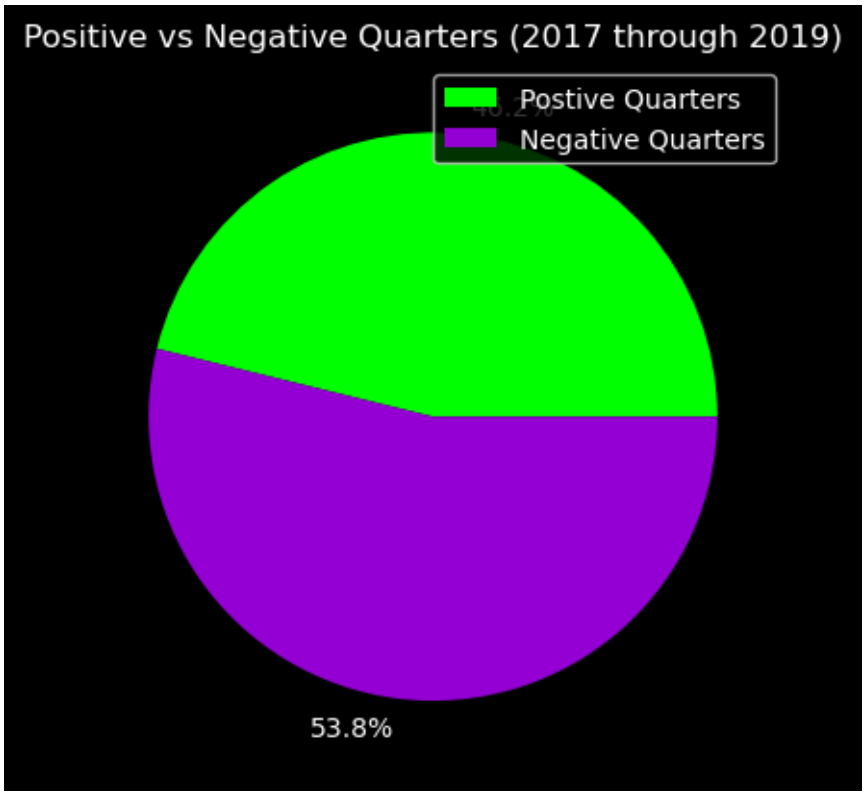
[ ]:
```
# See: analysis/scripts/earnings.py
eplot(9, 2014, 2022, 2014, -1, 2015.05, -0.09, 9, plt, df)
```

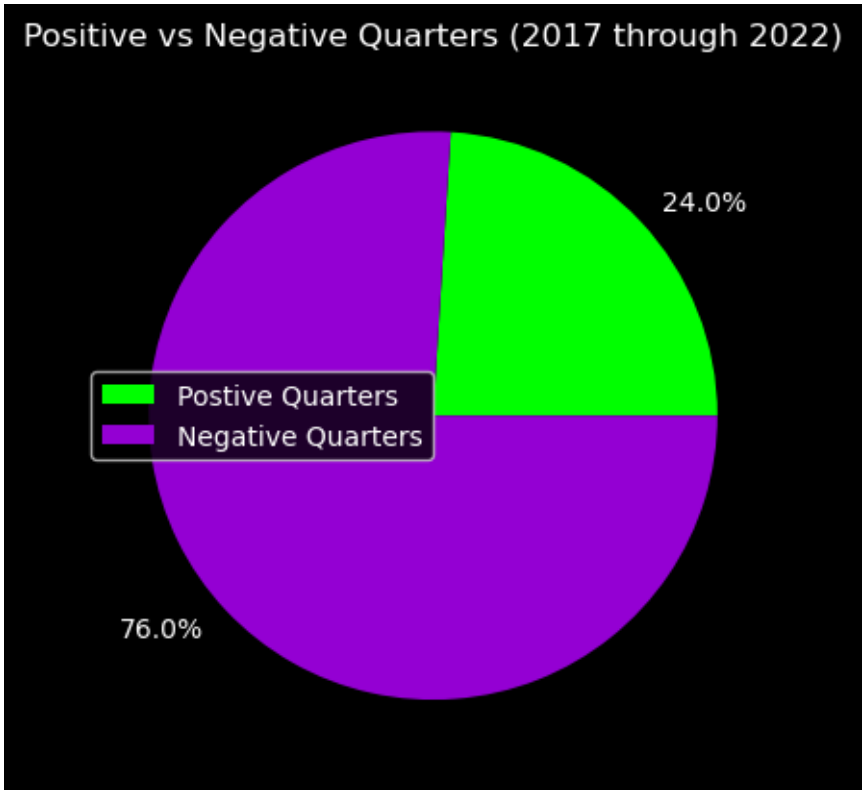


2.0.1 Ouch! Let's really see how much quarterly earnings have dropped off during Adams tenure.

[ ]:
```
# See: analysis/scripts/epies.py
epies(plt, df)
```


Positive vs Negative Quarters (2014 through 2016)
91.7%
Postive Quarters
Negative Quarters
8.3%


Positive vs Negative Quarters (2017 through 2019)
Postive Quarters
Negative Quarters
53.8%



2.0.2 Wow!

2.0.3 Summary about these exploratory analytics

AMC started trading publicly in 2014. Over that 2-year period, from 2014 through 2015, AMC made a total of $167,936,000 in profit. Adam became CEO in 2016. Between 2016 through 2019 AMC lost $-414,533,000 in profit. Despite the domestic box office increasing well above its 2014 through 2016 levels. From 2020 Q2 through 2022, Adam managed to multiply those losses by over an entire order of magintude, to $-4,656,500,000. Excluding 2020 Q1, during Adams full tenure he lost a total of $-5,071,033,000 in profit. Including 2020 Q1, altogether, Mr. Aron managed to lose the total astronomical amount of $-7,247,333,000. That is over a billion dollars loss per year, on average.

- Mean quarterly earnings (2014 through 2016): 20,992,000
- Mean quarterly earnings (2016 through 2019): -25,908,312
- Mean quarterly earnings (2016 through 2022): -258,833,321
- Mean quarterly earnings (2014 through 2022): -196,649,917

[ ]:
```
# Calculate P/L for key features, and summarize them.

pl1 = df.loc[:7].earnings.sum()
pl2 = df.loc[8:23].earnings.sum()
pl3 = df.loc[25:].earnings.sum()
pl4 = df.loc[8:].drop(24).earnings.sum()
pl5 = df.loc[8:].earnings.sum()

print(f"""
AMC started trading publicly in 2014. Over that 2-year period, from 2014␣
 ↪through 2015, AMC made a total of
${pl1:,.0f} in profit. Adam became CEO in 2016. Between 2016 through 2019 AMC␣
 ↪lost ${pl2:,.0f} in profit.
Despite the domestic box office increasing well above its 2014 through 2016␣
 ↪levels. From 2020 Q2 through
2022, Adam managed to multiply those losses by over an entire order of␣
 ↪magintude, to ${pl3:,.0f}. Excluding
2020 Q1, during Adams full tenure he lost a total of ${pl4:,.0f} in profit.␣
 ↪Including 2020 Q1, altogether,
Mr. Aron managed to lose the total astronomical amount of ${pl5:,.0f}That is␣
 ↪over a billion dollars per
year loss, on average.""")

print(f"""\n\n
    Mean quarterly earnings (2014 through 2016): {df.loc[:7].earnings.mean():,.
 ↪0f}

    Mean quarterly earnings (2016 through 2019): {df.loc[8:23].earnings.mean():
 ↪,.0f}

    Mean quarterly earnings (2016 through 2022): {df.loc[8:].earnings.mean():,.
 ↪0f}

    Mean quarterly earnings (2014 through 2022): {df.earnings.mean():,.0f}
""")
```

```
AMC started trading publicly in 2014. Over that 2-year period, from 2014 through
2015, AMC made a total of
$167,936,000 in profit. Adam became CEO in 2016. Between 2016 through 2019 AMC
lost $-414,533,000 in profit.
Despite the domestic box office increasing well above its 2014 through 2016
levels. From 2020 Q2 through
2022, Adam managed to multiply those losses by over an entire order of
magintude, to $-4,656,500,000. Excluding
2020 Q1, during Adams full tenure he lost a total of $-5,071,033,000 in profit.
Including 2020 Q1, altogether,
```

```
Mr. Aron managed to lose the total astronomical amount of $-7,247,333,000That is
over a billion dollars per
year loss, on average.



    Mean quarterly earnings (2014 through 2016): 20,992,000

    Mean quarterly earnings (2016 through 2019): -25,908,312

    Mean quarterly earnings (2016 through 2022): -258,833,321

    Mean quarterly earnings (2014 through 2022): -196,649,917
```

[ ]:
```
# Drop 2020 Q1 outlier, and superfluous columns. Extrapolate quarterly to␣
 ↪yearly values.
columns = ["DBO gross", "earnings"]
try:
    df = df.drop(24)
    df["DBO gross"] = df["DBO gross"] * 4
    df["earnings"]  = df["earnings"]  * 4
except KeyError: pass
df = df[columns]
x  = df["DBO gross"]
y  = df["earnings"]

# We need this for later when talking about dilution
num_quarters = len(df.iloc[8:]) + 1
```

3 Linear Regressions Predictive Models

We are going to predict 2023 earnings based on linear regression analysis. Moreover, we will compare how well AMC might have otherwise performed, in terms of profits (or losses) by constructing:

1. A model based on prior to the Odion purchase. In other words, before Adam disrupted the past profitability of AMC by capital misallocation.
2. A model based on after the Odion purchase, but before Covid. So we can fairly compare Adams performance against the prior performance of AMC, in terms of profitability.
3. The third model will be used to actually predict future earnings, and also can be compared to either of the other two models for the purpose of contrasting performance based on the different business structurings.

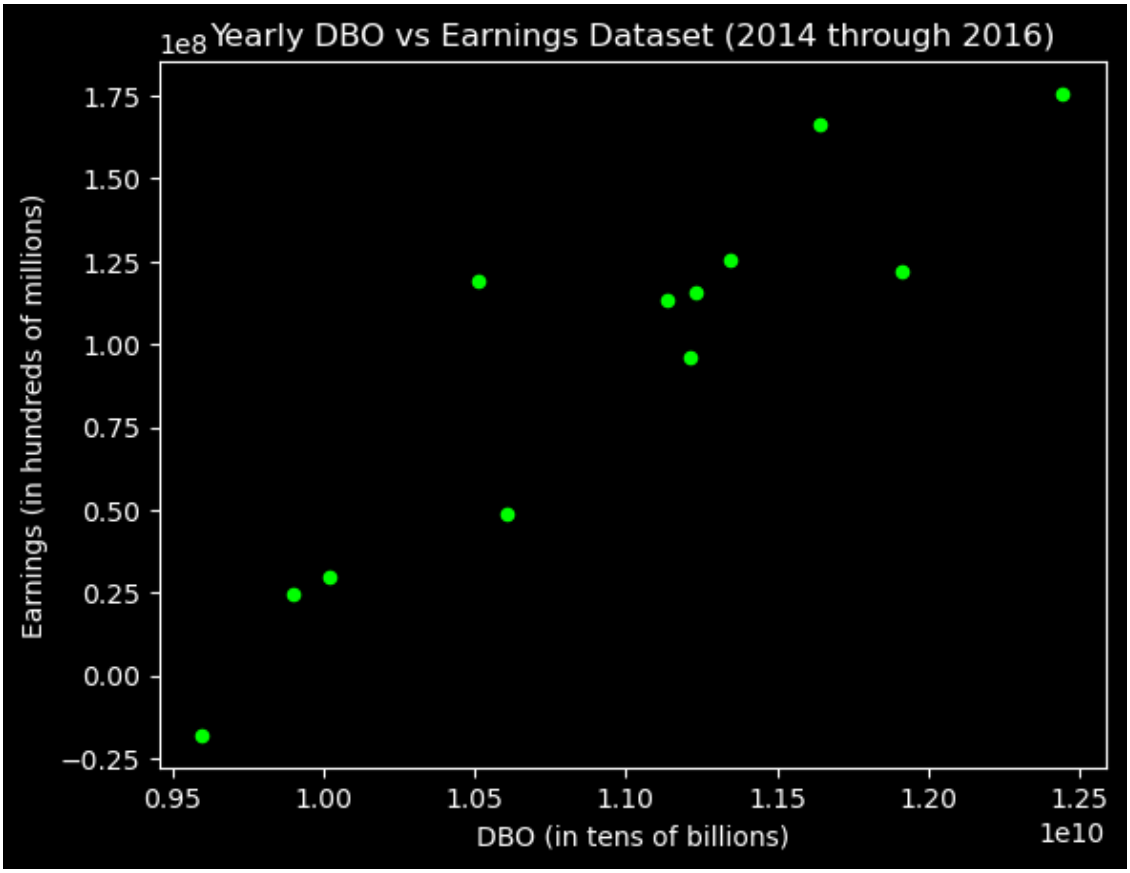
Descriptive summary about the dataset used for regression analysis.

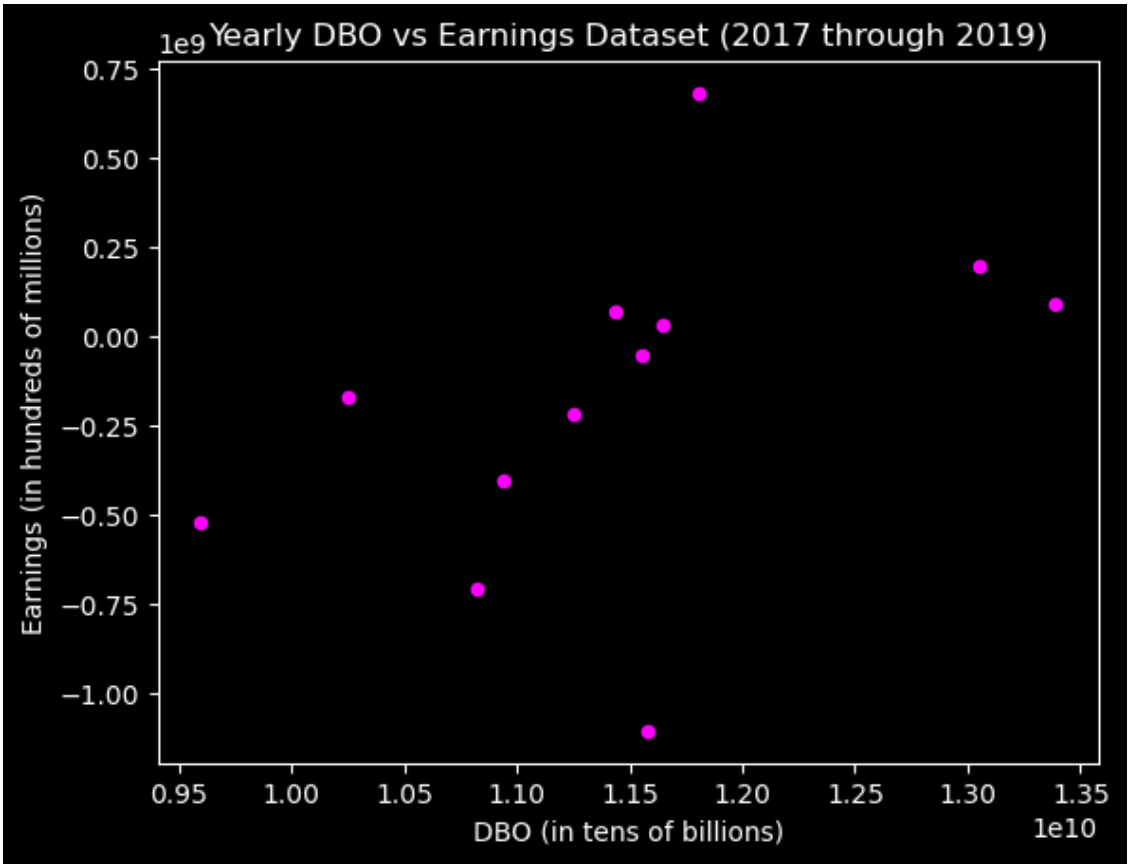
[ ]:
```
print(df.describe())
```

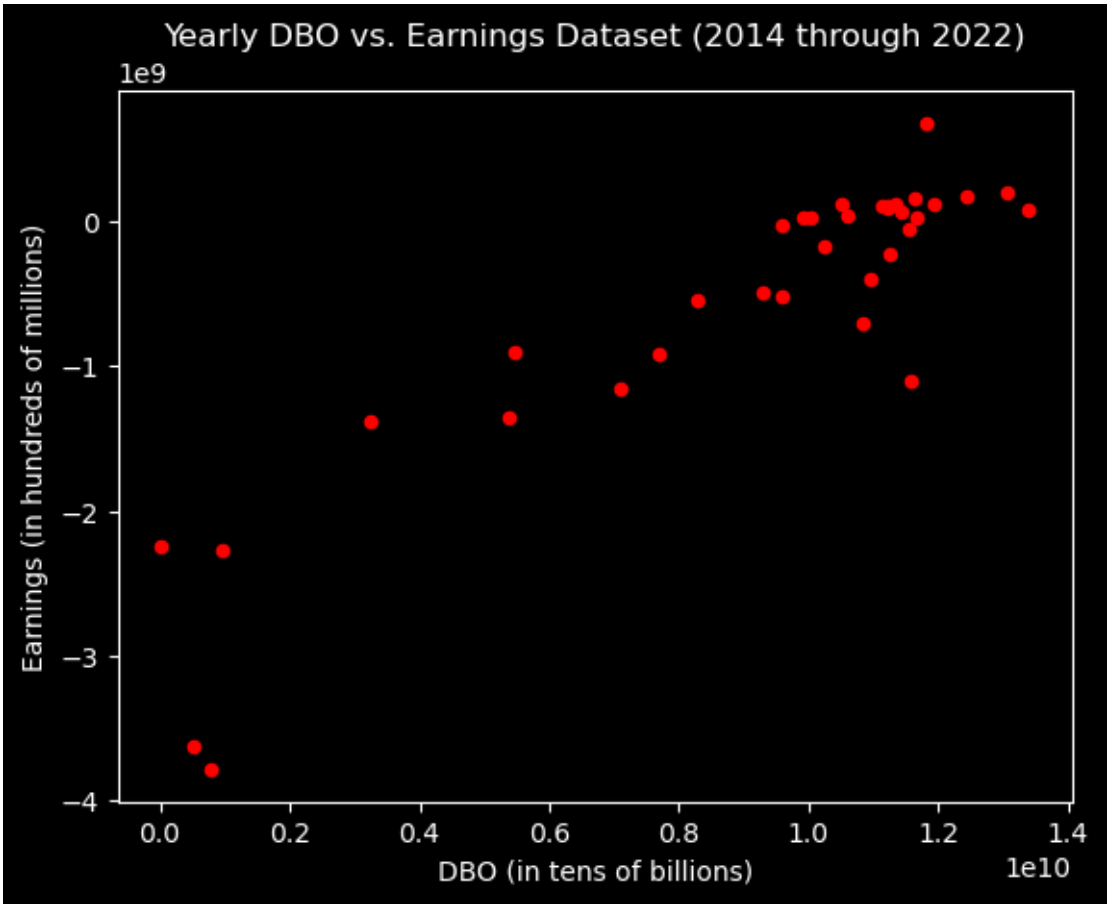
```
          DBO gross      earnings
count  3.500000e+01  3.500000e+01
mean   9.074312e+09 -5.603539e+08
std    3.788194e+09  1.039427e+09
min    1.890192e+07 -3.784400e+09
25%    7.982850e+09 -9.022000e+08
50%    1.060793e+10 -5.400000e+07
75%    1.149479e+10  1.045160e+08
max    1.338965e+10  6.824000e+08
```

3.0.1 Data visualization of the datasets used for modeling

[ ]:
```
# See: analysis/plots/datasets.py
pdatasets(plt, df)
```




Yearly DBO vs Earnings Dataset (2017 through 2019)
1e9
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
Earnings (in hundreds of millions)
0.95
1.00
1.05
1.10
1.15
1.20
1.25
1.30
1.35
1e10
DBO (in tens of billions)



3.0.2 Pearsons Correlation Coefficients

Here we find the z-scores for each model, so that we can evaluate whether a correlation exists, the nature about that correlation, and how strong any such correlation may be.

z-scores:

[ ]:
```
%%latex
$$ \zeta = \frac{x - \mu}{\sigma} $$
```

$$\zeta = \frac{x - \mu}{\sigma}$$

[ ]:
```
# Calculate the z-scores.
zeta = lambda x: (x - x.mean()) / x.std()

df["z-scoreX1"], df["z-scoreY1"] = zeta(x.iloc[:12]), zeta(y.iloc[:12])
df["z-scoreX2"], df["z-scoreY2"] = zeta(x.iloc[12:24]), zeta(y.iloc[12:24])
df["z-scoreX3"], df["z-scoreY3"] = zeta(x), zeta(y)
```

Pearsons Correlation Coefficient:

[ ]:
```
%%latex
$$ \rho = \frac{ \sum{\zeta_x \zeta_y} }{n - 1} $$
```

$$\rho = \frac{\sum \zeta_x \zeta_y}{n - 1}$$

[ ]:
```
# Calculate Pearsons Correlation Coefficients.
r1 = (df["z-scoreX1"] * df["z-scoreY1"]).sum() / (len(df.loc[:11]) - 1)
r2 = (df["z-scoreX2"] * df["z-scoreY2"]).sum() / (len(df.loc[12:23]) - 1)
r3 = (df["z-scoreX3"] * df["z-scoreY3"]).sum() / (len(df) - 1)

print(f"""
For 2014 through 2016, Pearsons Correlation Coefficient is: {r1}
For 2017 through 2019, Pearsons Correlation Coefficient is: {r2}
For 2014 through 2022, Pearsons Correlation Coefficient is: {r3}
""")
```

```
For 2014 through 2016, Pearsons Correlation Coefficient is: 0.9118679351959351
For 2017 through 2019, Pearsons Correlation Coefficient is: 0.45365018248882316
For 2014 through 2022, Pearsons Correlation Coefficient is: 0.9066831913698027
```

3.0.3 Summary about Pearsons Correlation Coefficients

We correlate DBO with earnings for three seperate time periods: 1) 2014 through 2016, 2) 2017 through 2019, and 3) 2014 through 2022. Each model is able to predict earnings from DBO, within the range of its DBO domain.

1. This is a very strong positive correlation of approximately: 0.91. This model will likely make very accurate predictions.
2. This correlation is a relatively weak positive correlation of approximately: 0.45, but we move forward with this model in an attempt to give Adam the benefit of the doubt. A more powerful model would be ideal, but it is better than nothing. Certainly it would not be fair to include Covid in the model. I assume in 2016 AMC was operationally much the same compared to 2014, and 2015. The major effect Adam had immediately after compeleting his first year as CEO was purchasing Odion, so that is the rational basis of the time period.
3. Like (1), this correlation is a very strong positive correlation of approximately: 0.91

Next we will determine the best-fit functions for these datasets.

3.0.4 Line of Best-fit

The slope of the least-squares line:

[ ]:
```latex
%%latex
$$ \beta = \frac{ \sum{ \langle x - \bar{x} \rangle \langle y - \bar{y} \rangle
}
}{ \sum{ \langle x - \bar{x} \rangle^{2} } } $$
```

$$\beta = \frac{\sum \langle x - \bar{x} \rangle \langle y - \bar{y} \rangle}{\sum \langle x - \bar{x} \rangle^2}$$

[ ]:
```
# Calculate the slope of the least-squares line.
slope = lambda x, y: ((x - x.mean()) * (y - y.mean())).sum() / ((x - x.
mean())**2).sum()
df["b1"] = b1 = slope(x.iloc[:12], y.iloc[:12])
df["b2"] = b2 = slope(x.iloc[12:24], y.iloc[12:24])
df["b3"] = b3 = slope(x, y)
```

The y-intercept of the least-squares line:

[ ]:
```latex
%%latex
$$ \alpha = \bar{y} - \beta \bar{x} $$
```

$$\alpha = \bar{y} - \beta \bar{x}$$

[ ]:
```
# Calculate the y-intercept of the least-squares line.

intercept = lambda x, y, b: y.mean() - b * x.mean()
df["a1"] = a1 = intercept(x.iloc[:12], y.iloc[:12], b1)
df["a2"] = a2 = intercept(x.iloc[12:24], y.iloc[12:24], b2)
df["a3"] = a3 = intercept(x, y, b3)
```

- For 2014 through 2016:
  $\alpha = -598,645,528$
  $\beta \approx 0.06309998813676994$
- For 2017 through 2019:
  $\alpha = -2,482,569,804$
  $\beta \approx 0.20161160108675694$
- For 2014 through 2022:
  $\alpha = -2,817,870,262$
  $\beta \approx 0.24878099226102765$

[ ]:
```
# Display a and b.

print(f"""
For 2014 through 2016:
 a = {a1:,.0f}
 b = {b1}
```

```
For 2017 through 2019:
 a = {a2:,.0f}
 b = {b2}

For 2014 through 2022:
 a = {a3:,.0f}
 b = {b3}
""")
```

```
For 2014 through 2016:
 a = -598,645,528
 b = 0.06309998813676994

For 2017 through 2019:
 a = -2,482,569,804
 b = 0.20161160108675694

For 2014 through 2022:
 a = -2,817,870,262
 b = 0.24878099226102765
```

The function for the least-squares line

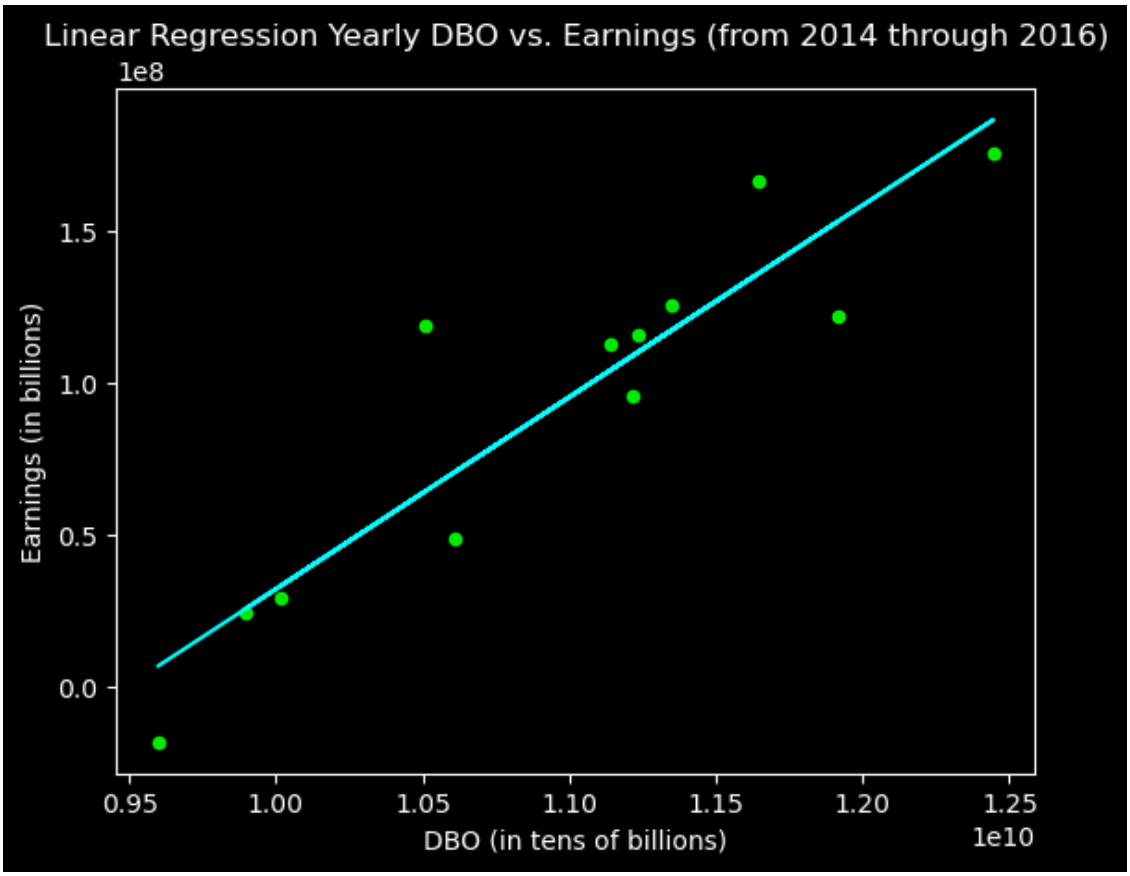
[ ]:
```
%%latex
$$ \hat{y} = f \langle x \rangle = \alpha + \beta x $$
```

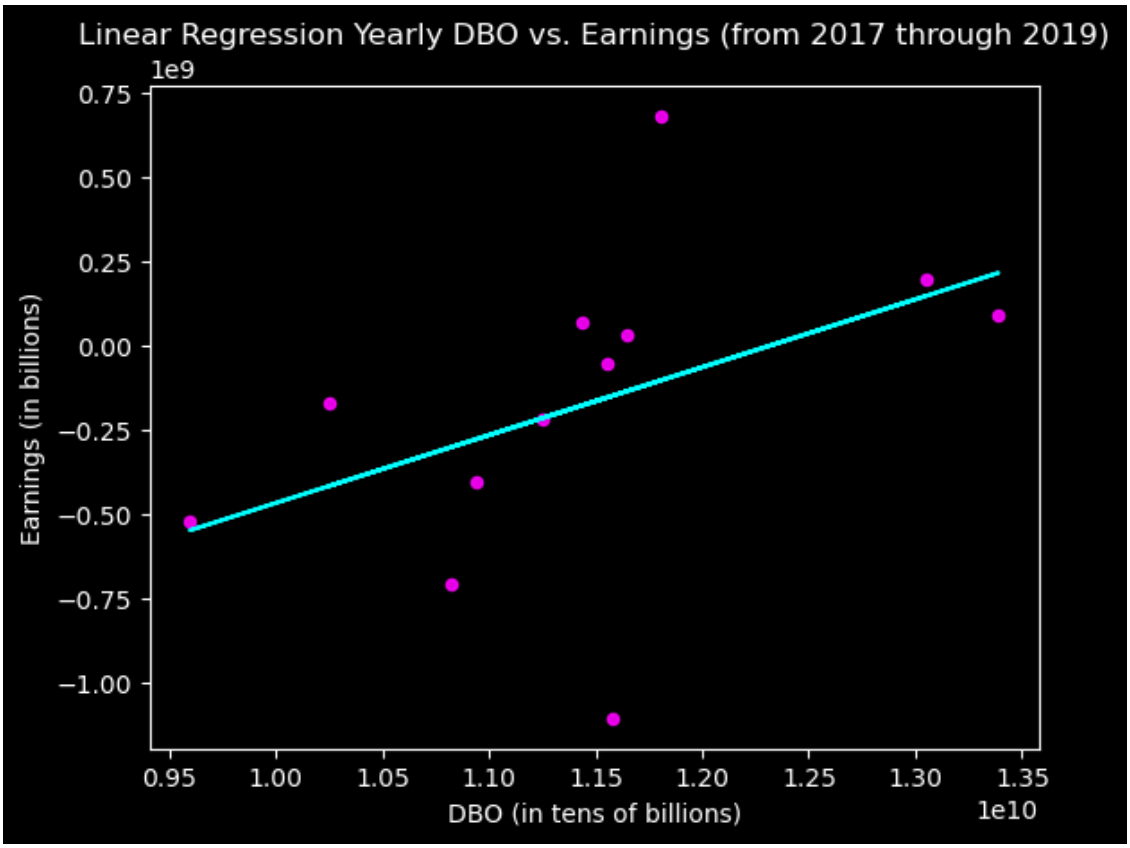
$$\hat{y} = f\langle x \rangle = \alpha + \beta x$$

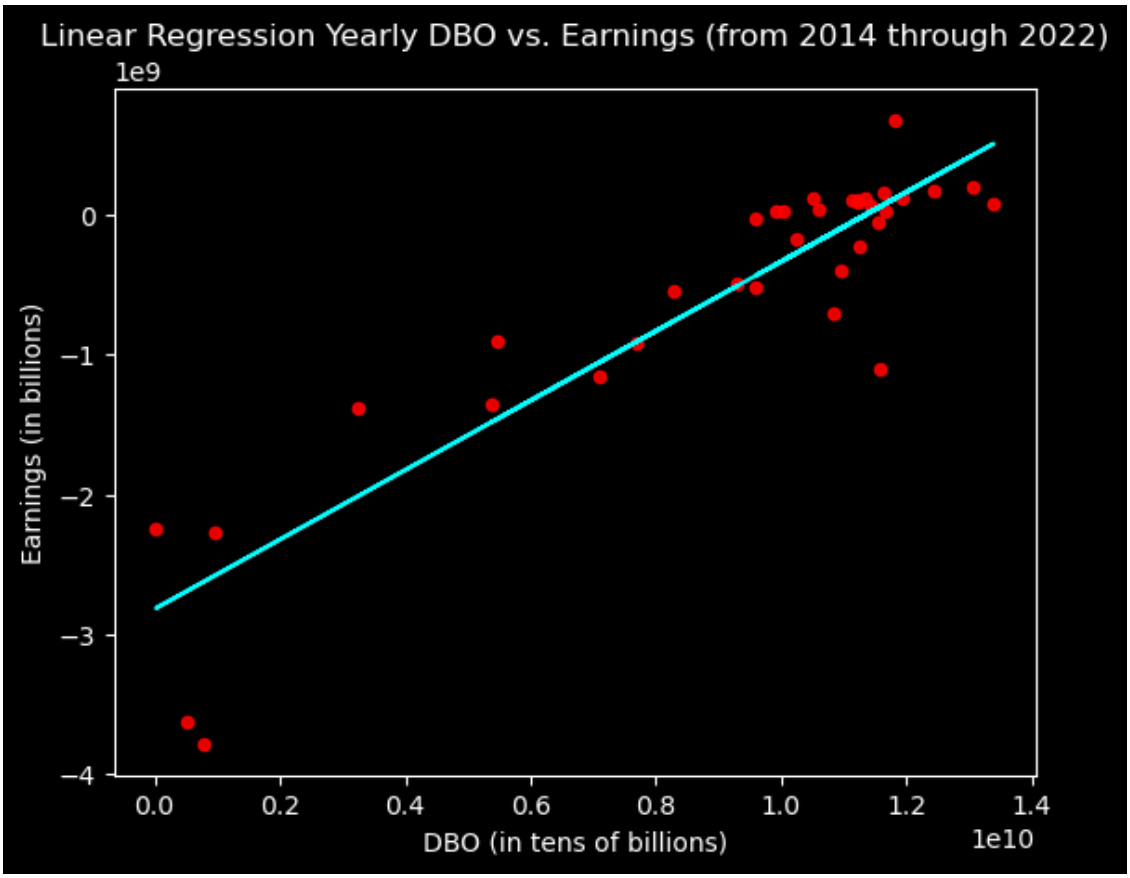
[ ]:
```
# Calculate y-hats.

hat = lambda a, b, x: a + b * x

df["y_hat1"] = y_hat1 = hat(a1, b1, x.iloc[:12])
df["y_hat2"] = y_hat2 = hat(a2, b2, x.iloc[12:24])
df["y_hat3"] = y_hat3 = hat(a3, b3, x)
```

3.0.5 Linear regression plots

[ ]:
```
# See: analysis/scripts/preg.py
rplot(x, y_hat1, y_hat2, y_hat3, plt, df)
```


Linear Regression Yearly DBO vs. Earnings (from 2014 through 2016)
1e8
1.5
1.0
0.5
0.0
Earnings (in billions)
0.95
1.00
1.05
1.10
1.15
1.20
1.25
DBO (in tens of billions)
1e10


Linear Regression Yearly DBO vs. Earnings (from 2017 through 2019)
1e9
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
Earnings (in billions)
0.95
1.00
1.05
1.10
1.15
1.20
1.25
1.30
1.35
DBO (in tens of billions)
1e10



3.0.6 Evaluating Residuals to Assess the Regression Lines

Now, to construct the residual plots. In these plots we shall look for patterns. Especially curvature, influential observations, or outliers. We see none so these plots look pretty good!

Residual:

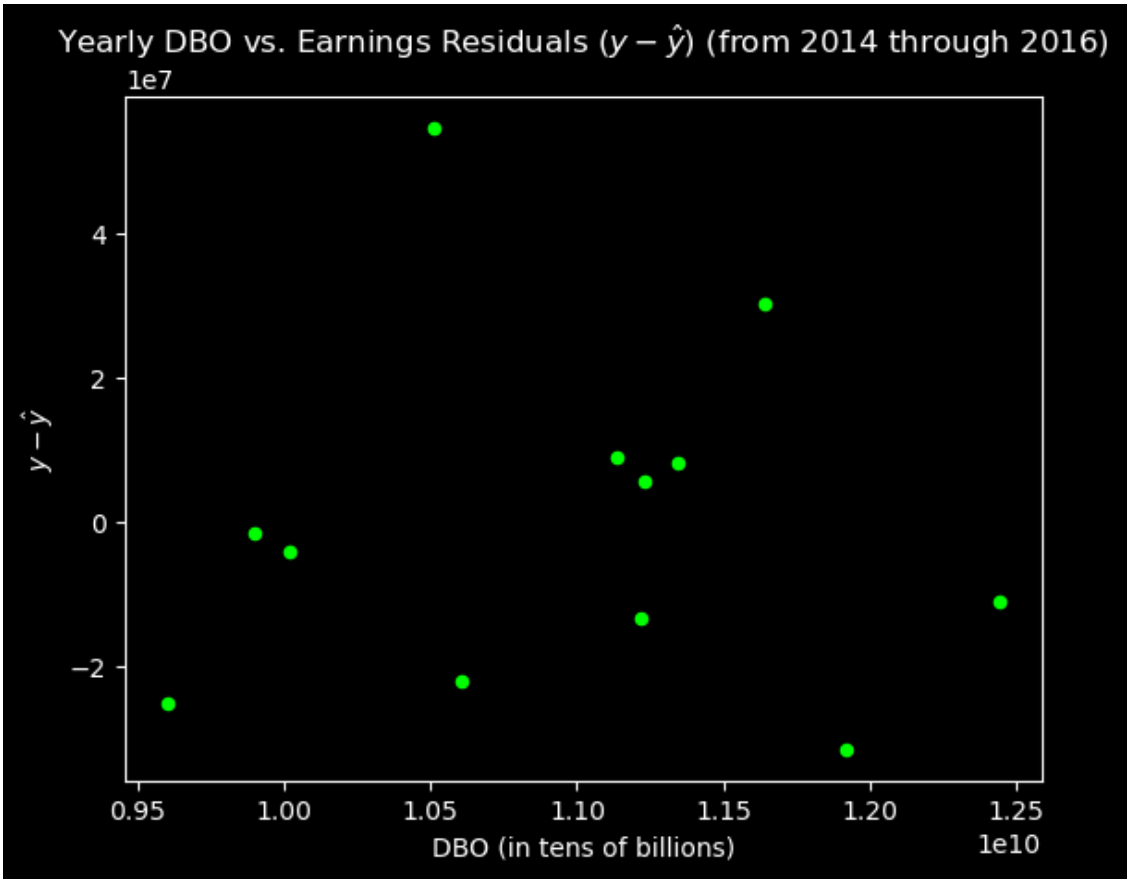
[ ]:
```
%%latex
$$ y - \hat{y} $$
```

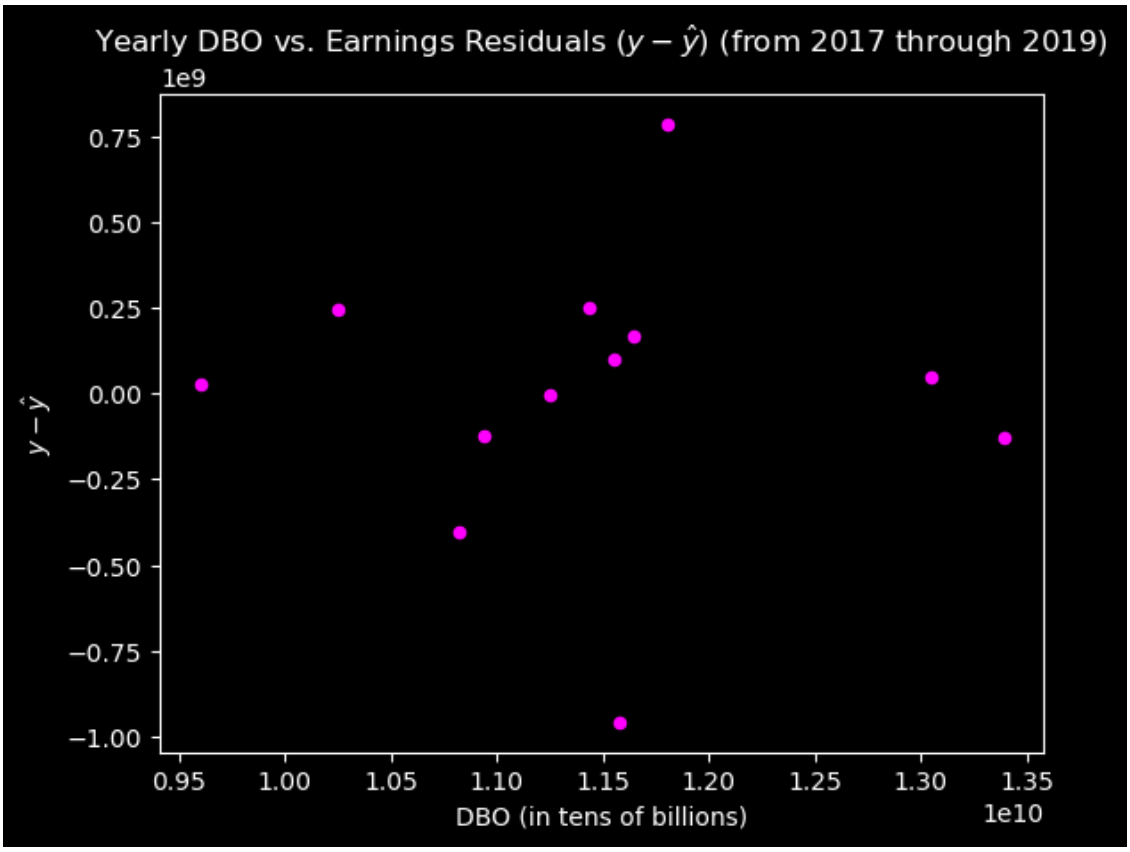
$$y - \hat{y}$$

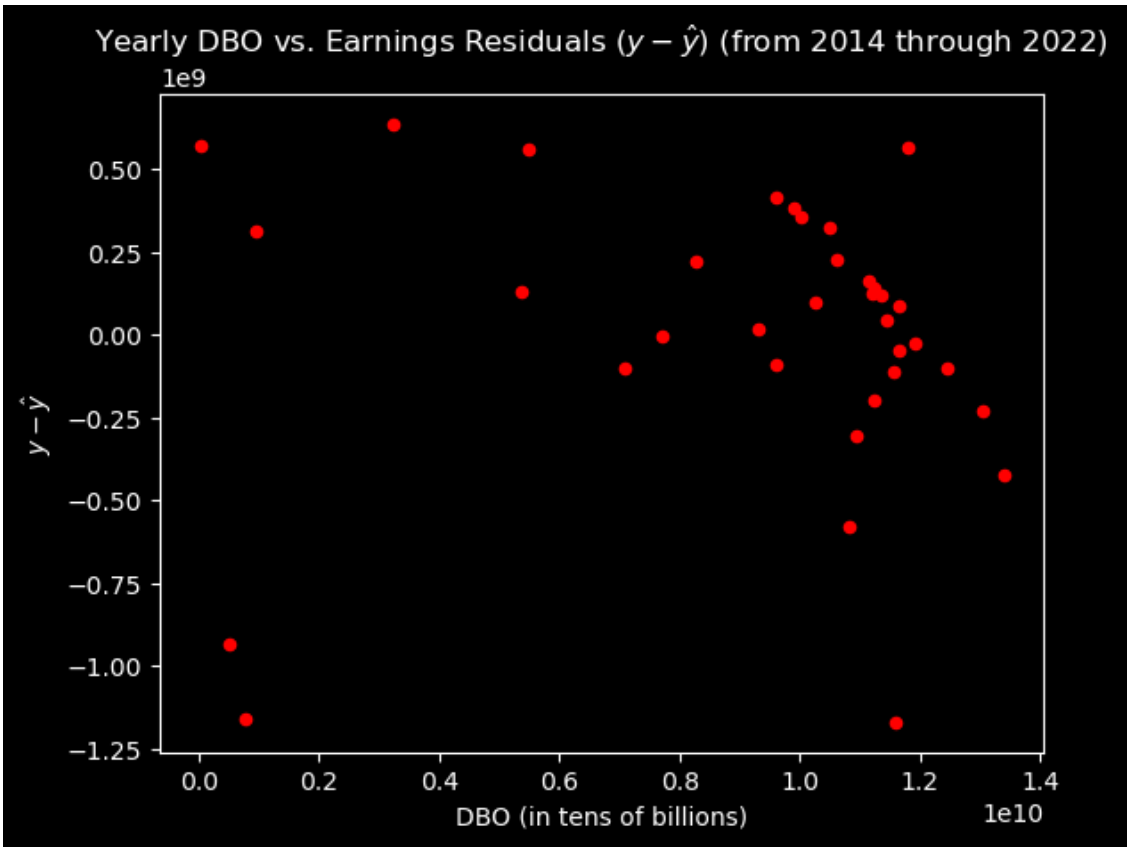
[ ]:
```
# Calculate the residuals.

df["residuals1"] = residuals1 = y.iloc[:12] - y_hat1
df["residuals2"] = residuals2 = y.iloc[12:24] - y_hat2
df["residuals3"] = residuals3 = y - y_hat3
```

3.0.7 Residual Plots

[ ]:
```
# See: analysis/scripts/presiduals.py
presiduals(plt, df)
```




Yearly DBO vs. Earnings Residuals ($y - \hat{y}$) (from 2017 through 2019)
1e9
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
$y - \hat{y}$
0.95
1.00
1.05
1.10
1.15
1.20
1.25
1.30
1.35
DBO (in tens of billions)
1e10



3.0.8 Coefficient of Determination.

This will tell us how well the functions predict the data. We find the Coefficient of Determination by:

1. Finding the total sum of squares
2. Finding the residual sum of squares
3. Subtracting the quotient of (1) divided by (2) from the integer 1

The total sum of squares:

[ ]:
```
%%latex
$$ \tau = \sum{ \langle y - \bar{y} \rangle^{2}} $$
```

$$\tau = \sum \langle y - \bar{y} \rangle^2$$

[ ]:
```
# Calculate the total sum of squares.

squares = lambda y: (y - y.mean())**2

df["squares1"] = squares1 = squares(y.iloc[:12])
```

```
df["squares2"] = squares2 = squares(y.iloc[12:24])
df["squares3"] = squares3 = squares(y)

t1 = squares1.sum()
t2 = squares2.sum()
t3 = squares3.sum()
```

The residual sum of squares:

[ ]:
```
%%latex
$$ \epsilon = \sum{ \langle y - \hat{y} \rangle^{2}} $$
```

$$\epsilon = \sum \langle y - \hat{y} \rangle^2$$

[ ]:
```
# Calculate the residual sum of squares.

df["residual squares1"] = df["residuals1"]**2
df["residual squares2"] = df["residuals2"]**2
df["residual squares3"] = df["residuals3"]**2

e1 = df["residual squares1"].sum()
e2 = df["residual squares2"].sum()
e3 = df["residual squares3"].sum()
```

3.0.9 Coefficient of Determination

[ ]:
```
%%latex
$$ r^{2} = 1 - \frac{\epsilon}{\tau} $$
```

$$r^2 = 1 - \frac{\epsilon}{\tau}$$

Possible values for the coefficient of determination is in the real-interval [0, 1]. 1 meanings the model is very good at making reliable predictions, and 0 meaning that the model essentially doesn't work.

For 2014 through 2016, the Coefficient of Determination is 0.8315031312384981

For 2017 through 2019, the Coefficient of Determination is 0.2057984880721423

For 2014 through 2022, the Coefficient of Determination is 0.8220744095125301

The second model leaves a lot to be desired, but we need it for making a comparison, and getting some idea about the facts.

[ ]:
```
# Calculate the Coefficient of Determination.

r_2_1 = 1 - (e1 / t1)
r_2_2 = 1 - (e2 / t2)
```

```
r_2_3 = 1 - (e3 / t3)

print(f"""
For 2014 through 2016:
 The Coefficient of Determination is: {r_2_1}

For 2017 through 2019:
 The Coefficient of Determination is: {r_2_2}

For 2014 through 2022:
 The Coefficient of Determination is: {r_2_3}
""")
```

```
For 2014 through 2016:
 The Coefficient of Determination is: 0.8315031312384981

For 2017 through 2019:
 The Coefficient of Determination is: 0.2057984880721423

For 2014 through 2022:
 The Coefficient of Determination is: 0.8220744095125301
```

3.0.10 The standard deviation about the least-squares line σ_ϵ

This will tell us the range of error in the prediction.

We want $\sigma < \sigma_\epsilon$. In all three models, such is the case.

[ ]:
```
%%latex
$$ \sigma_{\epsilon} = \sqrt{ \frac{\epsilon}{n - 2} } $$
```

$$\sigma_\epsilon = \sqrt{\frac{\epsilon}{n-2}}$$

For 2014 through 2016, the Standard deviation about y is 59,186,777.5202432. The Standard deviation about the least-squares line is 25,554,998.54506667

For 2017 through 2019, the Standard deviation about y is 465,442,163.1875729. The Standard deviation about the least-squares line is 435,038,226.38255721

For 2014 through 2022, the Standard deviation about y is: 1,039,426,652.4898386. The Standard deviation about the least-squares line: 445,036,411.52865213

[ ]:
```
# Calculate the standard deviation about the least-squares line.

rssd = lambda e, df: math.sqrt((e / (len(df) - 2)))
```

```
sd1  = y.loc[:12].std()
sd2  = y.loc[12:24].std()
sd3  = y.std()

r1   = rssd(e1, df.iloc[:12])
r2   = rssd(e2, df.iloc[12:24])
r3   = rssd(e3, df)

print(f"""
For 2014 through 2016:
 The Standard deviation about y is: {sd1:,.7f}
 The Standard deviation about the least-squares line: {r1:,.8f}

For 2017 through 2019:
 The Standard deviation about y is: {sd2:,.7f}
 The Standard deviation about the least-squares line: {r2:,.8f}

For 2014 through 2022:
 The Standard deviation about y is: {sd3:,.7f}
 The Standard deviation about the least-squares line: {r3:,.8f}
""")
```

```
For 2014 through 2016:
 The Standard deviation about y is: 59,186,777.5202432
 The Standard deviation about the least-squares line: 25,554,998.54506667

For 2017 through 2019:
 The Standard deviation about y is: 465,442,163.1875729
 The Standard deviation about the least-squares line: 435,038,226.38255721

For 2014 through 2022:
 The Standard deviation about y is: 1,039,426,652.4898386
 The Standard deviation about the least-squares line: 445,036,411.52865213
```

4 Predictions

Earnings is a function of DBO. So that means we can predict what the earnings will be based on DBO as input. We will input various DBO into the predictive functions to find earnings.

4.0.1 First we compare the 3 predictive models

Look at how each model differs between each column. Something fundamentally changed for the worse since Adam took over AMC. Even though the second model *(2017 - 2019)* isn't very powerful, together with third model we get a pretty good idea of the difference. Earnings were robust in *(2014 - 2016)*, and depended on far less DBO to be net postive. Adam became CEO in 2016, and

bought Odion in 2017, and it has been down hill ever since. In fact, other than being a set back, we can't even say Covid made it much worse. It almost appears to not even be a contributing factor to any fundamental issues.

Clearly AMC was fundamentally in a much better position prior to Adam Aron becoming CEO. Since far less DBO was required to turn a profit.

[ ]:
```
# Compute the lower and upper bound for prediction.

m1 = x.loc[:12].min()
m2 = x.loc[12:24].min()
m3 = x.min()
minimum = max([m1, m2, m3])

m1 = x.loc[:12].max()
m2 = x.loc[12:24].max()
m3 = x.max()
maximum = min([m1, m2, m3])

print("The DBO minimum and maximum predictive range for all 3 models together␣
 ↪is:\n"
      f" minimum = {minimum:,.0f}\n maximum = {maximum:,.0f}")
```

```
The DBO minimum and maximum predictive range for all 3 models together is:
 minimum = 9,600,109,748
 maximum = 12,445,502,384
```

[ ]:
```
# See: analysis/scripts/comparative.py
mY1, mY2, mY3 = comparative(a1, a2, a3, b1, b2, b3)
```

All Predictions

DBO	Earnings (2014 - 2016)	Earnings (2017 - 2019)	Earnings (2014 - 2022)
9,600,000,000	7,114,358	-547,098,434	-429,572,737
9,850,000,000	22,889,355	-496,695,534	-367,377,489
10,100,000,000	38,664,352	-446,292,633	-305,182,240
10,350,000,000	54,439,349	-395,889,733	-242,986,992
10,600,000,000	70,214,346	-345,486,833	-180,791,744
10,850,000,000	85,989,343	-295,083,933	-118,596,496
11,100,000,000	101,764,340	-244,681,032	-56,401,248
11,350,000,000	117,539,337	-194,278,132	5,794,000
11,600,000,000	133,314,334	-143,875,232	67,989,248
11,850,000,000	149,089,331	-93,472,332	130,184,496
12,100,000,000	164,864,329	-43,069,431	192,379,744
12,350,000,000	180,639,326	7,333,469	254,574,992

[ ]:
```
# Calculate summary statistics about each prediction.
```

```
print(f"""
Approximate descriptive statistics of the predicted earnings.

 For 2014 through 2016:

    mean:   {mY1[0]:,.0f}
    min:    {mY1[1]:,.0f}
    max:    {mY1[2]:,.0f}

 For 2017 through 2019:

    mean:   {mY2[0]:,.0f}
    min:    {mY2[1]:,.0f}
    max:    {mY2[2]:,.0f}

 For 2014 through 2022:

    mean:   {mY3[0]:,.0f}
    min:    {mY3[1]:,.0f}
    max:    {mY3[2]:,.0f}

""")
```

```
Approximate descriptive statistics of the predicted earnings.

 For 2014 through 2016:

    mean:   93,876,842
    min:    7,114,358
    max:    180,639,326

 For 2017 through 2019:

    mean:   -269,882,483
    min:    -547,098,434
    max:    7,333,469

 For 2014 through 2022:

    mean:   -87,498,872
    min:    -429,572,737
    max:    254,574,992
```

4.0.2 We can also see the fundamental differences by the summary statistics on the prediction output.

Approximated descriptive statistics about the predicted earnings.

For 2014 through 2016:

```
mean:    93,876,842
min:     7,114,358
max:     180,639,326
```

For 2017 through 2019:

```
mean:    -269,882,483
min:     -547,098,434
max:     7,333,469
```

For 2014 through 2022:

```
mean:    -87,498,872
min:     -429,572,737
max:     254,574,992
```

5 2023 Yearly Earnings Prediction

[ ]:
```
# See: analysis/scripts/prediction.py
predict(a3, b3, r3, df)
```

2023 Earnings from DBO Prediction

DBO	Lowest	Low	Earnings	High	Highest
7,500,000,000	-1,842,085,643	-1,397,049,232	-952,012,820	-506,976,409	-61,939,997
8,000,000,000	-1,717,695,147	-1,272,658,736	-827,622,324	-382,585,913	62,450,499
8,500,000,000	-1,593,304,651	-1,148,268,240	-703,231,828	-258,195,417	186,840,995
9,000,000,000	-1,468,914,155	-1,023,877,743	-578,841,332	-133,804,920	311,231,491
9,500,000,000	-1,344,523,659	-899,487,247	-454,450,836	-9,414,424	435,621,987
10,000,000,000	-1,220,133,163	-775,096,751	-330,060,340	114,976,072	560,012,483
10,500,000,000	-1,095,742,667	-650,706,255	-205,669,844	239,366,568	684,402,980
11,000,000,000	-971,352,170	-526,315,759	-81,279,347	363,757,064	808,793,476
11,500,000,000	-846,961,674	-401,925,263	43,111,149	488,147,560	933,183,972
12,000,000,000	-722,571,178	-277,534,767	167,501,645	612,538,056	1,057,574,468
12,500,000,000	-598,180,682	-153,144,271	291,892,141	736,928,553	1,181,964,964
13,000,000,000	-473,790,186	-28,753,774	416,282,637	861,319,049	1,306,355,460
13,500,000,000	-349,399,690	95,636,722	540,673,133	985,709,545	1,430,745,956

- The projected 2023 domestic box office is expected to be $9B
- The ‘Earnings’ column is the prediction
- There is an approximate 68% chance that the actual earnings will fall within the range ‘Low’ to ‘High’

- There is an approximate 98% chance that the actual earnings will fall within the range 'Lowest' to 'Highest'
- Notice that the model successfully predicted 2022 AMC earnings from a $7.5 billion DBO with extreme accuaracy!

This model has incredibly strong predictive power.

[ ]:
```
# Save the models.
df.to_csv("data/model.csv", index=True)
```

[ ]:
```
# Calculate and report float size percentage increase.

df = pd.read_csv("data/float_history.csv", index_col=0)

# 2016 to 2020 (excluding 2020) float size increase
f1 = df.loc[4].float / df.loc[0].float

# 2020 to 2023 float size increase
f2 = df.loc[11].float / df.loc[4].float

# Since 2016 float size increase
f3 = df.loc[11].float / df.loc[0].float

# If reverse split passes
f4 = 1.032 * 10**9 / df.loc[0].float

print(f"\nFrom 2016 through 2019 Adam increased the float {f1 * 100:,.2f}%")
print(f"From 2020 to 2023, only, Adam increased the float {f2 * 100:,.2f}%")
print(f"Adams total float increase is {f3 * 100:,.2f}%")
print(f"If rs-c passed the total float increase would be {f4 * 100:,.2f}%␣
 ↪before the split")
print(f"\nThat is nearly {47.7557:,.2f} times the size of the float "
      "before Adam took over AMC.")
```

```
From 2016 through 2019 Adam increased the float 240.86%
From 2020 to 2023, only, Adam increased the float 992.93%
Adams total float increase is 2,391.58%
If rs-c passed the total float increase would be 4,775.57% before the split

That is nearly 47.76 times the size of the float before Adam took over AMC.
```

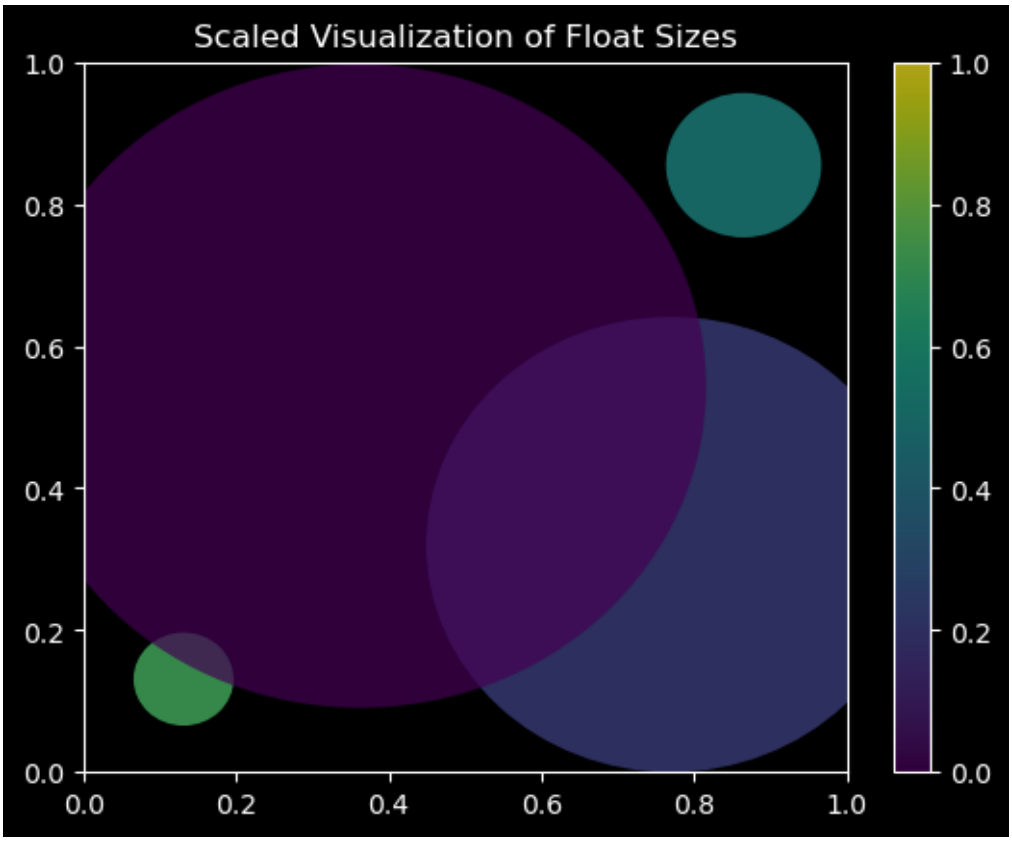
6 Float Size History Since 2016

- From 2016 through 2019 Adam increased the float 240.86%
- From 2020 to 2023, only, Adam increased the float 992.93%
- Adams total float increase is 2,391.58%
- If the reverse split were passed the total float increase would be 4,775.57%, before the split

That is nearly 47.76 times the size of the float before Adam took over AMC.

6.0.1 Float Increase Scaled Visualization

[ ]:
```
# See: analysis/scripts/pfloat.py
pfloat(f1, f2, f4, plt, df)
```



- There's a 39% chance Adam would dilute AMC, each quarter.
- There's an 157% chance Adam would dilute AMC, each year.
- From 2016 through 2022 is 7 years, and Adam has diluted AMC 11 times out of those 7 years.

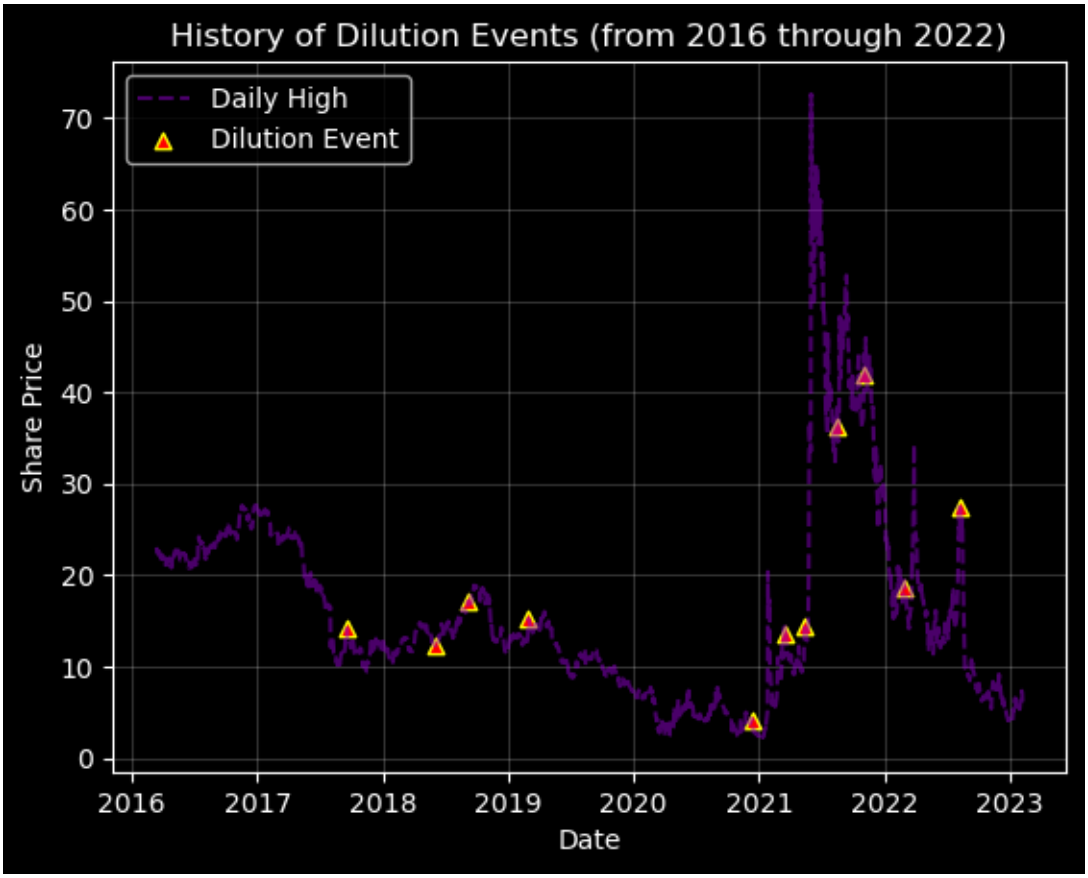
[ ]:
```
# Calculate dilution frequency.
events = len(df) - 1
quarterly_freq = events / num_quarters
yearly_freq    = quarterly_freq * 4
print(f"There's a {quarterly_freq * 100:,.0f} chance Adam would dilute AMC,␣
 ↪each quarter.")
print(f"There's an {yearly_freq * 100:,.0f} chance Adam would dilute AMC, each␣
 ↪year.")
print(f"From 2016 through 2022 is {num_quarters / 4:,.0f} years.")
print(f"Adam has diluted AMC {events} times out of those {num_quarters / 4:,.
 ↪0f} years.")
```

```
There's a 39 chance Adam would dilute AMC, each quarter.
There's an 157 chance Adam would dilute AMC, each year.
From 2016 through 2022 is 7 years.
Adam has diluted AMC 11 times out of those 7 years.
```

[ ]:
```
# Load data.

df = pd.read_csv("data/dilution.csv", index_col=0)
for e, row in enumerate(df.iterrows()):
    date = row[1].Date
    date = datetime.strptime(date, "%Y-%m-%d")
    df.at[e, "Date"] = date
```

6.0.2 Visualization of the AMC Dilution History From 2016 Through 2022

[ ]:
```
# See: analysis/scripts/dhist.py
hplot(plt, df)
```



[ ]:
```
# Calculate mean daily high share price from 2016 through 2022.
smean = df.High.mean()
```

```
dmean = df[np.isnan(df.dilution) == False].High.mean()
print(f"The mean daily high for AMC from March 2016 through 2022 was ${smean:,.
  ↪2f}")
print(f"The mean daily high for AMC dilutions from 2016 through 2022 was␣
  ↪${dmean:,.2f}")
```

```
The mean daily high for AMC from March 2016 through 2022 was $16.09
The mean daily high for AMC dilutions from 2016 through 2022 was $19.56
```

- The mean daily high for AMC from March 2016 through 2022 was $16.09
- The mean daily high for AMC dilutions from 2016 through 2022 was $19.56

6.1 Has Dilution Ever Caused AMC Price Increases Since 2016?