linear_regression_model

March 7, 2023

1 What did Adam do to AMC, and 2023 Earnings Prediction by Linear Regression

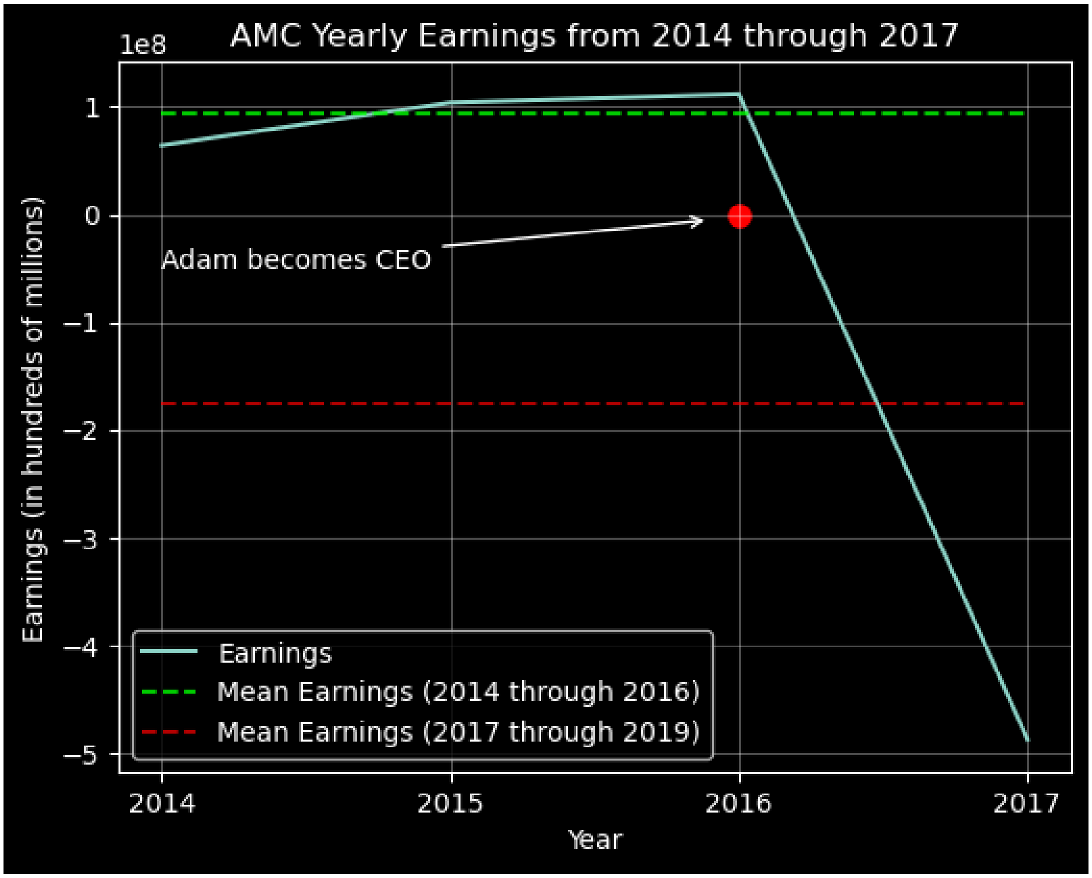
[ ]:
```python
from matplotlib.collections import PatchCollection
from matplotlib.patches import Circle
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import df2img
import math

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

[ ]:
```python
years = list(range(2014, 2023))

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

2 Descriptive Data Visualizations

[ ]:
```python
plt.plot(years[:4],  df.groupby("year").agg(["sum"])[:2017]["earnings"])
plt.plot(years[:4], [df.groupby("year").agg(["sum"])[:2016]["earnings"].mean()]␣
↪* 4, color="lime",
         alpha = 0.8, linestyle="--")
plt.plot(years[:4], [df.groupby("year").agg(["sum"])[2017:2019]["earnings"].
↪mean()] * 4, color="red",
         alpha = 0.7, linestyle="--")
plt.scatter([2016], [0], color="red", linewidth=3.0, edgecolor="red")
plt.annotate("Adam becomes CEO", xy=[2015.9, -0.05 * 10**8], xytext=[2014, -0.5␣
↪* 10**8], arrowprops={
    "facecolor":"red", "arrowstyle":"->", "connectionstyle":"arc3"})
plt.legend(["Earnings", "Mean Earnings (2014 through 2016)", "Mean Earnings␣
↪(2017 through 2019)"])
plt.grid(True, alpha = 0.3)
plt.title("AMC Yearly Earnings from 2014 through 2017")
plt.xlabel("Year")
plt.ylabel("Earnings (in hundreds of millions)")
```

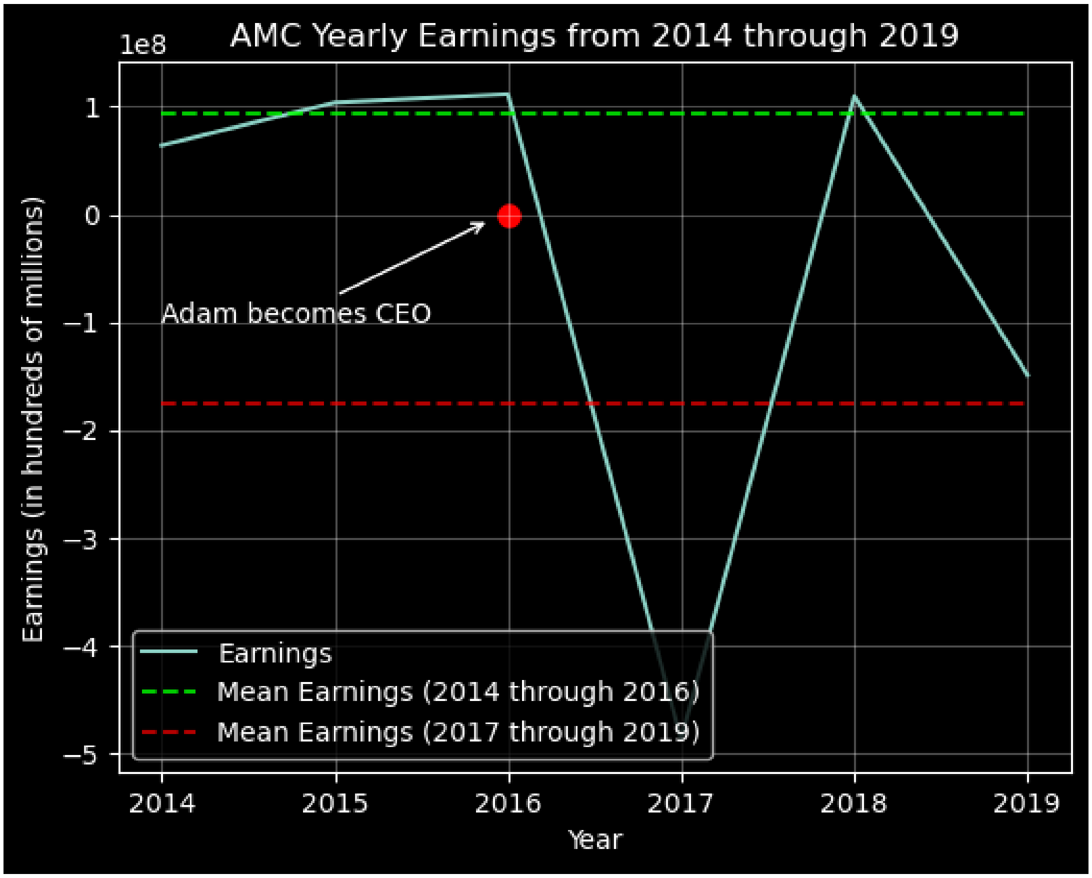
```
plt.xticks([2014, 2015, 2016, 2017])
plt.savefig("plots/earnings.2014.2017.png")
plt.show()
```



Zooming out for some context.

[ ]:
```
plt.plot(years[:6],  df.groupby("year").agg(["sum"])[:2019]["earnings"])
plt.plot(years[:6], [df.groupby("year").agg(["sum"])[:2016]["earnings"].mean()]␣
 ↪* 6, color="lime",
         alpha = 0.8, linestyle="--")
plt.plot(years[:6], [df.groupby("year").agg(["sum"])[2017:2019]["earnings"].
 ↪mean()] * 6, color="red",
         alpha = 0.7, linestyle="--")
plt.scatter([2016], [0], color="red", linewidth=3.0, edgecolor="red")
plt.annotate("Adam becomes CEO", xy=[2015.9, -0.05 * 10**8], xytext=[2014, -1 *␣
 ↪10**8], arrowprops={
    "facecolor":"red", "arrowstyle":"->", "connectionstyle":"arc3"})
plt.legend(["Earnings", "Mean Earnings (2014 through 2016)", "Mean Earnings␣
 ↪(2017 through 2019)"])
plt.grid(True, alpha = 0.3)
```

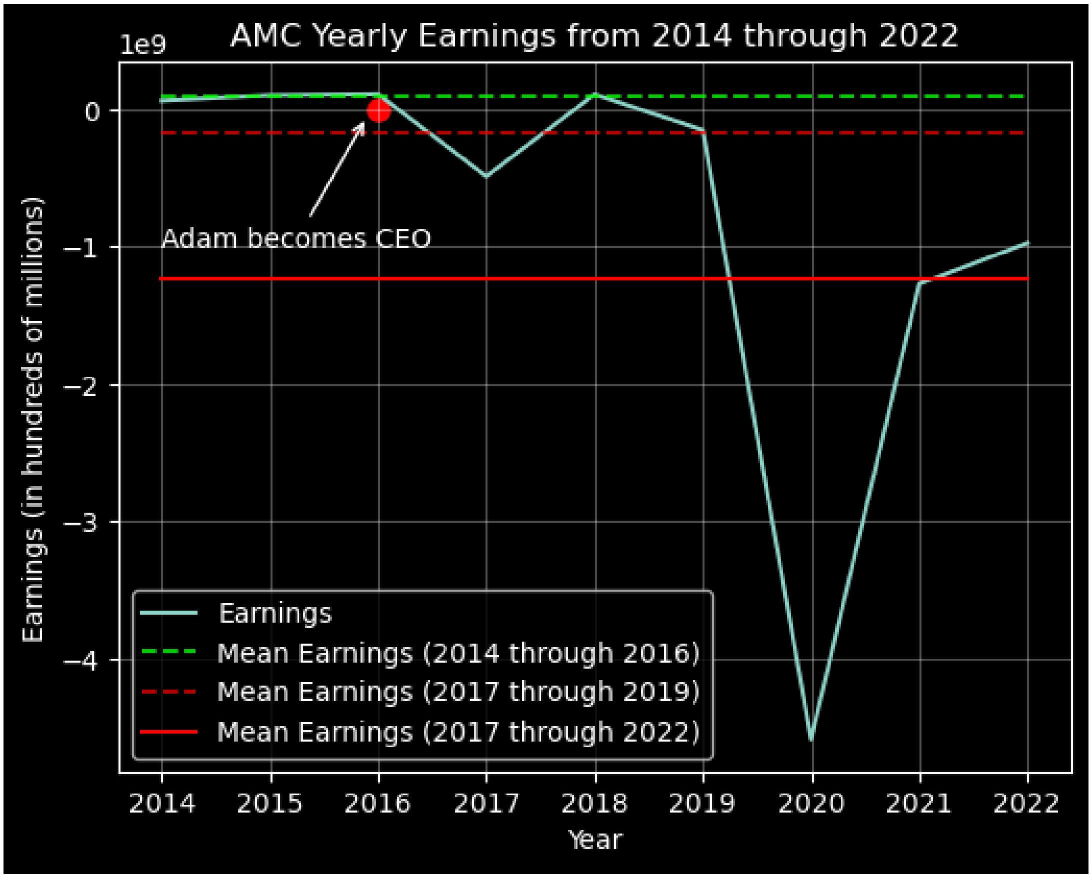
```
plt.title("AMC Yearly Earnings from 2014 through 2019")
plt.xlabel("Year")
plt.ylabel("Earnings (in hundreds of millions)")
plt.xticks([2014, 2015, 2016, 2017, 2018, 2019])
plt.savefig("plots/earnings.2014.2019.png")
plt.show()
```



The entire dataset.

```
[ ]: plt.plot(years[:],  df.groupby("year").agg(["sum"])[:]["earnings"])
plt.plot(years[:], [df.groupby("year").agg(["sum"])[:2016]["earnings"].mean()]␣
↪* len(years), color="lime",
         alpha = 0.8, linestyle="--")
plt.plot(years[:], [df.groupby("year").agg(["sum"])[2017:2019]["earnings"].
↪mean()] * len(years),
         color="red", alpha = 0.7, linestyle="--")
plt.plot(years, [df.groupby("year").agg(["sum"])[2017:]["earnings"].mean()] *␣
↪len(years),
         color="red")
plt.scatter([2016], [0], color="red", linewidth=3.0, edgecolor="red")
```

```
plt.annotate("Adam becomes CEO", xy=[2015.9, -0.05 * 10**9], xytext=[2014, -1 *␣
↪10**9], arrowprops={
    "facecolor":"red", "arrowstyle":"->", "connectionstyle":"arc3"})
plt.legend(["Earnings", "Mean Earnings (2014 through 2016)", "Mean Earnings␣
↪(2017 through 2019)",
            "Mean Earnings (2017 through 2022)"])
plt.grid(True, alpha = 0.3)
plt.title("AMC Yearly Earnings from 2014 through 2022")
plt.xlabel("Year")
plt.ylabel("Earnings (in hundreds of millions)")
plt.xticks([2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022])
plt.savefig("plots/earnings.2014.2022.png")
plt.show()
```

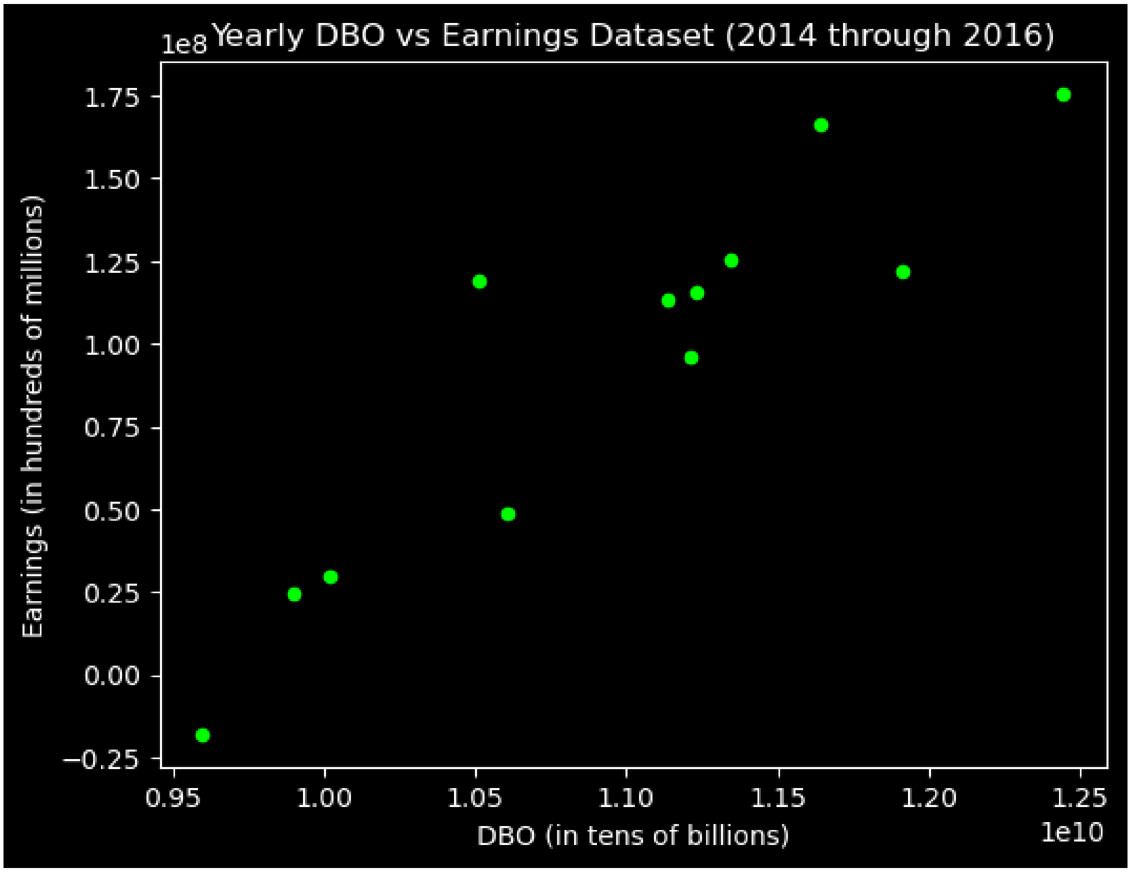


Drop 2020 Q1 outlier, and superfluous columns. Extrapolate quarterly to yearly values. Alias columns with x and y variables.

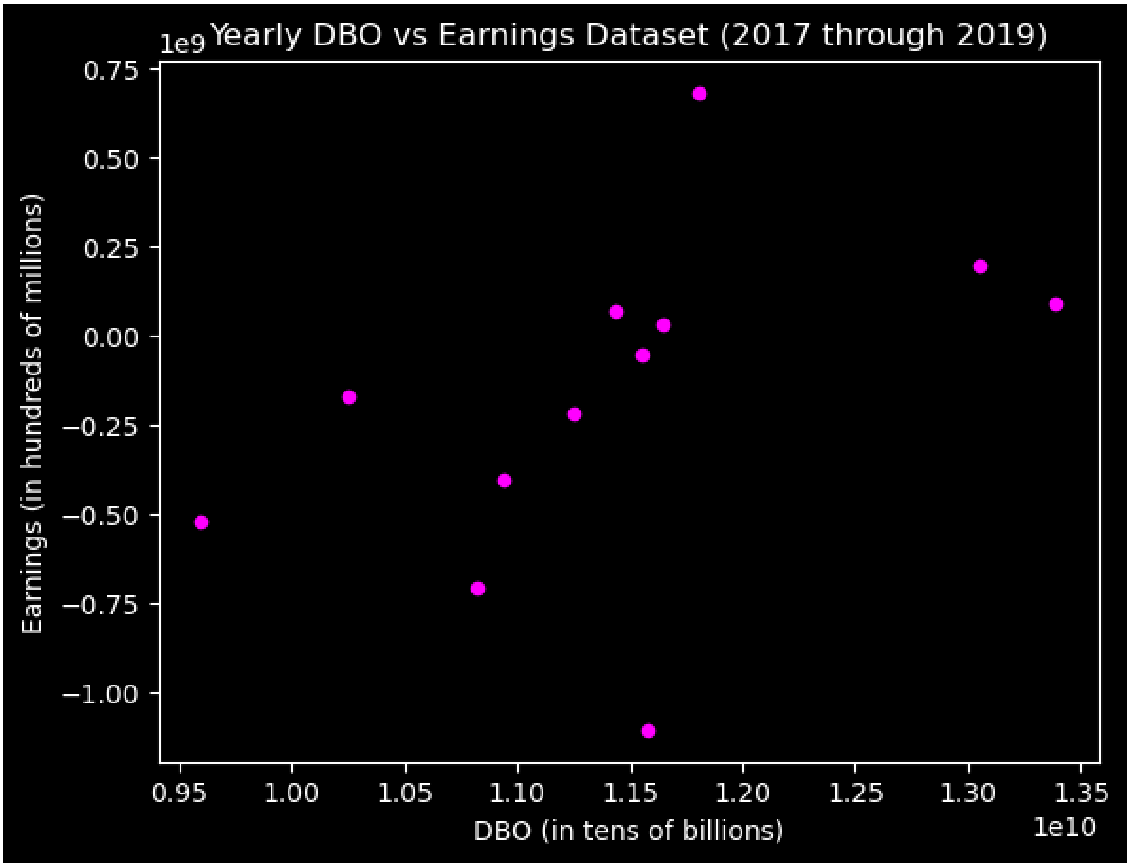
[ ]:
```
columns = ["DBO gross", "earnings"]
try:
    df = df.drop(24)
```

```python
    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"]
print(df.describe())
df.loc[:11].plot.scatter("DBO gross", "earnings", color="lime")
plt.title("Yearly DBO vs Earnings Dataset (2014 through 2016)")
plt.xlabel("DBO (in tens of billions)")
plt.ylabel("Earnings (in hundreds of millions)")
plt.savefig("plots/dataset.2014.2016.png")
plt.show()
df.loc[12:23].plot.scatter("DBO gross", "earnings", color="magenta")
plt.title("Yearly DBO vs Earnings Dataset (2017 through 2019)")
plt.xlabel("DBO (in tens of billions)")
plt.ylabel("Earnings (in hundreds of millions)")
plt.savefig("plots/dataset.2017.2019.png")
plt.show()
df.plot.scatter("DBO gross", "earnings", color="red")
plt.title("Yearly DBO vs. Earnings Dataset (2014 through 2022)")
plt.xlabel("DBO (in tens of billions)")
plt.ylabel("Earnings (in hundreds of millions)")
plt.savefig("plots/dataset.2014.2022.png")
plt.show()
```

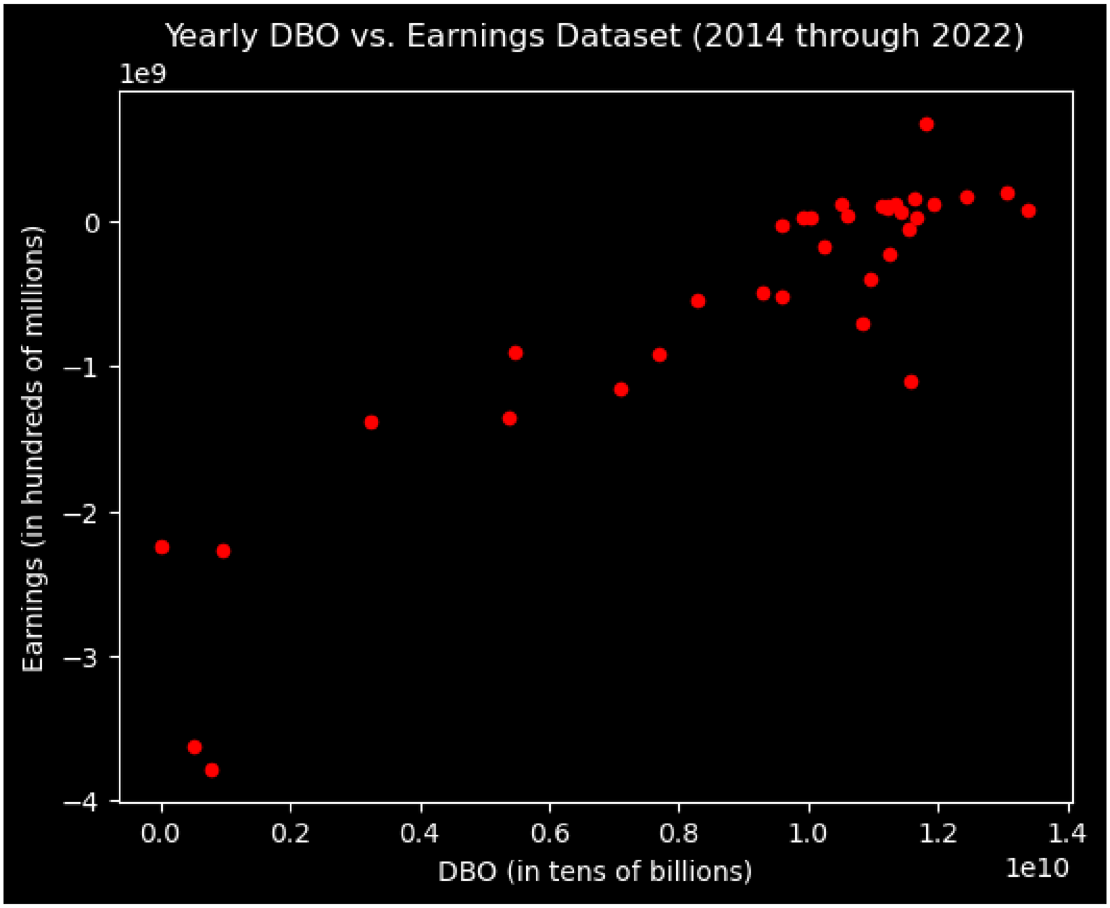
```
          DBO gross      earnings
count  3.500000e+01  3.500000e+01
mean   9.074312e+09 -5.603539e+08
std    3.788194e+09  1.039427e+09
min    1.890192e+07 -3.784400e+09
25%    7.982850e+09 -9.022000e+08
50%    1.060793e+10 -5.400000e+07
75%    1.149479e+10  1.045160e+08
max    1.338965e+10  6.824000e+08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



Yearly DBO vs Earnings Dataset (2014 through 2016)
1e8
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
−0.25
Earnings (in hundreds of millions)
0.95
1.00
1.05
1.10
1.15
1.20
1.25
DBO (in tens of billions)
1e10



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 Linear Regressions on the 3 Periods

z-scores

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

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

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

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

[ ]:
```
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}")
print(f"For 2017 through 2019, Pearsons Correlation Coefficient is: {r2}")
print(f"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
```

The slope of the least-squares line

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

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

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

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

[ ]:
```python
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)
```

The values for α and β

[ ]:
```python
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

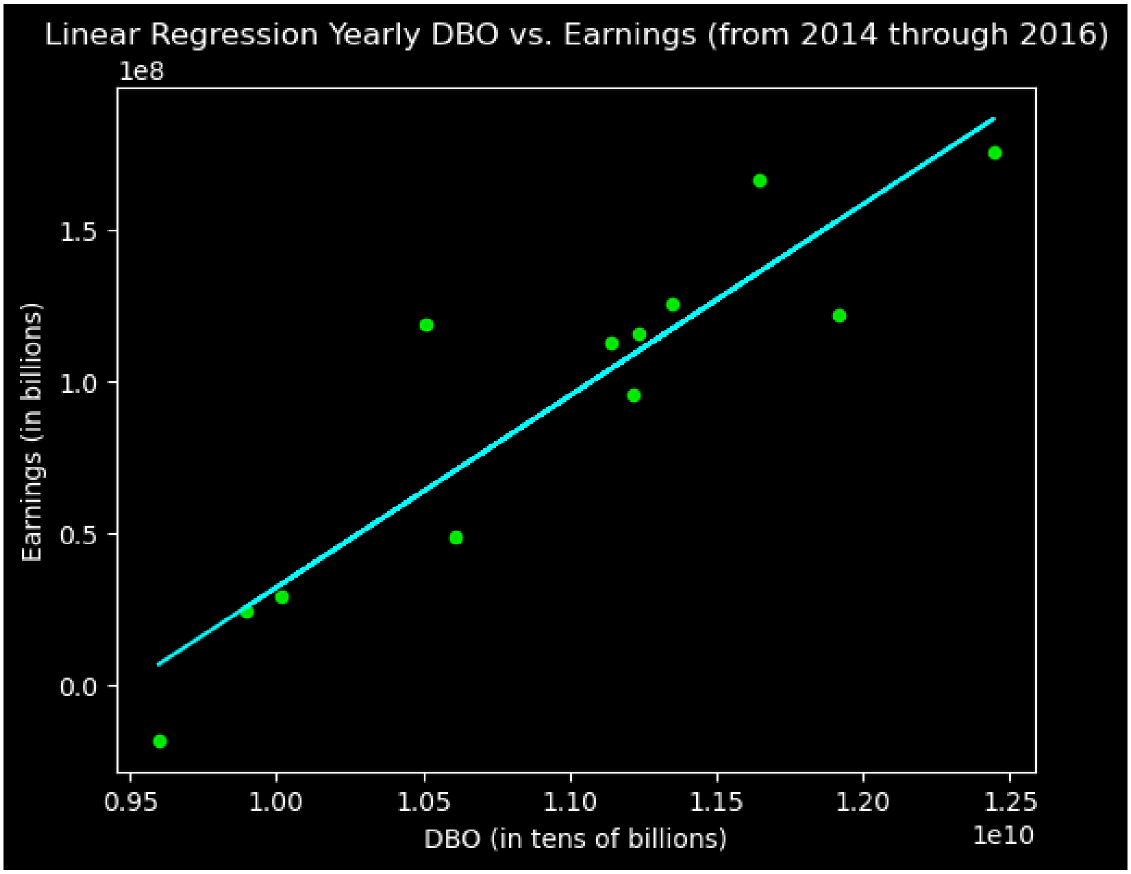
[ ]:
```
%%latex
$$
\hat{y} = f \langle x \rangle = \alpha + \beta x
$$
```

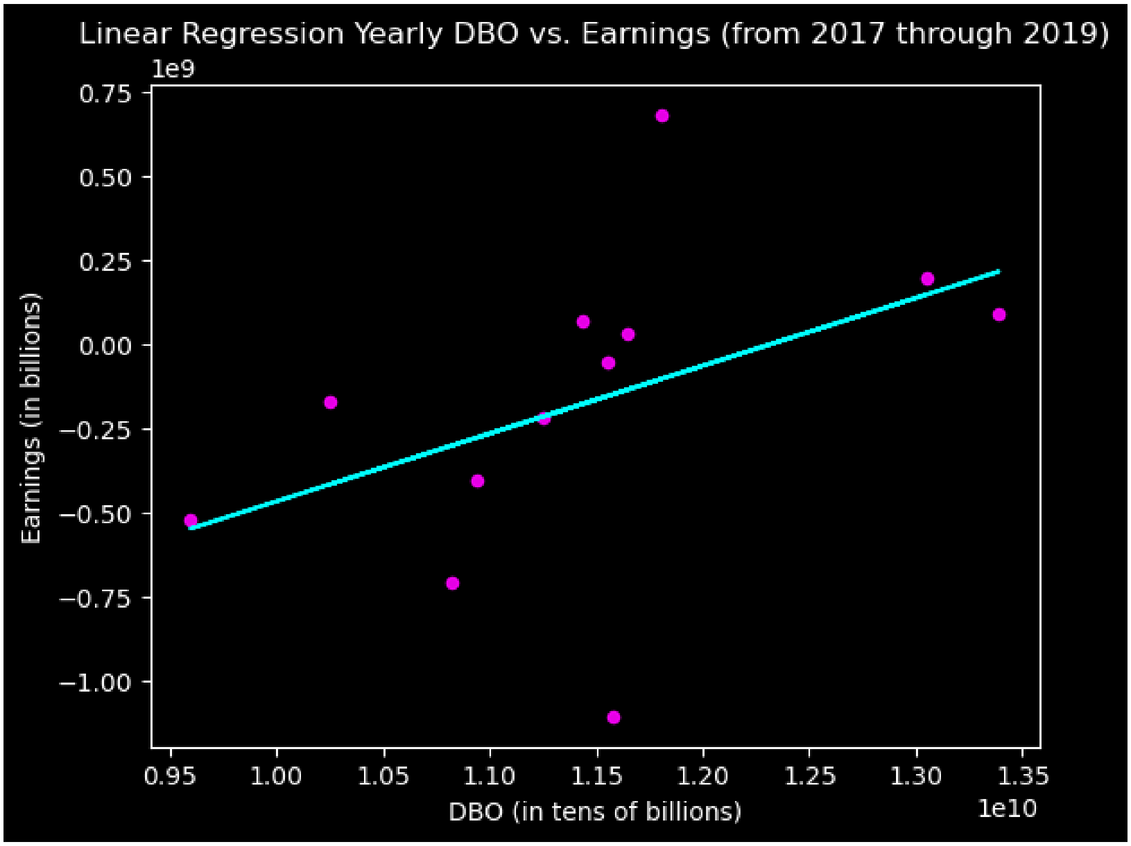
$$\hat{y} = f\langle x\rangle = \alpha + \beta x$$

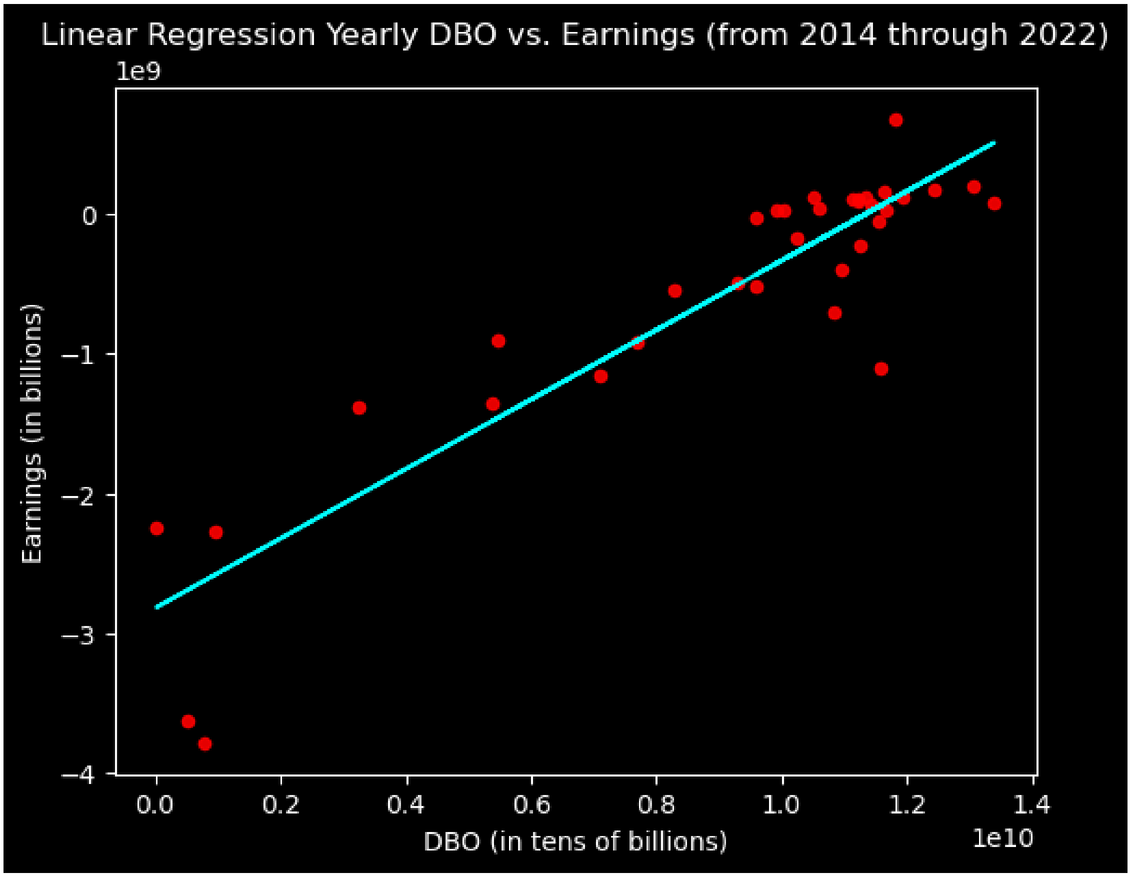
[ ]:
```python
hat = lambda a, b, x: a + b * x

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)
```

Linear regression plots

[ ]:
```python
df.iloc[:12].plot.scatter("DBO gross", "earnings", alpha = 0.9, color="lime")
plt.plot(x.iloc[:12], y_hat1, linewidth=1.5, color = "cyan")
plt.title("Linear Regression Yearly DBO vs. Earnings (from 2014 through 2016)")
plt.xlabel("DBO (in tens of billions)")
plt.ylabel("Earnings (in billions)")
plt.savefig("plots/regression.2014.2016.png")
plt.show()

df.iloc[12:24].plot.scatter("DBO gross", "earnings", alpha = 0.9,␣
 ↪color="magenta")
plt.plot(x.iloc[12:24], y_hat2, linewidth=1.5, color = "cyan")
plt.title("Linear Regression Yearly DBO vs. Earnings (from 2017 through 2019)")
plt.xlabel("DBO (in tens of billions)")
plt.ylabel("Earnings (in billions)")
plt.savefig("plots/regression.2017.2019.png")
plt.show()

df.plot.scatter("DBO gross", "earnings", alpha = 0.9, color="red")
plt.plot(x, y_hat3, linewidth=1.5, color = "cyan")
plt.title("Linear Regression Yearly DBO vs. Earnings (from 2014 through 2022)")
plt.xlabel("DBO (in tens of billions)")
plt.ylabel("Earnings (in billions)")
plt.savefig("plots/regression.2014.2022.png")
plt.show()
```


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
1e10
DBO (in tens of billions)



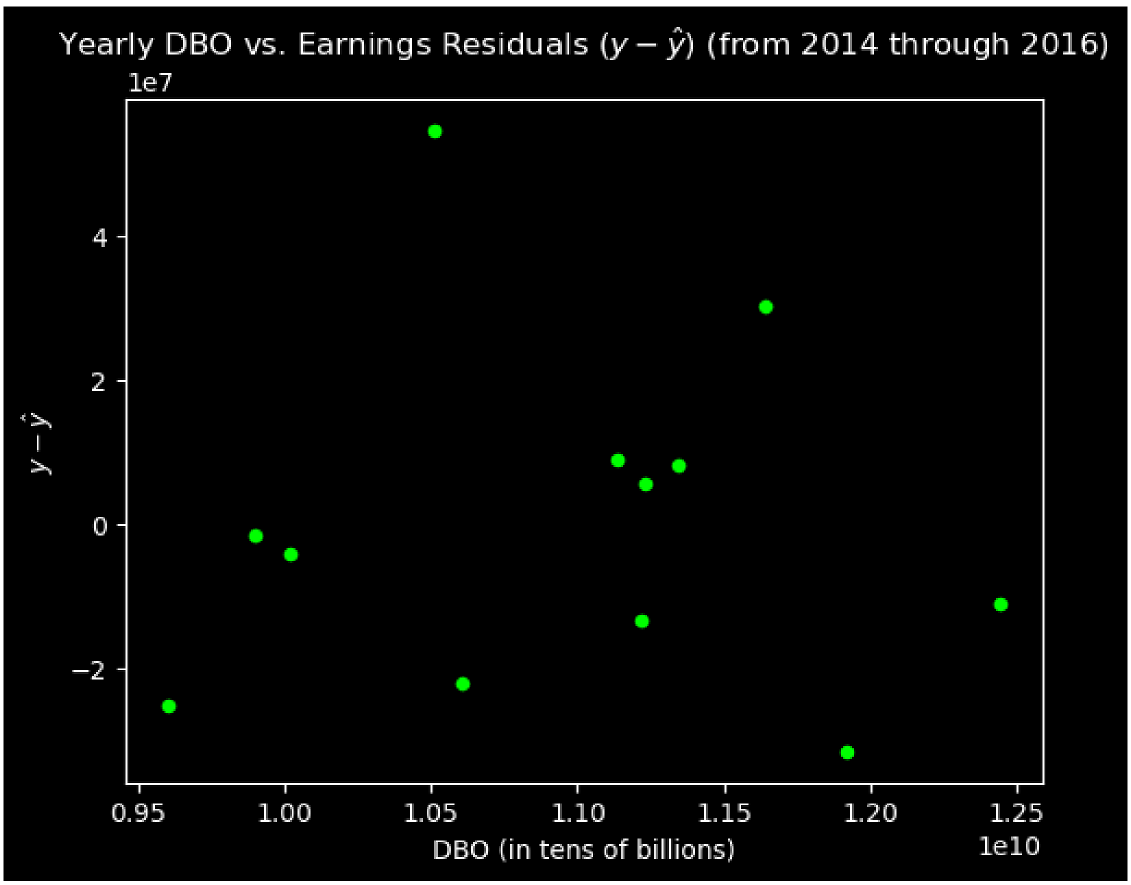
Residuals

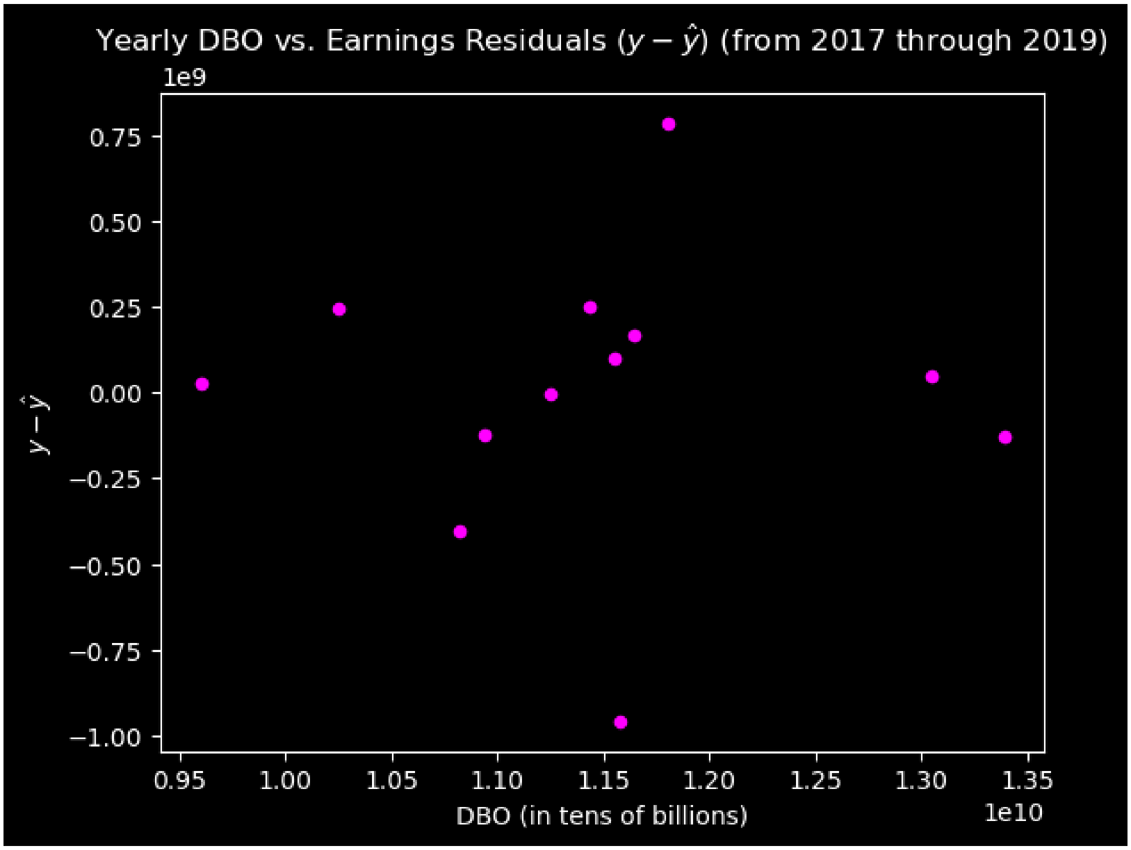
[ ]:
```
%%latex
$$
y - \hat{y}
$$
```

$$y - \hat{y}$$

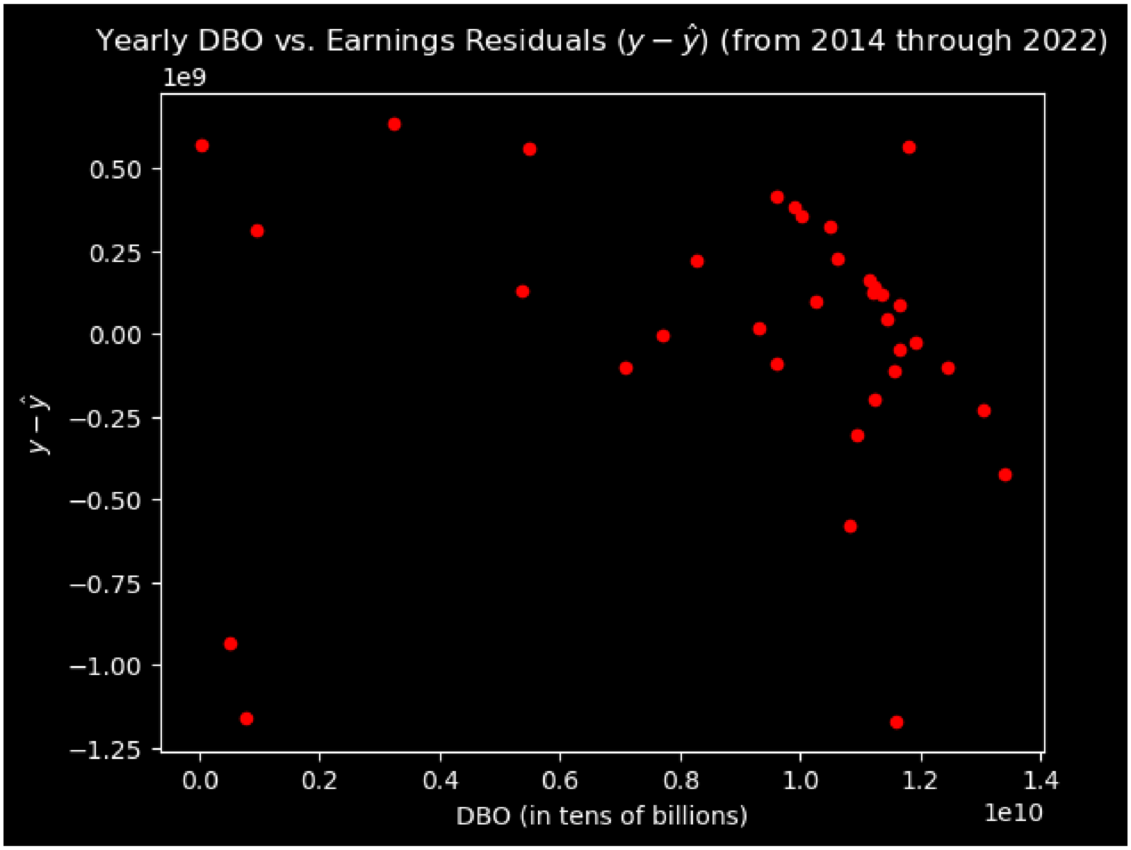
[ ]:
```
df["residuals1"] = residuals1 = y.iloc[:12] - y_hat1
df["residuals2"] = residuals2 = y.iloc[12:24] - y_hat2
df["residuals3"] = residuals3 = y - y_hat3

df.iloc[:12].plot.scatter("DBO gross", "residuals1", color="lime")
plt.title("Yearly DBO vs. Earnings Residuals ($y - \hat{y}$) (from 2014 through␣
↪2016)")
plt.xlabel("DBO (in tens of billions)")
plt.ylabel("$y - \hat{y}$")
plt.savefig("plots/residuals.2014.2016.png")
```

```python
plt.show()

df.iloc[12:24].plot.scatter("DBO gross", "residuals2", color="magenta")
plt.title("Yearly DBO vs. Earnings Residuals ($y - \hat{y}$) (from 2017 through␣
↪2019)")
plt.xlabel("DBO (in tens of billions)")
plt.ylabel("$y - \hat{y}$")
plt.savefig("plots/residuals.2017.2019.png")
plt.show()

df.plot.scatter("DBO gross", "residuals3", color="red")
plt.title("Yearly DBO vs. Earnings Residuals ($y - \hat{y}$) (from 2014 through␣
↪2022)")
plt.xlabel("DBO (in tens of billions)")
plt.ylabel("$y - \hat{y}$")
plt.savefig("plots/residuals.2014.2022.png")
plt.show()
```





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
1e10
DBO (in tens of billions)



The total sum of squares

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

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

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

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

[ ]:
```
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()
```

Coefficient of Determination

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

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

[ ]:
```
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
```

The standard deviation about the least-squares line σ_ϵ

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

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

[ ]:
```
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
```

[ ]:
```python
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
```

4 Predictions

4.0.1 First, let's compare predictive models

[ ]:
```python
clean = lambda v: f"{v:,.0f}"

X  = list(range(9600000000, 12500000000, 250000000))
Y1 = pd.Series([a1 + b1 * x for x in X])
Y2 = pd.Series([a2 + b2 * x for x in X])
Y3 = pd.Series([a3 + b3 * x for x in X])
X  = [clean(x) for x in X]

mY1 = Y1.mean(), Y1.min(), Y1.max()
mY2 = Y2.mean(), Y2.min(), Y2.max()
mY3 = Y3.mean(), Y3.min(), Y3.max()

Y1 = [clean(y) for y in Y1]
Y2 = [clean(y) for y in Y2]
Y3 = [clean(y) for y in Y3]

columns = ["DBO", "Earnings (2014 - 2016)", "Earnings (2017 - 2019)", "Earnings␣
 ↪(2014 - 2022)"]

predictions = pd.DataFrame(np.array([X, Y1, Y2, Y3]).T, columns = columns)
```

```
[ ]: bg   = "#333333"
font = "Arial"

fig = df2img.plot_dataframe(predictions,

    title={"text": "All Predictions", "font_color": "purple", "font_size": 32,
           "font_family": font, "x": 0.41, "yanchor": "middle"},

    tbl_header = {"align": "center", "fill_color": bg, "font_color":␣
 ↪"darkviolet",
                  "font_size": 20, "line": {"color": bg}, "font_family": font},

    tbl_cells = {"align": "center", "fill_color": bg, "font_color": "cyan",
                 "font_size": 16, "line": {"color": bg}, "height": 28,␣
 ↪"font_family": font},
                 row_fill_color = (bg, "purple"),

    print_index = False,
    paper_bgcolor = bg,
    fig_size = (1000, 420),
    col_width = 6)

df2img.save_dataframe(fig = fig, filename = "dataframes/all.predictions.png")
```

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

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.

```
[ ]: 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 2023 Yearly Earnings Predictions from DBO Isolate

[ ]:
```
minimum = int(max(df["DBO gross"].min(), 7500000000))
maximum = int(df["DBO gross"].max())

inc = 500000000

X = list(range(minimum, maximum + inc, inc))
Y = pd.Series([a3 + b3 * x for x in X])

DBO      = X
Lowest   = Y - (2 * r3)
Low      = Y - r3
Earnings = Y
High     = Y + r3
Highest  = Y + (2 * r3)

DBO      = [clean(x) for x in DBO]
Lowest   = [clean(s) for s in Lowest]
Low      = [clean(s) for s in Low]
Earnings = [clean(y) for y in Earnings]
High     = [clean(s) for s in High]
Highest  = [clean(s) for s in Highest]

columns = ["DBO", "Lowest", "Low", "Earnings", "High", "Highest"]

prediction2 = pd.DataFrame(np.array([DBO, Lowest, Low, Earnings, High,␣
 ↪Highest]).T,
                           columns = columns)
```

[ ]:
```
bg   = "#333333"
font = "Arial"

fig = df2img.plot_dataframe(prediction2,

    title={"text": "2023 Earnings from DBO Prediction", "font_color": "purple",␣
 ↪"font_size": 32,
           "font_family": font, "x": 0.25, "yanchor": "middle"},

    tbl_header = {"align": "center", "fill_color": bg, "font_color":␣
 ↪"darkviolet",
                  "font_size": 20, "line": {"color": bg}, "font_family": font},

    tbl_cells = {"align": "center", "fill_color": bg, "font_color": "cyan",
                 "font_size": 16, "line": {"color": bg}, "height": 28,␣
 ↪"font_family": font},
                 row_fill_color = (bg, "purple"),
```

```python
    print_index = False,
    paper_bgcolor = bg,
    fig_size = (1000, 450),
    col_width = 6)

df2img.save_dataframe(fig = fig, filename = "dataframes/2023.prediction.png")
```

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’

This model has incredibly strong predictive power.

[ ]:
```python
df.to_csv("model.csv", index=True)
```

5 Float Size History Since 2016

[ ]:
```python
df = pd.read_csv("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.
```

[ ]:

```
# a = pi r^2
# a / pi = r^2
# sqrt(a / pi) = r
scale = 40000

area = df.loc[0].float
r1 = math.sqrt(area / math.pi) / scale
r2 = math.sqrt((area * f1) / math.pi) / scale
area = df.loc[4].float
r3 = math.sqrt((area * f2) / math.pi) / scale
area = df.loc[0].float
r4 = math.sqrt((area * f4) / math.pi) / scale


fig, ax = plt.subplots()

patches = []
c1 = Circle((r1*2, r1*2), r1)
c2 = Circle((r2*.5*17, r2*1.4*6), r2)
c3 = Circle((r3*.6*4, r3*.25*4), r3)
c4 = Circle((r4*.2*4, r4*.3*4), r4)
patches.extend([c1, c2, c3, c4])

p = PatchCollection(patches, alpha=0.7)
colors = [.72, .5, .2, .0, 1, .0]
p.set_array(colors)
```

```
ax.add_collection(p)
fig.colorbar(p, ax=ax)
plt.title("Scaled Visualization of Float Sizes")
plt.savefig("plots/dilution.png")
plt.show()
```