project2

October 16, 2021

[151]:

```
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import statistics
import math
from statistics import median
import sqlite3, pandas as pd

#Create a database and connect to it
sqlite_file = 'lahman2014.sqlite'
conn = sqlite3.connect(sqlite_file)
cur = conn.cursor()


#Create a database and connect to it
sqlite_file = 'lahman2014.sqlite'
conn = sqlite3.connect(sqlite_file)


# Part 1
# Problem 1
#Use multiple left joins which means payroll data before 1985 will be missing
#Leave as NaN so it can be filled later if data is found
query = """WITH tempTable
AS (WITH tempTable2
    AS (SELECT Salaries.yearID, Salaries.teamID, SUM(Salaries.salary) as␣
 ↪total_payroll
        FROM Salaries
        GROUP BY Salaries.yearID, Salaries.teamID)
    SELECT Teams.yearID, Teams.teamID, Teams.franchID, tempTable2.
 ↪total_payroll, (CAST(Teams.W as REAL) / Teams.G * 100) as win_per, Teams.W,␣
 ↪Teams.G
    FROM Teams
    LEFT JOIN tempTable2
    ON tempTable2.yearID = Teams.yearID AND tempTable2.teamID = Teams.teamID)
```

```
SElECT Teams.yearID, Teams.franchID, Teams.teamID, tempTable.total_payroll,␣
↪tempTable.win_per
FROM Teams
LEFT JOIN tempTable
ON (tempTable.yearID = Teams.yearID AND tempTable.teamID = Teams.teamID)"""

df = pd.read_sql(query, conn)



display(df)
```

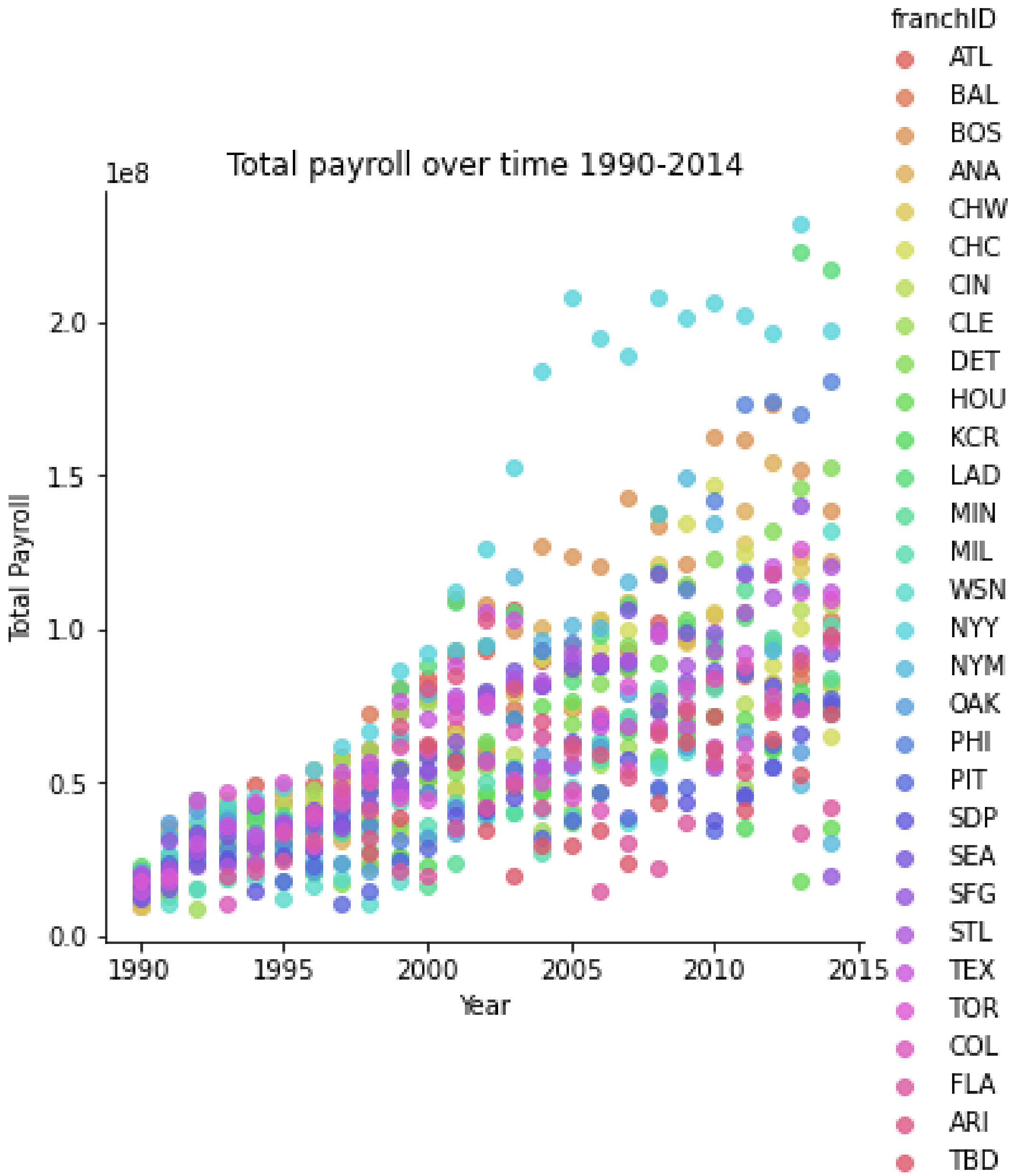
```
      yearID franchID teamID  total_payroll    win_per
0       1871      BNA    BS1            NaN  64.516129
1       1871      CNA    CH1            NaN  67.857143
2       1871      CFC    CL1            NaN  34.482759
3       1871      KEK    FW1            NaN  36.842105
4       1871      NNA    NY2            NaN  48.484848
…        …      …      …              …        …
2770    2014      PIT    PIT     77178000.0  54.320988
2771    2014      SDP    SDN     75685700.0  47.530864
2772    2014      SFG    SFN     20000000.0  54.320988
2773    2014      STL    SLN    120693000.0  55.555556
2774    2014      WSN    WAS    131983680.0  59.259259

[2775 rows x 5 columns]
```

Part 1: Problem 1 Writeup

I query using SQL to extract the data from the SQLite database and into a pandas dataframe. To do this, I use multiple left joins from the Salaries and Teams tables in the database. However, since the range of years isn't the same between tables, teams between 1871 and 1984 do not have payroll data and is left as NaN. Additionally, I chose to use franchID over teamID since it's common for teams to change city but it's uncommon for franchises to disband entirely.

[152]:
```
# Part 2
# Problem 2



#Get the total payroll for each year and team combination, store it in pandas␣
↪dataframe
salary_query = "WITH tempTable AS (SELECT Salaries.yearID, Salaries.teamID,␣
↪Teams.franchID, SUM(Salaries.salary) as total_payroll FROM Salaries, Teams␣
↪WHERE Salaries.teamID = Teams.teamID AND Salaries.yearID = Teams.yearID AND␣
↪Salaries.yearID >= 1990 AND Salaries.yearID <= 2014 GROUP BY Salaries.
↪yearID, Salaries.teamID) SELECT * FROM tempTable"
sal_df = pd.read_sql(salary_query, conn)
```

```
#Create a scatter plot and map a color to each team
sns.lmplot(x="yearID", y="total_payroll", data=sal_df, fit_reg=False,␣
 ↪hue='franchID', legend=True, palette=sns.color_palette("hls", len(sal_df.
 ↪franchID.unique())))
plt.xlabel("Year")
plt.ylabel("Total Payroll")
plt.title("Total payroll over time 1990-2014")
plt.show()
```



Part 2: Problem 2 Writeup

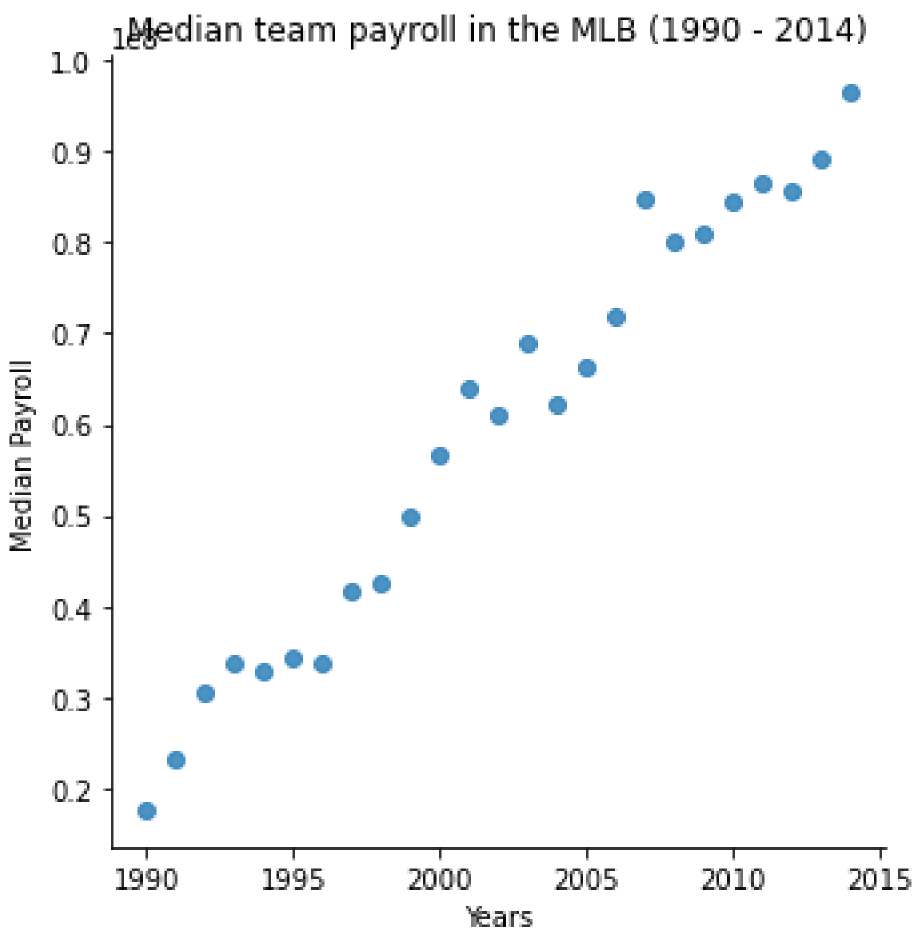
I query the SQLite database to get the total payroll for each team between 1990 to 2014 and store it in a pandas dataframe. I create a scatter plot where each franchise gets a unique color. Although some colors aren't visually distinct from others, the plot is useful as it shows how centrality and spread change over time.

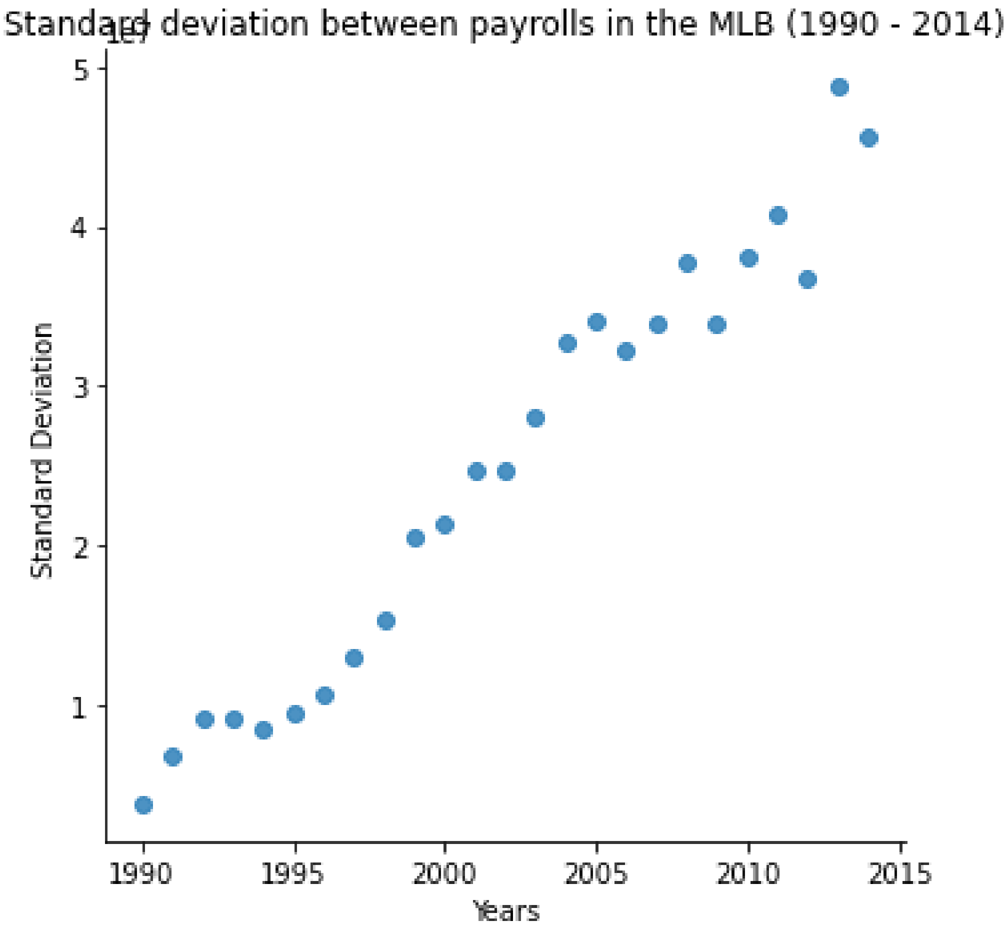
Part 2: Question 1

What statements can you make about the distribution of payrolls conditioned on time based on these plots? Since 1990, the spread between the distribution of payrolls for each franchise has dramtically increased. For the first few seasons, the distribution is relatively uniform which can be seen by the lack of outliers and how tightly packed together the points are. Beginning in the late 1990s and early 2000s however, certain teams began to spend more and more salary year over year. Although the median was certainly increasing during these years, some teams couldn't spend at a similar rate as other teams, thus increasing "payroll inequality" across the league. In terms of skewness, the distributions become more right skewed over time, with some left skewness in more recent years.

[153]:
```
#Part 2
#Problem 3

#Initialize lists
med_lst = []
std_lst = []
#For every year b/w 1990 - 2014, get the total payroll of each time and find␣
↪the median and std dev, store them in a list
for i in range(1990, 2015):
    lst = []
    for ind in sal_df.index:
        if sal_df['yearID'][ind] == i:
            lst.append(sal_df['total_payroll'][ind])
    [int(a) for a in lst]
    lst.sort()
    med = median(lst)
    sd = statistics.stdev(lst)
    med_lst.append(med)
    std_lst.append(sd)
#Store std dev list in a DataFrame
std_payroll = pd.DataFrame()
std_payroll['std_payroll'] = std_lst

#Store median list in a DataFrame
med_payroll = pd.DataFrame()
med_payroll['median_payroll'] = med_lst

#Get a list of every year b/w 1990 - 2014
year_lst = [i for i in range(1990,2015)]
```

```
#Add year_lst to each DataFrame
med_payroll['yearID'] = year_lst
std_payroll['yearID'] = year_lst

#Plot the median payroll data, the standard deviation payroll data, and the␣
↪distribution of payrolls over time
sns.lmplot(x="yearID",y="median_payroll", data=med_payroll, fit_reg=False)
plt.title("Median team payroll in the MLB (1990 - 2014)")
plt.xlabel("Years")
plt.ylabel("Median Payroll")
plt.show()
sns.lmplot(x="yearID",y="std_payroll", data=std_payroll, fit_reg=False)
plt.title("Standard deviation between payrolls in the MLB (1990 - 2014)")
plt.xlabel("Years")
plt.ylabel("Standard Deviation")
plt.show()
```





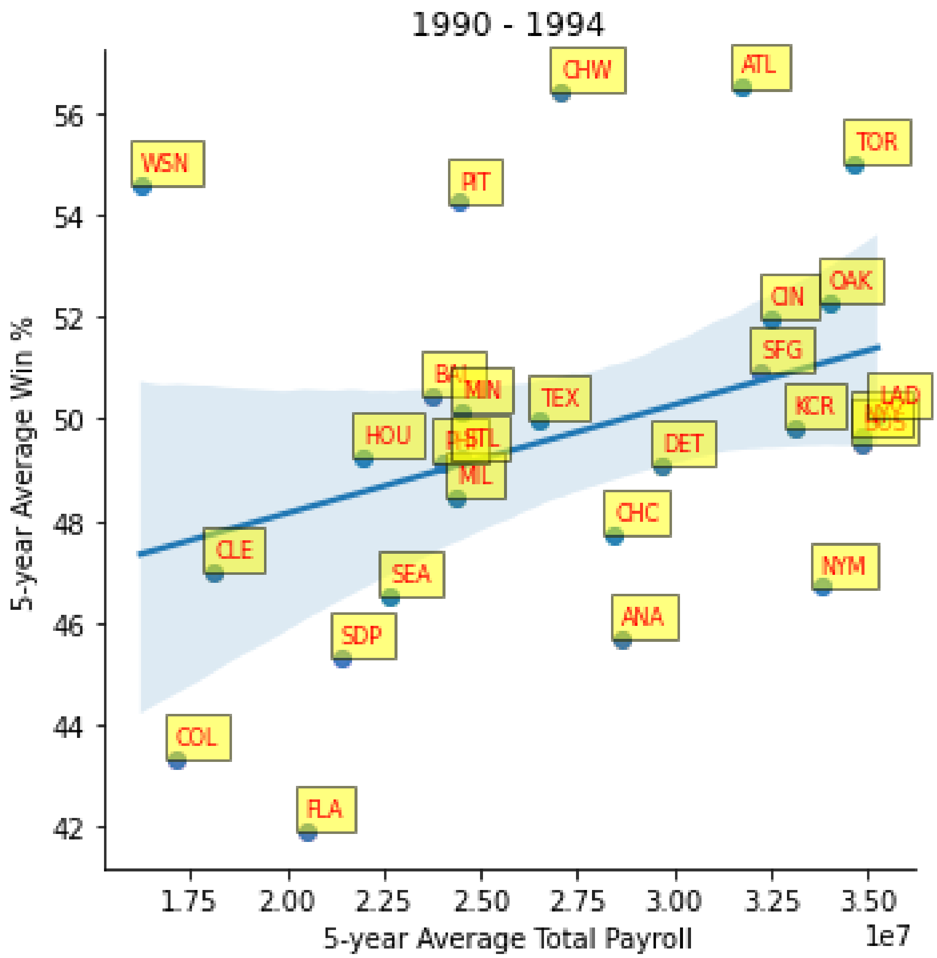
Part 2: Problem 3 Writeup

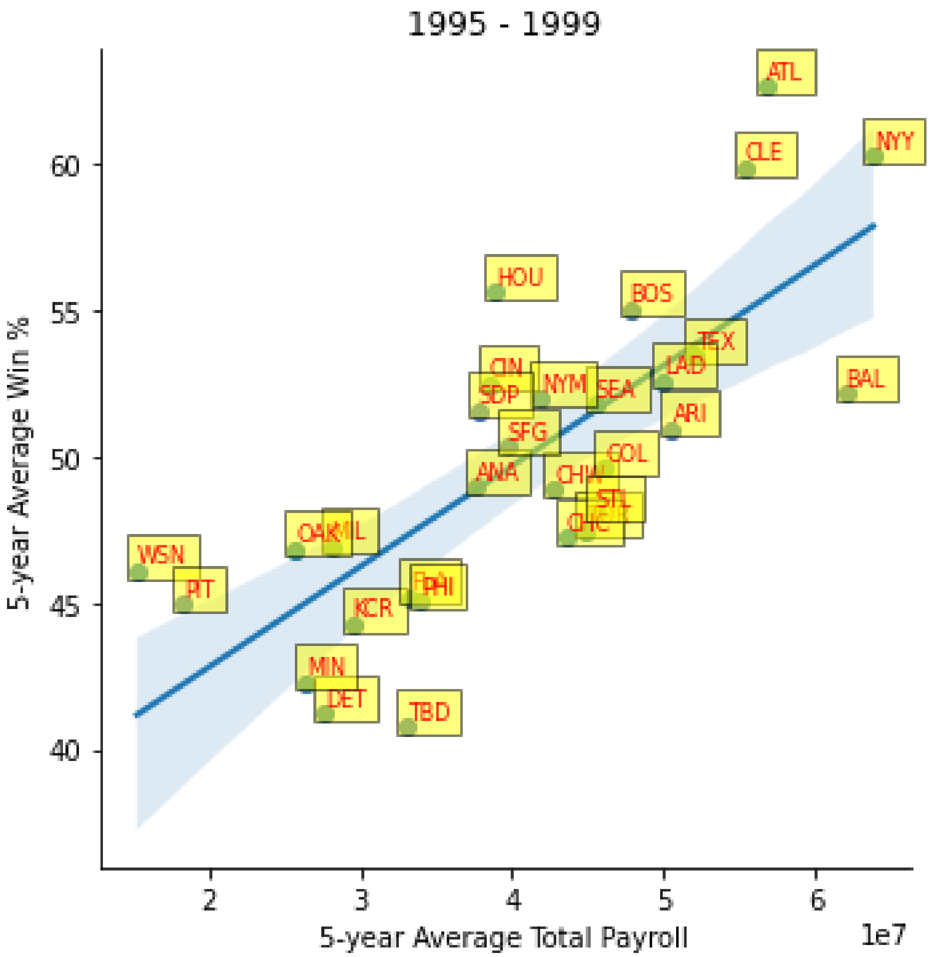
For each year, I take every team's total payroll data and compute the standard deviation and mean payroll.

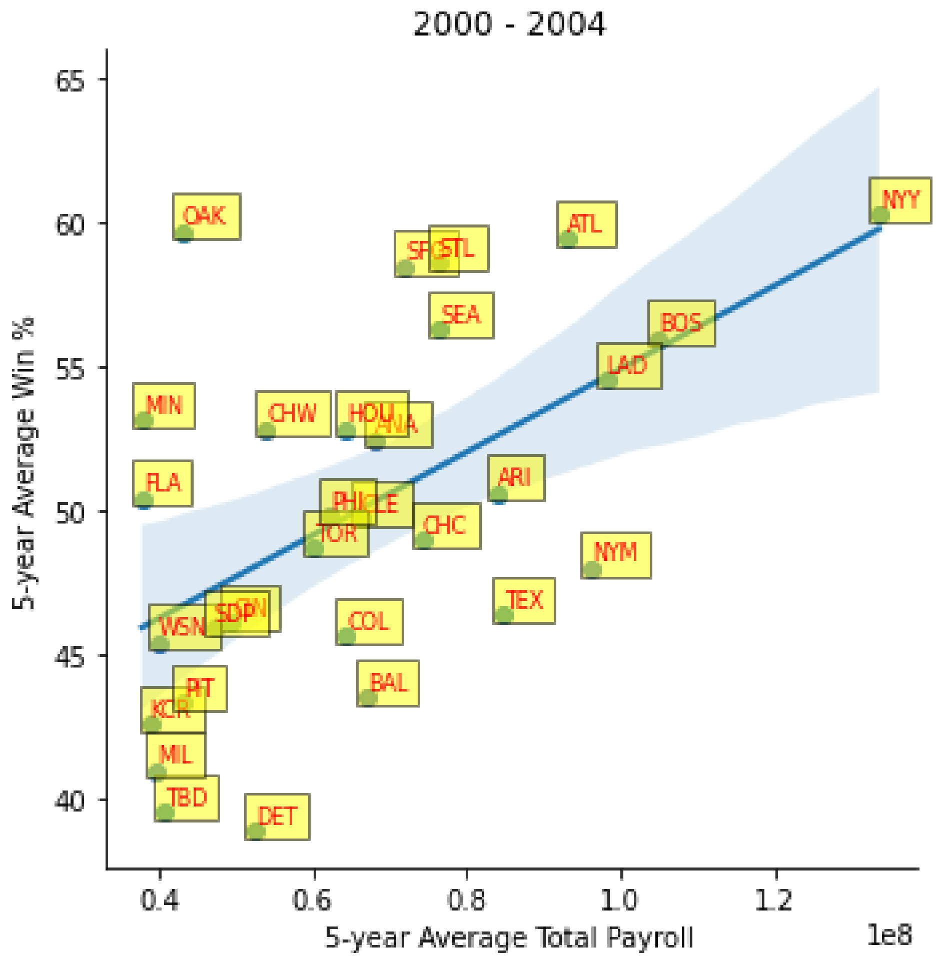
[154]:
```
#Part 2
#Problem 4
time_periods = pd.cut(np.array([i for i in range (1990,2015)]), 5)

time_periods = time_periods.unique()
#print(time_periods)

#temp = df.franchID.tolist()


franchID_periods = []
for per in time_periods:
    franch_lst2 = []
```

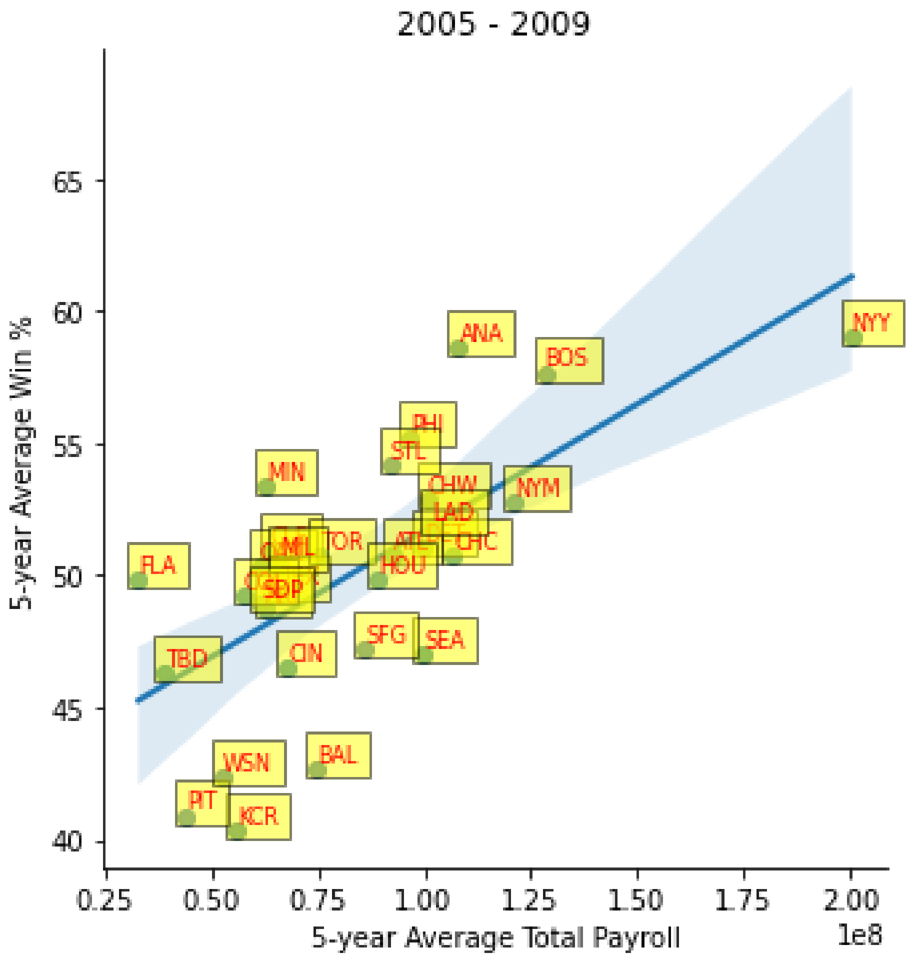
```
    lst = []
    for ind, row in df.iterrows():
        if row['yearID'] in per:
           lst.append(row['franchID'])
    [franch_lst2.append(x) for x in lst if x not in franch_lst2]
    franchID_periods.append(franch_lst2)

df_mast = []
years = []
df_90to14 = df.loc[df['yearID'] > 1989]
for i in range(5):
    df_temp = pd.DataFrame()
    franch_temp = []

    mean_pay_temp = []
    mean_win_temp = []
    per = time_periods[i]
    iv = str(math.ceil(per.left)) + " - " + str(math.floor(per.right))
    years.append(iv)

    for franch in franchID_periods[i]:
        franch_temp.append(franch)
        franch_per_pay_lst = []
        franch_per_win_lst = []
        for index, row in df_90to14.iterrows():
            if row['yearID'] in per and row['franchID'] == franch:
                franch_per_pay_lst.append(row['total_payroll'])
                franch_per_win_lst.append(row['win_per'])
        mean_pay_temp.append(statistics.mean(franch_per_pay_lst))
        mean_win_temp.append(statistics.mean(franch_per_win_lst))

    df_temp['franchID'] = franch_temp
    df_temp['mean_payroll'] = mean_pay_temp
    df_temp['mean_win_per'] = mean_win_temp
    df_mast.append(df_temp)

for i in range(5):
    df_temp = df_mast[i]
    sns.lmplot(x="mean_payroll", y="mean_win_per", data=df_temp, fit_reg=False,␣
 ↪hue='franchID', legend=False).set(title=years[i])
    for i in range(df_temp.shape[0]):
        plt.text(x=df_temp.mean_payroll[i]+0.3,y=df_temp.mean_win_per[i]+0.
 ↪3,s=df_temp.franchID[i],
          fontdict=dict(color='red',size=8),
          bbox=dict(facecolor='yellow',alpha=0.5))
    sns.regplot(x="mean_payroll", y="mean_win_per", data=df_temp)
    plt.ylabel("5-year Average Win %")
```

```python
plt.xlabel("5-year Average Total Payroll")
plt.show()
```

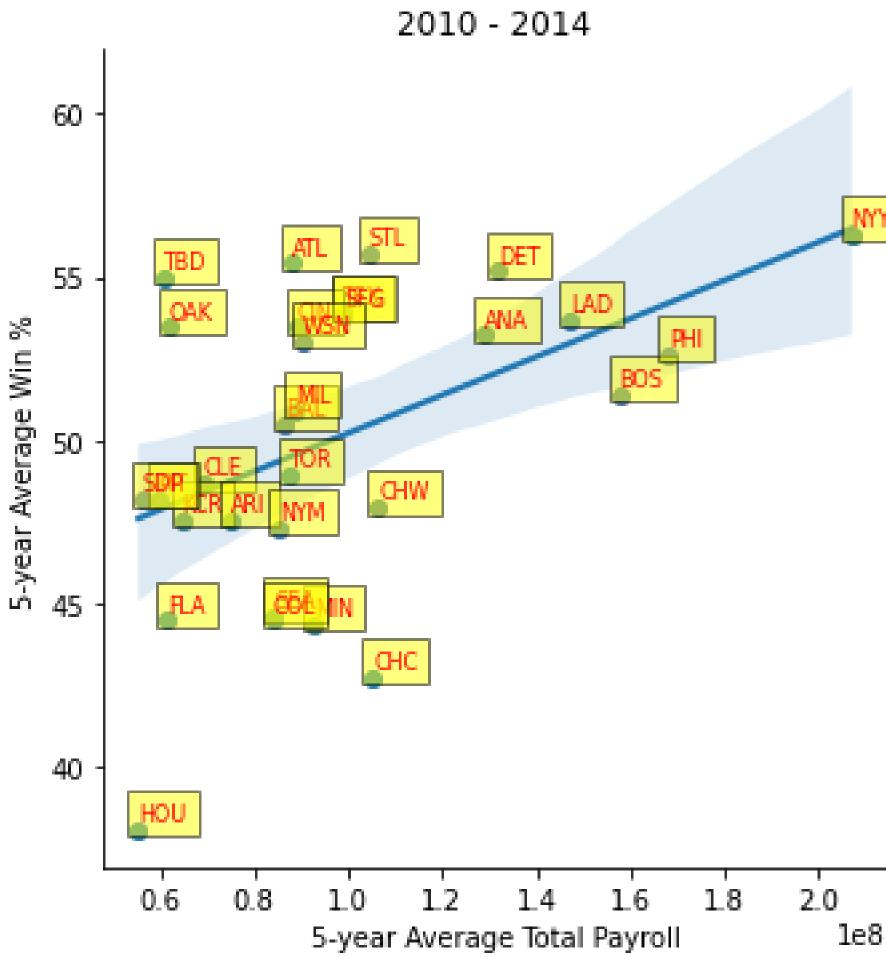



1995 - 1999
5-year Average Win %
5-year Average Total Payroll
1e7
40
45
50
55
60
2
3
4
5
6
ATL
NYY
CLE
HOU
BOS
TEX
LAD
BAL
CIN
NYM
SEA
SDP
ARI
SFG
COL
ANA
CHW
STL
OAK
MIL
WSN
PIT
PHI
KCR
MIN
DET
TBD


2000 - 2004
5-year Average Win %
5-year Average Total Payroll
1e8
65
60
55
50
45
40
0.4
0.6
0.8
1.0
1.2
OAK
SFG
STL
ATL
NYY
SEA
BOS
LAD
MIN
CHW
HOU
ANA
FLA
ARI
PHI
CLE
TOR
CHC
NYM
TEX
SDP
CIN
WSN
COL
PIT
BAL
KCR
MIL
TBD
DET



2005 - 2009
5-year Average Win %
5-year Average Total Payroll
1e8
65
60
55
50
45
40
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
NYY
ANA
BOS
PHI
STL
MIN
CHW
NYM
LAD
TOR
MIL
ATL
CHC
HOU
FLA
SDP
SFG
SEA
TBD
CIN
BAL
WSN
PIT
KCR



Part 2: Problem 4 Writeup

For each franchise I get the average total payroll and the average win percentage during each period. I then plot every team in respect to average payroll and average win percentage for a given period. For clarity, I include the franchID as a label for each point along with the regression line.

Part 2: Question 2

What can you say about team payrolls across these periods? Are there any teams that standout as being particularly good at paying for wins across these time periods? What can you say about the Oakland A's spending efficiency across these time periods

Generally, there is a strong correlation between a larger payroll with a higher winning percentage across the five periods. The correlation is less strong in the first period (1990-1994) but becomes stronger over time. Some of the teams that best demonstrate this correlation between payroll and win percentage are the Atlanta Braves, the New York Yankees, and the Boston Red Sox. However, over time it seems that more and more teams exceed their expected win percentage (based off their payroll). The 2000-2004 Oakland A's are the best example of this, as despite having less than 1/3 the payroll of the best team in baseball, the Yankees, the A's match their win percentage. Some other outlirs are the 1990-1994 Washington Nationals, the 2005-2009 Los Angeles Angels, and the 2010-2014 Tampa Bay Rays. However, the A's are an interesting case when analyizing spending efficiency because they were one of the more typical franchises during the first two periods of this analysis (1990-1994, 1995-1999). During the first period, the A's had one of the highest payrolls in baseball and they won more games than almost anyone. However, the next period, 1995-1999, saw their payroll decrease with their win percentage. However, during the 2000-2004 period, something within the A's organization changed, as they began to have success in spite of their small payroll. For the most part, they continued this trend during the next two periods, 2005-2009 and 2010-2014.

[155]:
```python
#Problem 3
#Part 5
df_90to14 = df.loc[df['yearID'] > 1989]
df_90to14 = df_90to14.reset_index()
df_90to14 = df_90to14.drop(columns=['index'])
avg_payroll_by_year = []
std_dev_payroll_by_year = []
years = [i for i in range(1990,2015)]
for year in years:
    lst = []
    for index, row in df_90to14.iterrows():
        if row['yearID'] == year:
            lst.append(df_90to14.at[index,'total_payroll'])
    avg_payroll_by_year.append(statistics.mean(lst))
    std_dev_payroll_by_year.append(statistics.stdev(lst))
df_std_payroll = pd.DataFrame()
df_std_payroll['Year'] = years
df_std_payroll['Average Payroll'] = avg_payroll_by_year
df_std_payroll['Std Dev Payroll'] = std_dev_payroll_by_year
display(df_std_payroll)
def standardized_payroll(tot_payroll, avg_payroll, stdev_payroll):
    return ((tot_payroll - avg_payroll) / stdev_payroll)
std_payroll_lst = []
for i,row1 in df_std_payroll.iterrows():
    for j, row2 in df_90to14.iterrows():
        if row1['Year'] == row2['yearID']:
            std_payroll_lst.append(standardized_payroll(row2['total_payroll'],␣
 ↪row1['Average Payroll'], row1['Std Dev Payroll']))

df_90to14['standardized_payroll'] = std_payroll_lst
display(df_90to14)
```

	Year	Average Payroll	Std Dev Payroll
0	1990	1.707235e+07	3.771834e+06
1	1991	2.357879e+07	6.894669e+06
2	1992	3.098244e+07	9.150607e+06
3	1993	3.220500e+07	9.232485e+06
4	1994	3.313701e+07	8.528749e+06
5	1995	3.398105e+07	9.447998e+06

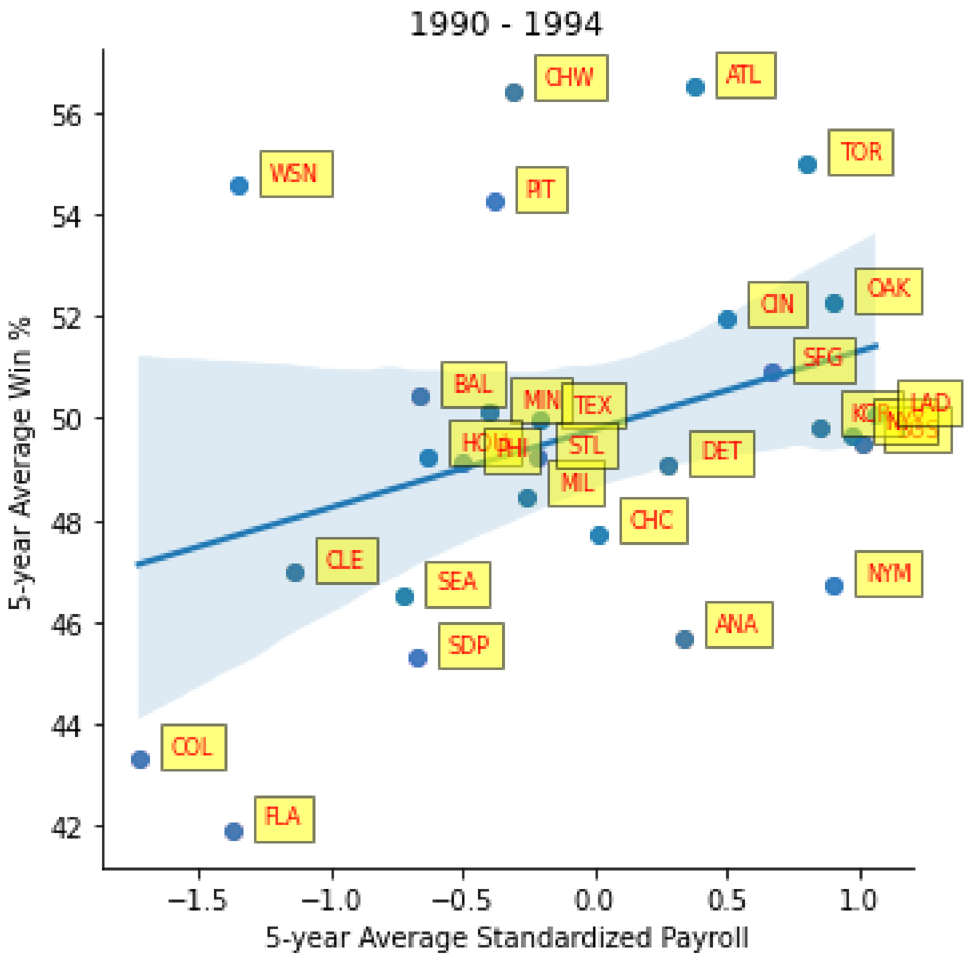
```
6    1996      3.417798e+07      1.068853e+07
7    1997      4.026021e+07      1.306073e+07
8    1998      4.260943e+07      1.538081e+07
9    1999      4.980762e+07      2.056133e+07
10   2000      5.553784e+07      2.141622e+07
11   2001      6.535544e+07      2.470771e+07
12   2002      6.746925e+07      2.469219e+07
13   2003      7.094207e+07      2.801196e+07
14   2004      6.902220e+07      3.282411e+07
15   2005      7.295711e+07      3.417478e+07
16   2006      7.738242e+07      3.226495e+07
17   2007      8.255630e+07      3.390705e+07
18   2008      8.949529e+07      3.780200e+07
19   2009      8.882423e+07      3.385709e+07
20   2010      9.071200e+07      3.811503e+07
21   2011      9.281684e+07      4.081197e+07
22   2012      9.775804e+07      3.681754e+07
23   2013      1.011509e+08      4.883029e+07
24   2014      9.980002e+07      4.570505e+07
     yearID franchID teamID  total_payroll    win_per  standardized_payroll
0      1990      BAL    BAL      9680084.0  47.204969             -1.959861
1      1990      BOS    BOS     20558333.0  54.320988              0.924213
2      1990      ANA    CAL     21720000.0  49.382716              1.232198
3      1990      CHW    CHA      9491500.0  58.024691             -2.009859
4      1990      CLE    CLE     14487000.0  47.530864             -0.685437
..      …        …   …             …         …                    …
723    2014      PIT    PIT     77178000.0  54.320988             -0.494957
724    2014      SDP    SDN     75685700.0  47.530864             -0.527607
725    2014      SFG    SFN     20000000.0  54.320988             -1.745978
726    2014      STL    SLN    120693000.0  55.555556              0.457126
727    2014      WSN    WAS    131983680.0  59.259259              0.704160

[728 rows x 6 columns]
```

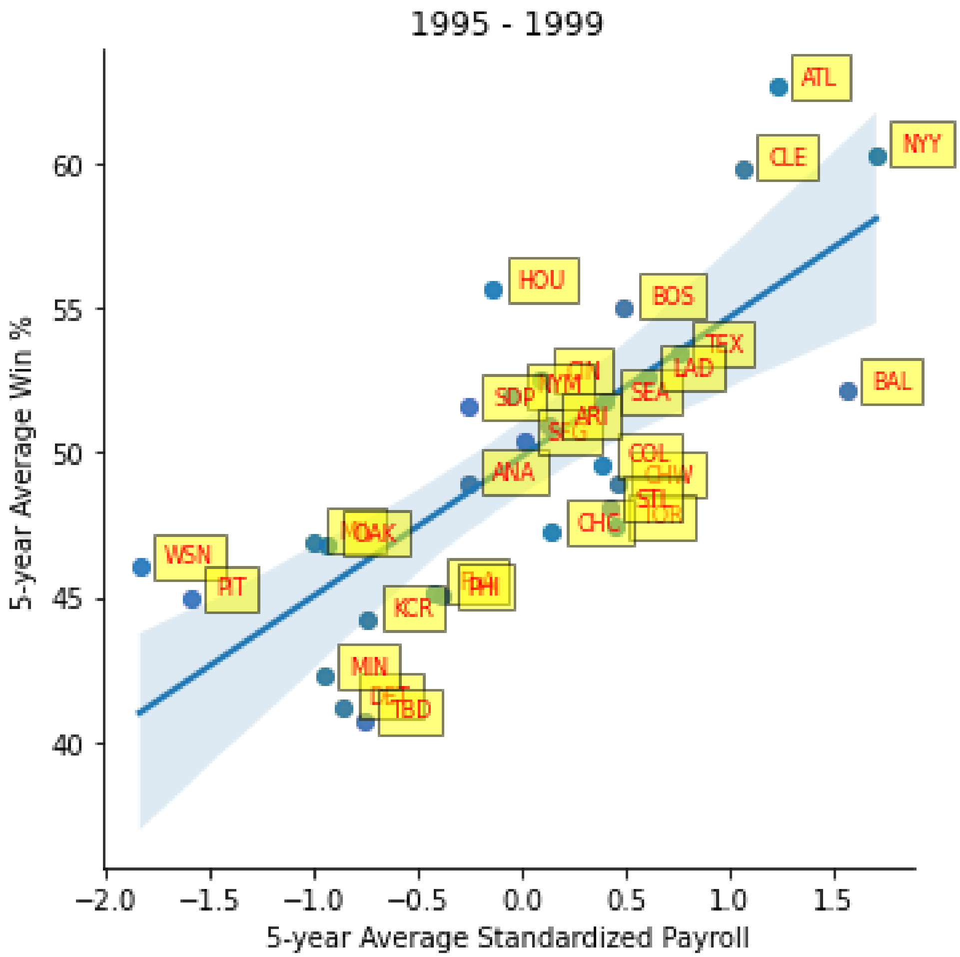
Part 3: Problem 5 Writeup

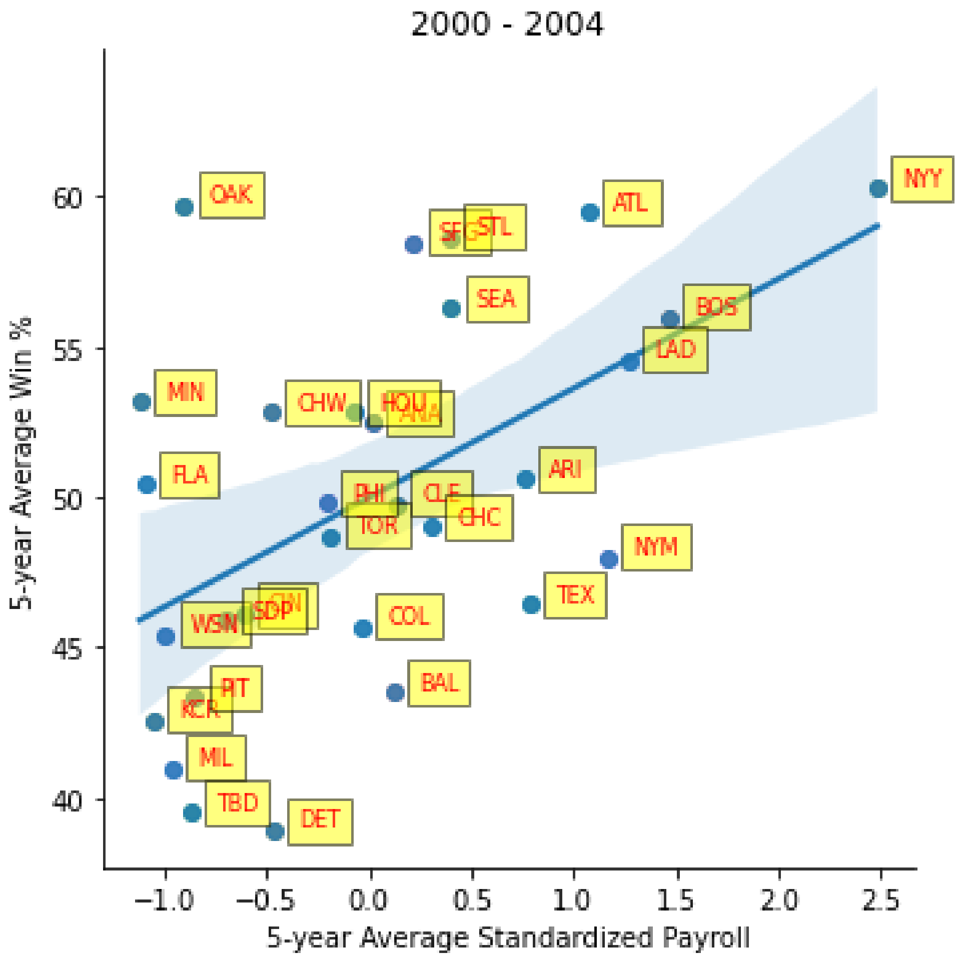
For each year, I find the average payroll and standard deviation. Using this data, I calculate the standardized payroll for each team between 1990 to 2014.

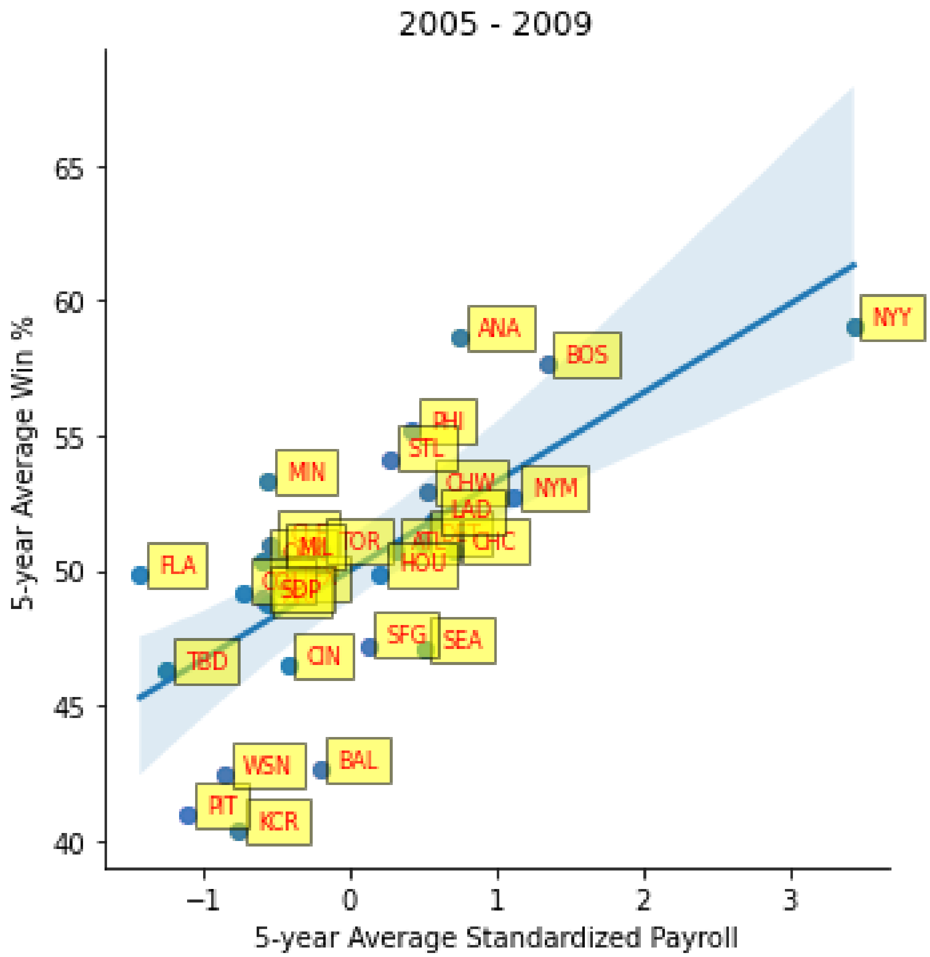
[156]:
```
#Problem 3
#Part 6
df_mast = []
years = []
for i in range(5):
    df_temp = pd.DataFrame()
    franch_temp = []

    mean_pay_temp = []
```

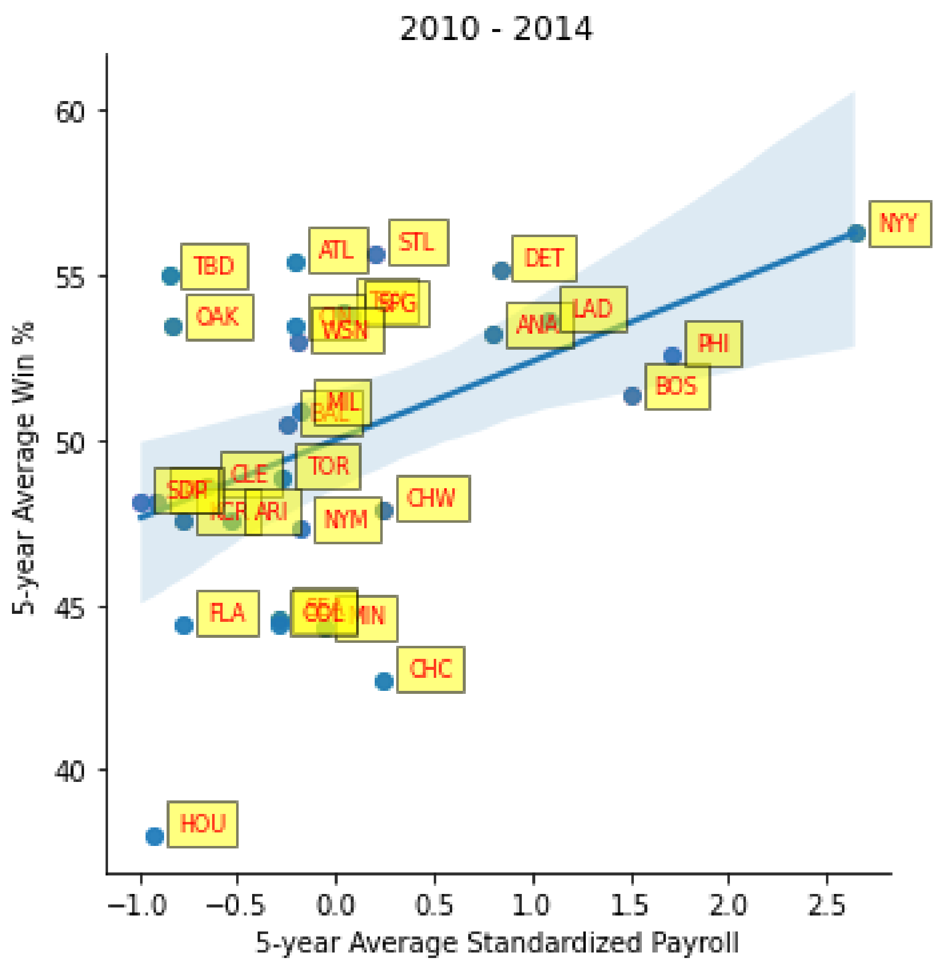
```
    mean_win_temp = []
    per = time_periods[i]
    iv = str(math.ceil(per.left)) + " - " + str(math.floor(per.right))
    years.append(iv)

    for franch in franchID_periods[i]:
        franch_temp.append(franch)
        franch_per_pay_lst = []
        franch_per_win_lst = []
        for index, row in df_90to14.iterrows():
            if row['yearID'] in per and row['franchID'] == franch:
                franch_per_pay_lst.append(row['standardized_payroll'])
                franch_per_win_lst.append(row['win_per'])
        mean_pay = sum(franch_per_pay_lst) / len(franch_per_pay_lst)
        mean_win = sum(franch_per_win_lst) / len(franch_per_win_lst)
        mean_pay_temp.append(mean_pay)
        mean_win_temp.append(mean_win)

    df_temp['franchID'] = franch_temp
    df_temp['mean_payroll'] = mean_pay_temp
    df_temp['mean_win_per'] = mean_win_temp
    df_mast.append(df_temp)


for i in range(5):
    df_temp = df_mast[i]
    sns.lmplot(x="mean_payroll", y="mean_win_per", data=df_temp, fit_reg=False, hue='franchID', legend=False).set(title=years[i])
    for i in range(df_temp.shape[0]):
        plt.text(x=df_temp.mean_payroll[i]+0.12,y=df_temp.mean_win_per[i]+0.12,s=df_temp.franchID[i],
            fontdict=dict(color='red',size=8),
            bbox=dict(facecolor='yellow',alpha=0.5))
    sns.regplot(x="mean_payroll", y="mean_win_per", data=df_temp)
    plt.ylabel("5-year Average Win %")
    plt.xlabel("5-year Average Standardized Payroll")
    plt.show()
```


1990 - 1994
5-year Average Win %
5-year Average Standardized Payroll
CHW
ATL
TOR
WSN
PIT
OAK
CIN
SFG
BAL
MIN
TEX
LAD
STL
DET
MIL
CHC
CLE
SEA
NYM
ANA
SDP
COL
FLA
56
54
52
50
48
46
44
42
−1.5
−1.0
−0.5
0.0
0.5
1.0


1995 - 1999
5-year Average Win %
5-year Average Standardized Payroll
ATL
NYY
CLE
HOU
BOS
TEX
LAD
BAL
SDP
NYM
SEA
ARI
SFG
COL
ANA
STL
CHC
OAK
WSN
PIT
KCR
PHI
MIN
TBD
60
55
50
45
40
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5


2000 - 2004
5-year Average Win %
5-year Average Standardized Payroll
60
55
50
45
40
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
OAK
STL
ATL
NYY
SEA
BOS
LAD
MIN
CHW
HOU
FLA
ARI
PHI
CLE
TOR
CHC
NYM
TEX
WSN
SDP
COL
PIT
BAL
MIL
TBD
DET


2005 - 2009
5-year Average Win %
5-year Average Standardized Payroll
65
60
55
50
45
40
−1
0
1
2
3
NYY
ANA
BOS
PHI
STL
MIN
CHW
NYM
LAD
TOR
ATL
CHC
FLA
MIL
HOU
SDP
SFG
SEA
TBD
CIN
WSN
BAL
PIT
KCR



Part 3: Probem 6 Writeup

I create the same plot from part 4 but now use the standardized payroll metric I created in the last problem.

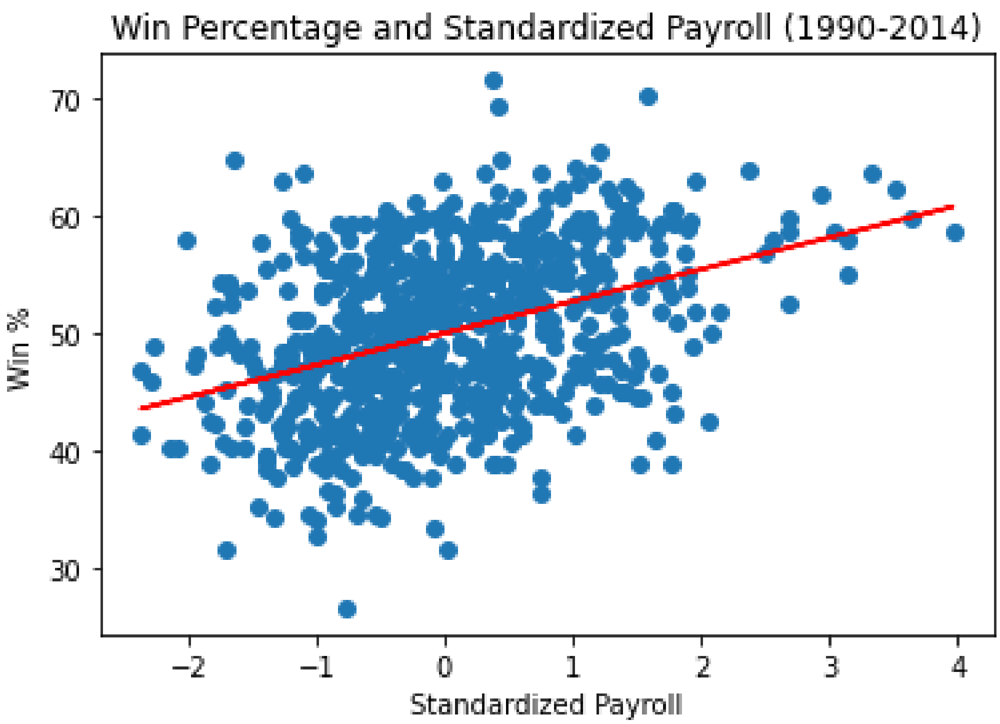
Part 3: Question 3

The transformation adjusts the team payroll to be relative to the period. Thus, we have a better way of comparing teams across eras since they payroll has the same units.

[157]:
```
#Part 3
#Problem 7
array = df_90to14.to_numpy()
y = array[:,4]
y = y.astype(str).astype(float)
x = array[:,5]
x = x.astype(str).astype(float)
slope, intercept = np.polyfit(x, y, deg=1)
print(slope, intercept)
```

```python
plt.scatter(df_90to14['standardized_payroll'], df_90to14['win_per'])
plt.plot(df_90to14['standardized_payroll'],␣
↪df_90to14['standardized_payroll']*slope + intercept, 'r')
plt.title("Win Percentage and Standardized Payroll (1990-2014)")
plt.xlabel("Standardized Payroll")
plt.ylabel("Win %")
plt.show()
exp_wins_lst = []
for ind, row in df_90to14.iterrows():
    exp_wins_lst.append(50 + 2.7 * row['standardized_payroll'])
df_90to14['exp_wins'] = exp_wins_lst
display(df_90to14)
```

```
2.7251036461557065 49.98855314843013
```



	yearID	franchID	teamID	total_payroll	win_per	standardized_payroll	\
0	1990	BAL	BAL	9680084.0	47.204969	-1.959861	
1	1990	BOS	BOS	20558333.0	54.320988	0.924213	
2	1990	ANA	CAL	21720000.0	49.382716	1.232198	
3	1990	CHW	CHA	9491500.0	58.024691	-2.009859	
4	1990	CLE	CLE	14487000.0	47.530864	-0.685437	
..	…	…	…	…	…	…	
723	2014	PIT	PIT	77178000.0	54.320988	-0.494957	
724	2014	SDP	SDN	75685700.0	47.530864	-0.527607	

```
725    2014       SFG     SFN      20000000.0   54.320988               -1.745978
726    2014       STL     SLN     120693000.0   55.555556                0.457126
727    2014       WSN     WAS     131983680.0   59.259259                0.704160

      exp_wins
0    44.708376
1    52.495376
2    53.326934
3    44.573382
4    48.149321
..         …
723  48.663617
724  48.575461
725  45.285860
726  51.234241
727  51.901232

[728 rows x 7 columns]
```

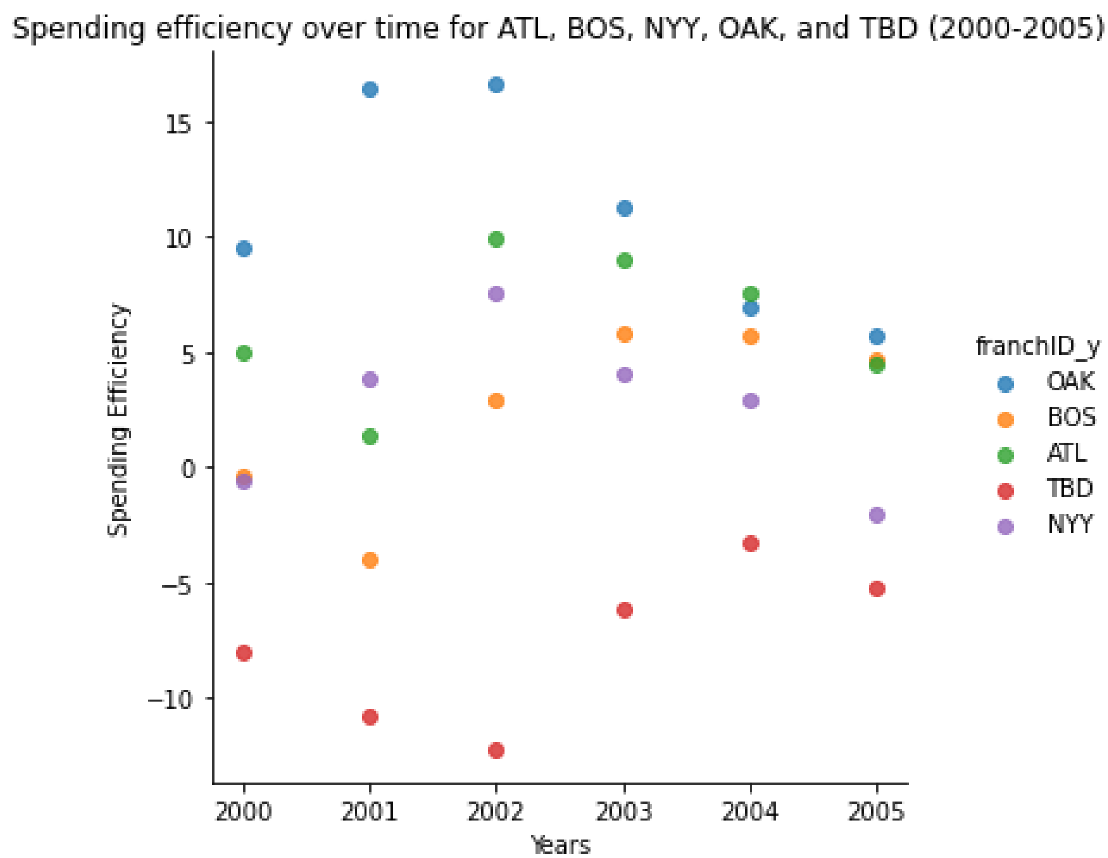
Part 3: Problem 7 Writeup

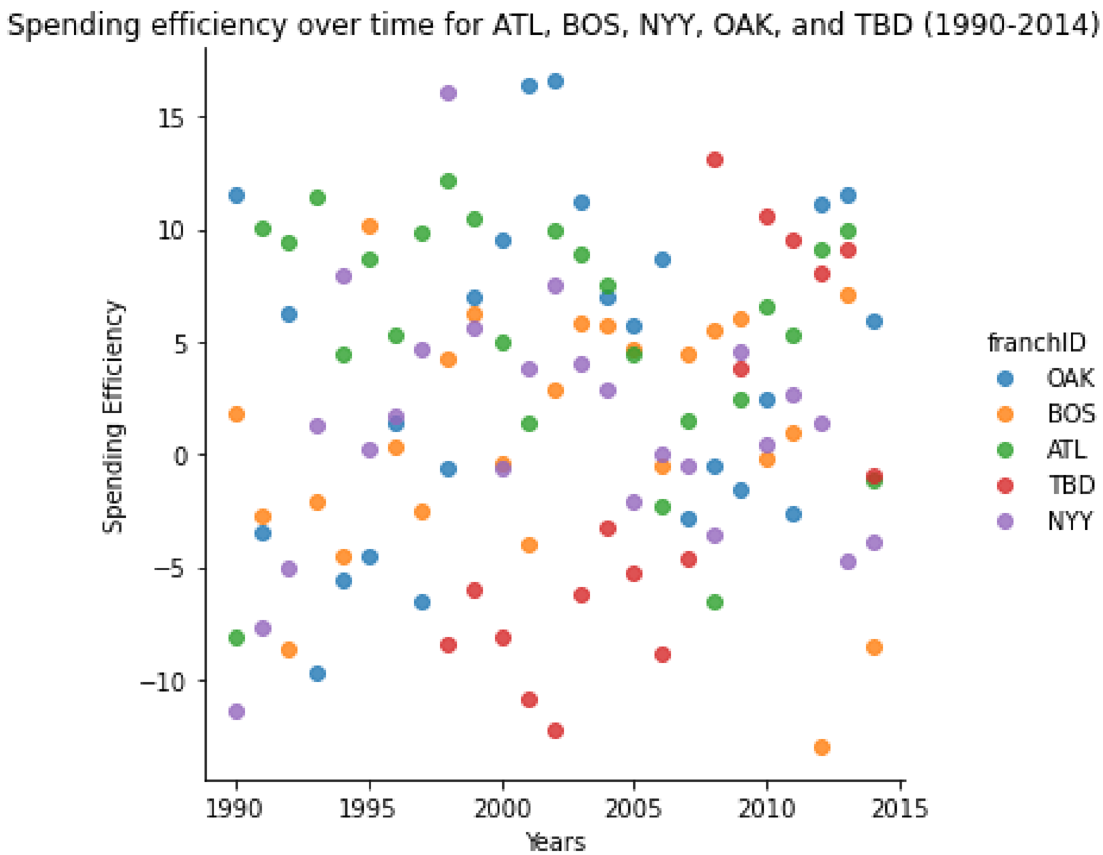
I find the line of regression for standardized payroll and win percentage. From this, I can find the expected wins using the formula 50 + 2.7 * standardized_payroll for each team and create a scatter plot of win percentage and standardized payroll.

[158]:

```
#Part 3
#Problem 8

eff_lst = []
for ind, row in df_90to14.iterrows():
    eff_lst.append(row['win_per'] - row['exp_wins'])
df_90to14['eff'] = eff_lst

df_90to14_oak =  df_90to14.loc[(df_90to14['franchID'] == "OAK")]
df_90to14_bos =  df_90to14.loc[(df_90to14['franchID'] == "BOS")]
df_90to14_atl =  df_90to14.loc[(df_90to14['franchID'] == "ATL")]
df_90to14_tbd =  df_90to14.loc[(df_90to14['franchID'] == "TBD")]
df_90to14_nyy =  df_90to14.loc[(df_90to14['franchID'] == "NYY")]
frames = [df_90to14_oak, df_90to14_bos, df_90to14_atl, df_90to14_tbd,␣
 ↪df_90to14_nyy]
result = pd.concat(frames)
result = result.reset_index()
result = result.drop(columns=['index'])
df_90to14 = df.loc[df['yearID'] > 1989]
result_temp1 = result.loc[result['yearID'] >= 2000]
result_temp2 = result.loc[result['yearID'] <= 2005]
#merged_inner = pd.merge(left=survey_sub, right=species_sub,␣
 ↪left_on='species_id', right_on='species_id')
```

```
result_inner = pd.merge(left=result_temp1, right=result_temp2,␣
↪left_on='yearID', right_on='yearID')
result_inner = result_inner.drop(columns=['exp_wins_x','teamID_x',␣
↪'franchID_x', 'total_payroll_x', 'win_per_x', 'standardized_payroll_x',␣
↪'eff_x'] )
result_inner = result_inner.drop_duplicates()
sns.lmplot(x="yearID", y="eff_y", data=result_inner, hue="franchID_y",␣
↪fit_reg=False)
plt.title("Spending efficiency over time for ATL, BOS, NYY, OAK, and TBD␣
↪(2000-2005)")
plt.xlabel("Years")
plt.ylabel("Spending Efficiency")
plt.show()
sns.lmplot(x="yearID", y="eff", data=result, hue="franchID", fit_reg=False)
plt.title("Spending efficiency over time for ATL, BOS, NYY, OAK, and TBD␣
↪(1990-2014)")
plt.xlabel("Years")
plt.ylabel("Spending Efficiency")
plt.show()
result_most_eff = result.loc[result['eff'] > 11]
result_most_eff = result_most_eff.reset_index()
result_most_eff = result_most_eff.drop(columns=['index'])
```





Part 3: Problem 8 Writeup

I first calculate the expected wins for every team between 1990 to 2014. Then, I select five franchises to anaylze in depth and plot their spending efficiency for 2000 - 2005 and 1990 - 2014 where the former represents the "Moneyball Era".

[159]:
```
conn.close()
```

Part 3: Question 4

The plots in questions 2 and 3 shows the correlation between payroll and win percentage. From this, we can see that the winningest teams in baseball are those that spend the most money. However, we also notice that there are historical outliers in which some of the best teams spent very little. So, if we're able to quantify how well teams spend on wins, we can compare franchises on their ability to evaluate talent. The more successful a team is at identifying winning players, the higher their efficiency is. For instance, despite NYY having a comparable win percentage to OAK, New York is much worse when it comes to spending their money efficienctly.

Between 2000 and 2005, the Oakland A's had an unprecedented efficiency when it came to converting dollars to wins. Their average efficiency during this period was 11.06, a mark no other team came close to in a single season. In fact, only four other teams have put up an efficiency score above 11 between 1990 to 2014 and of the ten highest efficiency scores on reocrd, six belong to the Oakland A's.

```
[ ]:
```