# Baseball Spending Efficiency

March 16, 2021

[1]: import sqlite3

import pandas as pd

```
import numpy as np
[2]: ## Part 1
     ## Problem 1
     sqlite_file = 'lahman2014.sqlite'
     conn = sqlite3.connect(sqlite_file)
     salary_query = "SELECT teamID, yearID, sum(salary) as total_payroll, u
      ⇒sum(salary)/count(salary) as team_payroll_mean FROM Salaries GROUP BY⊔
      →teamID, yearID"
     team_salaries = pd.read_sql(salary_query, conn)
[3]: team_salaries
[3]:
         teamID yearID total_payroll team_payroll_mean
     0
            ATL
                   1985
                             14807000.0
                                              6.730455e+05
     1
            BAL
                   1985
                            11560712.0
                                              5.254869e+05
            BOS
                   1985
                                              4.359024e+05
     2
                            10897560.0
     3
            CAL
                   1985
                            14427894.0
                                              5.152819e+05
     4
            CHA
                                              4.688656e+05
                   1985
                             9846178.0
     855
            SLN
                   2014
                           120693000.0
                                              4.310464e+06
     856
            TBA
                   2014
                                              2.907564e+06
                            72689100.0
     857
            TEX
                   2014
                           112255059.0
                                              4.677294e+06
     858
            TOR
                   2014
                                              4.396804e+06
                           109920100.0
                   2014
                                              4.399456e+06
     859
            WAS
                           131983680.0
     [860 rows x 4 columns]
[4]: conn = sqlite3.connect(sqlite_file)
     winning_query = "select teamID, yearID, (w*100.0/G) as winning_per, G from ∪
      →Teams group by teamID, yearID"
     winning_table = pd.read_sql(winning_query,conn)
```

```
result=pd.merge(winning_table, team_salaries, how='outer', □

→on=['teamID','yearID'])

result

# I use outer-join to join the 2 tables above, that is making any unmatched □

→pantry to NaN.
```

```
[4]:
          teamID
                   yearID
                           winning_per
                                              G
                                                 total_payroll
                                                                 team_payroll_mean
             ALT
                     1884
                              24.000000
     0
                                          25.0
                                                            NaN
                                                                                NaN
     1
                              51.851852 162.0
             ANA
                     1997
                                                    31135472.0
                                                                       1.004370e+06
     2
             ANA
                     1998
                              52.469136 162.0
                                                    41281000.0
                                                                       1.214147e+06
     3
             ANA
                     1999
                              43.209877
                                         162.0
                                                    55388166.0
                                                                       1.384704e+06
     4
             ANA
                     2000
                              50.617284 162.0
                                                    51464167.0
                                                                       1.715472e+06
                                         127.0
     2772
                              32.283465
             WS8
                     1889
                                                            NaN
                                                                                NaN
                     1891
     2773
                              31.654676
                                         139.0
             WS9
                                                            NaN
                                                                                NaN
     2774
             WSU
                     1884
                              41.228070
                                         114.0
                                                            NaN
                                                                                NaN
     2775
             NYM
                     2014
                                    NaN
                                            NaN
                                                    54806990.0
                                                                       2.283625e+06
     2776
             SFG
                     2014
                                    NaN
                                            NaN
                                                   143510167.0
                                                                       5.315191e+06
```

[2777 rows x 6 columns]

#### []:

```
[5]: import matplotlib.pyplot as plt

result['yearID']=result['yearID'].apply(lambda x:int(x))
temp=result[result['yearID']>=1990]
temp=temp[temp['yearID']<=2014]
team_ID_list = temp['teamID'].drop_duplicates()
temp.index=temp['teamID']
temp</pre>
```

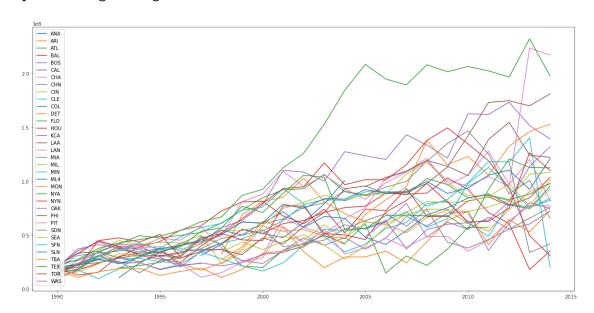
```
[5]:
            teamID
                     yearID winning_per
                                                   total_payroll
                                                                   team_payroll_mean
     teamID
     ANA
                ANA
                       1997
                                51.851852
                                            162.0
                                                       31135472.0
                                                                         1.004370e+06
     ANA
                       1998
                                           162.0
                ANA
                                52.469136
                                                       41281000.0
                                                                         1.214147e+06
     ANA
                ANA
                       1999
                                43.209877
                                            162.0
                                                       55388166.0
                                                                         1.384704e+06
     ANA
                ANA
                       2000
                                50.617284
                                            162.0
                                                       51464167.0
                                                                         1.715472e+06
     ANA
                ANA
                       2001
                                46.296296
                                            162.0
                                                       47535167.0
                                                                         1.584506e+06
                       2012
                                60.493827
                                            162.0
                                                                         2.695171e+06
     WAS
                WAS
                                                       80855143.0
     WAS
                WAS
                       2013
                                53.086420
                                            162.0
                                                      113703270.0
                                                                         4.548131e+06
     WAS
                WAS
                       2014
                                59.259259
                                            162.0
                                                                         4.399456e+06
                                                      131983680.0
     NYM
                                      NaN
                NYM
                       2014
                                              NaN
                                                       54806990.0
                                                                         2.283625e+06
     SFG
                SFG
                                              {\tt NaN}
                       2014
                                      {\tt NaN}
                                                      143510167.0
                                                                         5.315191e+06
```

[730 rows x 6 columns]

```
[6]: # Problem 2
     # for teamID in team_ID_list:
           if(type(temp.loc[teamID, 'yearID']) is not np.int64):
                plt.plot(temp.loc[teamID, 'yearID'], temp.
      → loc[teamID, 'total_payroll'], label=teamID)
                print("The figure below is for team " +teamID)
               plt.show()
     print("The figure below is a generalized one")
     plt.figure(figsize=(20,10))
     for teamID in team_ID_list:
         if(type(temp.loc[teamID, 'yearID']) is not np.int64):
             plt.plot(temp.loc[teamID, 'yearID'], temp.
      →loc[teamID, 'total_payroll'], label=teamID)
     plt.legend()
     # Question 1
     \# From the plot below, we can see that the total_payroll of each team is \sqcup
     \rightarrow increasing by time in the long term.
     # Also, the difference between the highest total_payroll and lowest_{\sqcup}
      →total_payroll is increasing by time as well.
```

The figure below is a generalized one

#### [6]: <matplotlib.legend.Legend at 0x7fc6bcd25cd0>

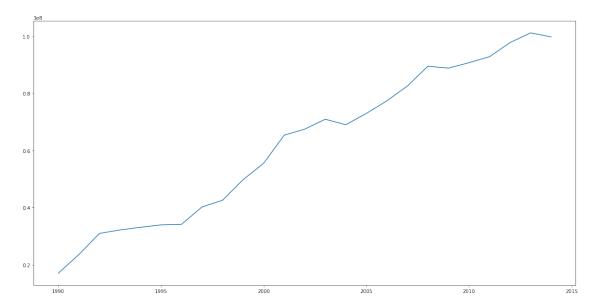


[7]: # Problem 3

```
[8]: plot_table=temp.groupby(['yearID']).mean()

plt.figure(figsize=(20,10))
plt.plot(plot_table.index,plot_table['total_payroll'])
```

# [8]: [<matplotlib.lines.Line2D at 0x7fc6bd2ea310>]



# [9]: plot\_table

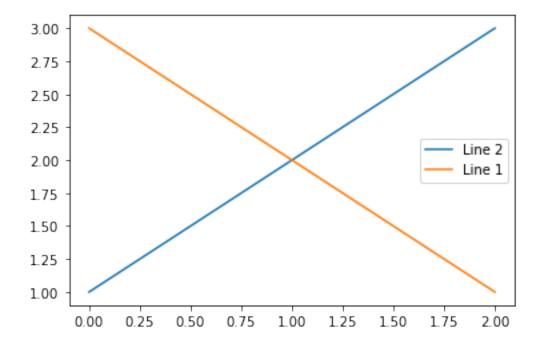
[9]:		winning_per	G	total_payroll	team_payroll_mean
	yearID				
	1990	49.998525	161.923077	1.707235e+07	5.139887e+05
	1991	49.997193	161.846154	2.357879e+07	8.970479e+05
	1992	50.000000	162.000000	3.098244e+07	1.056331e+06
	1993	49.975925	162.071429	3.220500e+07	9.879449e+05
	1994	49.993326	114.285714	3.313701e+07	1.063055e+06
	1995	49.970376	144.071429	3.398105e+07	9.721240e+05
	1996	49.976884	161.928571	3.417798e+07	1.038646e+06
	1997	49.998494	161.857143	4.026021e+07	1.233943e+06
	1998	49.955924	162.133333	4.260943e+07	1.299881e+06
	1999	49.967969	161.866667	4.980762e+07	1.505079e+06
	2000	49.980566	161.933333	5.553784e+07	2.001520e+06
	2001	49.981469	161.933333	6.535544e+07	2.266839e+06
	2002	49.978274	161.733333	6.746925e+07	2.398339e+06
	2003	49.978927	162.000000	7.094207e+07	2.579230e+06
	2004	49.994121	161.866667	6.902220e+07	2.485419e+06
	2005	49.979550	162.066667	7.295711e+07	2.658144e+06
	2006	49.999744	161.933333	7.738242e+07	2.846905e+06

```
2007
          49.997980
                     162.066667
                                   8.255630e+07
                                                       2.948564e+06
2008
          49.996443
                     161.866667
                                   8.949529e+07
                                                       3.145653e+06
2009
          49.996693
                     162.000000
                                   8.882423e+07
                                                       3.291229e+06
2010
                                                       3.304888e+06
          50.000000
                     162.000000
                                   9.071200e+07
2011
          50.000128
                     161.933333
                                   9.281684e+07
                                                       3.331578e+06
2012
                                                       3.446412e+06
          50.000000
                     162.000000
                                   9.775804e+07
2013
          49.997475
                     162.066667
                                   1.011509e+08
                                                       3.678754e+06
2014
          50.000000
                     162.000000
                                                       4.609605e+06
                                   9.975993e+07
```

```
[10]: l=temp['yearID'].tolist()
```

```
[11]: line_up, = plt.plot([1, 2, 3], label='Line 2')
line_down, = plt.plot([3, 2, 1], label='Line 1')
plt.legend(handles=[line_up, line_down])
```

# [11]: <matplotlib.legend.Legend at 0x7fc6bd9a1f10>

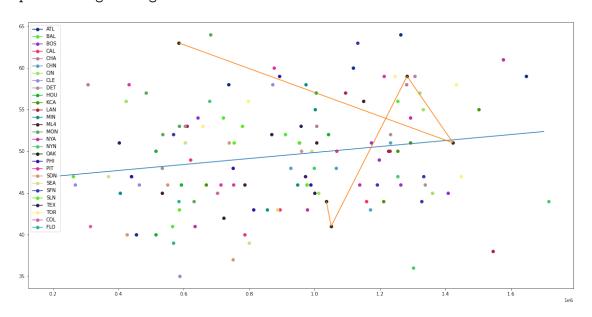


```
[12]: # Problem 4

[13]: salary_mean_query = "SELECT teamID,yearID, sum(salary)/count(salary) as_\( \to \text{payroll_mean FROM Salaries GROUP BY teamID,yearID"} \)
winning_query = "SELECT teamID,yearID, W*100/G as winning_percentage FROM_\( \to \text{Teams GROUP BY teamID,yearID"} \)
salary_mean_table = pd.read_sql(salary_mean_query, conn)
winning_table = pd.read_sql(winning_query,conn)
```

```
group_table = pd.merge(salary_mean_table, winning table, how='outer',_
      bins = [1989,1994,1999,2004,2009,2015]
     group names = ['1990-1994','1995-1999','2000-2004','2005-2009','2010-2015']
     #categories = pd.cut(group_table['yearID'],bins,labels=group_names)
     group_table['categories'] = pd.cut(group_table['yearID'], bins,__
      →labels=group_names)
     group_table['categories'].tolist()
     grouped = group_table.groupby('categories')
     group1 = grouped.get group('1990-1994')
     group2 = grouped.get_group('1995-1999')
     group3 = grouped.get_group('2000-2004')
     group4 = grouped.get_group('2005-2009')
     group5 = grouped.get_group('2010-2015')
     group1
         teamID yearID payroll_mean winning_percentage categories
Γ13]:
     130
            ATL
                   1990 4.548594e+05
                                                     40.0 1990-1994
            BAL
                   1990 2.616239e+05
                                                    47.0 1990-1994
     131
     132
            BOS
                   1990 6.424479e+05
                                                    54.0 1990-1994
                   1990 6.205714e+05
                                                     49.0 1990-1994
     133
            CAL
                   1990 3.061774e+05
                                                     58.0 1990-1994
     134
            CHA
      . .
                   1994 8.857121e+05
                                                    43.0 1990-1994
     259
            SEA
     260
            SFN
                   1994 1.332458e+06
                                                    47.0 1990-1994
     261
                   1994 9.758534e+05
                                                    46.0 1990-1994
            SLN
     262
                   1994 9.991999e+05
                                                    45.0 1990-1994
            TEX
                                                    47.0 1990-1994
     263
            TOR
                   1994 1.447789e+06
     [134 rows x 5 columns]
[14]: # For group 1
     team_list = group1['teamID']
     plot table=group1.drop(columns=['yearID','categories'])
     plot table.index=range(1,135)
     plot table
     plot table
     dict_team={}
     plt.figure(figsize=(20,10))
     for i, row in plot_table.iterrows():
         team_name = row['teamID']
         if team_name in dict_team:
```

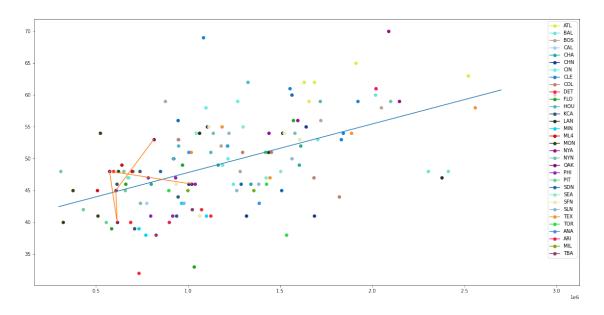
#### [14]: <matplotlib.legend.Legend at 0x7fc6bde30f10>



```
[15]: np.random.rand(3,)
[15]: array([0.10018232, 0.75966964, 0.39105821])
[16]: # For group 2
   team_list = group2['teamID']
   plot_table=group2.drop(columns=['yearID','categories'])
   plot_table.index=range(1,len(plot_table)+1)
   plot_table
```

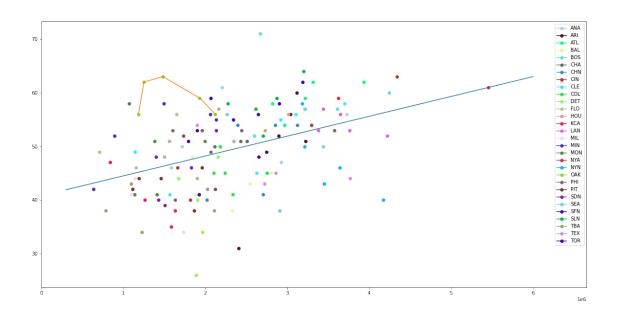
```
plot_table
dict_team={}
plt.figure(figsize=(20,10))
for i, row in plot_table.iterrows():
    team_name = row['teamID']
    if team_name in dict_team:
 →plot(row['payroll_mean'],row['winning_percentage'],marker='o',color=dict_team[team_name])
    else:
        a=np.random.rand(3,)
 →plot(row['payroll_mean'],row['winning_percentage'],marker='o',label=row['teamID'],color=a)
        dict_team[team_name] = a
line=np.polyfit(plot_table['payroll_mean'],plot_table['winning_percentage'],1)
p = np.poly1d(line)
xp=np.linspace(300000, 2700000, 2)
yp=p(xp)
plt.plot(xp,yp)
oak_table=group2.loc[group2['teamID']=='OAK']
plt.plot(oak_table['payroll_mean'], oak_table['winning_percentage'])
plt.legend()
```

[16]: <matplotlib.legend.Legend at 0x7fc6bde48eb0>



```
[17]: # For group 3
      team_list = group3['teamID']
      plot_table=group3.drop(columns=['yearID','categories'])
      plot_table.index=range(1,len(plot_table)+1)
      plot_table
      plot_table
      dict_team={}
      plt.figure(figsize=(20,10))
      for i, row in plot_table.iterrows():
          team_name = row['teamID']
          if team_name in dict_team:
       →plot(row['payroll_mean'],row['winning_percentage'],marker='o',color=dict_team[team_name])
          else:
              a=np.random.rand(3,)
              plt.
       →plot(row['payroll_mean'],row['winning_percentage'],marker='o',label=row['teamID'],color=a)
              dict_team[team_name] = a
      line=np.polyfit(plot_table['payroll_mean'],plot_table['winning_percentage'],1)
      p = np.poly1d(line)
      xp=np.linspace(300000, 6000000, 2)
      yp=p(xp)
      plt.plot(xp,yp)
      oak_table=group3.loc[group3['teamID']=='OAK']
      plt.plot(oak_table['payroll_mean'], oak_table['winning_percentage'])
      plt.legend()
```

[17]: <matplotlib.legend.Legend at 0x7fc6bde48df0>



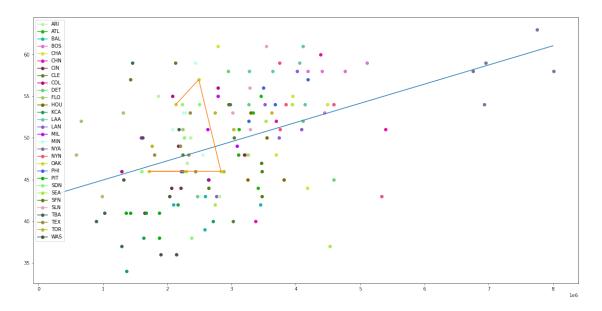
```
[18]: # For group 4
      team_list = group4['teamID']
      plot_table=group4.drop(columns=['yearID','categories'])
      plot_table.index=range(1,len(plot_table)+1)
      plot_table
      plot_table
      dict_team={}
      plt.figure(figsize=(20,10))
      for i, row in plot_table.iterrows():
          team_name = row['teamID']
          if team_name in dict_team:
              plt.
       →plot(row['payroll_mean'],row['winning_percentage'],marker='o',color=dict_team[team_name])
          else:
              a=np.random.rand(3,)
              plt.
       →plot(row['payroll_mean'],row['winning_percentage'],marker='o',label=row['teamID'],color=a)
              dict_team[team_name] = a
      line=np.polyfit(plot_table['payroll_mean'],plot_table['winning_percentage'],1)
      p = np.poly1d(line)
      xp=np.linspace(300000, 8000000, 2)
      yp=p(xp)
```

```
plt.plot(xp,yp)

oak_table=group4.loc[group4['teamID']=='OAK']
plt.plot(oak_table['payroll_mean'], oak_table['winning_percentage'])

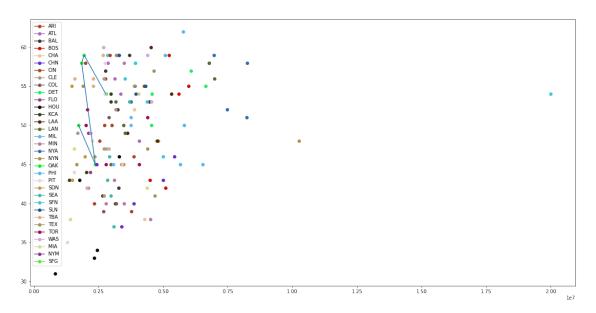
plt.legend()
```

### [18]: <matplotlib.legend.Legend at 0x7fc6be37d2b0>



```
a=np.random.rand(3,)
        plt.
 →plot(row['payroll_mean'],row['winning_percentage'],marker='o',label=row['teamID'],color=a)
        dict team[team name] = a
# line=np.
-polyfit(plot_table['payroll_mean'],plot_table['winning_percentage'],1)
\# p = np.poly1d(line)
# xp=np.linspace(300000, 8000000, 2)
# yp=p(xp)
# plt.plot(xp,yp)
oak table=group5.loc[group5['teamID']=='OAK']
plt.plot(oak_table['payroll_mean'], oak_table['winning_percentage'])
plt.legend()
# print(plot_table['payroll_mean'].tolist())
# print(plot_table['winning_percentage'].tolist())
# In this case, we cannot find a regression line by np.ployfit since it does \Box
→not converge by least square
```

#### [19]: <matplotlib.legend.Legend at 0x7fc6bec3efd0>



```
[20]: # Question 2
# The payroll increases across all these periods.
#
# For the Oakland A's spending efficiency, I notice that the lines of Oakland A□
→ go across the regression
# line for the first, second and fourth time period, which suggests that its□
→ spending efficiency is close to the mean.
```

```
# For the third time period, the lines of Oakland A is above the regression

→ line, which means the spending efficiency

# is high. For the fifth time period, np.polyfit() cannot give a regression

→ line, but it seems that Oakland A still have

# a spending efficiency close to the mean.
```

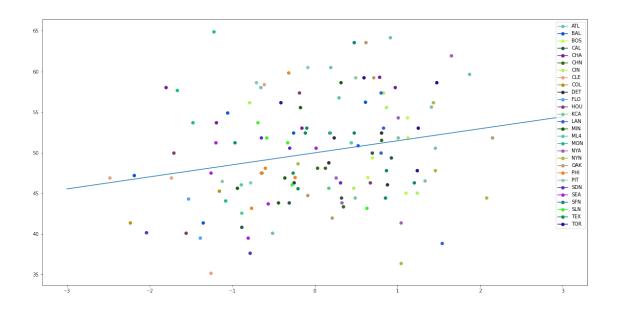
```
[21]: # Problem 5
      import statistics
      question3_df = team_salaries.copy()
      question3 df=question3 df.drop(columns=['total payroll'])
      mean_payroll_table=question3_df.groupby(['yearID']).mean()
      std payroll table=question3 df.groupby(['yearID']).std()
      std_payroll_table
      result['standardized payroll']=pd.Series(np.nan, index=result.index)
      for i, row in result.iterrows():
          year = row['yearID']
          if year>=1985 and year <=2014:</pre>
              mean=mean_payroll_table.loc[year, 'team_payroll_mean']
              std = std_payroll_table.loc[year, 'team_payroll_mean']
              team payroll mean = row['team payroll mean']
              std_payroll = (team_payroll_mean-mean)/std
              result.loc[i, 'standardized payroll'] = std payroll
              #print(row['standardized payroll'])
      result
```

```
[21]:
                  yearID
           teamID
                           winning_per
                                             G total_payroll team_payroll_mean \
              ALT
                     1884
                              24.000000
                                          25.0
      0
                                                           NaN
                                                                              NaN
      1
              ANA
                     1997
                             51.851852 162.0
                                                   31135472.0
                                                                     1.004370e+06
      2
              ANA
                     1998
                             52.469136 162.0
                                                   41281000.0
                                                                     1.214147e+06
      3
              ANA
                     1999
                             43.209877 162.0
                                                   55388166.0
                                                                     1.384704e+06
              ANA
                     2000
                             50.617284 162.0
                                                   51464167.0
                                                                     1.715472e+06
      2772
                     1889
                             32.283465 127.0
                                                                              NaN
              WS8
                                                           NaN
      2773
              WS9
                     1891
                             31.654676 139.0
                                                           NaN
                                                                              NaN
      2774
                     1884
                             41.228070
              WSU
                                        114.0
                                                           NaN
                                                                              NaN
      2775
              NYM
                     2014
                                    NaN
                                           NaN
                                                   54806990.0
                                                                     2.283625e+06
      2776
              SFG
                     2014
                                    NaN
                                           NaN
                                                  143510167.0
                                                                     5.315191e+06
            standardized_payroll
      0
                             NaN
      1
                       -0.528661
```

```
2
                       -0.168201
      3
                       -0.181448
      4
                       -0.362224
      2772
                              NaN
      2773
                              NaN
      2774
                              NaN
      2775
                       -0.694316
      2776
                        0.210621
      [2777 rows x 7 columns]
[22]: #Problem 6
      problem6_df = result.copy()
      problem6_df = problem6_df.loc[problem6_df['yearID']>=1990]
      problem6_df = problem6_df.loc[problem6_df['yearID']<=2014]</pre>
      problem6_df=problem6_df.drop(columns=['G','total_payroll','team_payroll_mean'])
      problem6_df.dropna()
[22]:
           teamID
                   yearID
                           winning_per standardized_payroll
      1
              ANA
                     1997
                              51.851852
                                                    -0.528661
      2
              ANA
                     1998
                              52.469136
                                                    -0.168201
      3
              ANA
                     1999
                              43.209877
                                                    -0.181448
      4
                     2000
              ANA
                              50.617284
                                                    -0.362224
      5
                     2001
                              46.296296
                                                    -0.856538
              ANA
      2683
              WAS
                     2010
                              42.592593
                                                    -0.856099
      2684
                     2011
                             49.689441
                                                    -0.774365
              WAS
      2685
              WAS
                     2012
                              60.493827
                                                    -0.623936
                     2013
      2686
              WAS
                              53.086420
                                                     0.536327
      2687
                     2014
              WAS
                              59.259259
                                                    -0.062730
      [728 rows x 4 columns]
[23]: bins = [1989,1994,1999,2004,2009,2015]
      group_names = ['1990-1994','1995-1999','2000-2004','2005-2009','2010-2015']
      #categories = pd.cut(group_table['yearID'],bins,labels=group_names)
      problem6_df['categories'] = pd.cut(problem6_df['yearID'], bins,__
       →labels=group_names)
      problem6_df['categories'].tolist()
      grouped = problem6_df.groupby('categories')
      group1 = grouped.get_group('1990-1994')
      group2 = grouped.get group('1995-1999')
```

group3 = grouped.get\_group('2000-2004')
group4 = grouped.get\_group('2005-2009')

```
group5 = grouped.get_group('2010-2015')
[24]: #Group1
     team list = group1['teamID']
     plot_table=group1.drop(columns=['yearID','categories'])
     plot_table.index=range(1,135)
     plot_table
     plot_table
     dict_team={}
     plt.figure(figsize=(20,10))
     for i, row in plot_table.iterrows():
         team_name = row['teamID']
         if team_name in dict_team:
             plt.
      else:
             a=np.random.rand(3,)
             plt.
      →plot(row['standardized_payroll'],row['winning_per'],marker='o',label=row['teamtD'],color=a)
             dict_team[team_name] = a
     line=np.polyfit(plot_table['standardized_payroll'],plot_table['winning_per'],1)
     p = np.poly1d(line)
     xp=np.linspace(-3, 3, 10)
     yp=p(xp)
     plt.plot(xp,yp)
     plt.legend()
     group1
[24]:
          teamID
                 yearID winning_per standardized_payroll categories
     50
             ATL
                   1990
                           40.123457
                                                -0.513311 1990-1994
     51
             ATL
                   1991
                           58.024691
                                                -0.656737 1990-1994
     52
             ATL
                   1992
                           60.493827
                                                 0.190807 1990-1994
     53
                   1993
             ATL
                           64.197531
                                                 0.908389 1990-1994
     54
             ATL
                   1994
                           59.649123
                                                 1.869895 1990-1994
     2639
             TOR
                   1990
                           53.086420
                                                 1.247239 1990-1994
                                                -0.412027 1990-1994
     2640
             TOR
                   1991
                           56.172840
     2641
             TOR
                   1992
                           59.259259
                                                0.591159 1990-1994
     2642
             TOR
                   1993
                           58.641975
                                                 1.474949 1990-1994
     2643
             TOR.
                   1994
                           47.826087
                                                 1.233851 1990-1994
     [134 rows x 5 columns]
```



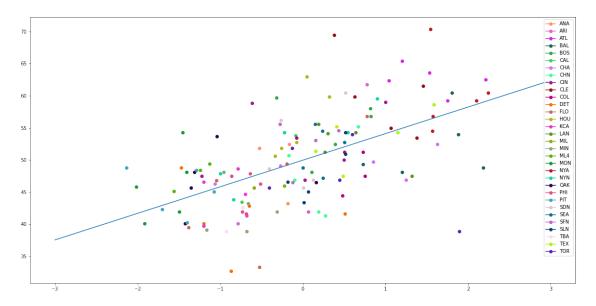
```
[25]: #Group2
      team_list = group2['teamID']
      plot_table=group2.drop(columns=['yearID','categories'])
      plot_table.index=range(1,len(plot_table)+1)
      plot_table
      plot_table
      dict_team={}
      plt.figure(figsize=(20,10))
      for i, row in plot_table.iterrows():
          team_name = row['teamID']
          if team_name in dict_team:

→plot(row['standardized_payroll'],row['winning_per'],marker='o',color=dict_team[team_name])
          else:
              a=np.random.rand(3,)
              plt.

→plot(row['standardized_payroll'],row['winning_per'],marker='o',label=row['team[D'],color=a)
              dict_team[team_name] = a
      line=np.polyfit(plot_table['standardized_payroll'],plot_table['winning_per'],1)
      p = np.poly1d(line)
      xp=np.linspace(-3, 3, 10)
      yp=p(xp)
      plt.plot(xp,yp)
```

```
plt.legend()
```

## [25]: <matplotlib.legend.Legend at 0x7fc6bee58760>

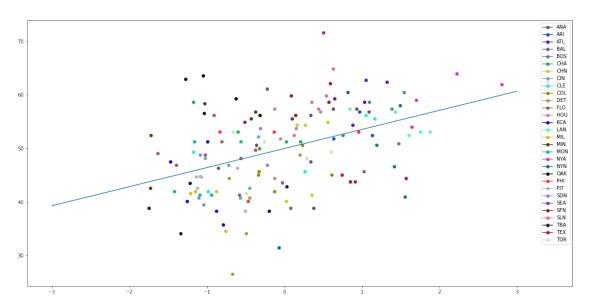


```
[26]: #Group2
      team_list = group3['teamID']
      plot_table=group3.drop(columns=['yearID','categories'])
      plot_table.index=range(1,len(plot_table)+1)
      plot_table
      plot_table
      dict_team={}
      plt.figure(figsize=(20,10))
      for i, row in plot_table.iterrows():
          team_name = row['teamID']
          if team_name in dict_team:
              plt.
       →plot(row['standardized_payroll'],row['winning_per'],marker='o',color=dict_team[team_name])
          else:
              a=np.random.rand(3,)
              plt.

→plot(row['standardized_payroll'],row['winning_per'],marker='o',label=row['team[D'],color=a)
              dict_team[team_name] = a
      line=np.polyfit(plot_table['standardized_payroll'],plot_table['winning_per'],1)
```

```
p = np.poly1d(line)
xp=np.linspace(-3, 3, 10)
yp=p(xp)
plt.plot(xp,yp)
plt.legend()
```

# [26]: <matplotlib.legend.Legend at 0x7fc6bf83eb50>



```
[27]: #Group4
team_list = group4['teamID']
plot_table=group4.drop(columns=['yearID','categories'])
plot_table.index=range(1,len(plot_table)+1)
plot_table

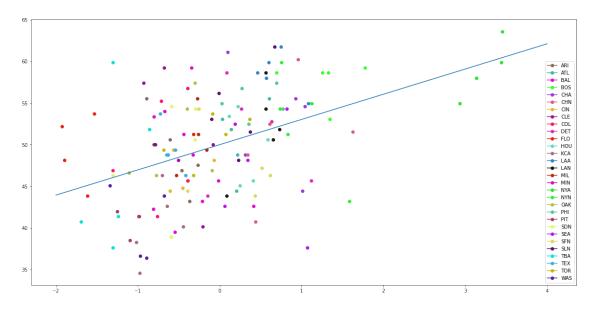
plot_table

plot_table
dict_team={}
plt.figure(figsize=(20,10))
for i, row in plot_table.iterrows():
    team_name = row['teamID']

    if team_name in dict_team:
        plt.
        plot(row['standardized_payroll'],row['winning_per'],marker='o',color=dict_team_name])

    else:
        a=np.random.rand(3,)
```

# [27]: <matplotlib.legend.Legend at 0x7fc6bf9e3bb0>



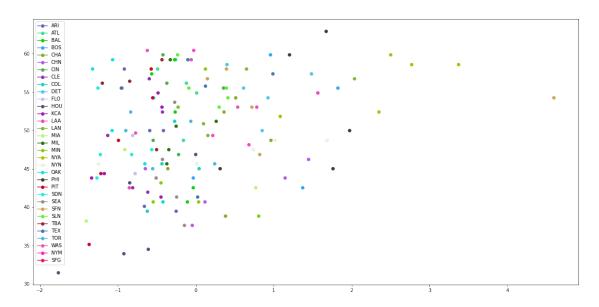
```
[28]: #Group5
    team_list = group5['teamID']
    plot_table=group5.drop(columns=['yearID','categories'])
    plot_table.index=range(1,len(plot_table)+1)
    plot_table

    plot_table

    dict_team={}
    plt.figure(figsize=(20,10))
    for i, row in plot_table.iterrows():
        team_name = row['teamID']

        if team_name in dict_team:
```

#### [28]: <matplotlib.legend.Legend at 0x7fc6c041cee0>



```
[29]: # Question 3

# The plot are very similar to each other, except that the unit of the

→horizontal axis changed a lot.

# By the transformation, we make the standardized_payroll close to 0 within a

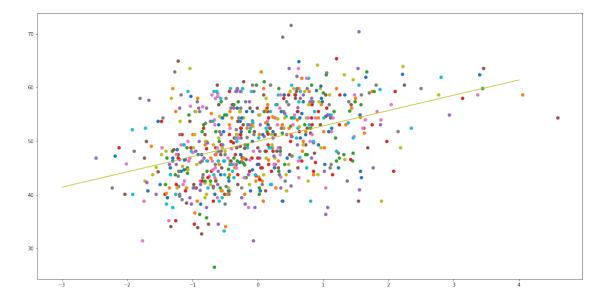
→much smaller range.
```

### [30]: group\_table

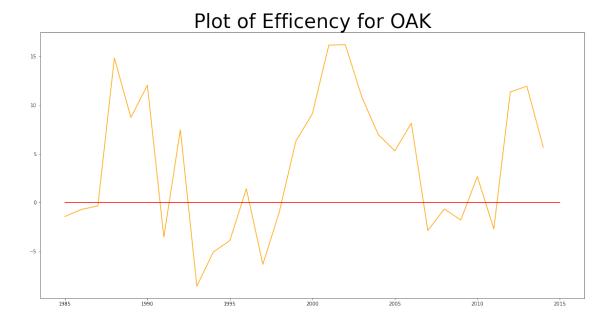
```
[30]:
           teamID
                   yearID
                             payroll_mean winning_percentage categories
      0
              ATL
                      1985
                            673045.454545
                                                           40.0
                                                                        NaN
      1
                      1985
                            525486.909091
                                                           51.0
                                                                        NaN
              BAL
      2
              BOS
                      1985
                            435902.400000
                                                           49.0
                                                                        NaN
      3
                            515281.928571
              CAL
                      1985
                                                           55.0
                                                                        NaN
      4
              CHA
                      1985
                            468865.619048
                                                           52.0
                                                                        NaN
                                                           36.0
      2772
              WS8
                      1887
                                       NaN
                                                                        NaN
      2773
              WS8
                      1888
                                       NaN
                                                           35.0
                                                                        NaN
      2774
                      1889
                                       NaN
                                                           32.0
              WS8
                                                                        NaN
      2775
              WS9
                      1891
                                       NaN
                                                           31.0
                                                                        NaN
      2776
              WSU
                      1884
                                       NaN
                                                           41.0
                                                                        NaN
```

[2777 rows x 5 columns]

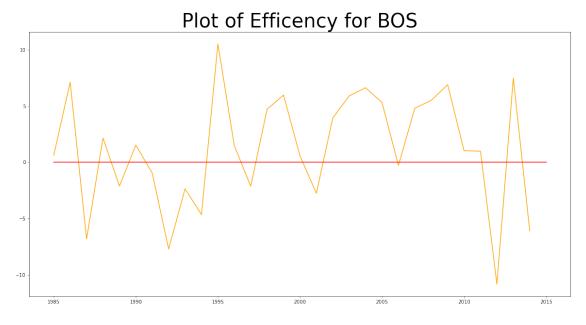
[31]: array([ 2.85310865, 49.9866575 ])



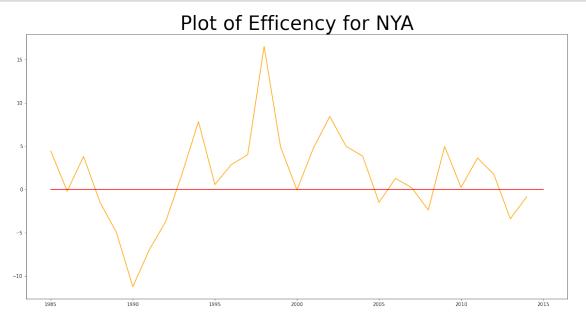
```
[32]: #Problem 8
      result['efficiency']=pd.Series(np.nan, index=result.index)
      for i, row in result.iterrows():
          std_payroll = row['standardized_payroll']
          exp_win_rate=50+2.5*std_payroll
          result.loc[i,'efficiency']=row['winning_per']-exp_win_rate
[33]: result
[33]:
           teamID
                   yearID winning_per
                                             G total_payroll team_payroll_mean \
      0
              ALT
                     1884
                              24.000000
                                          25.0
                                                           NaN
      1
              ANA
                     1997
                              51.851852 162.0
                                                   31135472.0
                                                                     1.004370e+06
      2
              ANA
                     1998
                              52.469136 162.0
                                                   41281000.0
                                                                     1.214147e+06
      3
              ANA
                     1999
                              43.209877 162.0
                                                   55388166.0
                                                                     1.384704e+06
      4
              ANA
                     2000
                              50.617284 162.0
                                                   51464167.0
                                                                     1.715472e+06
      2772
              WS8
                     1889
                              32.283465
                                        127.0
                                                           NaN
                                                                              NaN
      2773
              WS9
                     1891
                              31.654676
                                        139.0
                                                           NaN
                                                                              NaN
      2774
              WSU
                     1884
                              41.228070
                                         114.0
                                                           NaN
                                                                              NaN
      2775
              NYM
                     2014
                                    NaN
                                           NaN
                                                   54806990.0
                                                                     2.283625e+06
      2776
              SFG
                     2014
                                    NaN
                                                  143510167.0
                                                                     5.315191e+06
                                           NaN
            standardized_payroll efficiency
      0
                              NaN
                                          NaN
      1
                       -0.528661
                                     3.173505
      2
                       -0.168201
                                     2.889640
      3
                       -0.181448
                                    -6.336503
      4
                       -0.362224
                                     1.522845
      2772
                                          NaN
                              NaN
      2773
                              NaN
                                          NaN
      2774
                              NaN
                                          NaN
      2775
                       -0.694316
                                          NaN
      2776
                        0.210621
                                          NaN
      [2777 rows x 8 columns]
[34]: # Team OAK
      plt.figure(figsize=(20,10))
      temp set = result.loc[result['teamID']=='OAK']
      temp_set=temp_set.dropna()
      plt.plot(temp_set['yearID'],temp_set['efficiency'],color='orange')
      plt.title("Plot of Efficency for OAK", fontsize=40)
      plt.plot([1985,2015],[0,0],color='red')
      plt.show()
```



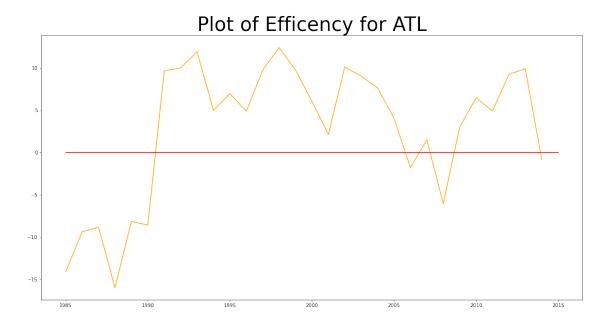
```
[35]: # Team BOS
plt.figure(figsize=(20,10))
temp_set = result.loc[result['teamID']=='BOS']
temp_set=temp_set.dropna()
plt.plot(temp_set['yearID'],temp_set['efficiency'],color='orange')
plt.title("Plot of Efficency for BOS", fontsize=40)
plt.plot([1985,2015],[0,0],color='red')
plt.show()
```



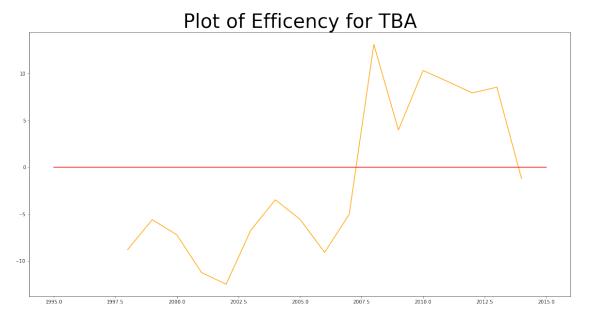
```
[36]: # Team NYA
plt.figure(figsize=(20,10))
temp_set = result.loc[result['teamID']=='NYA']
temp_set=temp_set.dropna()
plt.plot(temp_set['yearID'],temp_set['efficiency'],color='orange')
plt.title("Plot of Efficency for NYA", fontsize=40)
plt.plot([1985,2015],[0,0],color='red')
plt.show()
```



```
[37]: # Team ATL
plt.figure(figsize=(20,10))
temp_set = result.loc[result['teamID']=='ATL']
temp_set=temp_set.dropna()
plt.plot(temp_set['yearID'],temp_set['efficiency'],color='orange')
plt.title("Plot of Efficency for ATL", fontsize=40)
plt.plot([1985,2015],[0,0],color='red')
plt.show()
```

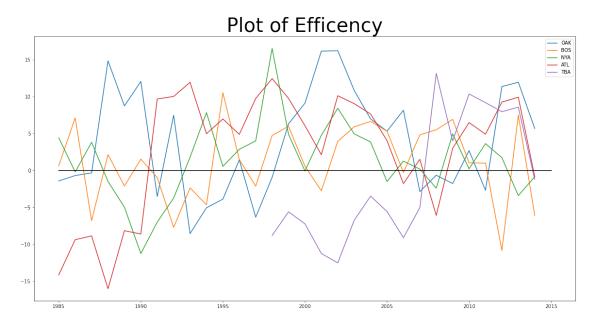


```
[38]: # Team TBA
plt.figure(figsize=(20,10))
temp_set = result.loc[result['teamID']=='TBA']
temp_set=temp_set.dropna()
plt.plot(temp_set['yearID'],temp_set['efficiency'],color='orange')
plt.title("Plot of Efficency for TBA", fontsize=40)
plt.plot([1995,2015],[0,0],color='red')
plt.show()
```



```
[39]: plt.figure(figsize=(20,10))
      temp_set = result.loc[result['teamID']=='OAK']
      temp_set=temp_set.dropna()
      plt.plot(temp_set['yearID'],temp_set['efficiency'],label='OAK')
      temp_set = result.loc[result['teamID']=='BOS']
      temp_set=temp_set.dropna()
      plt.plot(temp_set['yearID'],temp_set['efficiency'],label='BOS')
      temp_set = result.loc[result['teamID']=='NYA']
      temp set=temp set.dropna()
      plt.plot(temp_set['yearID'],temp_set['efficiency'],label='NYA')
      temp set = result.loc[result['teamID']=='ATL']
      temp_set=temp_set.dropna()
      plt.plot(temp_set['yearID'],temp_set['efficiency'],label='ATL')
      temp_set = result.loc[result['teamID']=='TBA']
      temp_set=temp_set.dropna()
      plt.plot(temp_set['yearID'],temp_set['efficiency'],label='TBA')
      plt.title("Plot of Efficency", fontsize=40)
      plt.plot([1985,2015],[0,0],color='black')
      plt.legend()
```

[39]: <matplotlib.legend.Legend at 0x7fc6c2964c70>



```
[40]: # Question 4:

# The plot is much more direct on showing whether a team's payroll is efficient → or not compared to the plot in problem 2 and 3.
```

# It seems from the plot that the efficiency of OAK is high on 1987 to 1992 and  $\rightarrow$  1997 to 2005, and the conclusion is more persuasive than the conclusion from  $\rightarrow$  problem 2 and 3.