CMSC320_P2_Shuo_Wang

March 19, 2022

[243]:
```
import sqlite3
import pandas
import matplotlib.pyplot as plt
import numpy as np
```

Part 1:

Problem 1:

[244]:
```
sqlite_file = 'lahman2014.sqlite'
conn = sqlite3.connect(sqlite_file)

# use sql to get data
salary_query = "SELECT yearID, teamID, sum(salary) as total_payroll FROM␣
↪Salaries GROUP BY yearID, teamID"
team_info_query = "SELECT yearID, teamID, franchID, W, L, G FROM Teams GROUP BY␣
↪yearID, teamID"

# generate dataframe from sql
team_salaries = pandas.read_sql(salary_query, conn)
team_info = pandas.read_sql(team_info_query, conn)

#calculating winning percentage
team_info["Winnig_Percentage"] = team_info["W"]/team_info["G"]*100
```

[245]:
```
#inner join(merge) two tables by "yearID", "teamID".
team_relation = pandas.merge(team_info, team_salaries, on = ["yearID",␣
↪"teamID"] )
```

[246]:
```
team_relation
```

[246]:
```
      yearID teamID franchID   W   L    G  Winnig_Percentage  total_payroll
0       1985    ATL      ATL  66  96  162          40.740741     14807000.0
1       1985    BAL      BAL  83  78  161          51.552795     11560712.0
2       1985    BOS      BOS  81  81  163          49.693252     10897560.0
3       1985    CAL      ANA  90  72  162          55.555556     14427894.0
4       1985    CHA      CHW  85  77  163          52.147239      9846178.0
..       …      …        …  ..  ..    …                  …              …
```

```
853     2014     SLN       STL   90   72   162           55.555556     120693000.0
854     2014     TBA       TBD   77   85   162           47.530864      72689100.0
855     2014     TEX       TEX   67   95   162           41.358025     112255059.0
856     2014     TOR       TOR   83   79   162           51.234568     109920100.0
857     2014     WAS       WSN   96   66   162           59.259259     131983680.0

[858 rows x 8 columns]
```

SQL code for creating this relation :

join_query = “SELECT yearID, teamID, franchID, W, L, G FROM Teams INNER JOIN Salaries”

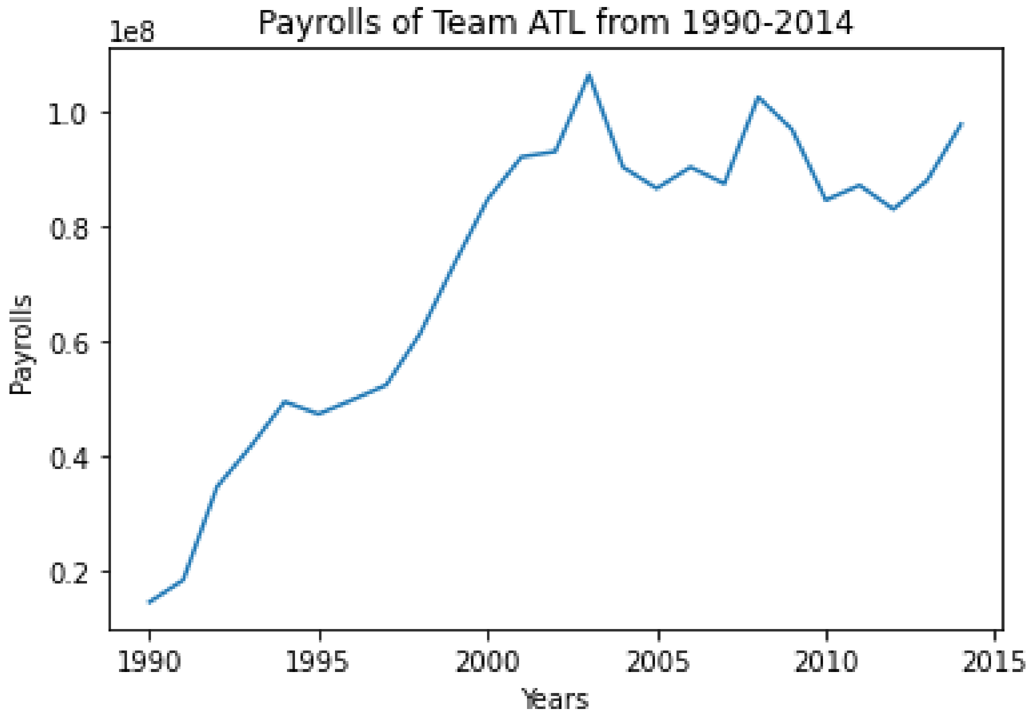
team = pandas.read_sql(join_query, conn)

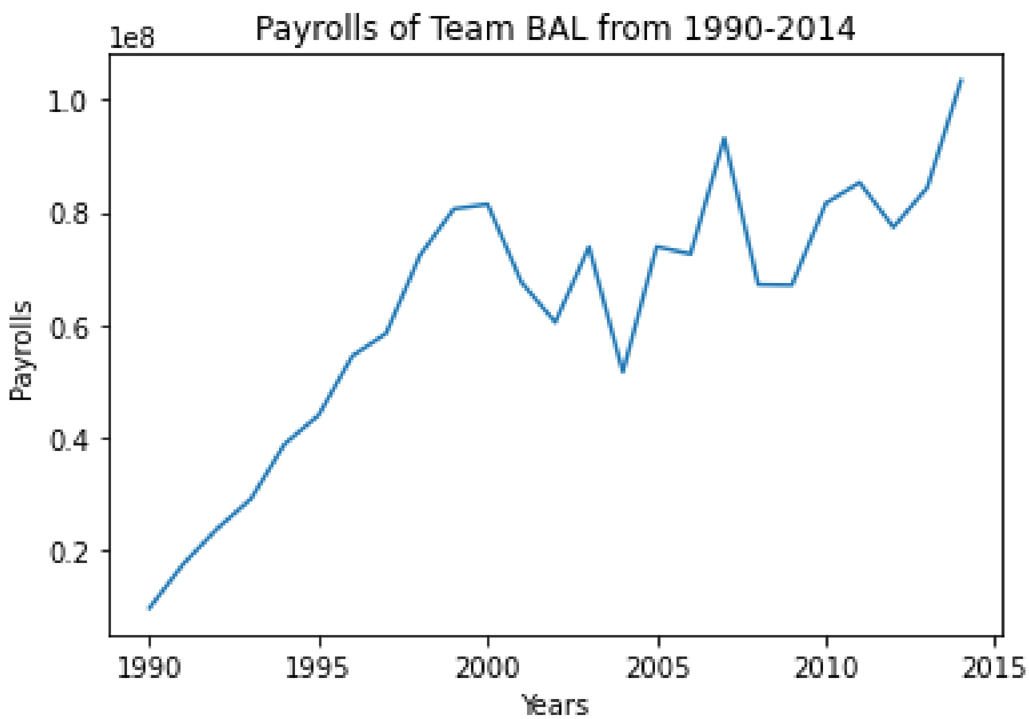
To avoid additional empty data(like some yearID and TeamID appear only in one table not the other), we use inner join to get mutual dataset. Using inner join based on the yearID and teamID to combine two tables: team_info and team_salaries. Thus, all data in the dataframe can be connected without unpaired data. In that way, we can clean the missing data.

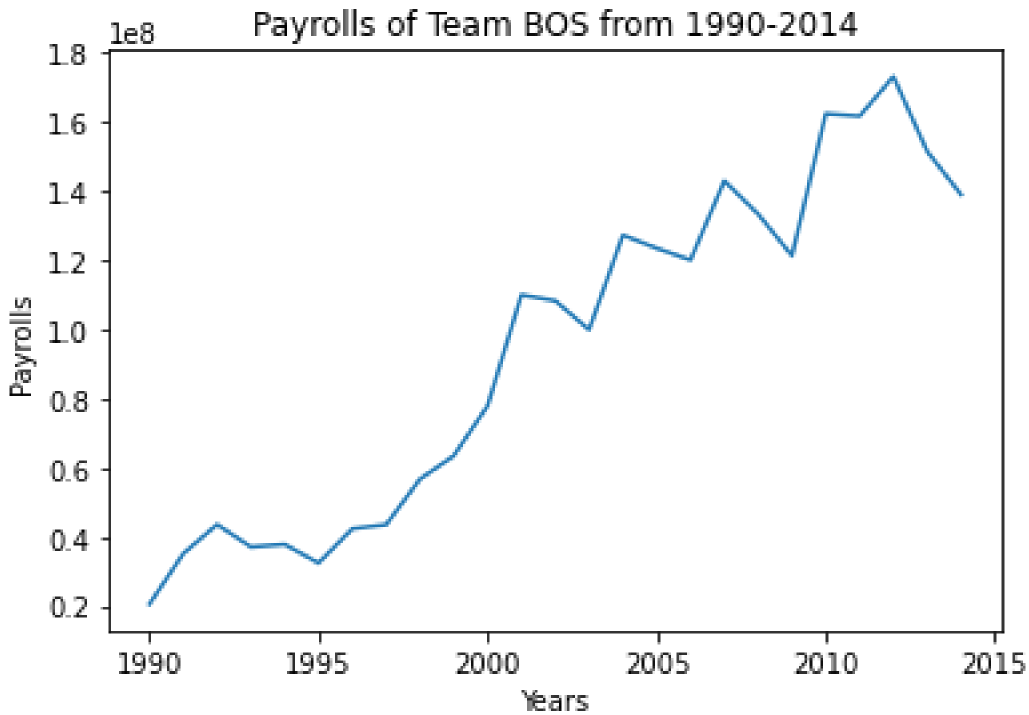
Part 2:

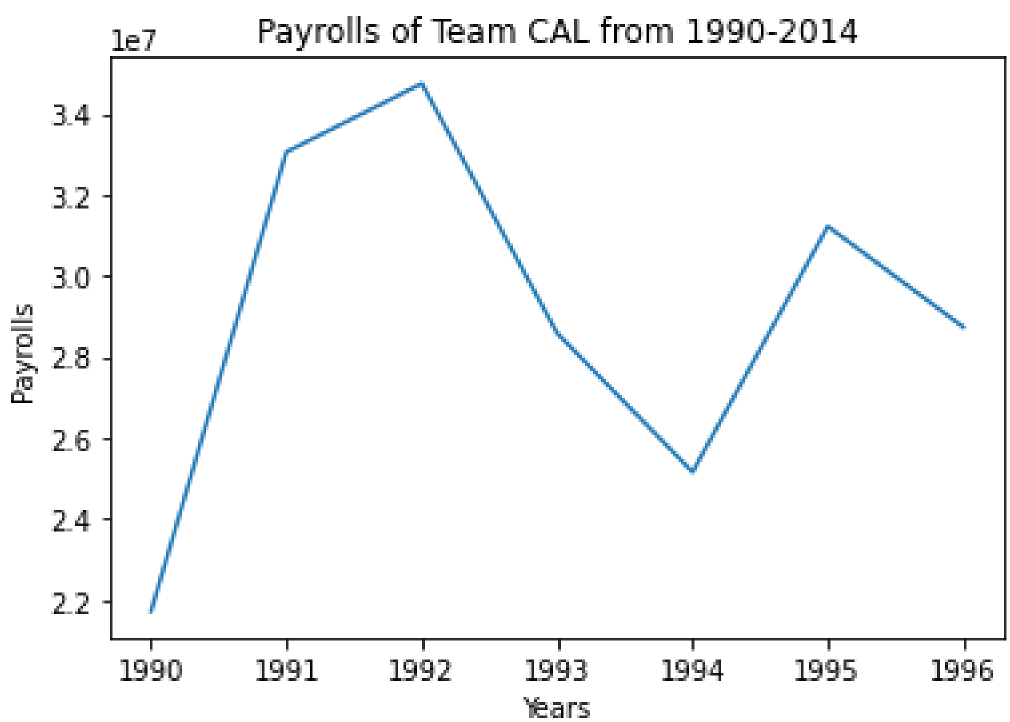
Problem 2:

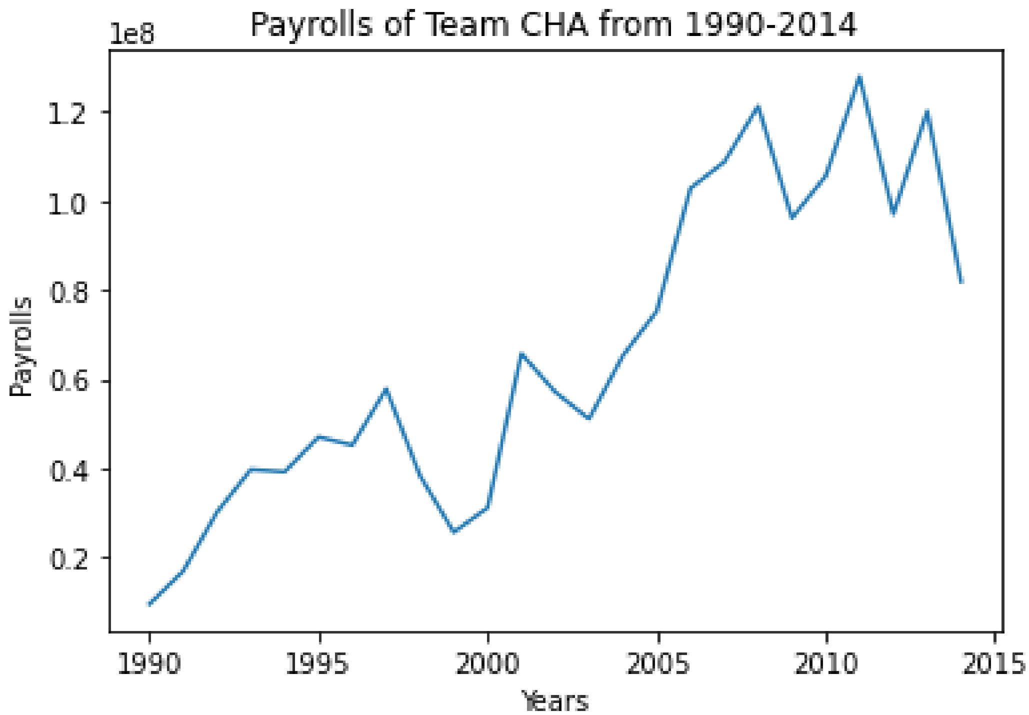
[247]:
```
year = []
payroll = []
team_name = pandas.unique(team_relation["teamID"])

#iterate through names and each element, add data to year list and payroll list.
for name in team_name:
    year.clear()
    payroll.clear()
    for x in range(0,858):
        if result.iat[x,1] == name and result.iat[x,0] >= 1990 and result.
 ↪iat[x,0] <= 2014:
            year.append(team_relation.iat[x,0])
            payroll.append(team_relation.iat[x,7])
    #label
    plt.title("Payrolls of Team " + name + " from 1990-2014")
    plt.xlabel("Years")
    plt.ylabel("Payrolls")
    #plot
    plt.plot(year, payroll)
    plt.show()
```

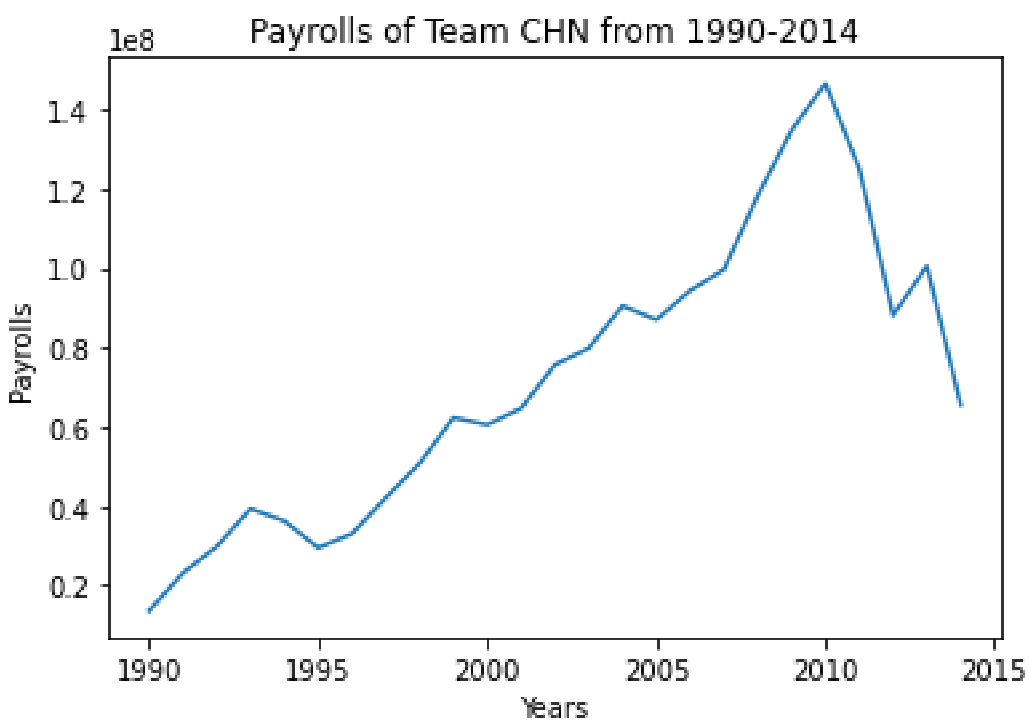

Payrolls of Team ATL from 1990-2014
1e8
1.0
0.8
0.6
0.4
0.2
Payrolls
1990
1995
2000
2005
2010
2015
Years

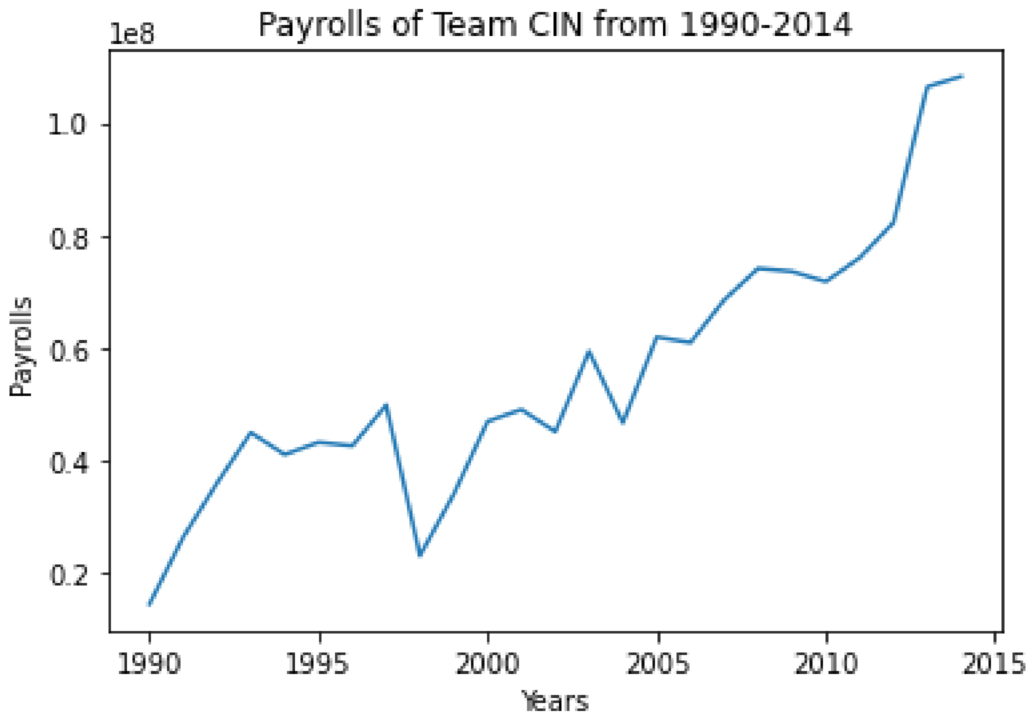

Payrolls of Team BAL from 1990-2014
1e8
1.0
0.8
0.6
0.4
0.2
Payrolls
1990
1995
2000
2005
2010
2015
Years

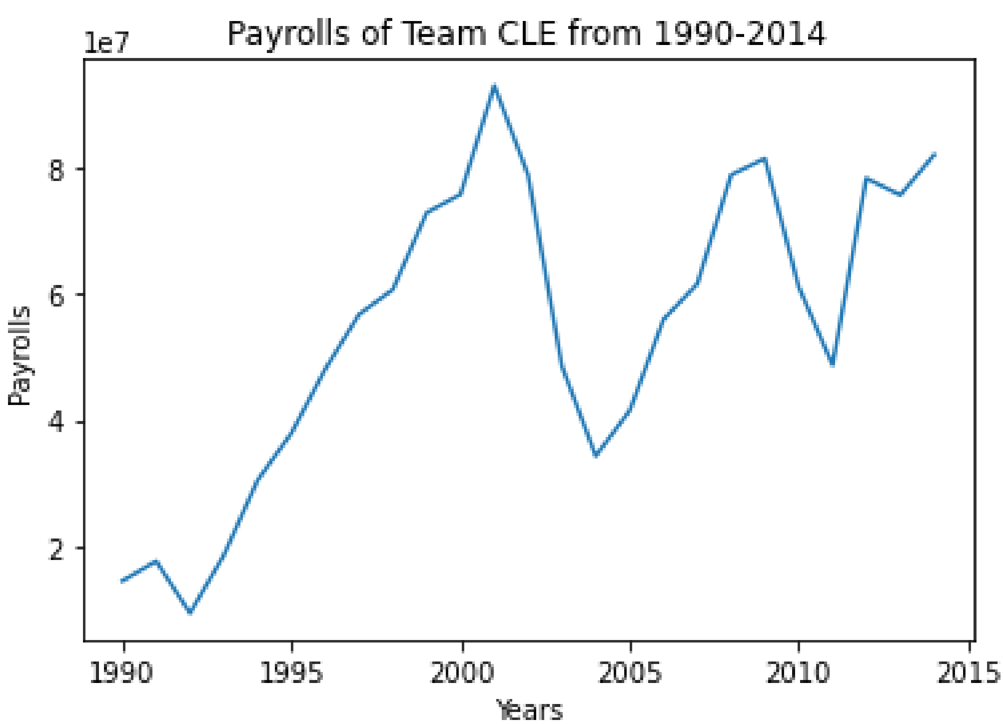

Payrolls of Team BOS from 1990-2014
1e8
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
Payrolls
1990
1995
2000
2005
2010
2015
Years

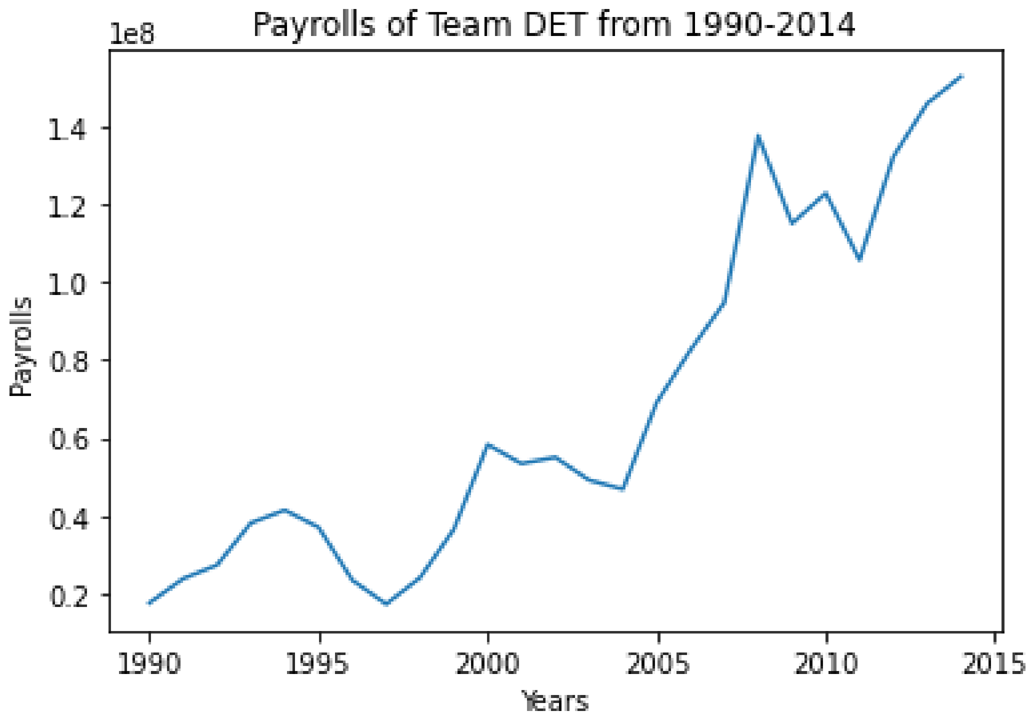

Payrolls of Team CAL from 1990-2014
1e7
3.4
3.2
3.0
2.8
2.6
2.4
2.2
Payrolls
1990
1991
1992
1993
1994
1995
1996
Years

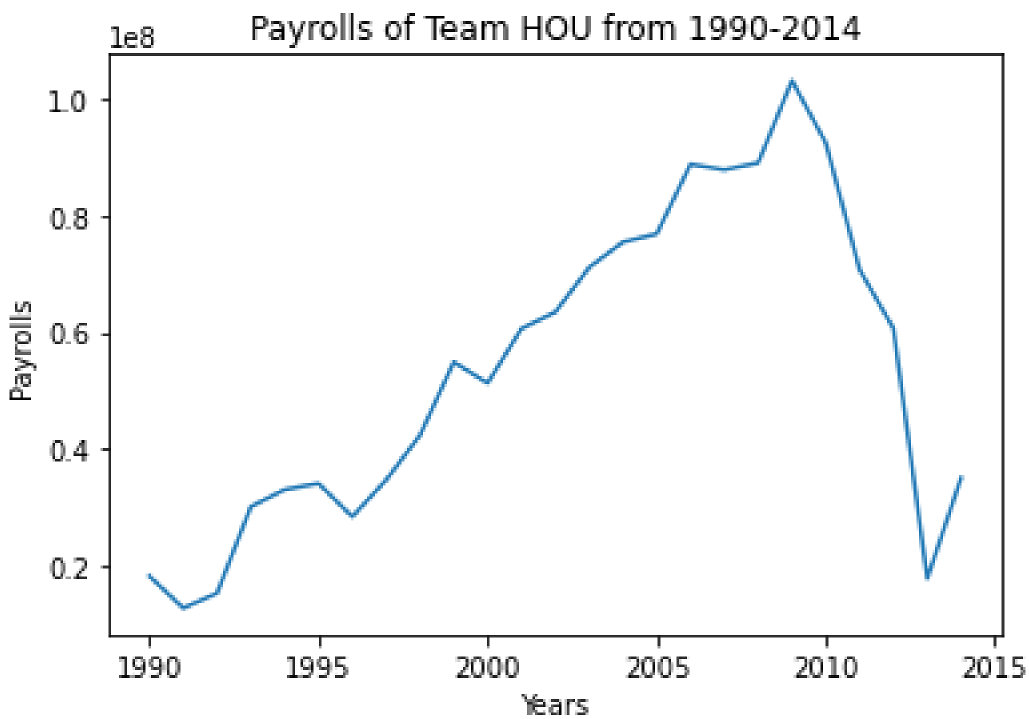

Payrolls of Team CHA from 1990-2014
1e8
1.2
1.0
0.8
0.6
0.4
0.2
Payrolls
1990
1995
2000
2005
2010
2015
Years

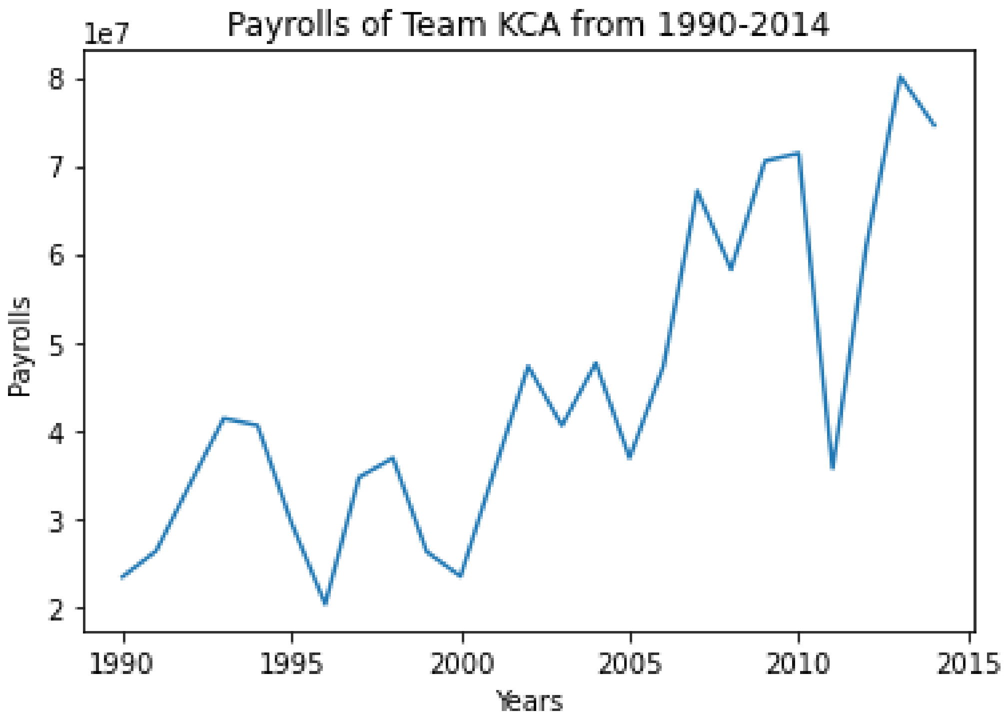

Payrolls of Team CHN from 1990-2014
1e8
1.4
1.2
1.0
0.8
0.6
0.4
0.2
Payrolls
1990
1995
2000
2005
2010
2015
Years


Payrolls of Team CIN from 1990-2014
1e8
1.0
0.8
0.6
0.4
0.2
Payrolls
1990
1995
2000
2005
2010
2015
Years

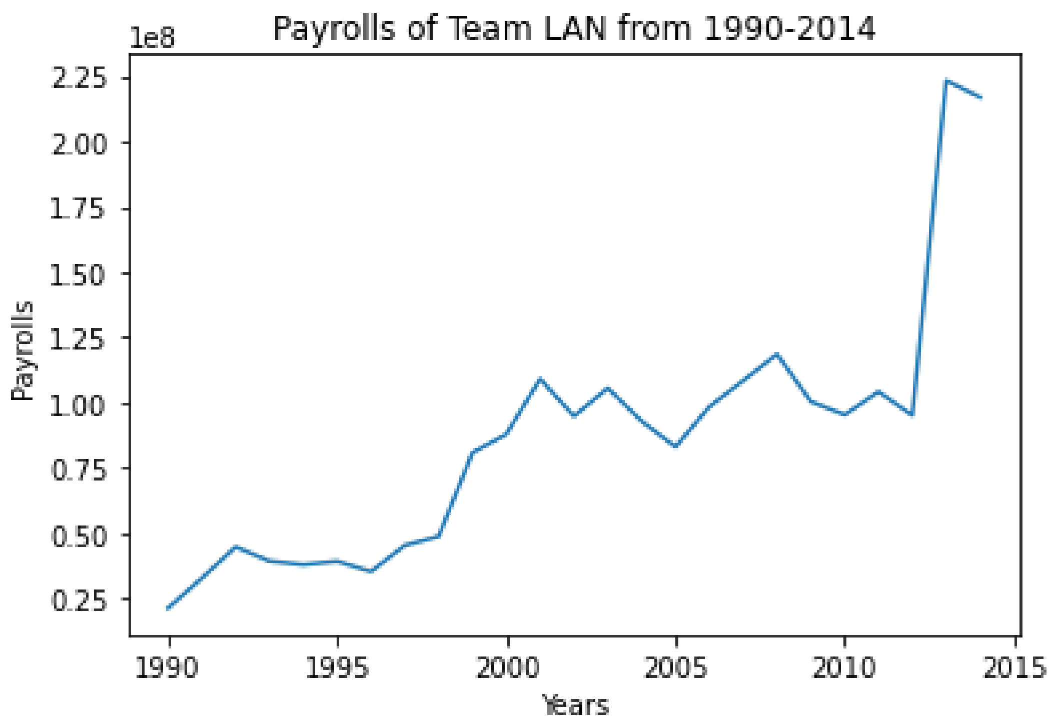

Payrolls of Team CLE from 1990-2014
1e7
8
6
4
2
Payrolls
1990
1995
2000
2005
2010
2015
Years


Payrolls of Team DET from 1990-2014
1e8
1.4
1.2
1.0
0.8
0.6
0.4
0.2
Payrolls
1990
1995
2000
2005
2010
2015
Years

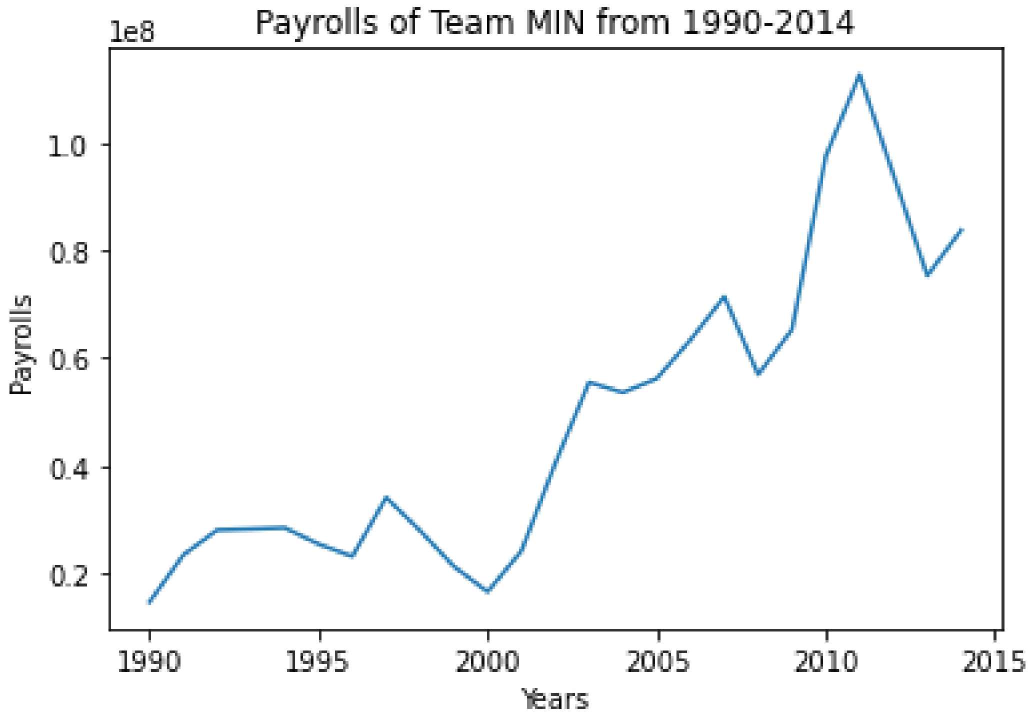

Payrolls of Team HOU from 1990-2014
1e8
1.0
0.8
0.6
0.4
0.2
Payrolls
1990
1995
2000
2005
2010
2015
Years

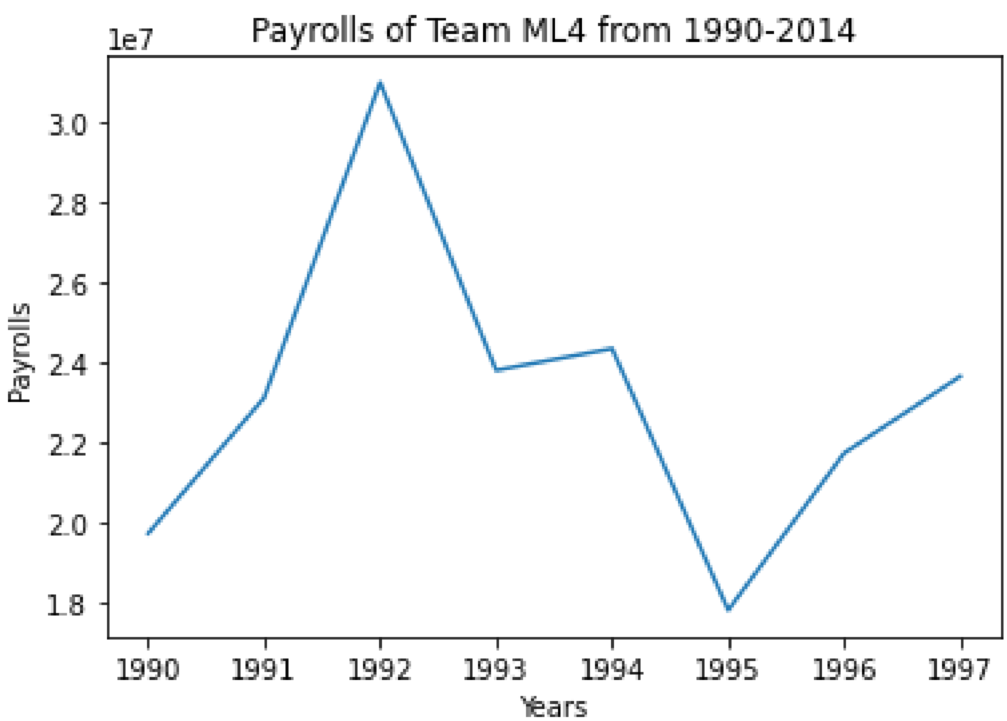


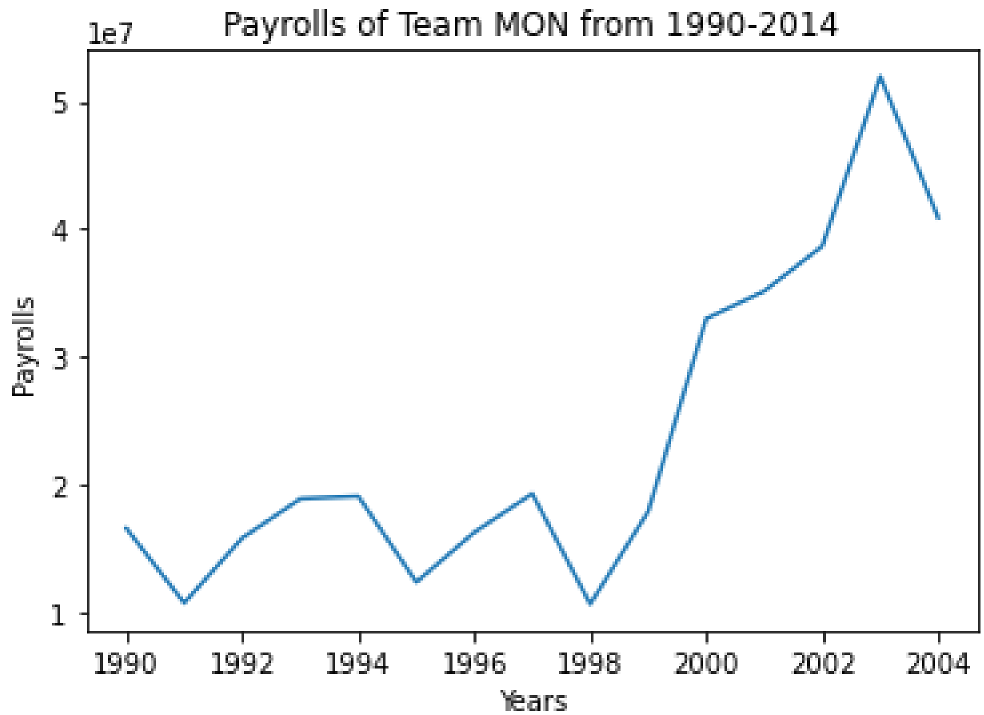
Payrolls of Team KCA from 1990-2014
1e7
8
7
6
5
4
3
2
Payrolls
1990
1995
2000
2005
2010
2015
Years

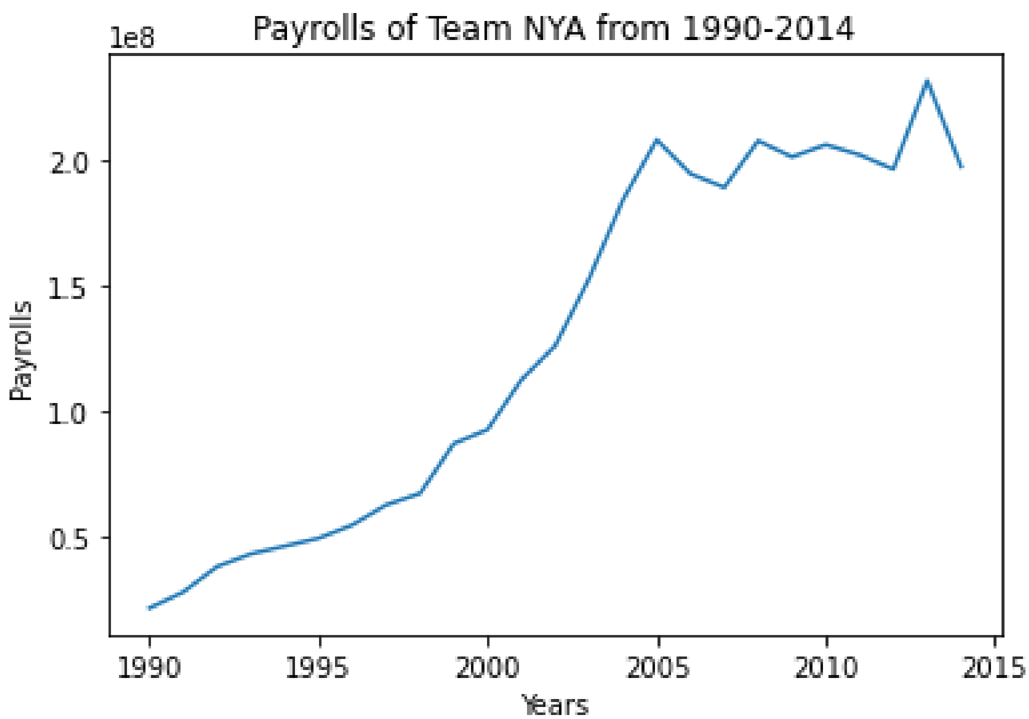


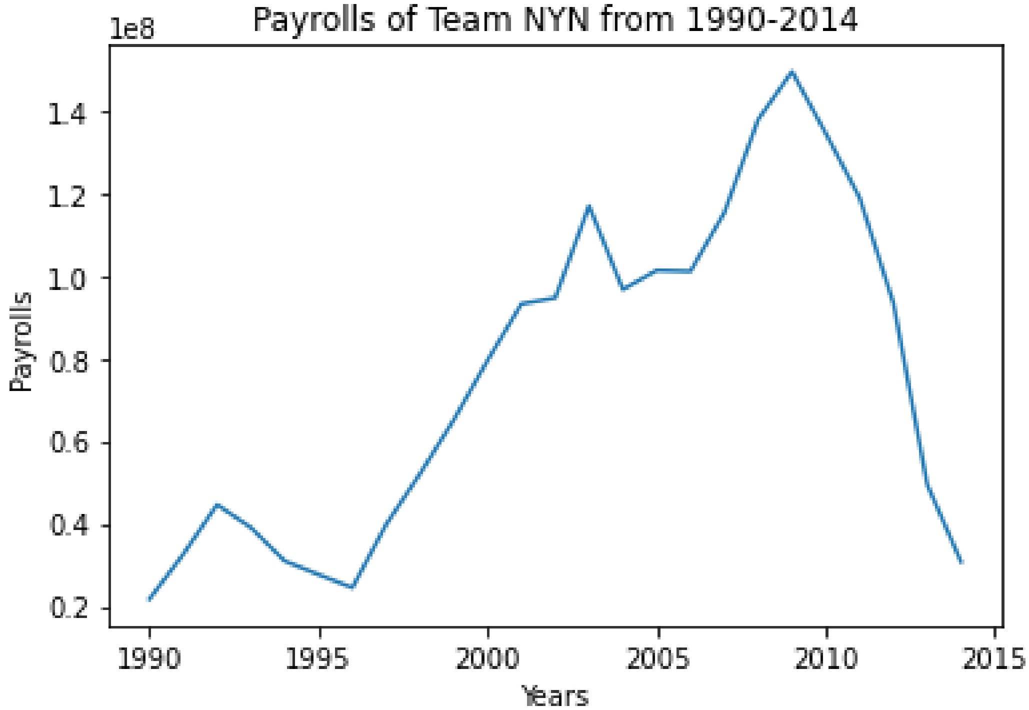
Payrolls of Team LAN from 1990-2014
1e8
2.25
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
Payrolls
1990
1995
2000
2005
2010
2015
Years


Payrolls of Team MIN from 1990-2014
1e8
1.0
0.8
0.6
0.4
0.2
Payrolls
1990
1995
2000
2005
2010
2015
Years

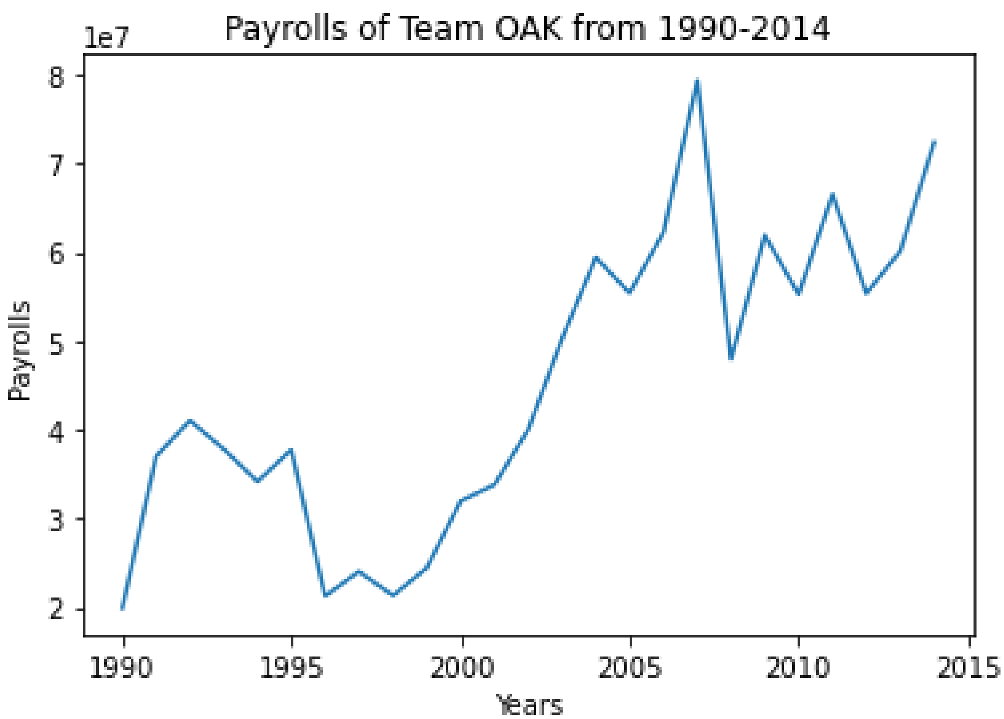

Payrolls of Team ML4 from 1990-2014
1e7
3.0
2.8
2.6
2.4
2.2
2.0
1.8
Payrolls
1990
1991
1992
1993
1994
1995
1996
1997
Years


Payrolls of Team MON from 1990-2014
1e7
5
4
3
2
1
Payrolls
1990
1992
1994
1996
1998
2000
2002
2004
Years

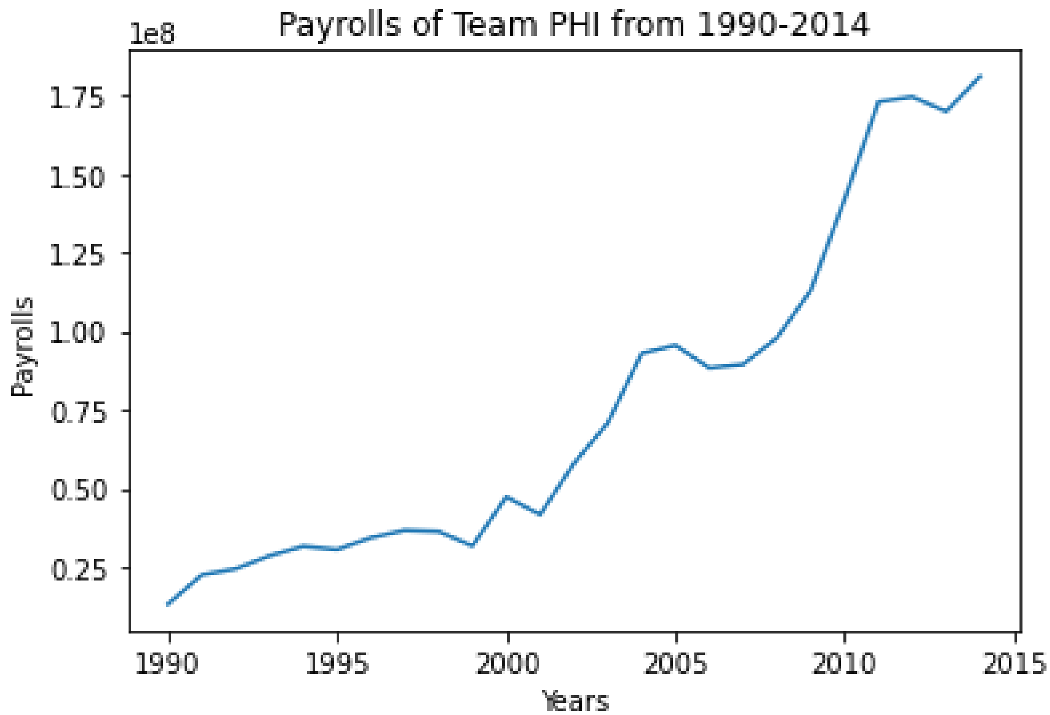

Payrolls of Team NYA from 1990-2014
1e8
2.0
1.5
1.0
0.5
Payrolls
1990
1995
2000
2005
2010
2015
Years

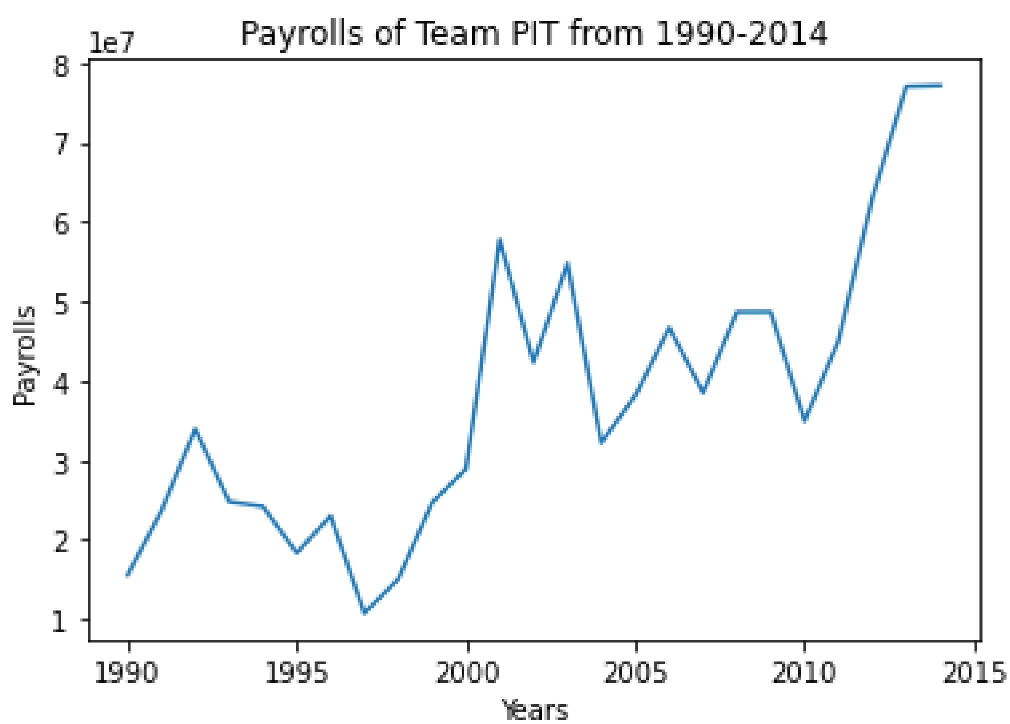


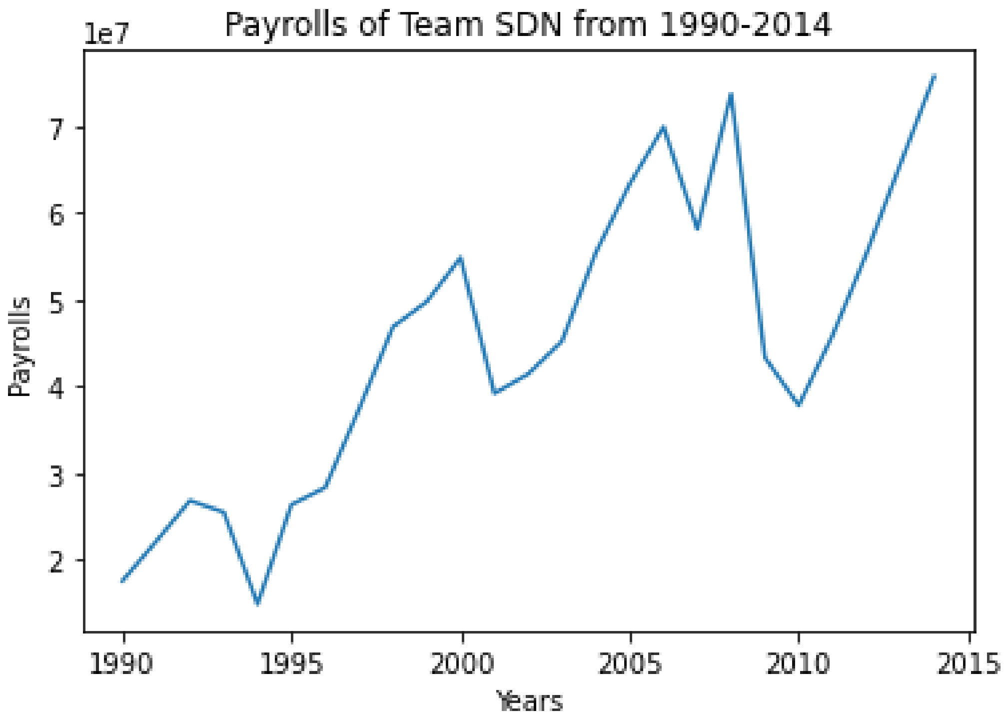
Payrolls of Team NYN from 1990-2014
1e8
1.4
1.2
1.0
0.8
0.6
0.4
0.2
Payrolls
1990
1995
2000
2005
2010
2015
Years

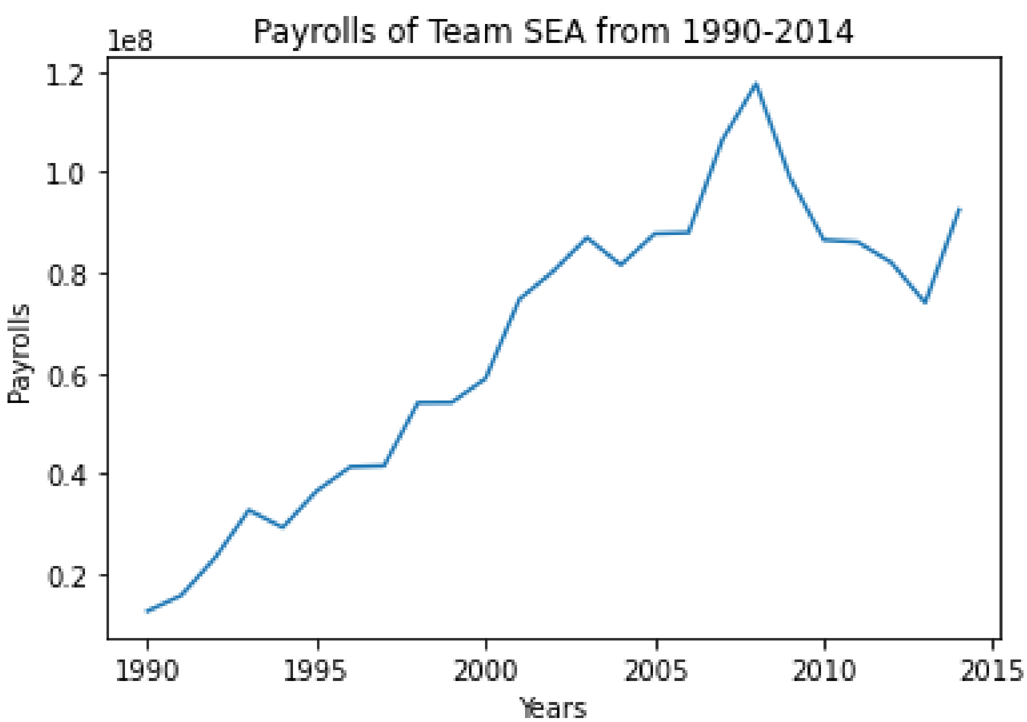


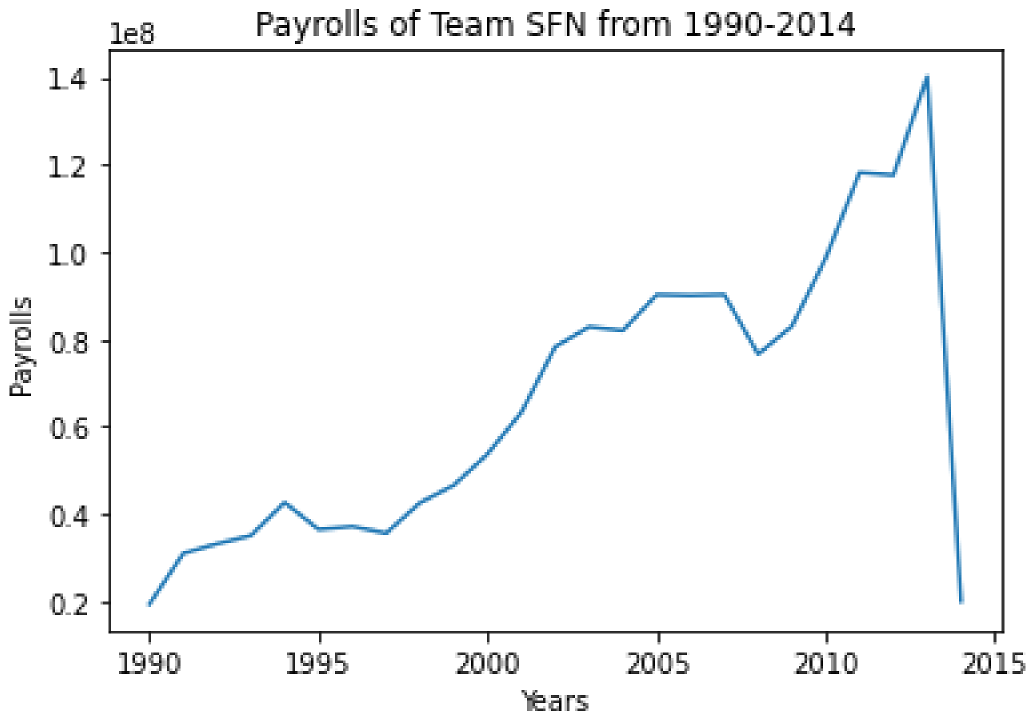
Payrolls of Team OAK from 1990-2014
1e7
8
7
6
5
4
3
2
Payrolls
1990
1995
2000
2005
2010
2015
Years

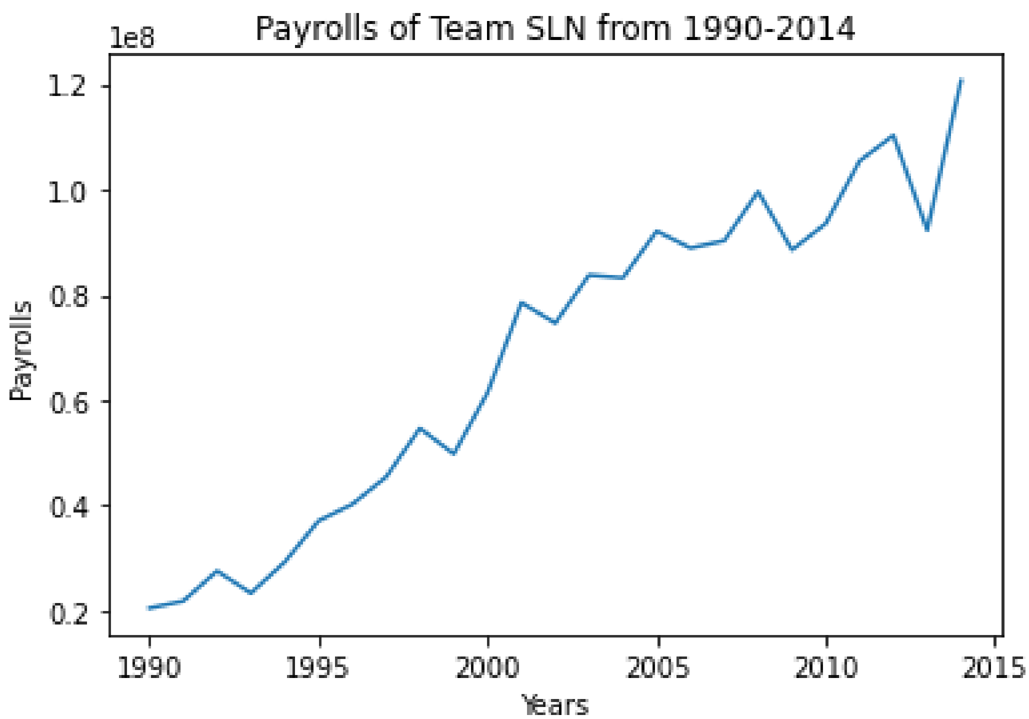

Payrolls of Team PHI from 1990-2014
1e8
1.75
1.50
1.25
1.00
0.75
0.50
0.25
Payrolls
1990
1995
2000
2005
2010
2015
Years

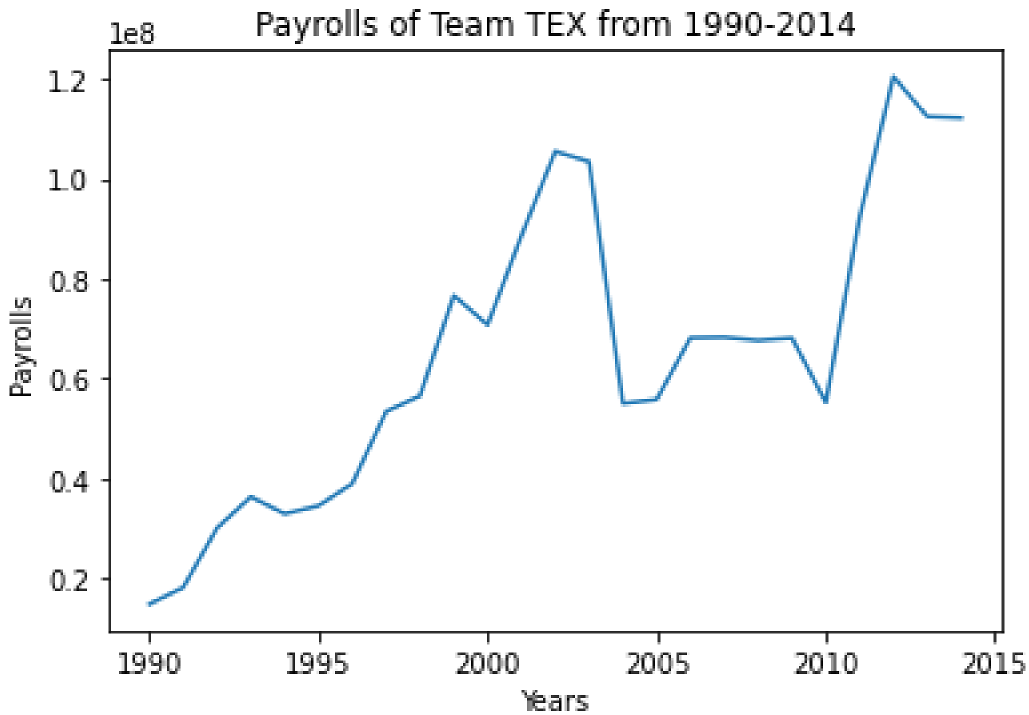

Payrolls of Team PIT from 1990-2014
1e7
8
7
6
5
4
3
2
1
Payrolls
1990
1995
2000
2005
2010
2015
Years

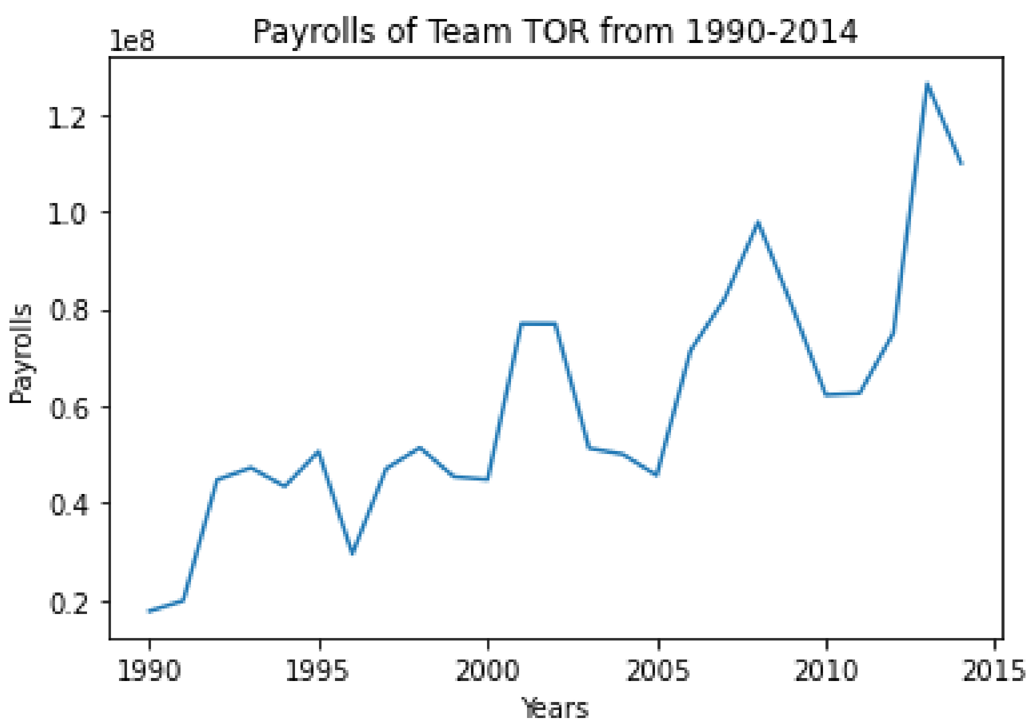

Payrolls of Team SDN from 1990-2014
1e7
7
6
5
4
3
2
Payrolls
1990
1995
2000
2005
2010
2015
Years

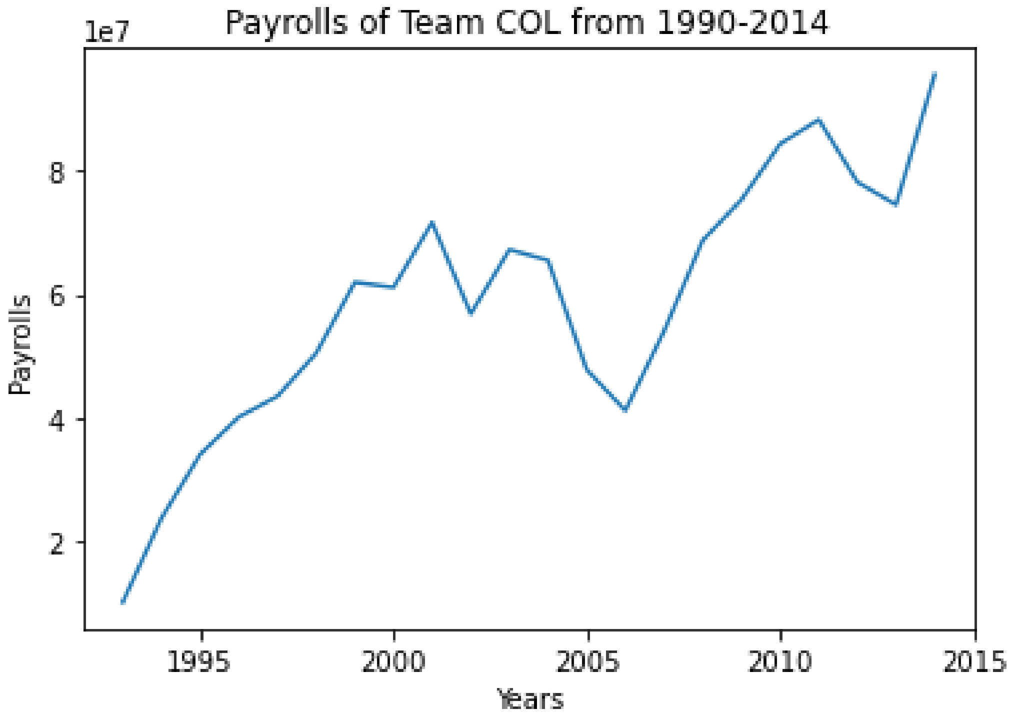

Payrolls of Team SEA from 1990-2014
1e8
1.2
1.0
0.8
0.6
0.4
0.2
Payrolls
1990
1995
2000
2005
2010
2015
Years

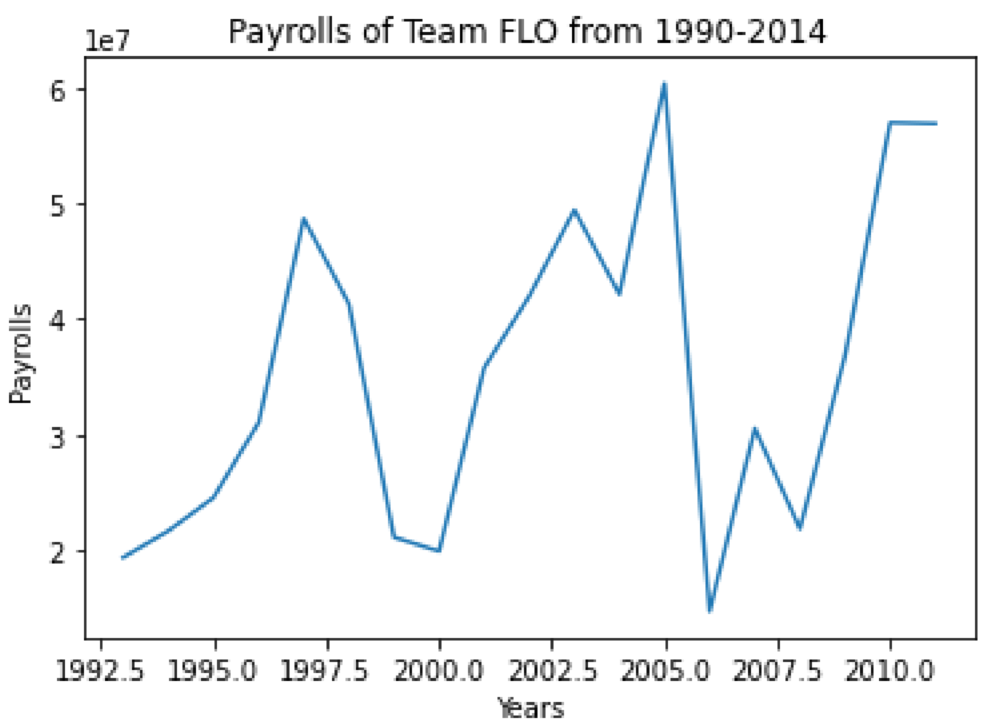

Payrolls of Team SFN from 1990-2014
1e8
1.4
1.2
1.0
0.8
0.6
0.4
0.2
Payrolls
1990
1995
2000
2005
2010
2015
Years

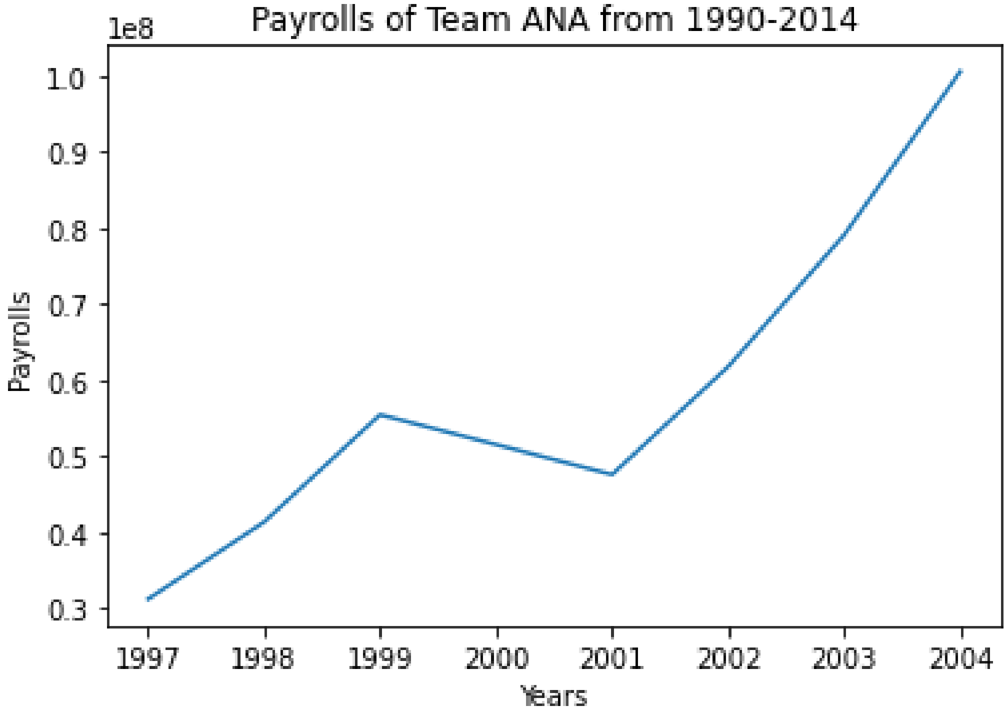

Payrolls of Team SLN from 1990-2014
1e8
1.2
1.0
0.8
0.6
0.4
0.2
Payrolls
1990
1995
2000
2005
2010
2015
Years

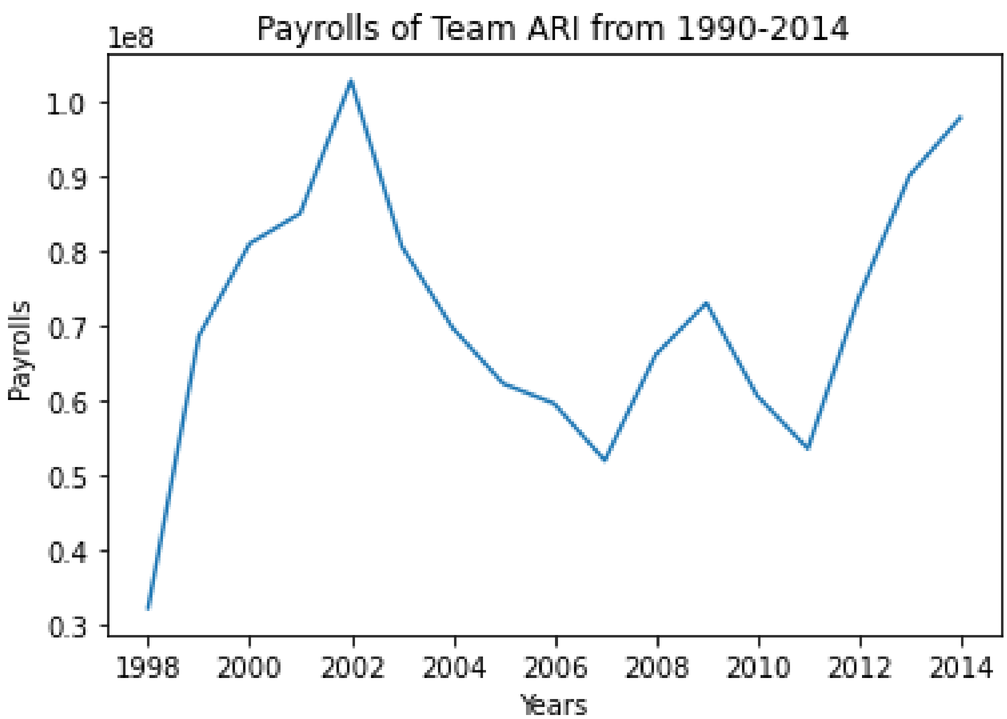

Payrolls of Team TEX from 1990-2014
1e8
1.2
1.0
0.8
0.6
0.4
0.2
Payrolls
1990
1995
2000
2005
2010
2015
Years

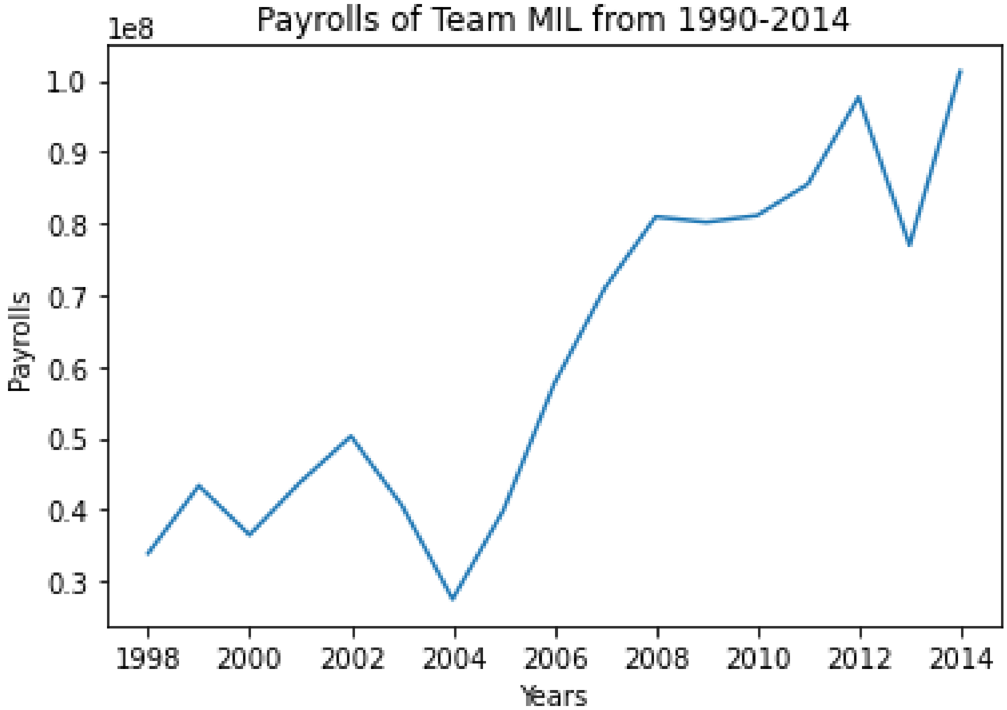

Payrolls of Team TOR from 1990-2014
1e8
1.2
1.0
0.8
0.6
0.4
0.2
Payrolls
1990
1995
2000
2005
2010
2015
Years


Payrolls of Team COL from 1990-2014
1e7
Payrolls
2
4
6
8
1995
2000
2005
2010
2015
Years

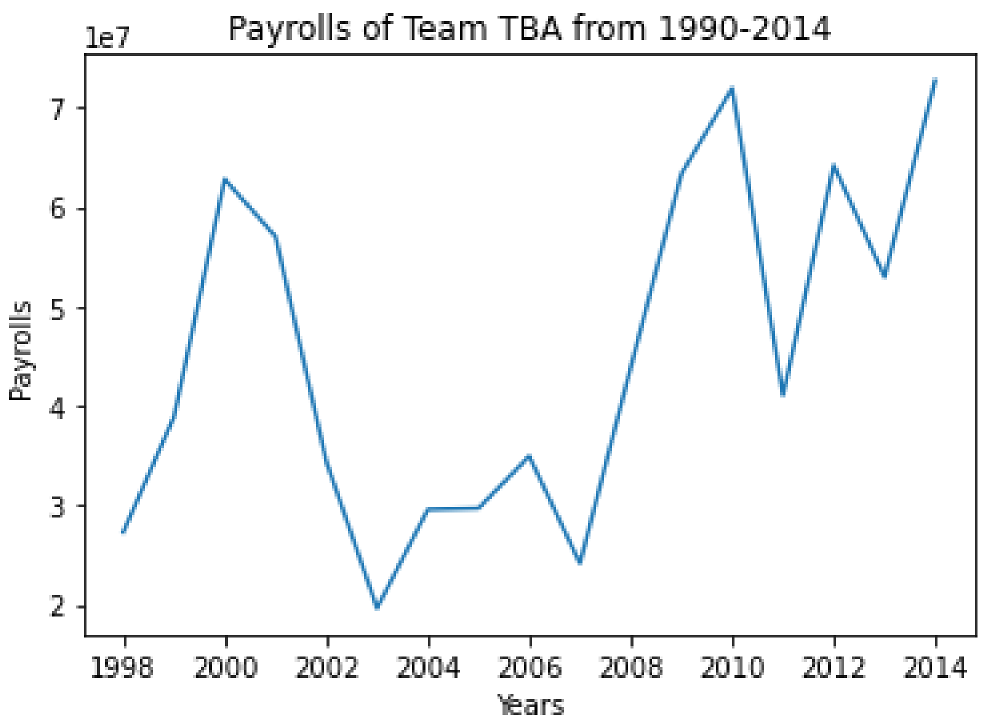

Payrolls of Team FLO from 1990-2014
1e7
Payrolls
2
3
4
5
6
1992.5
1995.0
1997.5
2000.0
2002.5
2005.0
2007.5
2010.0
Years


Payrolls of Team ANA from 1990-2014
1e8
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
Payrolls
1997
1998
1999
2000
2001
2002
2003
2004
Years

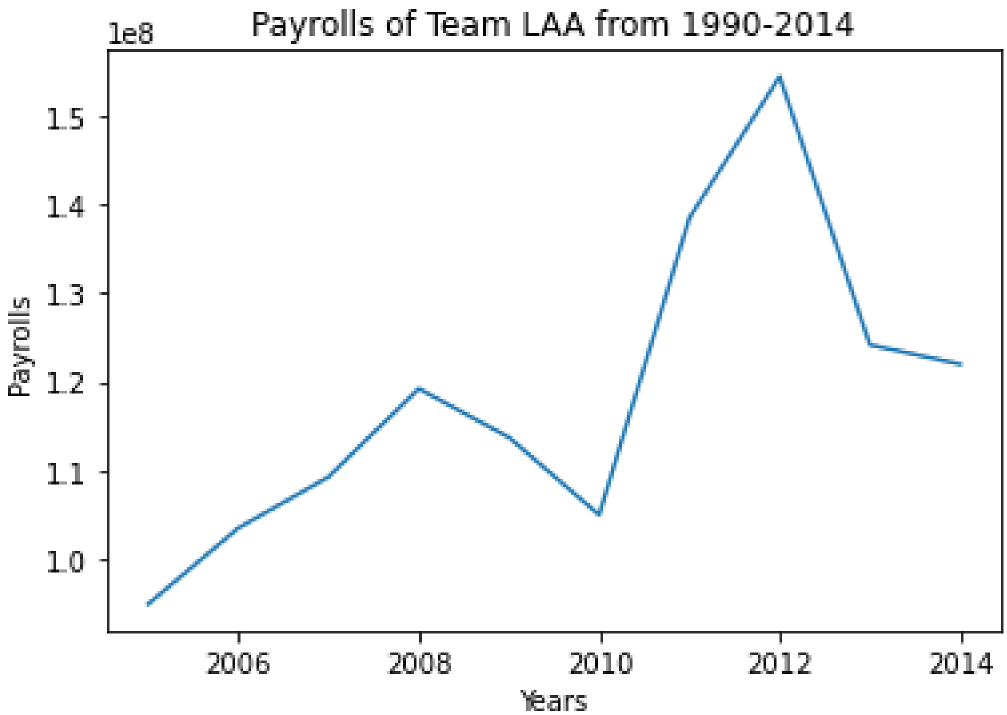

Payrolls of Team ARI from 1990-2014
1e8
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
Payrolls
1998
2000
2002
2004
2006
2008
2010
2012
2014
Years

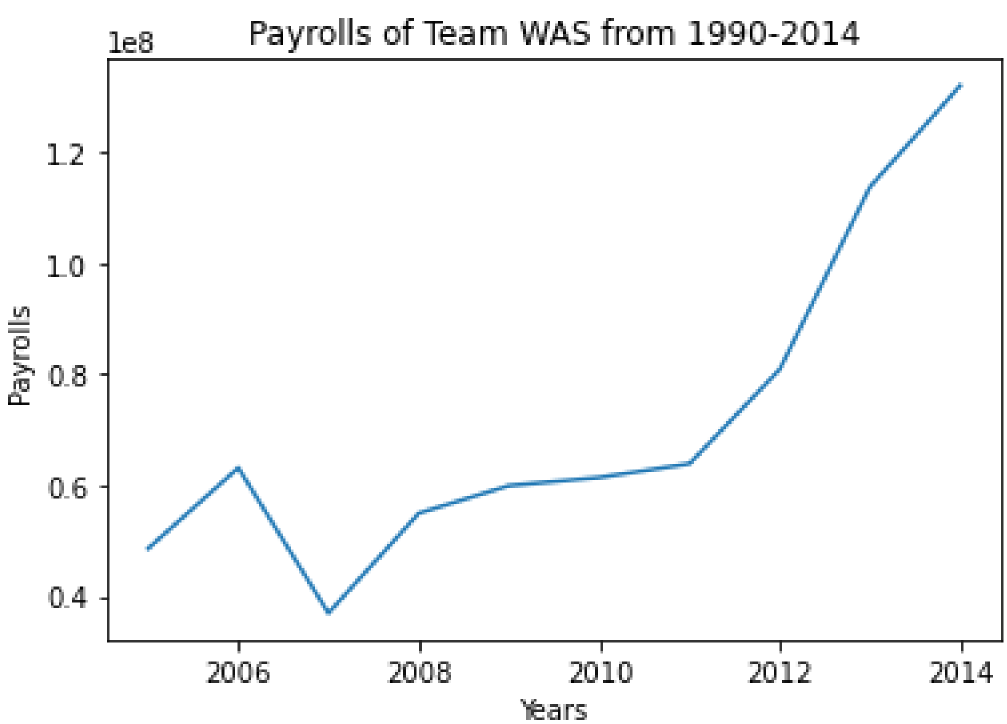


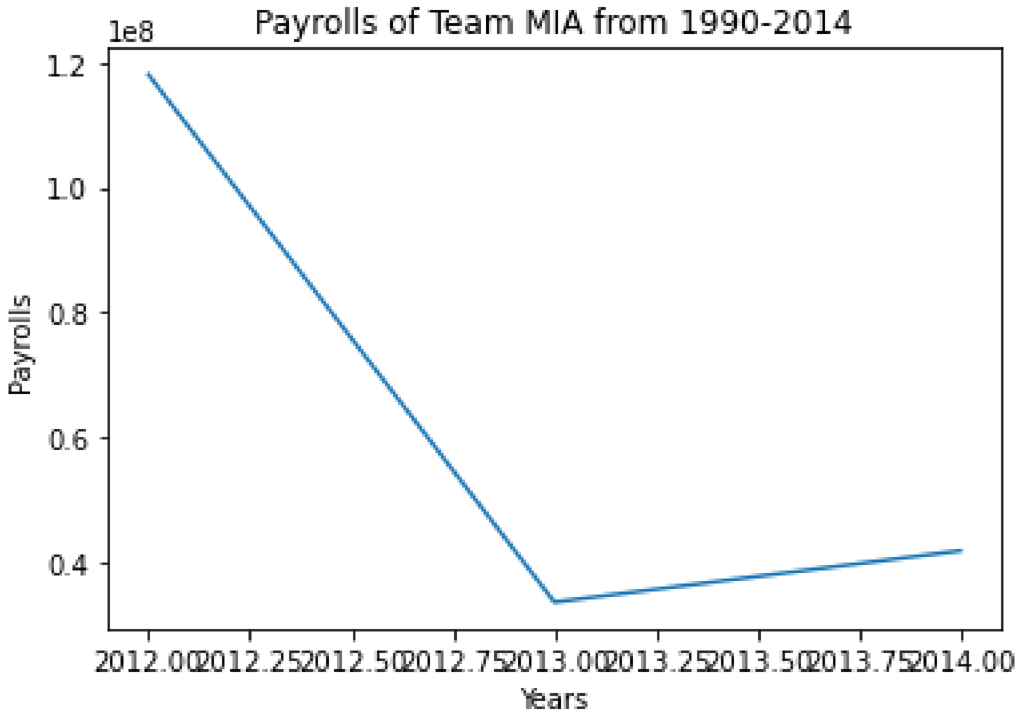
Payrolls of Team MIL from 1990-2014
1e8
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
Payrolls
1998
2000
2002
2004
2006
2008
2010
2012
2014
Years



Payrolls of Team TBA from 1990-2014
1e7
7
6
5
4
3
2
Payrolls
1998
2000
2002
2004
2006
2008
2010
2012
2014
Years


Payrolls of Team LAA from 1990-2014
1e8
1.5
1.4
1.3
1.2
1.1
1.0
Payrolls
2006
2008
2010
2012
2014
Years


Payrolls of Team WAS from 1990-2014
1e8
1.2
1.0
0.8
0.6
0.4
Payrolls
2006
2008
2010
2012
2014
Years



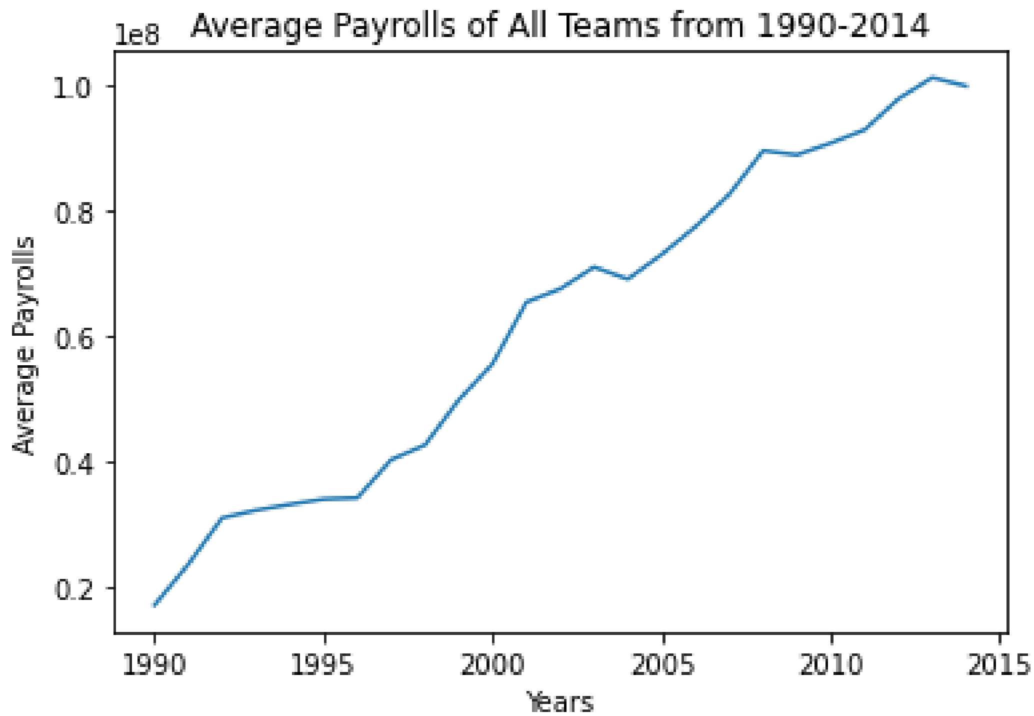
Question 1:

There is a trend for payrolls to increase over time(from 1990 to 2014).

Problem 3:

[248]:
```
year = list(range(1990, 2015, 1))
payroll = []
team_name = pandas.unique(team_relation["teamID"])
avg_payroll = []

#Iterate through years and each element, add data payroll list.
#Then calculate the average of each year, and add to avg_payroll.
#reset payroll for next iteration.
for y in year:
    for x in range(0,858):
        if team_relation.iat[x,0] == y:
            payroll.append(team_relation.iat[x,7])
    avg_payroll.append([np.average(np.array(payroll))])
    payroll.clear()
#label
plt.title("Average Payrolls of All Teams from 1990-2014")
plt.xlabel("Years")
plt.ylabel("Average Payrolls")
#plot
```

```python
plt.plot(year, avg_payroll)
plt.show()
```



[249]:
```python
#Create new column "bins"
team_relation["bins"] = pandas.cut(team_relation["yearID"],  5)
team_relation
```

[249]:
```
     yearID teamID franchID   W   L    G  Winnig_Percentage  total_payroll  \
0      1985    ATL      ATL  66  96  162          40.740741     14807000.0
1      1985    BAL      BAL  83  78  161          51.552795     11560712.0
2      1985    BOS      BOS  81  81  163          49.693252     10897560.0
3      1985    CAL      ANA  90  72  162          55.555556     14427894.0
4      1985    CHA      CHW  85  77  163          52.147239      9846178.0
..      …      …        …  ..  ..   …                 …              …
853    2014    SLN      STL  90  72  162          55.555556    120693000.0
854    2014    TBA      TBD  77  85  162          47.530864     72689100.0
855    2014    TEX      TEX  67  95  162          41.358025    112255059.0
856    2014    TOR      TOR  83  79  162          51.234568    109920100.0
857    2014    WAS      WSN  96  66  162          59.259259    131983680.0

                  bins
0    (1984.971, 1990.8]
1    (1984.971, 1990.8]
```

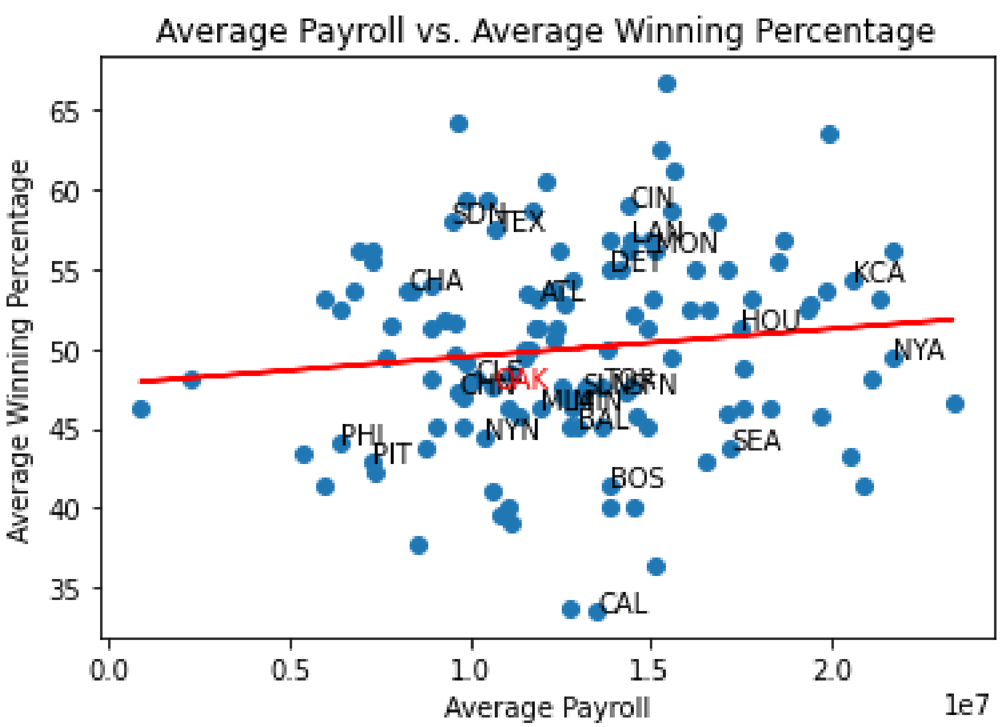
```
2    (1984.971, 1990.8]
3    (1984.971, 1990.8]
4    (1984.971, 1990.8]
..                  …
853     (2008.2, 2014.0]
854     (2008.2, 2014.0]
855     (2008.2, 2014.0]
856     (2008.2, 2014.0]
857     (2008.2, 2014.0]

[858 rows x 9 columns]
```

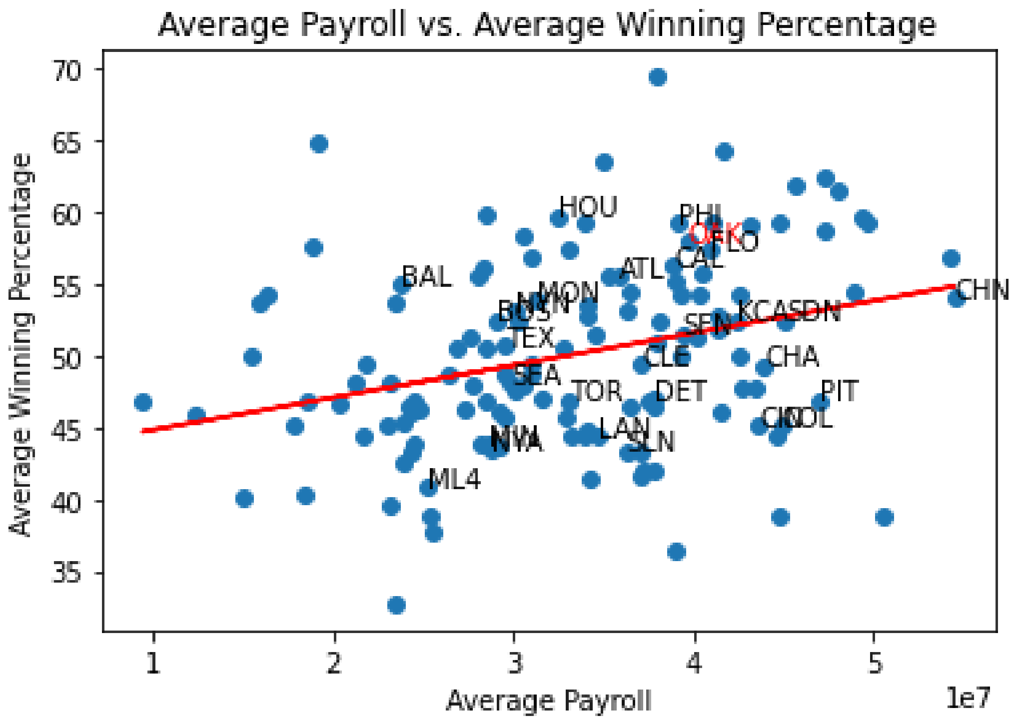
Problem 4:

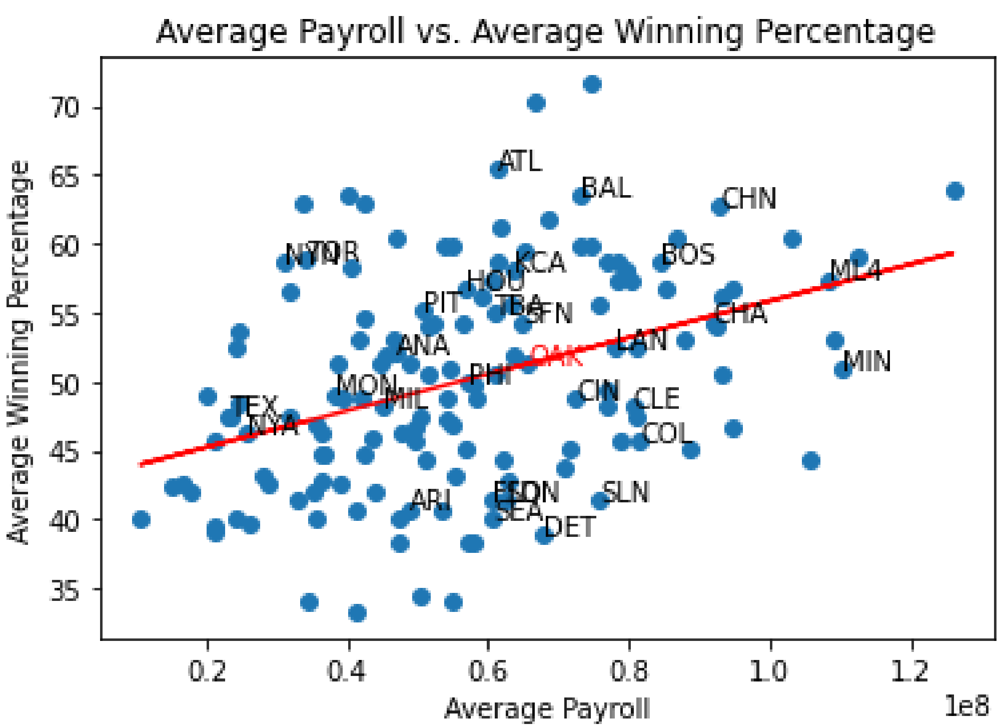
[250]:
```
bin = pandas.unique(team_relation["bins"])
#Create an empty dictionary
bin_dict = {}

#iterate through each element, using bin as a first key, nameId as second key␣
↪to store Payroll and Winning Percentage.
for i in range(0,858):
    if team_relation.iat[i,8] in bin_dict:
        if team_relation.iat[i,1] in bin_dict[team_relation.iat[i,8]]:
            bin_dict[team_relation.iat[i,8]][team_relation.iat[i,1]].
↪append((team_relation.iat[i,7],team_relation.iat[i,6]))
        else :
            bin_dict[team_relation.iat[i,8]][team_relation.iat[i,1]] = []
    else:
        bin_dict[team_relation.iat[i,8]] = {}
```

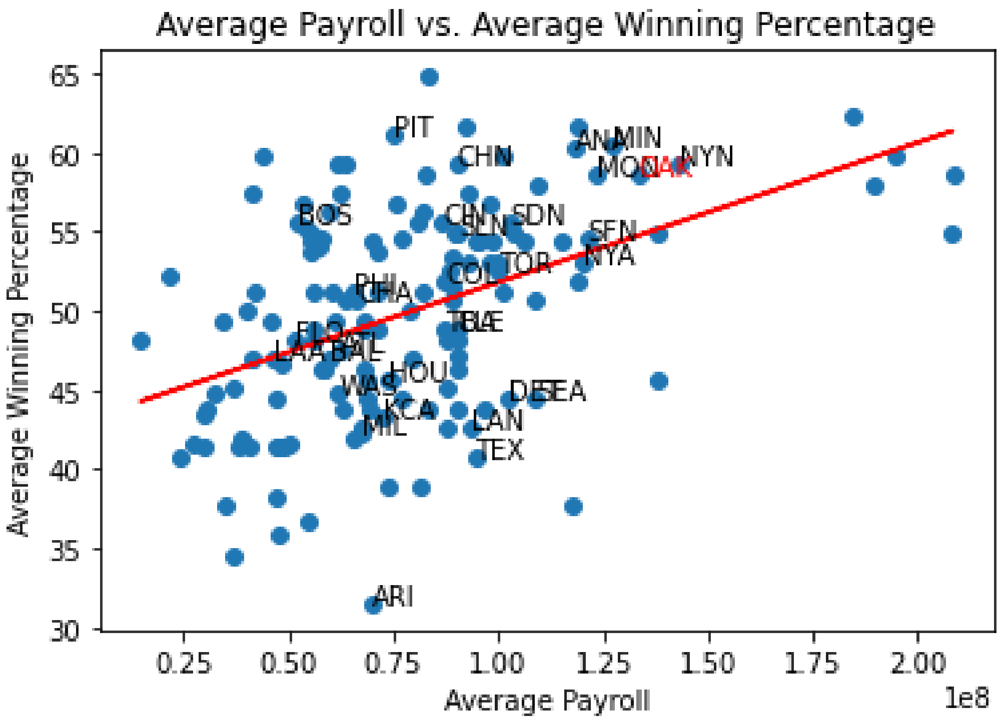
[251]:
```
avg_payroll = []
avg_winpercent = []
annotations = []

#iterate through each element, using bin as a first key, nameId as second key␣
↪to get Payroll and Winning Percentage.
#Store Payroll and Winning Percentage's average value in avg_payroll and␣
↪avg_winpercent respectively.
for keys in bin_dict:
    plt.clf()
    for names in bin_dict[keys]:
        annotations.append(names)
        for element in bin_dict[keys][names]:
            avg_payroll.append(np.average(np.array(element[0])))
            avg_winpercent.append(np.average(np.array(element[1])))
    #label and polt scatter graph
    plt.title("Average Payroll vs. Average Winning Percentage")
```

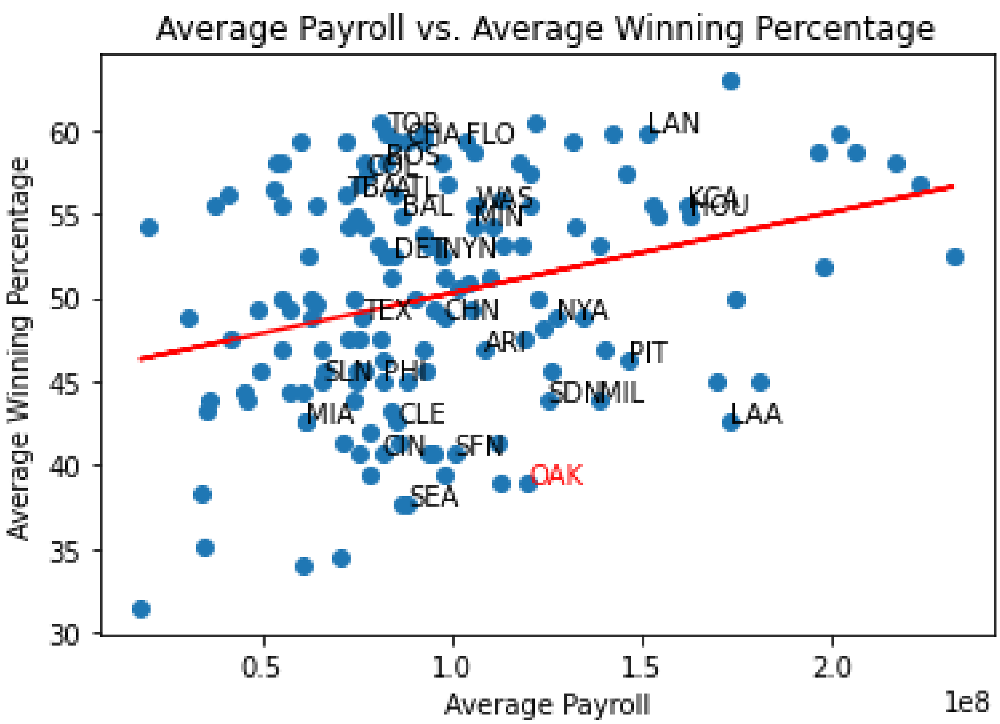
```
plt.xlabel("Average Payroll")
plt.ylabel("Average Winning Percentage")
plt.scatter(avg_payroll, avg_winpercent)
# polt line graph
z = np.polyfit(avg_payroll, avg_winpercent, 1)
p = np.poly1d(z)
plt.plot(avg_payroll,p(avg_payroll),"r-")
#Label each nameID
for i, label in enumerate(annotations):
    if label == "OAK":
        plt.text(avg_payroll[i], avg_winpercent[i],label,color = "red")
    else:
        plt.text(avg_payroll[i], avg_winpercent[i],label)
#reset for next iteration.
avg_payroll.clear()
avg_winpercent.clear()
annotations.clear()
plt.show()
```




Average Payroll vs. Average Winning Percentage
Average Winning Percentage
Average Payroll
1e7
70
65
60
55
50
45
40
35
1
2
3
4
5
HOU
PHI
OAK
FLO
CAL
ATL
BAL
MON
KCA
SDN
CHN
SFN
TEX
CLE
CHA
SEA
TOR
DET
PIT
COL
LAN
SLN
NYA
ML4


Average Payroll vs. Average Winning Percentage
Average Winning Percentage
Average Payroll
1e8
70
65
60
55
50
45
40
35
0.2
0.4
0.6
0.8
1.0
1.2
ATL
BAL
CHN
BOS
ML4
KCA
HOU
PIT
TBA
SFN
CHA
ANA
LAN
OAK
MIN
PHI
MON
MIL
CIN
CLE
TEX
NYA
COL
ARI
SLN
SEA
DET


Average Payroll vs. Average Winning Percentage
Average Winning Percentage
Average Payroll
1e8
65
60
55
50
45
40
35
30
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
PIT
MIN
CHN
NYN
OAK
BOS
SDN
SFN
NYA
TOR
PHI
CHA
FLO
HOU
WAS
SEA
KCA
MIL
LAN
TEX
ARI


Average Payroll vs. Average Winning Percentage
Average Winning Percentage
Average Payroll
1e8
60
55
50
45
40
35
30
0.5
1.0
1.5
2.0
TOR
CHA
FLO
LAN
BOS
TBA
ATL
BAL
WAS
MIN
KCA
HOU
DET
NYN
TEX
CHN
NYA
ARI
PIT
SLN
PHI
SDN
MIL
MIA
CLE
LAA
CIN
SFN
OAK
SEA

Question 2:

For the graph, the regression line means the average level of "paying for wins". Then, from those 5 graphs, the slope of regresion line is all positive, which means the more a team pays, they will win more. Also the slope of regresion line is approximately incresasing, which means every team increases their payoffs to get more wins. It means the outcome(win) is better than before when spending same amout of money.

We can see from those graphs that some teams are always higher than the regression line, which means they succeed in the "paying for wins". The distance(for those points higher than the line) is longer means they are more successful. For example, ATL is one of the most scuuessful one in graph 3. It also maintain the good level since, in each graph, it is above the regression line.

For OAK(marked in red), we can clearly see that in the first graph(1895-1991), it is below the line, which means it is not as efficient as others. However, in the second(1991-1997), third(1997-2003) and fourth(2003-2008) graph, are above (or on) the line. Especailly on second(1991-1997) and fourth(2003-2008) graph, it is much higher than the line, then it means OAK is much more efficient than others. On the last graph (2008-20015), it is below the line, which means it is not as efficient

Part 3:

Problem 5:

[252]:
```
year = pandas.unique(team_relation["yearID"])
payroll = []
team_name = pandas.unique(team_relation["teamID"])
avg_payroll = []
std_payroll = []
#iterate through each year and each element, store average payroll and standard␣
↪deviation of payroll
for y in year:
    for x in range(0,858):
        if result.iat[x,0] == y:
            payroll.append(team_relation.iat[x,7])
    avg_payroll.append([np.average(np.array(payroll))])
    std_payroll.append([np.std(np.array(payroll))])
    payroll.clear()

diff = 0
std = 0
team_relation["Standardized_Payroll"] = np.nan
# calculation Standardized_Payroll
for i in range(0,858):
    diff = (team_relation.iat[i,7] - avg_payroll[team_relation.iat[i,0] - 1985])
    std = (diff / std_payroll[team_relation.iat[i,0] - 1985])
    team_relation.loc[i,['Standardized_Payroll']] = std
```

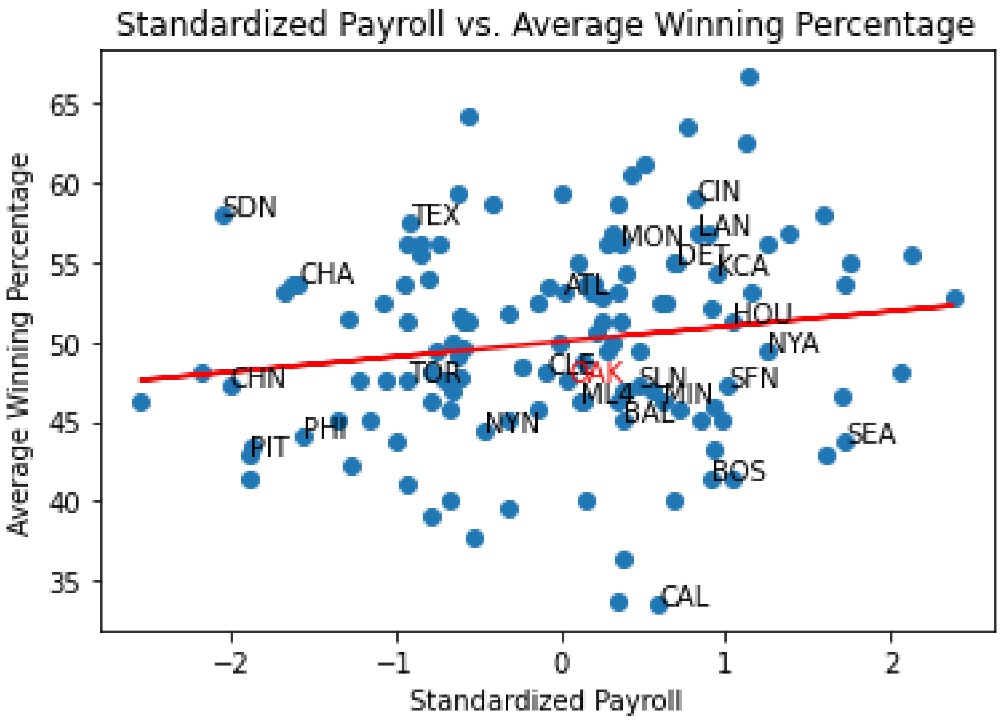
[253]:
```
team_relation
```

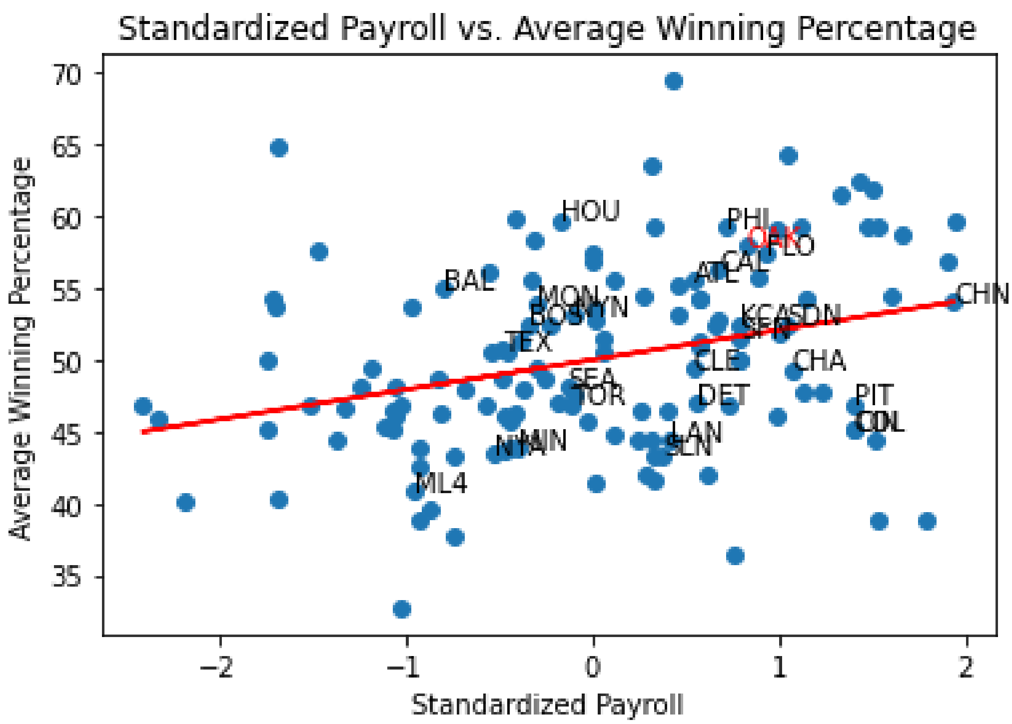
[253]:
```
     yearID teamID franchID   W   L    G  Winnig_Percentage  total_payroll  \
0      1985    ATL      ATL  66  96  162          40.740741     14807000.0
1      1985    BAL      BAL  83  78  161          51.552795     11560712.0
2      1985    BOS      BOS  81  81  163          49.693252     10897560.0
3      1985    CAL      ANA  90  72  162          55.555556     14427894.0
4      1985    CHA      CHW  85  77  163          52.147239      9846178.0
..      …      …        …  ..  ..  …                  …              …
853    2014    SLN      STL  90  72  162          55.555556    120693000.0
854    2014    TBA      TBD  77  85  162          47.530864     72689100.0
855    2014    TEX      TEX  67  95  162          41.358025    112255059.0
856    2014    TOR      TOR  83  79  162          51.234568    109920100.0
857    2014    WAS      WSN  96  66  162          59.259259    131983680.0

                   bins  Standardized_Payroll
0    (1984.971, 1990.8]              1.952828
1    (1984.971, 1990.8]              0.612972
2    (1984.971, 1990.8]              0.339266
3    (1984.971, 1990.8]              1.796358
4    (1984.971, 1990.8]             -0.094676
..                  …                    …
853    (2008.2, 2014.0]              0.464941
854    (2008.2, 2014.0]             -0.603311
855    (2008.2, 2014.0]              0.277168
856    (2008.2, 2014.0]              0.225207
857    (2008.2, 2014.0]              0.716198

[858 rows x 10 columns]
```

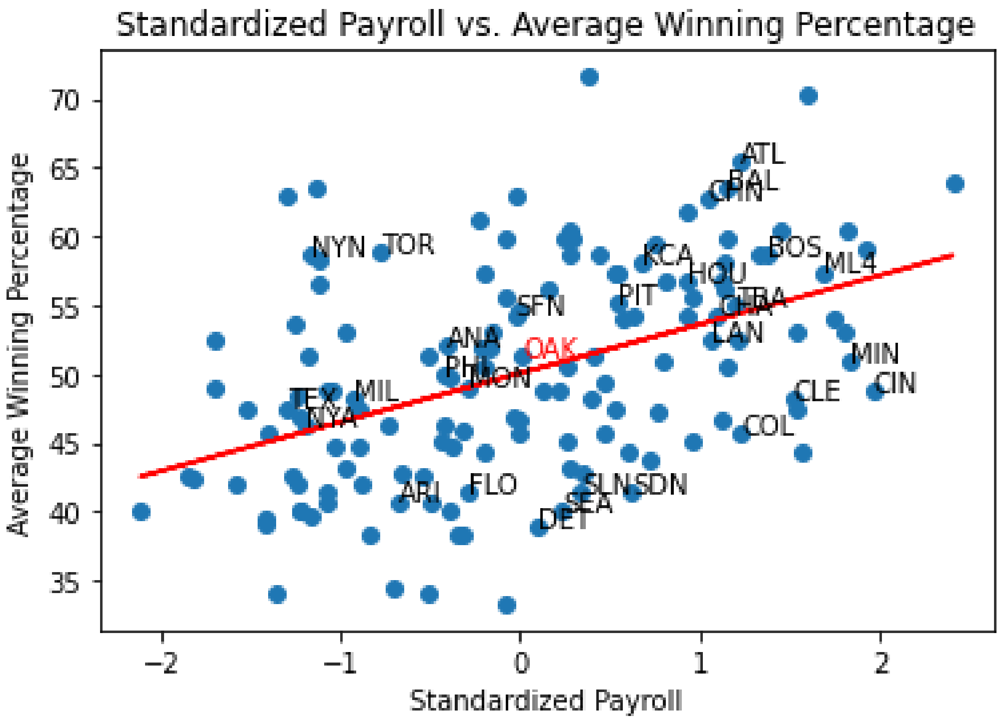
Problem 6:

[254]:
```
#Similar to previous parts. Firstly create an empty dictionary.
#Looping through elements to get payroll and winning percent
#Looping throught the dictionary to get average winning percentage and␣
 ↪standardized payroll and plot.
std_dict = {}
for i in range(0,858):
    if team_relation.iat[i,8] in std_dict:
        if team_relation.iat[i,1] in std_dict[team_relation.iat[i,8]]:
            std_dict[team_relation.iat[i,8]][team_relation.iat[i,1]].
 ↪append((team_relation.iat[i,9],team_relation.iat[i,6]))
        else :
            std_dict[team_relation.iat[i,8]][team_relation.iat[i,1]] = []
    else:
        std_dict[team_relation.iat[i,8]] = {}
```

```python
avg_payroll = []
avg_winpercent = []
annotations = []
for keys in std_dict:
    plt.clf()
    for names in std_dict[keys]:
        annotations.append(names)
        for element in std_dict[keys][names]:
            avg_payroll.append(np.average(np.array(element[0])))
            avg_winpercent.append(np.average(np.array(element[1])))
    plt.title("Standardized Payroll vs. Average Winning Percentage")
    plt.xlabel("Standardized Payroll")
    plt.ylabel("Average Winning Percentage")
    plt.scatter(avg_payroll, avg_winpercent)


    z = np.polyfit(avg_payroll, avg_winpercent, 1)
    p = np.poly1d(z)
    plt.plot(avg_payroll,p(avg_payroll),"r-")

    for i, label in enumerate(annotations):
        if label == "OAK":
            plt.text(avg_payroll[i], avg_winpercent[i],label,color = "red")
        else:
            plt.text(avg_payroll[i], avg_winpercent[i],label)

    avg_payroll.clear()
    avg_winpercent.clear()
    annotations.clear()
    plt.show()
```


Standardized Payroll vs. Average Winning Percentage
Average Winning Percentage
Standardized Payroll
65
60
55
50
45
40
35
−2
−1
0
1
2
SDN
TEX
CIN
LAN
MON
DET
KCA
CHA
ATL
HOU
NYA
CHN
TOR
CLE
OAK
SLN
SFN
ML4
MIN
BAL
NYN
PHI
PIT
SEA
BOS
CAL


Standardized Payroll vs. Average Winning Percentage
Average Winning Percentage
Standardized Payroll
70
65
60
55
50
45
40
35
−2
−1
0
1
2
HOU
PHI
OAK
FLO
CAL
ATL
BAL
MON
NYN
BOS
KCA
SDN
SFN
CHN
TEX
CLE
CHA
SEA
TOR
DET
PIT
COL
LAN
SLN
NYA
MIN
ML4


Standardized Payroll vs. Average Winning Percentage
Average Winning Percentage
Standardized Payroll
ATL
BAL
CHN
NYN
TOR
KCA
BOS
ML4
HOU
PIT
TBA
CHA
SFN
LAN
ANA
OAK
PHI
MON
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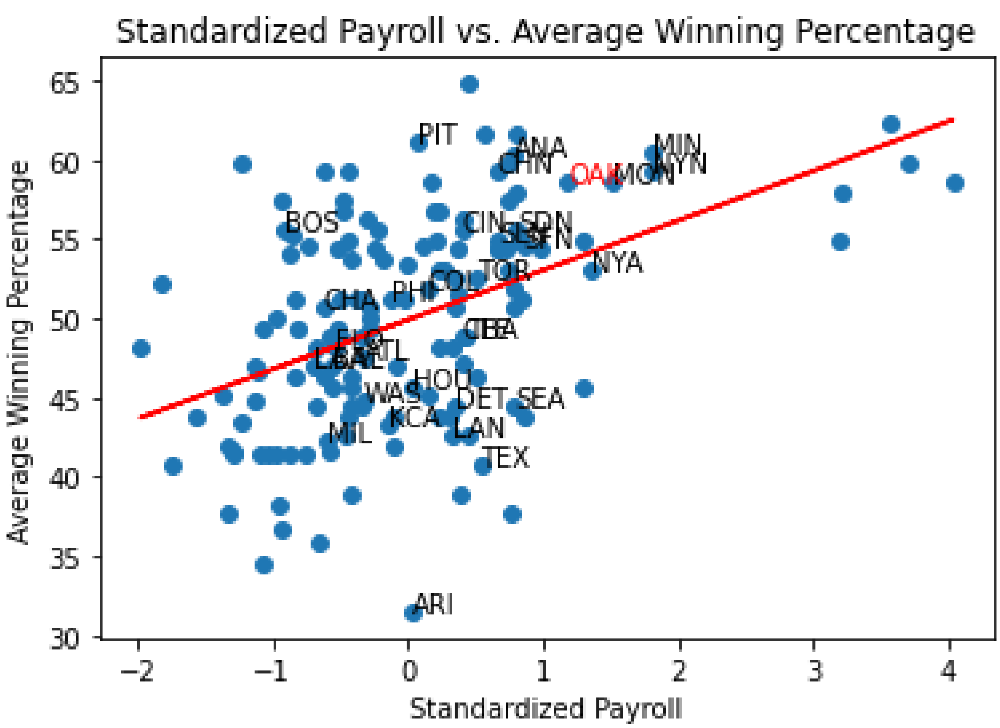
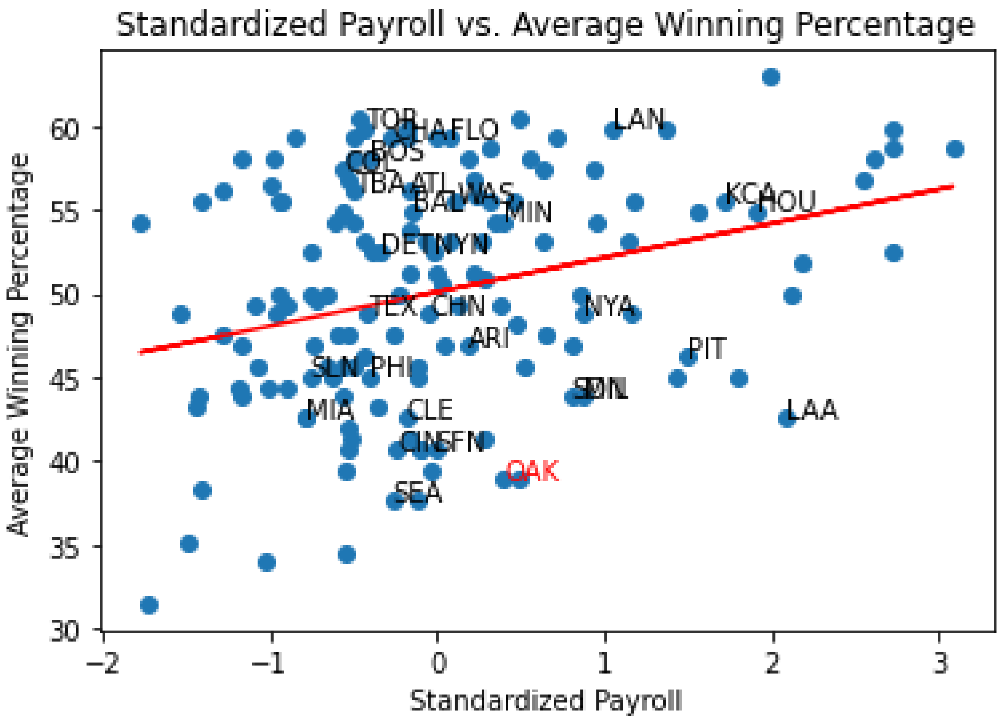
TEX
MIL
NYA
COL
ARI
FLO
SLN
SDN
SEA
DET


Standardized Payroll vs. Average Winning Percentage
Average Winning Percentage
Standardized Payroll
PIT
ANA
CHN
OAK
MON
MIN
NYN
BOS
CIN
SDN
SFN
NYA
TOR
CHA
PHI
COL
CLE
TBA
ATL
HOU
WAS
DET
SEA
KCA
LAN
MIL
TEX
ARI



Question 3:

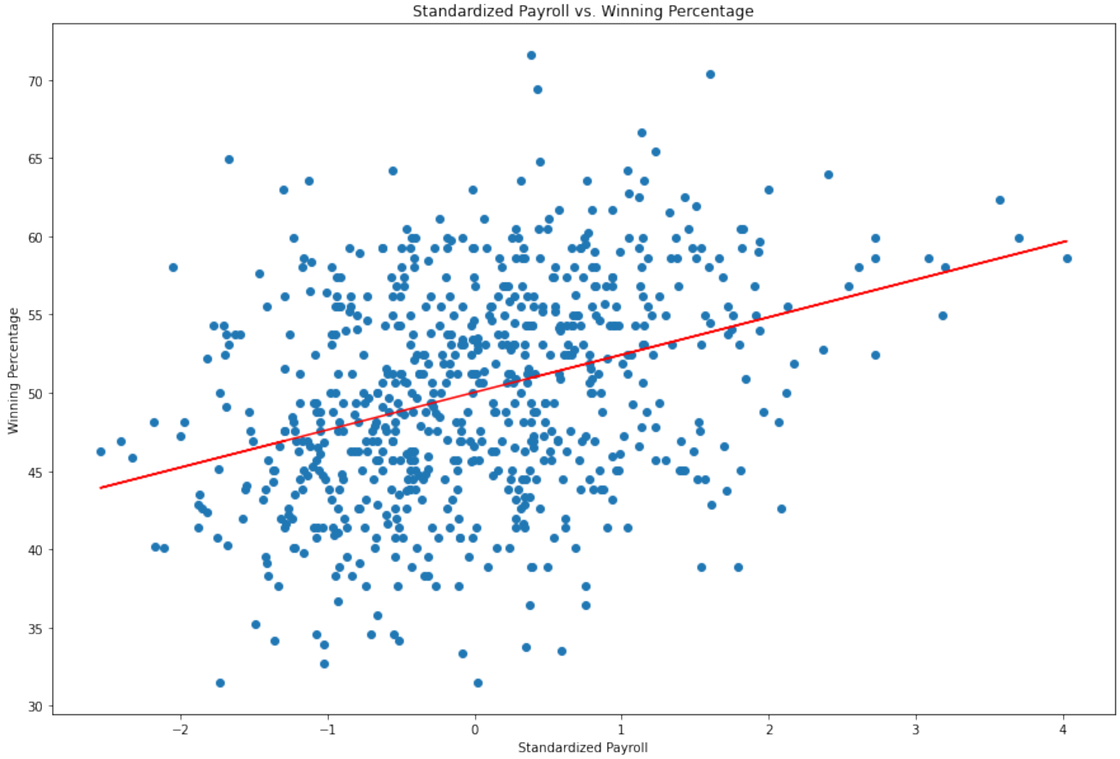
When we take each payroll minus its mean divided by its standard deviation, it is actually calculating its z-score. The x-axis is no longer always positive, however, there are negative number on the x-axis. This reflects the transformation on the payroll variable since we minus its mean, which can be positive or negaive. Also, the absolute value of payroll is smaller than before. This reflects the transformation on the payroll variable since we divide it by its standard deviation.

Problem 7:

[255]:
```
#Similar to previous parts. Firstly create an empty dictionary.
#Looping through elements to get payroll and winning percent
#Looping throught the dictionary to get total winning percentage and␣
↪standardized payroll and plot.
bin_dict = {}
for i in range(0,858):
    if team_relation.iat[i,8] in bin_dict:
        if team_relation.iat[i,1] in bin_dict[team_relation.iat[i,8]]:
            bin_dict[team_relation.iat[i,8]][team_relation.iat[i,1]].
↪append((team_relation.iat[i,9],team_relation.iat[i,6]))
        else :
            bin_dict[team_relation.iat[i,8]][team_relation.iat[i,1]] = []
    else:
        bin_dict[team_relation.iat[i,8]] = {}
standardized_payroll = []
```

```python
winpercent = []
annotations = []


for keys in bin_dict:
    plt.clf()
    for names in bin_dict[keys]:
        annotations.append(names)
        for element in bin_dict[keys][names]:
            standardized_payroll.append((np.array(element[0])))
            winpercent.append((np.array(element[1])))

#enlarge the graph size.
plt.figure(figsize=(15,10))
plt.title("Standardized Payroll vs. Winning Percentage")
plt.xlabel("Standardized Payroll")
plt.ylabel("Winning Percentage")
plt.scatter(standardized_payroll, winpercent)

z = np.polyfit(standardized_payroll, winpercent, 1)
p = np.poly1d(z)
plt.plot(standardized_payroll,p(standardized_payroll),"r-")
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```

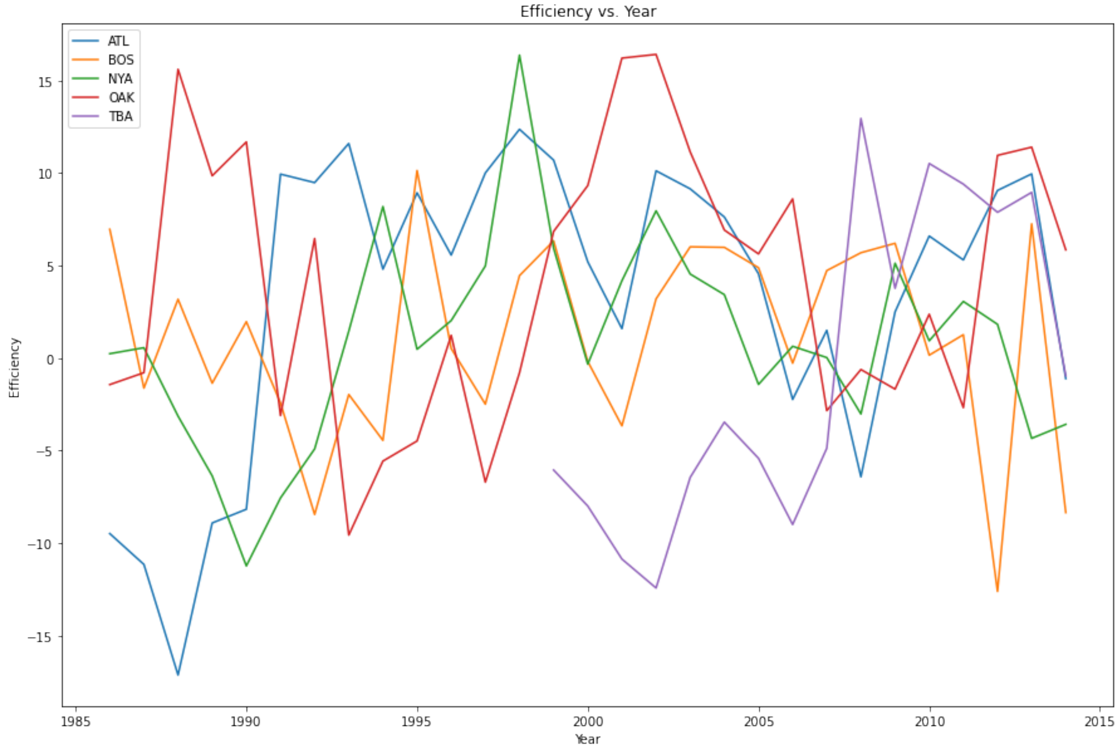


Problem 8:

[256]:
```
team_relation["Expected_Win"] = 50+2.5*team_relation["Standardized_Payroll"]
team_relation["Efficiency"] = team_relation["Winnig_Percentage"] -␣
 ↪team_relation["Expected_Win"]
```

[258]:
```
#Similar to previous parts. Firstly create an empty dictionary.
#Looping through elements to get payroll and winning percent
#Looping throught the dictionary to get total winning percentage and␣
 ↪standardized payroll and plot.
eff_dict = {}

for i in range(0,858):
    if team_relation.iat[i,1] in eff_dict:
        eff_dict[team_relation.iat[i,1]].append((team_relation.
 ↪iat[i,11],team_relation.iat[i,0]))
    else :
        eff_dict[team_relation.iat[i,1]] = []

efficiency = []
year = []
annotations = []
# nameID that we needed
```

```python
names_new = ['OAK', 'BOS','NYA', 'ATL', 'TBA']


for names in eff_dict:
    if names in names_new:
        annotations.append(names)
        for element in eff_dict[names]:
            efficiency.append((np.array(element[0])))
            year.append((np.array(element[1])))

plt.figure(figsize=(15,10))
plt.title("Efficiency vs. Year")
plt.xlabel("Year")
plt.ylabel("Efficiency")

for key in eff_dict:
    #Check nameID
    if key in names_new:
        years = []
        eff = []
        for pair in eff_dict[key]:
            eff.append(pair[0])
            years.append(pair[1])
        plt.plot(years, eff, label = key)
        plt.legend(loc= "upper left")
plt.show()
```



Question 4:

Condensed linear graph is more stragihtforward and easier to get the realtionship between two variable, compared to points.

From the graph, the efficiency is at first around 0 but then increased drmatically. It is very efficient till approximately 1990. After approximately 1990, it decreased till approximately 1997. At that time, it is not efficient. Then, it started to increase. Around 2000, the efficient was above 0. After approximately 2001, it decreased till 2010 but at that time, it is relatively efficient expecially around 2000. After 2010, it started to increase till 2013. At that time, it was efficient. After 2013, it decreased.

It reflects the statement in QUESTION that "not much more efficient than other teams in their spending before 2000, were much more efficient between 2000 and 2005, and by then other teams may have caught up"

```
[ ]:
```