

```
In [370...  
# ** CMSC 320 UMD**  
# *Project 2*  
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### Due date : March 26, 2021  
### Email : fnkokam@terpmail.umd.edu  
### UID : 117548327
```

```
In [400...  
import sqlite3  
import pandas  
from matplotlib import pyplot as plt  
import os
```

```
In [401...  
sqlite_file = 'lahman2014.sqlite'  
backup_database_file = 'blablabd.sqlite'  
conn = sqlite3.connect(sqlite_file)
```

Pre-required data. This part was added last. Due to running several queries. we found out that we will need access to a list of team ids for this project. We will therefore load the team ids into a list, and reuse that list everyt time.

```
In [402...  
select_team_details_query = " SELECT DISTINCT T.name , T.teamId from Teams as  
team_details_result = pandas.read_sql(select_team_details_query, conn)
```

```
In [403...  
team_details_result.columns
```

```
Out[403... Index(['name', 'teamID'], dtype='object')
```

```
In [404...  
team_names = [] # saving the team names in a list  
team_ids = []  
for index, row in team_details_result.iterrows():  
    team_id = str(row['teamID']) # the team ID should be in string format  
    team_name = str(row['name']) # The name should also be in a string format  
    if not(bool(str(team_id))) == False:  
        team_ids.append(team_id)  
        team_names.append(team_name)
```

## Part 1 : Wrangling

We need to compute the total payroll and winning percentage for each team. The total payroll will be a sum of salaries in the salaries table, grouping by the teamId or grouping by yearID, depending if we want to view per team or per year. The winning percentage is as defined the number of wins divided by number of games played(not games played at home), all multiplied by 100. Now we already have the list of team ids saved in a list. We can find that total payroll and winning percentage for each team by looping through that list of eam ids

In [405...

```
working_query = "SELECT Teams.name as `TEAM NAME`, Salaries.teamID as `TEAM ID`,  
                printf('%5.2f %', ((SUM(Teams.W)*1.0)/(SUM(Teams.G)*1.0))*100.0) AS `WINNING PERCENTAGE`,  
                printf('$%,d',SUM(Salaries.salary)) AS `TOTAL PAYROLL` " + \  
                "FROM Salaries " + \  
                "LEFT JOIN Teams ON Salaries.teamID = Teams.teamID " + \  
                "GROUP BY `TEAM ID` " + \  
                "ORDER BY `TEAM NAME`,`TEAM ID` "  
query_result = pandas.read_sql(working_query, conn)  
#query_result
```

In [406...

```
query_result
```

Out[406...

	TEAM NAME	TEAM ID	WINNING PERCENTAGE	TOTAL PAYROLL
0	None	NYM	0.00 %	\$54,806,990
1	None	SFG	0.00 %	\$143,510,167
2	Anaheim Angels	ANA	51.23 %	\$3,744,735,784
3	Arizona Diamondbacks	ARI	49.20 %	\$20,569,578,876
4	Atlanta Braves	ATL	51.76 %	\$92,264,392,416
5	Baltimore Orioles	BAL	51.23 %	\$99,442,202,318
6	Boston Red Sox	BOS	51.43 %	\$277,327,906,590
7	California Angels	CAL	48.24 %	\$8,703,325,760
8	Chicago White Sox	CHA	50.18 %	\$193,784,626,302
9	Chicago White Stockings	CHN	50.70 %	\$258,516,830,785
10	Cincinnati Reds	CIN	50.14 %	\$179,346,918,500
11	Cleveland Indians	CLE	50.66 %	\$160,171,838,592
12	Colorado Rockies	COL	46.86 %	\$28,466,034,058
13	Detroit Tigers	DET	50.56 %	\$201,916,536,318
14	Florida Marlins	FLO	47.67 %	\$12,825,304,095
15	Houston Astros	HOU	48.69 %	\$74,628,937,321
16	Kansas City Royals	KCA	48.23 %	\$54,163,480,528
17	Los Angeles Angels	LAA	53.55 %	\$16,585,403,604
18	Los Angeles Dodgers	LAN	53.56 %	\$127,552,702,071
19	Miami Marlins	MIA	42.80 %	\$580,550,400
20	Milwaukee Brewers	MIL	47.26 %	\$17,818,737,901
21	Milwaukee Brewers	ML4	48.47 %	\$6,542,082,512
22	Minnesota Twins	MIN	49.60 %	\$68,592,804,696
23	Montreal Expos	MON	48.32 %	\$14,695,335,396
24	New York Mets	NYN	47.76 %	\$104,184,073,243
25	New York Yankees	NYA	56.66 %	\$367,709,365,408

	TEAM NAME	TEAM ID	WINNING PERCENTAGE	TOTAL PAYROLL
26	Oakland Athletics	OAK	52.20 %	\$55,768,059,291
27	Philadelphia Quakers	PHI	47.02 %	\$261,670,965,600
28	Pittsburgh Pirates	PIT	50.19 %	\$127,302,043,904
29	San Diego Padres	SDN	46.37 %	\$54,164,998,252
30	San Francisco Giants	SFN	51.89 %	\$96,685,846,497
31	Seattle Mariners	SEA	46.78 %	\$63,579,450,378
32	St. Louis Cardinals	SLN	50.76 %	\$218,402,653,836
33	Tampa Bay Devil Rays	TBA	46.22 %	\$13,057,884,875
34	Texas Rangers	TEX	49.07 %	\$71,813,891,414
35	Toronto Blue Jays	TOR	49.47 %	\$59,693,263,414
36	Washington Senators	WAS	48.88 %	\$18,878,488,878

### Explanation of the working\_query

The first line selects the team id found in the Salaries table. The next line calculates the percentage wins. Here we multiply the sums by 1.0 to make sqlite convert it to floating points number, else the division operator will return zero for every sum of wins over sum of total games played, since the division operator returns zero if an numerator is divided by an denominator when the numerator is less than the denominator. The next line calculates the total salary paid to players for that particular team for a specific year. It uses the printf function to format the data to 5 spots(including the dot character) : two decimal places, and two places before the decimal like the C printf function would do. It's just a semi replica of the c printf function. The next line tells sqlite from what tables to pull the data from, both from Salaries and Teams table. The next line specifies the mathematical joining clause. In this instance the left join clause.

### Dealing with the empty values

Let's examine the query above, more precisely the left join clause : `SELECT Teams.name as TEAM NAME , Salaries.teamID as TEAM ID , printf('%5.2f',((SUM(Teams.W)/SUM(Teams.G))*100.0) AS WINNING PERCENTAGE , printf('$%,d',SUM(Salaries.salary)) AS TOTAL PAYROLL FROM Salaries LEFT JOIN Teams ON Salaries.teamID = teams.teamID GROUP BY TEAM ID ORDER BY TEAM ID`

The left join line tells sqlite to pull out results from the Salaries tables, and the teams table, for each row such that the team id for that row in the Salaries table is being foreign-keyed by a team id from the Teams table. So what this means is that we want the results to be in such a way that we only see results when the team id is found in the Salaries table. Now in our case, every row in the Salaries table has a team id that comes from the Teams table. Now some teams might not have any rows in the salaries table. So doing a left join on the Salaries table instead will bring out some null values. But doing a left join on the Teams table will not bring out any nulls unless

there are team ids in the Salaries table that have no teams in the Teams table, which does not make sense.

To find out where the empty sets come from, we decided to search for any team in the Salaries table that does not have a row in the Teams table. Thinking about that, it's not supposed to be possible. But in this case it is. Let's have a look at that. First let's select team ids in the salary table that are not present in the teams table

```
In [407... surprise_query = "SELECT DISTINCT teamID FROM Salaries " + \
                    "WHERE teamID NOT IN (" + \
                    "SELECT DISTINCT teamID FROM Teams" + \
                    ") "
surprise_result = pandas.read_sql(surprise_query, conn)
surprise_result
```

```
Out[407...    teamID
0      NYM
1      SFG
```

So there are two teams rows in the Salaries table not found in the Teams table. Let's find their total payroll

```
In [408... further_query = "SELECT teamID, " + \
                    "printf('%d',SUM(salary)) AS `TOTAL PAYROLL` " + \
                    "FROM Salaries " + \
                    "WHERE (teamID = 'NYM' OR teamID ='SFG') " + \
                    "GROUP BY teamID " + \
                    "ORDER BY teamID "
further_result = pandas.read_sql(further_query, conn)
further_result
```

```
Out[408...    teamID  TOTAL PAYROLL
0      NYM      $54,806,990
1      SFG     $143,510,167
```

This results matches the two None teamId starting rows we have in the beginning of this part. An alternative will be to left join on Teams table instead.

```
In [409... good_query = "SELECT Teams.name as `TEAM NAME`, Salaries.teamID as `TEAM ID`,
                    "printf('%5.2f%',((SUM(Teams.W)*1.0)/(SUM(Teams.G)*1.0))*100.0) AS `W
                    "printf('%d',SUM(Salaries.salary)) AS `TOTAL PAYROLL` " + \
                    "FROM Teams " + \
                    "LEFT JOIN Salaries ON Salaries.teamID = Teams.teamID " + \
                    "GROUP BY `TEAM ID` " + \
                    "ORDER BY `TEAM NAME`,`TEAM ID` "
```

```
In [410... good_result = pandas.read_sql(good_query, conn)
good_result
```

Out [410...

	TEAM NAME	TEAM ID	WINNING PERCENTAGE	TOTAL PAYROLL
0	Anaheim Angels	ANA	51.23%	\$3,744,735,784
1	Arizona Diamondbacks	ARI	49.20%	\$20,569,578,876
2	Atlanta Braves	ATL	51.76%	\$92,264,392,416
3	Baltimore Orioles	BAL	51.23%	\$99,442,202,318
4	Boston Americans	BOS	51.43%	\$277,327,906,590
5	Boston Red Stockings	None	48.06%	\$0
6	California Angels	CAL	48.24%	\$8,703,325,760
7	Chicago White Sox	CHA	50.18%	\$193,784,626,302
8	Chicago White Stockings	CHN	50.70%	\$258,516,830,785
9	Cincinnati Reds	CIN	50.14%	\$179,346,918,500
10	Cleveland Blues	CLE	50.66%	\$160,171,838,592
11	Colorado Rockies	COL	46.86%	\$28,466,034,058
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13	Florida Marlins	FLO	47.67%	\$12,825,304,095
14	Houston Colt .45's	HOU	48.69%	\$74,628,937,321
15	Kansas City Royals	KCA	48.23%	\$54,163,480,528
16	Los Angeles Angels	LAA	53.55%	\$16,585,403,604
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32	Tampa Bay Devil Rays	TBA	46.22%	\$13,057,884,875
33	Texas Rangers	TEX	49.07%	\$71,813,891,414

	TEAM NAME	TEAM ID	WINNING PERCENTAGE	TOTAL PAYROLL
34	Toronto Blue Jays	TOR	10.17%	\$50,603,263.114

With this query above, we get a result without None values.

## Part 2 : Exploratory Data Analysis

### Payroll Distribution

#### *Distribution of payrolls conditioned on time between the years 1990 and 2014*

For this section, we want to see how the payrolls distribute over time between 1990 and 2014.

For that we will use a similar query to the query above.

In [411...

```
payroll_query = \
    "SELECT Salaries.teamID as `TEAM ID`, " + \
    "Salaries.yearID AS `YEAR`, " + \
    "SUM(Salaries.salary) AS `TOTAL SALARY PAID` " + \
    "FROM Salaries " + \
    "WHERE Salaries.yearID >= '1990' AND " + \
    "Salaries.yearID <= '2014' " + \
    "GROUP BY `TEAM ID`, `YEAR` " + \
    "ORDER BY `TEAM ID`, `YEAR` "
payroll_result = pandas.read_sql(payroll_query, conn)
payroll_result.head()
```

Out[411...

	TEAM ID	YEAR	TOTAL SALARY PAID
0	ANA	1997	31135472.0
1	ANA	1998	41281000.0
2	ANA	1999	55388166.0
3	ANA	2000	51464167.0
4	ANA	2001	47535167.0

In [412...

```
payroll_result.tail()
```

Out[412...

	TEAM ID	YEAR	TOTAL SALARY PAID
725	WAS	2010	61400000.0
726	WAS	2011	63856928.0
727	WAS	2012	80855143.0
728	WAS	2013	113703270.0
729	WAS	2014	131983680.0

Above is what the results will look like. So we need to plot the results for all the years. We could do it as a query, then plot it. This will require manipulating the dataframe to pick the salaries paid

per team for each year. That is tedious, when sql can do the job for us in case we have the team IDs in a list. So a better way is to have the list of teamIds and names in a python list, then make an sql query selection based on each value for that list, then plot the result for each team, since each value in the list will correspond to a unique team. Luckily at the beginning of this document, we selected the list of team ids and team names and stored them in a list.

In [413...

```
# saving the result of running the read_sql function in a list
result_frames_objects = []

for index in range(len(team_ids)):
    team_id = str(team_ids[index]) # the team ID should be in string format
    team_name = str(team_names[index]) # The name should also be in a string
    the_query = "SELECT SUM(salary) as `Total_Payroll`, " + \
                "AVG(salary) AS `Average_Payroll`, " + \
                "yearID as `Year` " + \
                "FROM Salaries " + \
                "WHERE teamID = '" + team_id + "' " + \
                "AND yearID >= '1990' AND yearID <= '2014' " + \
                "GROUP BY yearID ORDER BY yearID "

    result_frames_objects.append(pandas.read_sql(the_query, conn))
```

### Explaining the query above

We are selecting the total payrolls and average payrolls for each year. That salary sum will be identified in the dataframe as Total\_Payroll. The where clause identifies the team for which the selection should be made, and the yearID should be between 1990 and 2014, inclusive. The result will be saved in a list. We will iterate over that list to plot it.

In [414...

```
len(result_frames_objects) # checking if the list is not empty
```

Out[414... 185

In [415...

```
len(result_frames_objects) # checking if the list is not empty
```

Out[415... 185

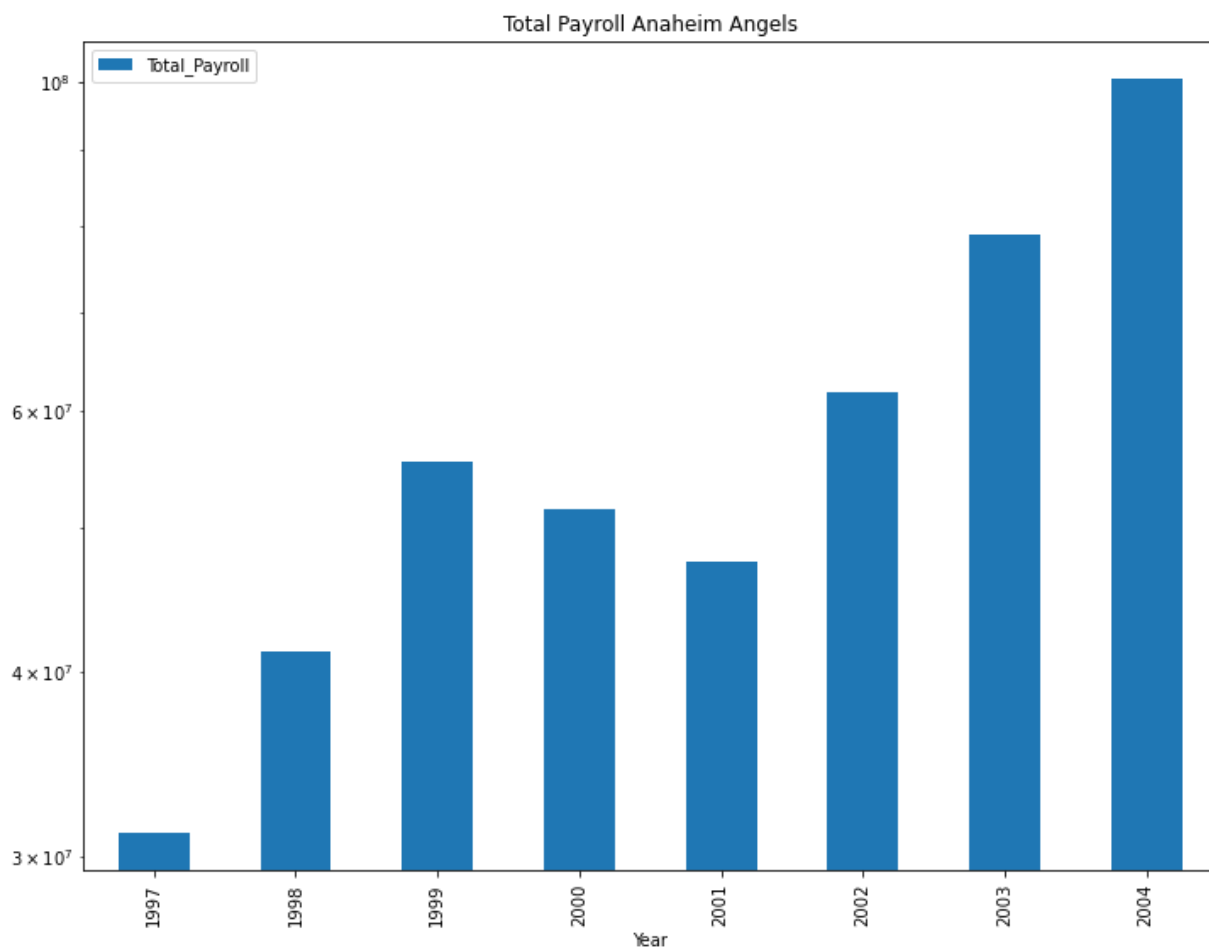
Now let's have fun plotting the results we just got. Plotting these results generate warnings because more than 20 figures are generated. The solution is to save the plots as images and just show the images after closing the opened figures

In [416...

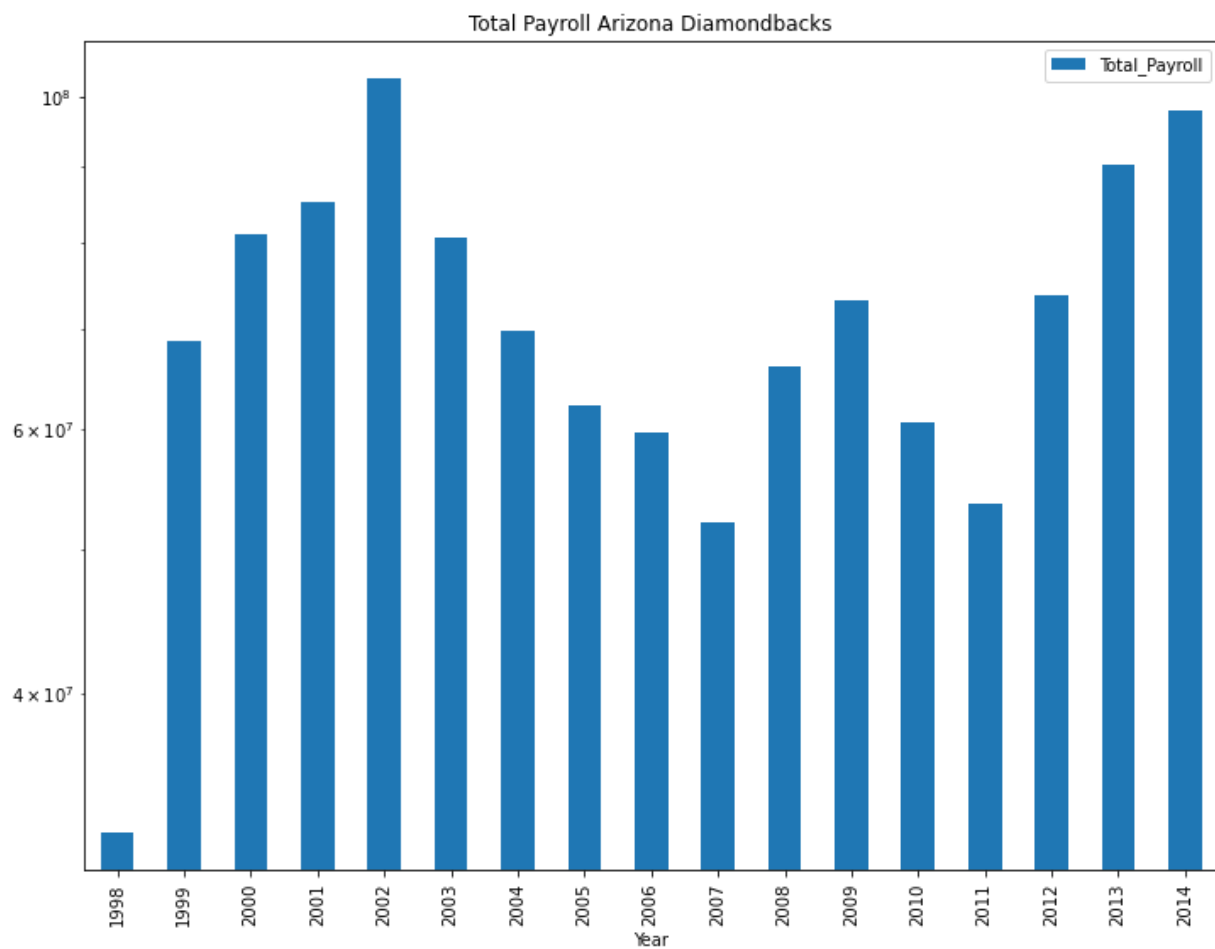
```
num_results = len(result_frames_objects)
#prevents warning after 20 figures shown
plt.rcParams.update({'figure.max_open_warning':0})
figsize = (12,9)
for i in range(num_results):
    dfr = result_frames_objects[i]
    team_name = team_names[i]
    team_id = team_ids[i]
    #we only plot if the data frame in
    #question is not empty
    if not dfr.empty:
        dfr.plot(x='Year', y='Total_Payroll', logy=True, \
                 title = 'Total Payroll ' + team_name, kind='bar',figsize=fi

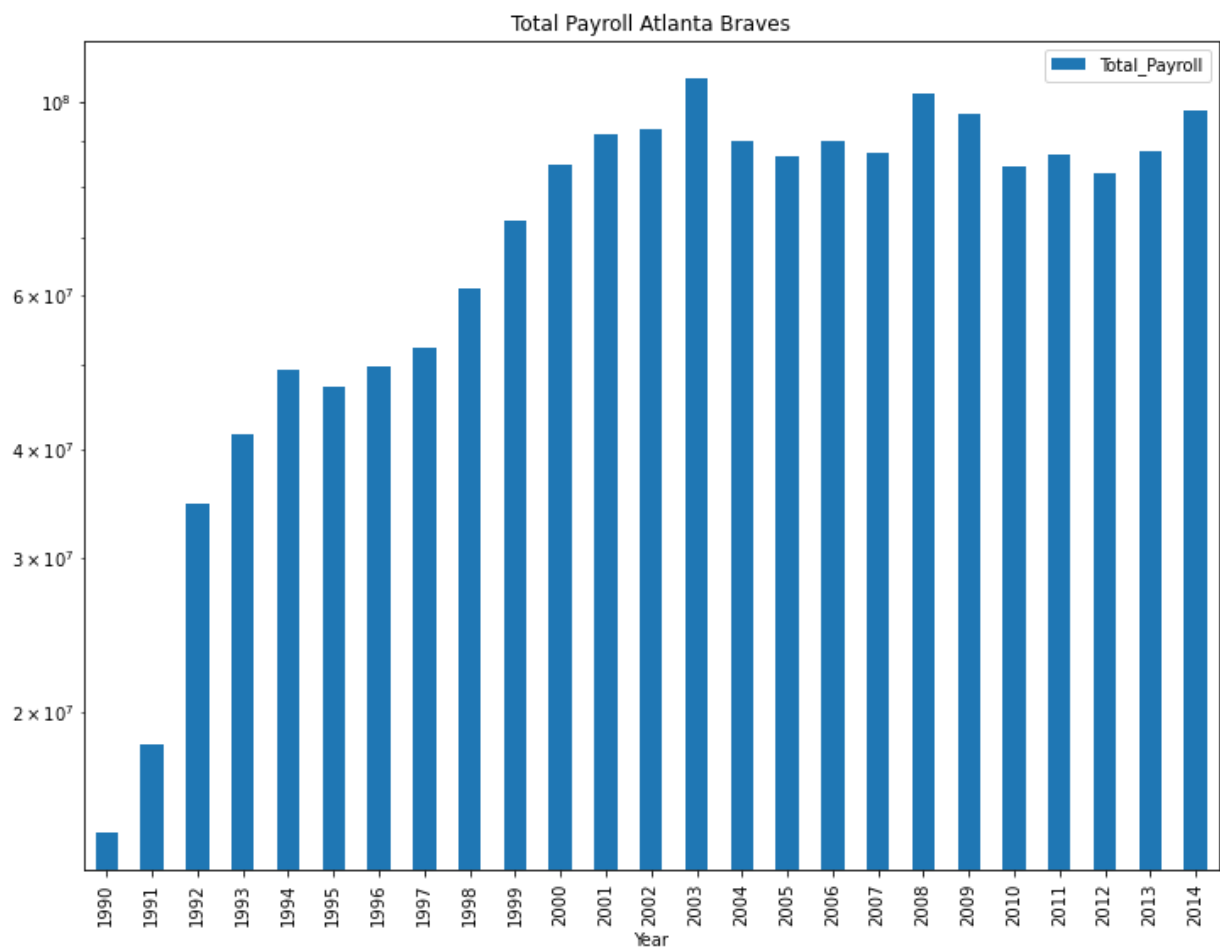
    #fig = plt.figure((i+1))
    #ax = fig.add_subplot(111)
    #image_name = 'figs/graph_{}_{}.png'.format(team_id, i)

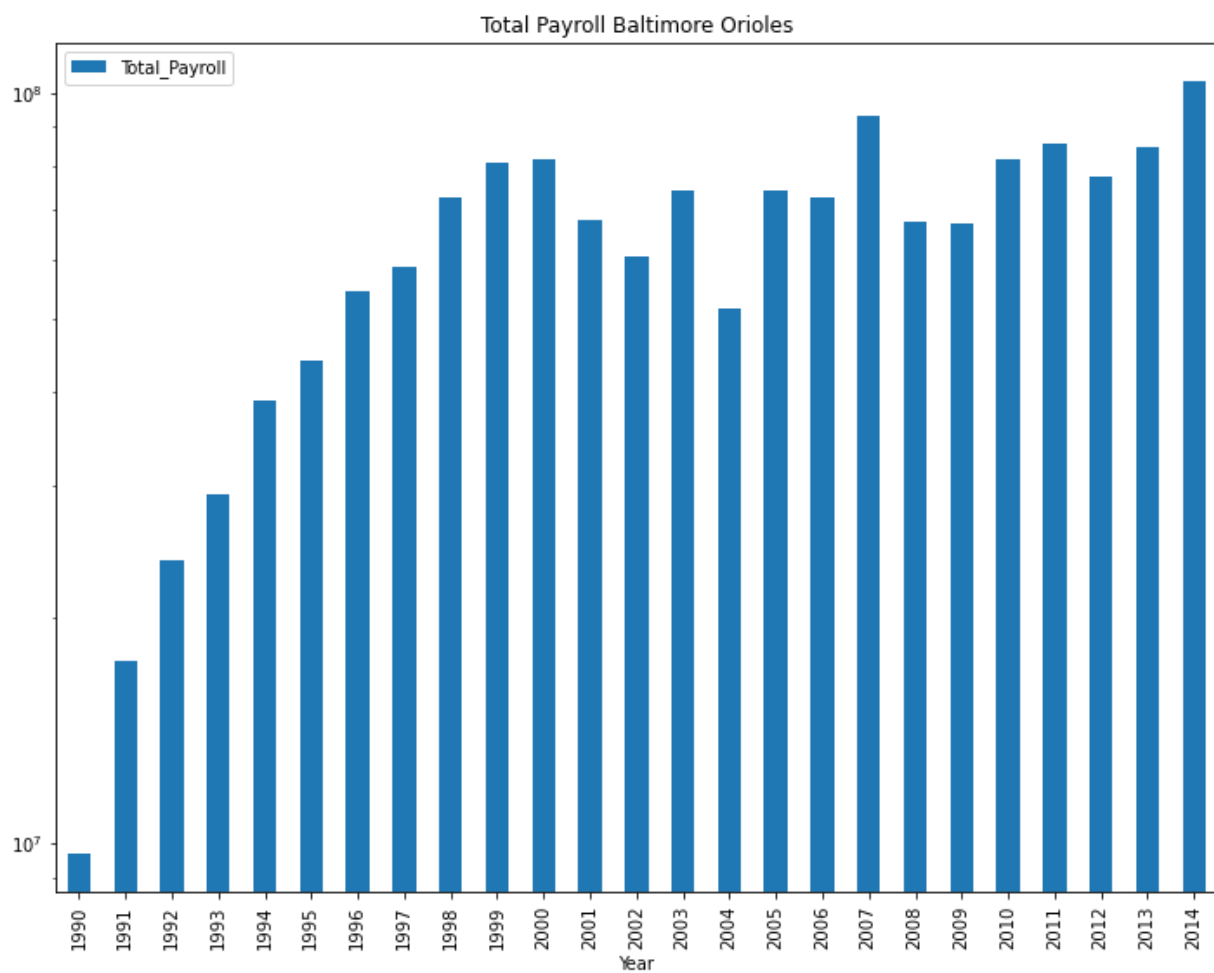
    #fig.savefig(image_name)
    #plt.close(fig)
```

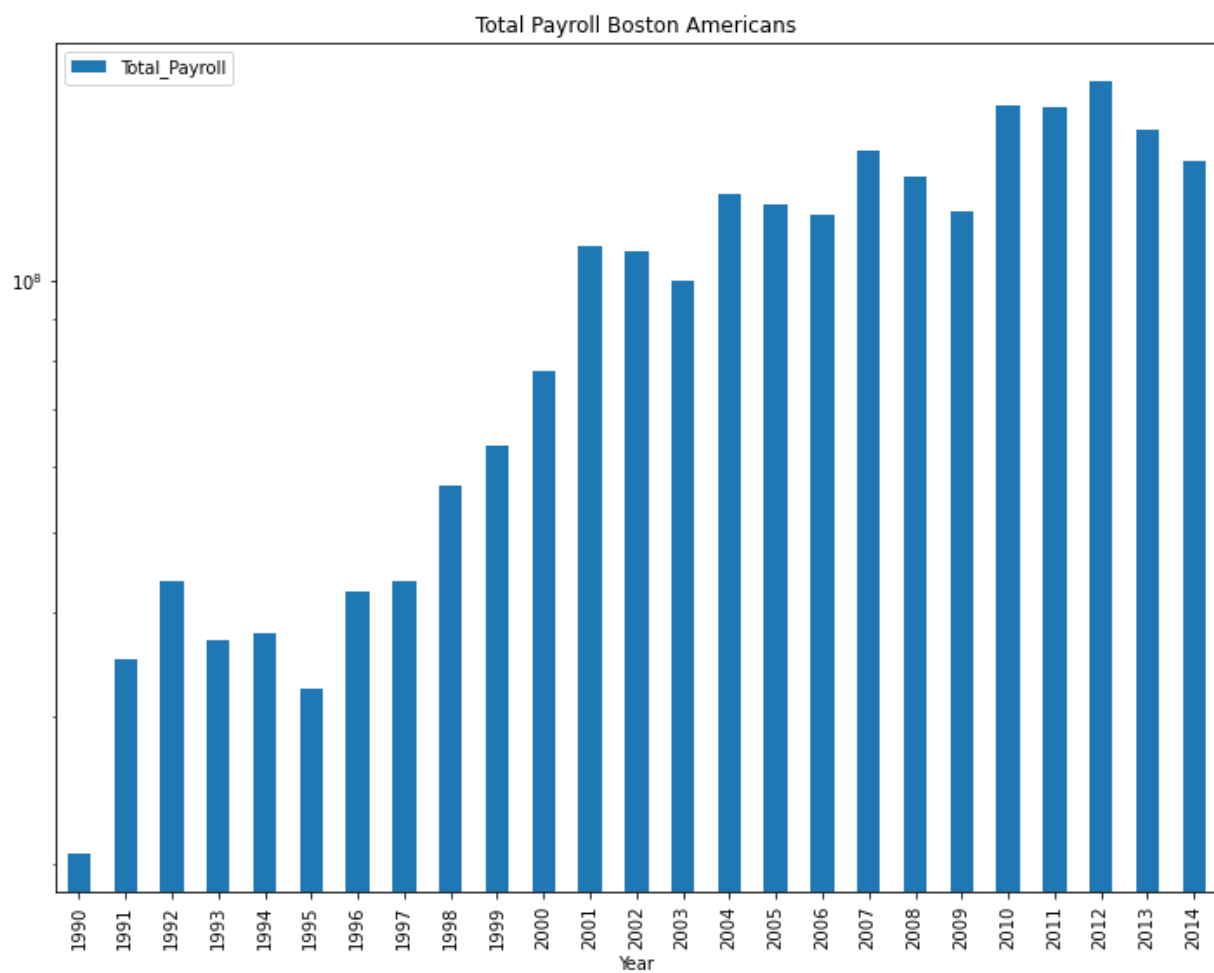


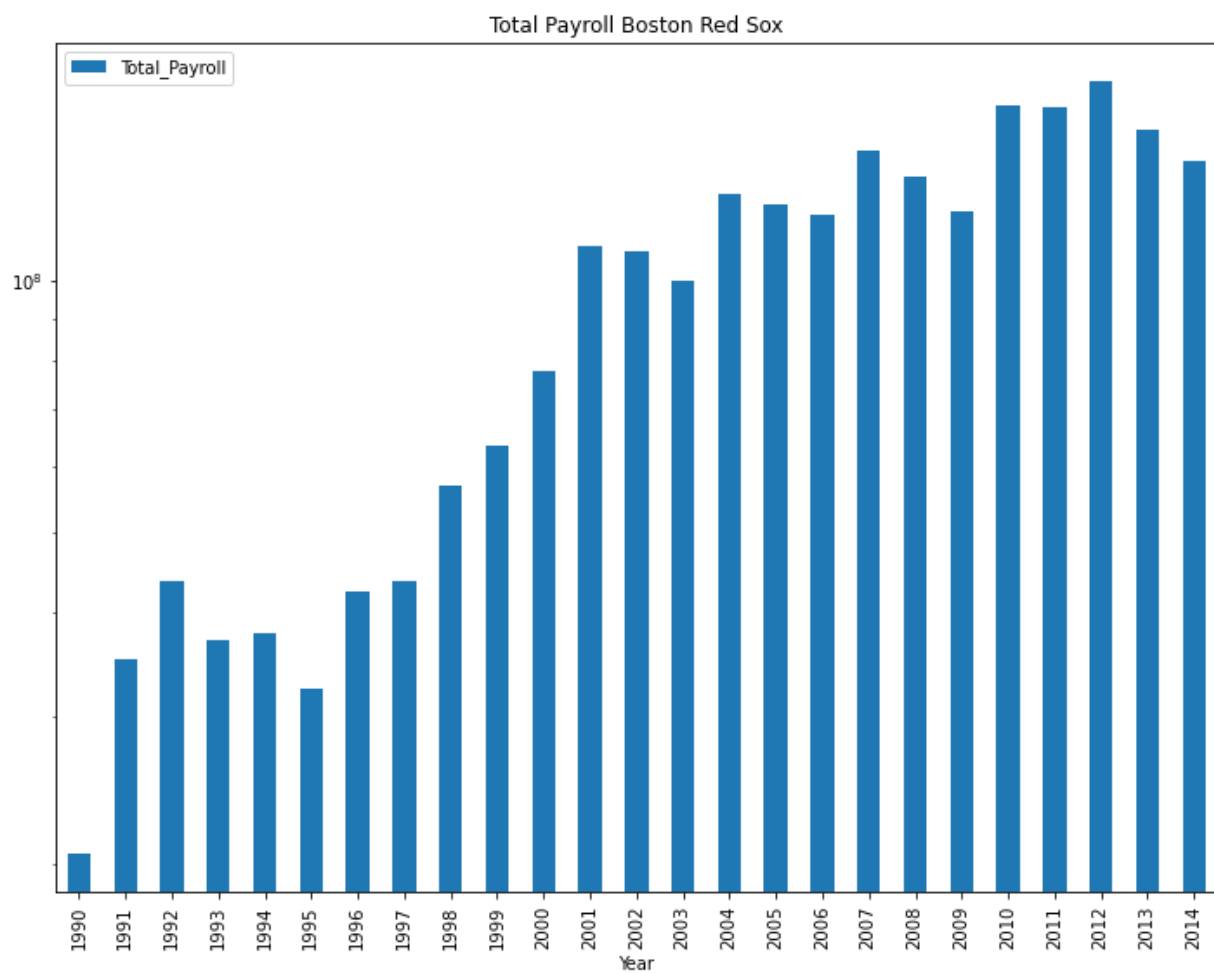


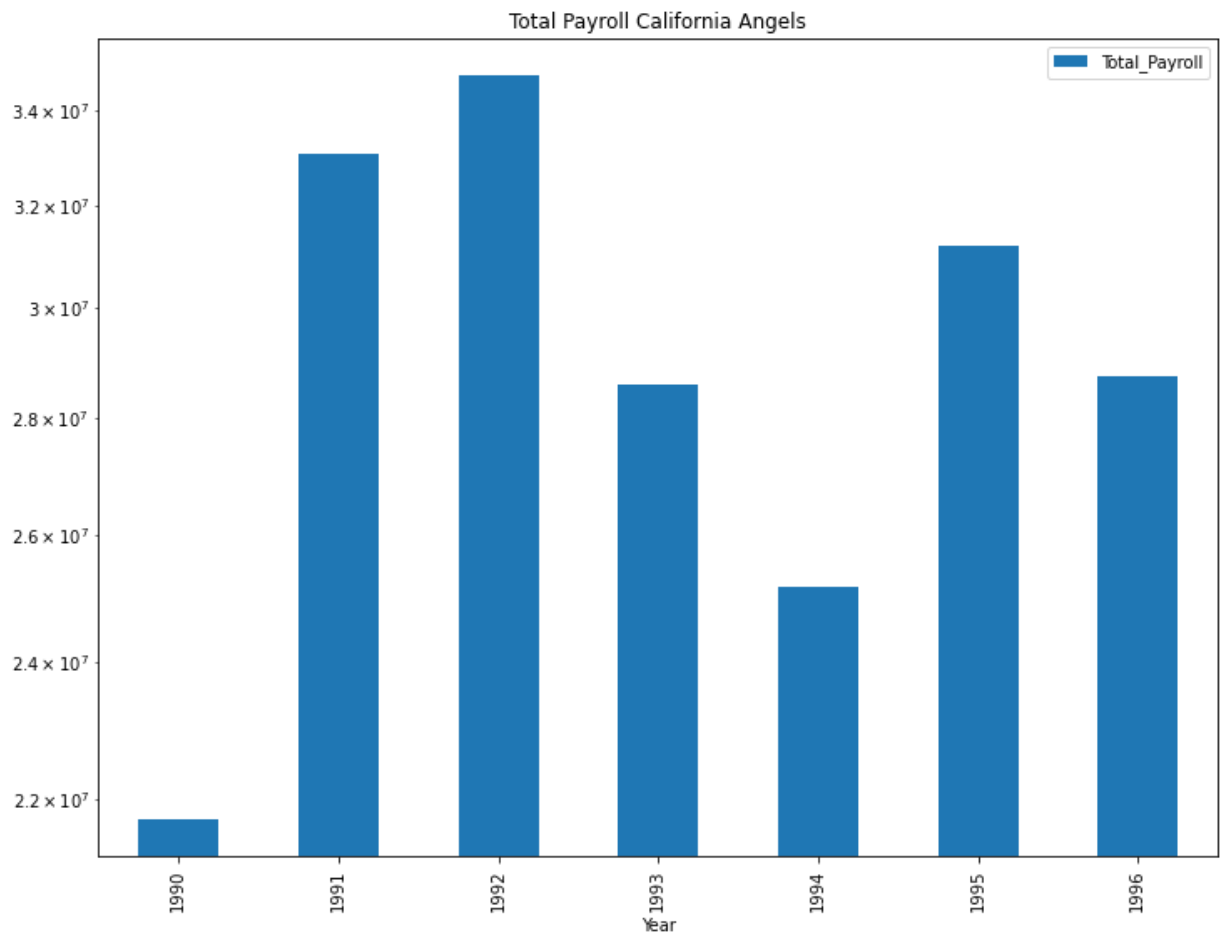


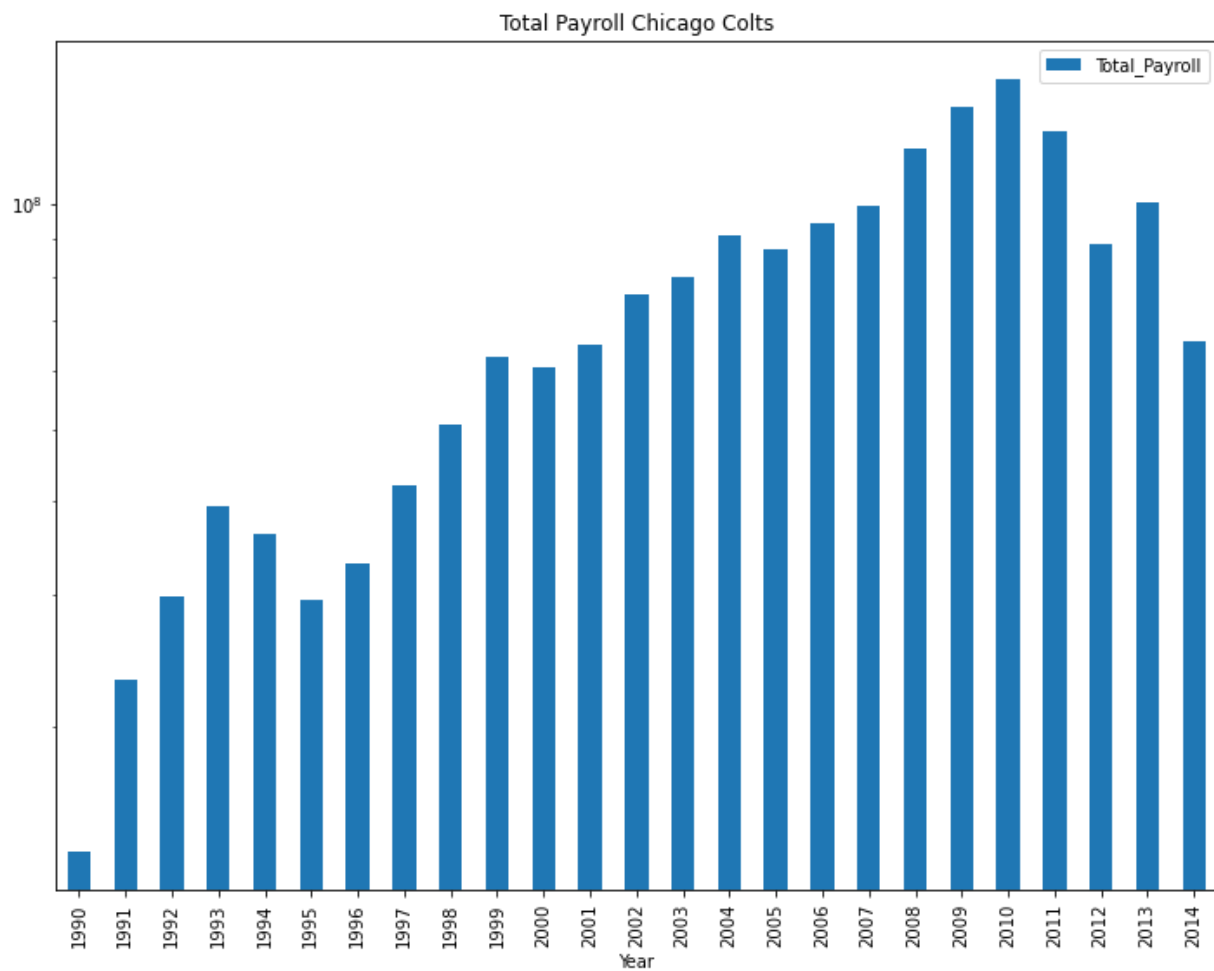


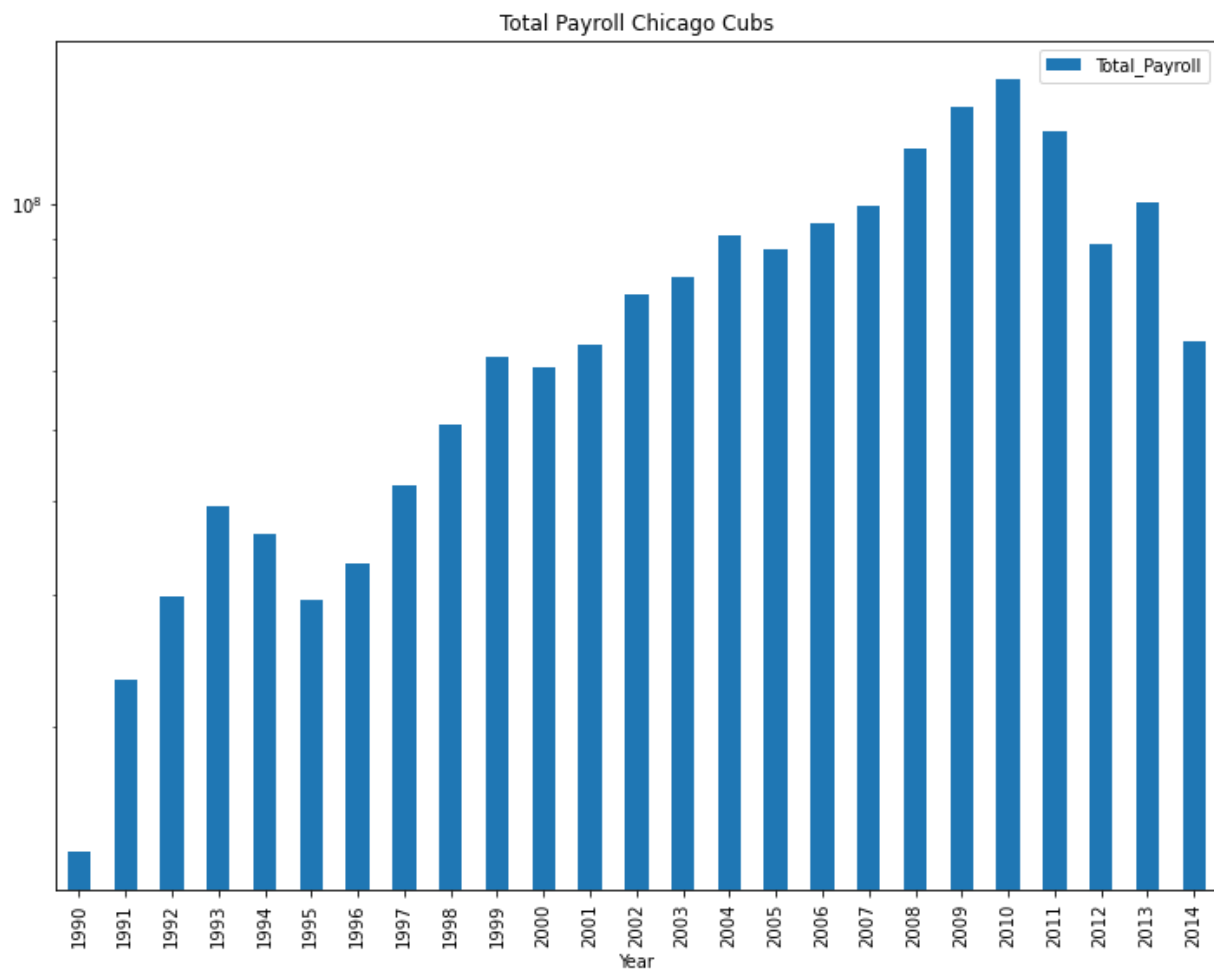




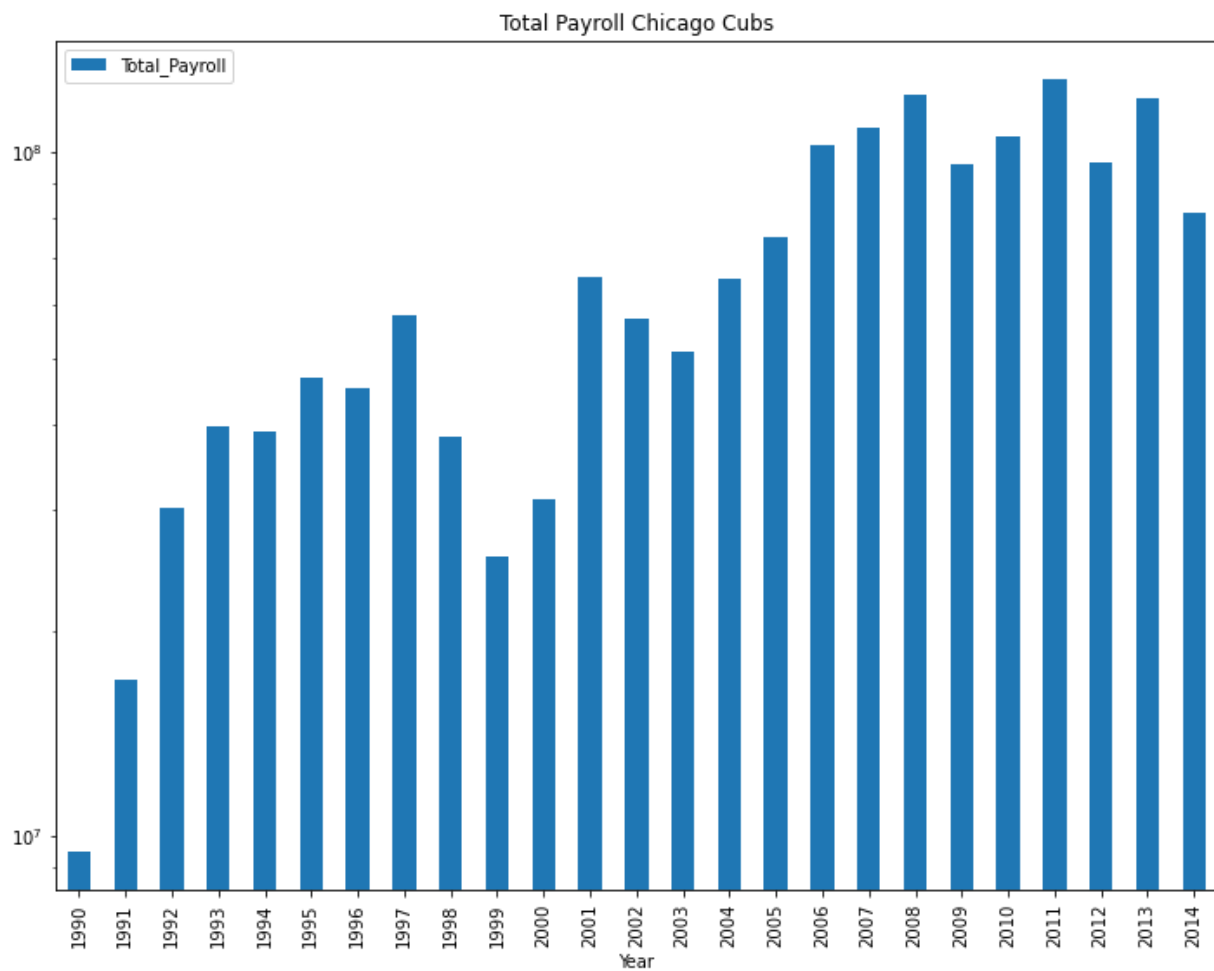


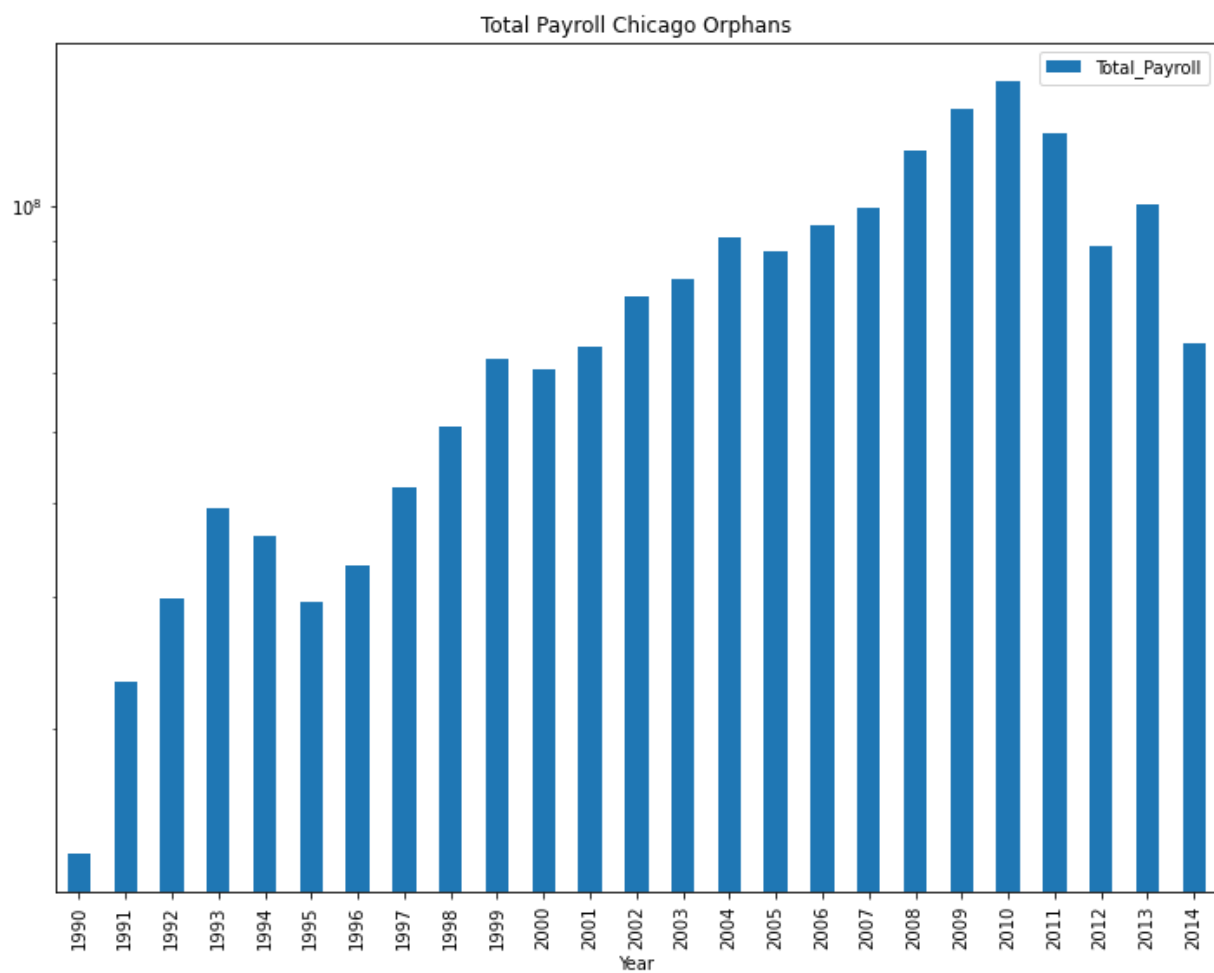


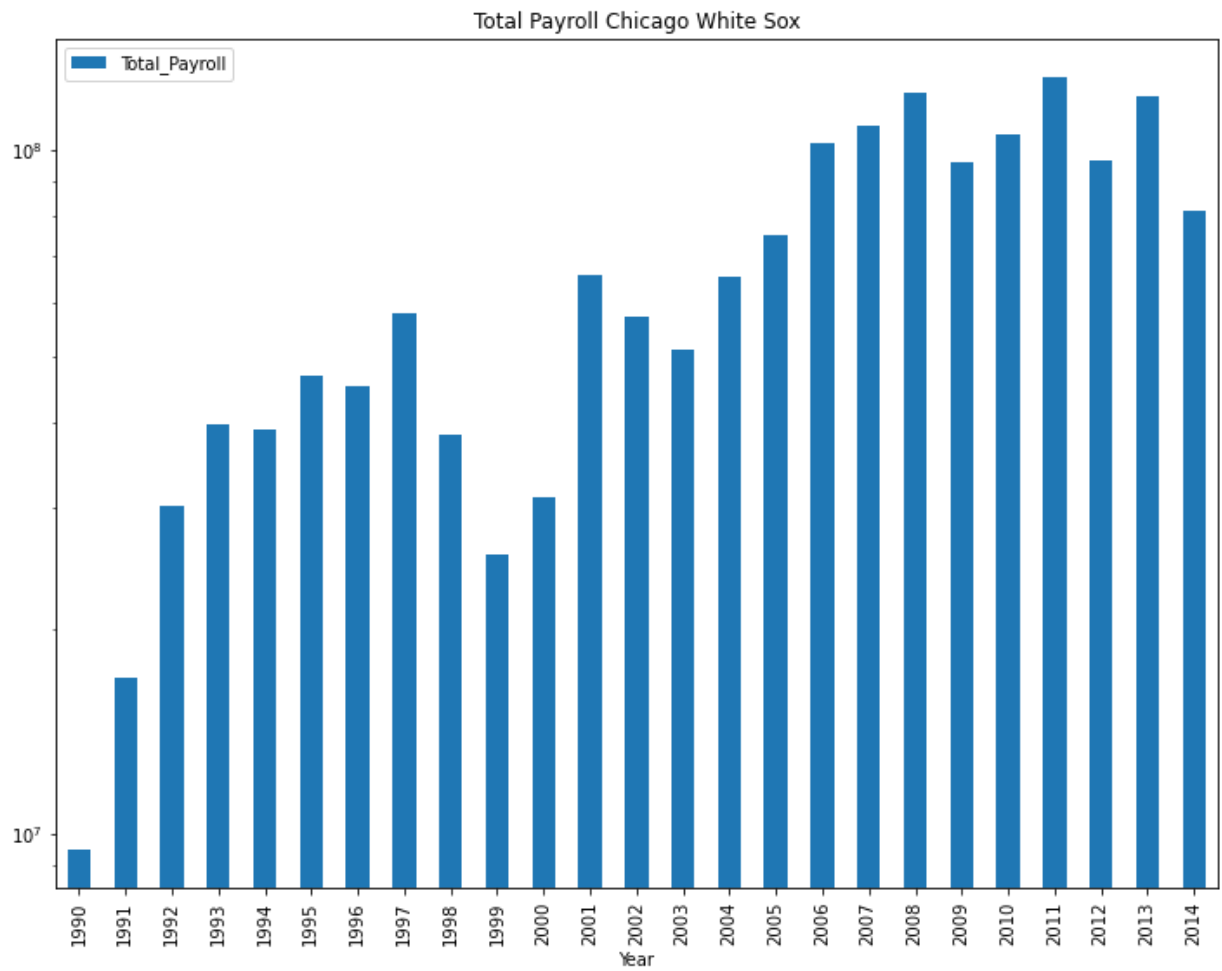


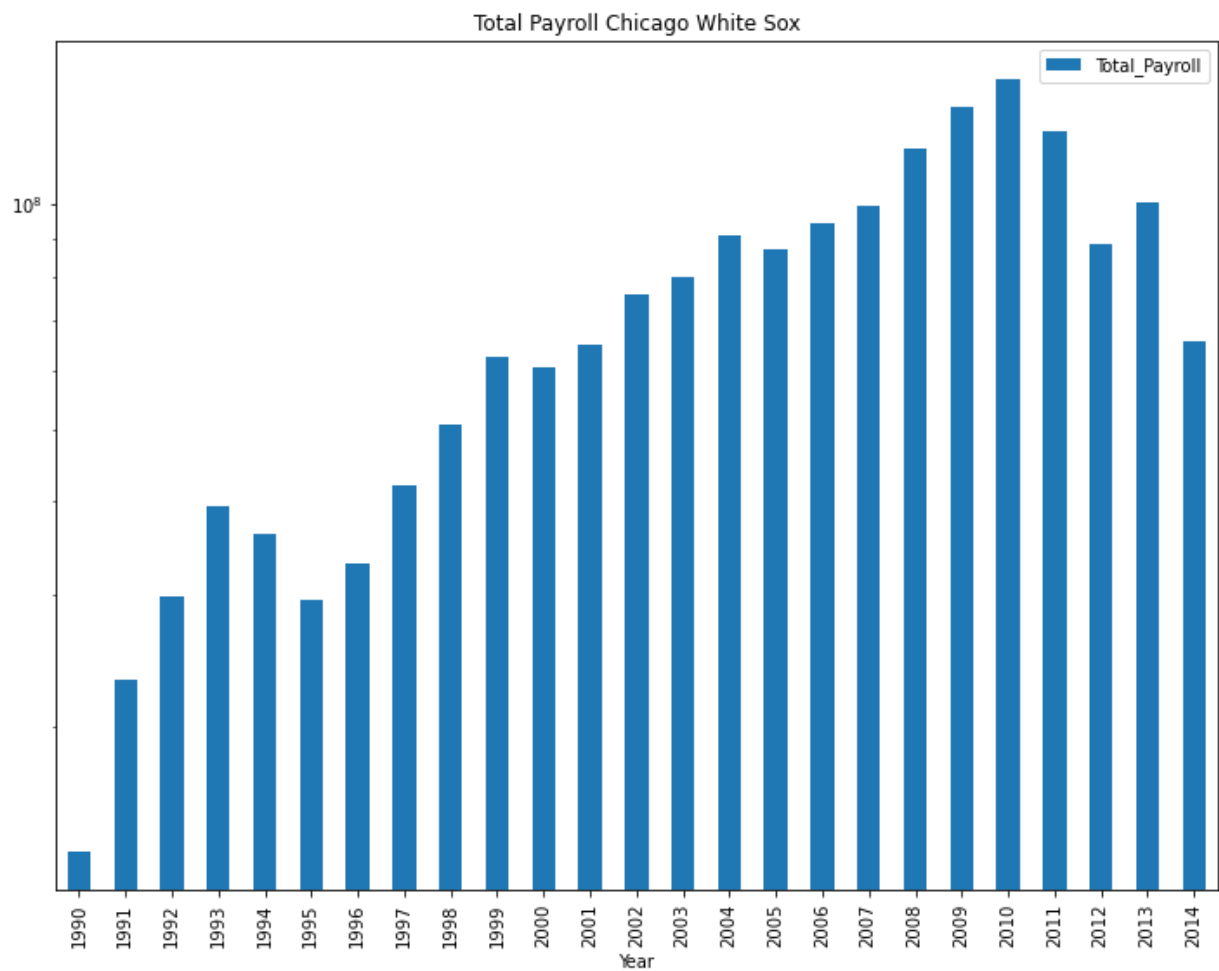


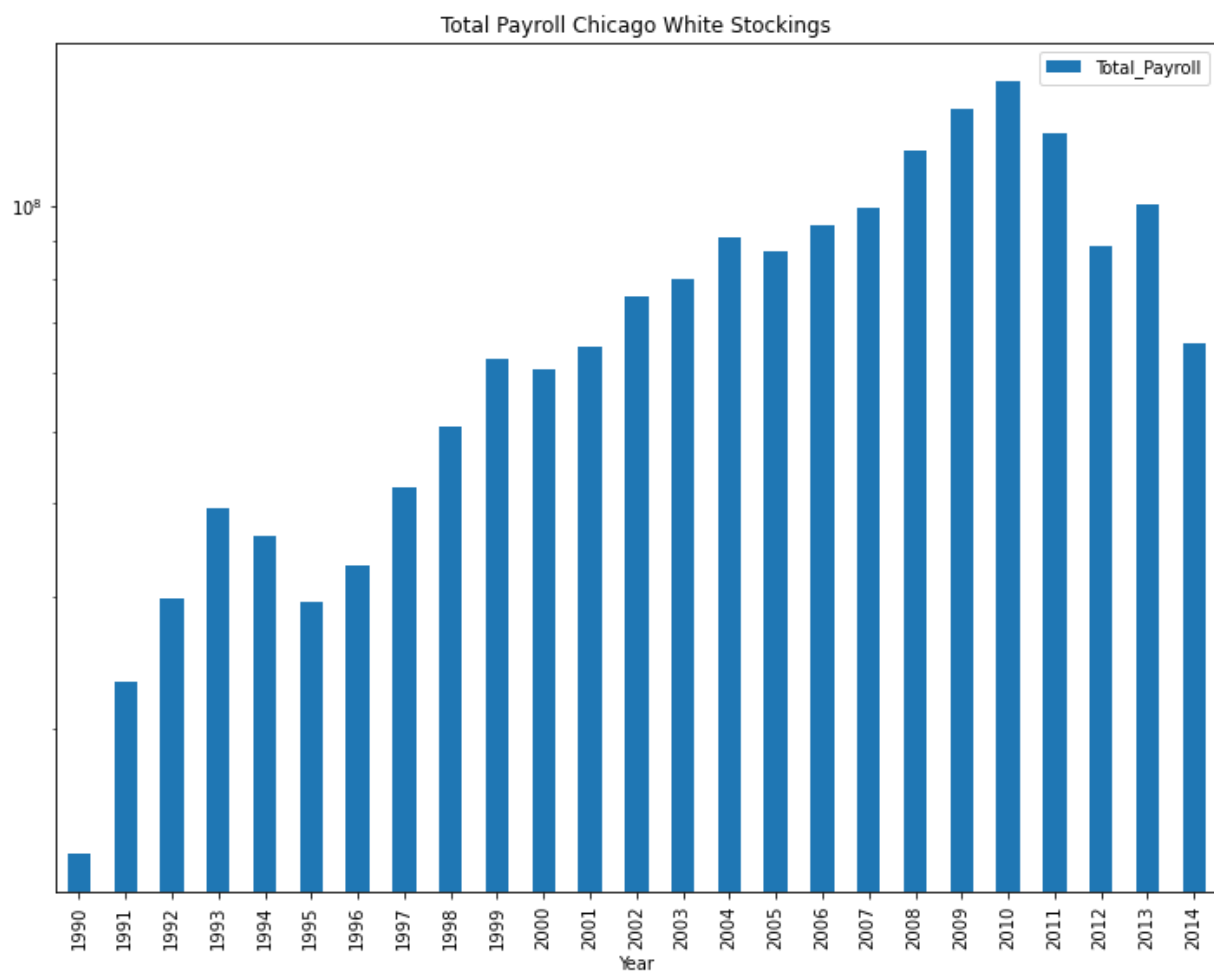


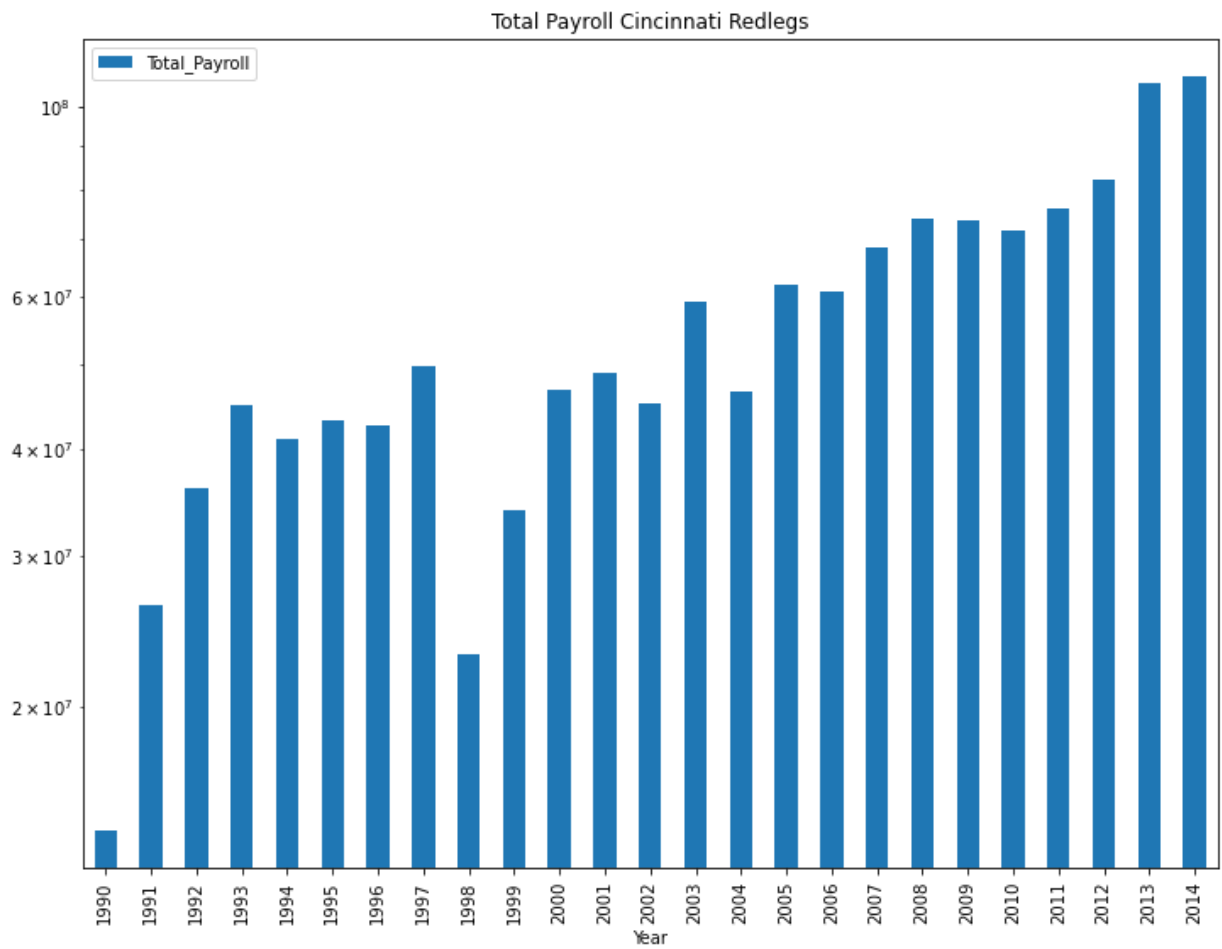


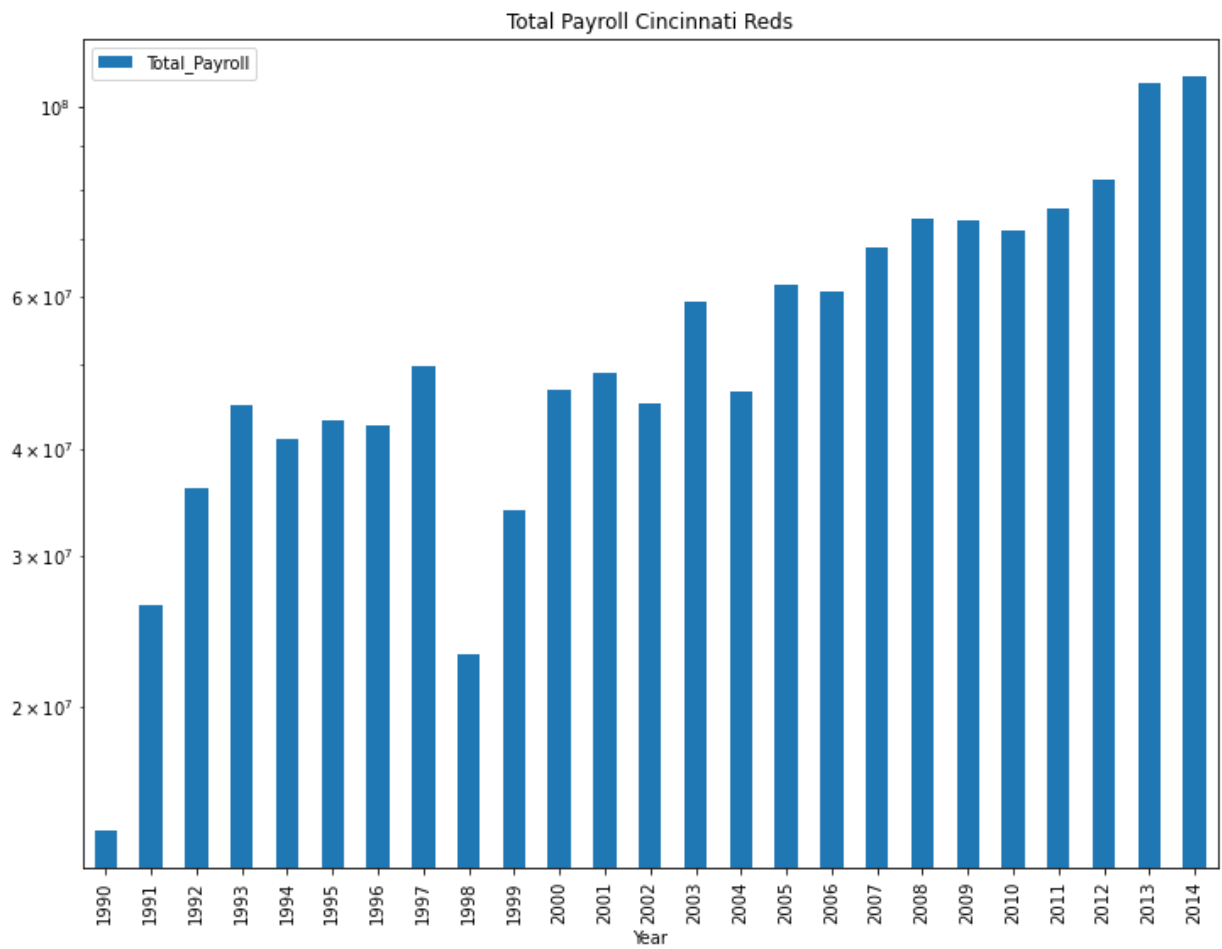


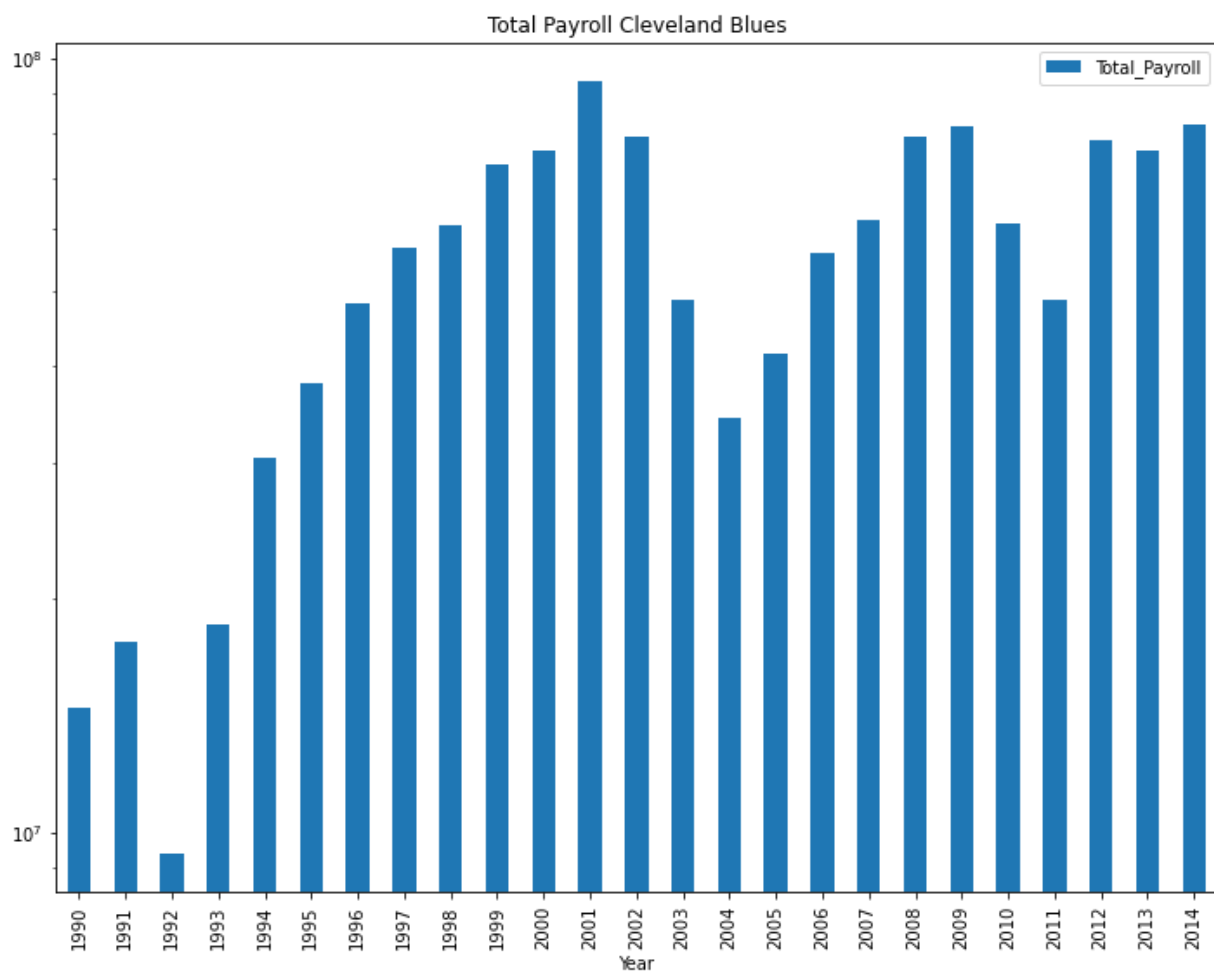




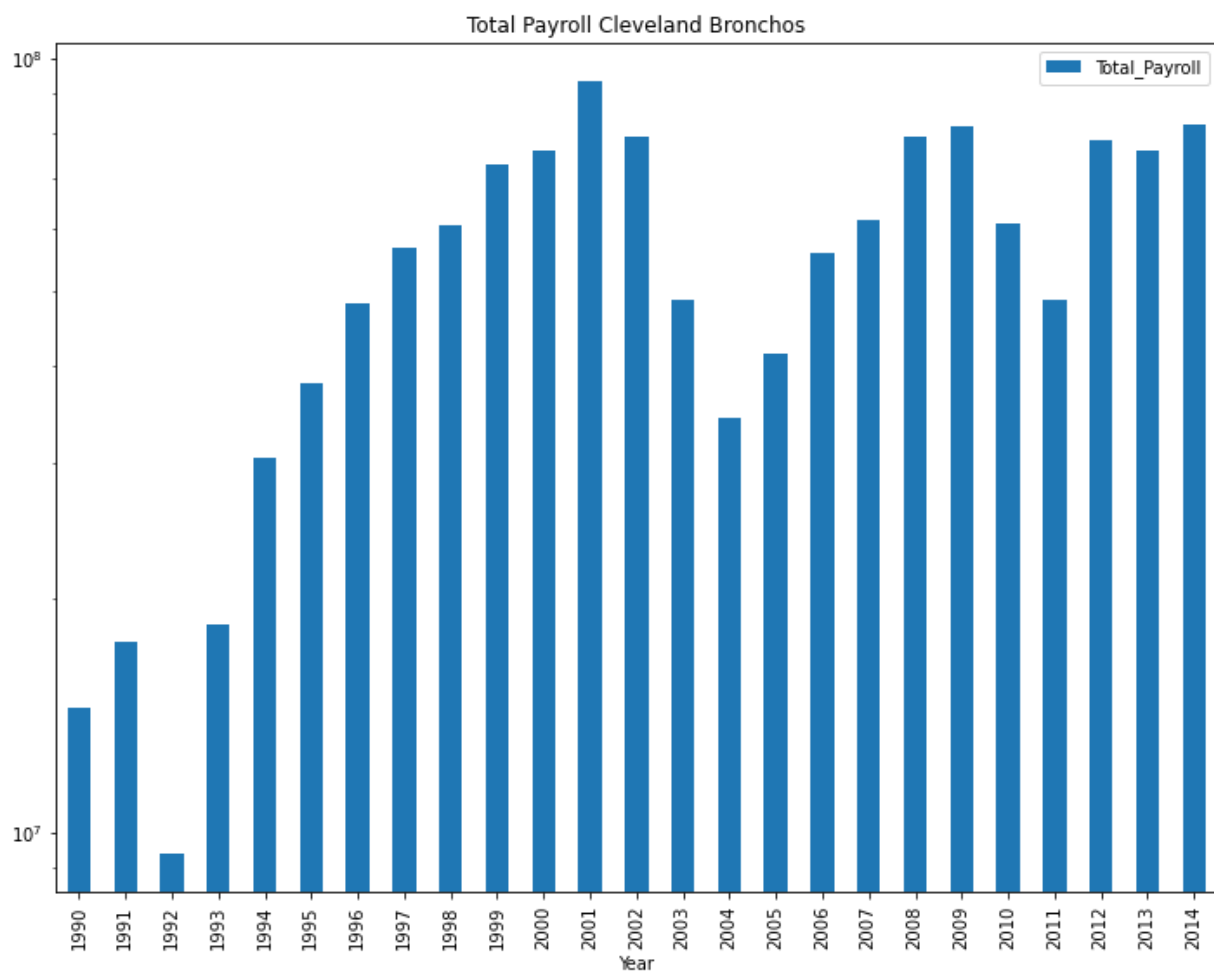


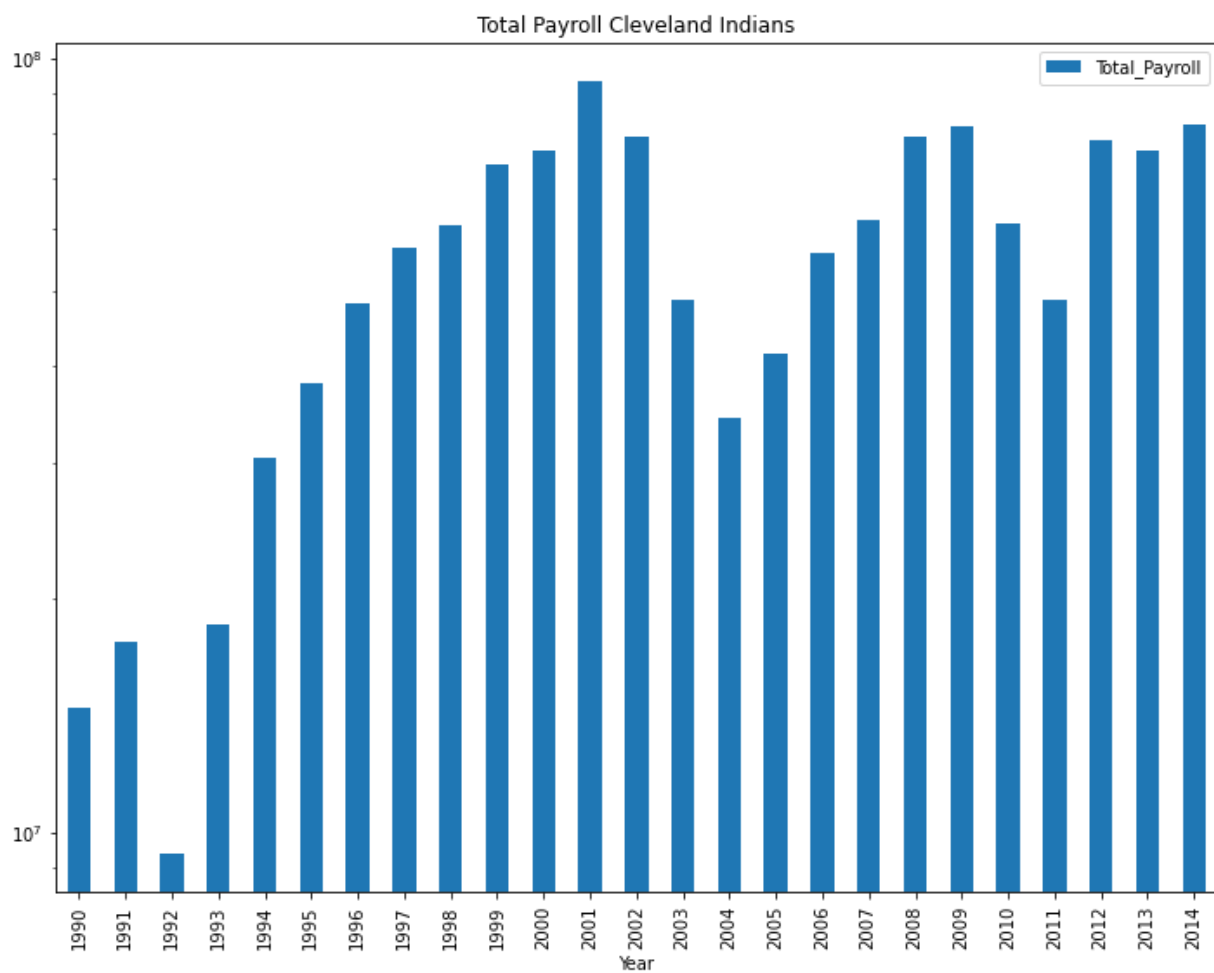


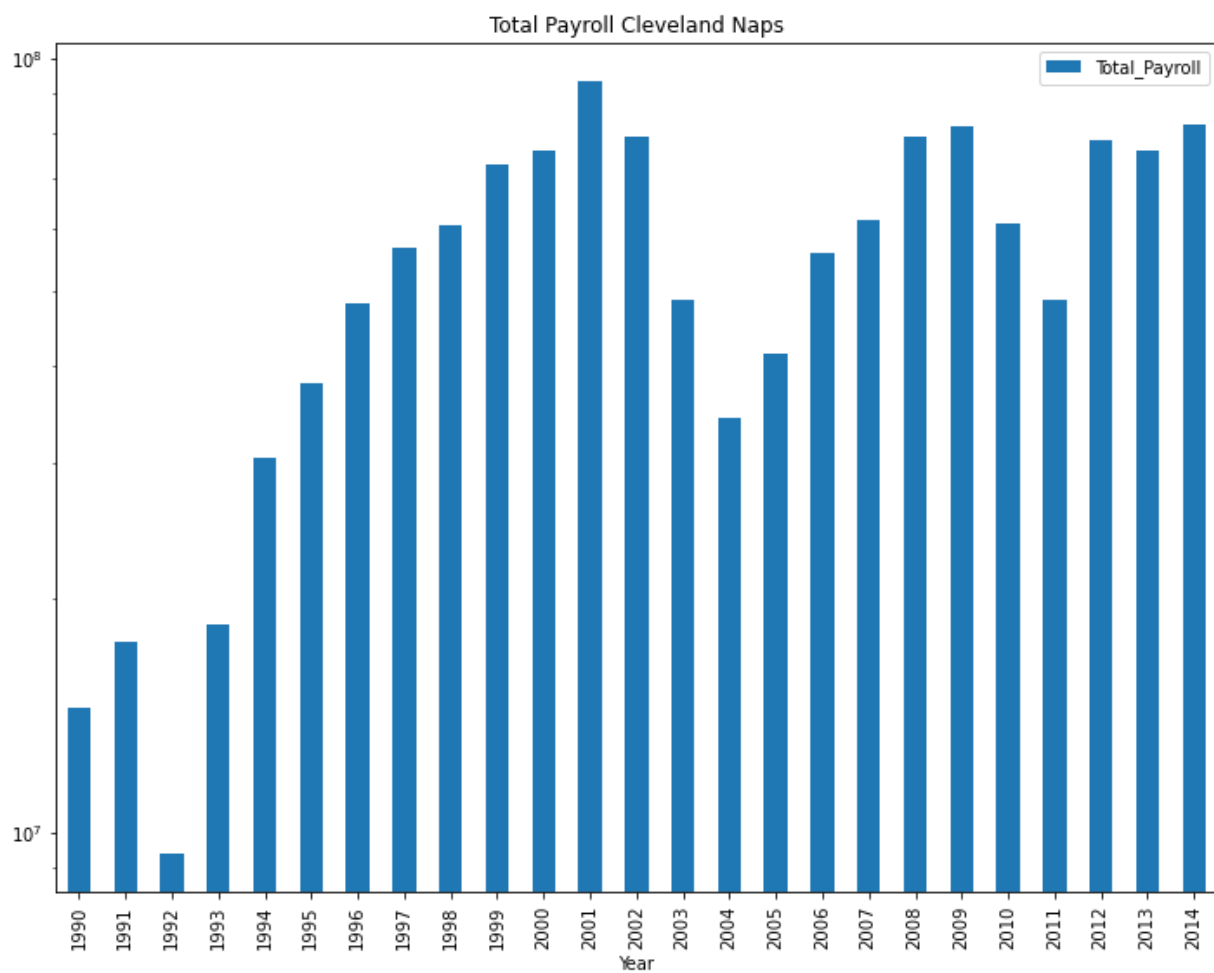


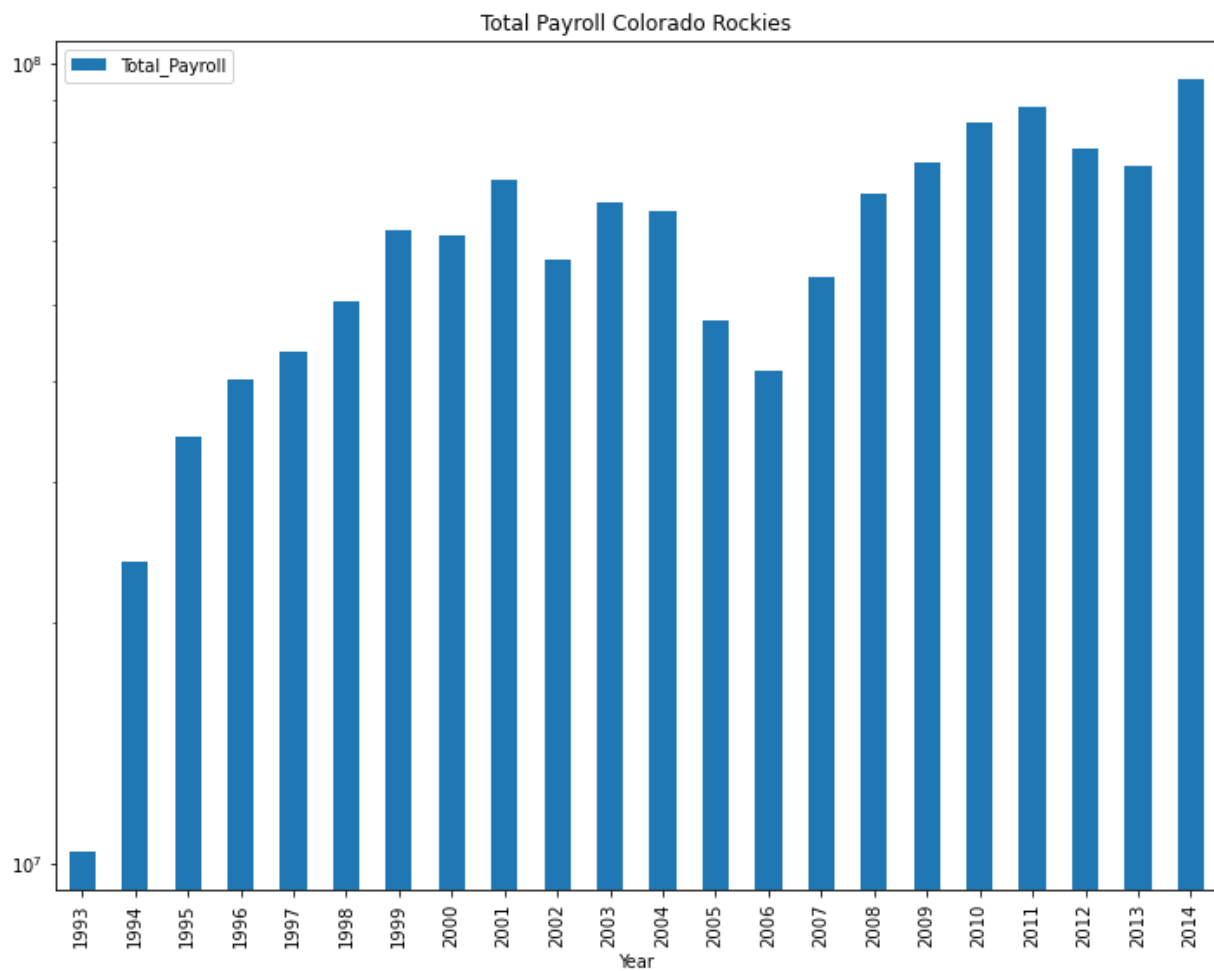


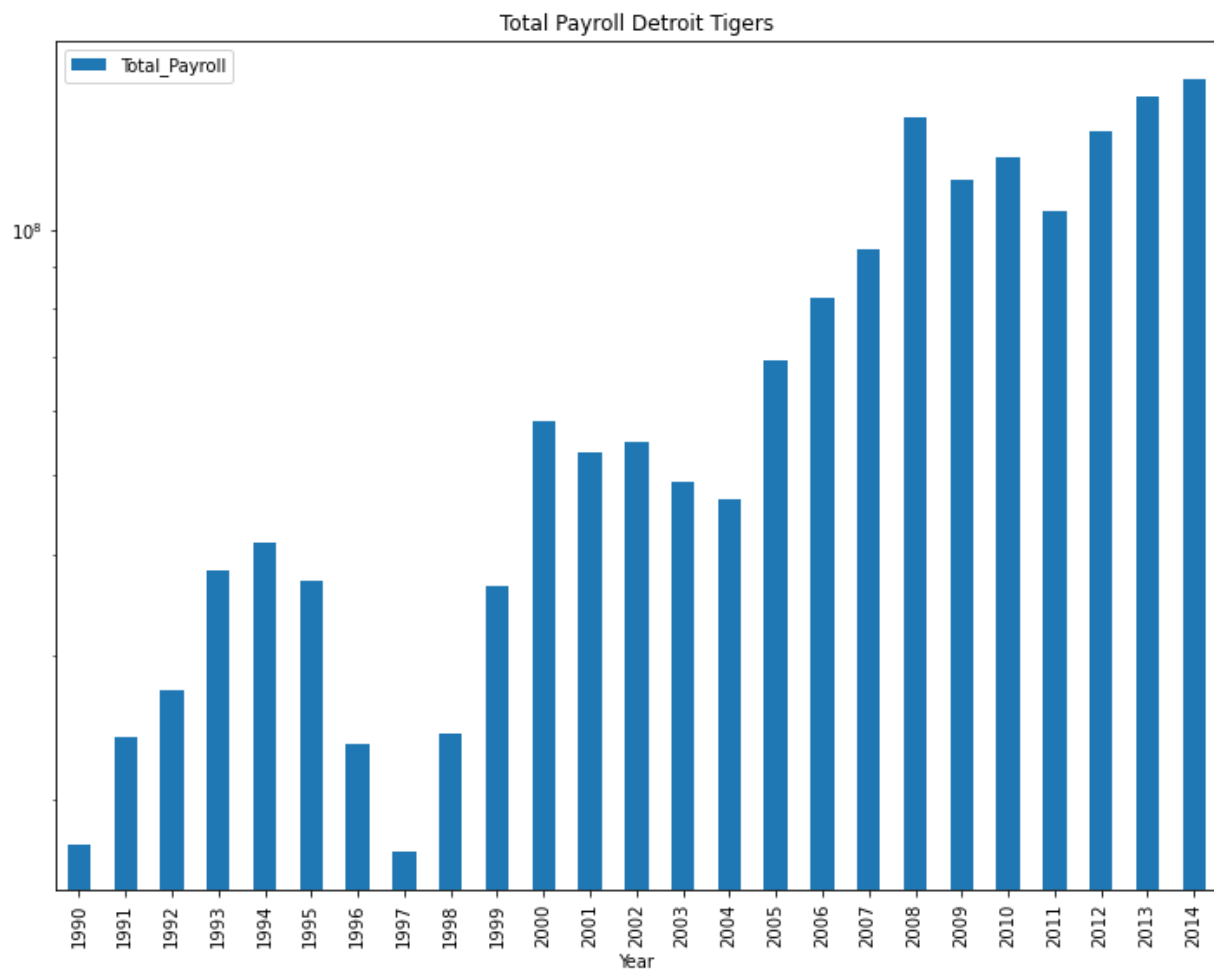


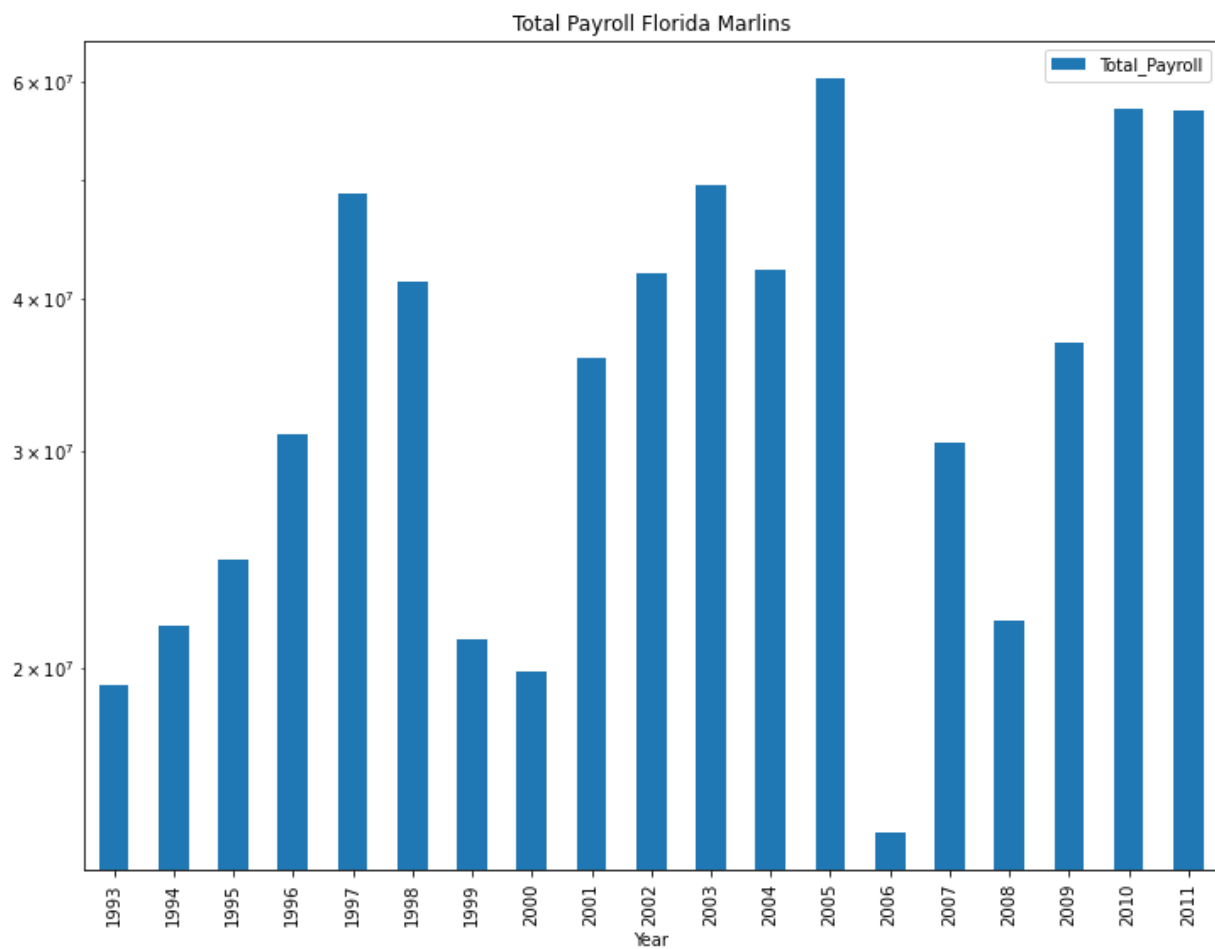


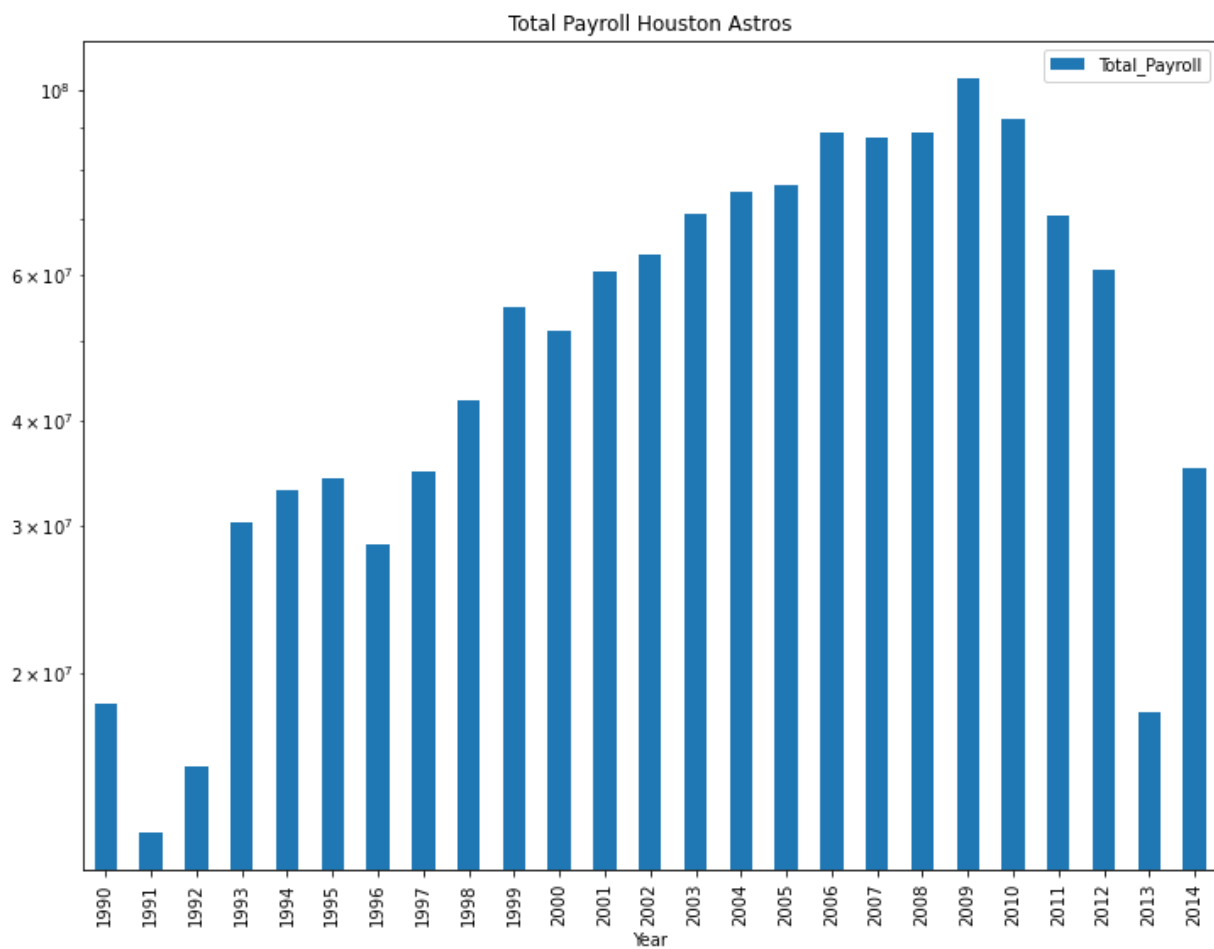


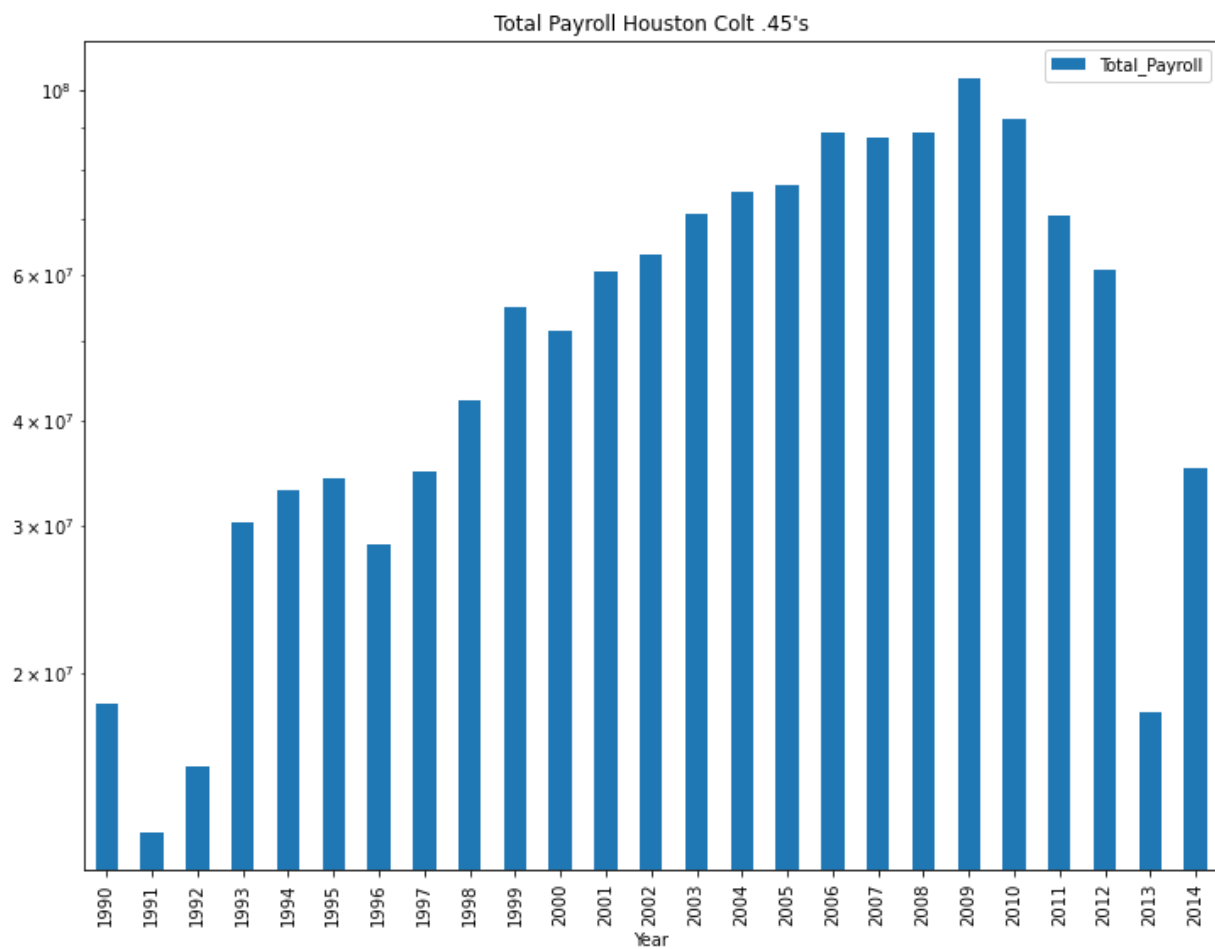




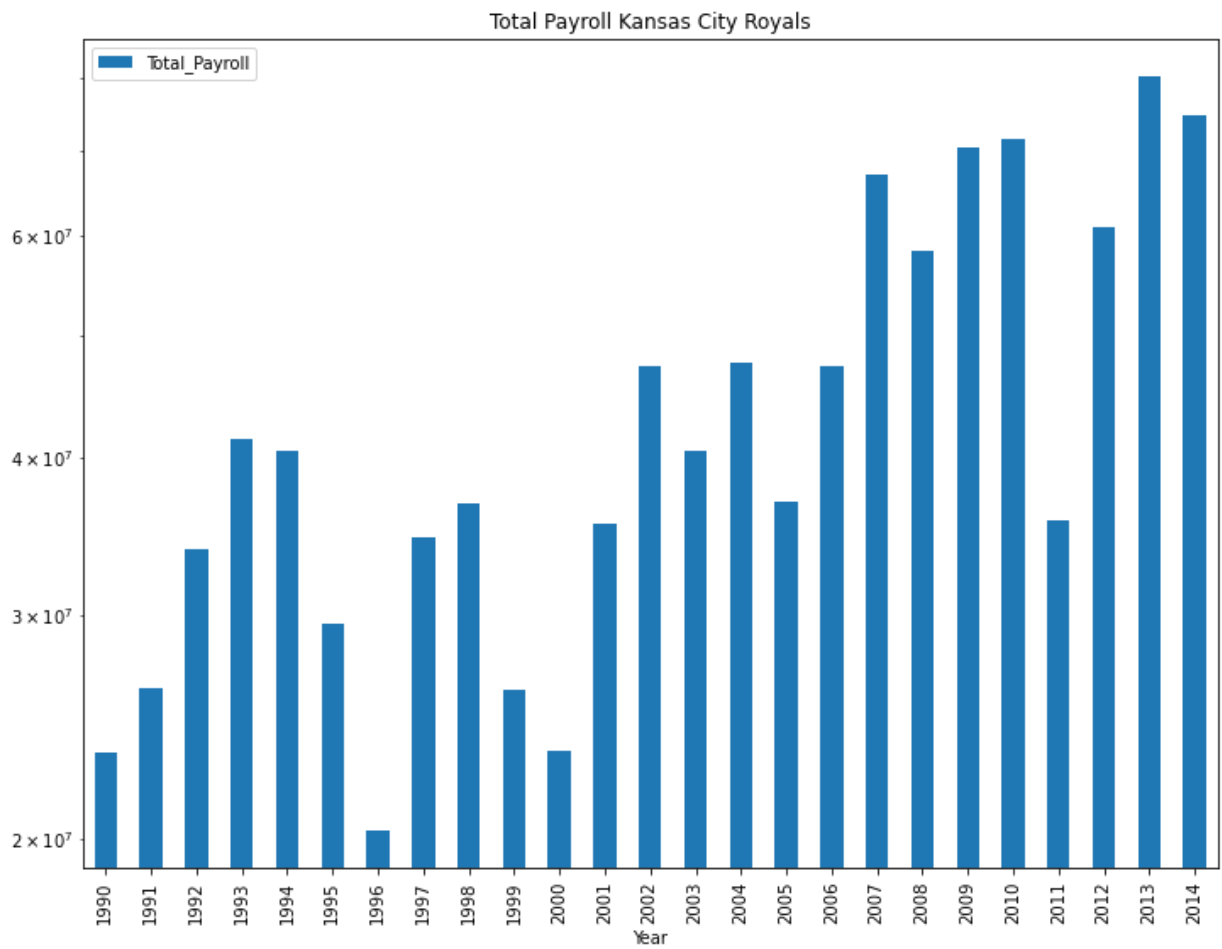


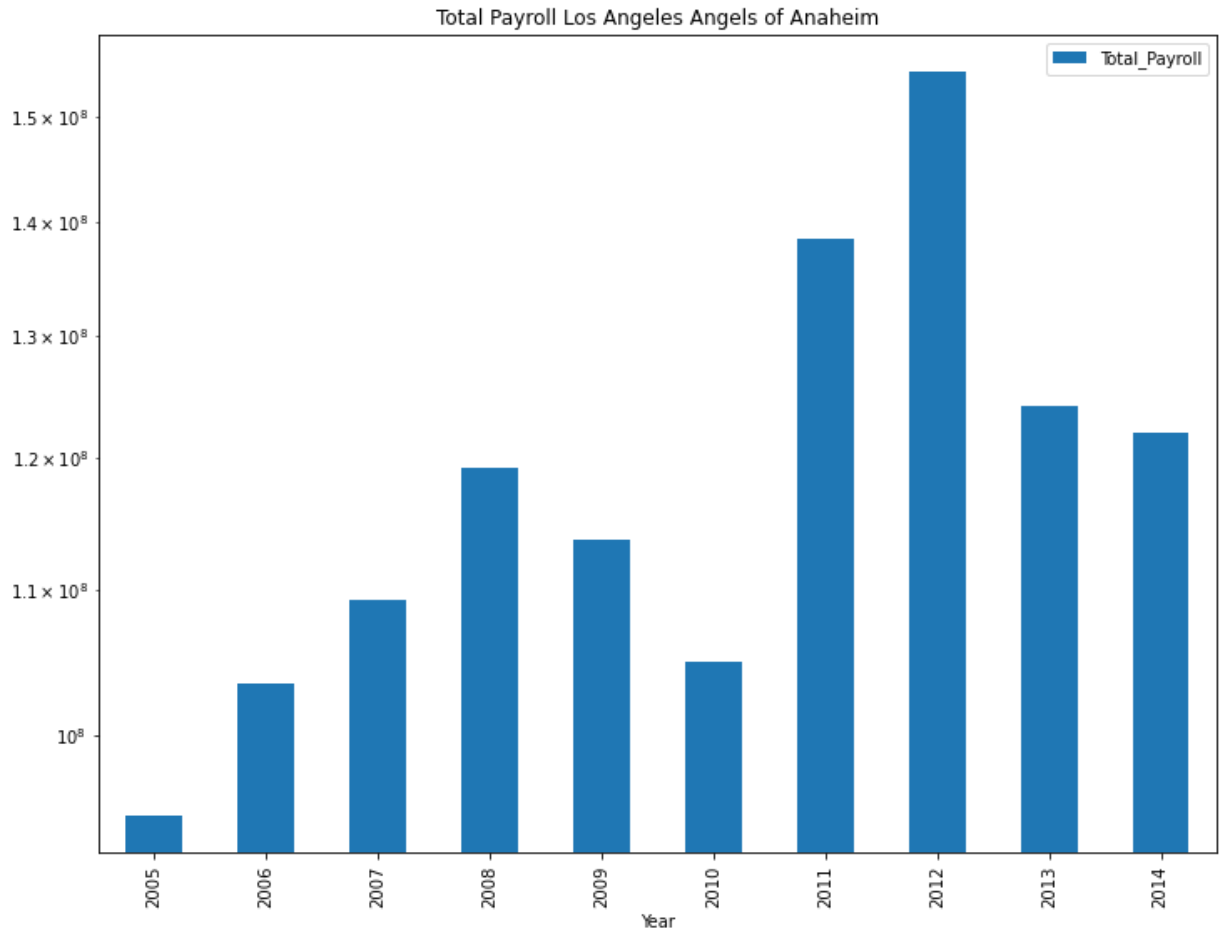
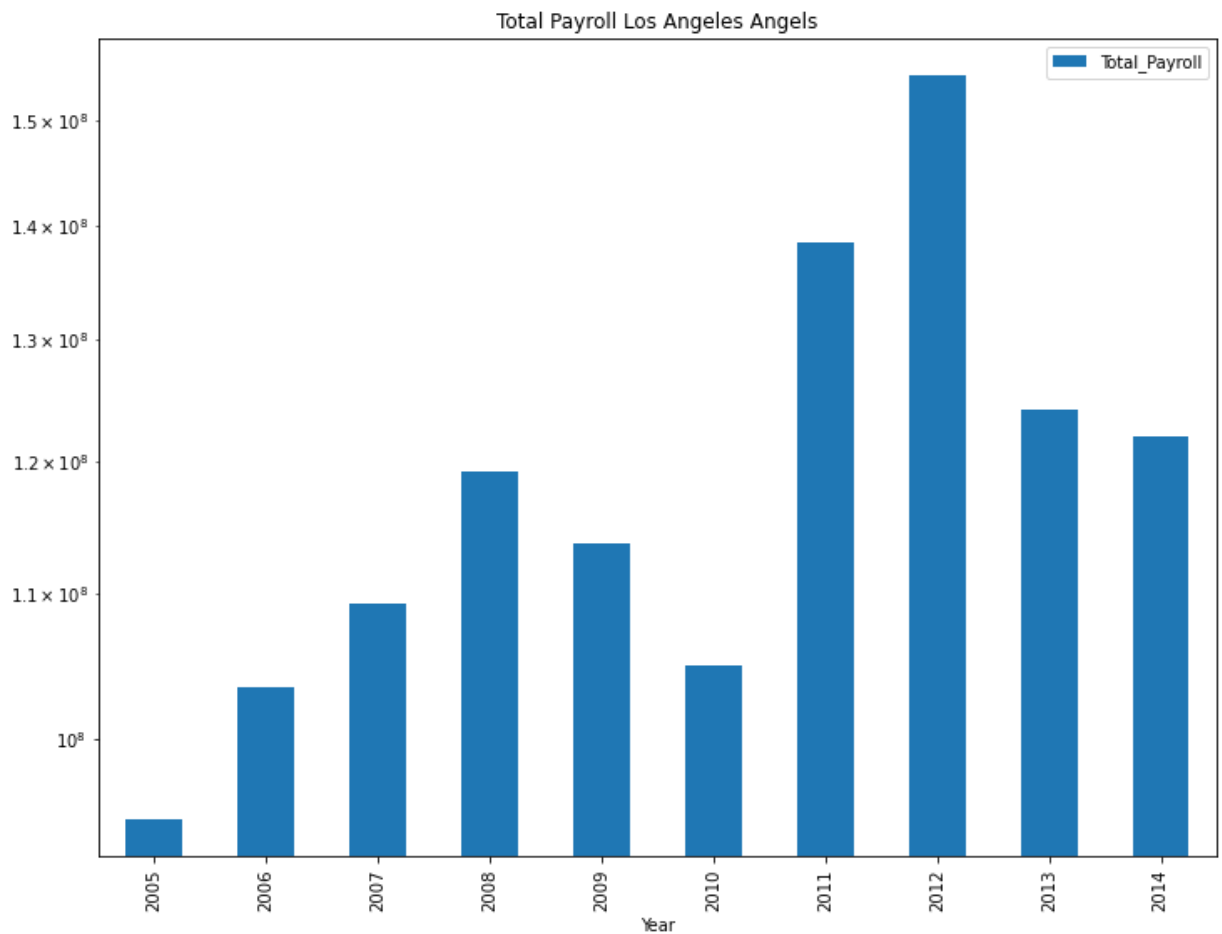


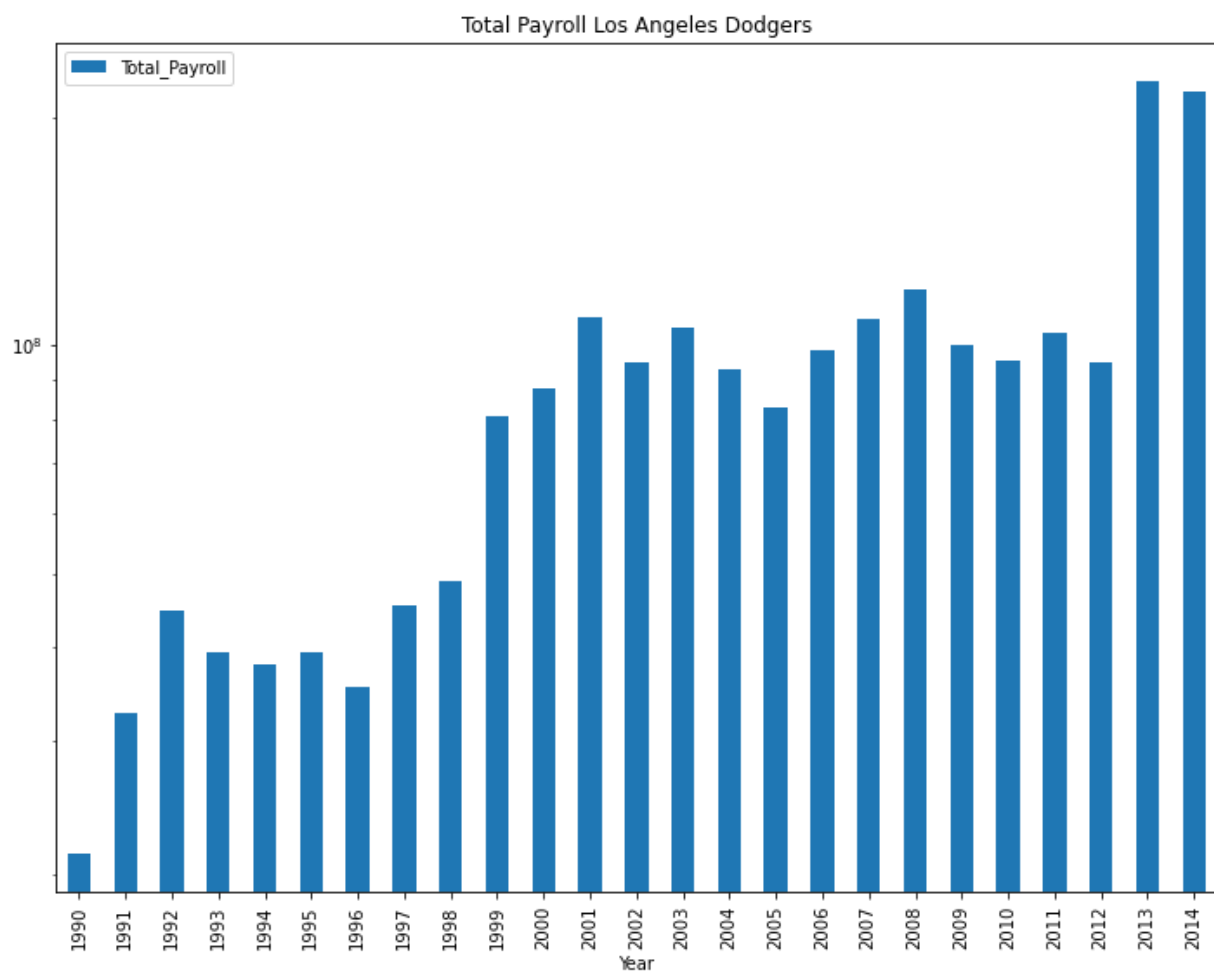


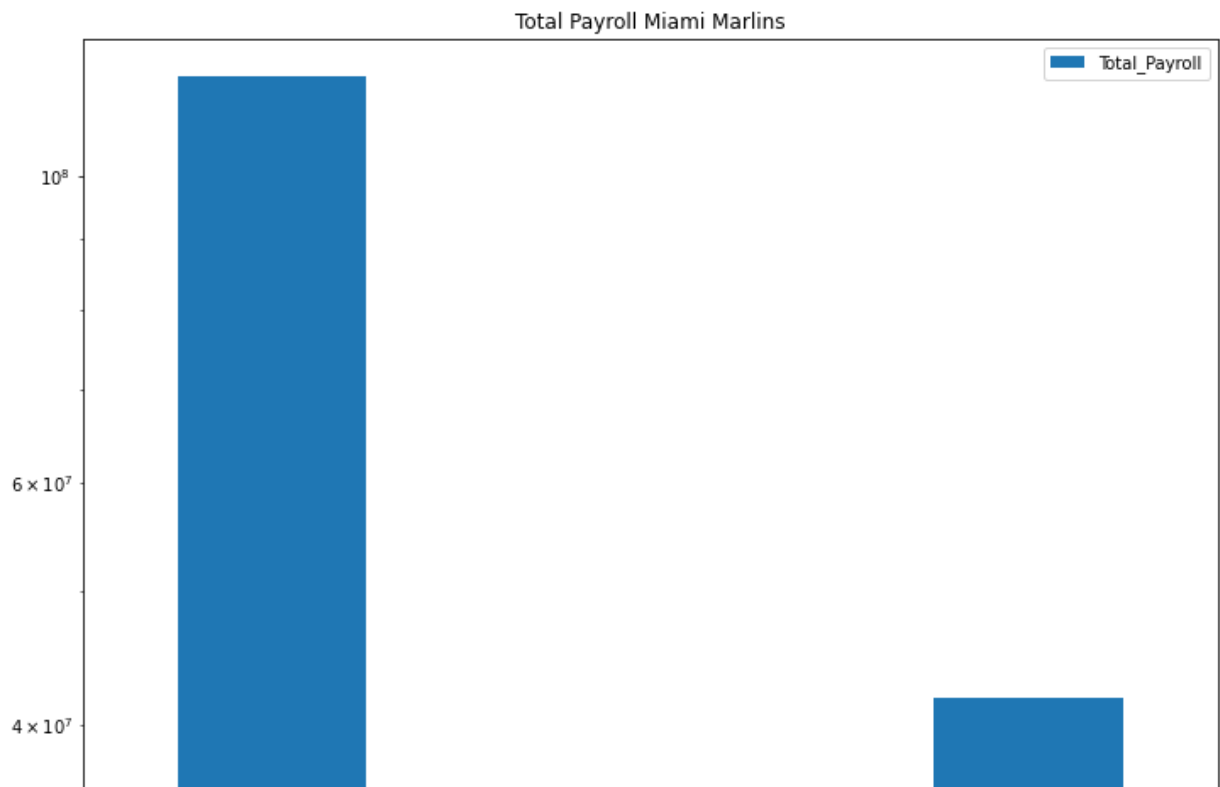












Observations about the plots :

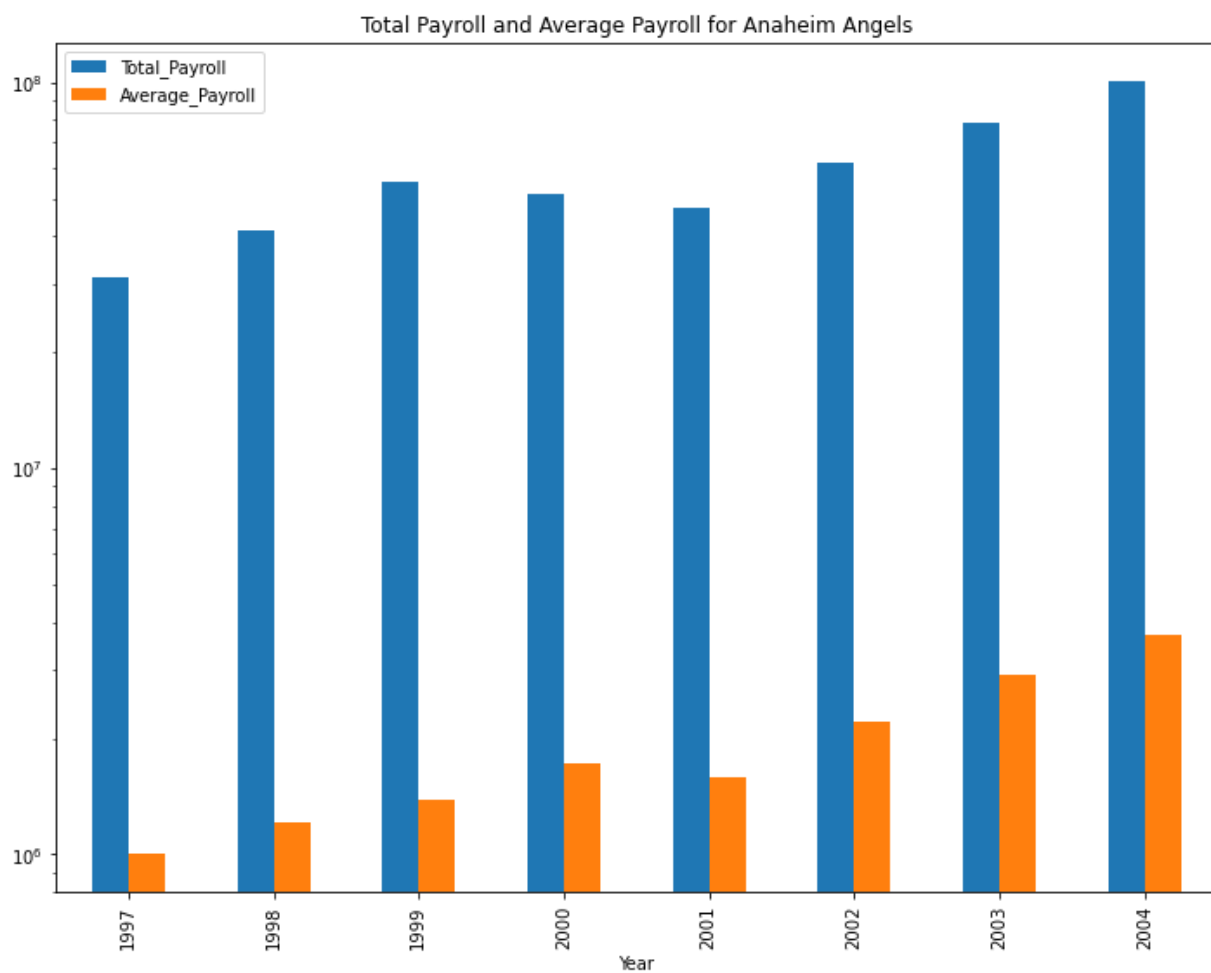
Over time, the payroll has increased for most of the teams.

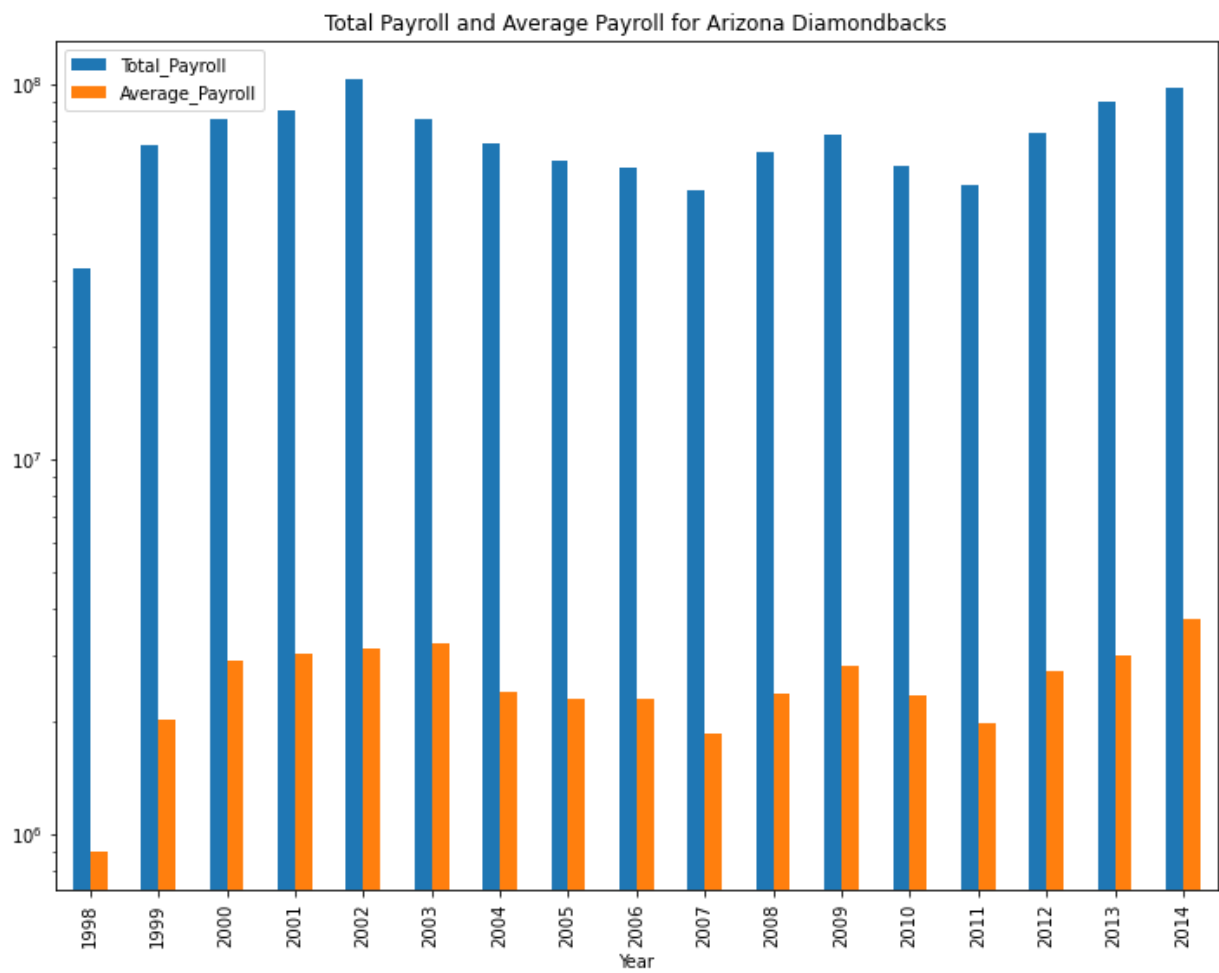
The average and total payroll have increased steadily over time.

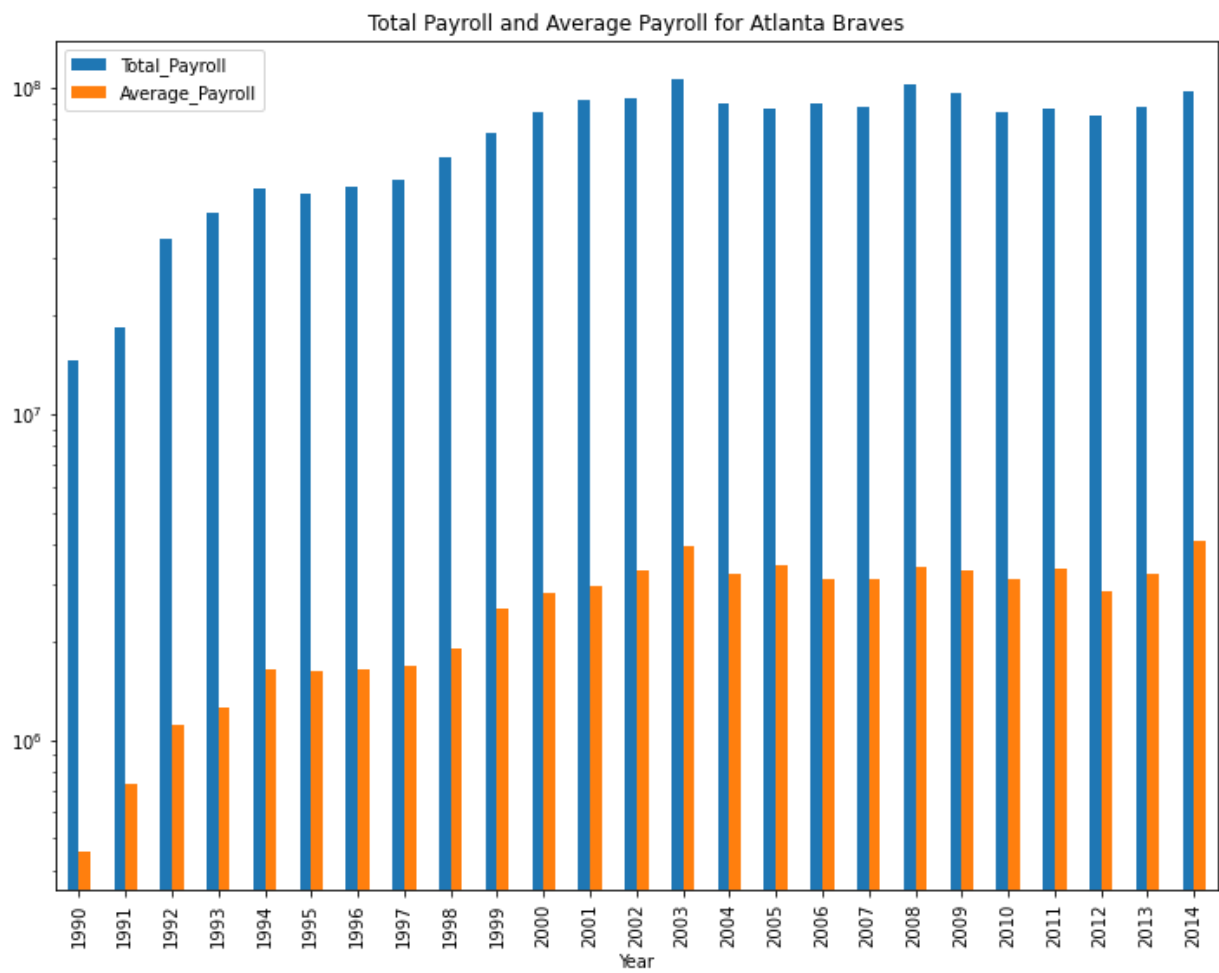
Here is a plot of the sums and the average over the years for each team. The bar plots below show an increasing trend.

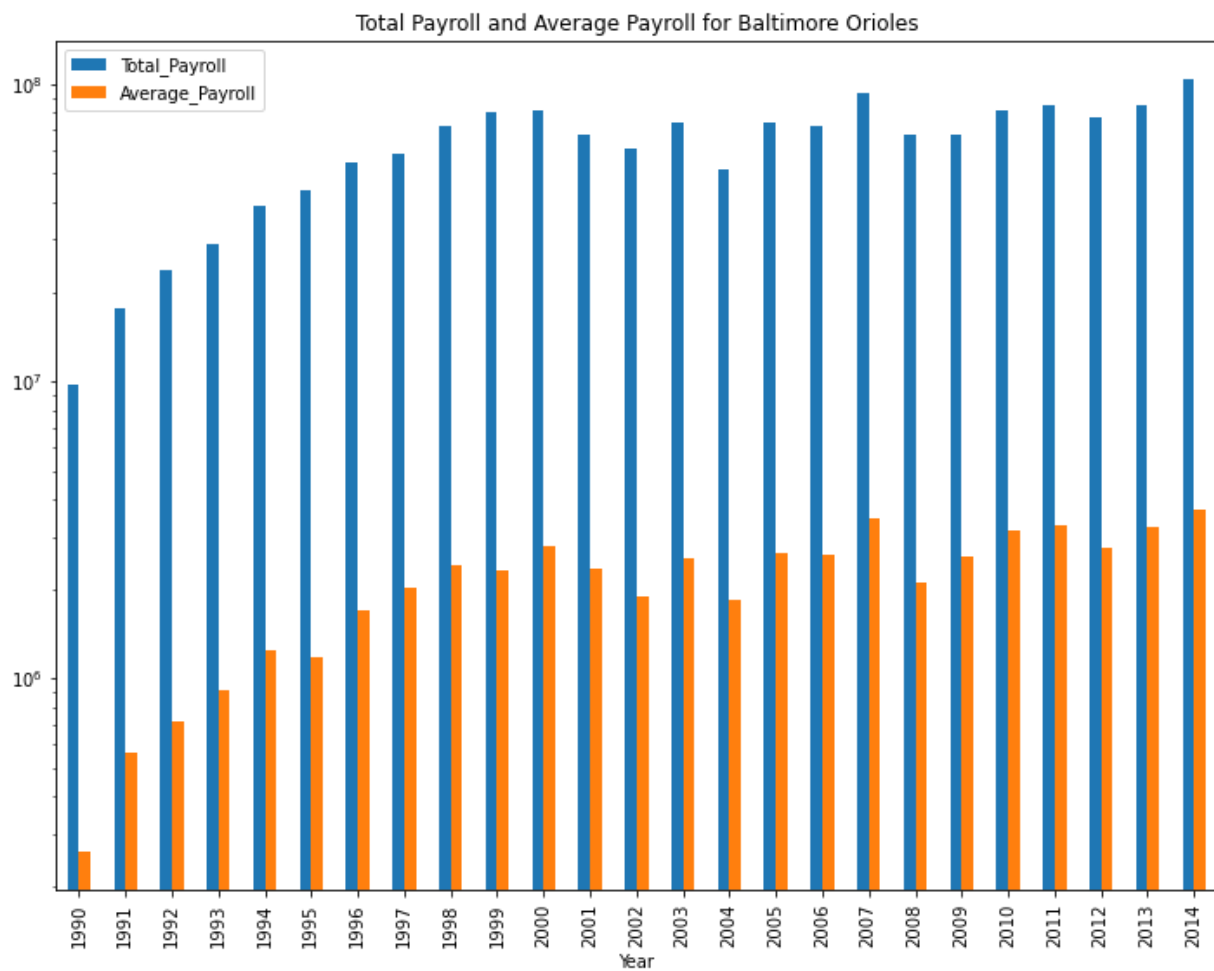
In [417...

```
num_results = len(result_frames_objects)
#prevents warning after 20 figures shown
plt.rcParams.update({'figure.max_open_warning':0})
figsize = (12,9)
for i in range(num_results):
    dfr = result_frames_objects[i]
    team_name = team_names[i]
    team_id = team_ids[i]
    #we only plot if the data frame in
    #question is not empty
    if not dfr.empty:
        dfr.plot(x='Year', y=['Total_Payroll','Average_Payroll'], logy=True,
                 title = 'Total Payroll and Average Payroll for ' + team_name)
```

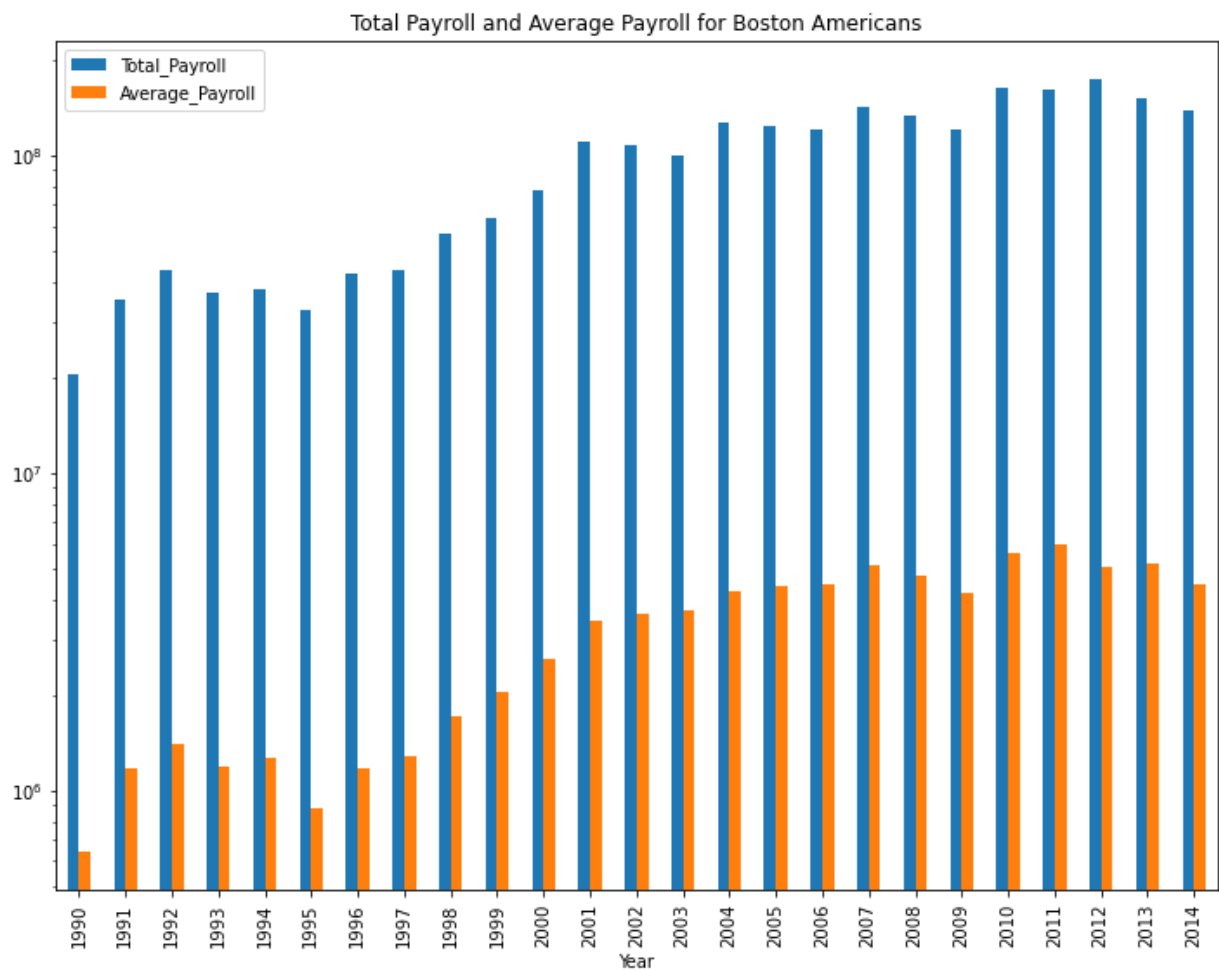


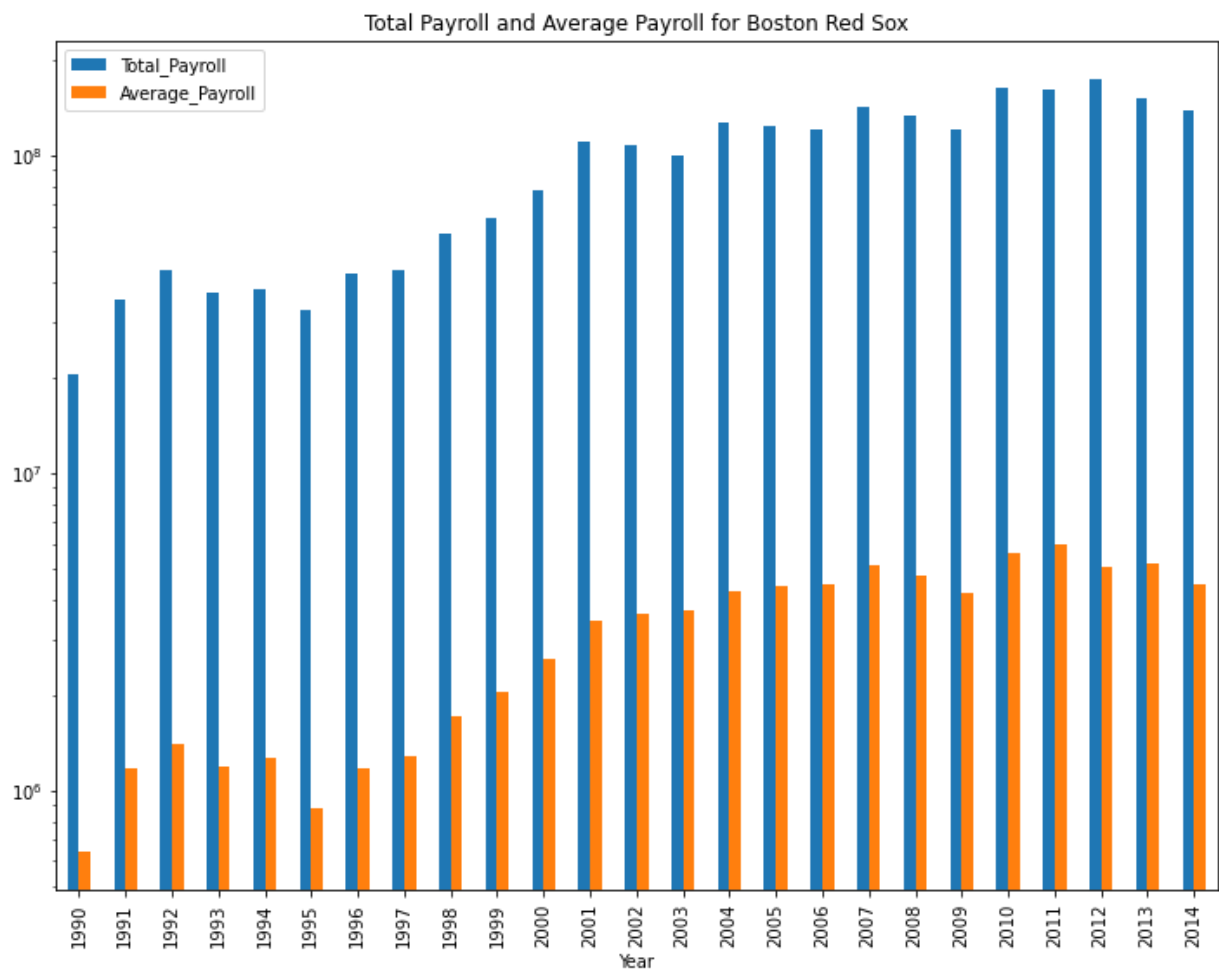


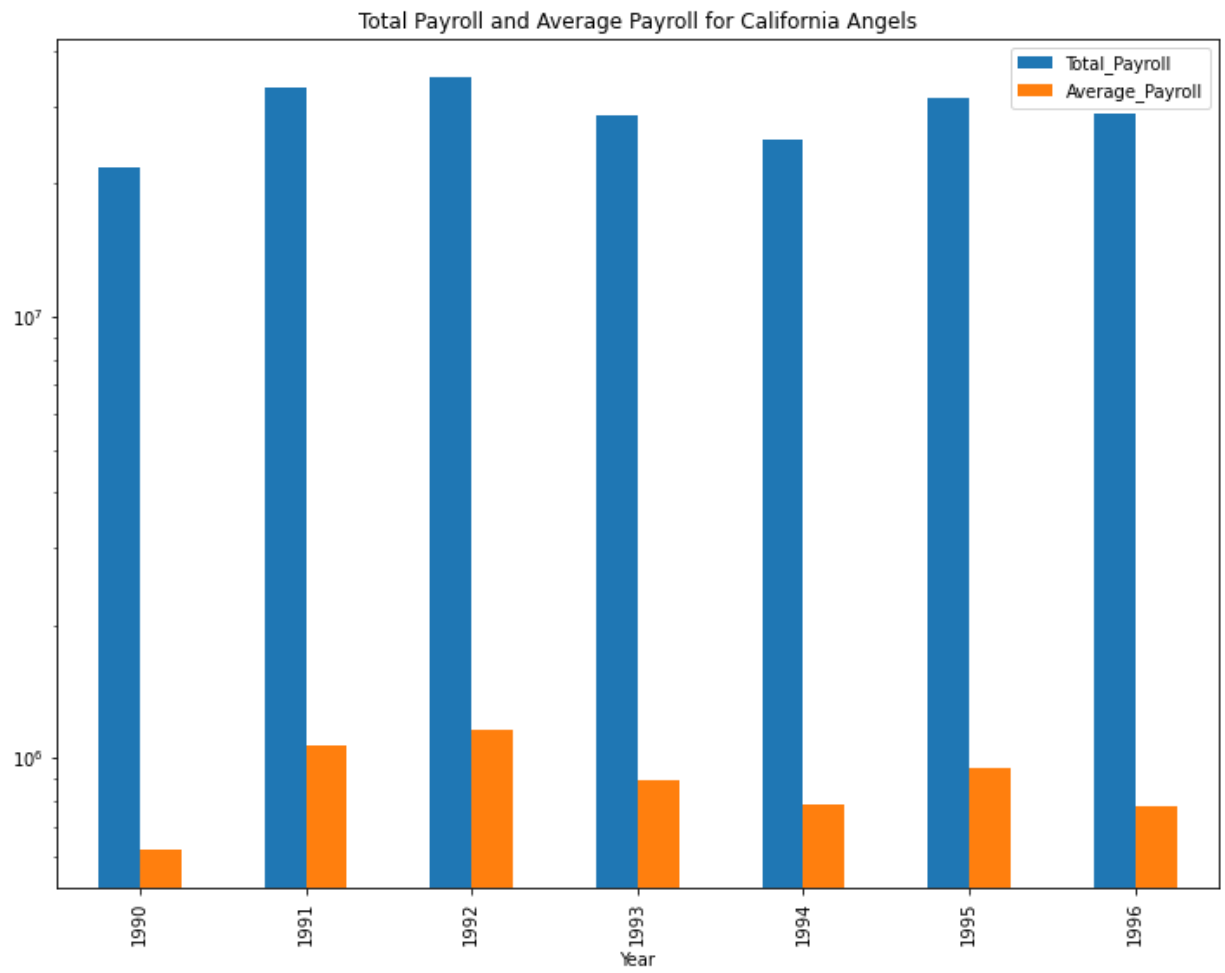


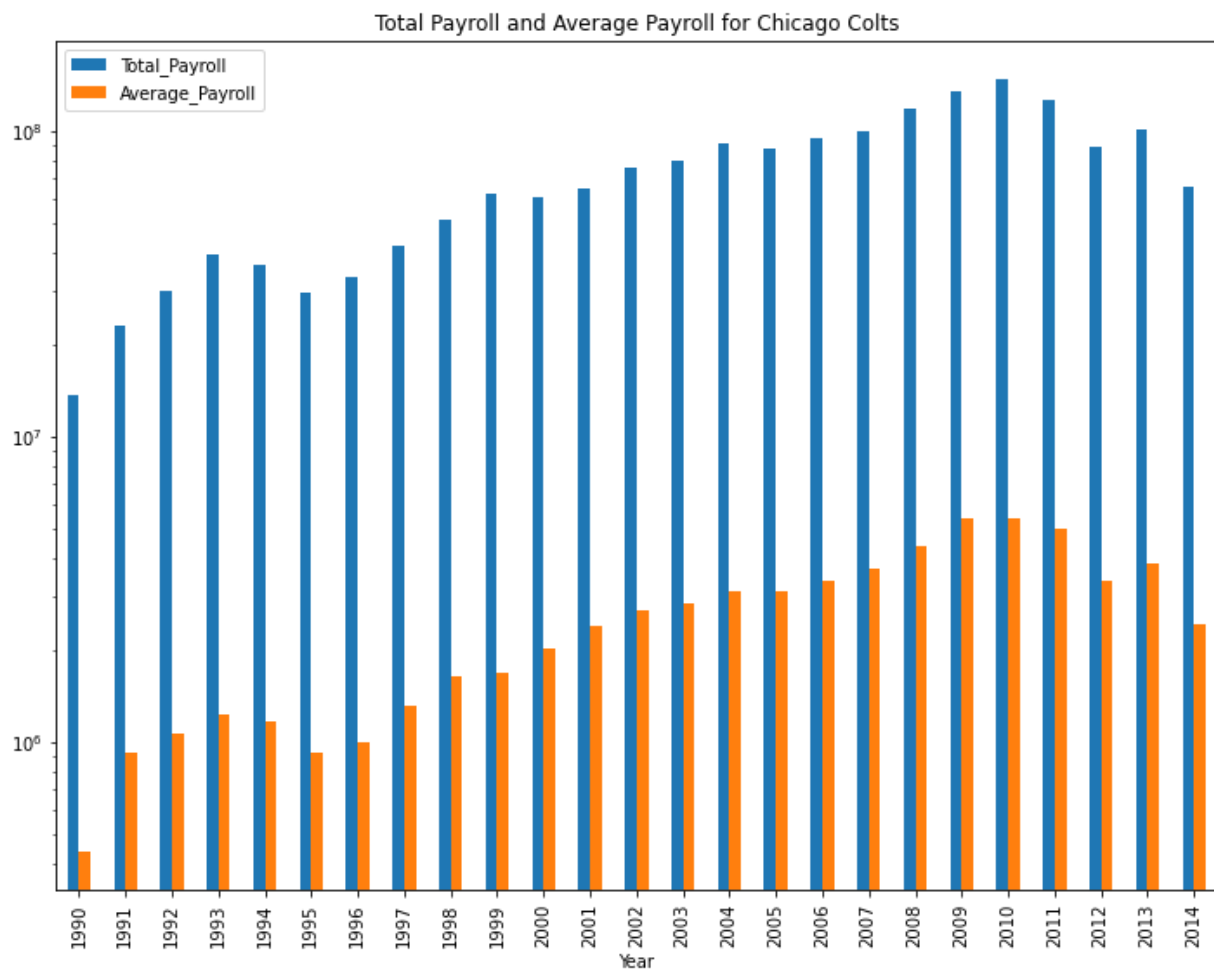


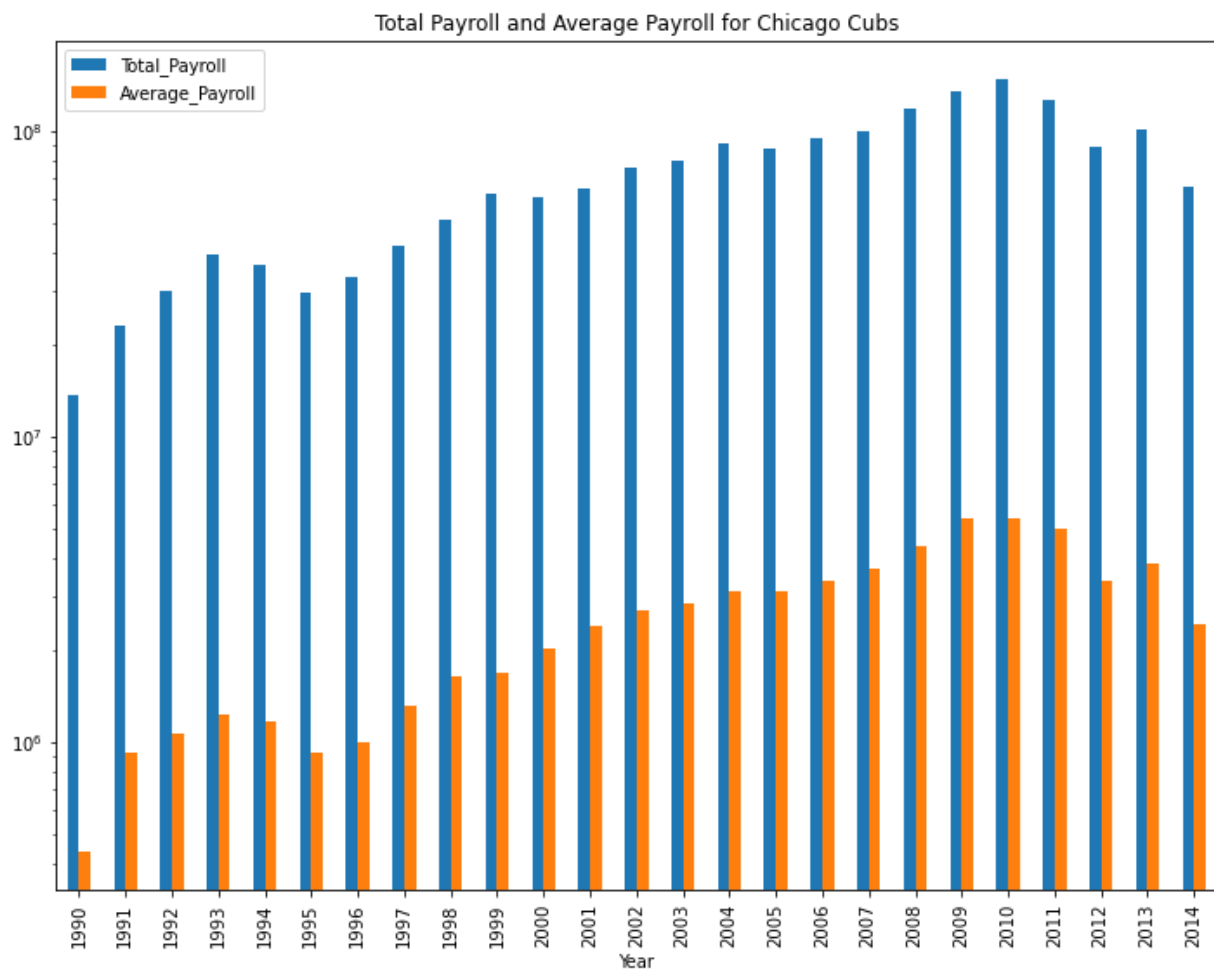


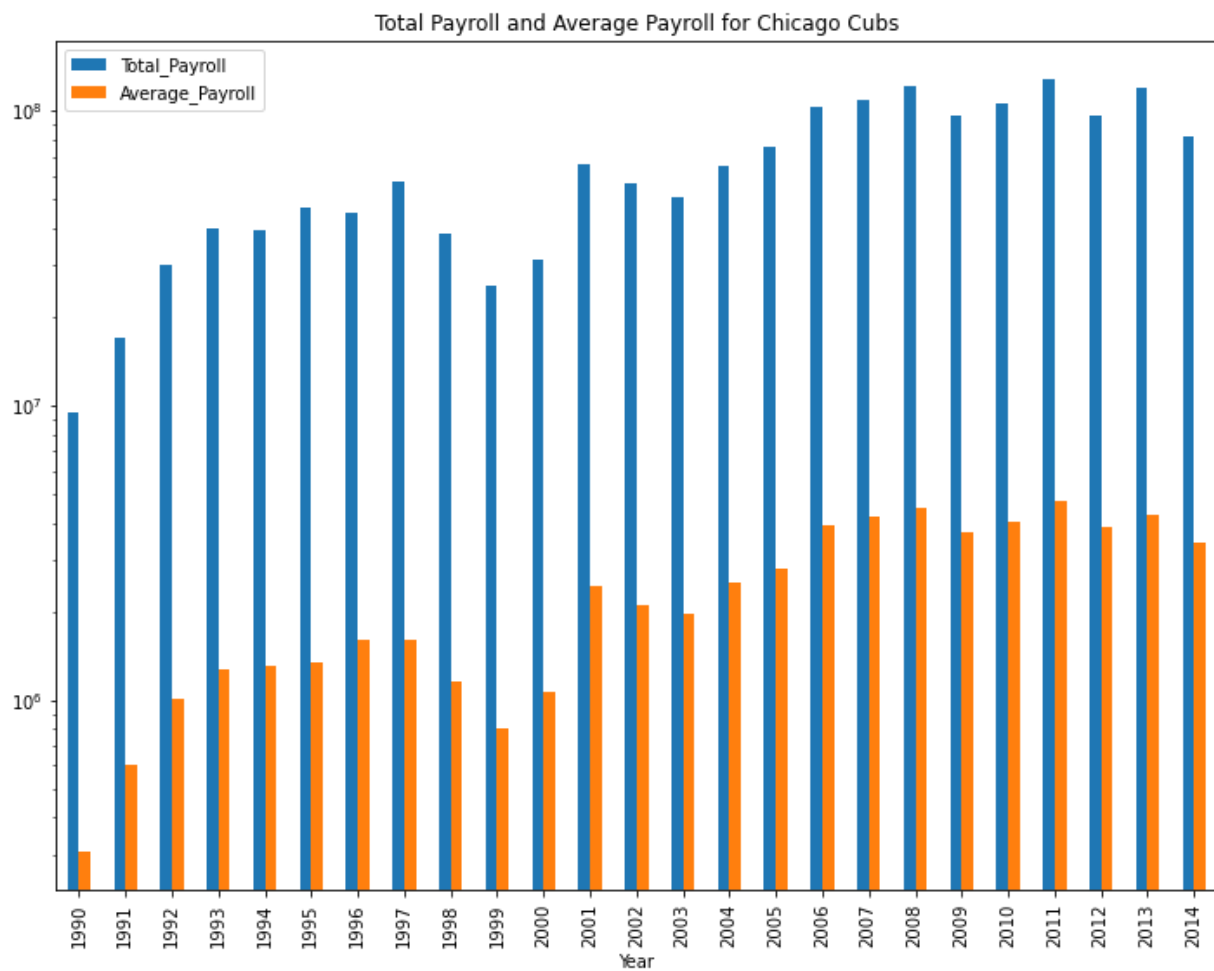


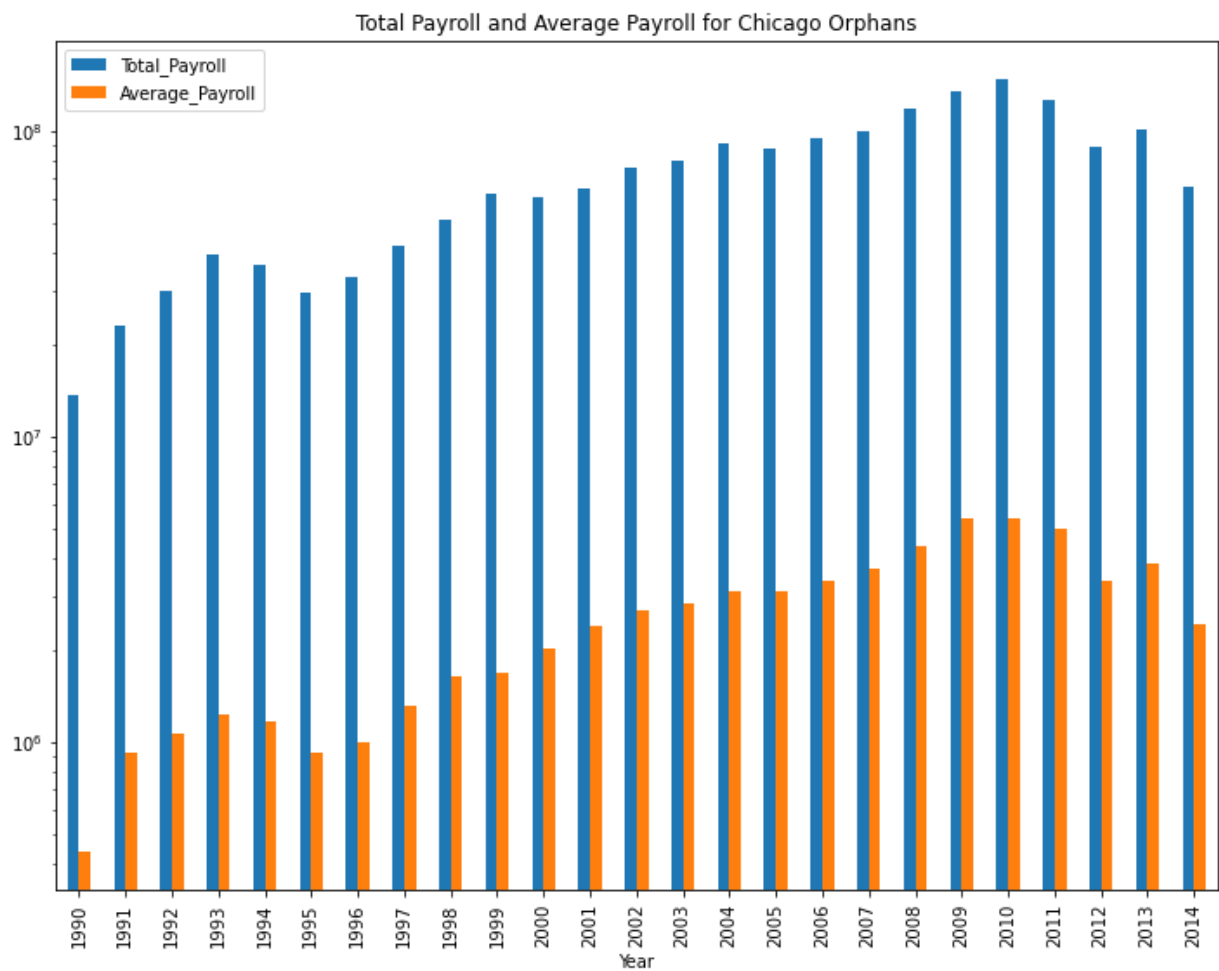


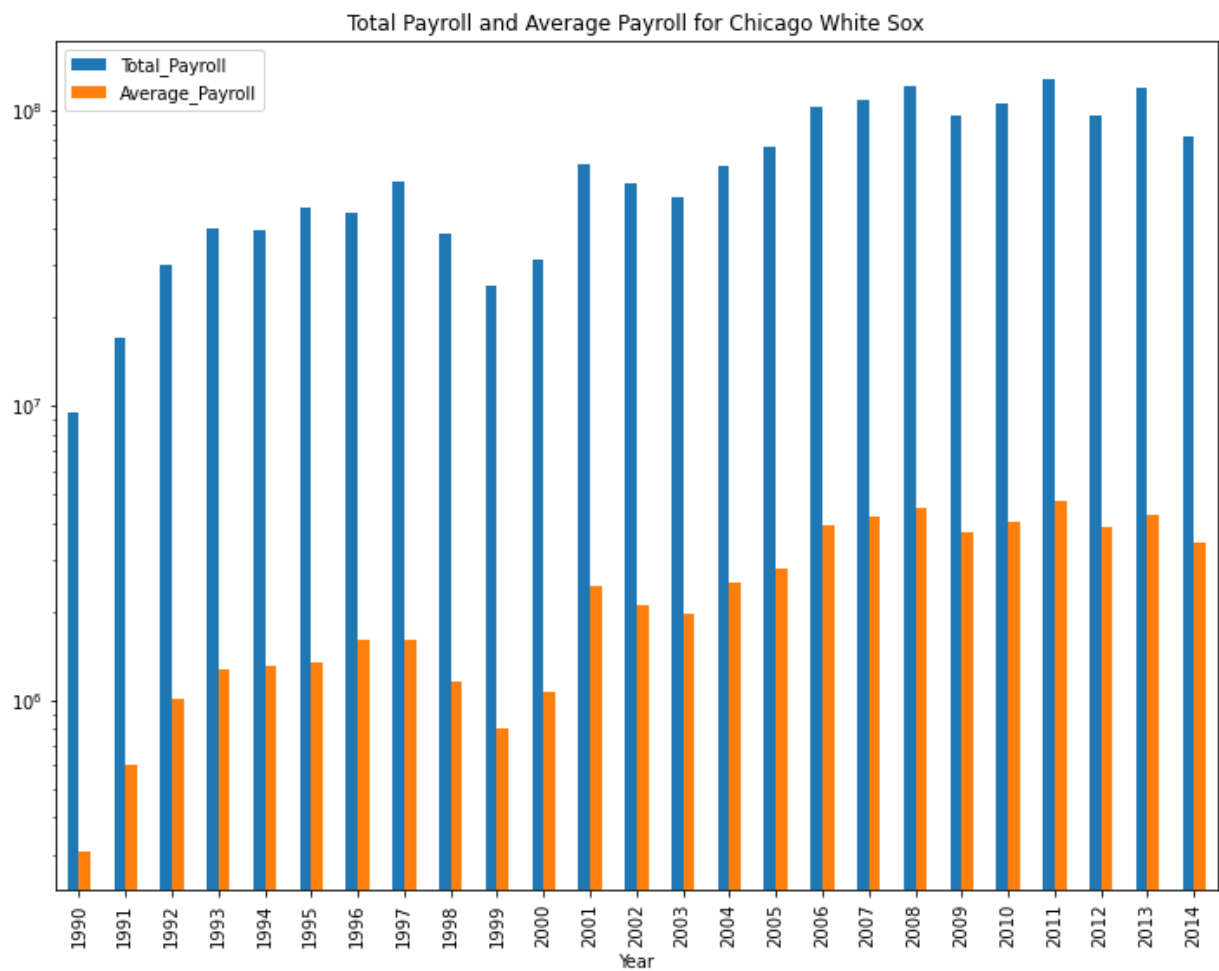




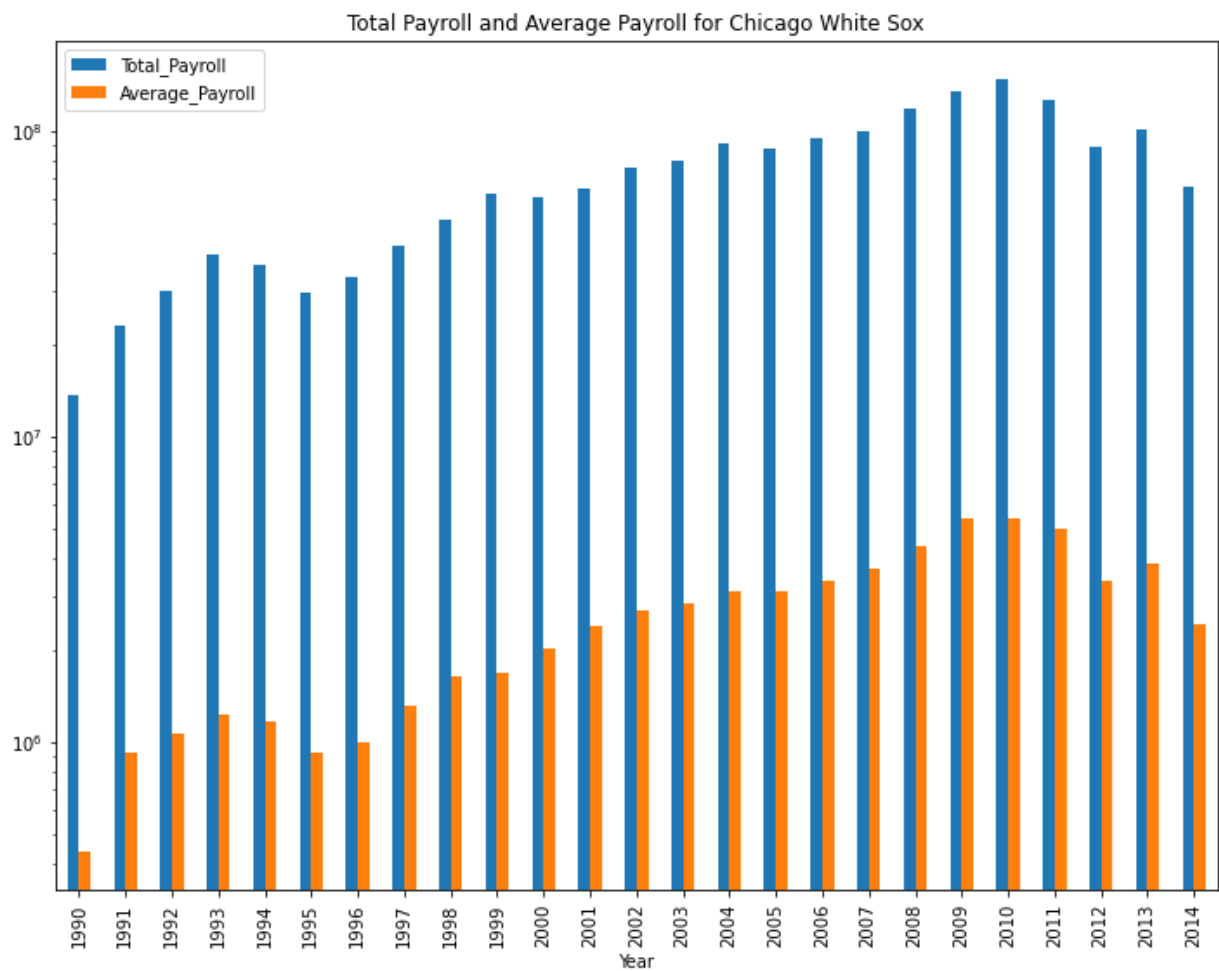


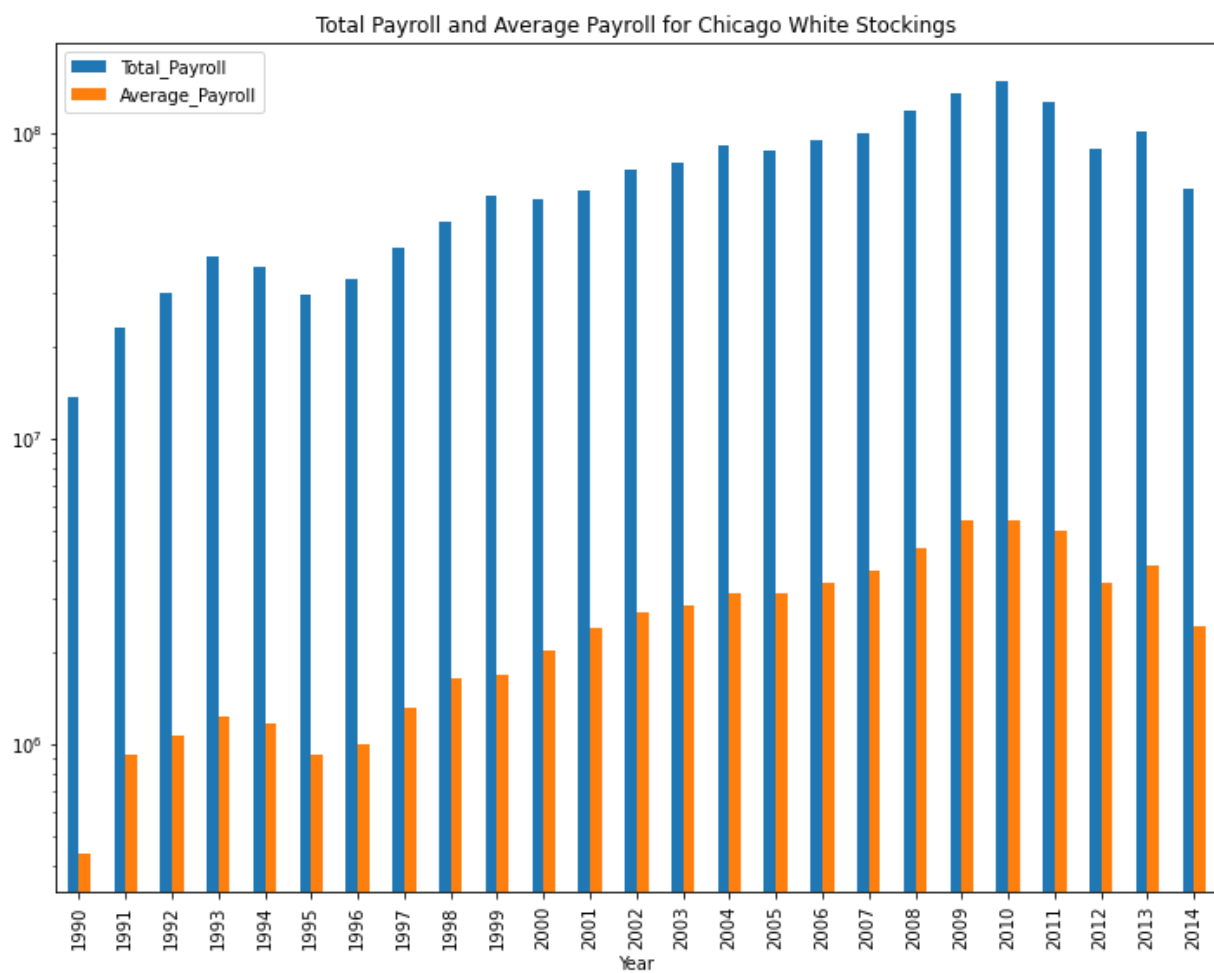


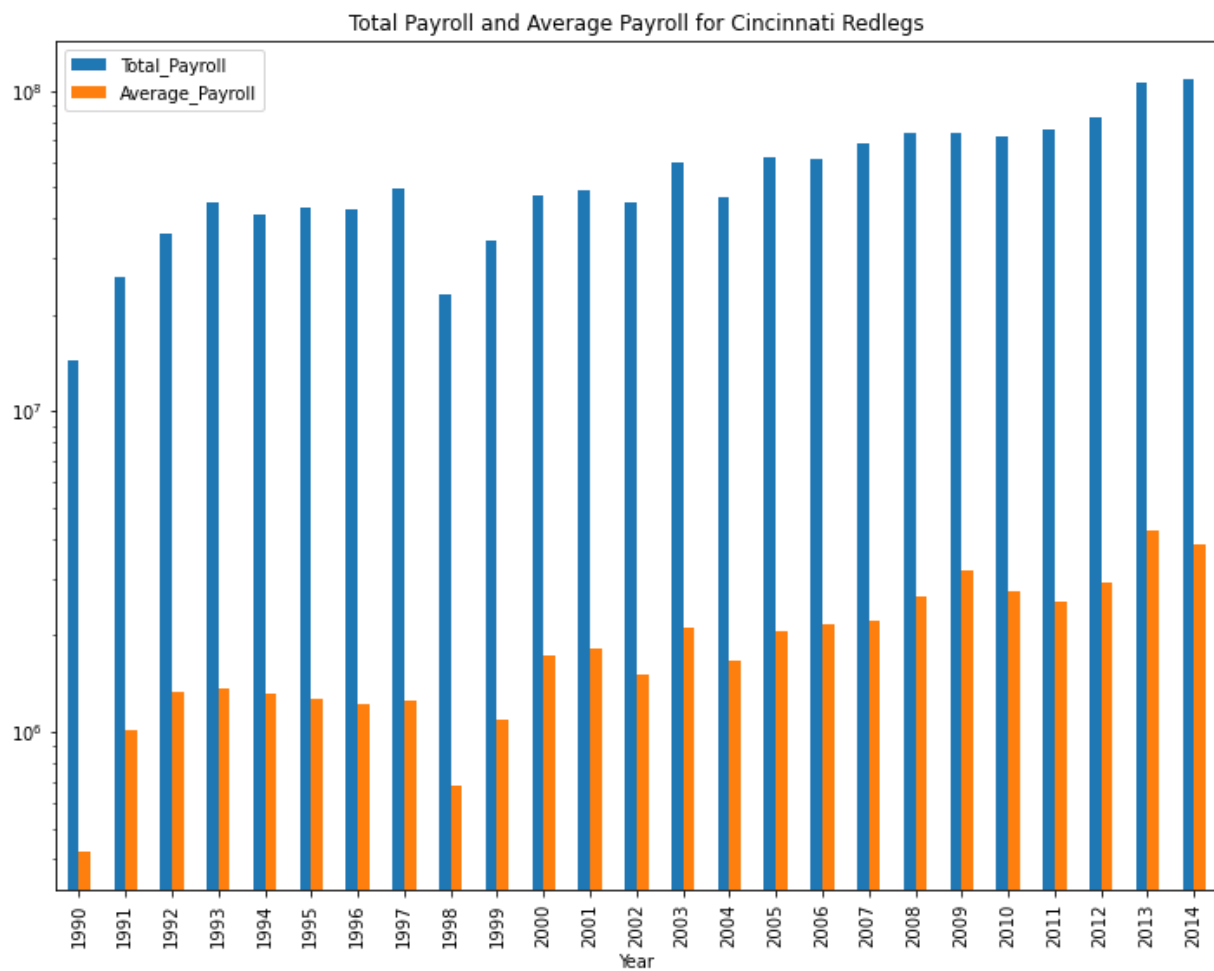


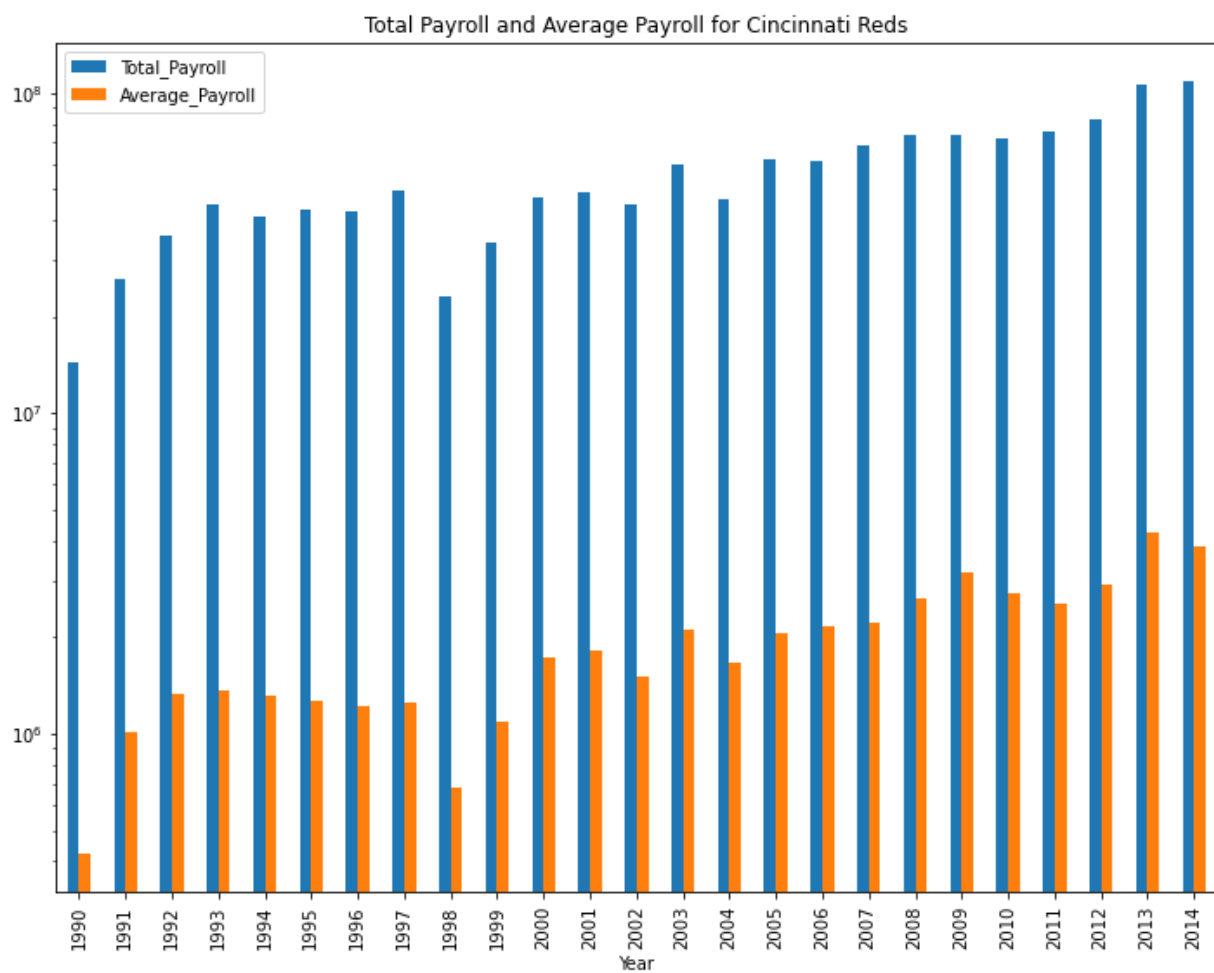


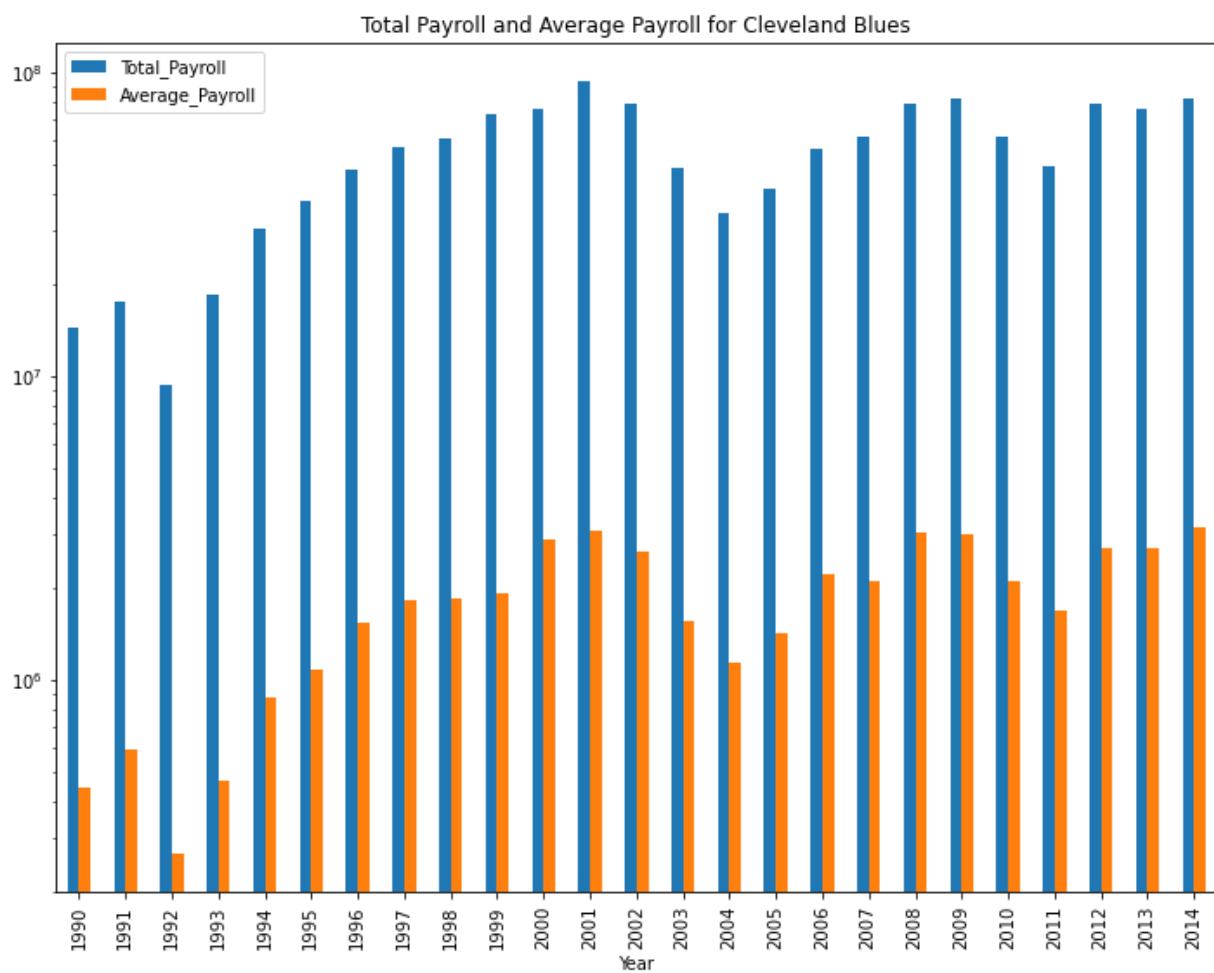


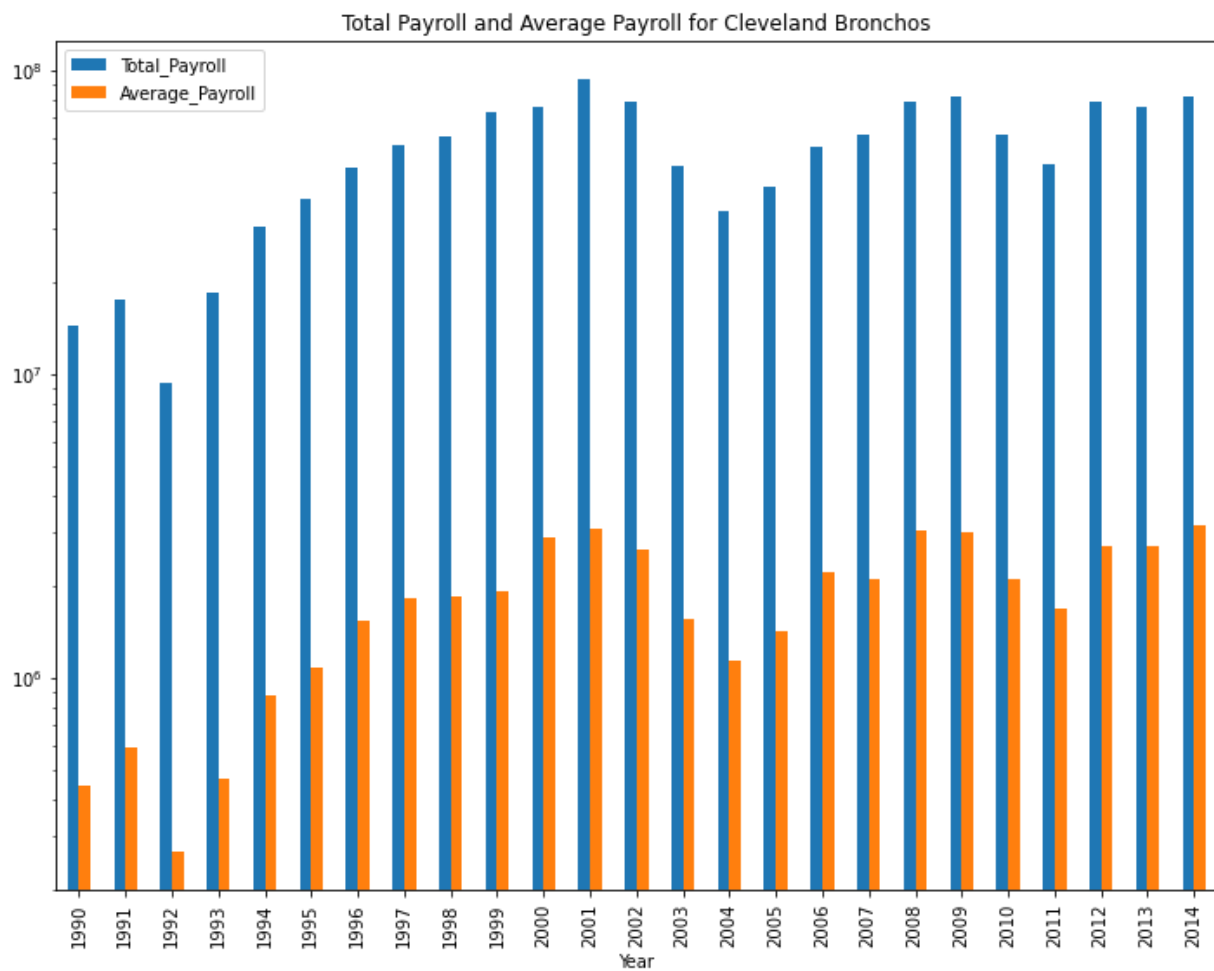


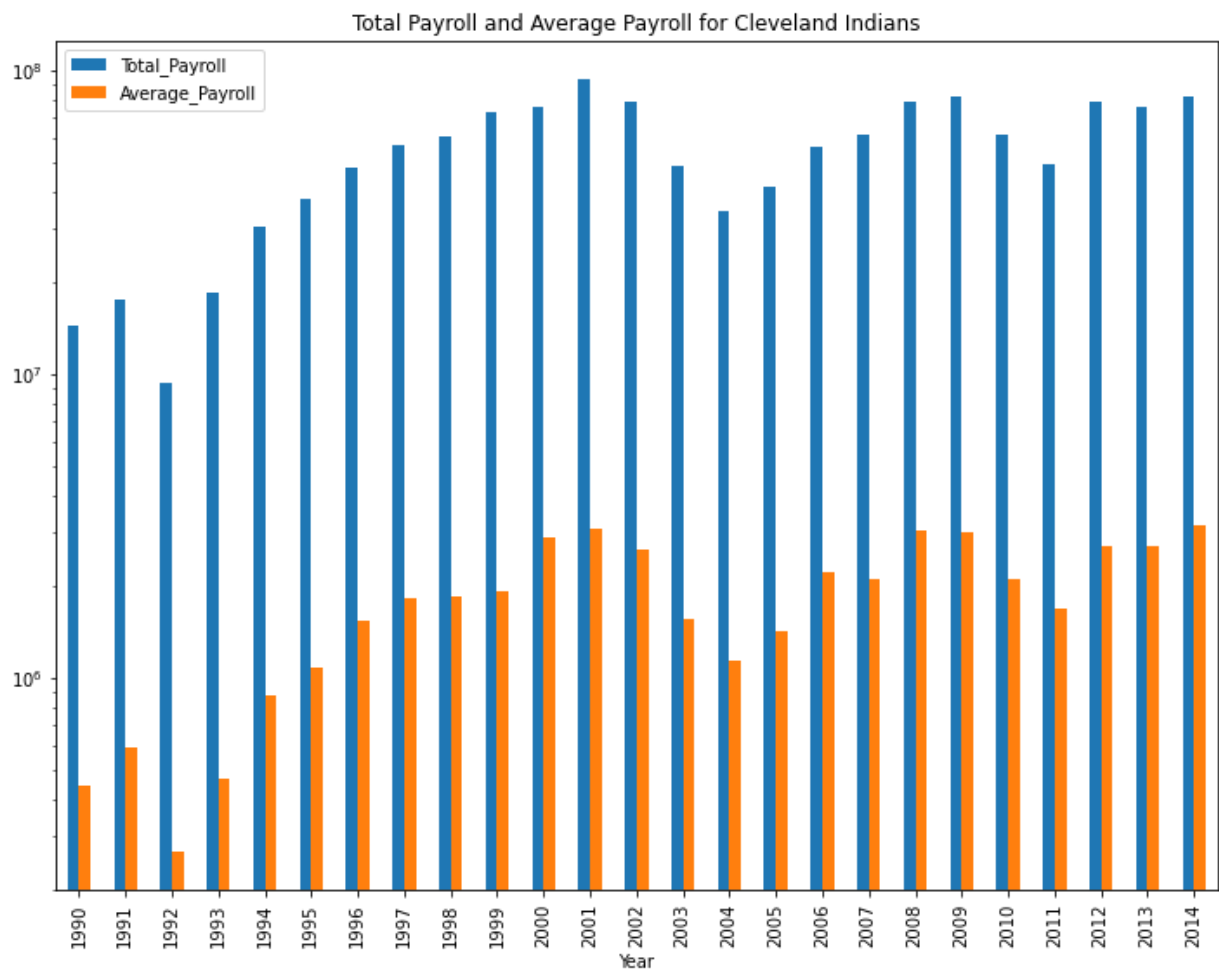


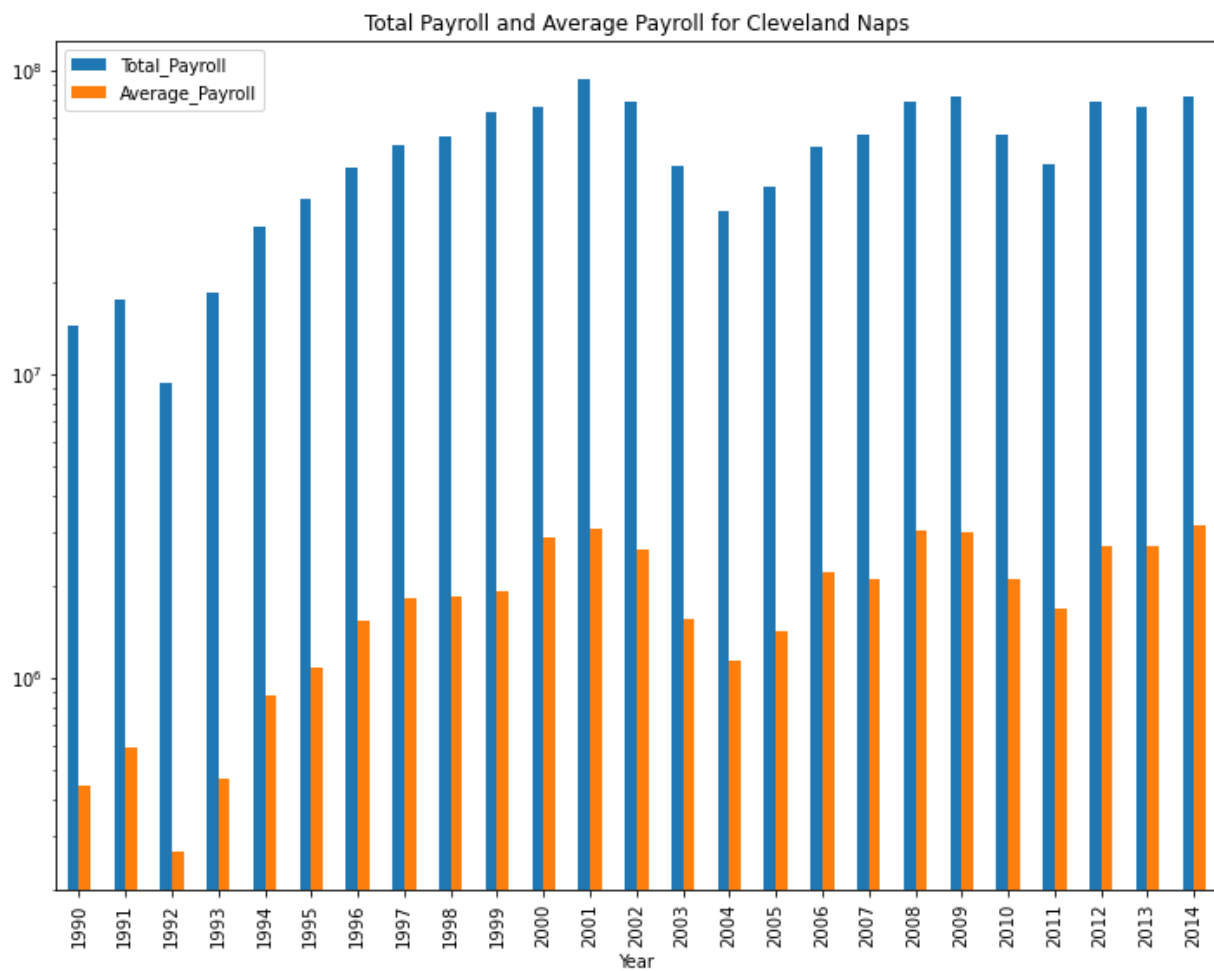




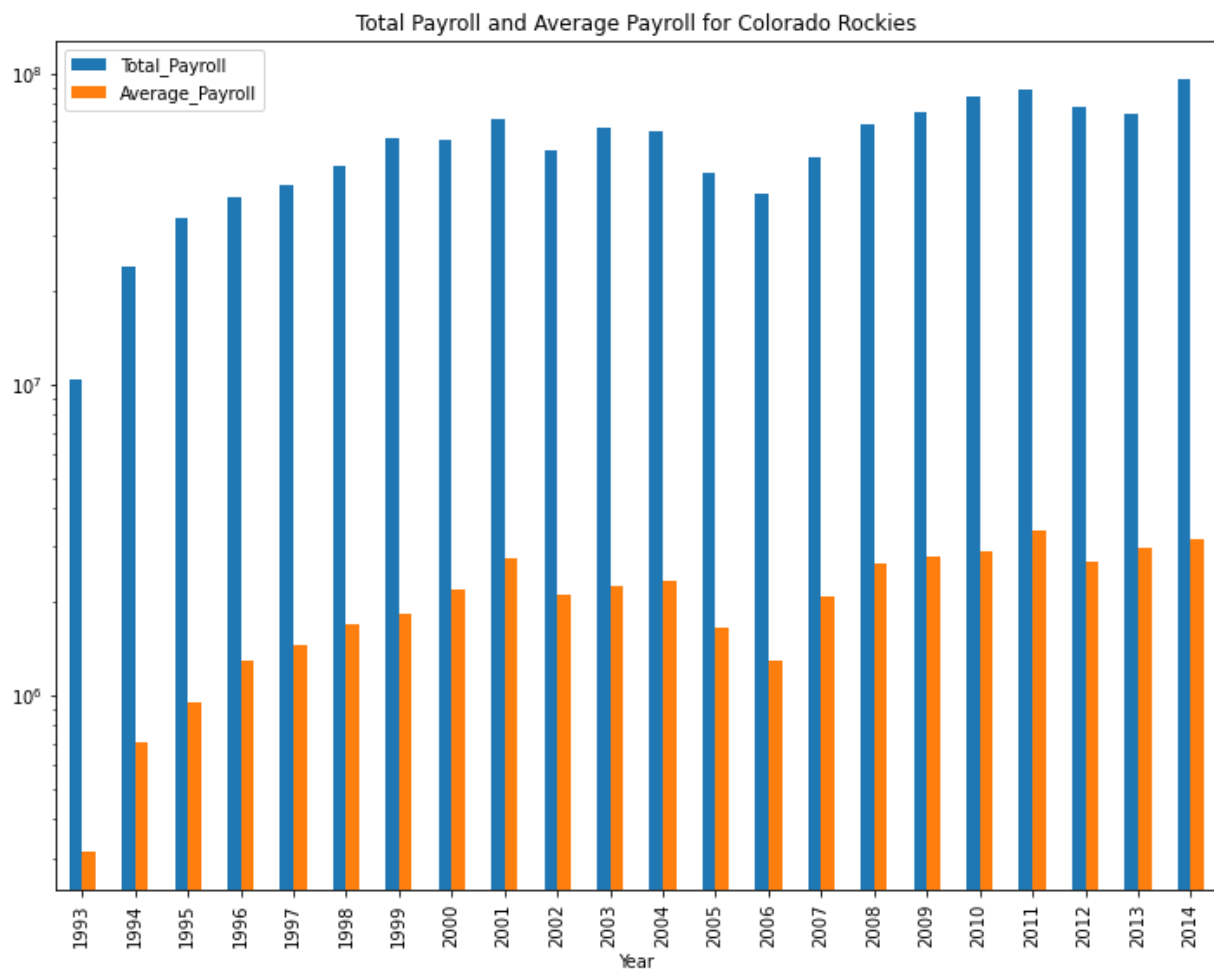


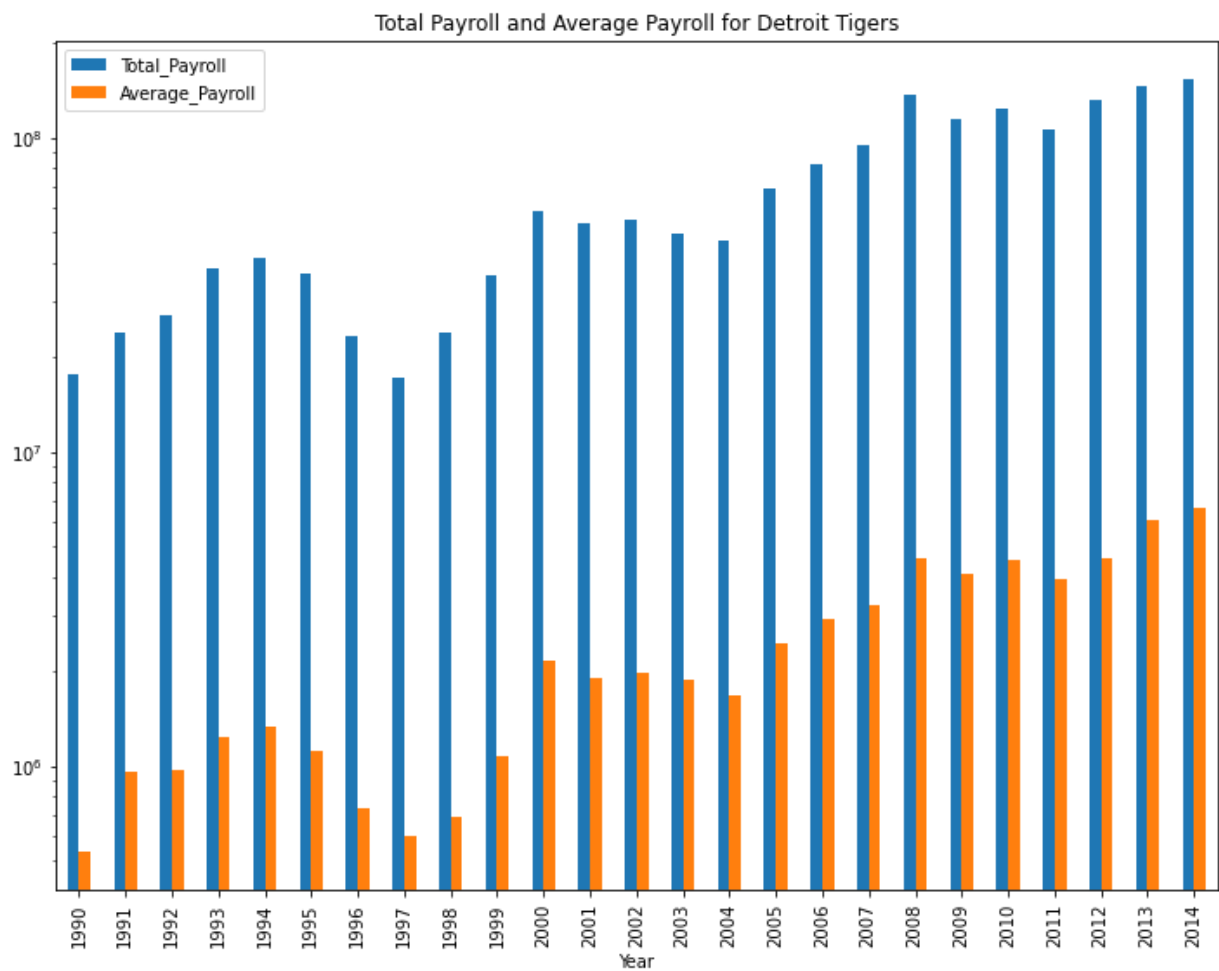


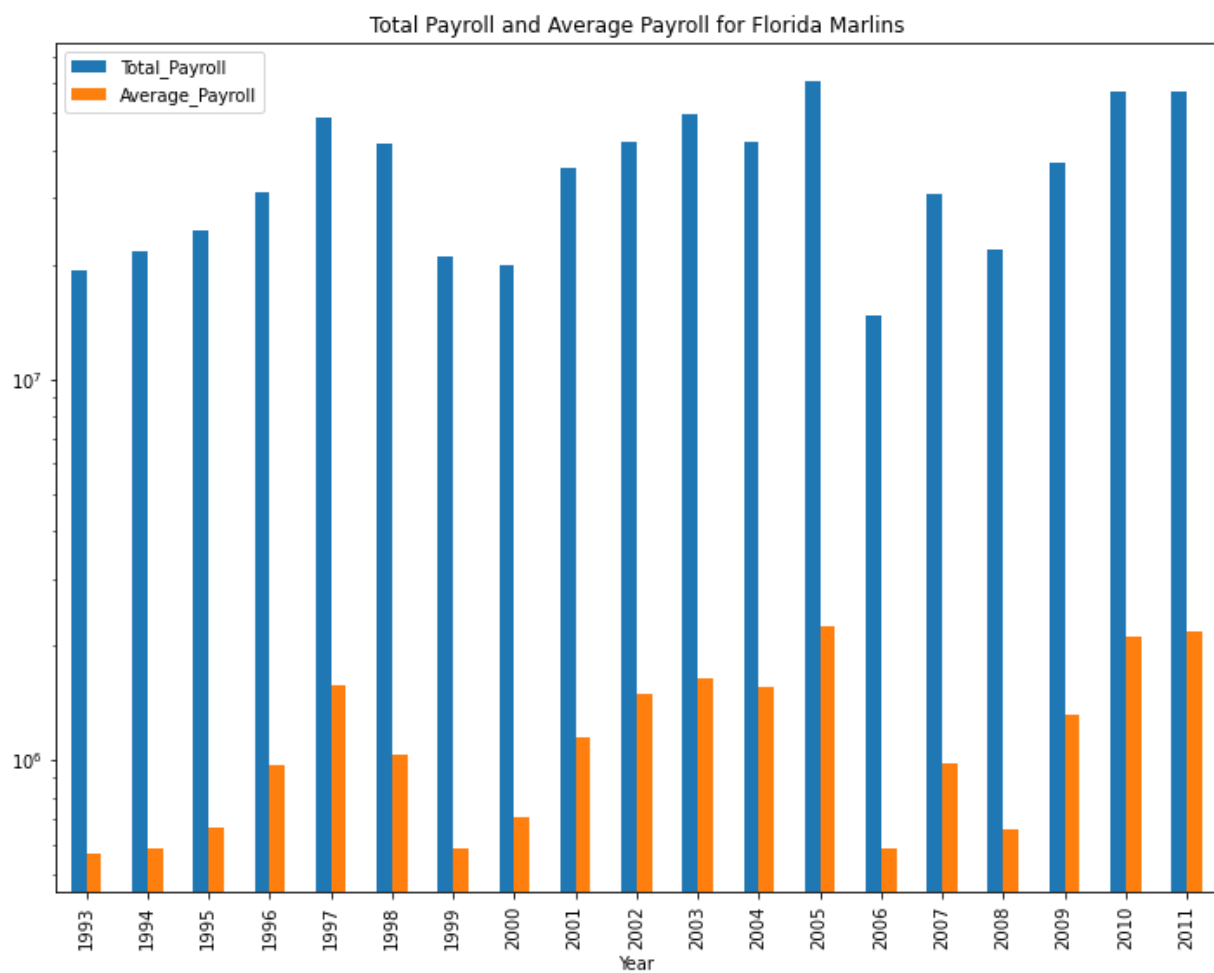


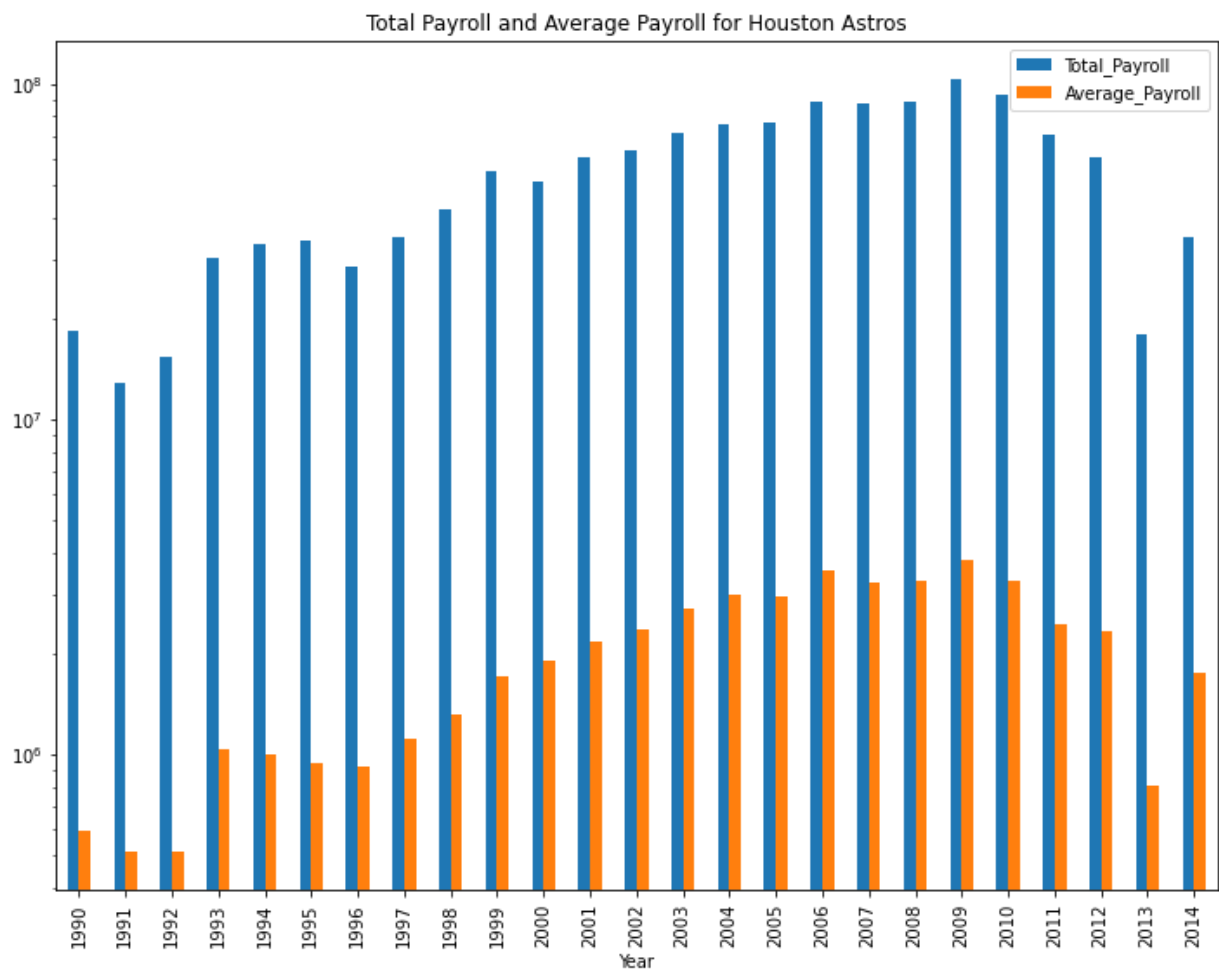


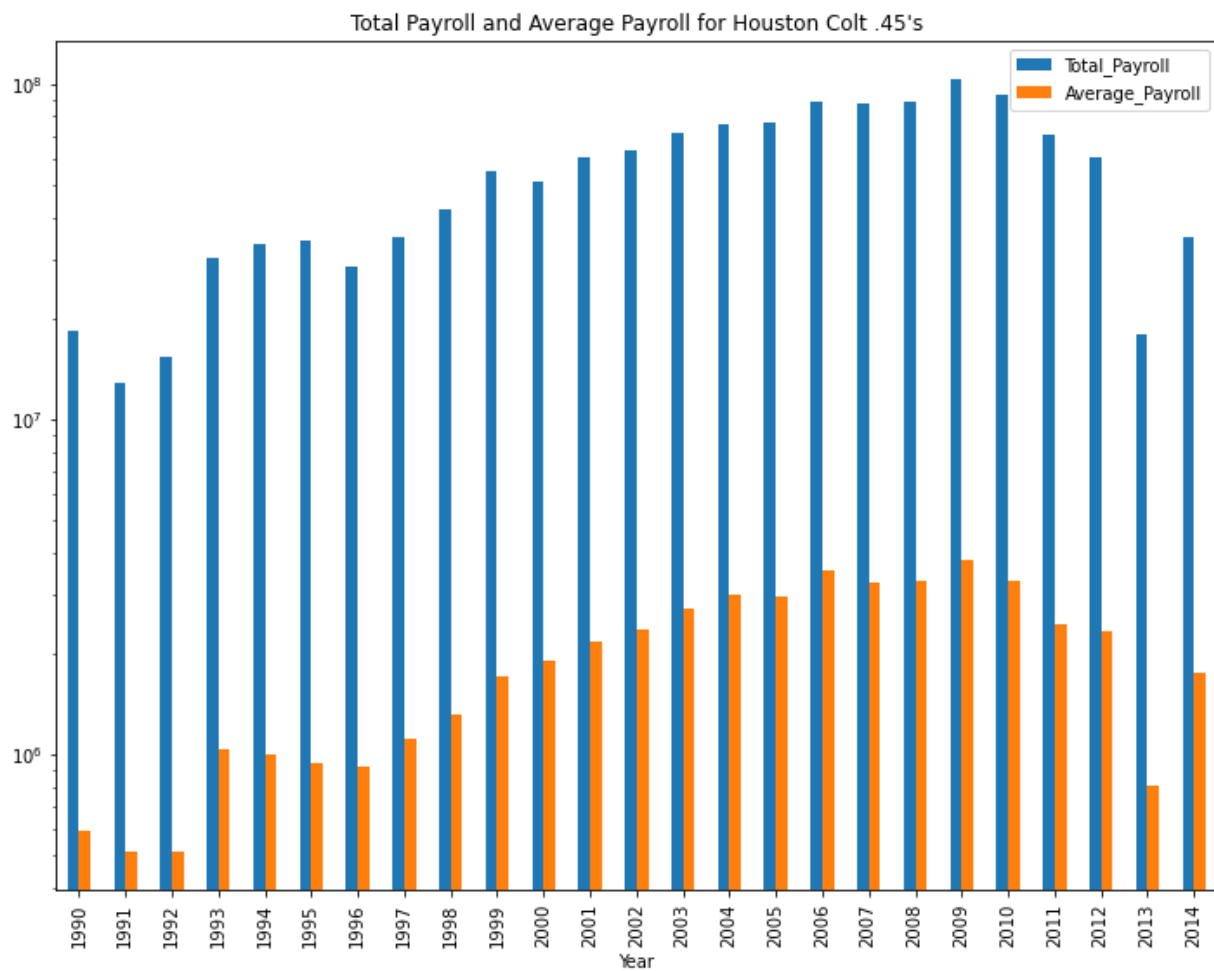


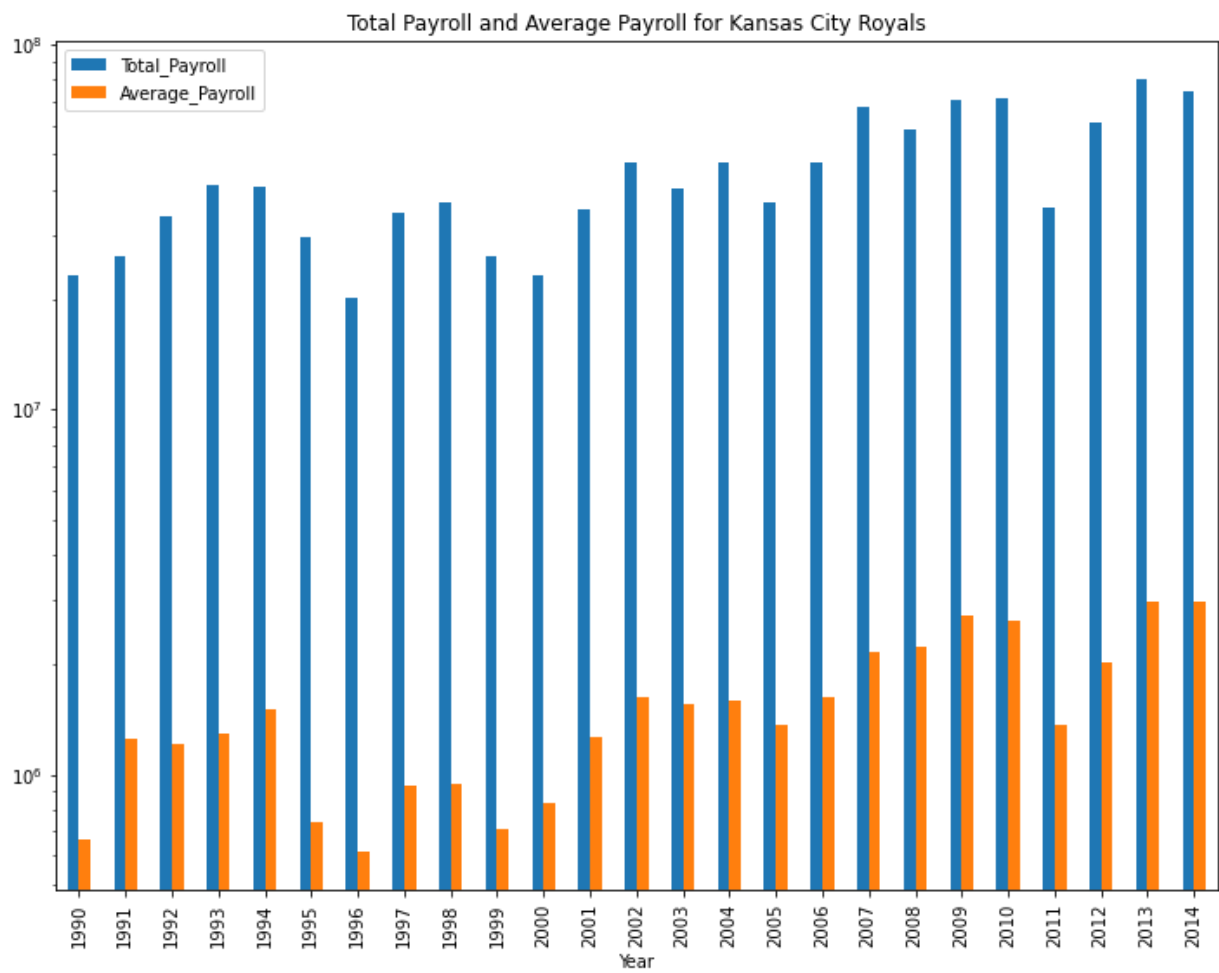


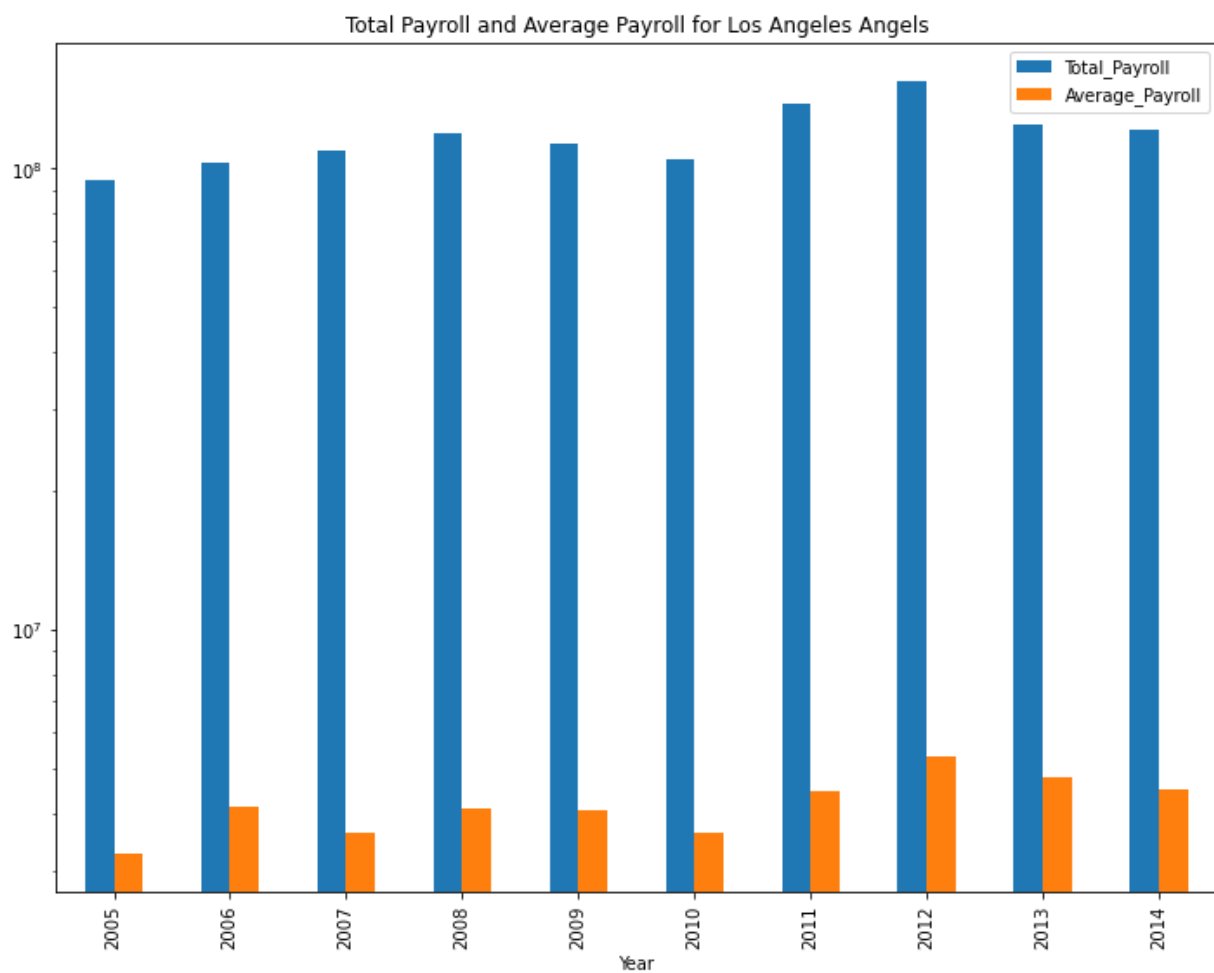


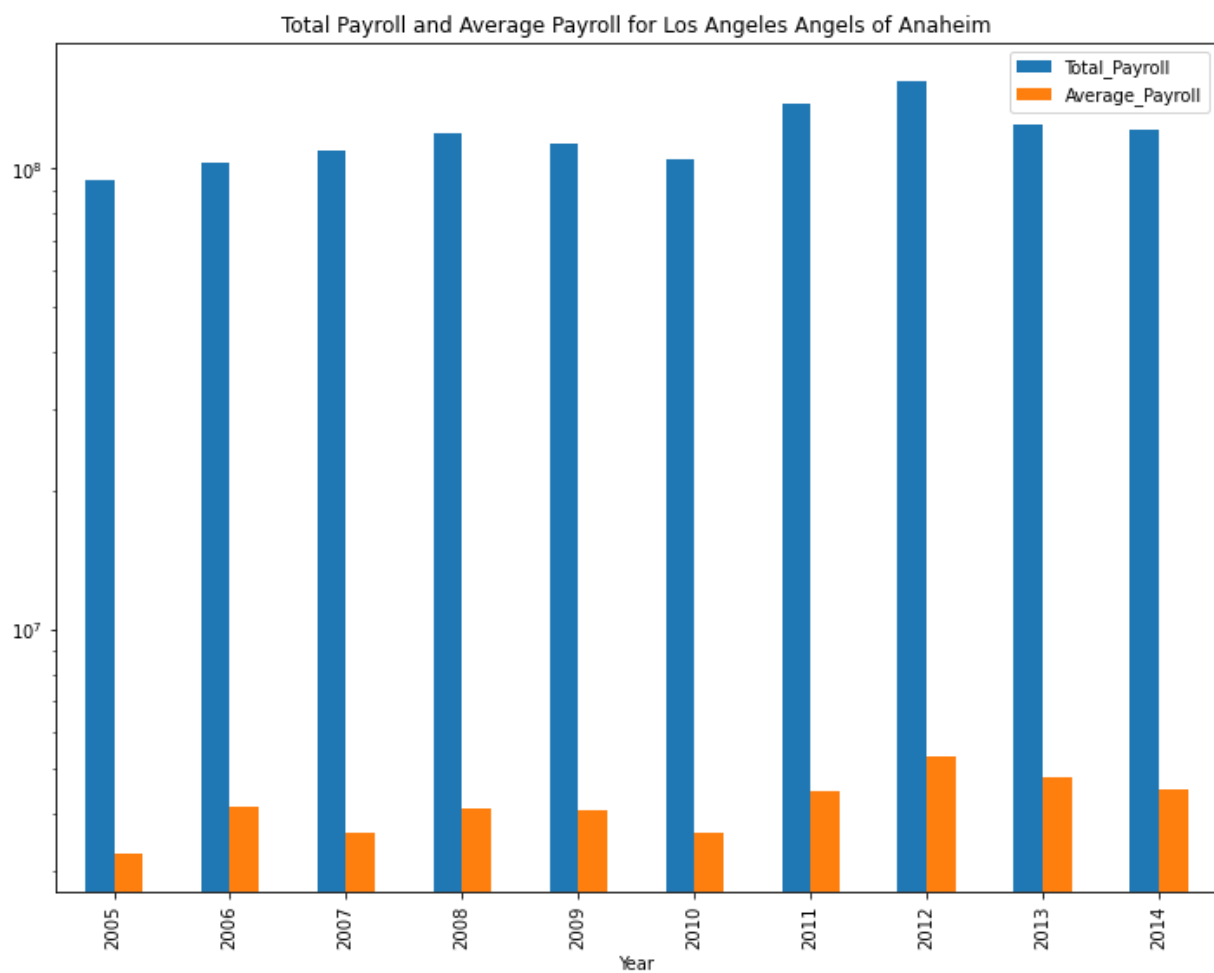




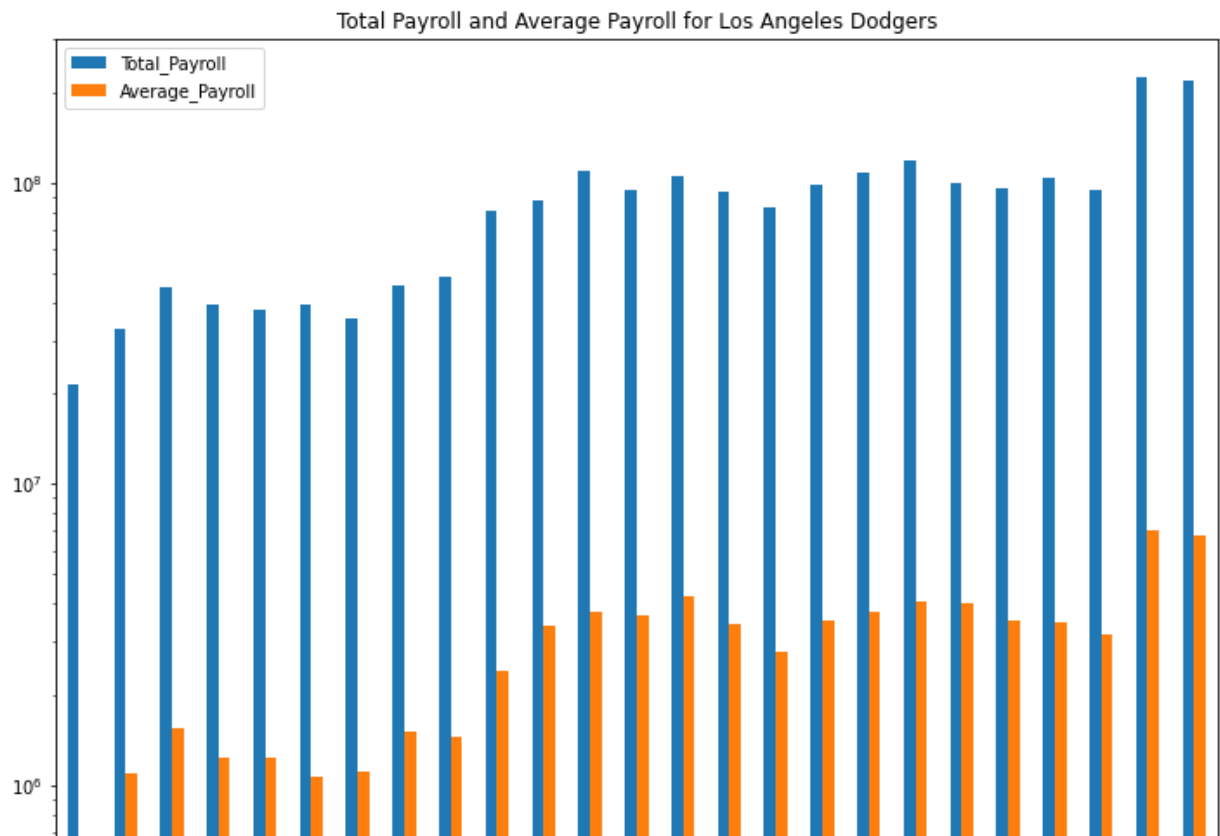












The total payroll seems to be very high compared to the average payroll. However, the average here shows the average salary paid to each player.

## Correlation between payroll and winning percentage

We will first select the percentage winnings for each team for each year. Then we select the average and total payroll for each team over the years, and then join the results together.

```
In [418... winning_query = "SELECT teamID, yearID , " + \
                  "(SUM(W)*1.0/(SUM(G)*1.0))*100.0 AS `PERCENTAGE WIN` " + \
                  "FROM Teams " + \
                  "GROUP BY teamID, yearID " + \
                  "ORDER BY teamID, yearID "
winning_percentage_result = pandas.read_sql(winning_query, conn)
winning_percentage_result
```

```
Out[418...   teamID  yearID  PERCENTAGE WIN
0      ALT    1884         24.000000
1      ANA    1997         51.851852
2      ANA    1998         52.469136
3      ANA    1999         43.209877
4      ANA    2000         50.617284
...     ...     ...             ...
2770   WS8    1887         36.507937
2771   WS8    1888         35.294118
```

	teamID	yearID	PERCENTAGE WIN
2772	WS8	1889	32.283465
2773	WS9	1891	31.654676
2774	WSU	1884	41.228070

2775 rows x 4 columns

In [419...

```

some_results = []
for index in range(len(team_ids)) :
    team_id = team_ids[index]
    some_query = " SELECT Salaries.yearID, " + \
        "((COUNT(Teams.W)*1.0)/(COUNT(Teams.W)*1.0 + COUNT(Teams.L)*1.0))*100 " + \
        "printf('%,d',AVG(Salaries.salary)) AS `AVERAGE PAYROLL` " + \
        "FROM Salaries, Teams " + \
        "WHERE Salaries.teamID = '" + team_id + "' " + \
        "AND Teams.teamID = '" + team_id + "' " + \
        "AND Teams.teamID = Salaries.teamID " + \
        "GROUP BY Salaries.yearID " + \
        "ORDER BY Salaries.teamID, Salaries.yearID "
    v = pandas.read_sql(some_query, conn)
    some_results.append(v)

some_results

```

Out[419...

```

[Empty DataFrame
Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]
Index: [],
  yearID  MEAN WINNING PERCENTAGE  AVERAGE PAYROLL
0    1997                    50.0         1,004,370
1    1998                    50.0         1,214,147
2    1999                    50.0         1,384,704
3    2000                    50.0         1,715,472
4    2001                    50.0         1,584,505
5    2002                    50.0         2,204,345
6    2003                    50.0         2,927,098
7    2004                    50.0         3,723,506,
  yearID  MEAN WINNING PERCENTAGE  AVERAGE PAYROLL
0    1998                    50.0           898,527
1    1999                    50.0         2,020,705
2    2000                    50.0         2,893,851
3    2001                    50.0         3,038,678
4    2002                    50.0         3,115,757
5    2003                    50.0         3,226,280
6    2004                    50.0         2,406,232
7    2005                    50.0         2,308,487
8    2006                    50.0         2,295,547
9    2007                    50.0         1,859,555
10   2008                    50.0         2,364,382
11   2009                    50.0         2,812,141
12   2010                    50.0         2,335,314
13   2011                    50.0         1,986,660
14   2012                    50.0         2,733,512
15   2013                    50.0         3,004,400
16   2014                    50.0         3,763,903,
  yearID  MEAN WINNING PERCENTAGE  AVERAGE PAYROLL
0    1985                    50.0           673,045

```

1	1986	50.0	589,751
2	1987	50.0	517,017
3	1988	50.0	438,902
4	1989	50.0	370,411
5	1990	50.0	454,859
6	1991	50.0	736,140
7	1992	50.0	1,116,946
8	1993	50.0	1,261,861
9	1994	50.0	1,646,117
10	1995	50.0	1,628,808
11	1996	50.0	1,656,616
12	1997	50.0	1,686,403
13	1998	50.0	1,912,062
14	1999	50.0	2,522,068
15	2000	50.0	2,817,927
16	2001	50.0	2,965,682
17	2002	50.0	3,316,798
18	2003	50.0	3,934,950
19	2004	50.0	3,220,803
20	2005	50.0	3,458,292
21	2006	50.0	3,108,857
22	2007	50.0	3,117,529
23	2008	50.0	3,412,189
24	2009	50.0	3,335,385
25	2010	50.0	3,126,802
26	2011	50.0	3,346,257
27	2012	50.0	2,856,204
28	2013	50.0	3,254,500
29	2014	50.0	4,067,041,

Empty DataFrame

Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

Empty DataFrame

Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

Empty DataFrame

Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

Empty DataFrame

Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

Empty DataFrame

Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

Empty DataFrame

Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

Empty DataFrame

Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
--	--------	-------------------------	-----------------

0	1985	50.0	525,486
---	------	------	---------

1	1986	50.0	448,319
---	------	------	---------

2	1987	50.0	463,342
---	------	------	---------

3	1988	50.0	501,187
---	------	------	---------

4	1989	50.0	318,275
---	------	------	---------

5	1990	50.0	261,623
---	------	------	---------

6	1991	50.0	565,129
---	------	------	---------

7	1992	50.0	720,626
---	------	------	---------

8	1993	50.0	909,265
---	------	------	---------

9	1994	50.0	1,253,218
10	1995	50.0	1,187,635
11	1996	50.0	1,702,822
12	1997	50.0	2,017,806
13	1998	50.0	2,411,854
14	1999	50.0	2,303,024
15	2000	50.0	2,808,532
16	2001	50.0	2,331,018
17	2002	50.0	1,890,421
18	2003	50.0	2,547,500
19	2004	50.0	1,843,690
20	2005	50.0	2,639,797
21	2006	50.0	2,592,342
22	2007	50.0	3,450,918
23	2008	50.0	2,099,882
24	2009	50.0	2,580,833
25	2010	50.0	3,138,942
26	2011	50.0	3,280,924
27	2012	50.0	2,762,642
28	2013	50.0	3,245,897
29	2014	50.0	3,693,428,

Empty DataFrame

Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	435,902
1	1986	50.0	496,628
2	1987	50.0	676,277
3	1988	50.0	579,003
4	1989	50.0	672,374
5	1990	50.0	642,447
6	1991	50.0	1,172,250
7	1992	50.0	1,406,793
8	1993	50.0	1,197,438
9	1994	50.0	1,261,969
10	1995	50.0	877,176
11	1996	50.0	1,177,597
12	1997	50.0	1,281,139
13	1998	50.0	1,719,909
14	1999	50.0	2,048,306
15	2000	50.0	2,598,011
16	2001	50.0	3,438,619
17	2002	50.0	3,612,202
18	2003	50.0	3,701,722
19	2004	50.0	4,243,283
20	2005	50.0	4,410,897
21	2006	50.0	4,448,141
22	2007	50.0	5,108,079
23	2008	50.0	4,763,929
24	2009	50.0	4,184,344
25	2010	50.0	5,601,632
26	2011	50.0	5,991,202
27	2012	50.0	5,093,724
28	2013	50.0	5,225,172
29	2014	50.0	4,484,513,

Empty DataFrame

Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

Empty DataFrame

Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

[illegible]

	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	515,281
1	1986	50.0	497,491
2	1987	50.0	475,685
3	1988	50.0	426,692
4	1989	50.0	580,685
5	1990	50.0	620,571
6	1991	50.0	1,066,451
7	1992	50.0	1,158,311
8	1993	50.0	893,385
9	1994	50.0	786,131
10	1995	50.0	946,156
11	1996	50.0	776,702,

Empty DataFrame

Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	577,405
1	1986	50.0	555,102
2	1987	50.0	550,307
3	1988	50.0	524,767
4	1989	50.0	444,500
5	1990	50.0	439,483
6	1991	50.0	927,026
7	1992	50.0	1,065,345
8	1993	50.0	1,230,833
9	1994	50.0	1,170,559
10	1995	50.0	922,057
11	1996	50.0	1,002,454
12	1997	50.0	1,317,354
13	1998	50.0	1,639,935
14	1999	50.0	1,684,945
15	2000	50.0	2,017,977
16	2001	50.0	2,396,882
17	2002	50.0	2,703,244
18	2003	50.0	2,852,440
19	2004	50.0	3,122,758
20	2005	50.0	3,108,319
21	2006	50.0	3,372,303
22	2007	50.0	3,691,493
23	2008	50.0	4,383,179
24	2009	50.0	5,392,360
25	2010	50.0	5,429,962
26	2011	50.0	5,001,893
27	2012	50.0	3,392,193
28	2013	50.0	3,867,989
29	2014	50.0	2,426,759,
	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	577,405
1	1986	50.0	555,102
2	1987	50.0	550,307
3	1988	50.0	524,767
4	1989	50.0	444,500
5	1990	50.0	439,483
6	1991	50.0	927,026
7	1992	50.0	1,065,345
8	1993	50.0	1,230,833
9	1994	50.0	1,170,559
10	1995	50.0	922,057
11	1996	50.0	1,002,454
12	1997	50.0	1,317,354
13	1998	50.0	1,639,935
14	1999	50.0	1,684,945
15	2000	50.0	2,017,977
16	2001	50.0	2,396,882
17	2002	50.0	2,703,244
18	2003	50.0	2,852,440
19	2004	50.0	3,122,758
20	2005	50.0	3,108,319
21	2006	50.0	3,372,303
22	2007	50.0	3,691,493
23	2008	50.0	4,383,179
24	2009	50.0	5,392,360

25	2010	50.0	5,429,962
26	2011	50.0	5,001,893
27	2012	50.0	3,392,193
28	2013	50.0	3,867,989
29	2014	50.0	2,426,759,
	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	468,865
1	1986	50.0	336,090
2	1987	50.0	443,410
3	1988	50.0	266,250
4	1989	50.0	290,616
5	1990	50.0	306,177
6	1991	50.0	604,273
7	1992	50.0	1,005,361
8	1993	50.0	1,280,521
9	1994	50.0	1,306,127
10	1995	50.0	1,341,750
11	1996	50.0	1,612,125
12	1997	50.0	1,603,888
13	1998	50.0	1,161,666
14	1999	50.0	800,625
15	2000	50.0	1,073,568
16	2001	50.0	2,431,617
17	2002	50.0	2,113,067
18	2003	50.0	1,961,923
19	2004	50.0	2,508,173
20	2005	50.0	2,784,370
21	2006	50.0	3,951,948
22	2007	50.0	4,179,685
23	2008	50.0	4,488,493
24	2009	50.0	3,694,942
25	2010	50.0	4,058,846
26	2011	50.0	4,732,925
27	2012	50.0	3,876,780
28	2013	50.0	4,288,045
29	2014	50.0	3,409,604,
	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	577,405
1	1986	50.0	555,102
2	1987	50.0	550,307
3	1988	50.0	524,767
4	1989	50.0	444,500
5	1990	50.0	439,483
6	1991	50.0	927,026
7	1992	50.0	1,065,345
8	1993	50.0	1,230,833
9	1994	50.0	1,170,559
10	1995	50.0	922,057
11	1996	50.0	1,002,454
12	1997	50.0	1,317,354
13	1998	50.0	1,639,935
14	1999	50.0	1,684,945
15	2000	50.0	2,017,977
16	2001	50.0	2,396,882
17	2002	50.0	2,703,244
18	2003	50.0	2,852,440
19	2004	50.0	3,122,758
20	2005	50.0	3,108,319
21	2006	50.0	3,372,303
22	2007	50.0	3,691,493



23	2008	50.0	4,383,179
24	2009	50.0	5,392,360
25	2010	50.0	5,429,962
26	2011	50.0	5,001,893
27	2012	50.0	3,392,193
28	2013	50.0	3,867,989
29	2014	50.0	2,426,759,

Empty DataFrame

Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

Empty DataFrame

Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	468,865
1	1986	50.0	336,090
2	1987	50.0	443,410
3	1988	50.0	266,250
4	1989	50.0	290,616
5	1990	50.0	306,177
6	1991	50.0	604,273
7	1992	50.0	1,005,361
8	1993	50.0	1,280,521
9	1994	50.0	1,306,127
10	1995	50.0	1,341,750
11	1996	50.0	1,612,125
12	1997	50.0	1,603,888
13	1998	50.0	1,161,666
14	1999	50.0	800,625
15	2000	50.0	1,073,568
16	2001	50.0	2,431,617
17	2002	50.0	2,113,067
18	2003	50.0	1,961,923
19	2004	50.0	2,508,173
20	2005	50.0	2,784,370
21	2006	50.0	3,951,948
22	2007	50.0	4,179,685
23	2008	50.0	4,488,493
24	2009	50.0	3,694,942
25	2010	50.0	4,058,846
26	2011	50.0	4,732,925
27	2012	50.0	3,876,780
28	2013	50.0	4,288,045
29	2014	50.0	3,409,604,

	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	577,405
1	1986	50.0	555,102
2	1987	50.0	550,307
3	1988	50.0	524,767
4	1989	50.0	444,500
5	1990	50.0	439,483
6	1991	50.0	927,026
7	1992	50.0	1,065,345
8	1993	50.0	1,230,833
9	1994	50.0	1,170,559
10	1995	50.0	922,057
11	1996	50.0	1,002,454
12	1997	50.0	1,317,354
13	1998	50.0	1,639,935
14	1999	50.0	1,684,945

15	2000	50.0	2,017,977
16	2001	50.0	2,396,882
17	2002	50.0	2,703,244
18	2003	50.0	2,852,440
19	2004	50.0	3,122,758
20	2005	50.0	3,108,319
21	2006	50.0	3,372,303
22	2007	50.0	3,691,493
23	2008	50.0	4,383,179
24	2009	50.0	5,392,360
25	2010	50.0	5,429,962
26	2011	50.0	5,001,893
27	2012	50.0	3,392,193
28	2013	50.0	3,867,989
29	2014	50.0	2,426,759,

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	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	577,405
1	1986	50.0	555,102
2	1987	50.0	550,307
3	1988	50.0	524,767
4	1989	50.0	444,500
5	1990	50.0	439,483
6	1991	50.0	927,026
7	1992	50.0	1,065,345
8	1993	50.0	1,230,833
9	1994	50.0	1,170,559
10	1995	50.0	922,057
11	1996	50.0	1,002,454
12	1997	50.0	1,317,354
13	1998	50.0	1,639,935
14	1999	50.0	1,684,945
15	2000	50.0	2,017,977
16	2001	50.0	2,396,882
17	2002	50.0	2,703,244
18	2003	50.0	2,852,440
19	2004	50.0	3,122,758
20	2005	50.0	3,108,319
21	2006	50.0	3,372,303
22	2007	50.0	3,691,493
23	2008	50.0	4,383,179
24	2009	50.0	5,392,360
25	2010	50.0	5,429,962
26	2011	50.0	5,001,893
27	2012	50.0	3,392,193
28	2013	50.0	3,867,989
29	2014	50.0	2,426,759,

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Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

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	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	379,996
1	1986	50.0	396,879
2	1987	50.0	356,980
3	1988	50.0	355,536
4	1989	50.0	381,793
5	1990	50.0	422,647
6	1991	50.0	1,011,743
7	1992	50.0	1,330,796
8	1993	50.0	1,359,989
9	1994	50.0	1,321,349
10	1995	50.0	1,268,960
11	1996	50.0	1,215,038
12	1997	50.0	1,244,200
13	1998	50.0	676,617
14	1999	50.0	1,095,572
15	2000	50.0	1,735,822
16	2001	50.0	1,814,296
17	2002	50.0	1,501,679
18	2003	50.0	2,119,845
19	2004	50.0	1,664,830
20	2005	50.0	2,063,086
21	2006	50.0	2,175,339
22	2007	50.0	2,210,483
23	2008	50.0	2,647,060
24	2009	50.0	3,198,195
25	2010	50.0	2,760,059
26	2011	50.0	2,531,571
27	2012	50.0	2,935,843
28	2013	50.0	4,256,178
29	2014	50.0	3,864,910,

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	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
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1	1986	50.0	396,879
2	1987	50.0	356,980
3	1988	50.0	355,536
4	1989	50.0	381,793
5	1990	50.0	422,647
6	1991	50.0	1,011,743
7	1992	50.0	1,330,796
8	1993	50.0	1,359,989
9	1994	50.0	1,321,349
10	1995	50.0	1,268,960
11	1996	50.0	1,215,038
12	1997	50.0	1,244,200
13	1998	50.0	676,617
14	1999	50.0	1,095,572
15	2000	50.0	1,735,822
16	2001	50.0	1,814,296
17	2002	50.0	1,501,679
18	2003	50.0	2,119,845
19	2004	50.0	1,664,830
20	2005	50.0	2,063,086

21	2006	50.0	2,175,339
22	2007	50.0	2,210,483
23	2008	50.0	2,647,060
24	2009	50.0	3,198,195
25	2010	50.0	2,760,059
26	2011	50.0	2,531,571
27	2012	50.0	2,935,843
28	2013	50.0	4,256,178
29	2014	50.0	3,864,910,

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	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	327,583
1	1986	50.0	251,919
2	1987	50.0	304,062
3	1988	50.0	406,204
4	1989	50.0	336,833
5	1990	50.0	439,000
6	1991	50.0	587,833
7	1992	50.0	267,801
8	1993	50.0	464,025
9	1994	50.0	871,157
10	1995	50.0	1,083,938
11	1996	50.0	1,551,850
12	1997	50.0	1,832,337
13	1998	50.0	1,842,429
14	1999	50.0	1,920,485
15	2000	50.0	2,918,491
16	2001	50.0	3,105,066
17	2002	50.0	2,630,314
18	2003	50.0	1,567,252
19	2004	50.0	1,143,976
20	2005	50.0	1,431,120
21	2006	50.0	2,241,260
22	2007	50.0	2,126,664
23	2008	50.0	3,037,310
24	2009	50.0	3,021,450
25	2010	50.0	2,110,481
26	2011	50.0	1,681,950
27	2012	50.0	2,704,493
28	2013	50.0	2,706,135
29	2014	50.0	3,159,688,

	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	327,583
1	1986	50.0	251,919
2	1987	50.0	304,062
3	1988	50.0	406,204
4	1989	50.0	336,833
5	1990	50.0	439,000
6	1991	50.0	587,833
7	1992	50.0	267,801
8	1993	50.0	464,025
9	1994	50.0	871,157
10	1995	50.0	1,083,938
11	1996	50.0	1,551,850
12	1997	50.0	1,832,337

13	1998	50.0	1,842,429
14	1999	50.0	1,920,485
15	2000	50.0	2,918,491
16	2001	50.0	3,105,066
17	2002	50.0	2,630,314
18	2003	50.0	1,567,252
19	2004	50.0	1,143,976
20	2005	50.0	1,431,120
21	2006	50.0	2,241,260
22	2007	50.0	2,126,664
23	2008	50.0	3,037,310
24	2009	50.0	3,021,450
25	2010	50.0	2,110,481
26	2011	50.0	1,681,950
27	2012	50.0	2,704,493
28	2013	50.0	2,706,135
29	2014	50.0	3,159,688,

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Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	327,583
1	1986	50.0	251,919
2	1987	50.0	304,062
3	1988	50.0	406,204
4	1989	50.0	336,833
5	1990	50.0	439,000
6	1991	50.0	587,833
7	1992	50.0	267,801
8	1993	50.0	464,025
9	1994	50.0	871,157
10	1995	50.0	1,083,938
11	1996	50.0	1,551,850
12	1997	50.0	1,832,337
13	1998	50.0	1,842,429
14	1999	50.0	1,920,485
15	2000	50.0	2,918,491
16	2001	50.0	3,105,066
17	2002	50.0	2,630,314
18	2003	50.0	1,567,252
19	2004	50.0	1,143,976
20	2005	50.0	1,431,120
21	2006	50.0	2,241,260
22	2007	50.0	2,126,664
23	2008	50.0	3,037,310
24	2009	50.0	3,021,450
25	2010	50.0	2,110,481
26	2011	50.0	1,681,950
27	2012	50.0	2,704,493
28	2013	50.0	2,706,135
29	2014	50.0	3,159,688,

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Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	327,583
1	1986	50.0	251,919
2	1987	50.0	304,062
3	1988	50.0	406,204
4	1989	50.0	336,833

5	1990	50.0	439,000
6	1991	50.0	587,833
7	1992	50.0	267,801
8	1993	50.0	464,025
9	1994	50.0	871,157
10	1995	50.0	1,083,938
11	1996	50.0	1,551,850
12	1997	50.0	1,832,337
13	1998	50.0	1,842,429
14	1999	50.0	1,920,485
15	2000	50.0	2,918,491
16	2001	50.0	3,105,066
17	2002	50.0	2,630,314
18	2003	50.0	1,567,252
19	2004	50.0	1,143,976
20	2005	50.0	1,431,120
21	2006	50.0	2,241,260
22	2007	50.0	2,126,664
23	2008	50.0	3,037,310
24	2009	50.0	3,021,450
25	2010	50.0	2,110,481
26	2011	50.0	1,681,950
27	2012	50.0	2,704,493
28	2013	50.0	2,706,135
29	2014	50.0	3,159,688,

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Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

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	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1993	50.0	313,742
1	1994	50.0	702,568
2	1995	50.0	948,742
3	1996	50.0	1,296,123
4	1997	50.0	1,451,988
5	1998	50.0	1,682,821
6	1999	50.0	1,821,642
7	2000	50.0	2,182,542
8	2001	50.0	2,751,589
9	2002	50.0	2,105,594
10	2003	50.0	2,239,322
11	2004	50.0	2,337,327
12	2005	50.0	1,649,620
13	2006	50.0	1,288,531
14	2007	50.0	2,078,500
15	2008	50.0	2,640,596
16	2009	50.0	2,785,222
17	2010	50.0	2,904,379
18	2011	50.0	3,390,310
19	2012	50.0	2,692,054
20	2013	50.0	2,976,362
21	2014	50.0	3,180,116,

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	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	517,407
1	1986	50.0	456,878

2	1987	50.0	527,081
3	1988	50.0	559,546
4	1989	50.0	582,554
5	1990	50.0	533,128
6	1991	50.0	953,533
7	1992	50.0	975,815
8	1993	50.0	1,230,650
9	1994	50.0	1,336,983
10	1995	50.0	1,122,550
11	1996	50.0	732,437
12	1997	50.0	595,586
13	1998	50.0	687,571
14	1999	50.0	1,073,225
15	2000	50.0	2,157,969
16	2001	50.0	1,907,720
17	2002	50.0	1,966,000
18	2003	50.0	1,891,076
19	2004	50.0	1,672,571
20	2005	50.0	2,467,571
21	2006	50.0	2,950,459
22	2007	50.0	3,268,978
23	2008	50.0	4,589,506
24	2009	50.0	4,110,183
25	2010	50.0	4,550,552
26	2011	50.0	3,914,823
27	2012	50.0	4,562,068
28	2013	50.0	6,082,895
29	2014	50.0	6,645,891,

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	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1993	50.0	568,545
1	1994	50.0	584,675
2	1995	50.0	662,588
3	1996	50.0	969,453
4	1997	50.0	1,570,725
5	1998	50.0	1,033,066
6	1999	50.0	585,694
7	2000	50.0	709,714
8	2001	50.0	1,153,629
9	2002	50.0	1,499,282
10	2003	50.0	1,648,333
11	2004	50.0	1,560,853
12	2005	50.0	2,237,364
13	2006	50.0	586,860
14	2007	50.0	984,096
15	2008	50.0	660,954
16	2009	50.0	1,315,500
17	2010	50.0	2,112,211
18	2011	50.0	2,190,153,

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Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

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	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	499,652
1	1986	50.0	411,386
2	1987	50.0	450,298
3	1988	50.0	472,544
4	1989	50.0	556,648
5	1990	50.0	591,290
6	1991	50.0	514,100
7	1992	50.0	513,583
8	1993	50.0	1,041,741
9	1994	50.0	1,003,818
10	1995	50.0	949,162
11	1996	50.0	918,935
12	1997	50.0	1,121,854
13	1998	50.0	1,324,187
14	1999	50.0	1,716,062
15	2000	50.0	1,899,596
16	2001	50.0	2,164,738
17	2002	50.0	2,349,941
18	2003	50.0	2,732,307
19	2004	50.0	3,015,880
20	2005	50.0	2,953,038
21	2006	50.0	3,547,777
22	2007	50.0	3,250,333
23	2008	50.0	3,293,719
24	2009	50.0	3,814,682
25	2010	50.0	3,298,410
26	2011	50.0	2,437,724
27	2012	50.0	2,332,730
28	2013	50.0	813,213
29	2014	50.0	1,755,815,
	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	499,652
1	1986	50.0	411,386
2	1987	50.0	450,298
3	1988	50.0	472,544
4	1989	50.0	556,648
5	1990	50.0	591,290
6	1991	50.0	514,100
7	1992	50.0	513,583
8	1993	50.0	1,041,741
9	1994	50.0	1,003,818
10	1995	50.0	949,162
11	1996	50.0	918,935
12	1997	50.0	1,121,854
13	1998	50.0	1,324,187
14	1999	50.0	1,716,062
15	2000	50.0	1,899,596
16	2001	50.0	2,164,738
17	2002	50.0	2,349,941
18	2003	50.0	2,732,307
19	2004	50.0	3,015,880
20	2005	50.0	2,953,038
21	2006	50.0	3,547,777
22	2007	50.0	3,250,333
23	2008	50.0	3,293,719
24	2009	50.0	3,814,682



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2     2007                50.0        3,641,711
3     2008                50.0        4,110,908
4     2009                50.0        4,061,035
5     2010                50.0        3,619,443
6     2011                50.0        4,469,134
7     2012                50.0        5,327,074
8     2013                50.0        4,775,951
9     2014                50.0        4,518,083,
   yearID  MEAN WINNING PERCENTAGE  AVERAGE PAYROLL
0     2005                50.0        3,271,304
1     2006                50.0        4,138,880
2     2007                50.0        3,641,711
3     2008                50.0        4,110,908
4     2009                50.0        4,061,035
5     2010                50.0        3,619,443
6     2011                50.0        4,469,134
7     2012                50.0        5,327,074
8     2013                50.0        4,775,951
9     2014                50.0        4,518,083,
   yearID  MEAN WINNING PERCENTAGE  AVERAGE PAYROLL
0     1985                50.0        476,865
1     1986                50.0        466,055
2     1987                50.0        488,407
3     1988                50.0        561,683
4     1989                50.0        679,727
5     1990                50.0        609,105
6     1991                50.0       1,093,022
7     1992                50.0       1,544,419
8     1993                50.0       1,229,124
9     1994                50.0       1,225,806
10    1995                50.0       1,061,437
11    1996                50.0       1,104,843
12    1997                50.0       1,512,676
13    1998                50.0       1,435,882
14    1999                50.0       2,378,307
15    2000                50.0       3,381,703
16    2001                50.0       3,762,274
17    2002                50.0       3,648,113
18    2003                50.0       4,222,904
19    2004                50.0       3,440,814
20    2005                50.0       2,767,966
21    2006                50.0       3,515,970
22    2007                50.0       3,739,811
23    2008                50.0       4,089,259
24    2009                50.0       4,016,583
25    2010                50.0       3,531,778
26    2011                50.0       3,472,966
27    2012                50.0       3,171,452
28    2013                50.0       6,980,068
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0      1985      50.0      303,411
1      1986      50.0      397,643
2      1987      50.0      710,833
3      1988      50.0      541,855
4      1989      50.0      621,266
5      1990      50.0      405,611
6      1991      50.0      973,409
7      1992      50.0      1,000,994
8      1993      50.0      855,088
9      1994      50.0      947,950
10     1995      50.0      770,015
11     1996      50.0      700,515
12     1997      50.0      1,099,112
13     1998      50.0      963,017
14     1999      50.0      733,017
15     2000      50.0      635,365
16     2001      50.0      893,703
17     2002      50.0      1,497,222
18     2003      50.0      2,134,807
19     2004      50.0      2,060,961
20     2005      50.0      2,080,962
21     2006      50.0      2,438,307
22     2007      50.0      2,551,410
23     2008      50.0      2,277,310
24     2009      50.0      2,251,698
25     2010      50.0      3,484,255
26     2011      50.0      4,509,480
27     2012      50.0      3,484,629
28     2013      50.0      2,790,277
29     2014      50.0      3,102,314,
      yearID  MEAN WINNING PERCENTAGE  AVERAGE  PAYROLL
0      1985      50.0      473,508
1      1986      50.0      346,987
2      1987      50.0      289,252
3      1988      50.0      384,133
4      1989      50.0      493,121
5      1990      50.0      535,044
6      1991      50.0      631,313
7      1992      50.0      586,012
8      1993      50.0      484,598
9      1994      50.0      682,071
10     1995      50.0      374,666
11     1996      50.0      524,661
12     1997      50.0      622,435
13     1998      50.0      322,469
14     1999      50.0      511,514
15     2000      50.0      1,137,735
16     2001      50.0      1,134,177
17     2002      50.0      1,381,089
18     2003      50.0      1,998,019
19     2004      50.0      1,410,258,
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Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]
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	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	711,910
1	1986	50.0	660,509
2	1987	50.0	488,563
3	1988	50.0	648,038
4	1989	50.0	552,076
5	1990	50.0	633,706
6	1991	50.0	976,577
7	1992	50.0	1,137,676
8	1993	50.0	1,291,663
9	1994	50.0	1,576,942
10	1995	50.0	1,437,495
11	1996	50.0	1,593,876
12	1997	50.0	2,146,260
13	1998	50.0	2,087,714
14	1999	50.0	2,990,839
15	2000	50.0	3,297,795
16	2001	50.0	3,622,165
17	2002	50.0	4,342,364
18	2003	50.0	5,455,350
19	2004	50.0	6,351,515
20	2005	50.0	8,011,800
21	2006	50.0	6,952,252
22	2007	50.0	6,759,251
23	2008	50.0	6,929,892
24	2009	50.0	7,748,045
25	2010	50.0	8,253,335
26	2011	50.0	6,975,000
27	2012	50.0	6,776,630
28	2013	50.0	7,483,189
29	2014	50.0	8,230,996,

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1	1986	50.0	549,775
2	1987	50.0	553,868
3	1988	50.0	610,772
4	1989	50.0	710,181
5	1990	50.0	678,838
6	1991	50.0	1,253,461
7	1992	50.0	1,715,461
8	1993	50.0	1,301,455
9	1994	50.0	998,599
10	1995	50.0	674,999
11	1996	50.0	741,803
12	1997	50.0	1,137,154
13	1998	50.0	1,578,121
14	1999	50.0	2,099,744
15	2000	50.0	3,180,391

16	2001	50.0	3,212,911
17	2002	50.0	3,639,753
18	2003	50.0	4,174,158
19	2004	50.0	3,452,177
20	2005	50.0	3,752,067
21	2006	50.0	3,743,887
22	2007	50.0	3,841,055
23	2008	50.0	4,593,112
24	2009	50.0	5,334,785
25	2010	50.0	4,800,819
26	2011	50.0	4,401,752
27	2012	50.0	3,457,554
28	2013	50.0	1,648,278
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1	1986	50.0	660,509
2	1987	50.0	488,563
3	1988	50.0	648,038
4	1989	50.0	552,076
5	1990	50.0	633,706
6	1991	50.0	976,577
7	1992	50.0	1,137,676
8	1993	50.0	1,291,663
9	1994	50.0	1,576,942
10	1995	50.0	1,437,495
11	1996	50.0	1,593,876
12	1997	50.0	2,146,260
13	1998	50.0	2,087,714
14	1999	50.0	2,990,839
15	2000	50.0	3,297,795
16	2001	50.0	3,622,165
17	2002	50.0	4,342,364
18	2003	50.0	5,455,350
19	2004	50.0	6,351,515
20	2005	50.0	8,011,800
21	2006	50.0	6,952,252
22	2007	50.0	6,759,251
23	2008	50.0	6,929,892
24	2009	50.0	7,748,045
25	2010	50.0	8,253,335
26	2011	50.0	6,975,000
27	2012	50.0	6,776,630
28	2013	50.0	7,483,189
29	2014	50.0	8,230,996,

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2	1987	50.0	449,263
3	1988	50.0	421,304
4	1989	50.0	624,522

5	1990	50.0	584,926
6	1991	50.0	1,423,044
7	1992	50.0	1,282,343
8	1993	50.0	1,050,342
9	1994	50.0	1,035,530
10	1995	50.0	1,019,979
11	1996	50.0	574,135
12	1997	50.0	615,858
13	1998	50.0	608,657
14	1999	50.0	814,394
15	2000	50.0	1,184,123
16	2001	50.0	1,252,250
17	2002	50.0	1,481,635
18	2003	50.0	1,933,109
19	2004	50.0	2,122,345
20	2005	50.0	2,131,760
21	2006	50.0	2,489,723
22	2007	50.0	2,834,533
23	2008	50.0	1,713,111
24	2009	50.0	2,292,962
25	2010	50.0	1,726,715
26	2011	50.0	2,376,303
27	2012	50.0	1,845,750
28	2013	50.0	1,939,758
29	2014	50.0	2,784,938,

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	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	532,892
1	1986	50.0	373,876
2	1987	50.0	479,759
3	1988	50.0	532,230
4	1989	50.0	407,846
5	1990	50.0	439,122
6	1991	50.0	749,577
7	1992	50.0	812,794
8	1993	50.0	891,822
9	1994	50.0	987,468
10	1995	50.0	783,485
11	1996	50.0	798,011
12	1997	50.0	916,412
13	1998	50.0	1,037,071
14	1999	50.0	932,132
15	2000	50.0	1,631,310
16	2001	50.0	1,602,455
17	2002	50.0	2,069,821
18	2003	50.0	2,440,689

19	2004	50.0	3,573,814
20	2005	50.0	3,673,923
21	2006	50.0	3,269,382
22	2007	50.0	2,980,940
23	2008	50.0	3,495,710
24	2009	50.0	4,185,335
25	2010	50.0	5,068,870
26	2011	50.0	5,765,879
27	2012	50.0	5,817,964
28	2013	50.0	6,533,199
29	2014	50.0	5,654,530,

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	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	532,892
1	1986	50.0	373,876
2	1987	50.0	479,759
3	1988	50.0	532,230
4	1989	50.0	407,846
5	1990	50.0	439,122
6	1991	50.0	749,577
7	1992	50.0	812,794
8	1993	50.0	891,822
9	1994	50.0	987,468
10	1995	50.0	783,485
11	1996	50.0	798,011
12	1997	50.0	916,412
13	1998	50.0	1,037,071
14	1999	50.0	932,132
15	2000	50.0	1,631,310
16	2001	50.0	1,602,455
17	2002	50.0	2,069,821
18	2003	50.0	2,440,689
19	2004	50.0	3,573,814
20	2005	50.0	3,673,923
21	2006	50.0	3,269,382
22	2007	50.0	2,980,940
23	2008	50.0	3,495,710
24	2009	50.0	4,185,335
25	2010	50.0	5,068,870
26	2011	50.0	5,765,879
27	2012	50.0	5,817,964
28	2013	50.0	6,533,199
29	2014	50.0	5,654,530,

	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	532,892
1	1986	50.0	373,876
2	1987	50.0	479,759
3	1988	50.0	532,230
4	1989	50.0	407,846
5	1990	50.0	439,122
6	1991	50.0	749,577
7	1992	50.0	812,794
8	1993	50.0	891,822
9	1994	50.0	987,468
10	1995	50.0	783,485



11	1996	50.0	798,011
12	1997	50.0	916,412
13	1998	50.0	1,037,071
14	1999	50.0	932,132
15	2000	50.0	1,631,310
16	2001	50.0	1,602,455
17	2002	50.0	2,069,821
18	2003	50.0	2,440,689
19	2004	50.0	3,573,814
20	2005	50.0	3,673,923
21	2006	50.0	3,269,382
22	2007	50.0	2,980,940
23	2008	50.0	3,495,710
24	2009	50.0	4,185,335
25	2010	50.0	5,068,870
26	2011	50.0	5,765,879
27	2012	50.0	5,817,964
28	2013	50.0	6,533,199
29	2014	50.0	5,654,530,

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	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	485,657
1	1986	50.0	373,913
2	1987	50.0	306,080
3	1988	50.0	222,166
4	1989	50.0	439,224
5	1990	50.0	432,111
6	1991	50.0	875,358
7	1992	50.0	1,212,291
8	1993	50.0	752,195
9	1994	50.0	712,272
10	1995	50.0	556,222
11	1996	50.0	657,642
12	1997	50.0	307,761
13	1998	50.0	430,428
14	1999	50.0	649,938
15	2000	50.0	1,112,628
16	2001	50.0	1,863,252
17	2002	50.0	1,459,434
18	2003	50.0	1,957,586
19	2004	50.0	1,193,627
20	2005	50.0	1,361,892
21	2006	50.0	1,668,491
22	2007	50.0	1,427,327
23	2008	50.0	1,872,683
24	2009	50.0	1,872,807
25	2010	50.0	1,294,185
26	2011	50.0	1,553,344
27	2012	50.0	2,248,285
28	2013	50.0	2,752,214
29	2014	50.0	2,756,357,

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	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
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0	1985	50.0	485,657
1	1986	50.0	373,913
2	1987	50.0	306,080
3	1988	50.0	222,166
4	1989	50.0	439,224
5	1990	50.0	432,111
6	1991	50.0	875,358
7	1992	50.0	1,212,291
8	1993	50.0	752,195
9	1994	50.0	712,272
10	1995	50.0	556,222
11	1996	50.0	657,642
12	1997	50.0	307,761
13	1998	50.0	430,428
14	1999	50.0	649,938
15	2000	50.0	1,112,628
16	2001	50.0	1,863,252
17	2002	50.0	1,459,434
18	2003	50.0	1,957,586
19	2004	50.0	1,193,627
20	2005	50.0	1,361,892
21	2006	50.0	1,668,491
22	2007	50.0	1,427,327
23	2008	50.0	1,872,683
24	2009	50.0	1,872,807
25	2010	50.0	1,294,185
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28	2013	50.0	2,752,214
29	2014	50.0	2,756,357,

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	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	501,662
1	1986	50.0	455,227
2	1987	50.0	409,844
3	1988	50.0	354,111
4	1989	50.0	525,740
5	1990	50.0	549,635
6	1991	50.0	738,333
7	1992	50.0	959,077
8	1993	50.0	750,333
9	1994	50.0	426,180
10	1995	50.0	851,043
11	1996	50.0	944,939
12	1997	50.0	1,288,402
13	1998	50.0	1,562,050

14	1999	50.0	1,508,126
15	2000	50.0	1,827,366
16	2001	50.0	1,399,386
17	2002	50.0	1,428,448
18	2003	50.0	1,507,000
19	2004	50.0	2,130,185
20	2005	50.0	2,260,386
21	2006	50.0	2,496,290
22	2007	50.0	2,235,021
23	2008	50.0	2,376,697
24	2009	50.0	1,604,951
25	2010	50.0	1,453,819
26	2011	50.0	1,479,649
27	2012	50.0	1,973,025
28	2013	50.0	2,342,339
29	2014	50.0	2,703,060,

	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	411,085
1	1986	50.0	319,535
2	1987	50.0	316,956
3	1988	50.0	495,200
4	1989	50.0	534,386
5	1990	50.0	568,686
6	1991	50.0	1,191,064
7	1992	50.0	1,326,526
8	1993	50.0	1,130,645
9	1994	50.0	1,332,458
10	1995	50.0	934,943
11	1996	50.0	1,061,277
12	1997	50.0	1,112,261
13	1998	50.0	1,520,208
14	1999	50.0	1,606,726
15	2000	50.0	2,066,839
16	2001	50.0	2,343,709
17	2002	50.0	2,899,993
18	2003	50.0	3,186,621
19	2004	50.0	2,645,779
20	2005	50.0	3,469,211
21	2006	50.0	3,463,708
22	2007	50.0	3,469,963
23	2008	50.0	2,641,189
24	2009	50.0	2,965,230
25	2010	50.0	3,522,904
26	2011	50.0	4,377,716
27	2012	50.0	3,920,689
28	2013	50.0	5,006,440
29	2014	50.0	20,000,000,

	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	256,277
1	1986	50.0	229,165
2	1987	50.0	251,500
3	1988	50.0	282,401
4	1989	50.0	407,479
5	1990	50.0	369,225
6	1991	50.0	603,532
7	1992	50.0	799,304
8	1993	50.0	990,797
9	1994	50.0	885,712
10	1995	50.0	1,042,323
11	1996	50.0	1,215,544

12	1997	50.0	1,298,145
13	1998	50.0	1,423,343
14	1999	50.0	1,503,472
15	2000	50.0	2,265,961
16	2001	50.0	2,668,601
17	2002	50.0	3,211,306
18	2003	50.0	3,220,709
19	2004	50.0	2,911,279
20	2005	50.0	2,742,322
21	2006	50.0	3,257,771
22	2007	50.0	3,942,993
23	2008	50.0	4,525,633
24	2009	50.0	3,532,291
25	2010	50.0	3,089,642
26	2011	50.0	2,969,331
27	2012	50.0	2,927,789
28	2013	50.0	2,846,347
29	2014	50.0	3,701,244,

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	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	472,683
1	1986	50.0	365,741
2	1987	50.0	379,290
3	1988	50.0	477,037
4	1989	50.0	574,244
5	1990	50.0	586,380
6	1991	50.0	753,793
7	1992	50.0	951,166
8	1993	50.0	778,911
9	1994	50.0	975,853
10	1995	50.0	976,342
11	1996	50.0	1,220,292
12	1997	50.0	1,262,685
13	1998	50.0	1,562,072
14	1999	50.0	1,382,727
15	2000	50.0	2,276,069
16	2001	50.0	2,617,944
17	2002	50.0	2,871,572
18	2003	50.0	2,702,795
19	2004	50.0	3,201,089
20	2005	50.0	3,542,570
21	2006	50.0	3,292,273
22	2007	50.0	3,224,529
23	2008	50.0	3,018,922
24	2009	50.0	3,278,829
25	2010	50.0	3,741,630

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26      2011                50.0          3,904,947
27      2012                50.0          3,939,316
28      2013                50.0          3,295,003
29      2014                50.0          4,310,464,
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1      1986                50.0          365,741
2      1987                50.0          379,290
3      1988                50.0          477,037
4      1989                50.0          574,244
5      1990                50.0          586,380
6      1991                50.0          753,793
7      1992                50.0          951,166
8      1993                50.0          778,911
9      1994                50.0          975,853
10     1995                50.0          976,342
11     1996                50.0          1,220,292
12     1997                50.0          1,262,685
13     1998                50.0          1,562,072
14     1999                50.0          1,382,727
15     2000                50.0          2,276,069
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18     2003                50.0          2,702,795
19     2004                50.0          3,201,089
20     2005                50.0          3,542,570
21     2006                50.0          3,292,273
22     2007                50.0          3,224,529
23     2008                50.0          3,018,922
24     2009                50.0          3,278,829
25     2010                50.0          3,741,630
26     2011                50.0          3,904,947
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1      1986                50.0          365,741
2      1987                50.0          379,290
3      1988                50.0          477,037
4      1989                50.0          574,244
5      1990                50.0          586,380
6      1991                50.0          753,793
7      1992                50.0          951,166
8      1993                50.0          778,911
9      1994                50.0          975,853
10     1995                50.0          976,342
11     1996                50.0          1,220,292
12     1997                50.0          1,262,685
13     1998                50.0          1,562,072
14     1999                50.0          1,382,727

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15	2000	50.0	2,276,069
16	2001	50.0	2,617,944
17	2002	50.0	2,871,572
18	2003	50.0	2,702,795
19	2004	50.0	3,201,089
20	2005	50.0	3,542,570
21	2006	50.0	3,292,273
22	2007	50.0	3,224,529
23	2008	50.0	3,018,922
24	2009	50.0	3,278,829
25	2010	50.0	3,741,630
26	2011	50.0	3,904,947
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29	2014	50.0	4,310,464,

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1	1999	50.0	1,022,894
2	2000	50.0	2,024,681
3	2001	50.0	2,110,370
4	2002	50.0	1,227,857
5	2003	50.0	785,200
6	2004	50.0	1,094,691
7	2005	50.0	1,023,416
8	2006	50.0	1,293,258
9	2007	50.0	893,462
10	2008	50.0	1,460,686
11	2009	50.0	2,183,208
12	2010	50.0	2,663,832
13	2011	50.0	1,578,983
14	2012	50.0	2,291,910
15	2013	50.0	2,302,403
16	2014	50.0	2,907,564,

	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1998	50.0	826,666
1	1999	50.0	1,022,894
2	2000	50.0	2,024,681
3	2001	50.0	2,110,370
4	2002	50.0	1,227,857
5	2003	50.0	785,200
6	2004	50.0	1,094,691
7	2005	50.0	1,023,416
8	2006	50.0	1,293,258
9	2007	50.0	893,462
10	2008	50.0	1,460,686

11	2009	50.0	2,183,208
12	2010	50.0	2,663,832
13	2011	50.0	1,578,983
14	2012	50.0	2,291,910
15	2013	50.0	2,302,403
16	2014	50.0	2,907,564,
	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	383,825
1	1986	50.0	259,350
2	1987	50.0	220,000
3	1988	50.0	242,824
4	1989	50.0	396,459
5	1990	50.0	402,010
6	1991	50.0	867,833
7	1992	50.0	971,876
8	1993	50.0	957,288
9	1994	50.0	999,199
10	1995	50.0	1,017,101
11	1996	50.0	1,183,076
12	1997	50.0	1,444,563
13	1998	50.0	1,885,736
14	1999	50.0	2,556,997
15	2000	50.0	2,722,920
16	2001	50.0	2,859,145
17	2002	50.0	3,768,790
18	2003	50.0	3,449,722
19	2004	50.0	1,898,290
20	2005	50.0	1,801,580
21	2006	50.0	2,200,924
22	2007	50.0	2,439,952
23	2008	50.0	2,334,907
24	2009	50.0	2,350,993
25	2010	50.0	1,905,191
26	2011	50.0	3,182,733
27	2012	50.0	4,635,037
28	2013	50.0	3,880,089
29	2014	50.0	4,677,294,

Empty DataFrame

Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

Empty DataFrame

Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
0	1985	50.0	440,627
1	1986	50.0	467,075
2	1987	50.0	455,630
3	1988	50.0	470,816
4	1989	50.0	580,773
5	1990	50.0	657,660
6	1991	50.0	796,096
7	1992	50.0	1,244,129
8	1993	50.0	1,432,702
9	1994	50.0	1,447,788
10	1995	50.0	1,533,030
11	1996	50.0	895,608
12	1997	50.0	1,426,661
13	1998	50.0	1,605,500
14	1999	50.0	1,420,135
15	2000	50.0	1,793,533

16	2001	50.0	2,746,285
17	2002	50.0	2,650,494
18	2003	50.0	1,898,851
19	2004	50.0	1,923,730
20	2005	50.0	1,758,442
21	2006	50.0	2,744,807
22	2007	50.0	3,034,918
23	2008	50.0	3,621,996
24	2009	50.0	2,876,367
25	2010	50.0	2,074,466
26	2011	50.0	2,018,316
27	2012	50.0	2,778,118
28	2013	50.0	4,073,809
29	2014	50.0	4,396,804,

Empty DataFrame

Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

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Empty DataFrame

Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
--	--------	-------------------------	-----------------

0	2005	50.0	1,619,383
---	------	------	-----------

1	2006	50.0	2,036,870
---	------	------	-----------

2	2007	50.0	1,319,553
---	------	------	-----------

3	2008	50.0	1,895,206
---	------	------	-----------

4	2009	50.0	2,140,285
---	------	------	-----------

5	2010	50.0	2,046,666
---	------	------	-----------

6	2011	50.0	2,201,963
---	------	------	-----------

7	2012	50.0	2,695,171
---	------	------	-----------

8	2013	50.0	4,548,130
---	------	------	-----------

9	2014	50.0	4,399,456,
---	------	------	------------

Empty DataFrame

Columns: [yearID, MEAN WINNING PERCENTAGE, AVERAGE PAYROLL]

Index: [],

	yearID	MEAN WINNING PERCENTAGE	AVERAGE PAYROLL
--	--------	-------------------------	-----------------

0	2005	50.0	1,619,383
---	------	------	-----------

1	2006	50.0	2,036,870
---	------	------	-----------

2	2007	50.0	1,319,553
---	------	------	-----------

3	2008	50.0	1,895,206
---	------	------	-----------

4	2009	50.0	2,140,285
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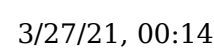
5	2010	50.0	2,046,666
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6	2011	50.0	2,201,963
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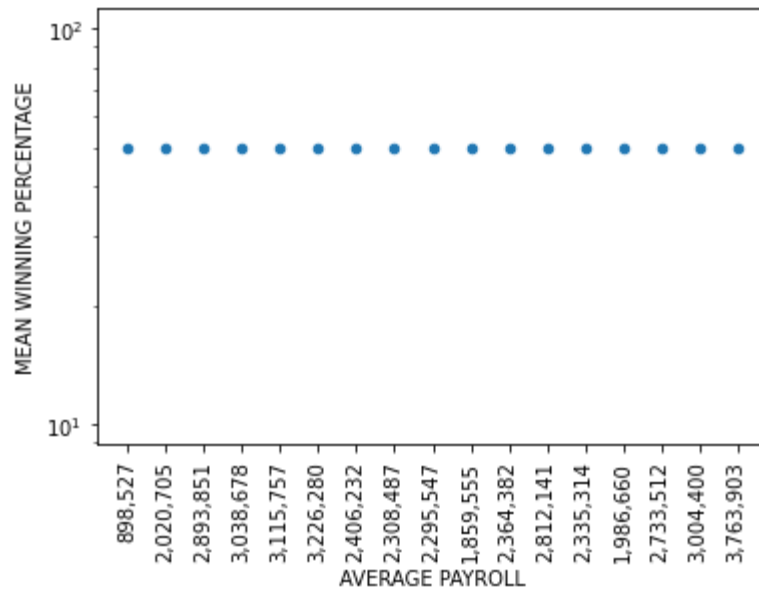


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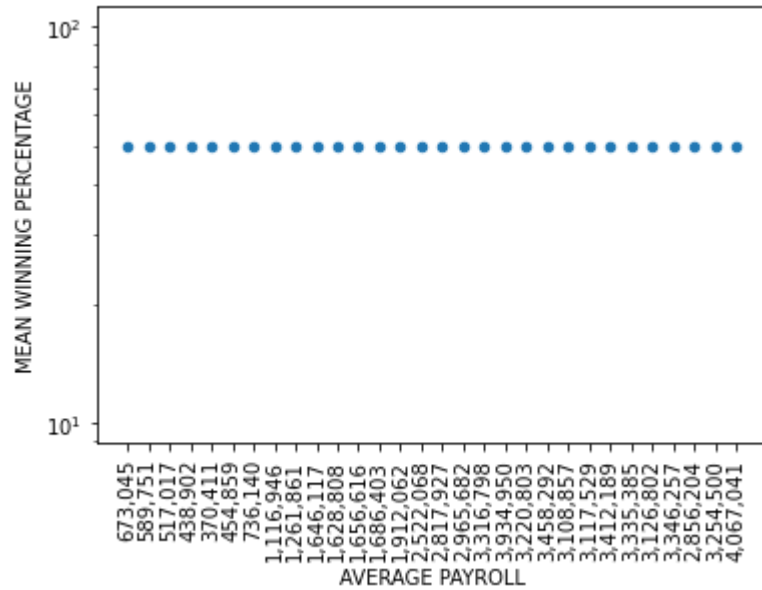
### AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Anaheim Angels



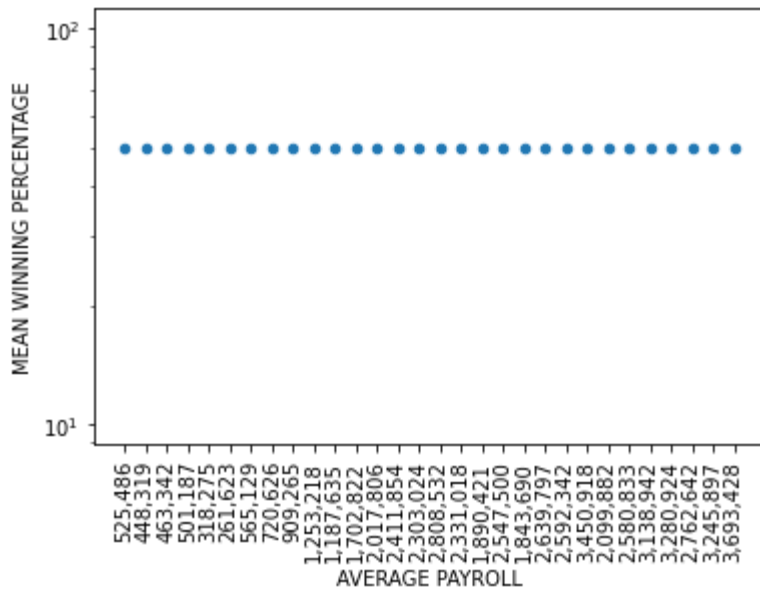
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Arizona Diamondbacks



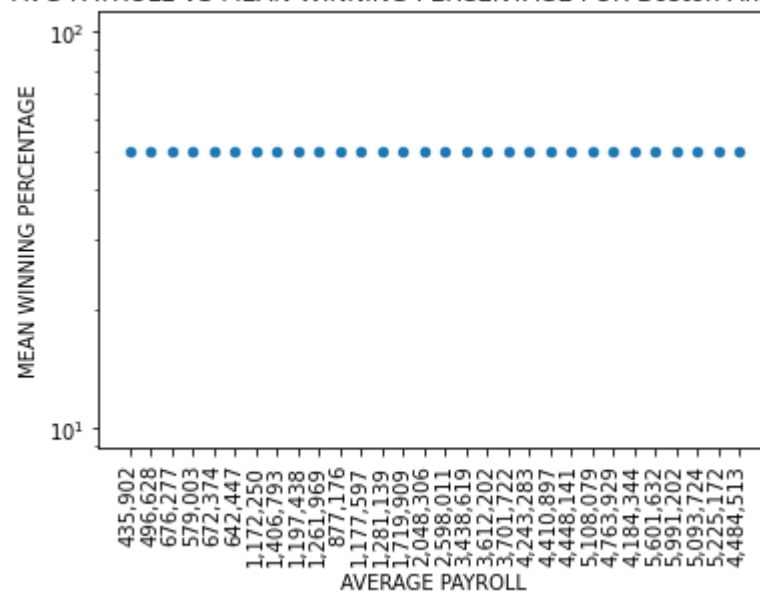
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Atlanta Braves



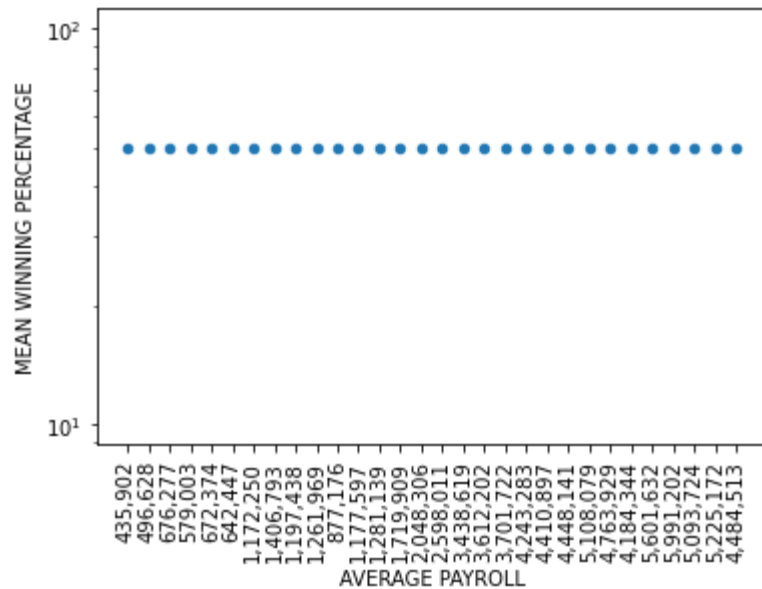
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Baltimore Orioles



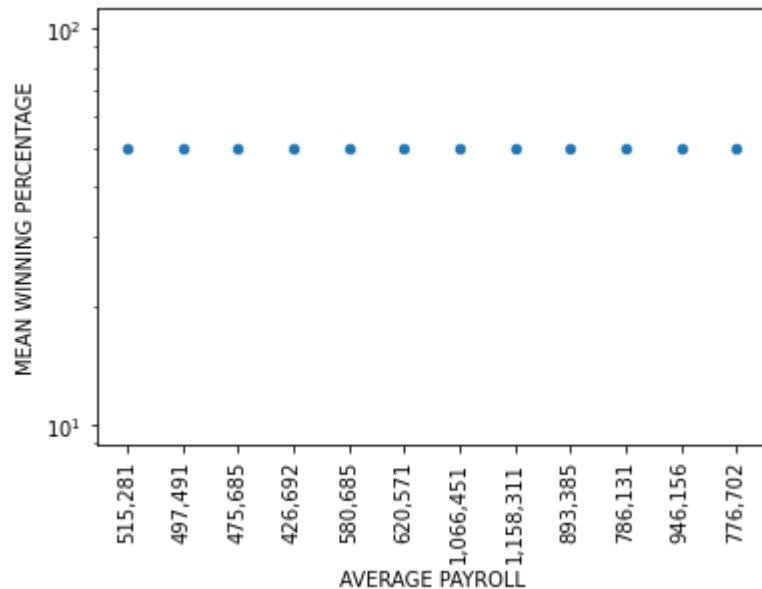
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Boston Americans



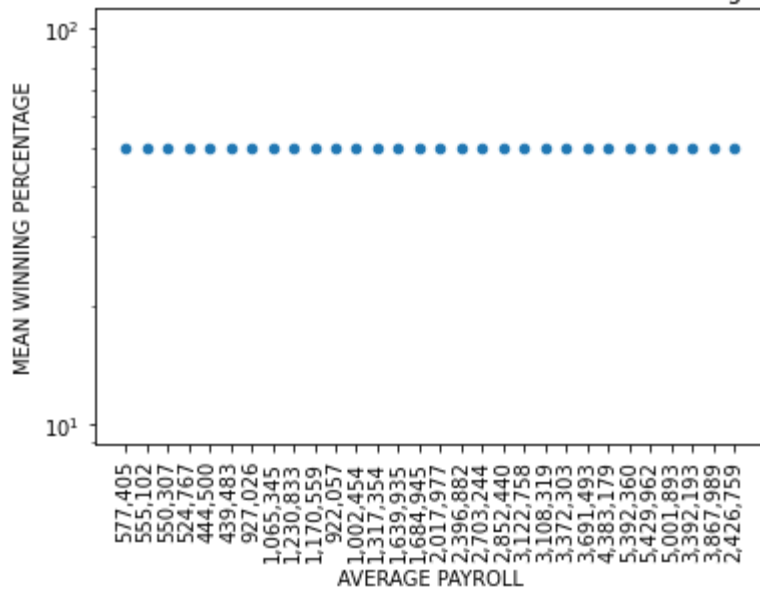
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Boston Red Sox



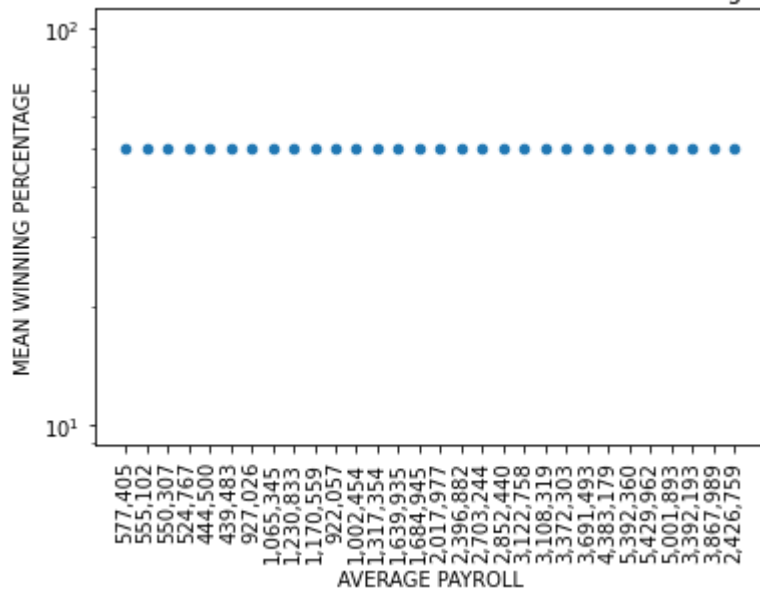
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR California Angels



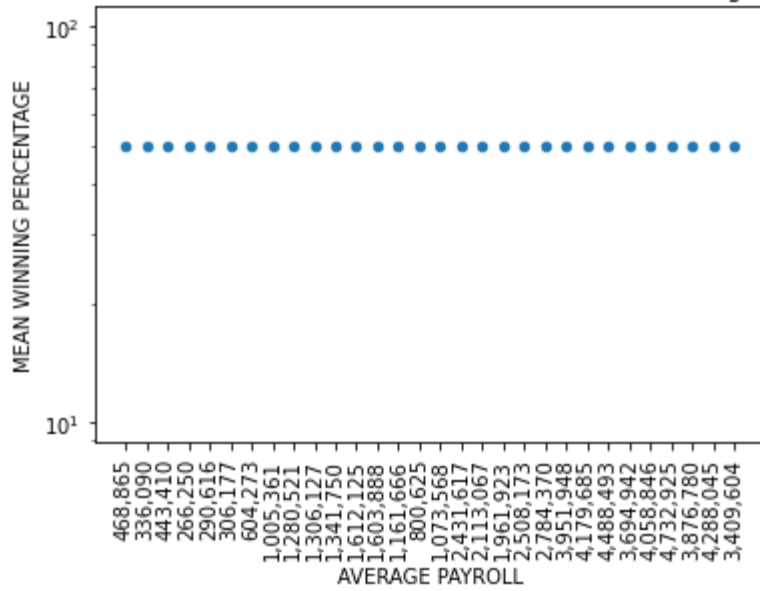
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Chicago Colts



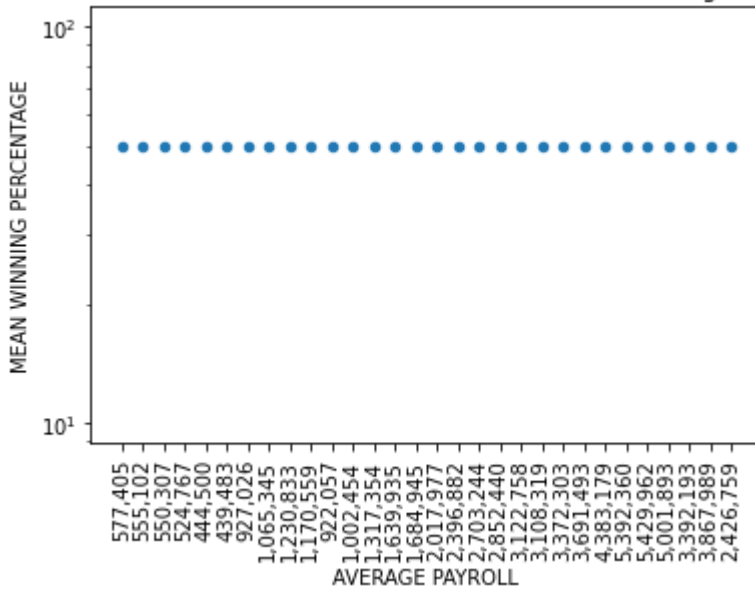
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Chicago Cubs



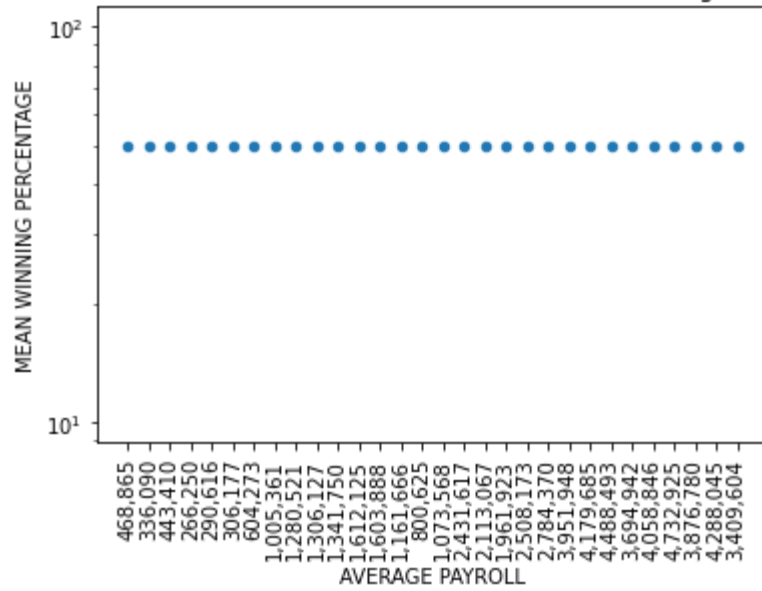
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Chicago Cubs



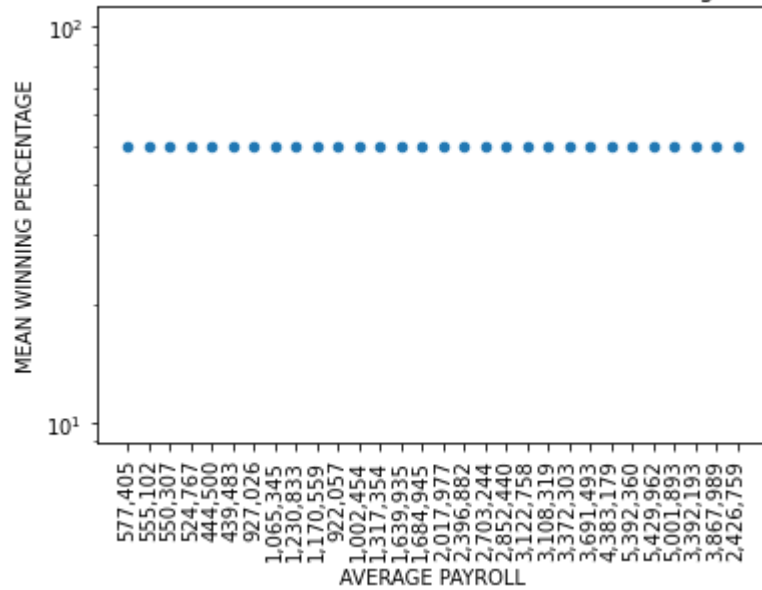
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Chicago Orphans



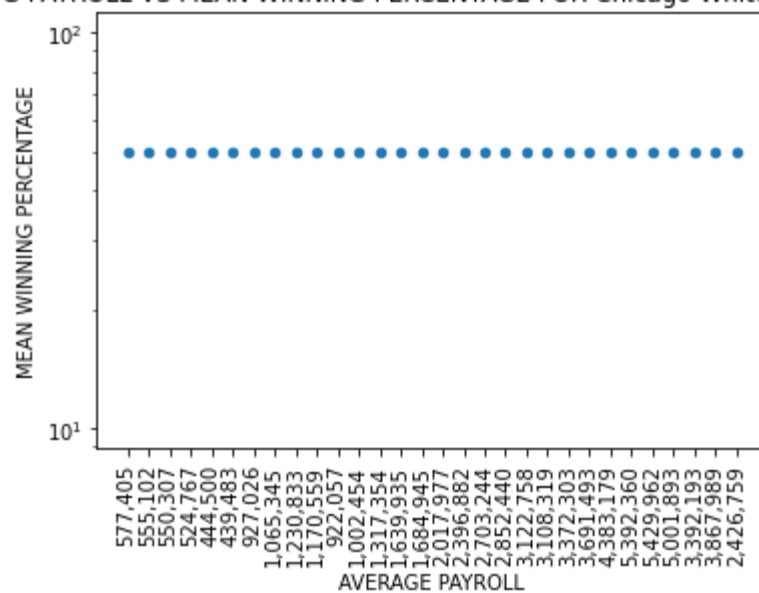
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Chicago White Sox



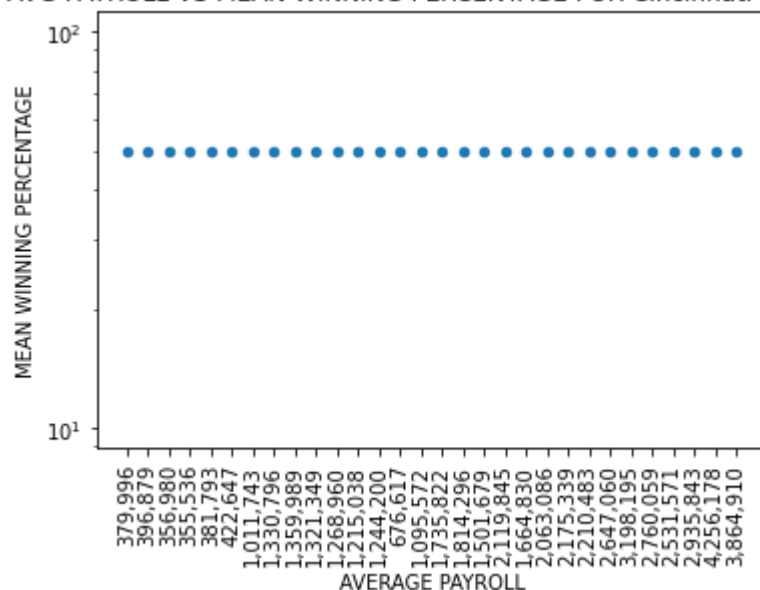
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Chicago White Sox



AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Chicago White Stockings

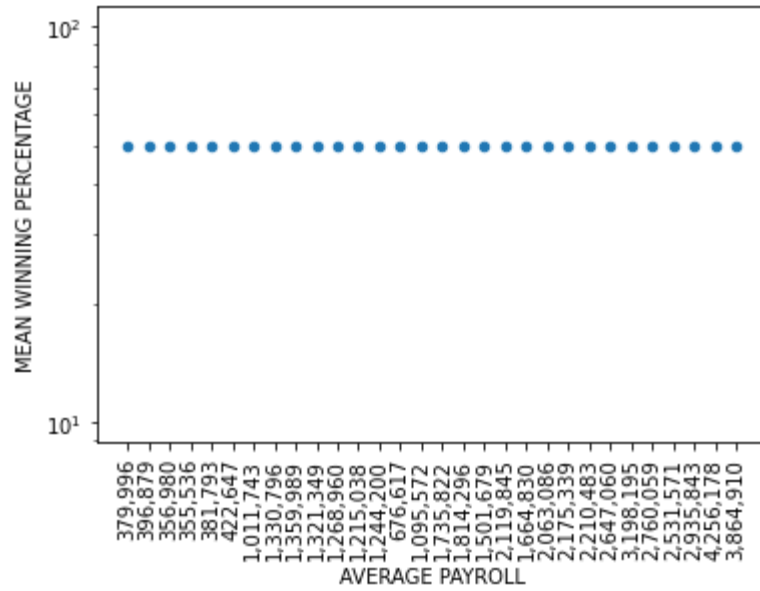


AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Cincinnati Redlegs

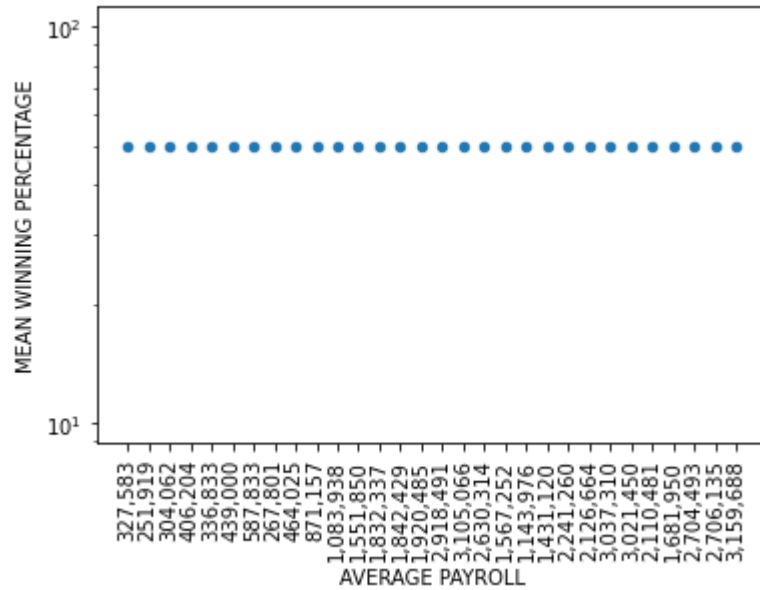




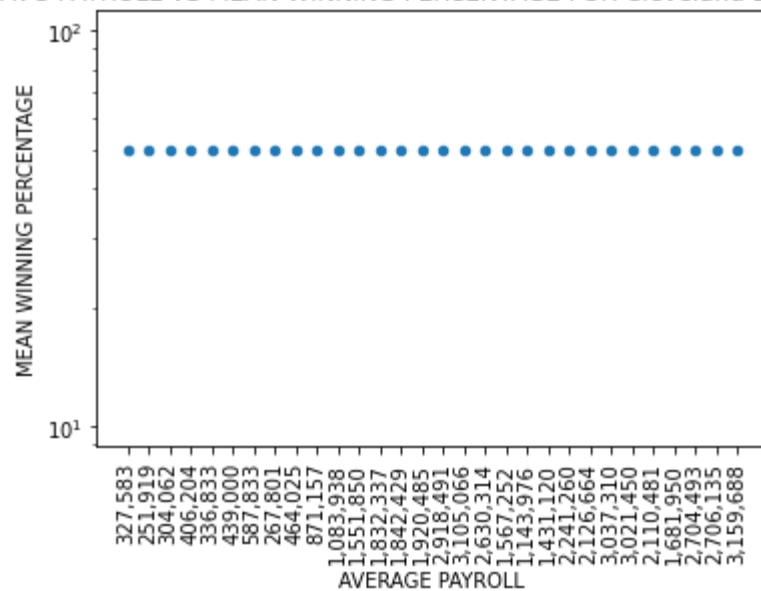
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Cincinnati Reds



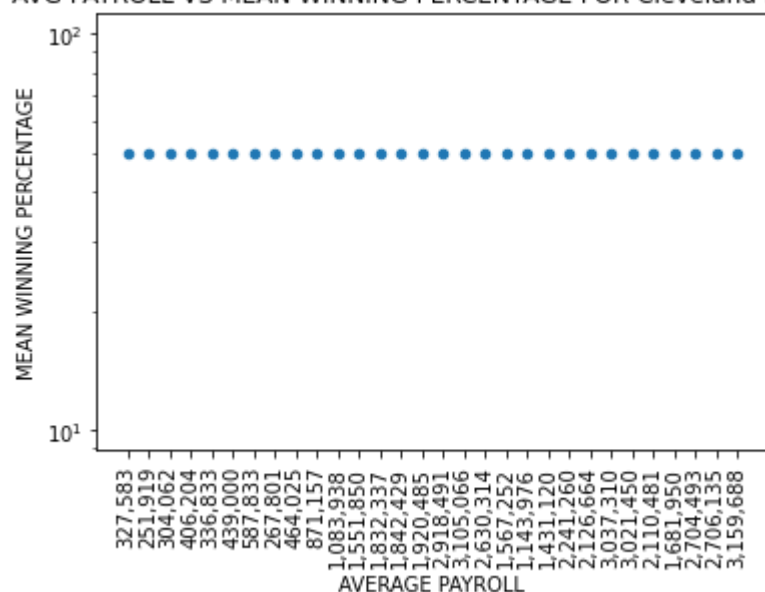
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Cleveland Blues



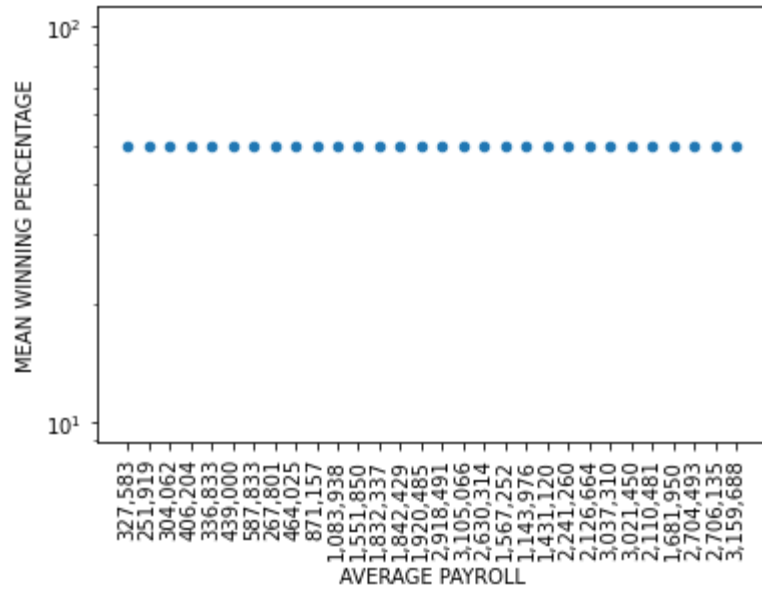
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Cleveland Bronchos



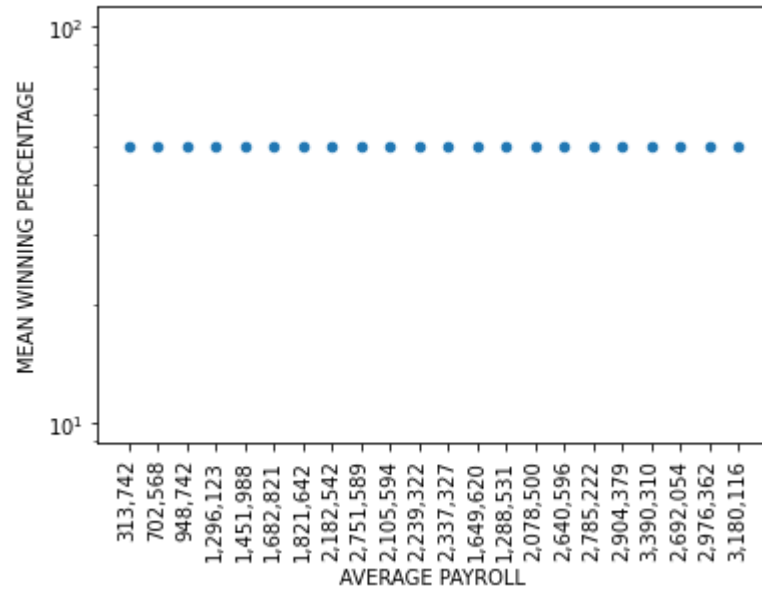
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Cleveland Indians



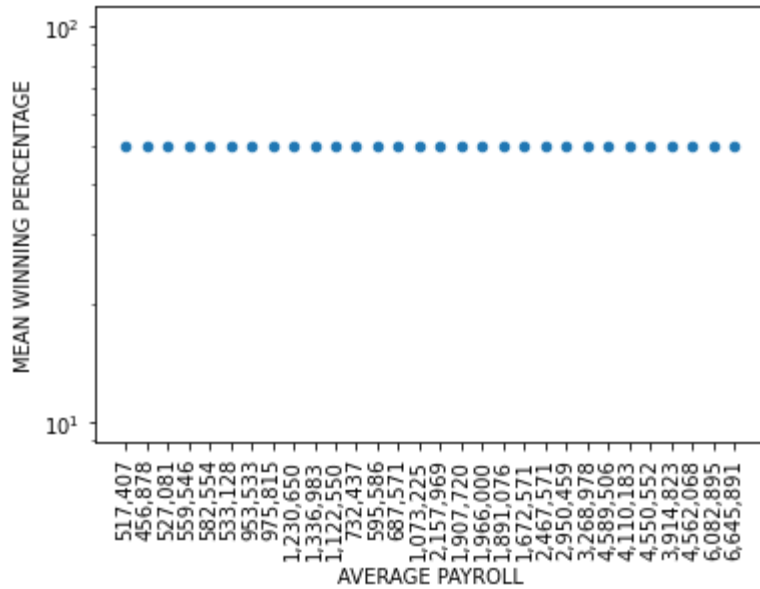
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Cleveland Naps



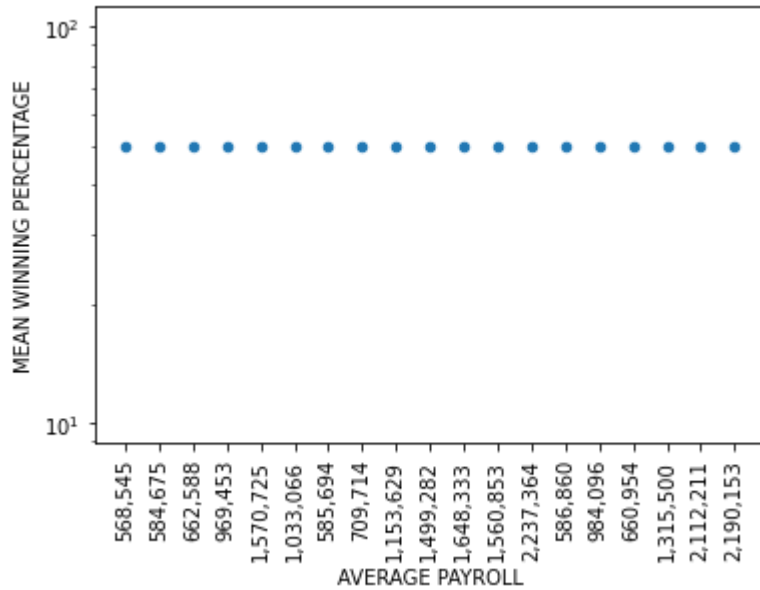
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Colorado Rockies



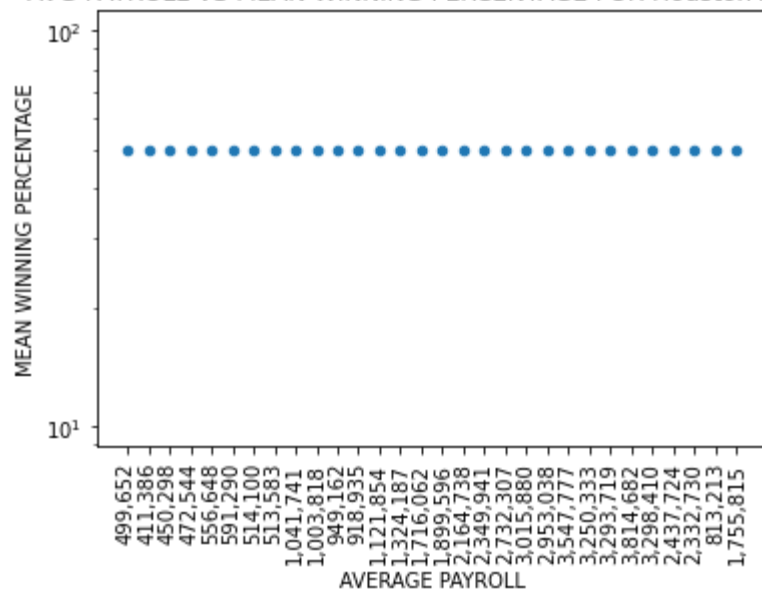
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Detroit Tigers



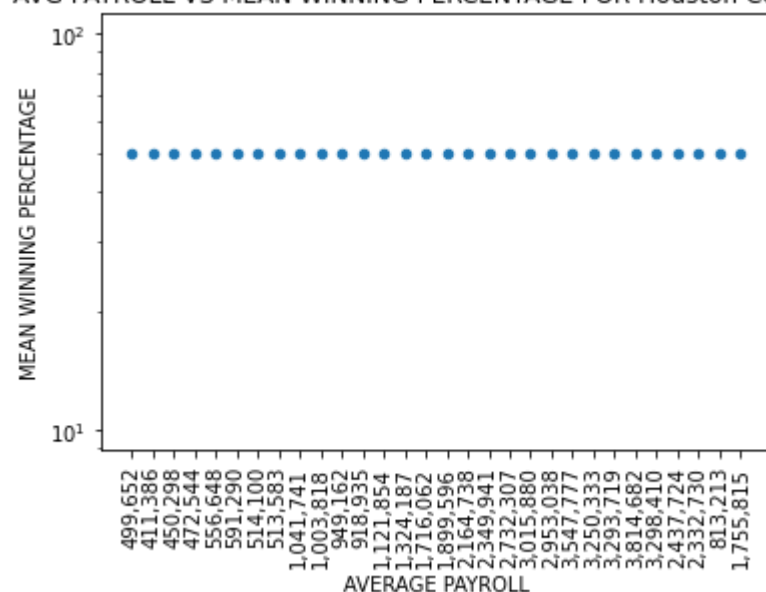
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Florida Marlins



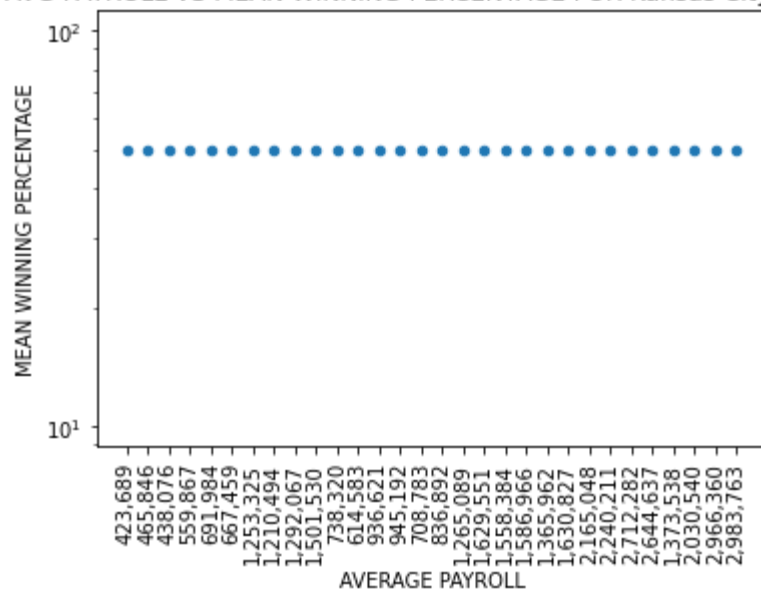
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Houston Astros



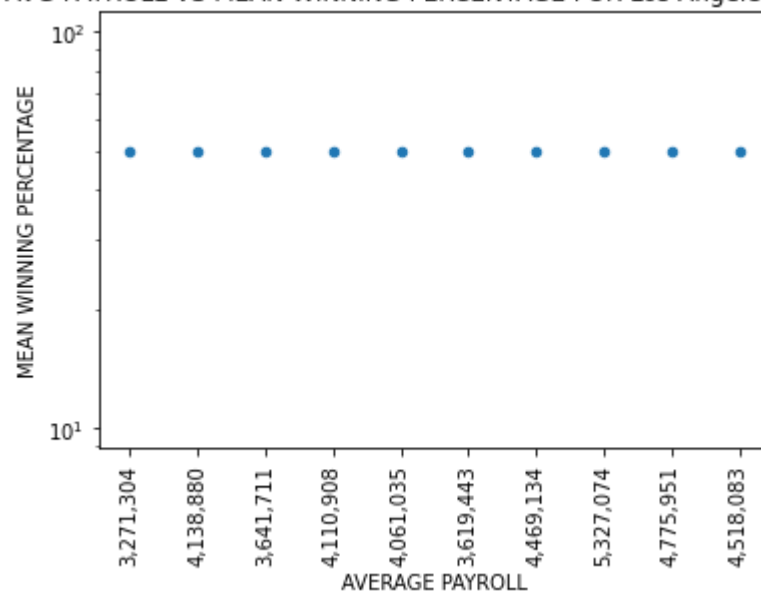
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Houston Colt .45's



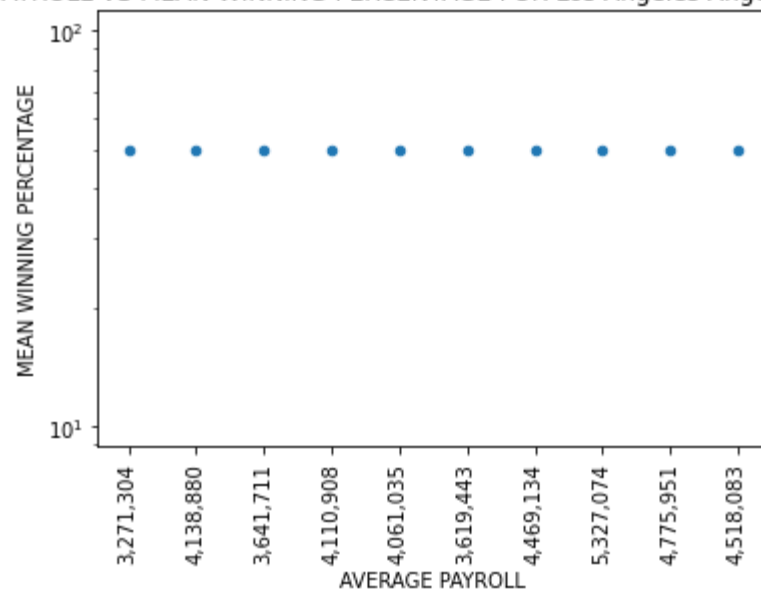
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Kansas City Royals



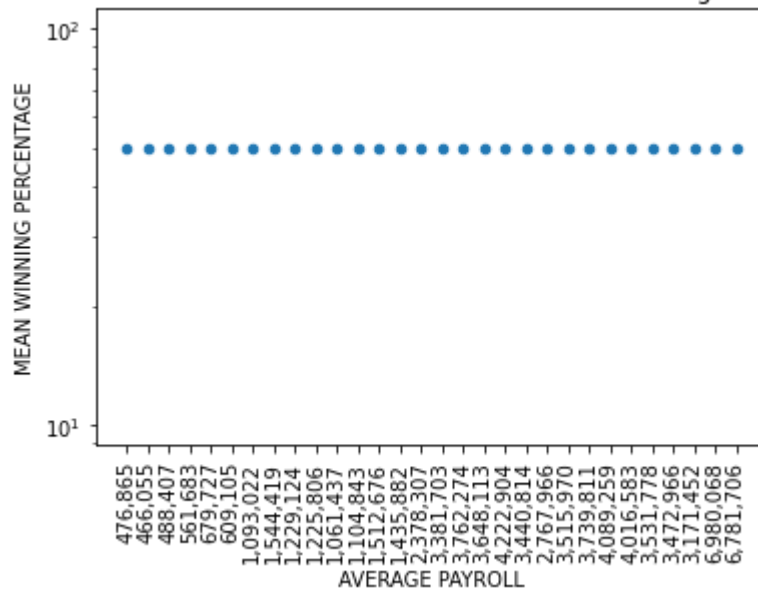
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Los Angeles Angels



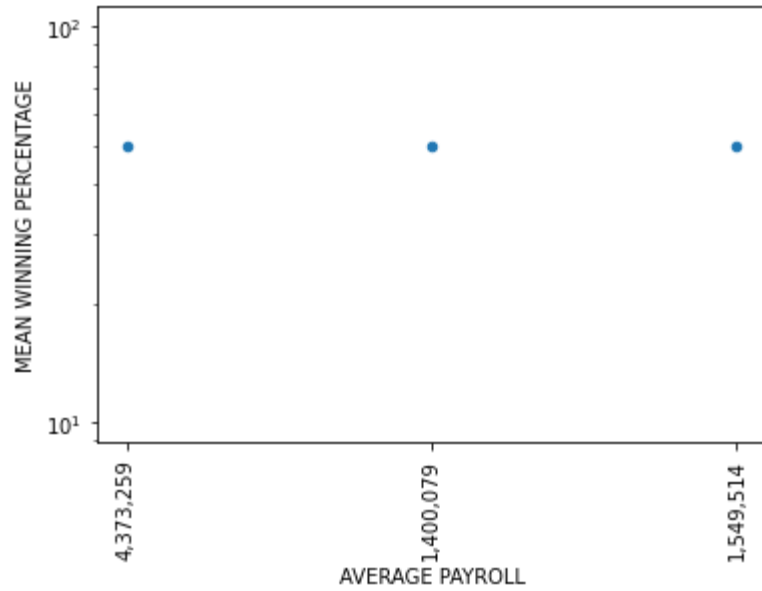
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Los Angeles Angels of Anaheim



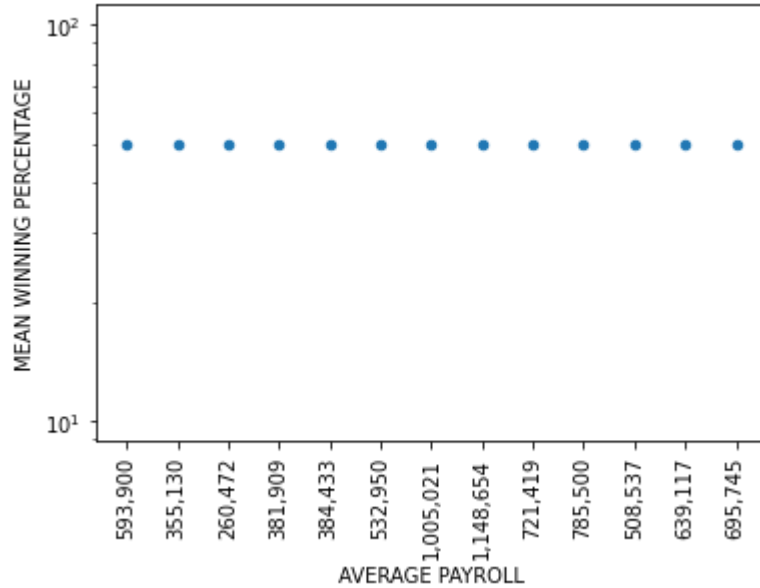
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Los Angeles Dodgers



AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Miami Marlins

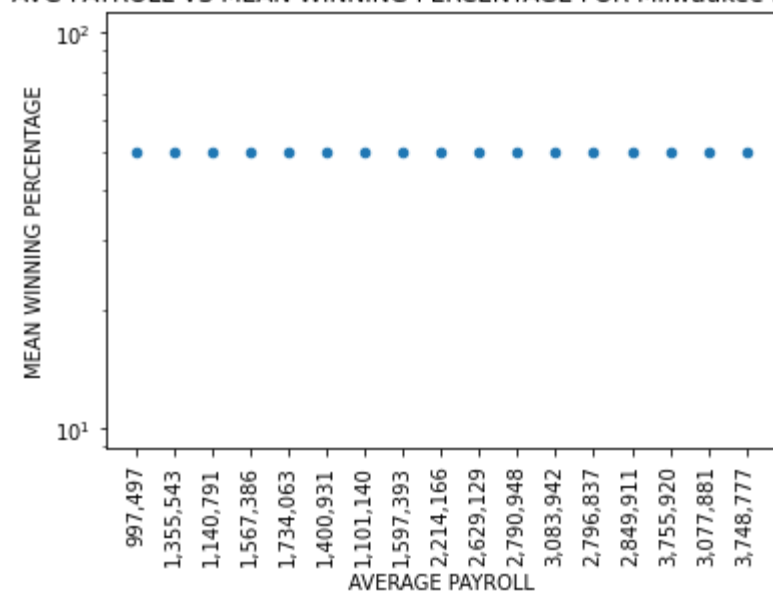


AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Milwaukee Brewers

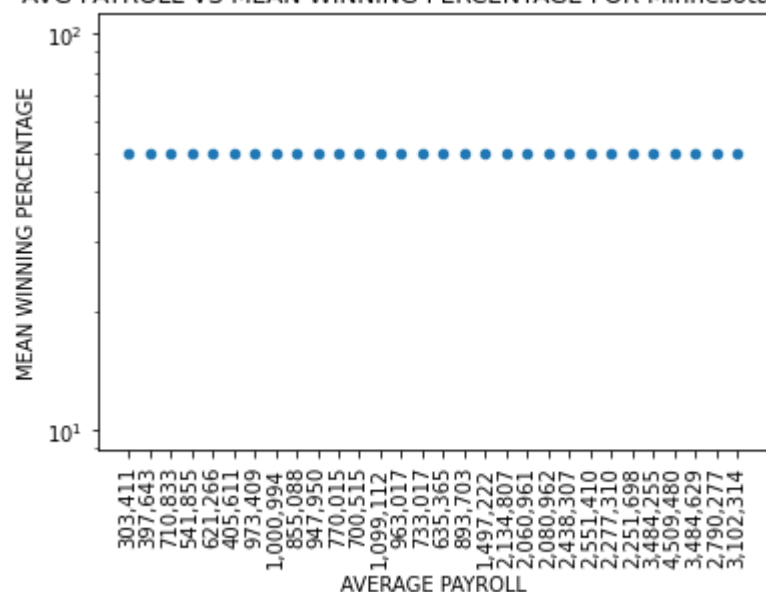




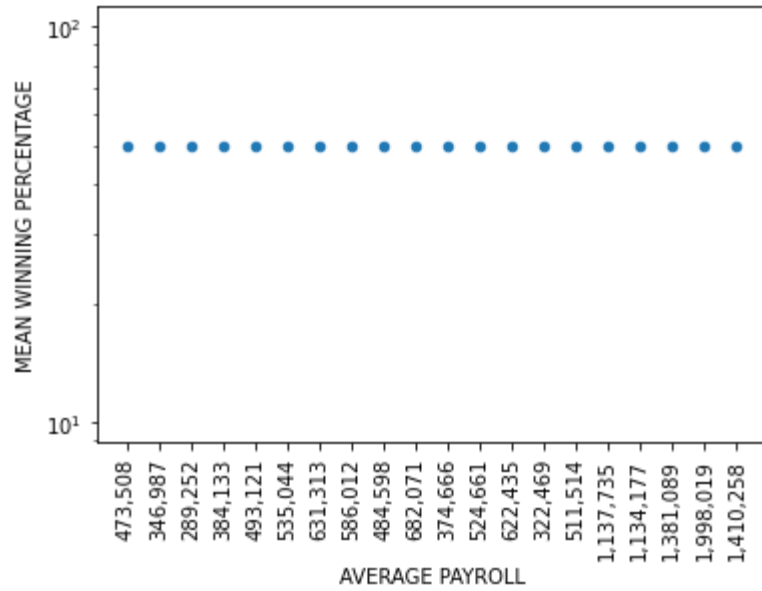
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Milwaukee Brewers



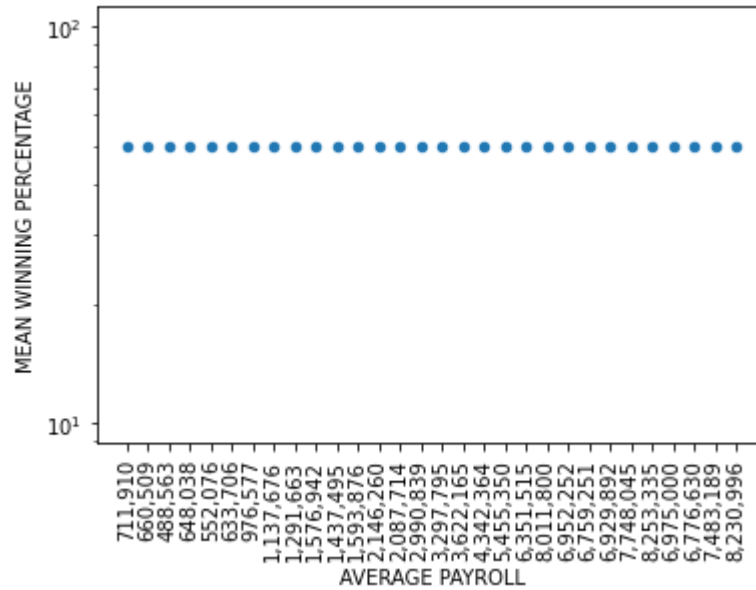
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Minnesota Twins



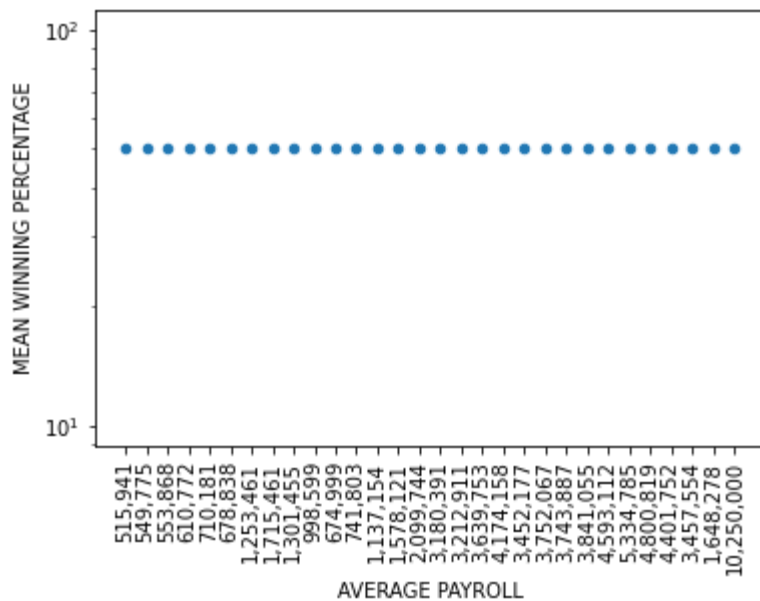
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Montreal Expos



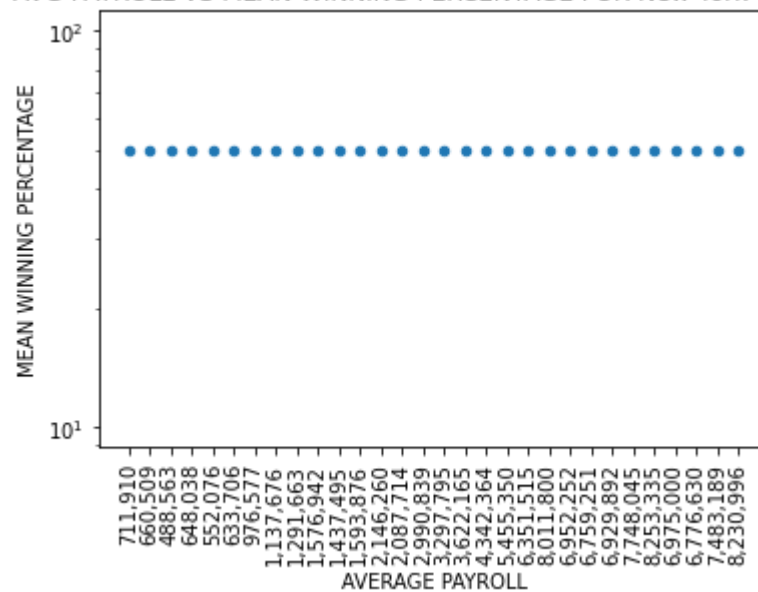
AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR New York Highlanders



AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR New York Mets



AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR New York Yankees



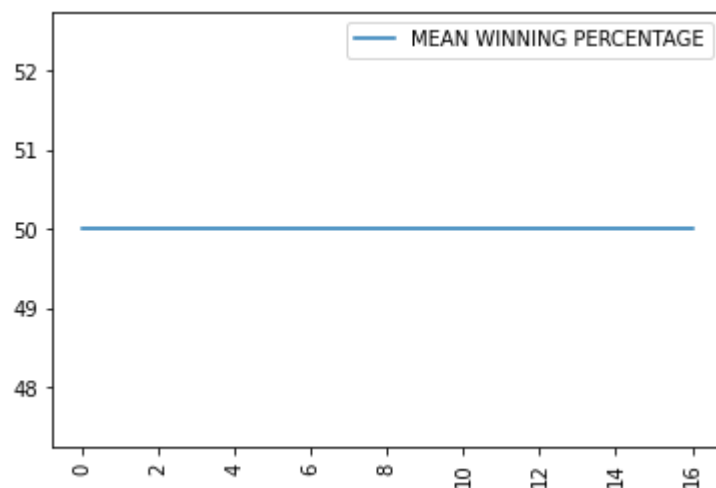
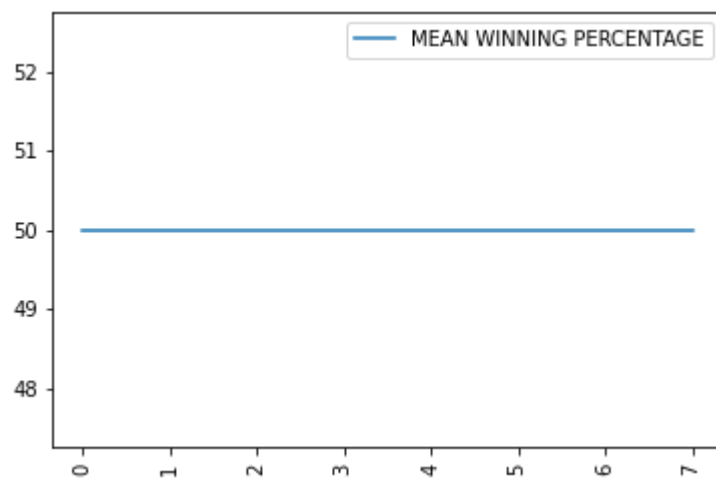
## AVG PAYROLL VS MEAN WINNING PERCENTAGE FOR Oakland Athletics

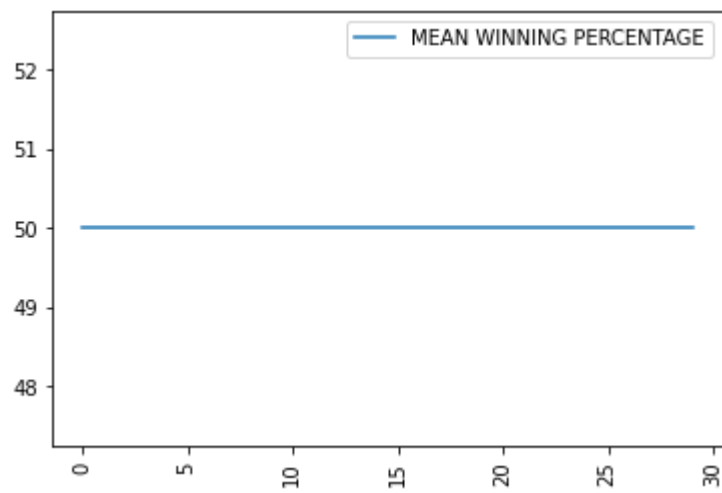
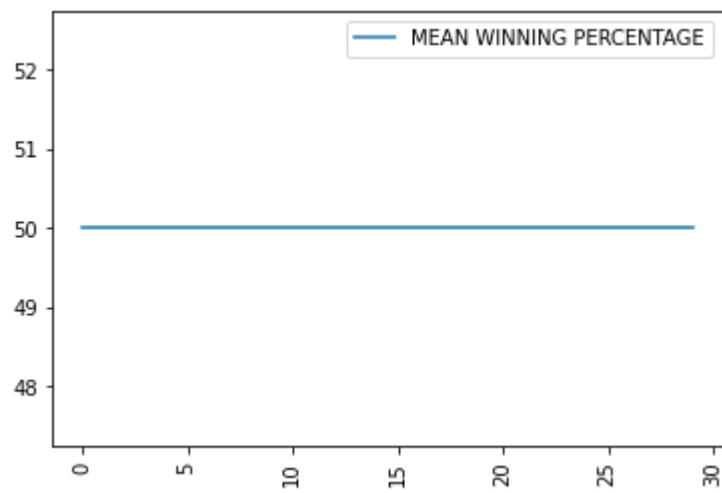
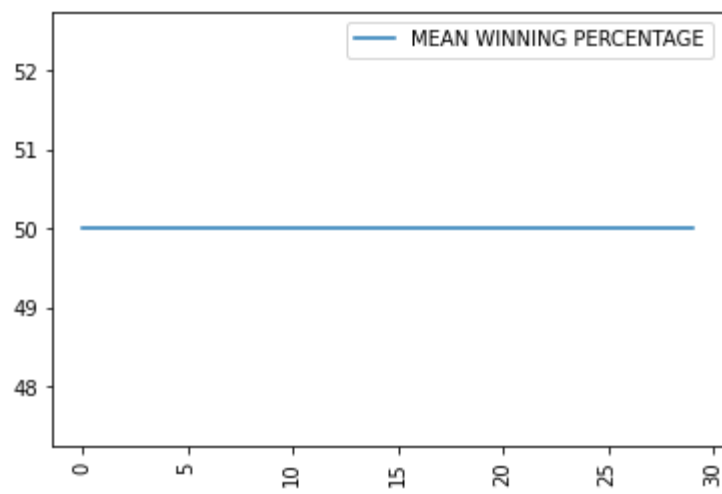


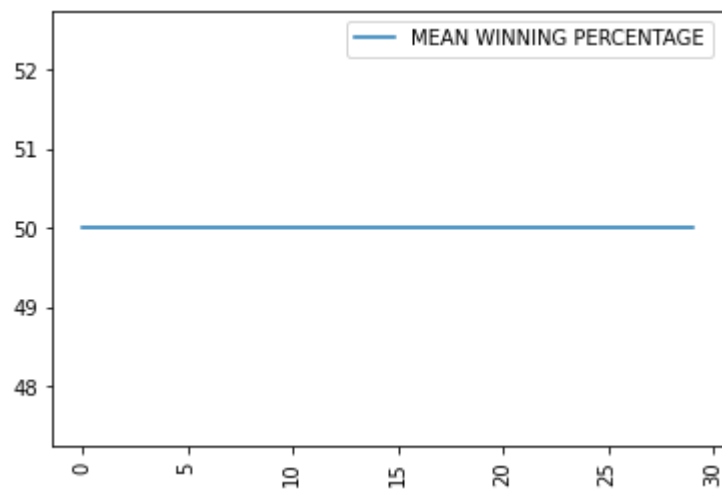
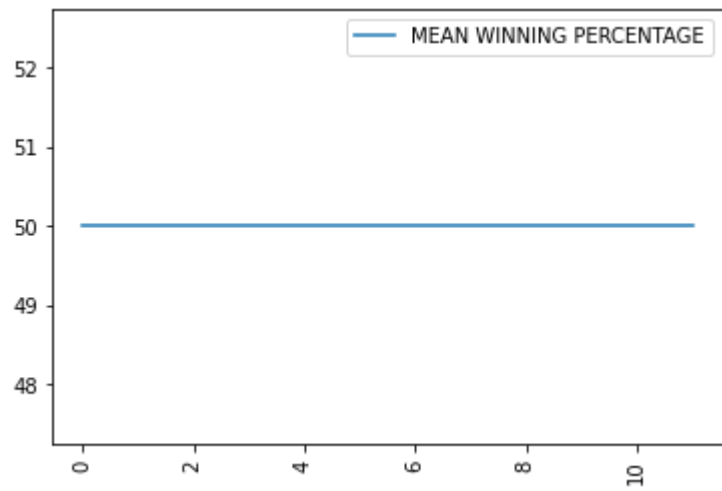
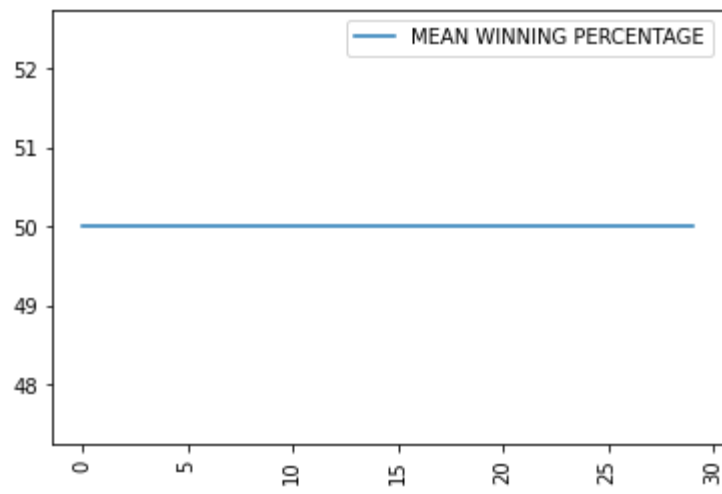
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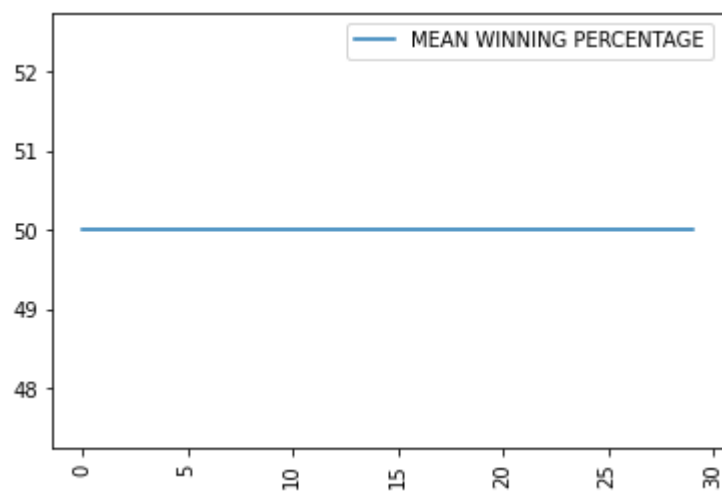
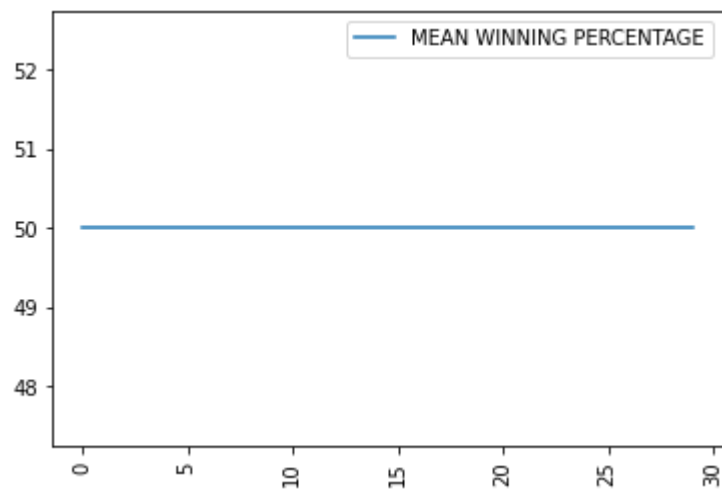
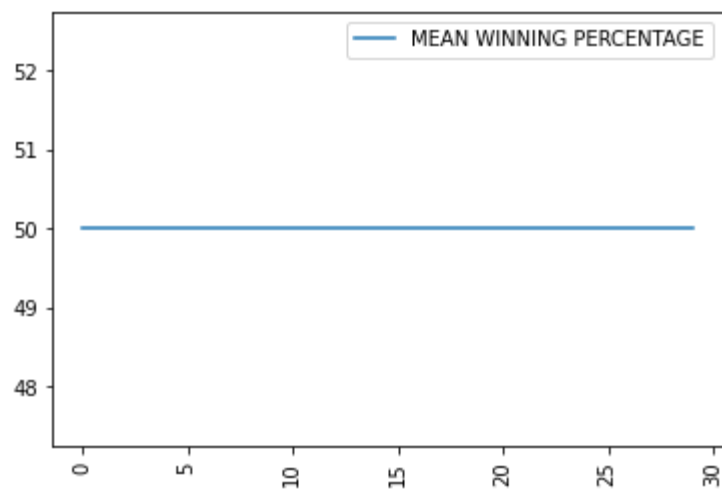
```
for r in some_results:
    if not r.empty:
        u = pandas.cut(r['yearID'], bins=5)
        r['Time Periods'] = u
        a = r.groupby(['Time Periods'])[['AVERAGE PAYROLL', 'MEAN WINNING PERC

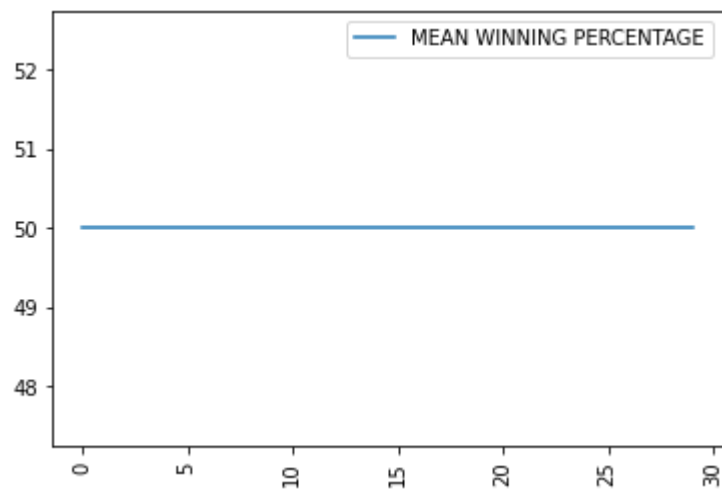
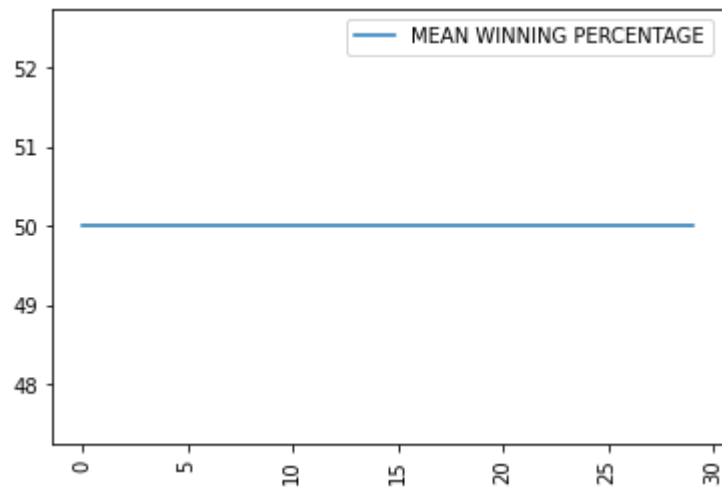
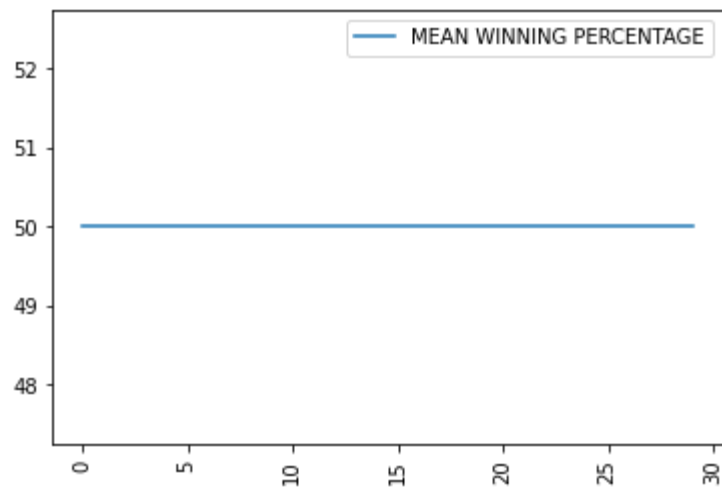
        r.plot(y=['AVERAGE PAYROLL', 'MEAN WINNING PERCENTAGE'], rot=90 )
```



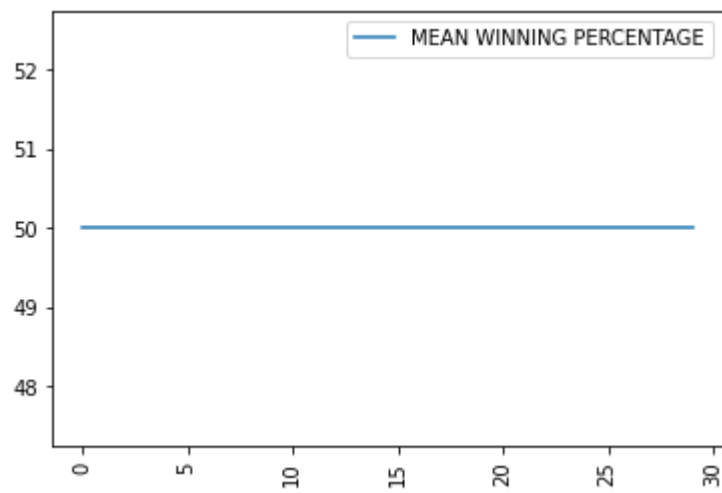
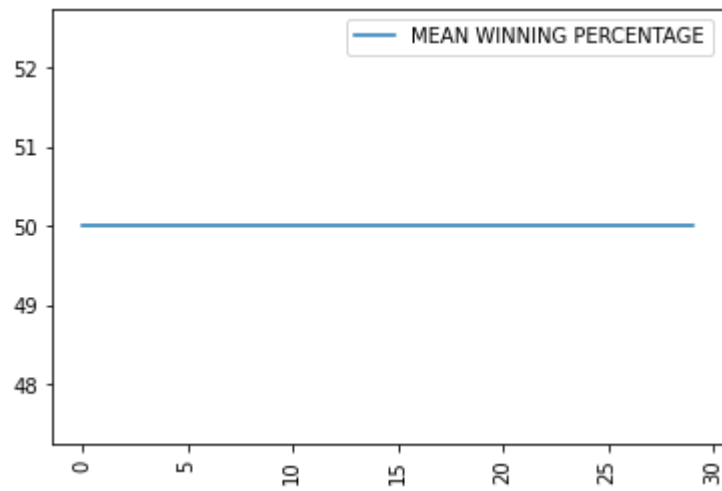
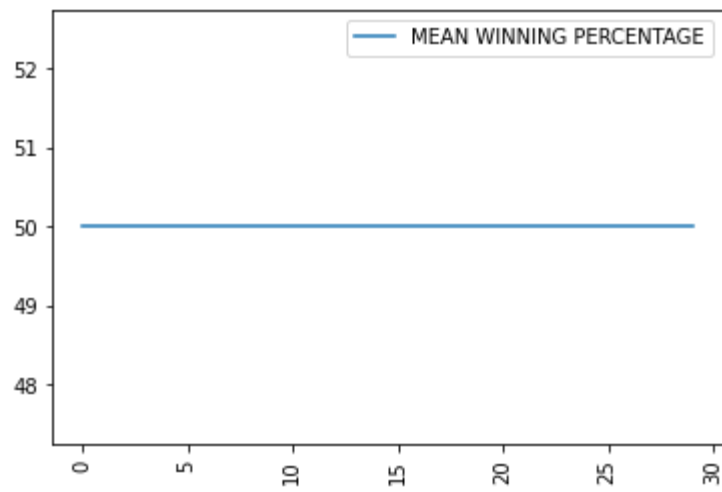


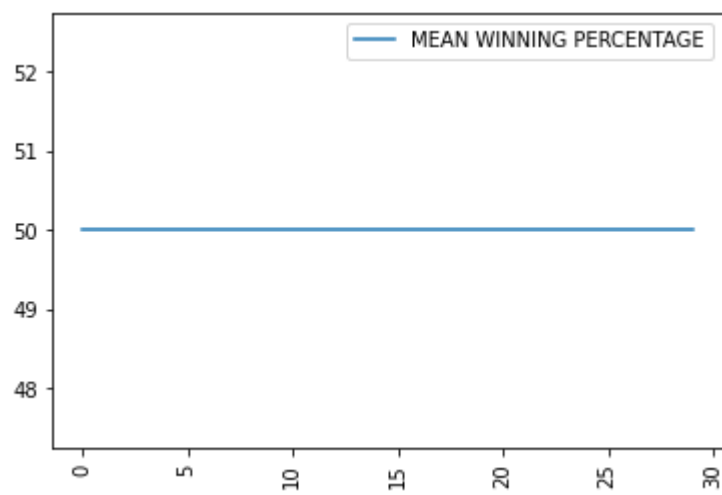
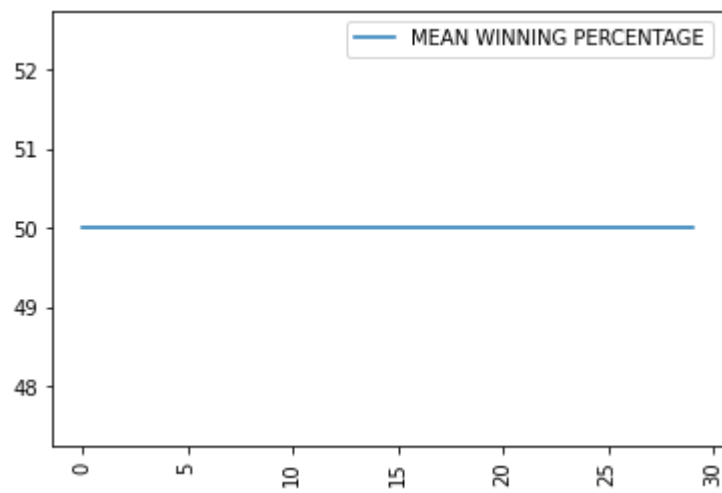
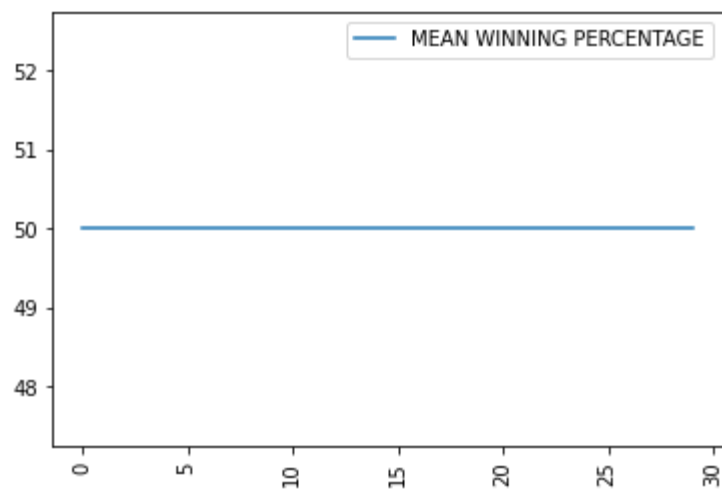


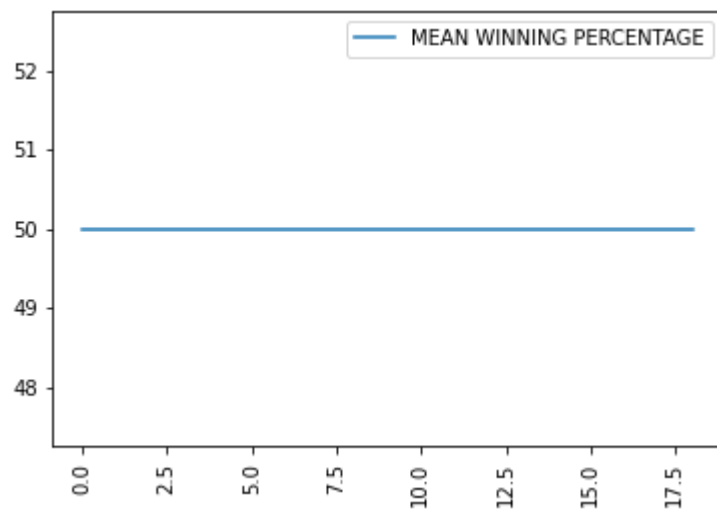
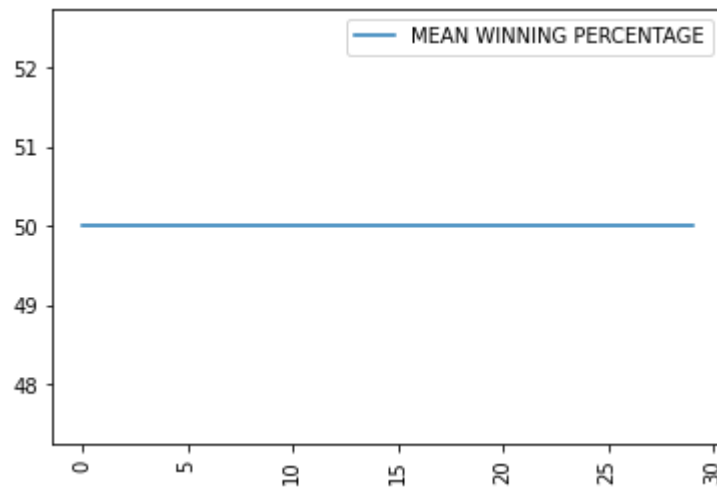
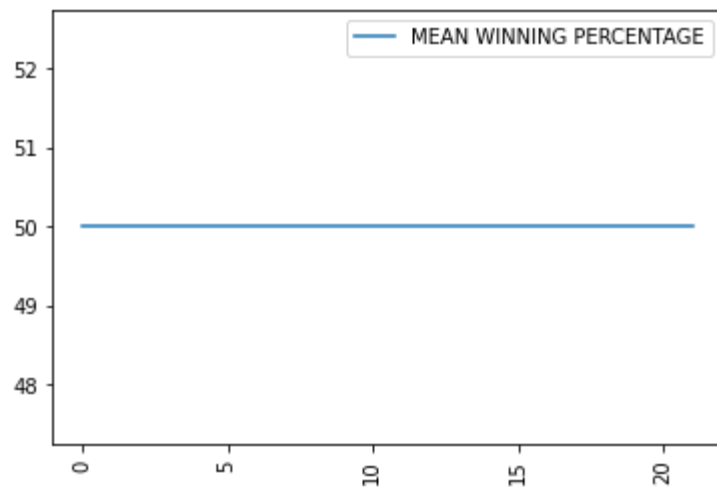


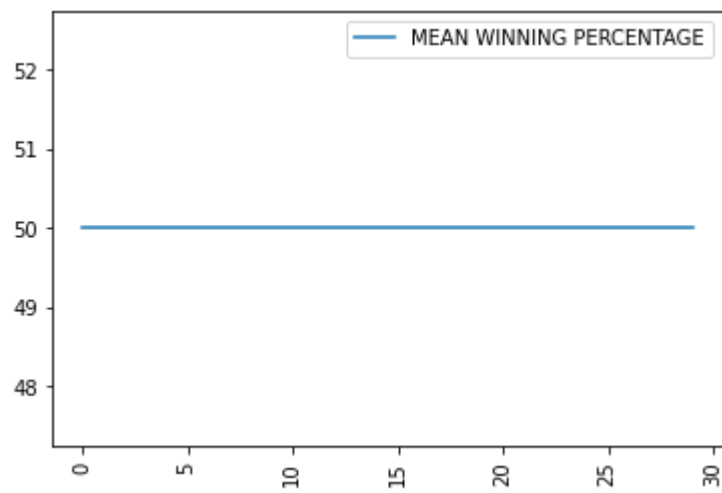
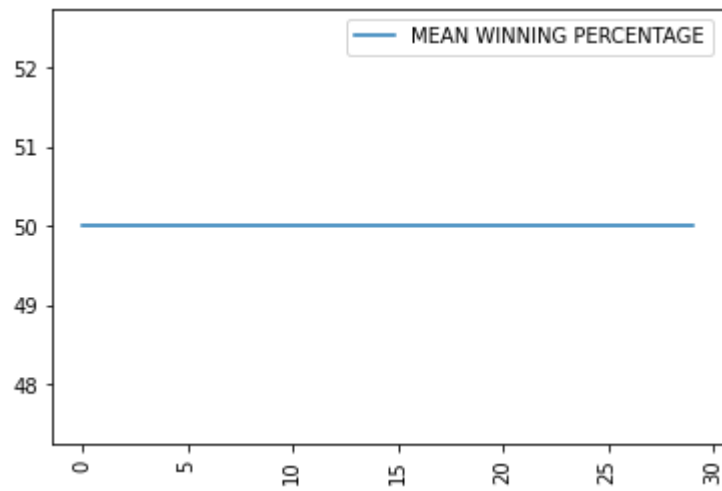
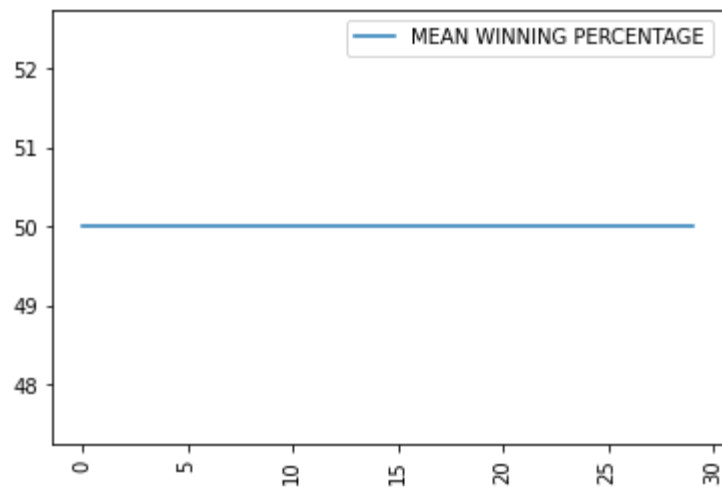


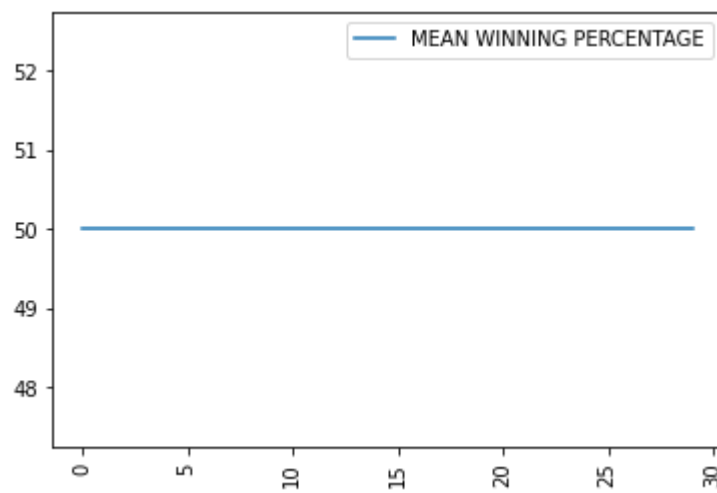
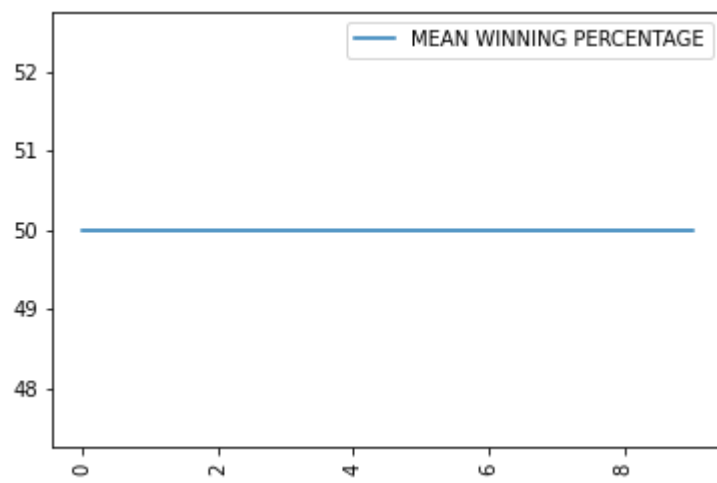
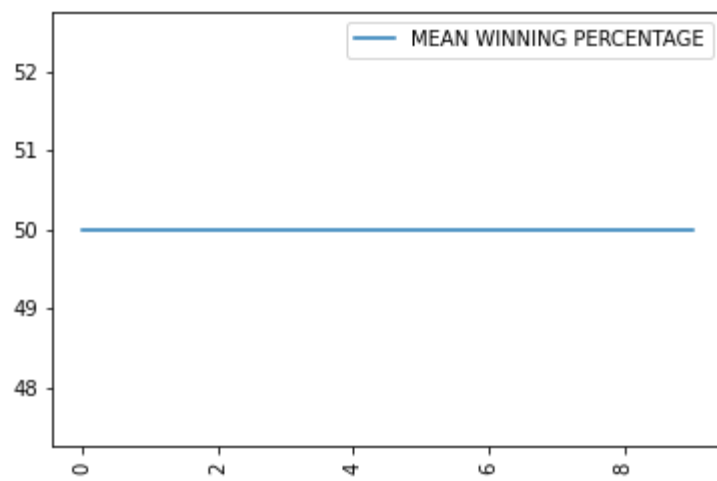


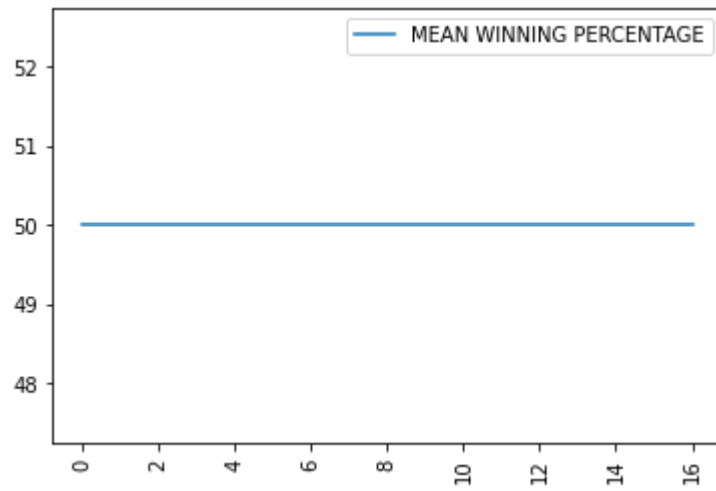
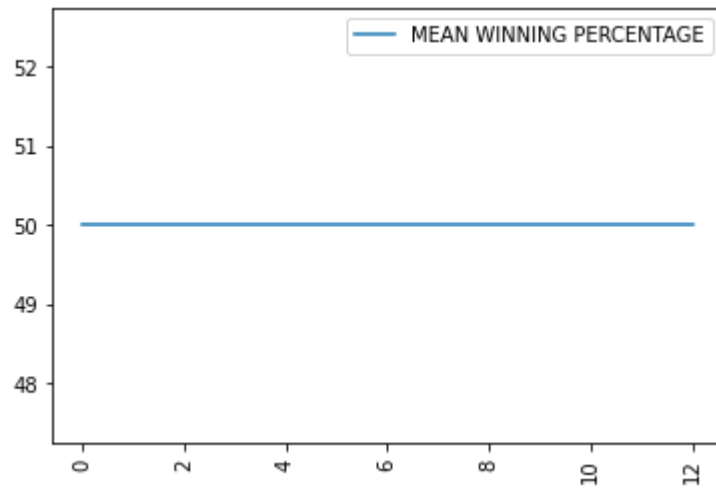
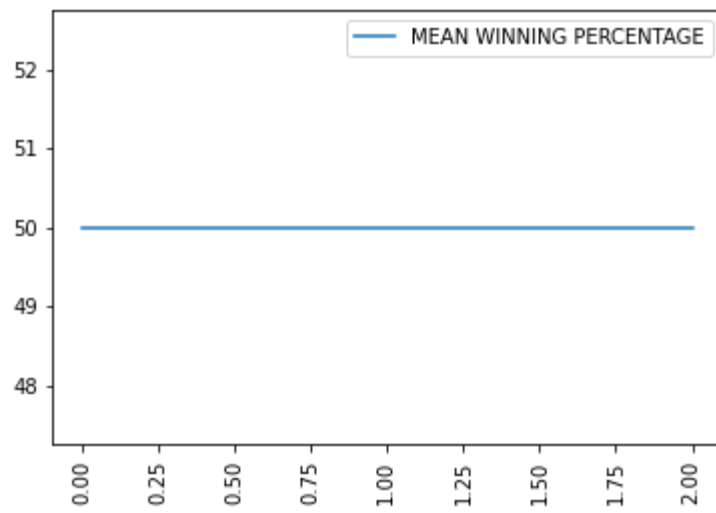


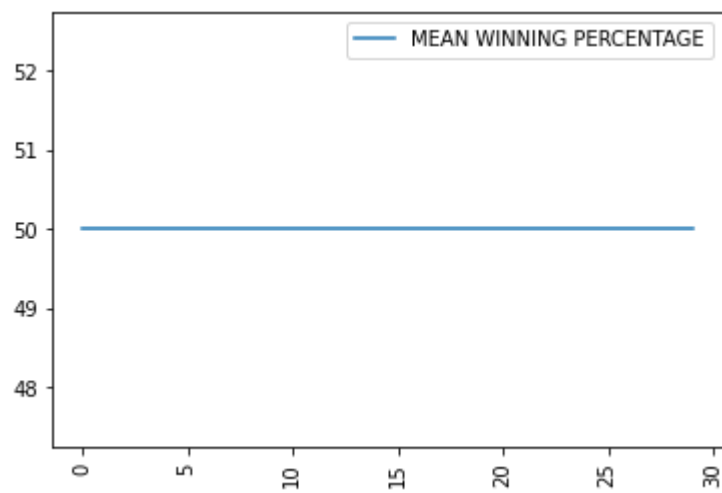
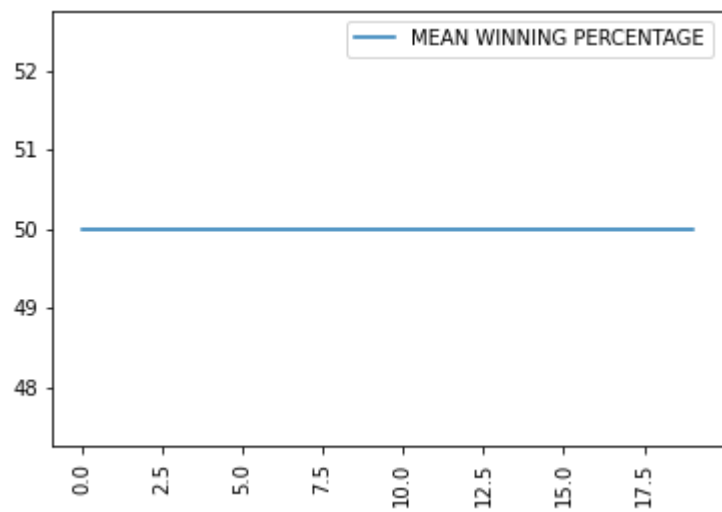
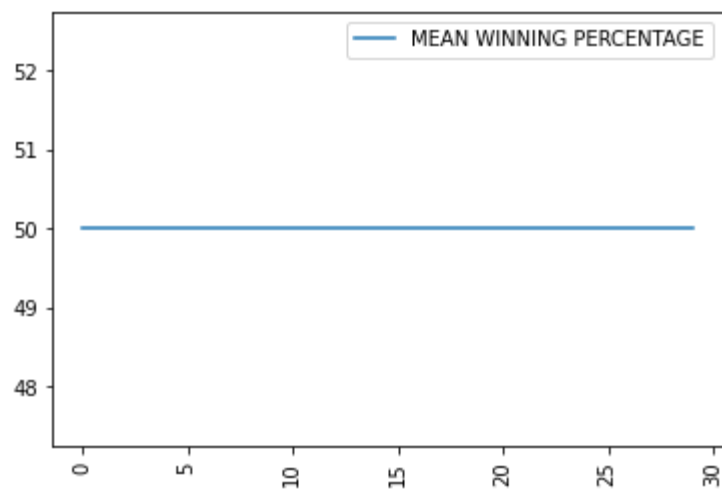


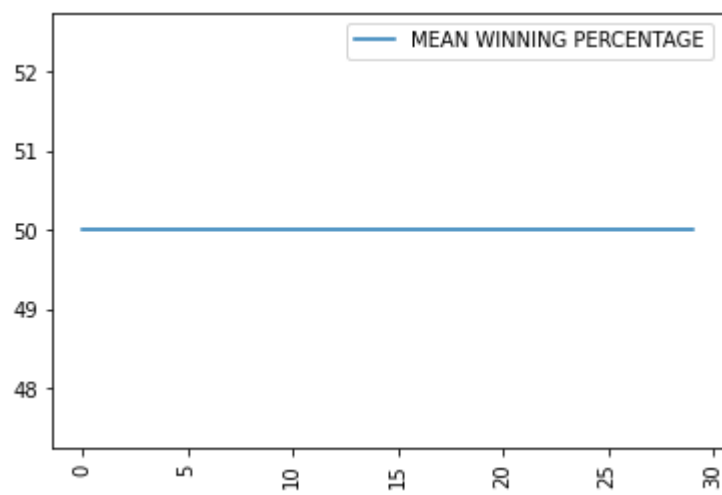
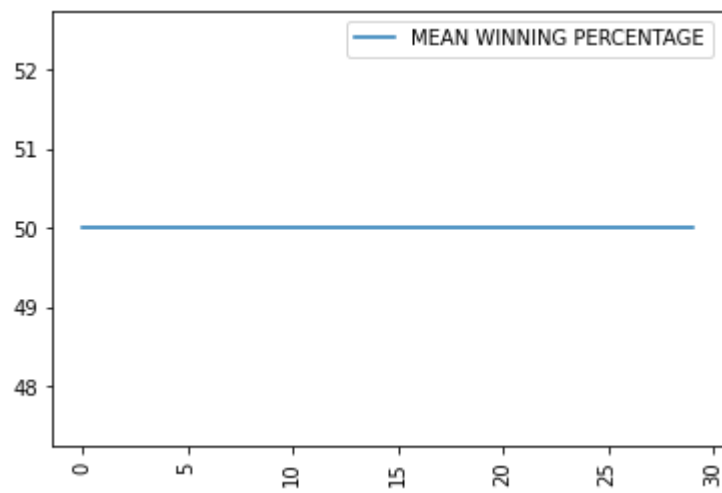
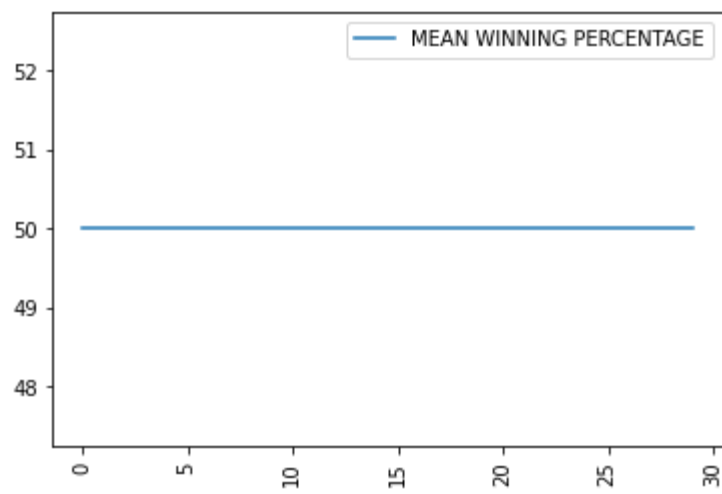




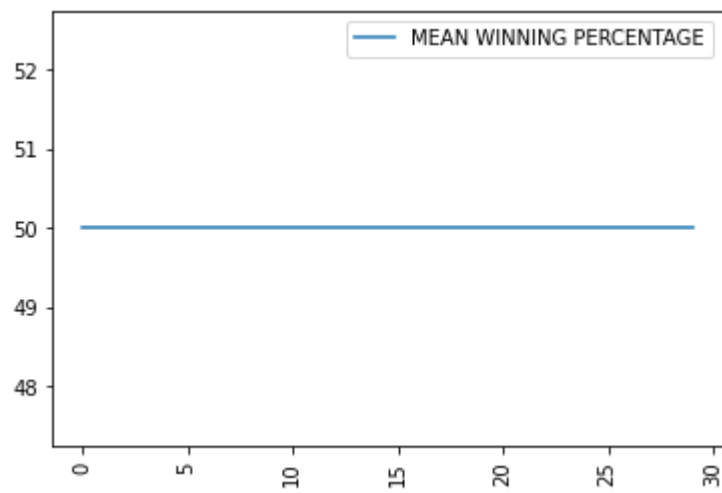
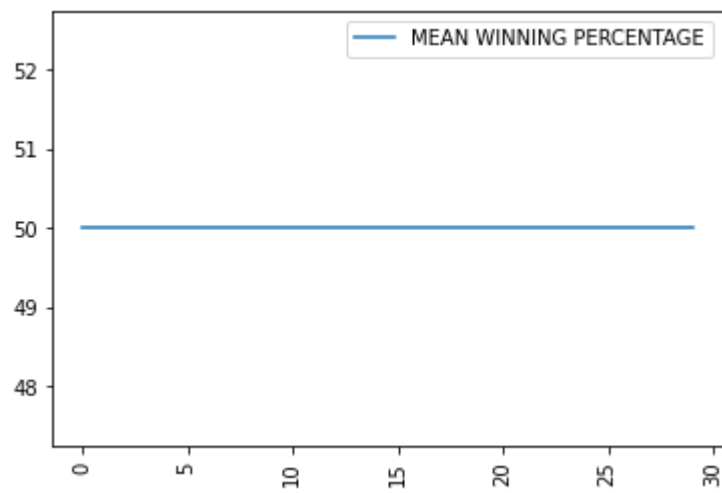
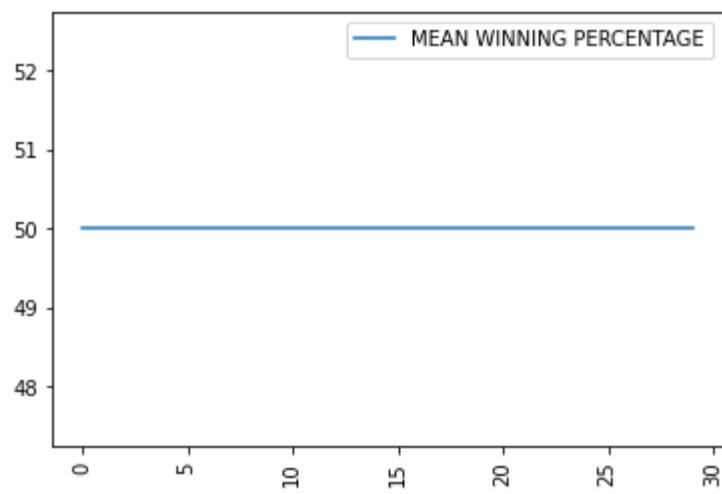


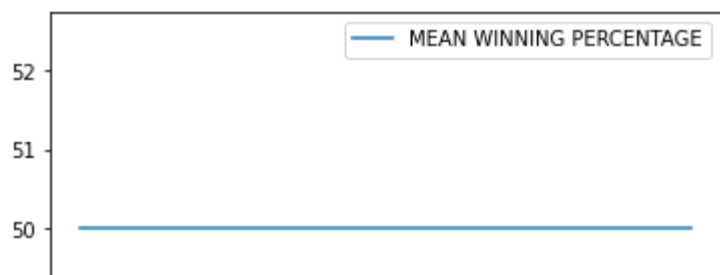
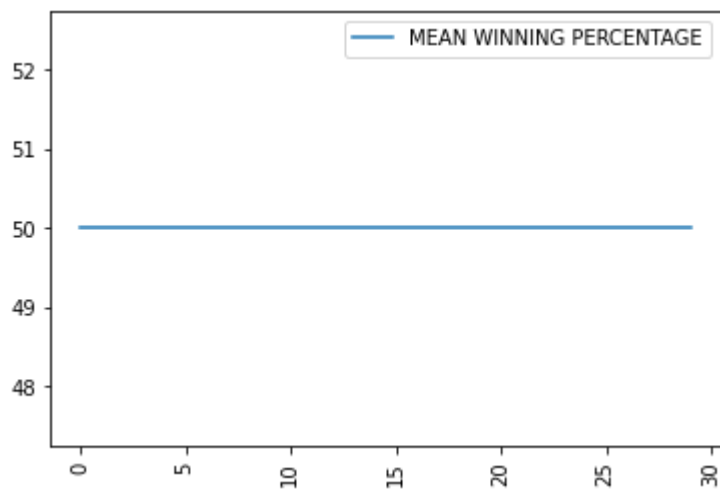
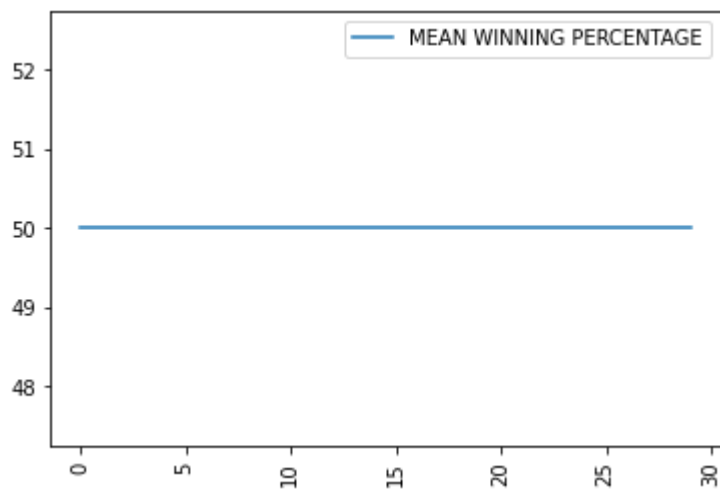
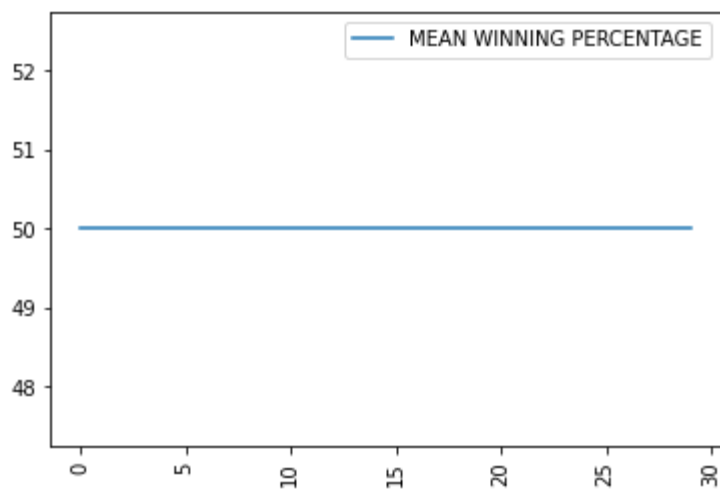










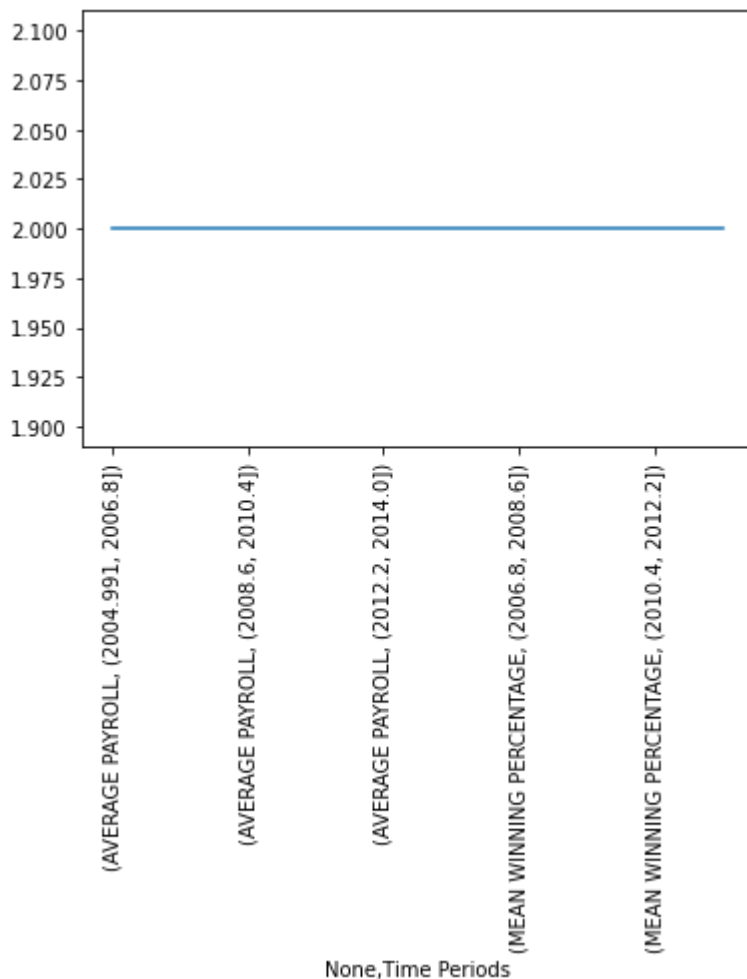


In [422...

```
a.count().unstack().plot(x='Average Payroll', y='Time Periods', rot=90)
```

Out[422...

&lt;AxesSubplot:xlabel='None,Time Periods'&gt;



## Extra Credit

Below we will be creating a new sqlite database that has the newest available data (up to 2020)

Some imports we need

In [429...

```
from os import path
import requests
```

We will try to re create the database with the most up to date files. We will first download the zip file using python. Then we will extract the zip file into a newly created folder.

The url containing the link to download the csv file can be seen beow

In [430...

```
url_csv_zip = "https://github.com/chadwickbureau/baseballatabank/archive/mas"
```

Now let us download the zip file

```
In [435... # download the file contents in binary format
r = requests.get(url_csv_zip)
zipfile_name = "uptodate_csv_files.zip"
# open method to open a file on your system and write the contents
with open(zipfile_name, "wb") as script:
    script.write(r.content)
```

We can see that a file called uptodate\_csv\_files.zip has just been created in the project folder(the same folder as this script rning.)

```
In [436... zipfile_exists = False
if path.exists(zipfile_name):
    zipfile_exists = True
    print("Zip file was downloaded successfully")
```

Zip file was downloaded successfully

Now we create a new directory to extract the zip file in it.

```
In [437... new_directory = "uptodate_csv_files"
read_mode = 0o777 # mode for read write execute
path_to_extract = os.path.join(os.getcwd(), new_directory)
```

```
In [438... os.mkdir(path_to_extract, read_mode)
```

```
In [439... import zipfile
with zipfile.ZipFile(zipfile_name, "r") as zip_variable:
    zip_variable.extractall(path_to_extract)
```

The above code extracts the downloaded zip file. There are two to three directories that are created during the extract. We will skip these directories and go to the files that are listed in the core directory.

```
In [440... root_dir = os.getcwd()
csv_locations = new_directory + "/baseballdatabank-master/core"
new_table_names_csv = os.listdir(csv_locations)
```

The list new\_table\_names\_csv contains all the csv files in the core directory. Each csv file corresponds to one table in the new database. One of the files in the list is a txt file called readme2014.txt. We have to remove that from the list.

```
In [441... # sort the list of table names
new_table_names_csv.sort()
```

```
In [442... len(new_table_names_csv)
```

```
Out[442... 28
```

```
In [443... new_table_names_csv
```

```
Out[443... ['AllstarFull.csv',  
            'Appearances.csv',  
            'AwardsManagers.csv',  
            'AwardsPlayers.csv',  
            'AwardsShareManagers.csv',  
            'AwardsSharePlayers.csv',  
            'Batting.csv',  
            'BattingPost.csv',  
            'CollegePlaying.csv',  
            'Fielding.csv',  
            'FieldingOF.csv',  
            'FieldingOFsplit.csv',  
            'FieldingPost.csv',  
            'HallOfFame.csv',  
            'HomeGames.csv',  
            'Managers.csv',  
            'ManagersHalf.csv',  
            'Parks.csv',  
            'People.csv',  
            'Pitching.csv',  
            'PitchingPost.csv',  
            'Salaries.csv',  
            'Schools.csv',  
            'SeriesPost.csv',  
            'Teams.csv',  
            'TeamsFranchises.csv',  
            'TeamsHalf.csv',  
            'readme2014.txt']
```

Removing readme2014.txt from the list

```
In [444... file_to_remove = 'readme2014.txt'  
if file_to_remove in new_table_names_csv:  
    new_table_names_csv.remove(file_to_remove)  
new_table_names_csv
```

```
Out[444... ['AllstarFull.csv',  
            'Appearances.csv',  
            'AwardsManagers.csv',  
            'AwardsPlayers.csv',  
            'AwardsShareManagers.csv',  
            'AwardsSharePlayers.csv',  
            'Batting.csv',  
            'BattingPost.csv',  
            'CollegePlaying.csv',  
            'Fielding.csv',  
            'FieldingOF.csv',  
            'FieldingOFsplit.csv',  
            'FieldingPost.csv',  
            'HallOfFame.csv',
```

```
'HomeGames.csv',  
'Managers.csv',  
'ManagersHalf.csv',  
'Parks.csv',  
'People.csv',  
'Pitching.csv',  
'PitchingPost.csv',  
'Salaries.csv',  
'Schools.csv',  
'SeriesPost.csv',  
'Teams.csv',  
'TeamsFranchises.csv',  
'TeamsHalf.csv']
```

Now let's get the list of tables in the old database we started this script with, to make sure that we have the same table names, and table structure. If we have the same names of tables and table structure for each table, then we can use the create table statement of the old database to create a new database.

In [445...

```
show_tables_query = "SELECT name FROM sqlite_master WHERE type='table';"  
old_db_tables_results = pandas.read_sql(show_tables_query, conn)  
old_db_tables_results.sort_values(by=['name'])
```

Out[445...

	name
0	AllstarFull
1	Appearances
2	AwardsManagers
3	AwardsPlayers
4	AwardsShareManagers
5	AwardsSharePlayers
6	Batting
7	BattingPost
8	CollegePlaying
9	Fielding
10	FieldingOF
11	FieldingPost
12	HallOfFame
13	Managers
14	ManagersHalf
15	Master
16	Pitching
17	PitchingPost
18	Salaries
19	Schools

	name
20	SeriesPost
21	Teams
22	TeamsFranchises
...	...

The above shows 24 tables. So the old database has 24 tables

```
In [446... len(new_table_names_csv)
```

```
Out[446... 27
```

Remove the csv extensions on the list of tables to have exactly the table names

The new database seems to have 3 more tables than the old one. Now let's extract the table name, by removing the extension for each of the csv file names.

```
In [447... new_db_table_names = []
for f in new_table_names_csv:
    t = os.path.splitext(f)
    new_db_table_names.append(t[0])
```

So we need to compare the list of tables in the new database to create with the list of tables in the old database. For that we will use the difference function of a set. We start by transforming each list to a set and comparing both

```
In [448... old_db_table_names = old_db_tables_results['name'].tolist()
```

Now let's have a look at the content of the new database table not found in the old database table.

```
In [449... set(new_db_table_names).difference(set(old_db_table_names))
```

```
Out[449... {'FieldingOfSplit', 'HomeGames', 'Parks', 'People'}
```

Now let's have a look at the content of the old database table not found in the new database table.

```
In [450... set(old_db_table_names).difference(set(new_db_table_names))
```

```
Out[450... {'Master'}
```

Remove the Master table because it is not part of the new database

```
In [451... old_db_table_names.remove('Master')
```

We can see that the new database is different than the old database. The old database has a Master table that the new database does not have. The new database has 4 tables that are not found in the old database. The easiest way to do it is to manually create tables for each csv file.

It will be tedious but we will get there. We will create the new database, and we will create each

table in the new downloaded extracted unzipped csv files.

```
In [452... new_2020_sqlite_file = 'lahman2020.sqlite'
new_db_conn = sqlite3.connect(new_2020_sqlite_file)
```

See the content of the old table names. It does not contain the Master table anymore.

Now for each of the old tables found in the new database, generate the schema and use that schema to create the table in the new database.

```
In [453... q = """
        SELECT sql
        FROM sqlite_master
        WHERE sql NOT NULL AND
              type == 'table'
        """
create_stmts = pandas.read_sql_query(q, conn)
```

```
In [454... lst_queries = create_stmts['sql'].tolist()
```

```
In [455... l = []
for q in lst_queries:
    l.append(q.replace("\n",""))
```

```
In [456... cursor = new_db_conn.cursor()

for t in l:
    cursor.execute(t)
```

Check to see if the tables where created. If they were then basically the database will have tables sql schema in the sqlite master table.

```
In [457... check_create = """
        SELECT sql
        FROM sqlite_master
        WHERE sql NOT NULL AND
              type == 'table'
        """
new_create_stmts = pandas.read_sql_query(check_create, new_db_conn)
```

```
In [458... new_create_stmts['sql']
```

```
Out[458... 0    CREATE TABLE AllstarFull (playerID TEXT,yearID...
1    CREATE TABLE Appearances (yearID INTEGER,teamI...
2    CREATE TABLE AwardsManagers (playerID TEXT,awa...
3    CREATE TABLE AwardsPlayers (playerID TEXT,awar...
4    CREATE TABLE AwardsShareManagers (awardID TEXT...
5    CREATE TABLE AwardsSharePlayers (awardID TEXT,...
6    CREATE TABLE Batting (playerID TEXT,yearID INT...
```



```
7 CREATE TABLE BattingPost (yearID INTEGER,round...
8 CREATE TABLE CollegePlaying (playerID TEXT,sch...
9 CREATE TABLE Fielding (playerID TEXT,yearID IN...
10 CREATE TABLE FieldingOF (playerID TEXT,yearID ...
11 CREATE TABLE FieldingPost (playerID TEXT,yearI...
12 CREATE TABLE HallOfFame (playerID TEXT,yearid ...
13 CREATE TABLE Managers (playerID TEXT,yearID IN...
14 CREATE TABLE ManagersHalf (playerID TEXT,yearI...
15 CREATE TABLE Master (playerID TEXT,birthYear I...
16 CREATE TABLE Pitching (playerID TEXT,yearID IN...
17 CREATE TABLE PitchingPost (playerID TEXT,yearI...
18 CREATE TABLE Salaries (yearID INTEGER,teamID T...
19 CREATE TABLE Schools (schoolID TEXT,name_full ...
20 CREATE TABLE SeriesPost (yearID INTEGER,round ...
21 CREATE TABLE Teams (yearID INTEGER,lgID TEXT,t...
22 CREATE TABLE TeamsFranchises (franchID TEXT,fr...
23 CREATE TABLE TeamsHalf (yearID INTEGER,lgID TE...
```

Now for the four new tables, let's add them to the new database. Here they are below :

```
In [459... set_difference = set(new_db_table_names).difference(set(old_db_table_names))
```

```
In [460... lst_difference = list(set_difference)
lst_difference
```

```
Out[460... ['People', 'FieldingOFsplit', 'Parks', 'HomeGames']
```

We will use the function found at

<https://www.geeksforgeeks.org/get-column-names-from-csv-using-python/>

In [461...

```
def list_columns(file_path_name):  
    import csv  
  
    # opening the csv file by specifying  
    # the location  
    # with the variable name as csv_file  
    with open(file_path_name) as csv_file:  
  
        # creating an object of csv reader  
        # with the delimiter as ,  
        csv_reader = csv.reader(csv_file, delimiter = ',')  
  
        # list to store the names of columns  
        list_of_column_names = []  
  
        # loop to iterate thorough the rows of csv  
        for row in csv_reader:  
  
            # adding the first row  
            list_of_column_names.append(row)  
  
            # breaking the loop after the  
            # first iteration itself  
            break  
  
    return list_of_column_names[0]
```

Now let's just create the 4 missing tables in the new databse. For that we need to open the file locations and list the columns for each file

In [462...

```
# create a ew dictionary  
d = dict()  
extension = ".csv"  
for file_name in lst_difference :  
    file_path_name = csv_locations + "/" + file_name + extension  
    list_of_column_names = list_columns(file_path_name)  
    d[file_name + extension] = list_of_column_names
```

In [463...

```
d.keys()
```

```
Out[463...] dict_keys(['People.csv', 'Fielding0Fspllit.csv', 'Parks.csv', 'HomeGames.csv',  
'])
```

From the above we can generate the create statements query

In [464...

```
d['People.csv']
```

Out[464...

```
['playerID',  
 'birthYear',  
 'birthMonth',  
 'birthDay',  
 'birthCountry',  
 'birthState',  
 'birthCity',
```

```
'deathYear',
'deathMonth',
'deathDay',
'deathCountry',
'deathState',
'deathCity',
'nameFirst',
'nameLast',
'nameGiven',
'weight',
'height',
'bats',
'throws',
'debut',
'finalGame',
'retroID',
'bbrefID']
```

Well just found out that the People table is basically the Master table in the old database. Simply rename Master to People.

```
In [465... rename_master_query = "ALTER TABLE Master RENAME TO People;"
nb_executes = pandas.read_sql_query(rename_master_query, new_db_conn)
```

```
In [466... nb_executes
```

```
Out[466... 1
```

Operation was a success

Create table for FieldingOfSplit

```
dict_keys(['People.csv', 'FieldingOfSplit.csv', 'Parks.csv', 'HomeGames.csv'])
```

```
In [467... d['FieldingOfSplit.csv']
```

```
Out[467... ['playerID',
'yearID',
'stint',
'teamID',
'lgID',
'POS',
'G',
'GS',
'InnOuts',
'PO',
'A',
'E',
'DP',
'PB',
'WP',
'SB',
'CS',
'ZR']
```

Based on the abpve, we can generate the following query.

In [468...

```
drop_first = "DROP TABLE IF EXISTS FieldingOFsplit ;";
FieldingOFsplit_query = """
    CREATE TABLE IF NOT EXISTS FieldingOFsplit(
        playerID TEXT PRIMARY KEY,
        yearID INTEGER,
        stint INTEGER ,
        teamID TEXT ,
        lgID TEXT ,
        POS TEXT,
        G INTEGER,
        GS INTEGER,
        InnOuts INTEGER,
        PO INTEGER,
        A INTEGER,
        E INTEGER,
        DP INTEGER,
        PB TEXT,
        WP TEXT,
        SB TEXT,
        CS TEXT,
        ZR TEXT

    );

    """
```

Create the above query

In [469...

```
success = cursor.execute(drop_first)
success
```

Out[469...] &lt;sqlite3.Cursor at 0x7f72ff38e3b0&gt;

In [470...

```
success = cursor.execute(FieldingOFsplit_query)
success
```

Out[470...] &lt;sqlite3.Cursor at 0x7f72ff38e3b0&gt;

Check the creation by looking into the schema

In [471...

```
check_create = """
    SELECT sql
    FROM sqlite_master
    WHERE sql NOT NULL AND
          type == 'table'
    """

new_create_stmts = pandas.read_sql_query(check_create, new_db_conn)
new_create_stmts['sql']
```

Out[471...

```
0    CREATE TABLE AllstarFull (playerID TEXT,yearID...
1    CREATE TABLE Appearances (yearID INTEGER,teamI...
2    CREATE TABLE AwardsManagers (playerID TEXT,awa...
3    CREATE TABLE AwardsPlayers (playerID TEXT,awar...
```

```

4 CREATE TABLE AwardsShareManagers (awardID TEXT...
5 CREATE TABLE AwardsSharePlayers (awardID TEXT,...
6 CREATE TABLE Batting (playerID TEXT,yearID INT...
7 CREATE TABLE BattingPost (yearID INTEGER,round...
8 CREATE TABLE CollegePlaying (playerID TEXT,sch...
9 CREATE TABLE Fielding (playerID TEXT,yearID IN...
10 CREATE TABLE FieldingOF (playerID TEXT,yearID ...
11 CREATE TABLE FieldingPost (playerID TEXT,yearI...
12 CREATE TABLE HallOfFame (playerID TEXT,yearid ...
13 CREATE TABLE Managers (playerID TEXT,yearID IN...
14 CREATE TABLE ManagersHalf (playerID TEXT,yearI...
15 CREATE TABLE "People" (playerID TEXT,birthYear...
16 CREATE TABLE Pitching (playerID TEXT,yearID IN...
17 CREATE TABLE PitchingPost (playerID TEXT,yearI...
18 CREATE TABLE Salaries (yearID INTEGER,teamID T...
19 CREATE TABLE Schools (schoolID TEXT,name_full ...
20 CREATE TABLE SeriesPost (yearID INTEGER,round ...
21 CREATE TABLE Teams (yearID INTEGER,lgID TEXT,t...
22 CREATE TABLE TeamsFranchises (franchID TEXT,fr...
23 CREATE TABLE TeamsHalf (yearID INTEGER,lgID TE...
24 CREATE TABLE FieldingOFsplit(\n          playerI...

```

In [472...

```
new_create_stmts['sql']
```

Out[472...

```

0 CREATE TABLE AllstarFull (playerID TEXT,yearID...
1 CREATE TABLE Appearances (yearID INTEGER,teamI...
2 CREATE TABLE AwardsManagers (playerID TEXT,awa...
3 CREATE TABLE AwardsPlayers (playerID TEXT,awar...
4 CREATE TABLE AwardsShareManagers (awardID TEXT...
5 CREATE TABLE AwardsSharePlayers (awardID TEXT,...
6 CREATE TABLE Batting (playerID TEXT,yearID INT...
7 CREATE TABLE BattingPost (yearID INTEGER,round...
8 CREATE TABLE CollegePlaying (playerID TEXT,sch...
9 CREATE TABLE Fielding (playerID TEXT,yearID IN...
10 CREATE TABLE FieldingOF (playerID TEXT,yearID ...
11 CREATE TABLE FieldingPost (playerID TEXT,yearI...
12 CREATE TABLE HallOfFame (playerID TEXT,yearid ...
13 CREATE TABLE Managers (playerID TEXT,yearID IN...
14 CREATE TABLE ManagersHalf (playerID TEXT,yearI...
15 CREATE TABLE "People" (playerID TEXT,birthYear...
16 CREATE TABLE Pitching (playerID TEXT,yearID IN...
17 CREATE TABLE PitchingPost (playerID TEXT,yearI...
18 CREATE TABLE Salaries (yearID INTEGER,teamID T...
19 CREATE TABLE Schools (schoolID TEXT,name_full ...
20 CREATE TABLE SeriesPost (yearID INTEGER,round ...
21 CREATE TABLE Teams (yearID INTEGER,lgID TEXT,t...
22 CREATE TABLE TeamsFranchises (franchID TEXT,fr...
23 CREATE TABLE TeamsHalf (yearID INTEGER,lgID TE...
24 CREATE TABLE FieldingOFsplit(\n          playerI...
Name: sql, dtype: object

```

Creating Parks table

In [473...

```
d['Parks.csv']
```

Out[473...] ['park.key', 'park.name', 'park.alias', 'city', 'state', 'country']

In [474...

```
drop_first = "DROP TABLE IF EXISTS Parks ;";
Parks_query = """
    CREATE TABLE IF NOT EXISTS Parks(
        id TEXT PRIMARY KEY,
        name TEXT,
        alias TEXT,
        city TEXT,
        state TEXT,
        country TEXT
    );
    """
```

In [475...

```
success = cursor.execute(drop_first)
success
```

Out[475... &lt;sqlite3.Cursor at 0x7f72ff38e3b0&gt;

In [476...

```
success = cursor.execute(Parks_query)
success
```

Out[476... &lt;sqlite3.Cursor at 0x7f72ff38e3b0&gt;

Now the whole new database has been created. Now we can insert the values into the tables

Open each csv file and insert their values in the table

In [477...

```
import csv
```

In [478...

```
# Batting generates an error. so remove it and deal with it seperately
new_table_names_csv.remove("Batting.csv")
for file_name in new_table_names_csv:
    file_path_name = csv_locations + "/" + file_name
    table_name = os.path.splitext(file_name)[0]
    with open(file_path_name, newline='') as f:
        reader = csv.reader(f)
        data = list(reader)
        k = len(data)
        if k > 1:
            for i in range(1, len(data)):
                words = data[i]
                values = ','.join(f'\'{w}\'' for w in words)
                if values:
                    delete_query = " DELETE FROM " + table_name + " WHERE TRUE"
                    #', '.join(f'\'{w}\'' for w in words)
                    query = "INSERT INTO " + table_name + \
                        " VALUES (" + values + " ) ; "
                    c = cursor.execute(delete_query)
                    c = cursor.execute(query)
```

-----  
OperationalError

Traceback (most recent call last)

```
<ipython-input-478-5f9bf4a19ab4> in <module>
    17         query = "INSERT INTO " + table_name + \
    18         " VALUES (" + values + " ) ; "
--> 19         c = cursor.execute(delete_query)
    20         c = cursor.execute(query)
```

~~Optional: For each table: HomeGames~~

In [479...

```
check_create = """
    SELECT sql
    FROM sqlite_master
    WHERE sql NOT NULL AND
           type == 'table'
    """

new_create_stmts = pandas.read_sql_query(check_create, new_db_conn)
new_create_stmts
```

Out[479...

	sql
0	CREATE TABLE AllstarFull (playerID TEXT,yearID...
1	CREATE TABLE Appearances (yearID INTEGER,teamI...
2	CREATE TABLE AwardsManagers (playerID TEXT,awa...
3	CREATE TABLE AwardsPlayers (playerID TEXT,awar...
4	CREATE TABLE AwardsShareManagers (awardID TEXT...
5	CREATE TABLE AwardsSharePlayers (awardID TEXT,...
6	CREATE TABLE Batting (playerID TEXT,yearID INT...
7	CREATE TABLE BattingPost (yearID INTEGER,round...
8	CREATE TABLE CollegePlaying (playerID TEXT,sch...
9	CREATE TABLE Fielding (playerID TEXT,yearID IN...
10	CREATE TABLE FieldingOF (playerID TEXT,yearID ...
11	CREATE TABLE FieldingPost (playerID TEXT,yearl...
12	CREATE TABLE HallofFame (playerID TEXT,yearid ...
13	CREATE TABLE Managers (playerID TEXT,yearID IN...
14	CREATE TABLE ManagersHalf (playerID TEXT,yearl...
15	CREATE TABLE "People" (playerID TEXT,birthYear...
16	CREATE TABLE Pitching (playerID TEXT,yearID IN...
17	CREATE TABLE PitchingPost (playerID TEXT,yearl...
18	CREATE TABLE Salaries (yearID INTEGER,teamID T...
19	CREATE TABLE Schools (schoolID TEXT,name_full ...
20	CREATE TABLE SeriesPost (yearID INTEGER,round ...
21	CREATE TABLE Teams (yearID INTEGER,lgID TEXT,t...
22	CREATE TABLE TeamsFranchises (franchID TEXT,fr...
23	CREATE TABLE TeamsHalf (yearID INTEGER,lgID TE...

**sql****24**

CREATE TABLE FieldingOFsplit(\n playerl...

In [ ]: