Project 2

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In [48]:
```
import sqlite3
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

In [2]:
```
sqlite_file = 'lahman2014.sqlite'
sql_conn = sqlite3.connect(sqlite_file)
```

Part 1: Wrangling

Problem 1

I think some of the more important pieces of data were:

Winning Percentage, Payroll, Number of Wins and Losses, Number of Games, Year and of course the Team ID.

I selected the rows of data that I needed (listed above) from each table using sql. The payroll came from the Salaries table but all the others were from the Teams table. For the winning percentage and payroll, I them for each teamID and yearID combination. I used left join to join the two tables (Salaries and Teams). This also helped me with the missing data. There were some unavailable data in the Salaries table, but using left join, it took care of all the missing information by joining the Salaries and Team tables.

In [3]:
```
# SQL command to query data from Salaries and Teams tables and join them together
teams_query = """SELECT Teams.teamID AS Team_ID, Teams.yearID AS Year, Teams.franchID AS Franchise_ID, Teams.W AS Number_of_Wins, Teams.L AS Number_of_Loses, Teams.G AS Number_of_Games,  (CAST(Teams.W AS float)/ CAST(Teams.G AS float) * 100) AS Winning_Percentage, total_payroll FROM
(SELECT SUM(salary) AS Total_Payroll, yearID, teamID, lgID FROM Salaries GROUP BY teamID, yearID) B LEFT JOIN Teams ON Teams.teamID = B.teamID AND Teams.yearID = B.yearID"""

teams = pd.read_sql(teams_query, sql_conn)
teams
```

Out[3]:

	Team_ID	Year	Franchise_ID	Number_of_Wins	Number_of_Loses	Number_of_Games	Winning_Percentage	Total_Payroll
0	ATL	1985.0	ATL	66.0	96.0	162.0	40.740741	14807000.0
1	BAL	1985.0	BAL	83.0	78.0	161.0	51.552795	11560712.0
2	BOS	1985.0	BOS	81.0	81.0	163.0	49.693252	10897560.0
3	CAL	1985.0	ANA	90.0	72.0	162.0	55.555556	14427894.0
4	CHA	1985.0	CHW	85.0	77.0	163.0	52.147239	9846178.0
...	...	...	...	...	...	...	...	...
855	SLN	2014.0	STL	90.0	72.0	162.0	55.555556	120693000.0
856	TBA	2014.0	TBD	77.0	85.0	162.0	47.530864	72689100.0
857	TEX	2014.0	TEX	67.0	95.0	162.0	41.358025	112255059.0
858	TOR	2014.0	TOR	83.0	79.0	162.0	51.234568	109920100.0
859	WAS	2014.0	WSN	96.0	66.0	162.0	59.259259	131983680.0

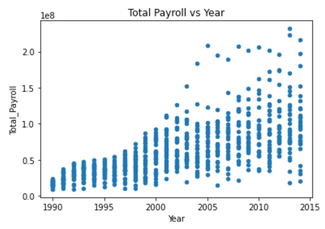
860 rows × 8 columns

Part 2: Exploratory Data Analysis

Problem 2

In [4]:
```
# Scatter plot spending of teams every year(1990- 2014).
teams.loc[teams['Year'] >= 1990].plot.scatter(y = 'Total_Payroll', x = 'Year').set_title('Total Payroll vs Year')
```

Out[4]:
```
Text(0.5, 1.0, 'Total Payroll vs Year')
```



Question 1

Based on the graph we can see that the total payroll has increased over the years 1990-2014 or more like a negative skewness. This means that the total payroll has been increasing on average (central tendancy) throughout these years.

We also see less outliers in the first 10 years, that might be due to the fact that, even if there was any outliers it wouldn't show itself as much concidering the amount of growth the payrolls have had.

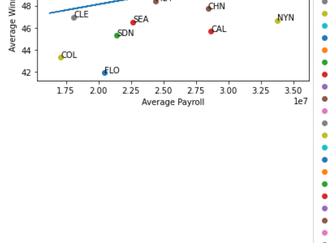
Problem 3

I made a plot of the average total payroll per year to show the central tendancy of the payroll.

We can easily see that the average total payroll is increasing every year at a relatively constant rate. This can be due to any reason, be it inflation or just the sport being injected with more money with more fame and supporters.

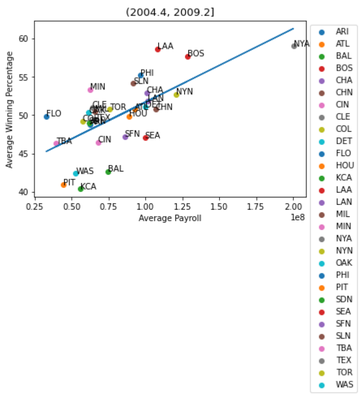
In [5]:
```
# First copy all the teams data into a new dataframe called teams_average so the changes won't affect the actual data.
# Then add a new column called the Year_ID to group the data by it then get the mean of the payroll and do a scatter plot on it.
teams_average = teams.copy()
teams_average['Year_ID'] = teams_average['Year']
teams_average = teams_average.loc[teams_average['Year_ID'] >= 1990].groupby('Year_ID').mean()
teams_average.plot.scatter(y = 'Total_Payroll', x = 'Year').set_title('Average Payroll vs Year')
```

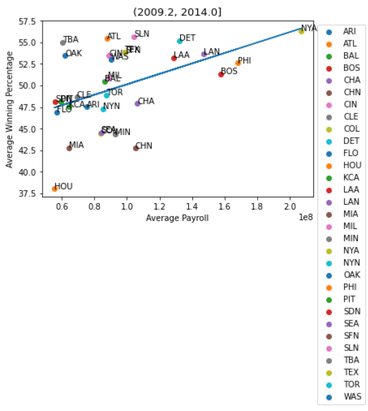
Out[5]:
```
Text(0.5, 1.0, 'Average Payroll vs Year')
```



Problem 4

In [6]:
```
# First copy the data into a new dataframe so all the changes won't effect our original data.
# Then cut the data into 5 equivalent pieces based on Year.
# Then group them by periods.
teams_winning_payroll = teams.loc[teams['Year'] >= 1990].copy()
teams_winning_payroll['periods'] = pd.cut(teams_winning_payroll['Year'],5)
teams_winning_payroll_plot = teams_winning_payroll.groupby(['periods'])

# Make separate plot for each of the 5 time periods by iterating through them.
for i, gp in teams_winning_payroll_plot:
    fig, ax = plt.subplots()
    x_pos = []
    y_pos = []

    # group each time period by Team_ID and iterate through it.
    for i2, gp2 in gp.groupby(['Team_ID']):
        # get the mean of total payroll and winning percentage to use later
        payroll_mean = gp2['Total_Payroll'].mean()
        winning_mean = gp2['Winning_Percentage'].mean()
        # Append teams total_payroll and winning percentage respectively later used for regression line.
        x_pos.append(payroll_mean)
        y_pos.append(winning_mean)

        # do a scatter plot with x-axis being the mean of payroll and y-axis being mean of winning, also add label
        ax.scatter(x=payroll_mean, y=winning_mean, label = gp2.iloc[0,0])
        # Annotate the plot by team name
        ax.annotate(gp2.iloc[0,0], (payroll_mean, winning_mean))

    ax.set_title(i, fontsize=13)
    ax.set_ylabel('Average Winning Percentage')
    ax.set_xlabel('Average Payroll')

    # plot regression line
    m, b = np.polyfit(np.array(x_pos), np.array(y_pos), 1)
    plt.plot(np.array(x_pos), m*np.array(x_pos)+b)
    # put legend based on team name
    plt.legend(bbox_to_anchor=(1, 1))
plt.show()
```





Question 2

One thing we can see is that the winning rate vs payroll changes constantly through time. But we can definetly say that the winning rate usually increases based on payroll all throughout these years, however, I would expect the payroll to have a larger effect but even though it does increase the average winning rate in the years 1990-1995 it did not have a drastic effect as we can see based on the regression line. We can best see the correlation between payroll and winning rate in years 1995-2000 where teams with lower salaries didn't get nearly as good results as teams with higher salaries. This correlation is also good in years 2005-2010.

However, this does not mean that teams with lower payroll have not gotten good results. We can infact see many teams throughout these periods getting results with much lower payrolls. From years 1990-1995 team MON was in the top 5 in winning rate with the absolute lowest salary. In years 2000-2005 teams were not too good with spending efficiently, because teams with higher salaries got better results. In years 2000-2005 OAK was probably the best with spending efficiency getting second place in terms of winning rate and having close to a third of the spending of the highest. In years 2005-2010 again teams were not that efficient in there spending. However, in the last five years (2010-2015), teams like TBA, OAK, ATL were omongst the most efficient of those years having low spendings ang getting good results. However, NYA has consistantly been one of the highest payers and has also consistently gotten good results.

OAK have not been consistant throught this entire timeline, but they have been one of the better teams in terms spending efficiency after the year 2000. Before that, however, in years 1990-1995, they were among the high spenders and they were only 6th in winning rate. And in years 1995-2000 they were among the lowest spenders and they also got very poor results. However, from years 2000-2005 and 2010-2015, they have managed to get very good results with low wages. They're best years were from 2000-2005 becoming 2nd in winning rate, while having one of the lowest spendings.

Problem 5

In [7]:
```
teams_winning_payroll
```

Out[7]:

	Team_ID	Year	Franchise_ID	Number_of_Wins	Number_of_Loses	Number_of_Games	Winning_Percentage	Total_Payroll	periods
130	ATL	1990.0	ATL	65.0	97.0	162.0	40.123457	14555501.0	(1989.976, 1994.8]
131	BAL	1990.0	BAL	76.0	85.0	161.0	47.204969	9680084.0	(1989.976, 1994.8]
132	BOS	1990.0	BOS	88.0	74.0	162.0	54.320988	20558333.0	(1989.976, 1994.8]
133	CAL	1990.0	ANA	80.0	82.0	162.0	49.382716	21720000.0	(1989.976, 1994.8]
134	CHA	1990.0	CHW	94.0	68.0	162.0	58.024691	9491500.0	(1989.976, 1994.8]
...	...	...	...	...	...	...	...	...	...
855	SLN	2014.0	STL	90.0	72.0	162.0	55.555556	120693000.0	(2009.2, 2014.0]
856	TBA	2014.0	TBD	77.0	85.0	162.0	47.530864	72689100.0	(2009.2, 2014.0]
857	TEX	2014.0	TEX	67.0	95.0	162.0	41.358025	112255059.0	(2009.2, 2014.0]
858	TOR	2014.0	TOR	83.0	79.0	162.0	51.234568	109920100.0	(2009.2, 2014.0]
859	WAS	2014.0	WSN	96.0	66.0	162.0	59.259259	131983680.0	(2009.2, 2014.0]

728 rows × 9 columns

In [8]:
```
std_payroll = []

# create STD_Payroll column
teams_winning_payroll['STD_Payroll'] = teams_winning_payroll['Total_Payroll']
# group the data by periods and iterate through it
x = teams_winning_payroll.groupby('periods')
for i, gp in x:
    # get the mean and standard deviation of the total payroll
    average = gp['Total_Payroll'].mean()
    std = gp['Total_Payroll'].std()

    # apply the equatin to each row in the STD_Payroll column
    x = gp['STD_Payroll'].apply(lambda x: (x - average) / std)
    # append each to the std_payroll to add to STD_Payroll at the end
    for i in x:
        std_payroll.append(i)

# update STD_Payroll column with correct values
teams_winning_payroll['STD_Payroll'] = std_payroll
teams_winning_payroll
```

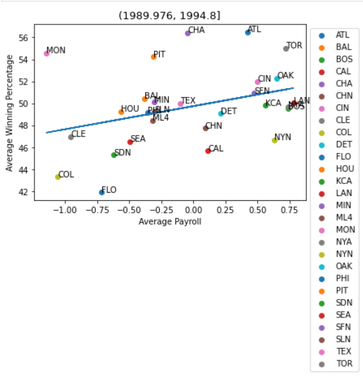
Out[8]:

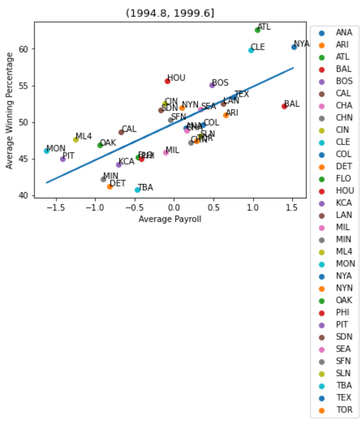
	Team_ID	Year	Franchise_ID	Number_of_Wins	Number_of_Loses	Number_of_Games	Winning_Percentage	Total_Payroll	periods	STD_Payroll
130	ATL	1990.0	ATL	65.0	97.0	162.0	40.123457	14555501.0	(1989.976, 1994.8]	-1.316941
131	BAL	1990.0	BAL	76.0	85.0	161.0	47.204969	9680084.0	(1989.976, 1994.8]	-1.810947
132	BOS	1990.0	BOS	88.0	74.0	162.0	54.320988	20558333.0	(1989.976, 1994.8]	-0.708700
133	CAL	1990.0	ANA	80.0	82.0	162.0	49.382716	21720000.0	(1989.976, 1994.8]	-0.590993
134	CHA	1990.0	CHW	94.0	68.0	162.0	58.024691	9491500.0	(1989.976, 1994.8]	-1.830055
...	...	...	...	...	...	...	...	...	...	...
855	SLN	2014.0	STL	90.0	72.0	162.0	55.555556	120693000.0	(2009.2, 2014.0]	0.578298
856	TBA	2014.0	TBD	77.0	85.0	162.0	47.530864	72689100.0	(2009.2, 2014.0]	-0.566682
857	TEX	2014.0	TEX	67.0	95.0	162.0	41.358025	112255059.0	(2009.2, 2014.0]	0.377038
858	TOR	2014.0	TOR	83.0	79.0	162.0	51.234568	109920100.0	(2009.2, 2014.0]	0.321345
859	WAS	2014.0	WSN	96.0	66.0	162.0	59.259259	131983680.0	(2009.2, 2014.0]	0.847601

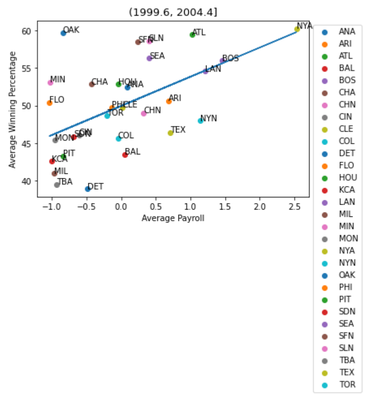
728 rows × 10 columns

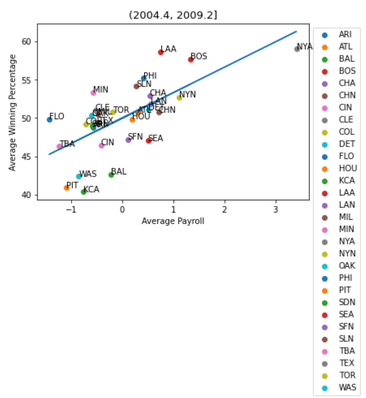
Problem 6

In [9]:
```
# group data by periods.
teams_winning_stdpayroll_plot = teams_winning_payroll.groupby(['periods'])

# Make separate plot for each of the 5 time periods by iterating through them.
for i, gp in teams_winning_stdpayroll_plot:
    fig, ax = plt.subplots()
    x_pos = []
    y_pos = []

    # group each time period by Team_ID and iterate through it.
    for i2, gp2 in gp.groupby(['Team_ID']):
        # get the mean of std payroll and winning percentage to use later
        stdpayroll_mean = gp2['STD_Payroll'].mean()
        winning_mean = gp2['Winning_Percentage'].mean()
        # Append teams total_payroll and winning percentage respectively later used for regression line.
        x_pos.append(stdpayroll_mean)
        y_pos.append(winning_mean)

        # do a scatter plot with x-axis being the mean of payroll and y-axis being mean of winning, also add label
        ax.scatter(x=stdpayroll_mean, y=winning_mean, label = gp2.iloc[0,0])
        # Annotate the plot by team name
        ax.annotate(gp2.iloc[0,0], (stdpayroll_mean, winning_mean))

    ax.set_title(i, fontsize=13)
    ax.set_ylabel('Average Winning Percentage')
    ax.set_xlabel('Average Payroll')

    # plot regression line
    m, b = np.polyfit(np.array(x_pos), np.array(y_pos), 1)
    plt.plot(np.array(x_pos), m*np.array(x_pos)+b)
    # put legend based on team name
    plt.legend(bbox_to_anchor=(1, 1))
plt.show()
```

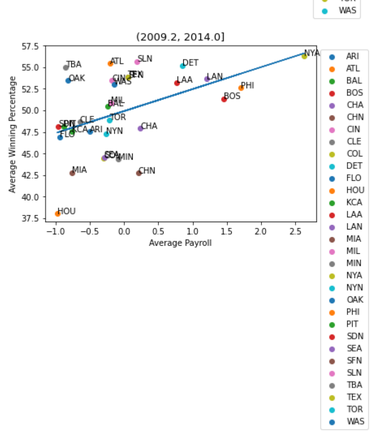








(2009.2, 2014.0]

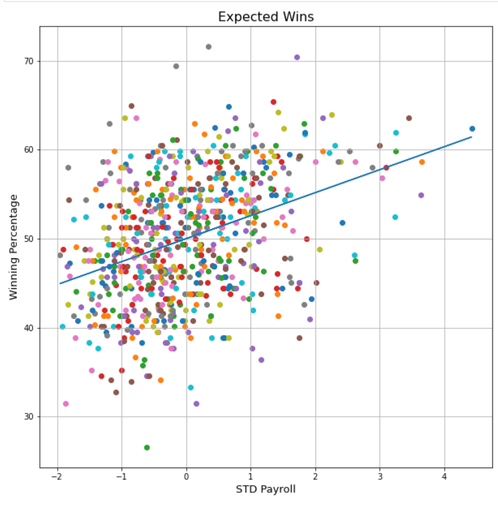


Question 3

The two plots from Problem 4 and 6 are very similar, with a slight difference. The data on Problem 6 are centered closer to 0 thus it makes it easier to compare values. This is because, when we standardize the data we are comparing it to the mean of the data. In this case the mean is the average total payroll. Thus data on he 0 mark mean the they are exactly on the average thus making it easier to compare.

Problem 7

In [10]:
```
# made the plot similar to the ones I have done above, except we only have one thus we don't group the data by periods
# Adds a regression line to highlight the relationship.
x_pos = []
y_pos = []
fig, ax = plt.subplots(figsize=(10,10))
ax.set_title('Expected Wins', fontsize=16)
ax.set_ylabel('Winning Percentage', fontsize=13)
ax.set_xlabel('STD Payroll', fontsize=13)
for i, gp in teams_winning_payroll.groupby(['Team_ID']):
    for i2, gp2 in gp.groupby(['Year']):
        stdpayroll_mean = gp2['STD_Payroll'].mean()
        winning_mean = gp2['Winning_Percentage'].mean()
        x_pos.append(stdpayroll_mean)
        y_pos.append(winning_mean)
        ax.scatter(x=stdpayroll_mean, y=winning_mean)
    ax.grid()

m, b = np.polyfit(np.array(x_pos), np.array(y_pos), 1)
plt.plot(np.array(x_pos), m*np.array(x_pos)+b)
plt.show()
```



Expected_Win_PCT

We use the formula provided to calculate the exptected_win_pct = 50 + 2.5 * standardized_payroll.

In [11]:
```
# apply the equation to the std_payroll column using apply and lambda then set the new column Expected_Win_PCT to the result of the equation
exptected_win_pct = teams_winning_payroll['STD_Payroll'].apply(lambda x: 50 + 2.5 * x )
teams_winning_payroll['Expected_Win_PCT'] = exptected_win_pct
teams_winning_payroll
```

Out[11]:

	Team_ID	Year	Franchise_ID	Number_of_Wins	Number_of_Loses	Number_of_Games	Winning_Percentage	Total_Payroll	periods	STD_Payroll	Expected_Win_PCT
130	ATL	1990.0	ATL	65.0	97.0	162.0	40.123457	14555501.0	(1989.976, 1994.8]	-1.316941	46.707646
131	BAL	1990.0	BAL	76.0	85.0	161.0	47.204969	9680084.0	(1989.976, 1994.8]	-1.810947	45.472633
132	BOS	1990.0	BOS	88.0	74.0	162.0	54.320988	20558333.0	(1989.976, 1994.8]	-0.708700	48.228250
133	CAL	1990.0	ANA	80.0	82.0	162.0	49.382716	21720000.0	(1989.976, 1994.8]	-0.590993	48.522517
134	CHA	1990.0	CHW	94.0	68.0	162.0	58.024691	9491500.0	(1989.976, 1994.8]	-1.830055	45.424862
...	...	...	...	...	...	...	...	...	...	...	...
855	SLN	2014.0	STL	90.0	72.0	162.0	55.555556	120693000.0	(2009.2, 2014.0]	0.578298	51.445744
856	TBA	2014.0	TBD	77.0	85.0	162.0	47.530864	72689100.0	(2009.2, 2014.0]	-0.566682	48.583295
857	TEX	2014.0	TEX	67.0	95.0	162.0	41.358025	112255059.0	(2009.2, 2014.0]	0.377038	50.942594
858	TOR	2014.0	TOR	83.0	79.0	162.0	51.234568	109920100.0	(2009.2, 2014.0]	0.321345	50.803362
859	WAS	2014.0	WSN	96.0	66.0	162.0	59.259259	131983680.0	(2009.2, 2014.0]	0.847601	52.119002

728 rows × 11 columns

Spending Efficiency

Problem 8

We use the formula provided to calculate the efficiency = win_pct - expected_win_pct.

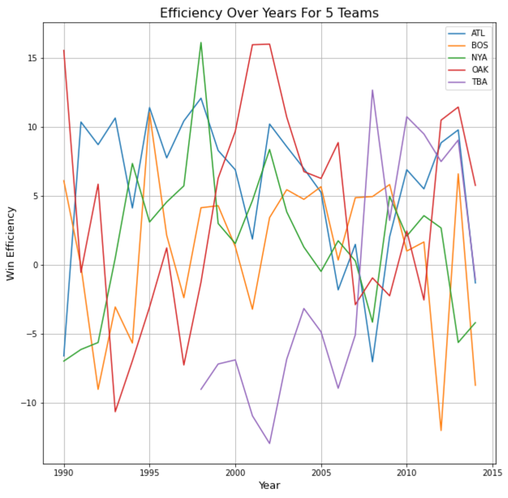
In [12]:
```
efficiency_arr = []
# use the equation to get the efficiency of each row and add the list to our dataframe.
for i, row in teams_winning_payroll.iterrows():
    eff = row['Winning_Percentage'] - row['Expected_Win_PCT']
    efficiency_arr.append(eff)
teams_winning_payroll['Efficiency'] = efficiency_arr
teams_winning_payroll
```

Out[12]:

	Team_ID	Year	Franchise_ID	Number_of_Wins	Number_of_Loses	Number_of_Games	Winning_Percentage	Total_Payroll	periods	STD_Payroll	Expected_Win_PCT	Efficiency
130	ATL	1990.0	ATL	65.0	97.0	162.0	40.123457	14555501.0	(1989.976, 1994.8]	-1.316941	46.707646	-6.584190
131	BAL	1990.0	BAL	76.0	85.0	161.0	47.204969	9680084.0	(1989.976, 1994.8]	-1.810947	45.472633	1.732336
132	BOS	1990.0	BOS	88.0	74.0	162.0	54.320988	20558333.0	(1989.976, 1994.8]	-0.708700	48.228250	6.092738
133	CAL	1990.0	ANA	80.0	82.0	162.0	49.382716	21720000.0	(1989.976, 1994.8]	-0.590993	48.522517	0.860199
134	CHA	1990.0	CHW	94.0	68.0	162.0	58.024691	9491500.0	(1989.976, 1994.8]	-1.830055	45.424862	12.599829
...	...	...	...	...	...	...	...	...	...	...	...	...
855	SLN	2014.0	STL	90.0	72.0	162.0	55.555556	120693000.0	(2009.2, 2014.0]	0.578298	51.445744	4.109811
856	TBA	2014.0	TBD	77.0	85.0	162.0	47.530864	72689100.0	(2009.2, 2014.0]	-0.566682	48.583295	-1.052431
857	TEX	2014.0	TEX	67.0	95.0	162.0	41.358025	112255059.0	(2009.2, 2014.0]	0.377038	50.942594	-9.584569
858	TOR	2014.0	TOR	83.0	79.0	162.0	51.234568	109920100.0	(2009.2, 2014.0]	0.321345	50.803362	0.431206
859	WAS	2014.0	WSN	96.0	66.0	162.0	59.259259	131983680.0	(2009.2, 2014.0]	0.847601	52.119002	7.140257

728 rows × 12 columns

In [19]:
```
# only get the data that has Team_ID that is in the array teams_array then group them by Team_ID and put it in new dataframe "teams".
teams_array = ['ATL','BOS', 'NYA', 'OAK', 'TBA']
teams = teams_winning_payroll.loc[teams_winning_payroll['Team_ID'].isin(teams_array)].groupby(['Team_ID'])

x_pos = []
y_pos = []
fig, ax = plt.subplots(figsize=(10,10))
# Iterate through the teams
for i, gp in teams:
    team_year = []
    team_eff = []
    # group the teams by year
    for i2, gp2 in gp.groupby(['Year']):
        # add the mean for each of year and efficiency to the arrays
        team_year.append(gp2['Year'].mean())
        team_eff.append(gp2['Efficiency'].mean())
    ax.grid()
    x_pos.append(team_year)
    y_pos.append(team_eff)

# Set title and labels
ax.set_title('Efficiency Over Years For 5 Teams', fontsize=16)
ax.set_ylabel('Win Efficiency', fontsize=13)
ax.set_xlabel('Year', fontsize=13)

# Plot the lines
for i in range(5):
    plt.plot(x_pos[i], y_pos[i], label=teams_array[i])

plt.legend()
plt.show()
```



Line plot of efficiency over year for teams: Oakland, the New York Yankees, Boston, Atlanta and Tampa Bay.

Question 4

One main differe between this plot and the previous plots in quesionts 2 and 3 is that in this plot we have the plot of spending efficiency which is very useful for interpretation and actually analysing the data. In the other two questions we saw the spending of each team vs their winning percentage which can be very useful in certain circumstances, but the efficiency is way more helpful in drawing conclusions by looking at the plot.

One fact for sure that we can say by analysing the plots from both questions 2 and 3 we can say that money does play a huge role in the winning rate, but winning effieciency is also extremely important in the real world for teams to thrive by spending less and getting good results. We can see that teams such as Oakland have spent very efficiently, specially since the year 2000 based on the plots.

In [ ]: