In [26]:
```
import sqlite3
import pandas as pd

sqlite_file = 'lahman2014.sqlite'
conn = sqlite3.connect(sqlite_file)

salary_query = "SELECT yearID, sum(salary) as total_payroll FROM Salaries WHERE lgID == 'AL' GROUP BY yearID"

team_salaries = pd.read_sql(salary_query, conn)
team_salaries.head()
```

Out[26]:

	yearID	total_payroll
0	1985	134401120.0
1	1986	157716444.0
2	1987	136088747.0
3	1988	157049812.0
4	1989	188771688.0

Part 1: Wrangling

The data you need to answer these questions is in the Salaries and Teams tables of the database.

Problem 1

Using SQL compute a relation containing the total payroll and winning percentage (number of wins / number of games * 100) for each team (that is, for each teamID and yearID combination). You should include other columns that will help when performing EDA later on (e.g., franchise ids, number of wins, number of games).

Include the SQL code you used to create this relation in your writeup. Describe how you dealt with any missing data in these two relations. Specifically, indicate if there is missing data in either table, and how the type of join you used determines how you dealt with this missing data. One note, for SQL you have to be mindful of integer vs. float division.

In [27]:
```
salary_table_q = "SELECT * FROM Salaries"
team_table_q = "SELECT * FROM Teams"
salary_table= pd.read_sql(salary_table_q, conn)
team_table = pd.read_sql(team_table_q, conn)
#salary_table, Teams
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
display(salary_table)
# SELECT yearID, teamID, sum(salary) AS total_payroll FROM Salary GROUP BY yearID, TEAMID
```

	yearID	teamID	lgID	playerID	salary
0	1985	ATL	NL	barkele01	870000.0
1	1985	ATL	NL	bedrost01	550000.0
2	1985	ATL	NL	benedbr01	545000.0
3	1985	ATL	NL	campri01	633333.0
4	1985	ATL	NL	ceronri01	625000.0
5	1985	ATL	NL	chambch01	800000.0
6	1985	ATL	NL	dedmoje01	150000.0
7	1985	ATL	NL	forstte01	483333.0
8	1985	ATL	NL	garbege01	772000.0
9	1985	ATL	NL	harpete01	250000.0
10	1985	ATL	NL	hornebo01	1500000.0

In [28]:
```
# total payroll for each team in each year
salary_for_each_team_year_p = "SELECT yearID, teamID, sum(salary) AS total_payroll FROM Salaries GROUP BY teamID, yearID"
salary_for_each_team_year_table = pd.read_sql(salary_for_each_team_year_p, conn)
#display(salary_for_each_team_year_table)

# winrate for each team in each year

win_rate_for_each_team_year_p = "SELECT yearID, teamID, franchID, G, W, (CAST(W AS float )/CAST(G AS float)) AS win_rate FROM Teams GROUP BY teamID, yearID"
win_rate_for_each_team_year_table = pd.read_sql(win_rate_for_each_team_year_p, conn)
#display(win_rate_for_each_team_year_table)

"WITH payroll_table(yearID, teamID,total_payroll) as (SELECT yearID, teamID, sum(salary) AS total_payroll FROM Salaries GROUP BY teamID, yearID), "
"WITH Team_table(yearID, teamID, franchID, G, W, win_rate) as (SELECT yearID, teamID, franchID, G, W, (CAST(W AS float )/CAST(G AS float)) AS win_rate FROM Teams GROUP BY teamID, yearID) "
"SELECT Team_table.yearID, Team_table.teamID, franchID, G, W, win_rate, total_payroll FROM payroll_table, Team_table WHERE Team_table.yearID = payroll_table.yearID AND Team_table.teamID = pa
"""
# salary_win_rate_p = "WITH payroll_table(yearID, teamID, total_payroll) AS (SELECT yearID, teamID, sum(salary) AS total_payroll FROM Salaries GROUP BY teamID, yearID) SELECT Teams.yearID, T
salary_win_rate_p = "WITH payroll_table(yearID, teamID, total_payroll) AS (SELECT yearID, teamID, sum(salary) AS total_payroll FROM Salaries GROUP BY teamID, yearID), WITH Teams_table (yearI
salary_win_rate_table = pd.read_sql(salary_win_rate_p, conn)
display(salary_win_rate_table)
"""

salary_win_rate_p = "WITH payroll_table(yearID, teamID,total_payroll) as (SELECT yearID, teamID, sum(salary) AS total_payroll FROM Salaries GROUP BY teamID, yearID), Team_table(yearID, teamI
salary_win_rate_table = pd.read_sql(salary_win_rate_p, conn)
display(salary_win_rate_table)
```

	yearID	teamID	franchID	G	W	win_rate	total_payroll
0	1985	ATL	ATL	162	66	0.407407	14807000.0
1	1985	BAL	BAL	161	83	0.515528	11560712.0
2	1985	BOS	BOS	163	81	0.496933	10897560.0
3	1985	CAL	ANA	162	90	0.555556	14427894.0
4	1985	CHA	CHW	163	85	0.521472	9846178.0
5	1985	CHN	CHC	162	77	0.475309	12702917.0
6	1985	CIN	CIN	162	89	0.549383	8359917.0
7	1985	CLE	CLE	162	60	0.370370	6551666.0
8	1985	DET	DET	161	84	0.521739	10348143.0
9	1985	HOU	HOU	162	83	0.512346	9993051.0
10	1985	KCA	KCR	162	91	0.561728	9321179.0

Part 2: Exploratory Data Analysis

Problem 2

Write code to produce plots that illustrate the distribution of payrolls across teams conditioned on time (from 1990-2014).

Question 1

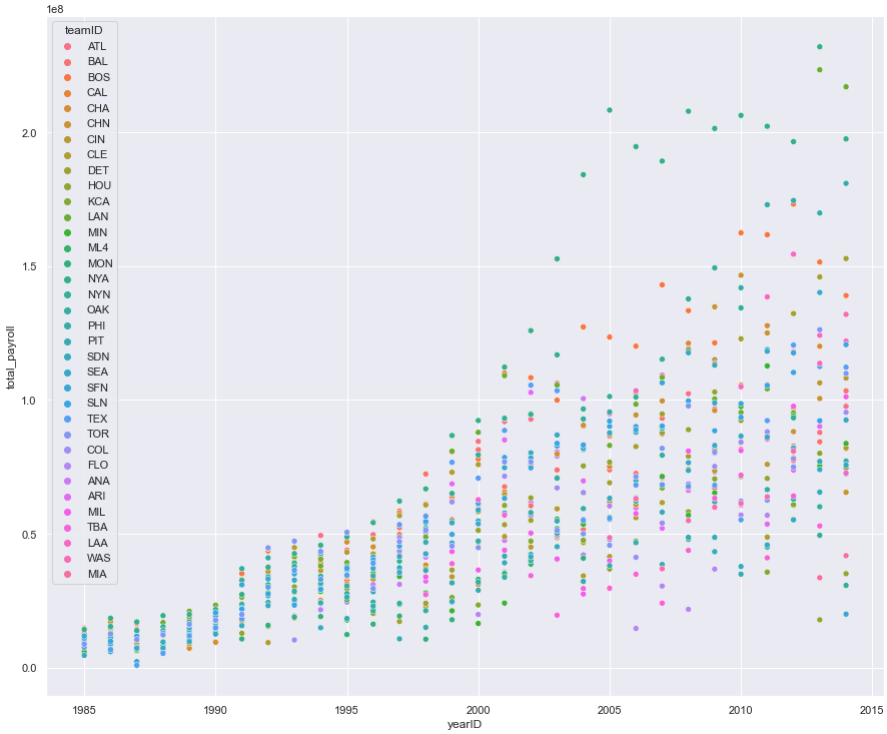
What statements can you make about the distribution of payrolls conditioned on time based on these plots? Remember you can make statements in terms of central tendency, spread, etc.

Problem 3

Write code to produce plots that specifically show at least one of the statements you made in Question 1. For example, if you make a statement that there is a trend for payrolls to decrease over time, make a plot of a statistic for central tendency (e.g., mean payroll) vs. time to show that specficially.

In [29]:
```
# Problem 2:
"""
import matplotlib.pyplot as plt
plt.scatter(salary_win_rate_table["yearID"], salary_win_rate_table["total_payroll"])
plt.show()
"""

import seaborn

seaborn.set(style='whitegrid')
#salary_win_rate_table_seaborn = seaborn.load_dataset(salary_win_rate_table)
seaborn.set(rc={'figure.figsize':(15,12.5)})
seaborn.scatterplot(x="yearID",
                    y="total_payroll",
                    hue="teamID",
                    #style="event",
                    data=salary_win_rate_table)
```

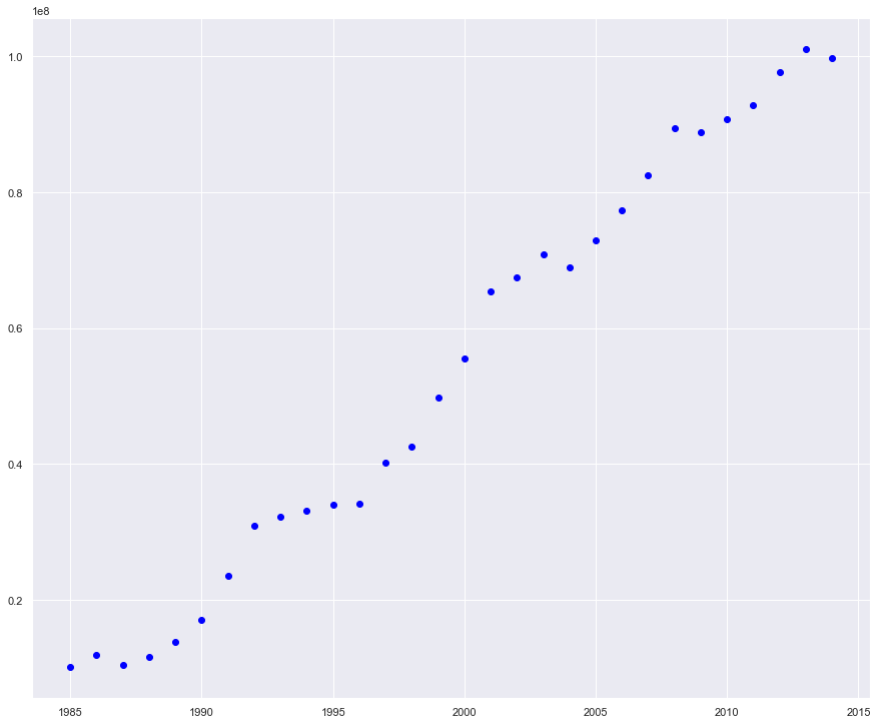
Out[29]: <AxesSubplot: xlabel='yearID', ylabel='total_payroll'>



Question 1:

From the graph, I can see that as the year growth, most of the time, the mean of total payroll increase over years. Also, as the year growth, the total payroll for each team becomes more and more diverse which means the variance of total payroll keep growing year by year.

In [30]:
```
# Problem 3:
dfs = dict(tuple(salary_win_rate_table.groupby("yearID")))
#display(dfs[1985])


keys = dfs.keys()
total_pay_each_year = []
for i in keys:
    temp_table = dfs[i]
    sum_of_each_year = 0
    row_num = 0
    for index, row in temp_table.iterrows():
        sum_of_each_year += row["total_payroll"]
        row_num +=1
    total_pay_each_year.append(sum_of_each_year/row_num)
#print(keys)
#print(total_pay_each_year)

#seaborn.scatterplot
import matplotlib.pyplot as plt
plt.scatter(keys,total_pay_each_year, c = "blue")
plt.show()
```



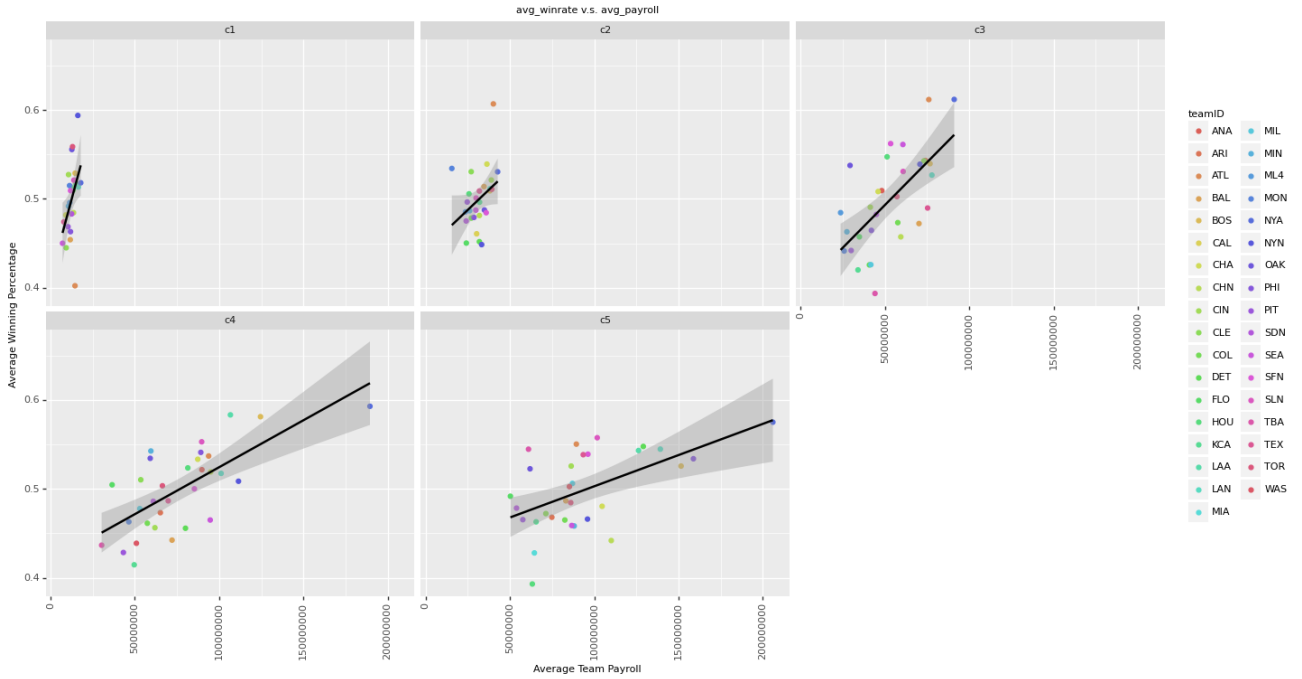
Problem 4

Write code to discretize year into five time periods (you can use pandas.cut to accomplish this) and then make a scatterplot showing mean winning percentage (y-axis) vs. mean payroll (x-axis) for each of the five time periods. You could add a regression line (using, e.g., NumPy's polyfit) in each scatter plot to ease interpretation.

In [31]:
```
# step 1 load the data into a dataframe
# use cut to set labels
# use seaborn to draw lines

#df_table = pd.DataFrame({"year":keys, "mean_payroll" :total_pay_each_year}, columns = ["year","mean_payroll"])
#df_table
#
sw_table = salary_win_rate_table.copy()

#sw_table["year_catergories"] = pd.cut(x = sw_table.yearID, 5 , labels = ["c1","c2","c3","c4","c5"])
#sw_table["year_catergories"] = sw_table.cut(x = sw_table['yearID'])
sw_table["year_catergories"] = pd.cut(x = sw_table["yearID"], bins = 5 , labels = ["c1","c2","c3","c4","c5"])
catergories_table = dict(tuple(sw_table.groupby("teamID")))
team_key = catergories_table.keys()
each_team_each_catergories = []
#print(team_key)
for i in team_key:
    #print(i)
    t_table = catergories_table[i]
    temp_table = dict(tuple(t_table.groupby("year_catergories")))
    #display(temp_table)
    temp_key = temp_table.keys()
    #each_team_catergories = []
    for j in temp_key:
        tt_table = temp_table[j]
        sum_of_each_year = 0
        sum_of_win_rate = 0
        row_num = 0
        if tt_table.empty:
            continue
        else:
            for index, row in tt_table.iterrows():
                sum_of_each_year += row["total_payroll"]
                sum_of_win_rate += row["win_rate"]
                row_num +=1
        #each_team_catergories.append([tt_table["teamID"].unique()[0],sum_of_each_year/row_num,sum_of_win_rate/row_num,j])
        each_team_each_catergories.append([tt_table["teamID"].unique()[0],sum_of_each_year/row_num,sum_of_win_rate/row_num,j])
    #each_team_each_catergories.append(each_team_catergories)
#print(each_team_each_catergories)
Table_catergories = pd.DataFrame(each_team_each_catergories, columns = ["teamID", "avg_payroll", "avg_winrate", "year_catergories"])
display(Table_catergories)
#display(catergories_table)
```

	teamID	avg_payroll	avg_winrate	year_catergories
0	ANA	4.808761e+07	0.509259	c3
1	ANA	8.978317e+07	0.521605	c4
2	ARI	7.399637e+07	0.543210	c3
3	ARI	6.512023e+07	0.473251	c4
4	ARI	7.487867e+07	0.468107	c5
5	ATL	1.447506e+07	0.402204	c1
6	ATL	4.016462e+07	0.606874	c2
7	ATL	7.599148e+07	0.611757	c3
8	ATL	9.378281e+07	0.537037	c4
9	ATL	8.941050e+07	0.550412	c5
10	BAL	1.165826e+07	0.454036	c1

In [32]:
```
"""
seaborn.scatterplot(x="avg_payroll",
                    y="avg_winrate",
                    hue="teamID",
                    #style="event",
                    data=Table_catergories)
"""

"""
different_period_table = dict(tuple(Table_catergories.groupby("year_catergories")))
#display(different_period_table)
period_key = different_period_table.keys()

#print(period_key)
index = 0
fig, axs = plt.subplots(5)
for i in period_key:
    seaborn.boxplot(x='avg_payroll', y='avg_winrate', hue="teamID", data=different_period_table[i],ax = axes[index])
    index+=1
"""
"""

sea = seaborn.FacetGrid(Table_catergories, col="year_catergories", hue="teamID")
sea.map(seaborn.scatterplot, "avg_payroll", "avg_winrate",alpha = 0.9)
#sea.map(seaborn.lmplot, "avg_payroll", "avg_winrate")
#sea.lmplot(x ="avg_payroll", y = "avg_winrate")
sea.add_legend()
#seaborn.lmplot(data = Table_catergories, x = "avg_payroll", y = "avg_winrate" ,col="year_catergories", hue="teamID")

seaborn.catplot(x="avg_payroll",
                    y="avg_winrate",
                    hue="teamID",
                    col="year_catergories",
                    #style="event",
                    data=Table_catergories)
import numpy as np
different_period_table = dict(tuple(Table_catergories.groupby("year_catergories")))
period_key = different_period_table.keys()
for i in period_key:
    z = np.polyfit(different_period_table[i]["avg_payroll"], different_period_table[i]["avg_winrate"], 1)
    print(i)
    print(z)

"""
#ggplot
from plotnine import *
ggplot(Table_catergories,aes(x='avg_payroll',y = 'avg_winrate')) +\
    geom_point(aes(color='teamID')) +\
    facet_wrap('year_catergories') +\
    xlab("Average Team Payroll") +\
    ylab("Average Winning Percentage") +\
    geom_smooth(method = 'lm',color = "black") +\
    ggtitle("avg_winrate v.s. avg_payroll") + theme(text = element_text(size = 8), figure_size=(16, 8),axis_text_x = element_text(angle=90, vjust=1))
```



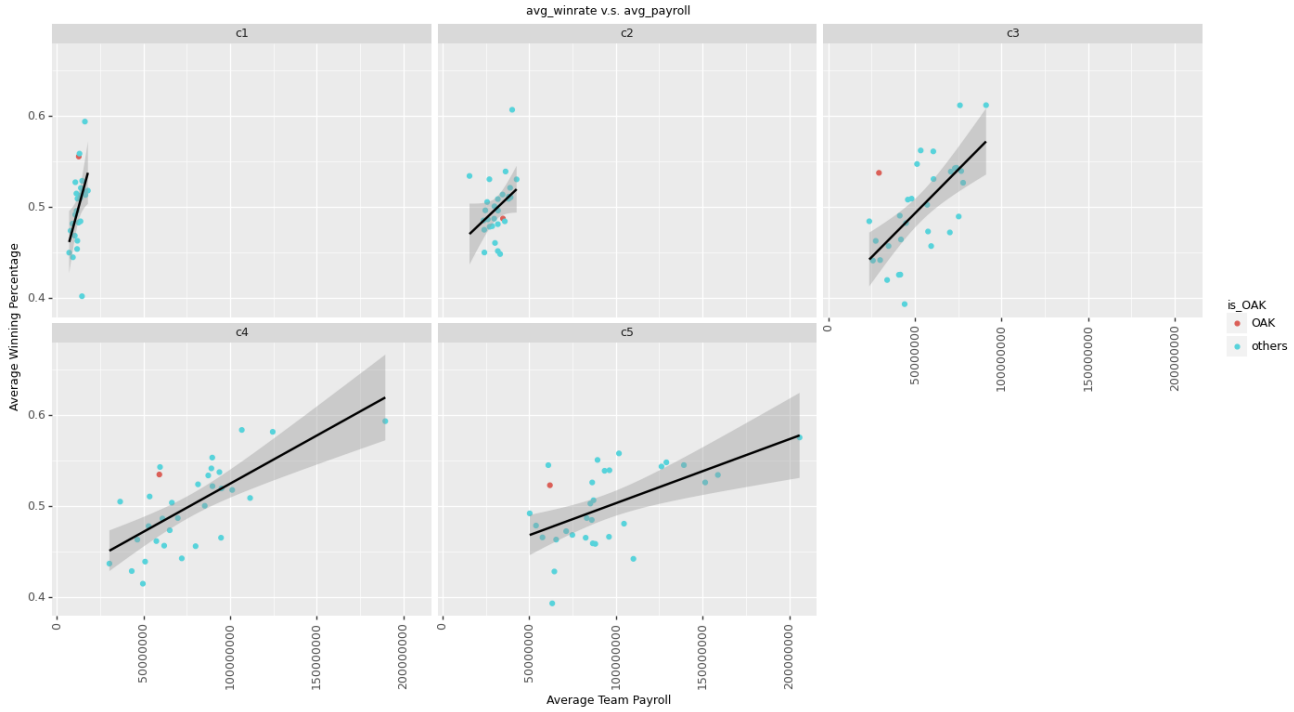
Out[32]: <ggplot: (91495980484)>

In [33]:
```
OAK_table = Table_catergories[Table_catergories["teamID"] == "OAK"]
OAK_table
```

Out[33]:

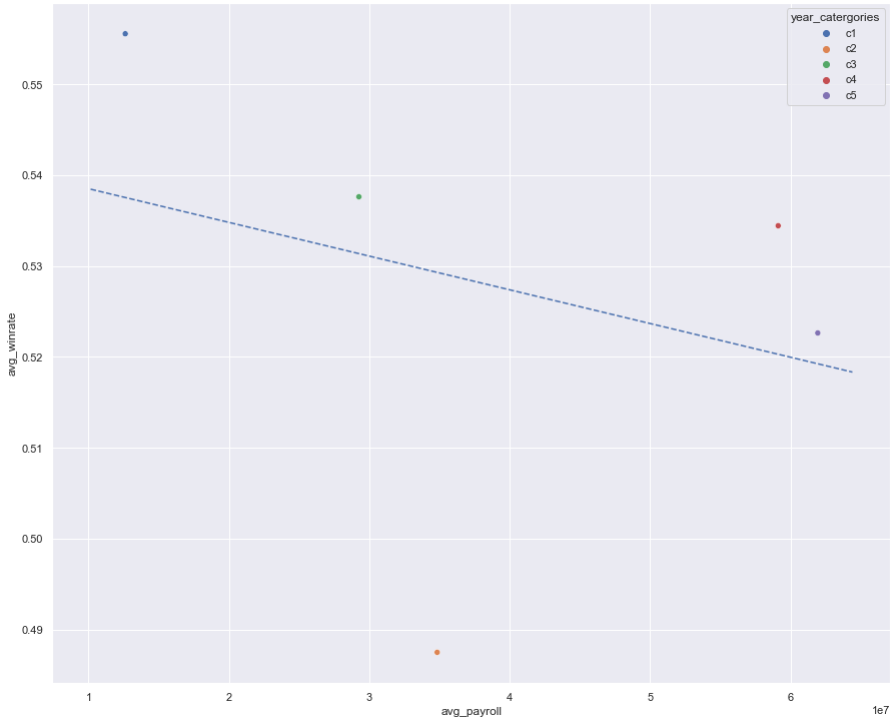
	teamID	avg_payroll	avg_winrate	year_catergories
98	OAK	1.261824e+07	0.555556	c1
99	OAK	3.483354e+07	0.487499	c2
100	OAK	2.925660e+07	0.537619	c3
101	OAK	5.911490e+07	0.534430	c4
102	OAK	6.193580e+07	0.522634	c5

In [34]:
```
Table_catergories["is_OAK"] = 0
for index,row in Table_catergories.iterrows():
    #print ("yes")
    if row["teamID"] == "OAK":
        Table_catergories.loc[index , "is_OAK"] = "OAK"
    else:
        Table_catergories.loc[index , "is_OAK"] = "others"

#Table_catergories
ggplot(Table_catergories,aes(x='avg_payroll',y = 'avg_winrate')) +\
    geom_point(aes(color='is_OAK')) +\
    facet_wrap('year_catergories') +\
    xlab("Average Team Payroll") +\
    ylab("Average Winning Percentage") +\
    geom_smooth(method = 'lm',color = "black") +\
    ggtitle("avg_winrate v.s. avg_payroll") + theme(text = element_text(size = 9), figure_size=(16, 8),axis_text_x = element_text(angle=90, vjust=1))
```



Out[34]: <ggplot: (91497004165)>

In [35]:
```
seaborn.scatterplot(x="avg_payroll",
                    y="avg_winrate",
                    hue="year_catergories",
                    #style="event",
                    data=OAK_table)


def abline(slope, intercept):
    axes = plt.gca()
    x_vals = np.array(axes.get_xlim())
    y_vals = intercept + slope * x_vals
    plt.plot(x_vals, y_vals, '--')
import numpy as np
z = np.polyfit(OAK_table["avg_payroll"], OAK_table["avg_winrate"], 1)
#y = z[0]*x + z[1]
#plt.scatter(OAK_table["avg_payroll"], OAK_table["avg_winrate"])
abline(z[0], z[1])
plt.show()
#print(z)
```



Question 2

What can you say about team payrolls across these periods? Are there any teams that standout as being particularly good at paying for wins across these time periods? What can you say about the Oakland A's spending efficiency across these time periods (labeling points in the scatterplot can help interpretation).

While the year range change over time, the regression line for later period get less steep than regression line from earlier period. The payroll for each team increased over time and the average payroll of each team in each period increase over period. Teams such as NYA and BOS is good at paying for wins across thees period. For OAK, for the graph above, I can see OAK made a bad choice during period 2 and for the rest of the period, OAK had good spending efficency.

Problem 5

Create a new variable in your dataset that standardizes payroll conditioned on year. So, this column for team i in year j should equal:

sdlized ij = (payrollij - ave_payrollj)/sd j

for team i in year j.where avg_payrollj is the average payroll for year j, and sj is the standard deviation of payroll for year j.

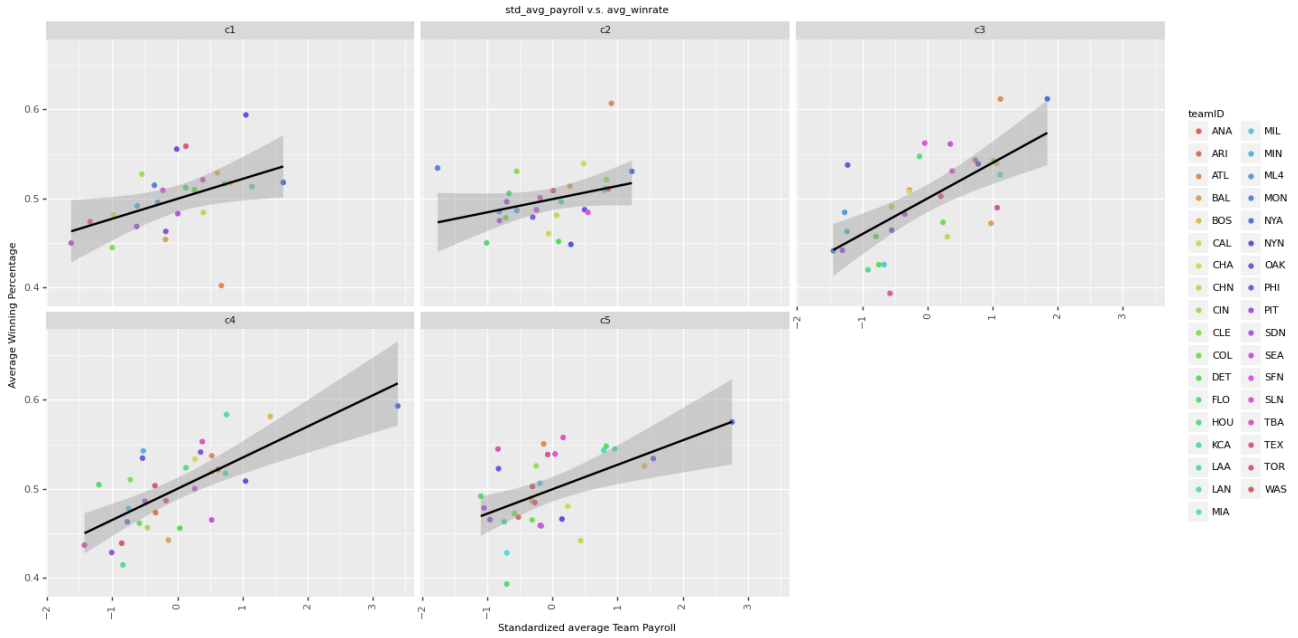
Problem 6

Repeat the same plots as Problem 4, but use this new standardized payroll variable.

In [36]:
```
year_different_table = dict(tuple(salary_win_rate_table.groupby("yearID")))
#display(year_different_table)
year_key = year_different_table.keys()
year_mean_sd = []
for i in year_key:
    temp_table = year_different_table[i]
    """
    summ = 0
    team_num = 0
    for index, row in temp_table.iterrows():
        summ += row["total_payroll"]
        team_num += 1
    year_average.append([i,summ/team_num])
    """
    mean = temp_table["total_payroll"].mean()
    sd = temp_table["total_payroll"].std()
    year_mean_sd.append([i,mean, sd])
#print(year_mean_sd)

def stardard_func(x, mean, sd):
    return ((x-mean)/sd)
standardlized_salary_table = salary_win_rate_table.copy()
# create new col
standardlized_salary_table["year_avg"] = 0
standardlized_salary_table["year_sd"] = 0
standardlized_salary_table["standarlized_payroll"] = 0

#display(standardlized_salary_table)
for index,row in standardlized_salary_table.iterrows():
    year = row["yearID"]
    for i in year_mean_sd:
        if i[0] == year:
            #print ("yes")
            standardlized_salary_table.loc[index,"year_avg"] = i[1]
            standardlized_salary_table.loc[index,"year_sd"] = i[2]
            standardlized_salary_table.loc[index,"standarlized_payroll"] = stardard_func(row["total_payroll"],i[1],i[2])

display(standardlized_salary_table)
```

	yearID	teamID	franchID	G	W	win_rate	total_payroll	year_avg	year_sd	standarlized_payroll
0	1985	ATL	ATL	162	66	0.407407	14807000.0	1.007557e+07	2.470845e+06	1.914905
1	1985	BAL	BAL	161	83	0.515528	11560712.0	1.007557e+07	2.470845e+06	0.601068
2	1985	BOS	BOS	163	81	0.496933	10897560.0	1.007557e+07	2.470845e+06	0.332678
3	1985	CAL	ANA	162	90	0.555556	14427894.0	1.007557e+07	2.470845e+06	1.761474
4	1985	CHA	CHW	163	85	0.521472	9846178.0	1.007557e+07	2.470845e+06	-0.092838
5	1985	CHN	CHC	162	77	0.475309	12702917.0	1.007557e+07	2.470845e+06	1.063341
6	1985	CIN	CIN	162	89	0.549383	8359917.0	1.007557e+07	2.470845e+06	-0.694357
7	1985	CLE	CLE	162	60	0.370370	6551666.0	1.007557e+07	2.470845e+06	-1.426192
8	1985	DET	DET	161	84	0.521739	10348143.0	1.007557e+07	2.470845e+06	0.110318
9	1985	HOU	HOU	162	83	0.512346	9993051.0	1.007557e+07	2.470845e+06	-0.033395
10	1985	KCA	KCR	162	91	0.561728	9321179.0	1.007557e+07	2.470845e+06	-0.305315

In [37]:
```
"""
subsitude salary_win_rate_table as standardlized_salary_table
sw_table = salary_win_rate_table.copy()

#sw_table["year_catergories"] = pd.cut(x = sw_table.yearID, 5 , labels = ["c1","c2","c3","c4","c5"])
#sw_table["year_catergories"] = sw_table.cut(x = sw_table['yearID'])
sw_table["year_catergories"] = pd.cut(x = sw_table["yearID"], bins = 5 , labels = ["c1","c2","c3","c4","c5"])
catergories_table = dict(tuple(sw_table.groupby("teamID")))
team_key = catergories_table.keys()
each_team_each_catergories = []
#print(team_key)
for i in team_key:
    #print(i)
    t_table = catergories_table[i]
    temp_table = dict(tuple(t_table.groupby("year_catergories")))
    #display(temp_table)
    temp_key = temp_table.keys()
    #each_team_catergories = []
    for j in temp_key:
        tt_table = temp_table[j]
        sum_of_each_year = 0
        sum_of_win_rate = 0
        row_num = 0
        if tt_table.empty:
            continue
        else:
            for index, row in tt_table.iterrows():
                sum_of_each_year += row["total_payroll"]
                sum_of_win_rate += row["win_rate"]
                row_num +=1
        #each_team_catergories.append([tt_table["teamID"].unique()[0],sum_of_each_year/row_num,sum_of_win_rate/row_num,j])
        each_team_each_catergories.append([tt_table["teamID"].unique()[0],sum_of_each_year/row_num,sum_of_win_rate/row_num,j])
    #each_team_each_catergories.append(each_team_catergories)
#print(each_team_each_catergories)
Table_catergories = pd.DataFrame(each_team_each_catergories, columns = ["teamID", "avg_payroll", "avg_winrate", "year_catergories"])
display(Table_catergories)
"""

sw_table_sd = standardlized_salary_table.copy()
sw_table_sd["year_catergories"] = pd.cut(x = sw_table_sd["yearID"], bins = 5 , labels = ["c1","c2","c3","c4","c5"])
catergories_table_sd = dict(tuple(sw_table_sd.groupby("teamID")))
#display(catergories_table_sd)
team_key_sd = catergories_table_sd.keys()
each_team_each_catergories_sd = []
for i in team_key_sd:
    t_table = catergories_table_sd[i]
    temp_table = dict(tuple(t_table.groupby("year_catergories")))
    temp_key = temp_table.keys()
    for j in temp_key:
        tt_table = temp_table[j]
        sum_of_each_year = 0
        sum_of_win_rate = 0
        row_num = 0
        if tt_table.empty:
            continue
        else:
            for index, row in tt_table.iterrows():
                sum_of_each_year += row["standarlized_payroll"]
                sum_of_win_rate += row["win_rate"]
                row_num +=1
        each_team_each_catergories_sd.append([tt_table["teamID"].unique()[0],sum_of_each_year/row_num,sum_of_win_rate/row_num,j])
Table_catergories_sd = pd.DataFrame(each_team_each_catergories_sd, columns = ["teamID", "std_avg_payroll", "avg_winrate", "year_catergories"])
#Table_catergories_sd
ggplot(Table_catergories_sd,aes(x='std_avg_payroll',y = 'avg_winrate')) +\
    geom_point(aes(color='teamID')) +\
    facet_wrap('year_catergories') +\
    xlab("Standardized average Team Payroll") +\
    ylab("Average Winning Percentage") +\
    geom_smooth(method = 'lm',color = "black") +\
    ggtitle("std_avg_payroll v.s. avg_winrate") + theme(text = element_text(size = 8), figure_size=(16, 8),axis_text_x = element_text(angle=90, vjust=1))
```



Out[37]: <ggplot: (91498521037)>

Question 3

Discuss how the plots from Problem 4 and Problem 6 reflect the transformation you did on the payroll variable.

New graph shows standardized payroll which means mean payroll center the data at 0 and the standard deviation has been change to 1.

The biggest advagntage of these graph is creating a scale of data. In question 4, the data is hard to interpret since the mean and standard deviation is different for each sample in each period. After standardlized the data, it is easier to observe how data change in different period.

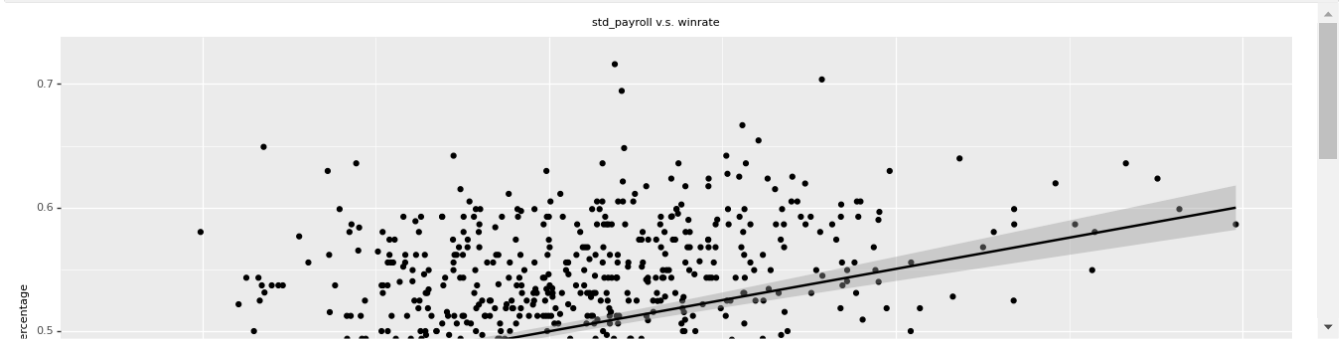
Problem 7

Make a single scatter plot of winning percentage (y-axis) vs. standardized payroll (x-axis). Add a regression line to highlight the relationship.

The regression line gives you expected winning percentage as a function of standardized payroll. Looking at the regression line, it looks like teams that spend roughly the average payroll in a given year will win 50% of their games (i.e. win_pct is 50 when standardized_payroll is 0), and teams increase 5% wins for every 2 standard units of payroll (i.e., win_pct is 55 when standardized_payroll is 2). We will see how this is done in general using linear regression later in the course.

From these observations we can calculate the expected win percentage for team i in year j as

In [38]:
```
ggplot(sw_table_sd,aes(x='standarlized_payroll',y = 'win_rate')) +\
    geom_point() +\
    xlab("Standardized Team Payroll") +\
    ylab("Winning Percentage") +\
    geom_smooth(method = 'lm',color = "black") +\
    ggtitle("std_payroll v.s. winrate") + theme(text = element_text(size = 8), figure_size=(16, 8),axis_text_x = element_text(angle=90, vjust=1))
```



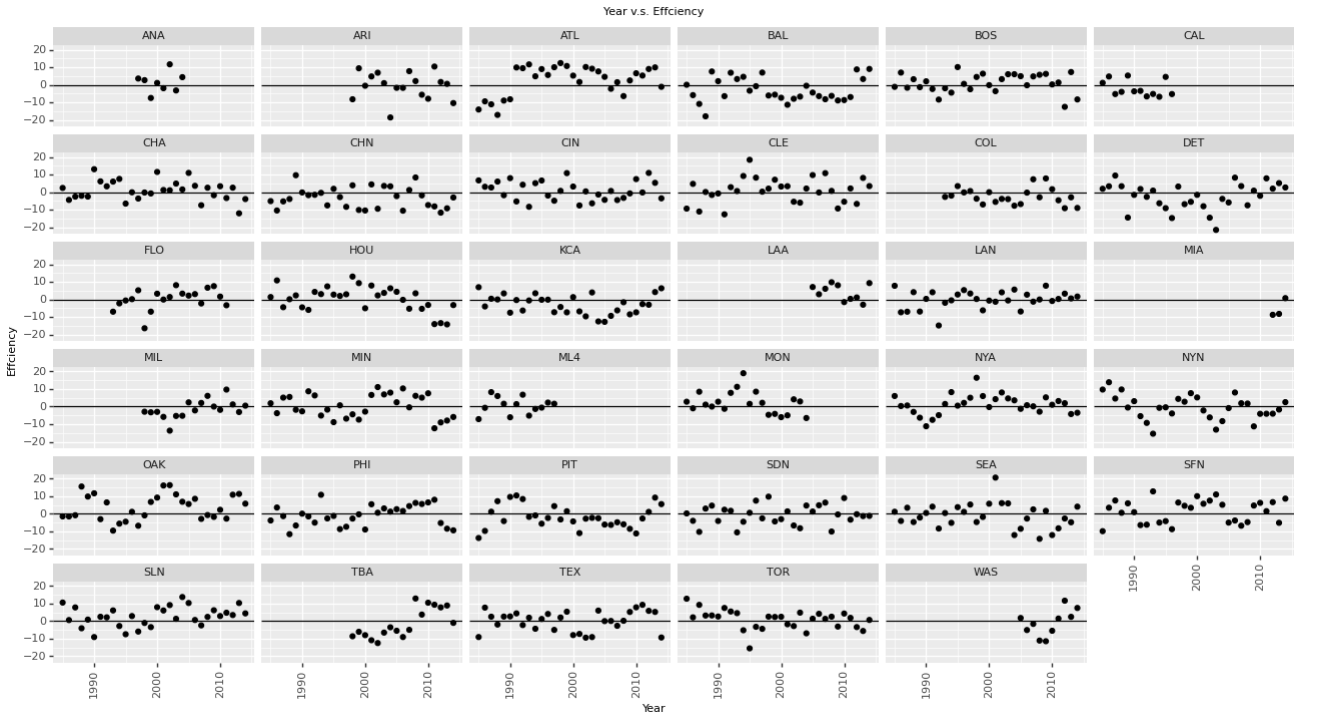
In [39]:
```
slope, intercept = np.polyfit(sw_table_sd["standarlized_payroll"], sw_table_sd["win_rate"], 1)
print(slope*100)
print(intercept*100)
```

```
2.5269495394885744
49.984051861166506
```

Problem 8

Make a line plot with year on the x-axis and efficiency on the y-axis. A good set of teams to plot are Oakland, the New York Yankees, Boston, Atlanta and Tampa Bay (teamIDs OAK, BOS, NYA, ATL, TBA).

In [40]:
```
effciency_table = sw_table_sd.copy()
effciency_table["effciency"] = 0
for index, row in effciency_table.iterrows():
    effciency_table.loc[index,"effciency"] = row["win_rate"]*100 - (50+2.5*row["standarlized_payroll"])
effciency_table

ggplot(effciency_table,aes(x='yearID',y = 'effciency')) +\
    geom_point() +\
    geom_hline(yintercept = 0)+\
    facet_wrap('teamID') +\
    xlab("Year") +\
    ylab("Effciency") +\
    ggtitle("Year v.s. Effciency") + theme(text = element_text(size = 8), figure_size=(16, 8),axis_text_x = element_text(angle=90, vjust=1))
```



Out[40]: <ggplot: (91498625386)>

Question 4

What can you learn from this plot compared to the set of plots you looked at in Question 2 and 3? How good was Oakland's efficiency during the Moneyball period?

Compared to question 2 and 3 which observe the correlationship between average win rate and average payroll in some period, this polt focus on each efficiency on each year. In this case, I can observe the reason why the win rate in some period is higher than other period and some outliner which significantly infulenced the data but cannot discoverd by correlationship between average win rate and average payroll in some period.

OAK at Moneyball period had really high efficiency which was the best efficiency over all period. For OAK after Moneyball period which is 2002, the efficiency did drop after the period. However, even the efficiency of OAK dropped after Moneyball period, the efficiency is still around 0.

In [ ]: