Data Bootcamp Final Project: NFL Salary Composition in the 2017 Season

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The salary cap was instituted in the National Football League in 1994 in an attempt to promote parity and fair competition among the league. Starting at $34 million, the salary cap has grown every year and is calculated by equally distributing league revenues. In 2017, the salary cap was $167 million. The new rule achieved its goals as NFL dynasties and long-term dominance has declined since the inception of the salary cap. Each year, General Managers (GMs) must distribute their fixed cap among 53 active players, injured reserve players, and practice squad players. Despite a few obscure ceilings and floors, GMs can distribute their salary cap in any way. This analysis will research a) the way that GMs distribute their salary cap and b) the effects of different salary cap distributions among position groups.

Data Report

The data for this project comes from [Spotrac (http://www.spotrac.com)](http://www.spotrac.com), a division of USA Today Sports Media Group. Spotrac is the leading salary aggregator across all major American sports leagues. It is a trusted resource that has been sourced in the New York Times (https://archive.nytimes.com/www.nytimes.com/interactive/2013/10/18/sports/The-Quarterbacks-Share.html), Wall Street Journal (https://www.wsj.com/articles/the-jets-have-reasons-to-let-muhammad-wilkerson-walk-1433899397), Washington Post (https://www.washingtonpost.com/lifestyle/magazine/whos-the-highest-paid-athlete-in-dc-/2015/02/12/16509416-856a-11e4-b9b7-b8632ae73d25_story.html?noredirect=on&utm_term=.8bab8f85a77a), and many others. The Spotrac datasets, specifically for the NFL, combine all forms of salary (base, signing bonus, incentive-based, etc.) to produce a final "cap hit" (total amount the player counts against the team's salary cap) for each player.

The data was acquired from Spotrac by scraping the website using the BeautifulSoup package. Because of the hit-or-miss nature of scraping and a worry that it may not work when the time comes to grade my project, the data was downloaded to a local file and then uploaded to my GitHub repository. The scrape, in its entirety, can be found at https://github.com/ChadT35/Data_Bootcamp_Final_Project/blob/master/SpotRac_Scrape.ipynb (https://github.com/ChadT35/Data_Bootcamp_Final_Project/blob/master/SpotRac_Scrape.ipynb).

Packages

The following packages will be used throughout the code:

- `display` generates the NFL logo above
- `Pandas` core tool that produces and manipulates dataframes
- `Matplotlib` ploting
- `numpy` mathematical operations
- `functools/reduce` merge many datasets into one dataframe

In [161]:

```
import os
import pandas as pd
import matplotlib.pyplot as plt
from functools import reduce
import numpy as np
from IPython.display import display, Image
plt.style.use('fivethirtyeight')
```

Bringing in Raw Data

The following link will bring in the data from the Spotrac scrape. I converted the data into a Pandas dataframe and changed Cap Hit (the only column needed) into a float within the SpotracScrape file.

In [162]:

```
salaries_url = "https://github.com/ChadT35/Data_Bootcamp_Final_Project/blob/mast
er/SpotracScrapeData.xlsx?raw=true"
```

In [163]:

```
dfsal = pd.read_excel(salaries_url)
dfsal.head(10)
```

Out[163]:

	Player	Team	Side	Pos.	Base_Salary	Signing_Bonus	Roster_Bonus	Option_I
1	Joel Bitonio	Browns	Off	G	$3,164,777	$573,036	$8,500,000	-
2	Kevin Zeitler	Browns	Off	G	$6,000,000	$2,400,000	-	-
3	Myles Garrett	Browns	Def	DE	$465,000	$5,064,501	-	-
4	Christian Kirksey	Browns	Def	ILB	$3,797,000	$1,365,625	-	-
5	J.C. Tretter	Browns	Def	C	$2,000,000	$1,500,000	$109,375	-
6	Jamar Taylor	Browns	Def	CB	$2,500,000	$750,000	-	-
7	Danny Shelton	Browns	Def	DT	$1,498,970	$1,692,939	-	-
8	Britton Colquitt	Browns	ST	P	$1,650,000	-	$1,500,000	-
9	Isaiah Crowell	Browns	Off	RB	$2,746,000	-	-	-
10	Corey Coleman	Browns	Off	WR	$979,773	$1,669,090	-	-

For readability, a new column will be created that shows the cap hit in millions.

In [164]:

```
dfsal["Cap_Hit_$Ms"]=dfsal["Cap_Hit"]/1000000
dfsal.head(10)
```

Out[164]:

	Player	Team	Side	Pos.	Base_Salary	Signing_Bonus	Roster_Bonus	Option_I
1	Joel Bitonio	Browns	Off	G	$3,164,777	$573,036	$8,500,000	-
2	Kevin Zeitler	Browns	Off	G	$6,000,000	$2,400,000	-	-
3	Myles Garrett	Browns	Def	DE	$465,000	$5,064,501	-	-
4	Christian Kirksey	Browns	Def	ILB	$3,797,000	$1,365,625	-	-
5	J.C. Tretter	Browns	Def	C	$2,000,000	$1,500,000	$109,375	-
6	Jamar Taylor	Browns	Def	CB	$2,500,000	$750,000	-	-
7	Danny Shelton	Browns	Def	DT	$1,498,970	$1,692,939	-	-
8	Britton Colquitt	Browns	ST	P	$1,650,000	-	$1,500,000	-
9	Isaiah Crowell	Browns	Off	RB	$2,746,000	-	-	-
10	Corey Coleman	Browns	Off	WR	$979,773	$1,669,090	-	-

Every NFL player has a *position* they play for the team, with 11 starting positions on both offense and defense and 2 more on special teams (punter, kicker). The list below shows an abbreviation for each starting position.

In [533]:

```
dfsal["Pos."].unique()
```

Out[533]:

```
array(['G', 'DE', 'ILB', 'C', 'CB', 'DT', 'P', 'RB', 'WR', 'S', 'TE'
, 'LS',
       'OLB', 'QB', 'T', 'FB', 'K', 'SS', 'LT', 'FS', 'RT', 'LB'], d
type=object)
```

Positions can be allocated into *groups* that will be called "position groups" for this analysis. The code below is a function that assigns players their position group. The primary position groups are as follows:

- #### QB: Quarterbacks
- #### O_Line: Offensive linemen (tackles, guards, centers)
- #### Backfield: Running backs (running back, full back)
- #### Receiving_Core: Receivers and tight ends
- #### D_Line: Defensive linemen (nose tackle, defensive end, defensive tackle)
- #### Linebackers: Linebackers (linebackers, outside linebacker, inside lineback)
- #### Secondary: Defensive coverage (cornerback, safety, free safety, strong safety)
- #### Special Teams: Kickers, punters, long snappers

In [166]:

```
def setPosGroup(position):
    if position == "QB":
        return "QB"
    elif position == "T" or position == "G" or position == "C" or position == "R
T" or position == "LT":
        return "O_Line"
    elif position == "RB" or position == "FB":
        return "Backfield"
    elif position == "WR" or position == "TE":
        return "Receiving_Core"
    elif position == "NT" or position == "DE" or position == "DT":
        return "D_Line"
    elif position == "LB" or position == "OLB" or position == "ILB":
        return "Linebackers"
    elif position == "CB" or position == "S" or position == "FS" or position ==
"SS":
        return "Secondary"
    elif position == "K" or position == "P" or position == "LS":
        return "Spec_Teams"
```

This creates a new column that assigns the primary position group:

In [167]:

```
dfsal["Pos_Group"] = dfsal["Pos."].apply(setPosGroup)
dfsal.head(10)
```

Out[167]:

	Player	Team	Side	Pos.	Base_Salary	Signing_Bonus	Roster_Bonus	Option_I
1	Joel Bitonio	Browns	Off	G	$3,164,777	$573,036	$8,500,000	-
2	Kevin Zeitler	Browns	Off	G	$6,000,000	$2,400,000	-	-
3	Myles Garrett	Browns	Def	DE	$465,000	$5,064,501	-	-
4	Christian Kirksey	Browns	Def	ILB	$3,797,000	$1,365,625	-	-
5	J.C. Tretter	Browns	Def	C	$2,000,000	$1,500,000	$109,375	-
6	Jamar Taylor	Browns	Def	CB	$2,500,000	$750,000	-	-
7	Danny Shelton	Browns	Def	DT	$1,498,970	$1,692,939	-	-
8	Britton Colquitt	Browns	ST	P	$1,650,000	-	$1,500,000	-
9	Isaiah Crowell	Browns	Off	RB	$2,746,000	-	-	-
10	Corey Coleman	Browns	Off	WR	$979,773	$1,669,090	-	-

Positions can be grouped in a few different ways. The following secondary position grouping has broader categories that will also be valuable for analysis.

- #### Skill: Any player that handles the ball on offense (quarterbacks, running backs, full backs, wide receivers, tight ends)
- #### O_Line: Offensive linemen (tackles, guards, centers)
- #### Front_Seven: Defensive linemen and linebackers (nose tackle, defensive end, defensive tackle, linebackers, outside linebackers, inside linebackers)
- #### Secondary: Defensive coverage (cornerback, safety, free safety, strong safety)
- #### Special Teams: Kickers, punters, long snappers

In [168]:

```
def setSecPosGroup(position):
    if position == "QB" or position == "RB" or position == "FB" or position == "
WR" or position == "TE":
        return "Skill"
    elif position == "T" or position == "G" or position == "C" or position == "R
T" or position == "LT":
        return "O_Line_2"
    elif (position == "NT" or position == "DE" or position == "DT"
          or position == "LB" or position == "OLB" or position == "ILB"):
        return "Front_Seven"
    elif position == "CB" or position == "S" or position == "FS" or position ==
"SS":
        return "Secondary_2"
    elif position == "P" or position == "K" or position == "LS":
        return "Spec_Teams_2"
```

This creates a new column that assigns the secondary position group.

In [169]:

```
dfsal["2nd_Pos_Group"] = dfsal["Pos."].apply(setSecPosGroup)
dfsal.head(10)
```

Out[169]:

	Player	Team	Side	Pos.	Base_Salary	Signing_Bonus	Roster_Bonus	Option_I
1	Joel Bitonio	Browns	Off	G	$3,164,777	$573,036	$8,500,000	-
2	Kevin Zeitler	Browns	Off	G	$6,000,000	$2,400,000	-	-
3	Myles Garrett	Browns	Def	DE	$465,000	$5,064,501	-	-
4	Christian Kirksey	Browns	Def	ILB	$3,797,000	$1,365,625	-	-
5	J.C. Tretter	Browns	Def	C	$2,000,000	$1,500,000	$109,375	-
6	Jamar Taylor	Browns	Def	CB	$2,500,000	$750,000	-	-
7	Danny Shelton	Browns	Def	DT	$1,498,970	$1,692,939	-	-
8	Britton Colquitt	Browns	ST	P	$1,650,000	-	$1,500,000	-
9	Isaiah Crowell	Browns	Off	RB	$2,746,000	-	-	-
10	Corey Coleman	Browns	Off	WR	$979,773	$1,669,090	-	-

Salaries by Position Group

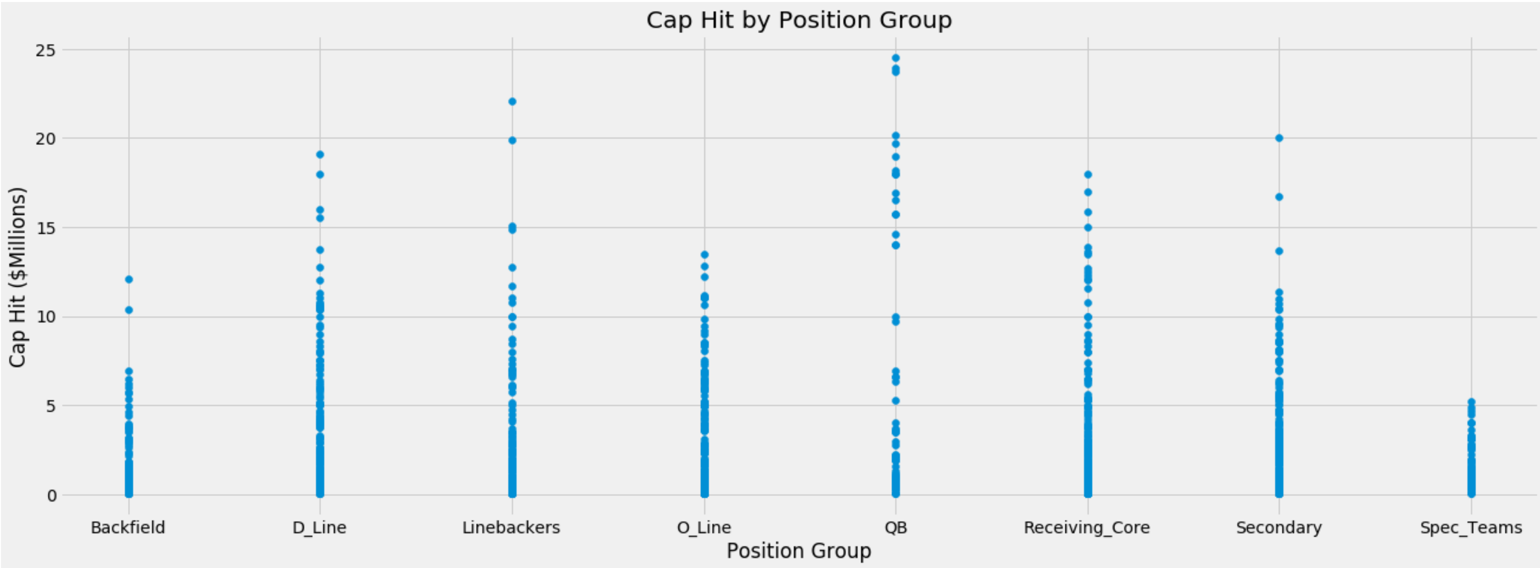
The following chart is scatter plot that displays all of the cap hits for each player in each position group.

Reign of the Quarterbacks

As shown below, quarterbacks (generally considered the most important position) have the highest range of salaries. Their distribution is somewhat bimodal as the starting QBs garner large salaries while backup quarterbacks are paid much less.

In [465]:

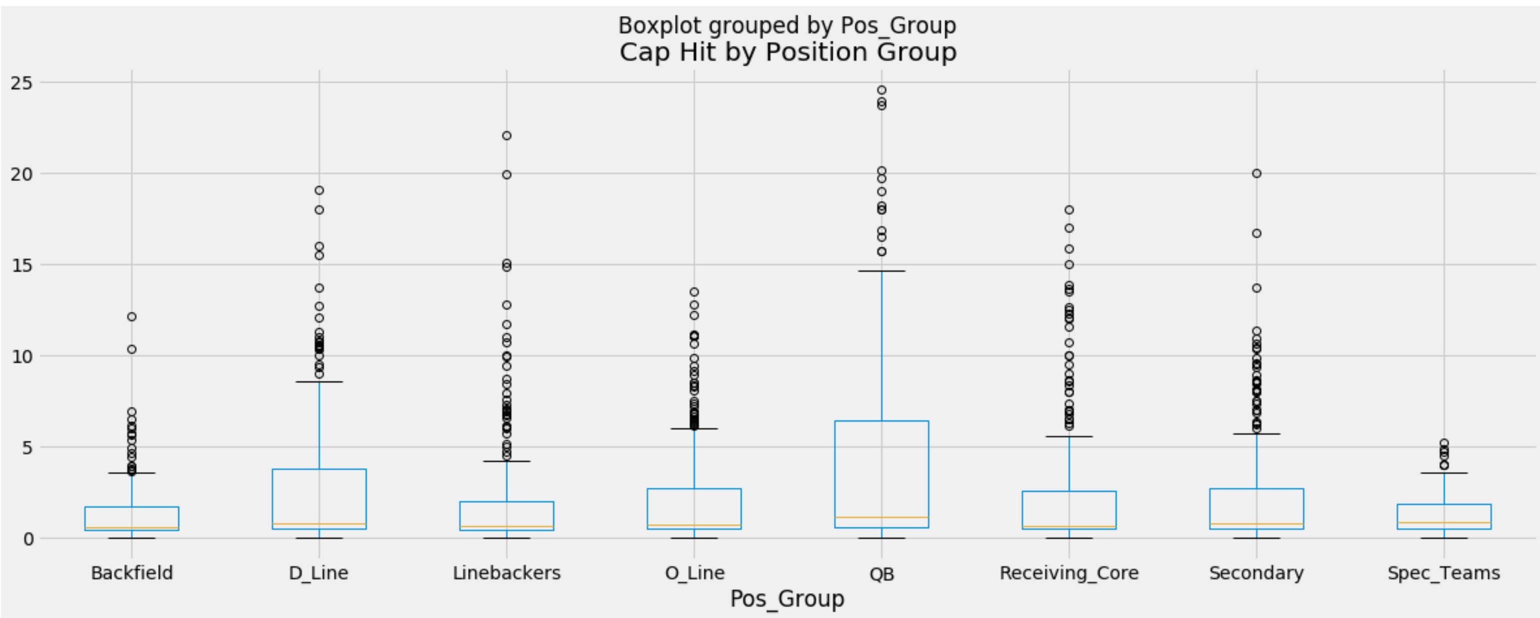
```
fig, ax = plt.subplots(figsize=(20,7))
ax.scatter(dfsal["Pos_Group"], dfsal["Cap_Hit_$Ms"])
ax.set_title("Cap Hit by Position Group")
ax.set_xlabel("Position Group")
ax.set_ylabel("Cap Hit ($Millions)")
plt.show()
```



The Quarterback difference is illustrated even more by the following boxplot:

In [171]:

```
dfsal.boxplot(column = "Cap_Hit_$Ms",by = "Pos_Group",figsize=(20,7))
plt.title("Cap Hit by Position Group")
plt.show()
```



15 Highest Paid Players by total Cap Hit

And, of the 15 highest paid players in the NFL, 9 are Quarterbacks, including 4 of the top 5.

In [173]:

```
dfsal[["Player","Team","Pos.","Cap_Hit_$Ms"]].set_index("Pos.").sort_values("Cap
_Hit_$Ms",ascending=False).head(15)
```

Out[173]:

	Player	Team	Cap_Hit_$Ms
Pos.			
QB	Joe Flacco	Ravens	24.550000
QB	Kirk Cousins	Redskins	23.943600
QB	Matt Ryan	Falcons	23.750000
OLB	Justin Houston	Chiefs	22.100000
QB	Cam Newton	Panthers	20.166666
CB	Josh Norman	Redskins	20.000000
OLB	Von Miller	Broncos	19.900000
QB	Eli Manning	Giants	19.700000
DT	Ndamukong Suh	Dolphins	19.100000
QB	Drew Brees	Saints	19.000000
QB	Ben Roethlisberger	Steelers	18.200000
QB	Sam Bradford	Vikings	18.000000
WR	DeAndre Hopkins	Texans	18.000000
QB	Philip Rivers	Chargers	18.000000
DE	Muhammad Wilkerson	Jets	18.000000

However, Quarterbacks make up only one position on the field. In terms of position groups, the defensive line is paid the most in terms of total cap hit across the NFL, followed closely by defensive secondary.

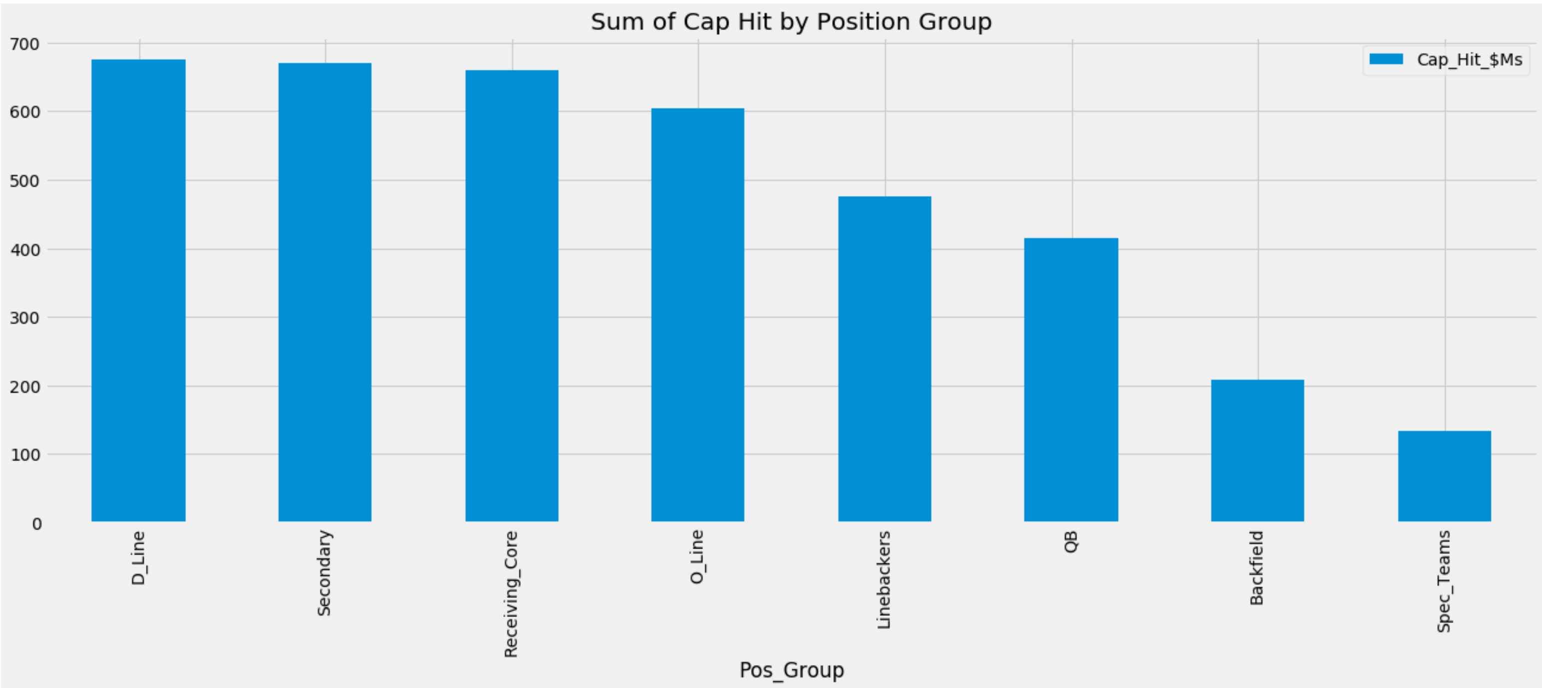
In [174]:

```
df_pos_group_sum= dfsal.set_index("Pos_Group").groupby('Pos_Group')['Cap_Hit_$Ms
'].sum().sort_values(ascending=False).reset_index()
print(df_pos_group_sum.set_index("Pos_Group"))
```

```
                Cap_Hit_$Ms
Pos_Group
D_Line           674.907619
Secondary        670.705508
Receiving_Core   659.335236
O_Line           604.411413
Linebackers      475.865008
QB               414.200316
Backfield        208.038427
Spec_Teams       133.274135
```

In [175]:

```
df_pos_group_sum.set_index("Pos_Group").plot.bar(figsize=(20,7))
plt.title("Sum of Cap Hit by Position Group")
plt.show()
```



Within mean salary for each position group, the quarterbacks are on top again, with the average QB (starter and backup) being paid about $5M. Defensive lineman are second, being slightly more than half of quarterbacks: $2.7M.

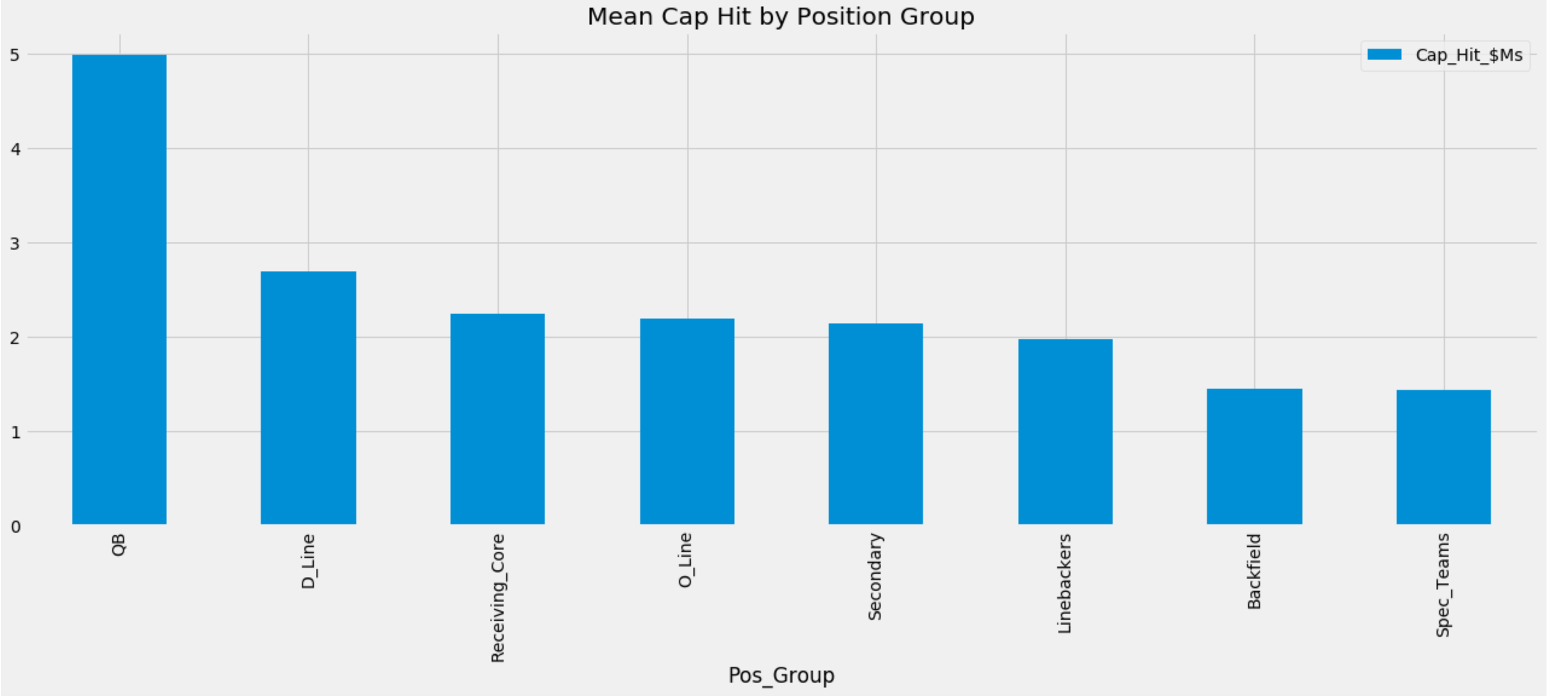
In [176]:

```
df_pos_group_mean= dfsal.set_index("Pos_Group").groupby('Pos_Group')['Cap_Hit_$M
s'].mean().sort_values(ascending=False).reset_index()
print(df_pos_group_mean.set_index("Pos_Group"))
```

```
                 Cap_Hit_$Ms
Pos_Group
QB                  4.990365
D_Line              2.699630
Receiving_Core      2.250291
O_Line              2.197860
Secondary           2.149697
Linebackers         1.982771
Backfield           1.454814
Spec_Teams          1.433055
```

In [177]:

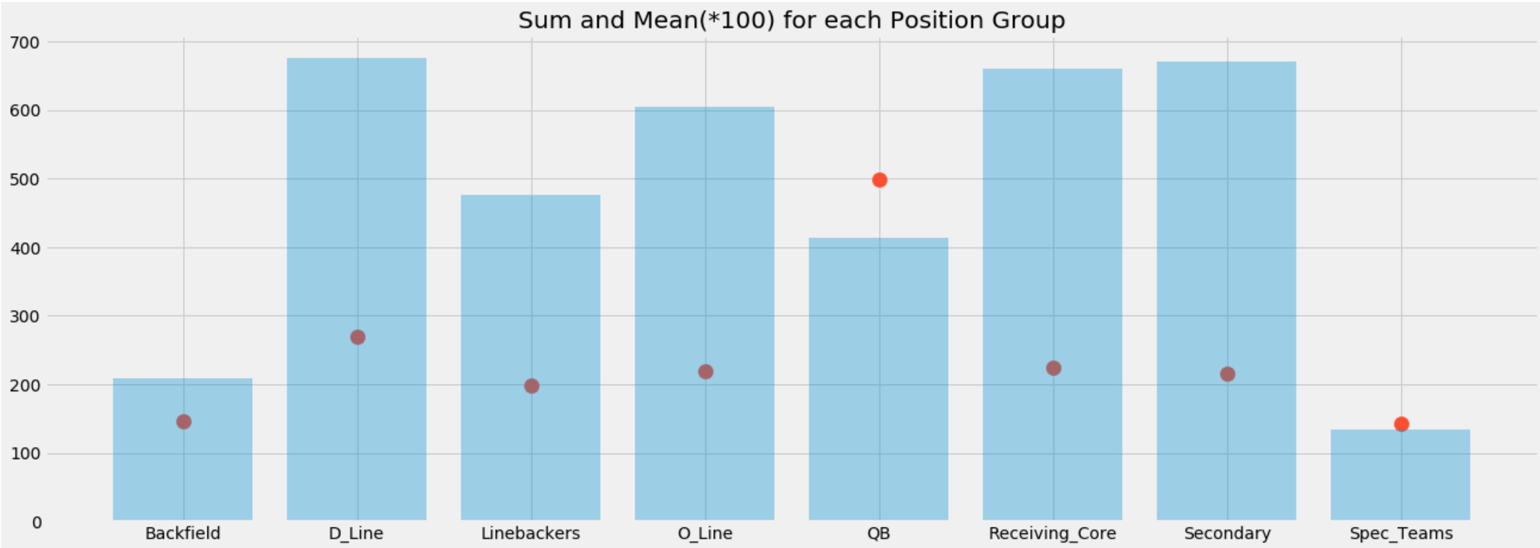
```
df_pos_group_mean.set_index("Pos_Group").plot.bar(figsize=(20,7))
plt.title("Mean Cap Hit by Position Group")
plt.show()
```



The following chart shows both the sum for each position group and the mean (multiplied by 100 for illustrative purposes).

In [178]:

```
fig, ax = plt.subplots(figsize=(20,7))
ax.bar(df_pos_group_sum["Pos_Group"],df_pos_group_sum["Cap_Hit_$Ms"],alpha=0.35)
ax.scatter(df_pos_group_mean["Pos_Group"],df_pos_group_mean["Cap_Hit_$Ms"]*100,s
=150)
ax.set_title("Sum and Mean(*100) for each Position Group")
plt.show()
```



The Big Merge

The current dataframe has data listed by individual player. The rest of the analysis will focus on how *teams* distribute their salary cap, so the dataframe must have team as the index with columns that represent positon groups, sides of the ball, etc. To do this, I created four new dataframes that are sorted by team and include the cap hit for the various categories, and later performed a many-to-one merge on the team index. The following code is the creation of new dataframes that will be merged:

In [179]:

```
df_team_spend= dfsal.set_index("Team").groupby('Team')['Cap_Hit_$Ms'].sum().sort
_values(ascending=False).reset_index()
df_team_spend["Cap_Utilization_%"] = (df_team_spend["Cap_Hit_$Ms"] / 167) *100
df_t_s = dfsal.set_index("Team").groupby(['Team', 'Side'])['Cap_Hit_$Ms'].sum().
reset_index()
df_t_s = df_t_s.pivot(index="Team",columns="Side",values="Cap_Hit_$Ms").reset_in
dex()
df_t_s2 = dfsal.set_index("Team").groupby(['Team', 'Pos.'])['Cap_Hit_$Ms'].sum()
.reset_index()
df_t_s2 = df_t_s2.pivot(index="Team",columns="Pos.",values="Cap_Hit_$Ms").reset_
index()
df_t_s3 = dfsal.set_index("Team").groupby(['Team', 'Pos_Group'])['Cap_Hit_$Ms'].
sum().reset_index()
df_t_s3 = df_t_s3.pivot(index="Team",columns="Pos_Group",values="Cap_Hit_$Ms").r
eset_index()
df_t_s4 = dfsal.set_index("Team").groupby(['Team', '2nd_Pos_Group'])['Cap_Hit_$M
s'].sum().reset_index()
df_t_s4 = df_t_s4.pivot(index="Team",columns="2nd_Pos_Group",values="Cap_Hit_$Ms
").reset_index()
```

Loading in the season results

In order to examine the effects of different salary allocations, I will load in the results from the 2017 season. The data comes from Pro-Football-Reference (https://www.pro-football-reference.com), the most trusted data repository for NFL statistics.

In [180]:

```
results_url = "https://github.com/ChadT35/Data_Bootcamp_Final_Project/blob/maste
r/NFLResults2017.xlsx?raw=true"
df_results = pd.read_excel(results_url) #Data frame listing all of the team seas
on results
df_results
```

Out[180]:

	City	Team	W	L	Playoffs?	W-L%	PF	PA	PD	MoV	SoS	SRS
0	New England	Patriots	13	3	Y	0.813	458	296	162	10.1	-1.2	8.9
1	Buffalo	Bills	9	7	Y	0.563	302	359	-57	-3.6	-0.5	-4.0
2	Miami	Dolphins	6	10	N	0.375	281	393	-112	-7.0	0.7	-6.3
3	New York	Jets	5	11	N	0.313	298	382	-84	-5.3	0.3	-4.9
4	Pittsburgh	Steelers	13	3	Y	0.813	406	308	98	6.1	-1.1	5.0

5	Baltimore	Ravens	9	7	N	0.563	395	303	92	5.8	-2.4	3.4
6	Cincinnati	Bengals	7	9	N	0.438	290	349	-59	-3.7	-1.3	-5.0
7	Cleveland	Browns	0	16	N	0.000	234	410	-176	-11.0	0.0	-11.0
8	Jacksonville	Jaguars	10	6	N	0.625	417	268	149	9.3	-2.8	6.5
9	Tennessee	Titans	9	7	Y	0.563	334	356	-22	-1.4	-2.1	-3.5
10	Houston	Texans	4	12	N	0.250	338	436	-98	-6.1	-0.3	-6.4
11	Indianapolis	Colts	4	12	N	0.250	263	404	-141	-8.8	-1.3	-10.1
12	Kansas City	Chiefs	10	6	Y	0.625	415	339	76	4.8	-1.3	3.4
13	Los Angeles	Chargers	9	7	N	0.563	355	272	83	5.2	-1.5	3.6
14	Oakland	Raiders	6	10	N	0.375	301	373	-72	-4.5	-0.2	-4.7
15	Denver	Broncos	5	11	N	0.313	289	382	-93	-5.8	-0.9	-6.7
16	Philadelphia	Eagles	13	3	Y	0.813	457	295	162	10.1	-0.7	9.4
17	Dallas	Cowboys	9	7	N	0.563	354	332	22	1.4	0.2	1.6
18	Washington	Redskins	7	9	N	0.438	342	388	-46	-2.9	1.6	-1.3
19	New York	Giants	3	13	N	0.188	246	388	-142	-8.9	1.3	-7.6
20	Minnesota	Vikings	13	3	Y	0.813	382	252	130	8.1	1.0	9.1
21	Detroit	Lions	9	7	N	0.563	410	376	34	2.1	0.6	2.7
22	Green Bay	Packers	7	9	N	0.438	320	384	-64	-4.0	2.1	-1.9
23	Chicago	Bears	5	11	N	0.313	264	320	-56	-3.5	2.2	-1.3
24	New Orleans	Saints	11	5	Y	0.688	448	326	122	7.6	1.5	9.2
25	Carolina	Panthers	11	5	Y	0.688	363	327	36	2.3	2.1	4.3
26	Atlanta	Falcons	10	6	Y	0.625	353	315	38	2.4	1.9	4.3
27	Tampa Bay	Buccaneers	5	11	N	0.313	335	382	-47	-2.9	1.7	-1.3
28	Los Angeles	Rams	11	5	Y	0.688	478	329	149	9.3	-0.2	9.2
29	Seattle	Seahawks	9	7	N	0.563	366	332	34	2.1	-0.2	1.9
30	Arizona	Cardinals	8	8	N	0.500	295	361	-66	-4.1	0.4	-3.7
31	San Francisco	49ers	6	10	N	0.375	331	383	-52	-3.3	0.4	-2.9

Now to merge all of these new dataframes on the team index...

Note: Because this analysis examines the effects of salary spending to on-field results, the data only includes data for **active players** during the 2017 season and does NOT include data for injured reserve players or practice squad players. Beacuse of this, the salary cap utilization rate may seem low, but some teams had large cap space tied up in injured player contracts.

In [181]:

```
dfs = [df_team_spend, df_t_s,df_t_s3, df_t_s4,df_results ]
df_ts = reduce(lambda left,right: pd.merge(left,right,on='Team'), dfs)
df_ts
```

Out[181]:

	Team	Cap_Hit_$Ms	Cap_Utilization_%	Def	Off	ST	Bac
0	Jaguars	151.852626	90.929716	97.279494	52.083720	2.489412	13.8
1	Titans	149.109415	89.287075	85.181937	56.642810	7.284668	8.74
2	Falcons	146.513869	87.732856	64.647600	76.082935	5.783334	6.58
3	Steelers	145.814413	87.314020	61.954255	82.090158	1.770000	13.0
4	Panthers	144.903005	86.768266	71.936796	67.386209	5.580000	11.7
5	Raiders	144.377592	86.453648	62.128811	78.538781	3.710000	5.56
6	Rams	141.371844	84.653799	78.644258	60.376329	2.351257	6.25
7	Vikings	135.742794	81.283110	70.596515	63.568926	1.577353	4.53
8	Redskins	130.905482	78.386516	60.342647	67.320335	3.242500	0.82
9	Eagles	130.626714	78.219589	73.811286	54.462781	2.352647	3.21
10	Lions	130.190524	77.958398	58.742123	62.203401	9.245000	5.17
11	Patriots	129.467285	77.525320	56.474032	65.908253	7.085000	12.3
12	Bengals	128.092498	76.702095	66.498295	56.604203	4.990000	7.43
13	Chargers	127.034223	76.068397	58.623795	66.722266	1.688162	4.78
14	Seahawks	126.672119	75.851568	66.802894	56.694850	3.174375	4.97
15	Buccaneers	124.997175	74.848608	74.293604	45.707395	4.996176	8.95
16	Chiefs	117.859059	70.574287	68.996056	42.855062	6.007941	3.76
17	Broncos	117.229335	70.197207	65.420705	48.458628	3.350002	6.20
18	Cowboys	115.867306	69.381620	46.365263	62.732043	6.770000	9.20
19	Packers	114.988840	68.855593	57.704344	52.847242	4.437254	2.27

20	Bears	111.117906	66.537668	47.034192	62.442093	1.641621	3.00
21	Giants	109.096283	65.327116	63.350404	42.180879	3.565000	6.34
22	Ravens	108.395774	64.907649	40.243551	60.905557	7.246666	4.78
23	Bills	105.484437	63.164334	50.658442	50.610995	4.215000	12.9
24	Cardinals	103.743297	62.121735	61.869980	37.470170	4.403147	1.21
25	Dolphins	103.637809	62.058568	65.699090	36.087386	1.851333	3.27
26	Texans	100.044781	59.907054	52.651533	43.975748	3.417500	9.81
27	Jets	98.416921	58.932288	65.320161	31.172812	1.923948	5.16
28	Saints	95.464093	57.164128	37.998423	52.225670	5.240000	7.23
29	Colts	94.815871	56.775971	44.086258	47.510613	3.219000	4.56
30	Browns	78.561523	47.042828	34.085024	39.374210	5.102289	4.62
31	49ers	78.342849	46.911886	40.606419	34.172880	3.563550	5.52

32 rows × 32 columns

Finding the average team allocation

To find the average team allocation, I performed a mean operation on the dataframe and then extracted the primary position groups into a dictionary. I then used the dictionary to create a dataframe that could be easily viewed and manipulated.

In [468]:

```
df_avg = df_ts.mean()
df_ts_entry2 = {"D-Line":df_avg["D_Line"],"Secondary":df_avg["Secondary"],
                'Receiving Core':df_avg["Receiving_Core"],'O-Line':df_avg["O_Lin
e"],
                "Linebackers":df_avg["Linebackers"],"QB":df_avg["QB"],
                'Backfield':df_avg["Backfield"],
                "Spec. Teams":df_avg["Spec_Teams"]}
```

The following dataframe displays the average allocation for all NFL teams. The "% of Average Total" column is calculated by dividing the cap hit by the average total salary for each team - roughly $120M. Teams use about 17% of their cap on the D-Line, Secondary, and Receiving Core.

In [469]:

```
df_ts_manual = pd.DataFrame(data=df_ts_entry2,index = ["Cap"]).reindex()
df_ts_manual = df_ts_manual.transpose()
df_ts_manual.sort_values(by = "Cap",ascending=False,inplace=True)
df_ts_manual["% of Average Total"]= (df_ts_manual["Cap"] / 1.200231e+02) *100
df_ts_manual
```

Out[469]:

	Cap	% of Average Total
D-Line	21.090863	17.572337
Secondary	20.959547	17.462928
Receiving Core	20.604226	17.166884
O-Line	18.887857	15.736851
Linebackers	14.870781	12.389933
QB	12.943760	10.784391
Backfield	6.501201	5.416625
Spec. Teams	4.164817	3.470013

Teams spend about $6M more for defensive players than offensive players.

In [472]:

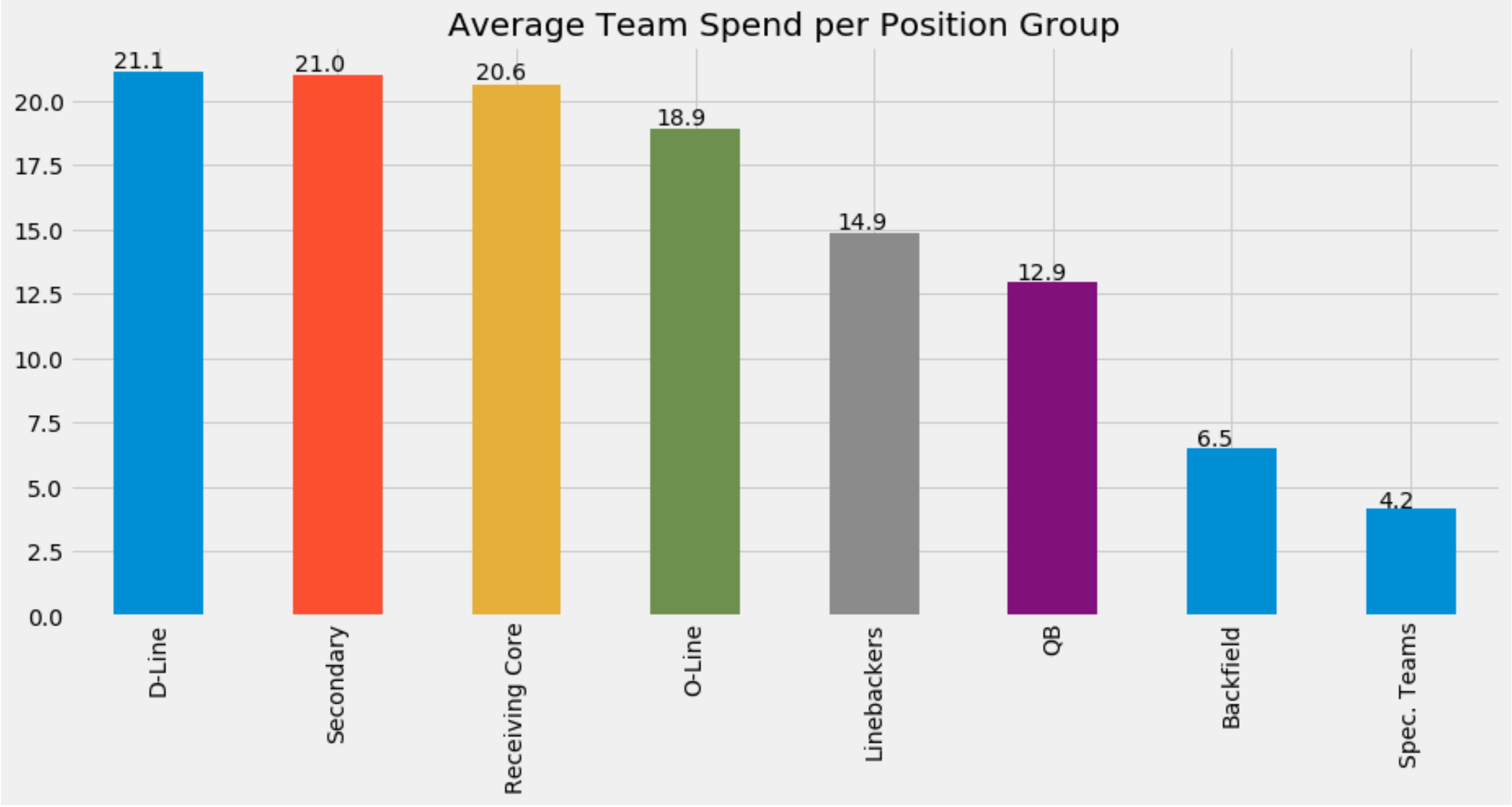
```
print("Offense:", df_avg["Off"])
print("Defense:", df_avg["Def"])
```

```
Offense: 54.919229375
Defense: 60.9390058437
```

Bar chart displaying the average total spend for each position group:

In [473]:

```
ax = df_ts_manual["Cap"].plot.bar(figsize=(14,6),width = 0.5,legend = False)
ax.set_title("Average Team Spend per Position Group")
for p in ax.patches:
    ax.annotate(str((round(p.get_height(),1))), (p.get_x() * 1.01, p.get_height(
) * 1.01))
plt.show()
```



Trends between Spending and Performance

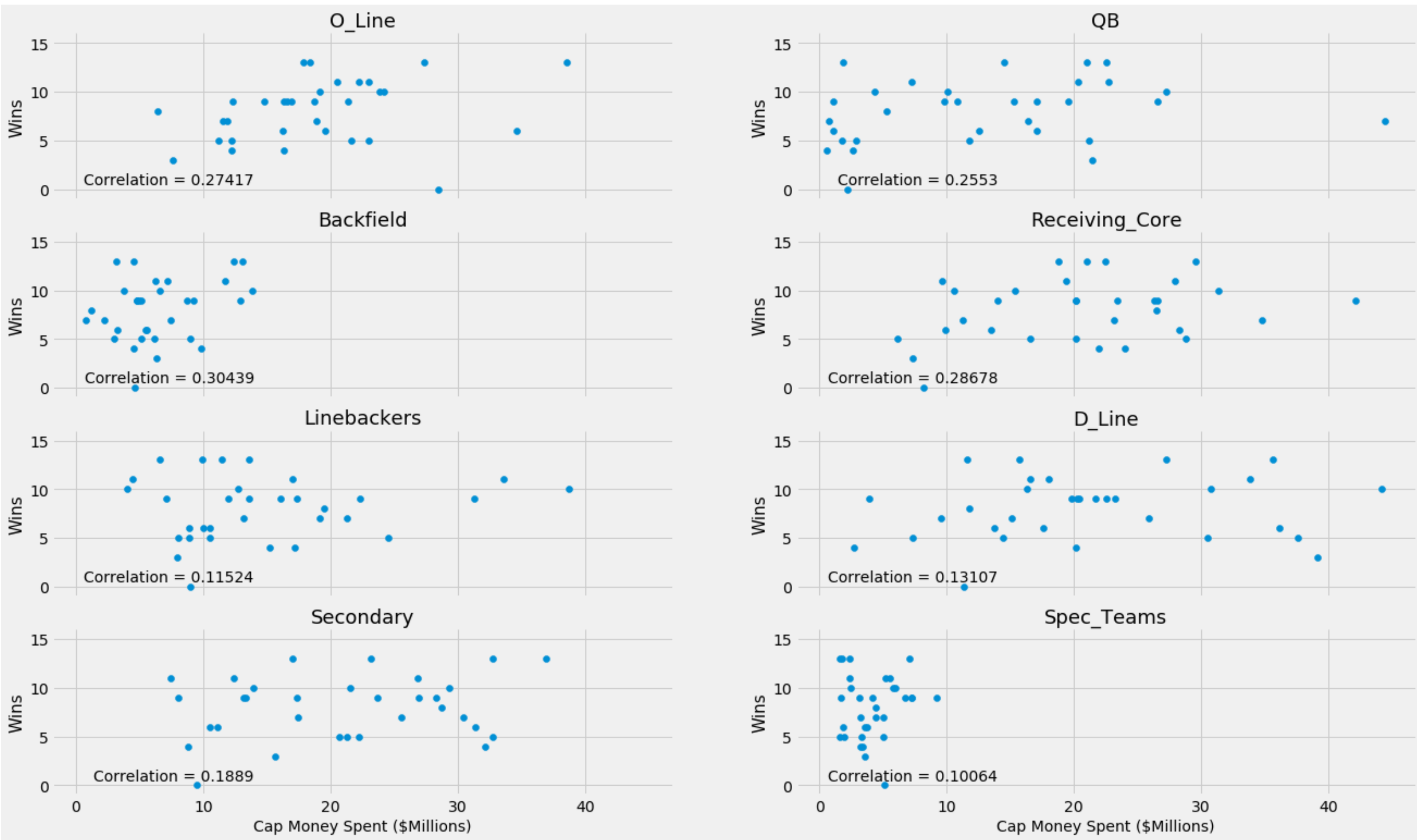
The following section will investigate how spending among different position groups effects winning and team ratings.

Primary Position Groups vs. Wins

As seen below, correlation between wins and position group spending is much higher for offensive groups than defensive groups.

In [264]:

```
fig, ax = plt.subplots(nrows=4,ncols=2,sharex=True,figsize=(20,12))
ax=ax.ravel()
var_list = ["O_Line", "QB", "Backfield","Receiving_Core", "Linebackers", "D_Line
", "Secondary", "Spec_Teams"]
count = 0
corr_mat = df_ts.corr()
for chart in ax:
    chart.scatter(df_ts[var_list[count]],df_ts["W"])
    chart.spines["right"].set_visible(False)
    chart.spines["top"].set_visible(False)
    chart.set_title(var_list[count], fontsize = 18)
    chart.set_ylabel("Wins", fontsize = 15)
    chart.set_ylim(-1,16)
    if count > 5:
        chart.set_xlabel("Cap Money Spent ($Millions)",fontsize=14)
    cr = corr_mat.W[var_list[count]]
    message = "Correlation = " + str(round(cr,5))
    chart.text(14, 0.5, message, horizontalalignment='right')
    count = count + 1
plt.show()
```

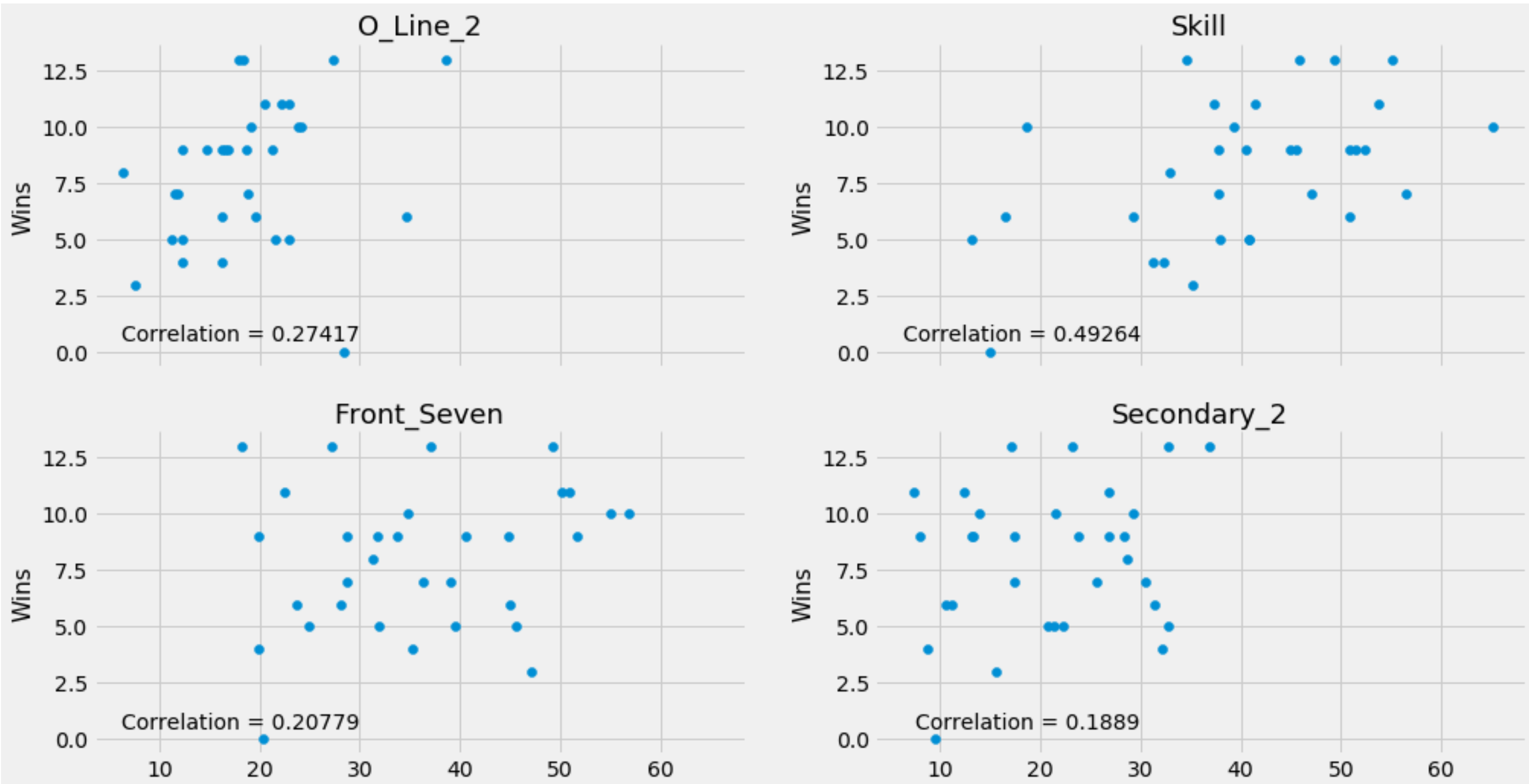


Secondary Position Groups vs Wins

The first big finding: Skill player positional spending is highly correlated with win total (0.49264).

In [261]:

```
fig, ax = plt.subplots(nrows=2,ncols=2,sharex=True,figsize=(15,8))
ax=ax.ravel()
var_list = ["O_Line_2", "Skill", "Front_Seven", "Secondary_2"]
count = 0
corr_mat = df_ts.corr()
for chart in ax:
    chart.scatter(df_ts[var_list[count]],df_ts["W"])
    chart.spines["right"].set_visible(False)
    chart.spines["top"].set_visible(False)
    chart.set_title(var_list[count], fontsize = 18)
    chart.set_ylabel("Wins", fontsize = 15)
    if count > 5:
        chart.set_xlabel("Cap Money Spent ($Millions)",fontsize=14)
    cr = corr_mat.W[var_list[count]]
    message = "Correlation = " + str(round(cr,5))
    chart.text(30, 0.5, message, horizontalalignment='right')
    count = count + 1
plt.show()
```



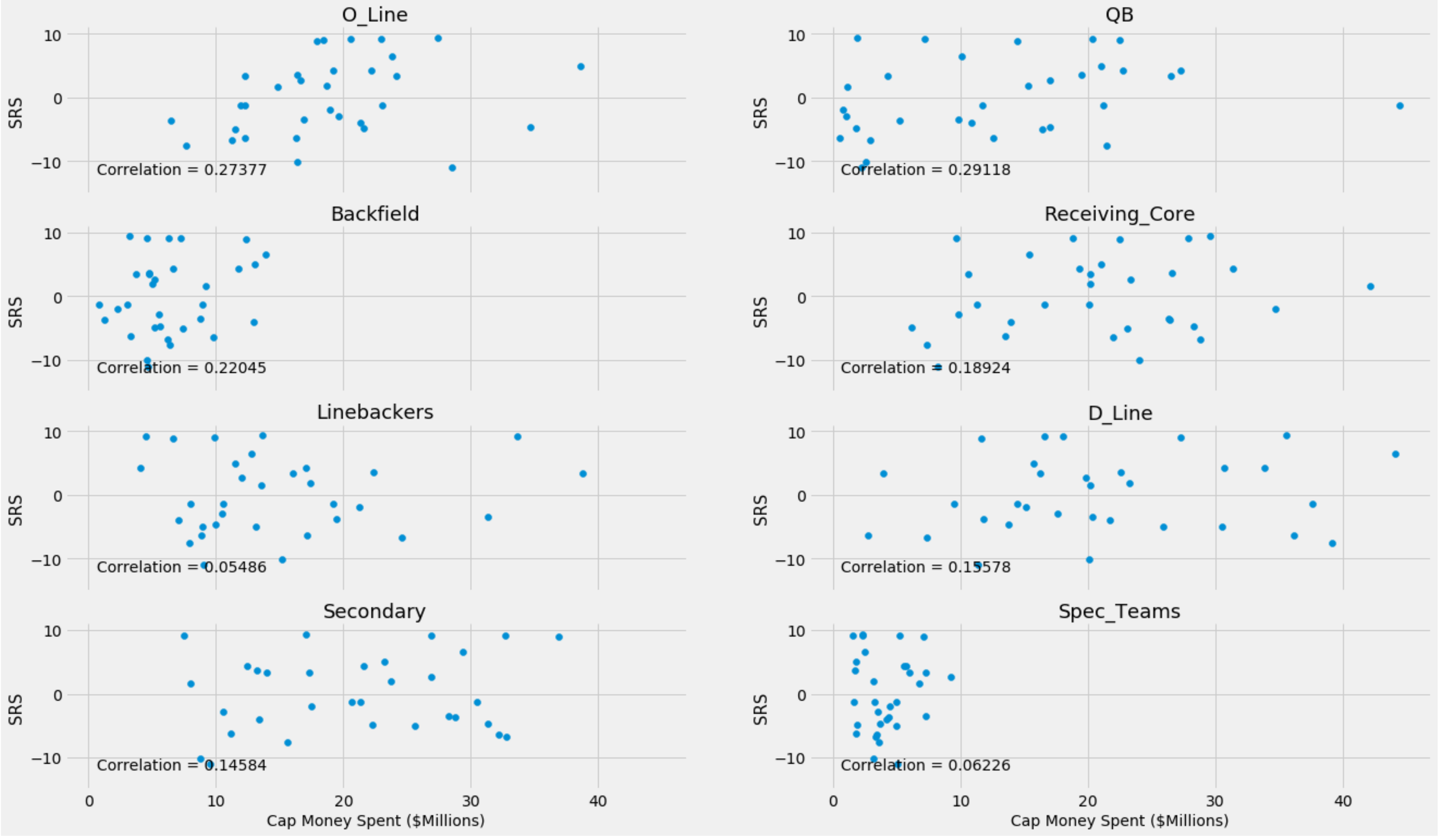
SRS

The Simple Rating System (SRS) is a metric created by Pro-Football-Reference that assigns a rating to each team with 0 being average, positive numbers meaning better than average, and negative numbers meaning worse than average. The following chart will plot position group spending vs. SRS. Again, the correlations are considerably higher for offensive position groups than defensive position groups.

Primary Position Groups vs. SRS

In [474]:

```
fig, ax = plt.subplots(nrows=4,ncols=2,sharex=True,figsize=(20,12))
ax=ax.ravel()
var_list = ["O_Line", "QB", "Backfield","Receiving_Core", "Linebackers", "D_Line
", "Secondary", "Spec_Teams"]
count = 0
corr_mat = df_ts.corr()
for chart in ax:
    chart.scatter(df_ts[var_list[count]],df_ts["SRS"])
    chart.spines["right"].set_visible(False)
    chart.spines["top"].set_visible(False)
    chart.set_title(var_list[count], fontsize = 18)
    chart.set_ylabel("SRS", fontsize = 15)
    chart.set_ylim(-15,11)
    if count > 5:
        chart.set_xlabel("Cap Money Spent ($Millions)",fontsize=14)
    cr = corr_mat.SRS[var_list[count]]
    message = "Correlation = " + str(round(cr,5))
    chart.text(14, -12, message, horizontalalignment='right')
    count = count + 1
plt.show()
```

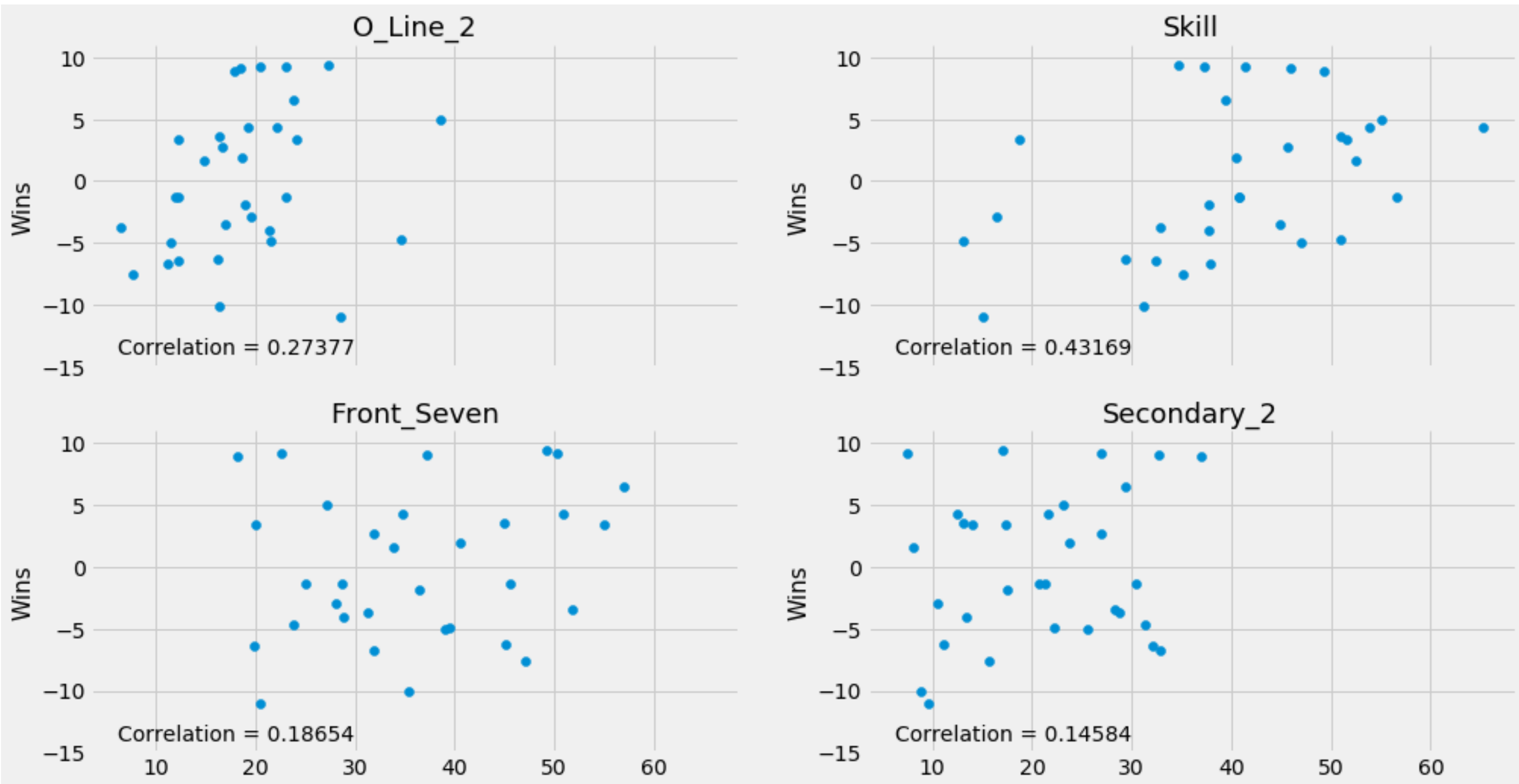


Secondary Position Groups vs. SRS

Again, skill position spending seems to be the most noticeable trend with a .43 correlation with SRS.

In [475]:

```
fig, ax = plt.subplots(nrows=2,ncols=2,sharex=True,figsize=(15,8))
ax=ax.ravel()
var_list = ["O_Line_2", "Skill", "Front_Seven", "Secondary_2"]
count = 0
corr_mat = df_ts.corr()
for chart in ax:
    chart.scatter(df_ts[var_list[count]],df_ts["SRS"])
    chart.spines["right"].set_visible(False)
    chart.spines["top"].set_visible(False)
    chart.set_title(var_list[count], fontsize = 18)
    chart.set_ylabel("Wins", fontsize = 15)
    chart.set_ylim(-15,11)
    if count > 5:
        chart.set_xlabel("Cap Money Spent ($Millions)",fontsize=14)
    cr = corr_mat.SRS[var_list[count]]
    message = "Correlation = " + str(round(cr,5))
    chart.text(30, -14, message, horizontalalignment='right')
    count = count + 1
plt.show()
```



OSRS and DSRS

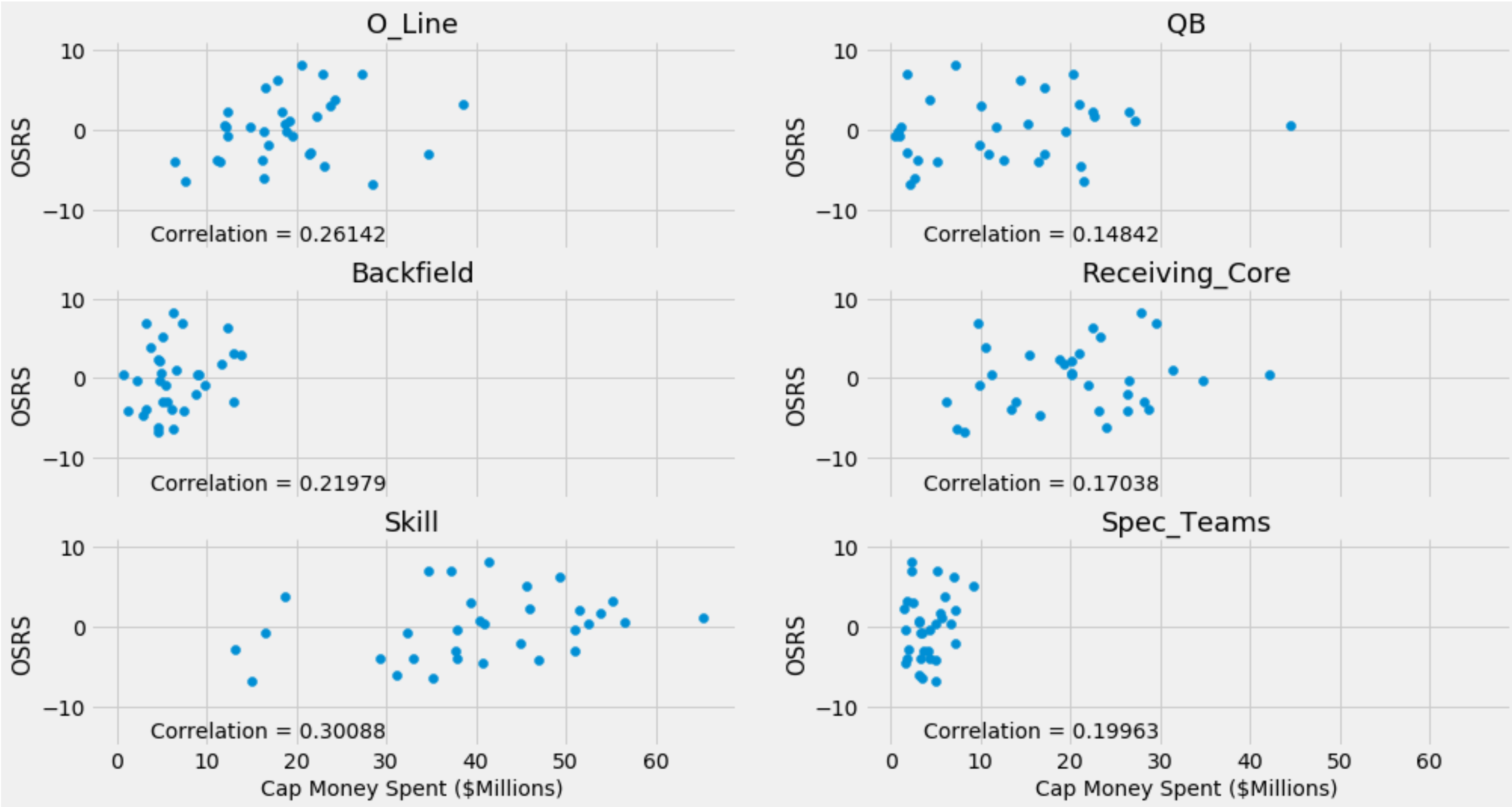
OSRS and DSRS work in the same way as SRS but are ratings of offensive (OSRS) and defensive (DSRS) strength. The following plots offensive position groups vs. OSRS. Again, skill players have the highest correlation with .30

Quarterback spending correlation is surprisingly low with only 0.14842 correlation. This is most likely due to teams spending highly on young quarterbacks who have the potential to be great but have not yet reached their potential.

Offensive Position Groups vs. OSRS

In [476]:

```
fig, ax = plt.subplots(nrows=3,ncols=2,sharex=True,figsize=(15,8))
ax=ax.ravel()
var_list = ["O_Line", "QB", "Backfield", "Receiving_Core","Skill","Spec_Teams"]
count = 0
corr_mat = df_ts.corr()
for chart in ax:
    chart.scatter(df_ts[var_list[count]],df_ts["OSRS"])
    chart.spines["right"].set_visible(False)
    chart.spines["top"].set_visible(False)
    chart.set_title(var_list[count], fontsize = 18)
    chart.set_ylabel("OSRS", fontsize = 15)
    chart.set_ylim(-15,11)
    if count > 3:
        chart.set_xlabel("Cap Money Spent ($Millions)",fontsize=14)
    cr = corr_mat.OSRS[var_list[count]]
    message = "Correlation = " + str(round(cr,5))
    chart.text(30, -14, message, horizontalalignment='right')
    count = count + 1
plt.show()
```

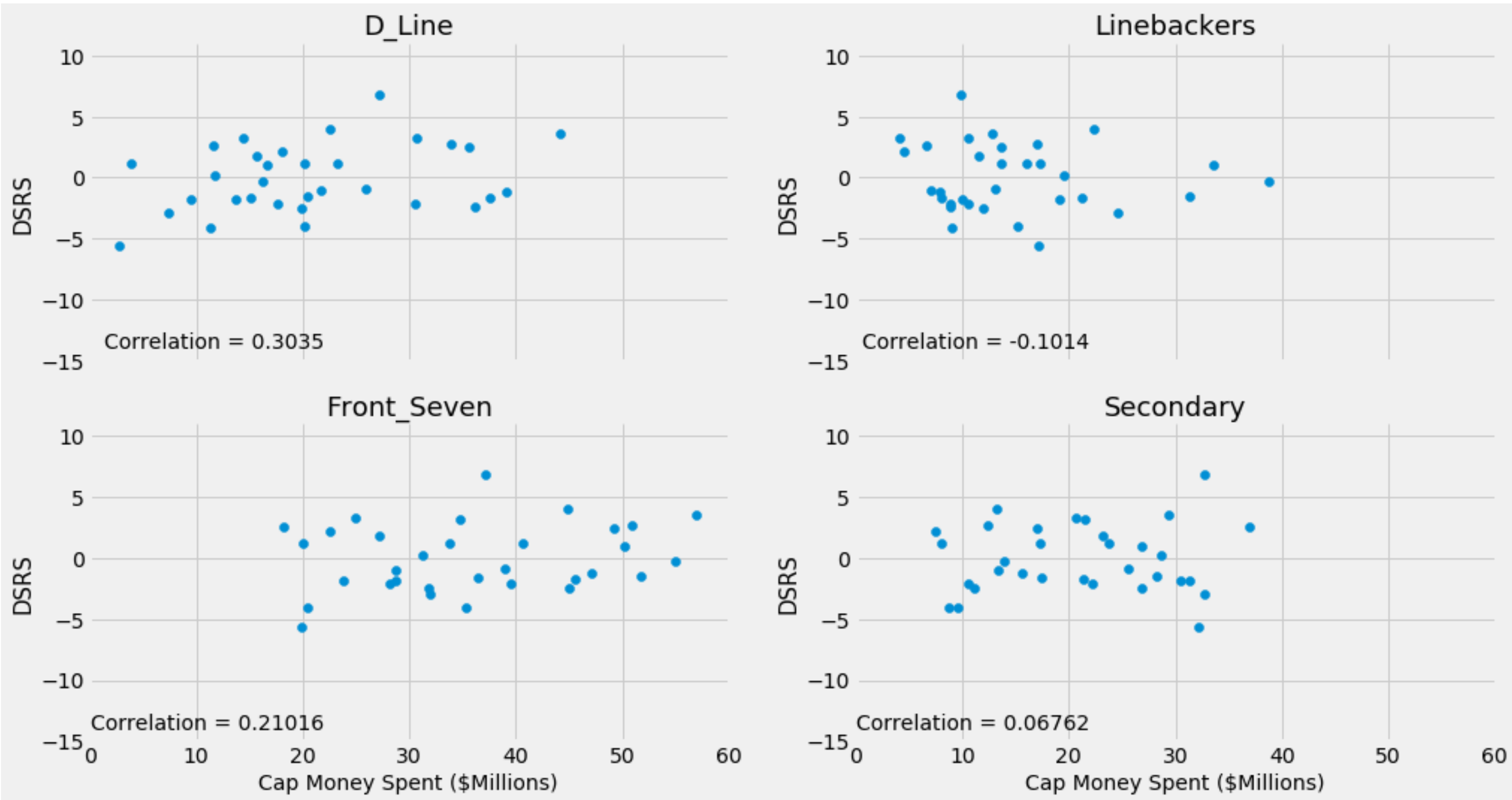


Defensive Pos Groups vs. DSRS

Surprisingly, linebackers have a negative correlation with defensive SRS. Thus, teams who allocate their money to other positions (mostly D_line - .30 correlation) have a better defensive rating.

In [536]:

```
fig, ax = plt.subplots(nrows=2,ncols=2,sharex=True,figsize=(15,8))
ax=ax.ravel()
var_list = ["D_Line", "Linebackers", "Front_Seven", "Secondary"]
count = 0
corr_mat = df_ts.corr()
for chart in ax:
    chart.scatter(df_ts[var_list[count]],df_ts["DSRS"])
    chart.spines["right"].set_visible(False)
    chart.spines["top"].set_visible(False)
    chart.set_title(var_list[count], fontsize = 18)
    chart.set_ylabel("DSRS", fontsize = 15)
    chart.set_ylim(-15,11)
    if count > 1:
        chart.set_xlabel("Cap Money Spent ($Millions)",fontsize=14)
    cr = corr_mat.DSRS[var_list[count]]
    message = "Correlation = " + str(round(cr,5))
    chart.text(22, -14, message, horizontalalignment='right')
    count = count + 1
plt.show()
```



Points for and Points Against

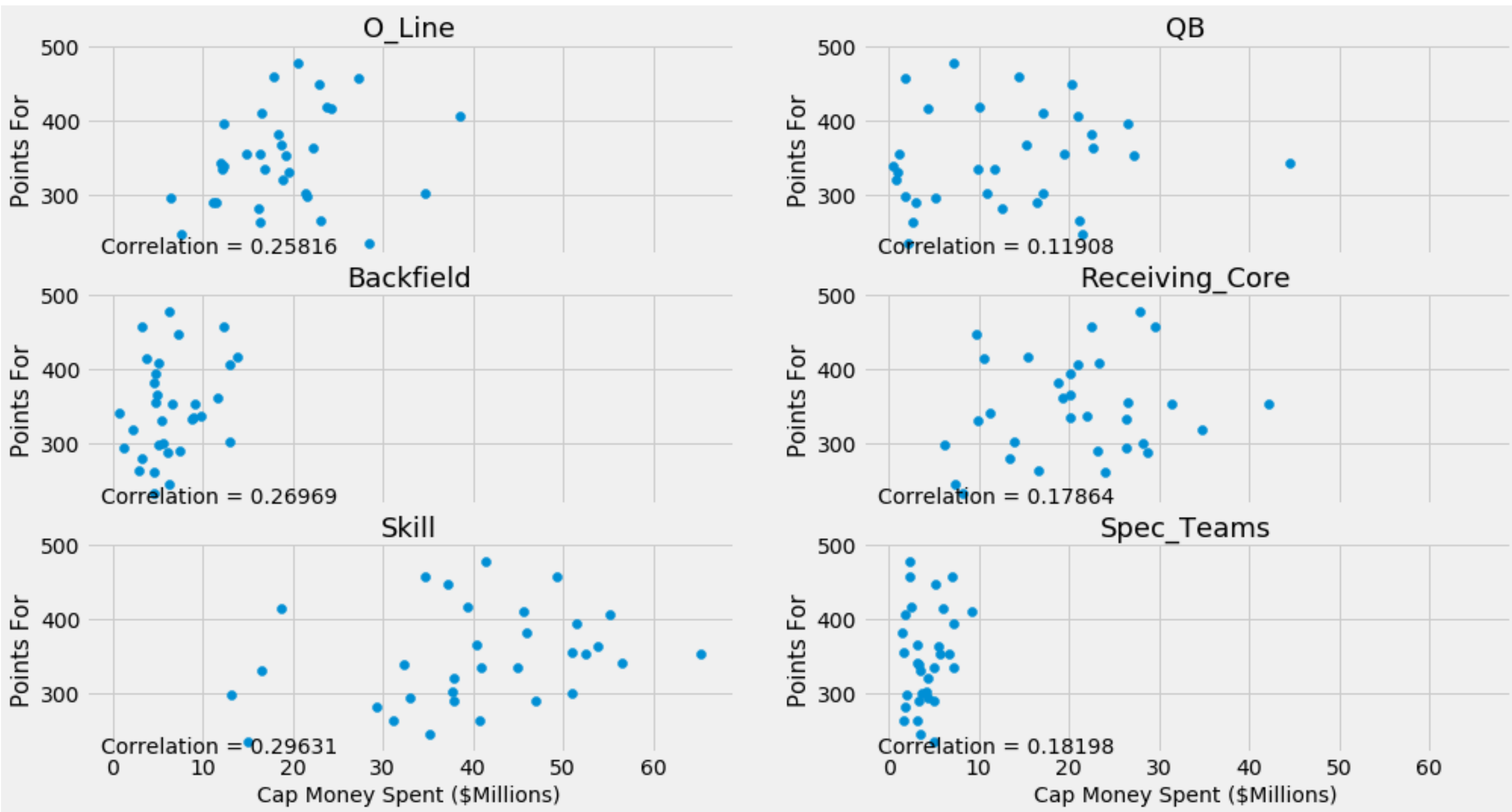
Points For (PF) is the total amount that a team scores in a given season, while Points Against (PA) is the total number scored against the team. A high PF indicates a strong offense and a low PA indicates a strong defense.

Points For vs. Offensive Positional Groups

The pattern continues that spending on the backfield and receiving core (collectively "Skill") pays dividends on the field.

In [484]:

```
fig, ax = plt.subplots(nrows=3,ncols=2,sharex=True,figsize=(15,8))
ax=ax.ravel()
var_list = ["O_Line", "QB", "Backfield", "Receiving_Core","Skill","Spec_Teams"]
count = 0
corr_mat = df_ts.corr()
for chart in ax:
    chart.scatter(df_ts[var_list[count]],df_ts["PF"])
    chart.spines["right"].set_visible(False)
    chart.spines["top"].set_visible(False)
    chart.set_title(var_list[count], fontsize = 18)
    chart.set_ylabel("Points For", fontsize = 15)
    chart.set_ylim(220,500)
    if count > 3:
        chart.set_xlabel("Cap Money Spent ($Millions)",fontsize=14)
    cr = corr_mat.PF[var_list[count]]
    message = "Correlation = " + str(round(cr,5))
    chart.text(25, 220, message, horizontalalignment='right')
    count = count + 1
plt.show()
```

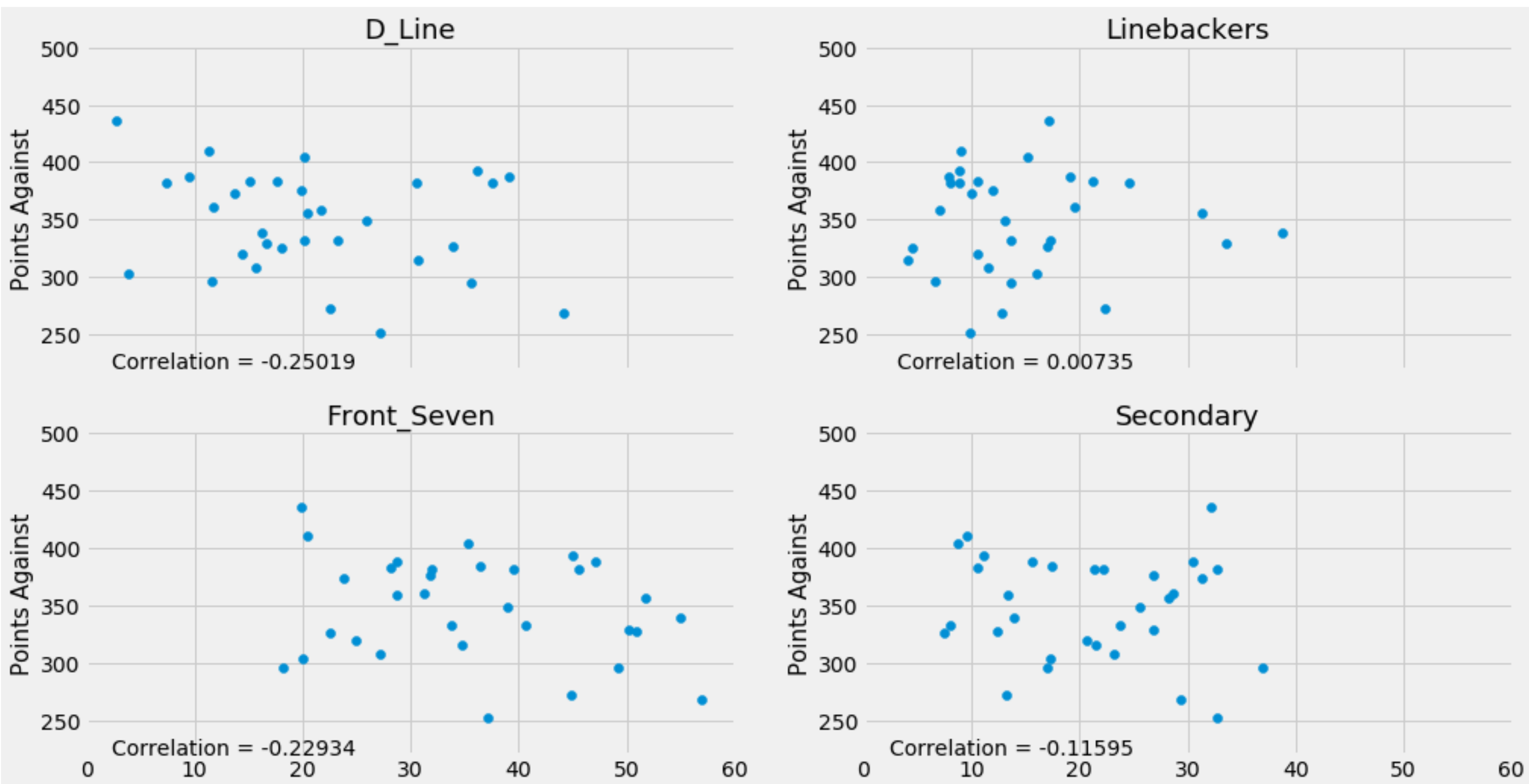


Defensive Position Groups vs. Points Against

For defense, teams want as few points against as possible, so it makes sense that we are seeing **negative correlation** for defensive positional spending. The D-Line again seems to be the best way to spend defensive money, correlation = 0.25.

In [488]:

```
fig, ax = plt.subplots(nrows=2,ncols=2,sharex=True,figsize=(15,8))
ax=ax.ravel()
var_list = ["D_Line", "Linebackers", "Front_Seven", "Secondary"]
count = 0
corr_mat = df_ts.corr()
for chart in ax:
    chart.scatter(df_ts[var_list[count]],df_ts["PA"])
    chart.spines["right"].set_visible(False)
    chart.spines["top"].set_visible(False)
    chart.set_title(var_list[count], fontsize = 18)
    chart.set_ylabel("Points Against", fontsize = 15)
    chart.set_ylim(220,500)
    if count > 3:
        chart.set_xlabel("Cap Money Spent ($Millions)",fontsize=14)
    cr = corr_mat.PA[var_list[count]]
    message = "Correlation = " + str(round(cr,5))
    chart.text(25, 220, message, horizontalalignment='right')
    count = count + 1
plt.show()
```



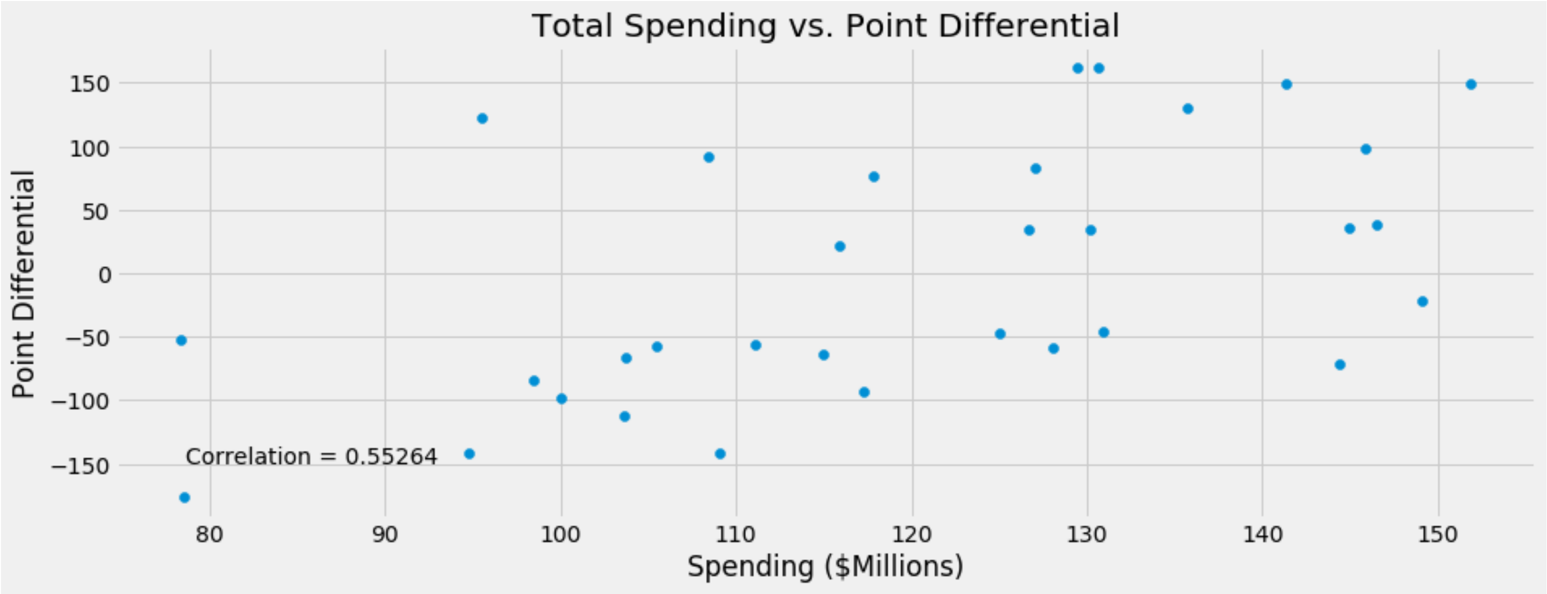
Total Spending vs. Team Performance

Now that we have compared positional groups to different success metrics, let's take a look at total team spending vs. team performance.

The correlations are much stronger here. Point differential is a simple equation that subtracts Points Against from Points Allowed. The following graphic plots Team Spending vs Point Differential and yields a 0.55 correlation.

In [528]:

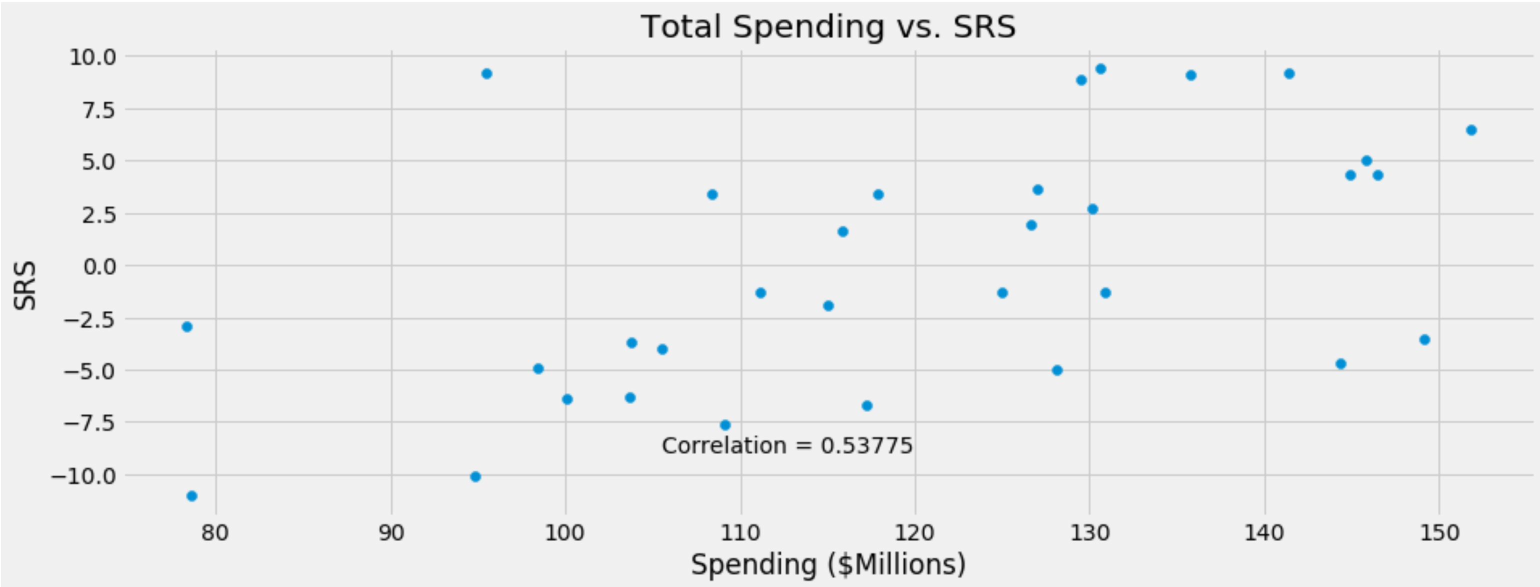
```
fig, ax = plt.subplots(figsize=(14,5))
corr_mat = df_ts.corr()
ax.scatter(df_ts["Cap_Hit_$Ms"], df_ts["PD"])
ax.set_title("Total Spending vs. Point Differential")
ax.set_xlabel("Spending ($Millions)")
ax.set_ylabel("Point Differential")
cr = corr_mat.PD["Cap_Hit_$Ms"]
message = "Correlation = " + str(round(cr,5))
ax.text(93, -150, message, horizontalalignment='right')
plt.show()
```



The following graphic plots total spending vs. SRS, and the correlation is about the same as point differential. This is not surprising as Point Differential is a variable within SRS.

In [529]:

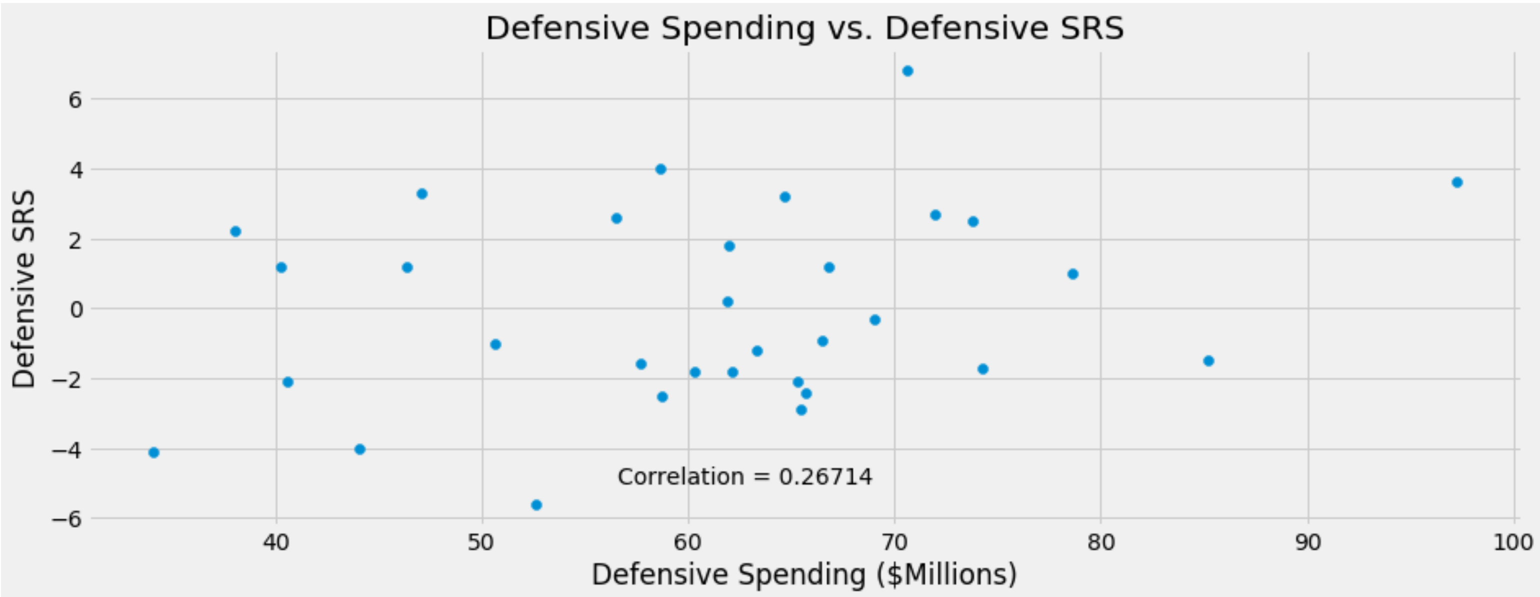
```
fig, ax = plt.subplots(figsize=(14,5))
corr_mat = df_ts.corr()
ax.scatter(df_ts["Cap_Hit_$Ms"], df_ts["SRS"])
ax.set_title("Total Spending vs. SRS")
ax.set_xlabel("Spending ($Millions)")
ax.set_ylabel("SRS")
cr = corr_mat.SRS["Cap_Hit_$Ms"]
message = "Correlation = " + str(round(cr,5))
ax.text(120, -9, message, horizontalalignment='right')
plt.show()
```



Following previous patterns, Defensive spending vs. Defensive SRS does not yield a high correlation, only 0.26.

In [530]:

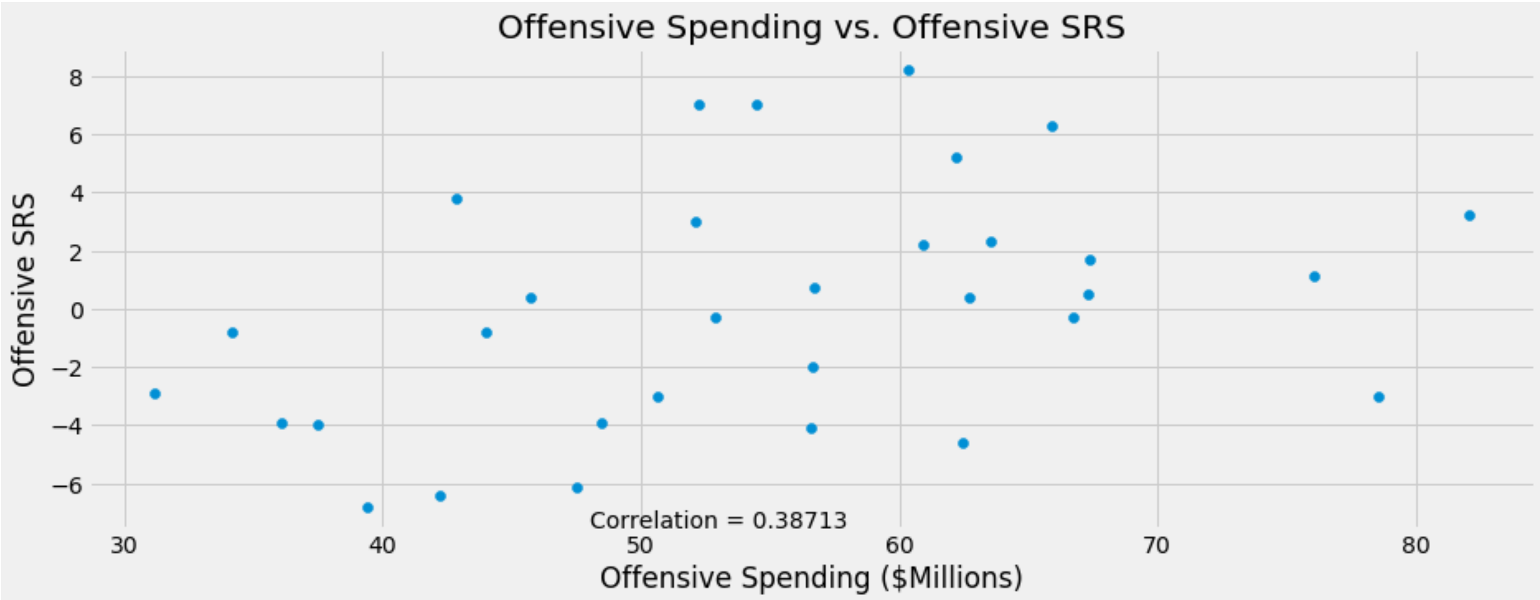
```
fig, ax = plt.subplots(figsize=(14,5))
corr_mat = df_ts.corr()
ax.scatter(df_ts["Def"], df_ts["DSRS"])
ax.set_title("Defensive Spending vs. Defensive SRS")
ax.set_xlabel("Defensive Spending ($Millions)")
ax.set_ylabel("Defensive SRS")
cr = corr_mat.DSRS["Def"]
message = "Correlation = " + str(round(cr,5))
ax.text(69, -5, message, horizontalalignment='right')
plt.show()
```



Offensive spending vs. Offensive SRS has a higher correlation with 0.38.

In [531]:

```
fig, ax = plt.subplots(figsize=(14,5))
corr_mat = df_ts.corr()
ax.scatter(df_ts["Off"], df_ts["OSRS"])
ax.set_title("Offensive Spending vs. Offensive SRS")
ax.set_xlabel("Offensive Spending ($Millions)")
ax.set_ylabel("Offensive SRS")
cr = corr_mat.OSRS["Off"]
message = "Correlation = " + str(round(cr,5))
ax.text(58, -7.5, message, horizontalalignment='right')
plt.show()
```



Conclusion and Findings

1) Quarterbacks are the highest paid: No matter how you slice it, quarterbacks are paid, on average, twice as much as any other position. This is to be expected because the QB is generally regarded as the most important position.

2) Defensive line is the highest paid positional group: Despite only having four positions on the defensive line, the D-Line (starters and backups) are paid a collective average of $20M. Defensive secondary is a close second.

3) Skill players have the highest return on salary : With a correlation of 0.49 for Wins, 0.43 for SRS, 0.30 for OSRS, and 0.29 for Points for, skill position spending stands out far above any other group in terms of correlation to on-field success. Traditional football philosophy considers skill players to be the icing on the cake, with QBs and Offensive Lineman creating the true success. However, in both SRS correlation (.43 to .27) and OSRS correlation (0.30 to 0.26), higher skill player salaries are more correlated with success.

4) Linebackers have the lowest return : Although LBs weakness does not stand out as much as the Skill strength, linebackers seem to have a low (and sometimes negative (-.10 vs. DSRS)) correlation with both team and defensive success.

5) Teams that spend more on active players have more general success : As expected, if the active player payroll is higher, teams are much better in Point Differential (0.55) and SRS (0.53).

Thank you!