Effect of Stadium Dimensions on Baseball Outcomes

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Outline:

One aspect of baseball that makes it unique among American professional sports is that the fields on which it is played are not completely standardized. Every Major League Baseball Team sets the distances and shape of its outfield walls, influencing the outcomes of identically hit baseballs in different stadiums. For example, a batted ball that results in a homerun in Boston might result in an out in St. Louis. This leads to different results occurring in games played at different stadiums, independent of player or team talent.

This project analyzes the relationship between team statistics and the shape and qualities of their stadiums. This project takes the total statistics accumulated by each team from the years 1998-2018 and examines the relationship between these statistics and the dimensions of the team's home stadium. Since each team plays most of its games in its home stadium, variations in field dimensions influenced the results seen by each team over the 20 year period. This project also anayzes the relationship between altitude of the stadiums and team stats, given that games played at higher altitude will see batted balls travel further, since the air is thinner at higher altitudes. Finally, the project also examines what happened to the Yankees and Mets before and after they each began to play in a newly built stadium.

The player data for this project was pulled from Sean Lahman's Database, and the data for each of the Stadiums was pulled from Seamheads.com.

Importing Packages

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib as mpl
import numpy as np
import seaborn as sns
```

Run Production Statistical Trends

First I read in a Master List of all the players included in the dataset, to give TeamID and Player Names.

In [2]:
```
url="https://raw.githubusercontent.com/dannyalleva"
mas="/my_first_repository/master/Master.csv"
Master=pd.read_csv(url+mas)
Master.drop(["birthYear","birthMonth","birthDay","birthCountry",
             "birthState","birthCity","deathYear","deathMonth",
           "deathDay","deathCountry","deathState","deathCity",
             "nameGiven","retroID","bbrefID"],axis=1,inplace=True)  ##
unncessary columns dropped
```

I next read in the Batting Stats for all players included in Sean Lahman's Database, select the stats for the years between 1998 and 2017, and merged it with the Master list, to connect player and team names to the statistics.

In [3]:
```
bat="/my_first_repository/master/Batting.csv"
Batting_Stats=pd.read_csv(url+bat)
Batting_Stats.set_index("yearID",inplace=True)  ##sets index to years
so I can pull specific years out easily
Years=list(range(1998,2018))  ## creates a list of every year from 199
8 to 2017
Batting_Stats=Batting_Stats.loc[Years]  ##selects just the years from
1998 to 2017 from DataFrame
```

In [4]:
```
Batting_Stats.drop(["stint","lgID"],axis=1,inplace=True)
Batting_Stats.reset_index(inplace=True) ## resets index so yearID beco
mes a normal column
Batting_Data=pd.merge(Batting_Stats,Master,how="inner",
                      on="playerID",indicator=True)  ##merges Batting
Stats with the Master List to get player info
                                                          ## attached to
stats
```

3 teams changed teamID over the time period considered. Montreal became Washington, Florida became Miami and Anaheim became Los Angeles I wanted the teams to be considered as one continuous entity for the purpose of this project so I used the replace function to make all players in these franchises appear under the same teamID

In [5]:
```
Batting_Data["teamID"].replace({"MON":"WAS","FLO":"MIA",
                                "ANA":"LAA"},
                               inplace=True)
Batting_Data.head()
```

Out[5]:

	yearID	playerID	teamID	G	AB	R	H	2B	3B	HR	...	GIDP	nameFirst	nameLa
0	1998	abbotje01	CHA	89	244	33	68	14	1	12	...	2.0	Jeff	Abbott
1	1999	abbotje01	CHA	17	57	5	9	0	0	2	...	4.0	Jeff	Abbott
2	2000	abbotje01	CHA	80	215	31	59	15	1	3	...	2.0	Jeff	Abbott
3	2001	abbotje01	MIA	28	42	5	11	3	0	0	...	1.0	Jeff	Abbott
4	1998	abbotji01	CHA	5	0	0	0	0	0	0	...	0.0	Jim	Abbott

5 rows × 29 columns

Next, I read in a dataset that included the Win-Loss records for all Major League teams for each season between 1998 and 2017.

In [6]:
```
tms="/my_first_repository/master/Teams.csv"
wins=pd.read_csv(url+tms)
wins.drop(['Ghome','lgID','DivWin', 'WCWin', 'LgWin', 'WSWin', 'R', 'A
B', 'H', '2B',
       '3B', 'HR', 'BB', 'SO', 'SB', 'CS', 'HBP', 'SF', 'RA', 'ER', 'E
RA',
       'CG', 'SHO', 'SV', 'IPouts', 'HA', 'HRA', 'BBA', 'SOA', 'E', 'D
P', 'FP',
       'name', 'park', 'attendance', 'BPF', 'PPF', 'teamIDBR',
       'teamIDlahman45', 'teamIDretro'],axis=1,inplace=True)
wins.set_index("yearID",inplace=True)
wins=wins.loc[Years]
wins.drop(["franchID","divID","Rank"],axis=1,inplace=True)
wins["w_pct"]=round((wins["W"]/wins["G"])*100,2) ## creates a column f
or win percentage, defined by wins/games*100
wins["teamID"].replace({"MON":"WAS","FLO":"MIA",
                                "ANA":"LAA"},
                               inplace=True) ## replace teams with cha
nged ID's
wins.head()
```

Out[6]:

	teamID	G	W	L	w_pct
yearID					
1998	LAA	162	85	77	52.47
1998	ARI	162	65	97	40.12
1998	ATL	162	106	56	65.43
1998	BAL	162	79	83	48.77
1998	BOS	162	92	70	56.79

Next, I used the groupby function to create DataFrames consisting of the acculumated stats for each team for Runs Batted In and Home Runs.

In [7]:
```
Team_Batting=Batting_Data.groupby("teamID")  ##groups batting Data by
team
Team_RBI=Team_Batting["RBI"].describe() ##creates statistical summary
for RBI grouped by team
Team_HR=Team_Batting["HR"].describe() ##same statistical summary for H
R
Team_RBI["RBI_Sum"]=Team_Batting.RBI.sum()  ## adds sums to the statis
tical summaries
Team_HR["HR_Sum"]=Team_Batting.HR.sum()
```

In [8]:
```
Team_RBI.head()
```

Out[8]:

	count	mean	std	min	25%	50%	75%	max	RBI_Sum
teamID									
ARI	921.0	15.235613	25.450845	0.0	0.0	2.0	18.00	142.0	14032.0
ATL	898.0	15.677060	27.179332	0.0	0.0	1.0	19.75	132.0	14078.0
BAL	938.0	15.105544	27.009713	0.0	0.0	0.0	16.75	150.0	14169.0
BOS	979.0	16.204290	29.412223	0.0	0.0	0.0	18.00	148.0	15864.0
CHA	833.0	17.374550	29.354005	0.0	0.0	0.0	23.00	152.0	14473.0

In [9]:
```
Team_HR.head()
```

Out[9]:

	count	mean	std	min	25%	50%	75%	max	HR_Sum
teamID									
ARI	921.0	3.688382	7.320873	0.0	0.0	0.0	4.0	57.0	3397
ATL	898.0	3.724944	7.824942	0.0	0.0	0.0	3.0	51.0	3345
BAL	938.0	3.955224	7.968596	0.0	0.0	0.0	4.0	53.0	3710
BOS	979.0	3.812053	7.970768	0.0	0.0	0.0	3.5	54.0	3732
CHA	833.0	4.600240	8.885887	0.0	0.0	0.0	5.0	49.0	3832

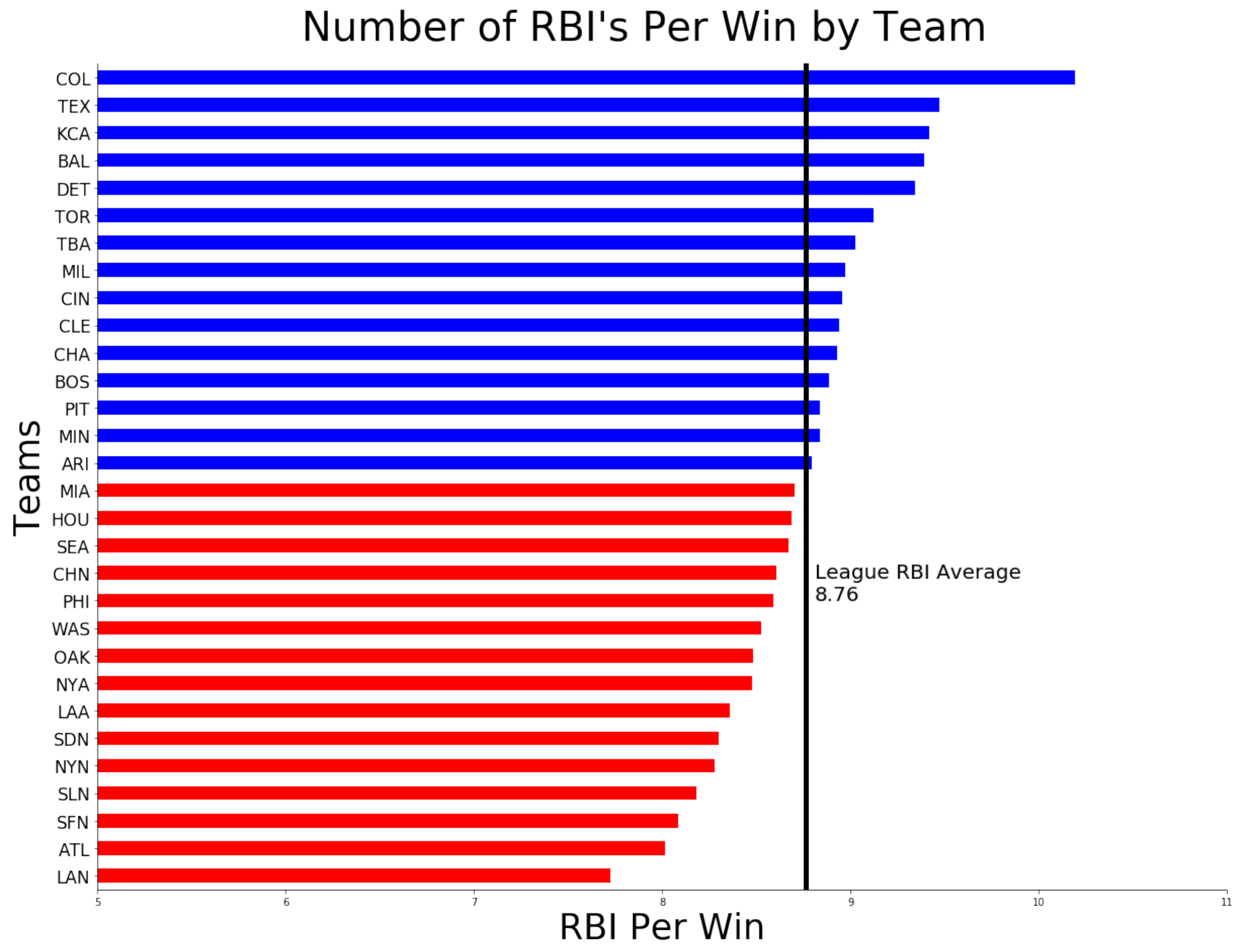
Next I apply the groupby function to the Team Win-Loss Records to get a dataframe that shows the sum of Team Wins across the time frame. I then added the wins sum dataframe to the RBI and HR dataframes for each team.

In [10]:
```
Team_Wins=wins.groupby("teamID")  ## groups team records by TeamID
Total_Wins=Team_Wins.W.sum()  ## creates a series which gives the sum of win for each team over the 20 year period
Team_RBI=Team_RBI.join(Total_Wins,how="outer") ## adds the win sums to the statistical summary data frames for RBI and
Team_HR=Team_HR.join(Total_Wins,how="outer")      ## HR
```

For the project, I chose to use Runs Batted In and Home Runs divided by the Total Number of Wins to compare teams to each other. I chose to do this in an attempt to isolate the effect playing in different home stadiums has on the statistical differences. If I had not divided by wins, it might be the case that a given team with a consistently high-talent roster over the 20 year period would have a higher RBI or HR totals due mostly to the disparity in talent. Giving these statistics per win allows for a measure of how many RBI's or HR's a team accumulated for every win they got, which I felt was a more accurate measure of how conducive a given stadium was to RBI or HR production. If a team scored a large number of runs for every win it got, it follows that that team also gave up a lot of runs. Because of this, it is logical to assume that a team with a high number for a stat like RBI/Win plays in a stadium where a lot of runs are scored by both teams.

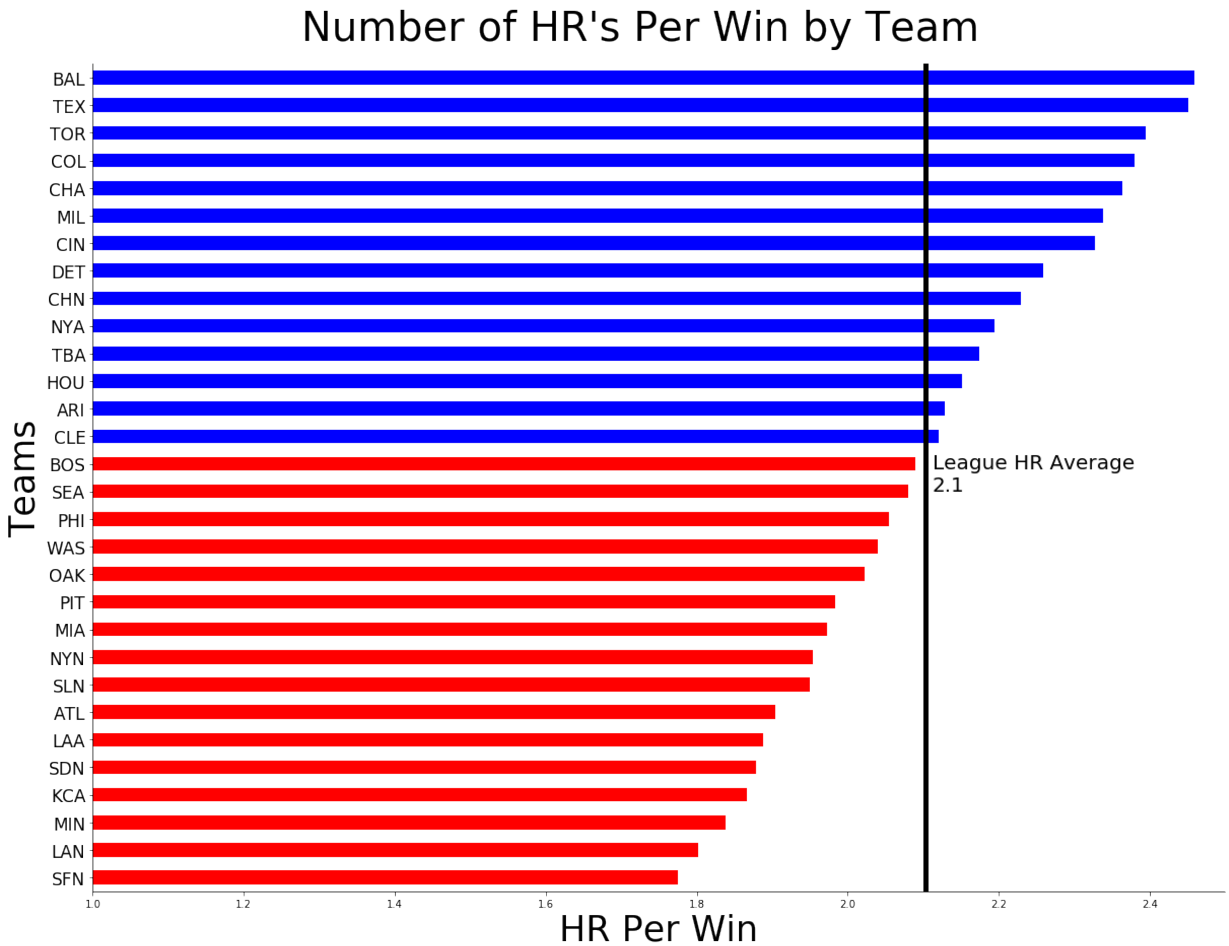
In [11]:
```
Team_RBI["RBI/Wins"]=Team_RBI["RBI_Sum"]/Team_RBI["W"]  ## x/Win colum
n created by dividing the Sum of x for each team
Team_HR["HR/Wins"]=Team_HR["HR_Sum"]/Team_HR["W"]       ## by the tota
l number of wins that team has
```

In [38]:
```
fig,ax=plt.subplots(figsize=(20,15))

colors_1=[]   ## creates an empty list of colors and then adds blue to
that list for each entry that is above average
                ## and red for each entry below average.  For some rea
son this only works when the cell has been run
                ## twice. The first time it runs it does not assign th
e colors properly.  I was not able to figure out
                ## why it doesn't work initially but it works fine whe
n it has been multiple times.
for item in Team_RBI["RBI/Wins"]:
    if item>Team_RBI["RBI/Wins"].mean():
        colors_1.append("b")
    else:
        colors_1.append("r")

Team_RBI=Team_RBI.sort_values("RBI/Wins")  ##sorts the values in Team_
RBI by RBI/Win from high to low
Team_RBI.plot(ax=ax,y="RBI/Wins",kind="barh",color=colors_1)  ##plots
a bar graph of RBI/Wins

ax.spines["right"].set_visible(False)
ax.spines["top"].set_visible(False)

ax.set_ylabel("Teams",fontsize=35)
ax.set_xlabel("RBI Per Win", fontsize=35)


avg_r=Team_RBI["RBI/Wins"].mean()
ax.axvline(x=avg_r,
          color="k", label="Average",linewidth=5)
message_r= "League RBI Average \n" + str(round(avg_r,2))  ##creates th
e line for the average

ax.text(avg_r+.05,10,message_r,fontsize=20)  ##denotes the average wit
h text


ax.legend().set_visible(False)

ax.set_xlim(5,11)

ax.set_ymargin(0)

plt.yticks(fontsize=17)

fig.suptitle("Number of RBI's Per Win by Team",fontsize=40,y=.93)

plt.show()
```



This graph gives the RBI per Win for each Major League Team from 1998 to 2017. It indicates the League Average of 8.76. Teams that are above the average are printed in blue, while teams below the average are printed in red. The Colorado Rockies, a team that plays at a significantly higher altitude than most teams, tallied by far the Most Runs Batted In per game won in the Major Leagues, while the Los Angeles Dodgers are the team that needed the fewest Runs Batted In per Game Won. This suggests that Coors Field, Colorado's Stadium, is the most friendly stadium for RBI production, while Dodger Stadium is the least friendly.

In [39]:
```
fig,ax=plt.subplots(figsize=(20,15))

colors_2=[]
for item in Team_HR["HR/Wins"]:
    if item>Team_HR["HR/Wins"].mean():
        colors_2.append("b")
    else:
        colors_2.append("r")

Team_HR=Team_HR.sort_values("HR/Wins")
Team_HR.plot(ax=ax,y="HR/Wins",kind="barh",color=colors_2)

ax.spines["right"].set_visible(False)
ax.spines["top"].set_visible(False)

ax.set_ylabel("Teams",fontsize=35)
ax.set_xlabel("HR Per Win", fontsize=35)

ax.set_xlim(1,2.5)

ax.set_ymargin(0)

avg=Team_HR["HR/Wins"].mean()
ax.axvline(x=avg,
          color="k", label="Average",linewidth=5)
message= "League HR Average \n" + str(round(avg,2))

ax.text(avg+.01,14,message,fontsize=20)

ax.legend().set_visible(False)

plt.yticks(fontsize=17)

fig.suptitle("Number of HR's Per Win by Team",fontsize=40,y=.93)
plt.show()
```



Similarly to the above graph of RBI per Win, this graph plots HR per Win for every MLB teams and indicates the League Average of 2.1. Again, blue lines indicate teams with above average home runs per win and red line indicate teams below the average. Colorado, who had the highest RBI/Win, has the 4th highest HR/Win and Los Angeles, the lowest RBI/Win team, has the 2nd lowest HR/Win, which suggest correlation between stadiums in RBI and HR production.

In [14]:
```
pitch="/my_first_repository/master/Pitching.csv"
Pitching=pd.read_csv(url+pitch)
Pitching.set_index("yearID",inplace=True)
Pitching_Stats=Pitching.loc[Years]
Pitching_Stats.drop(["stint","lgID"],axis=1,inplace=True)
Pitching_Stats.reset_index(inplace=True)
Pitching_Data=pd.merge(Pitching_Stats,Master,how="inner",
                       on="playerID",indicator=True)
Pitching_Data["teamID"].replace({"MON":"WAS","FLO":"MIA",
                                 "ANA":"LAA"},
                                inplace=True)
Pitching_Data.head()
```

```
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:5: Sett
ingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
  """
```

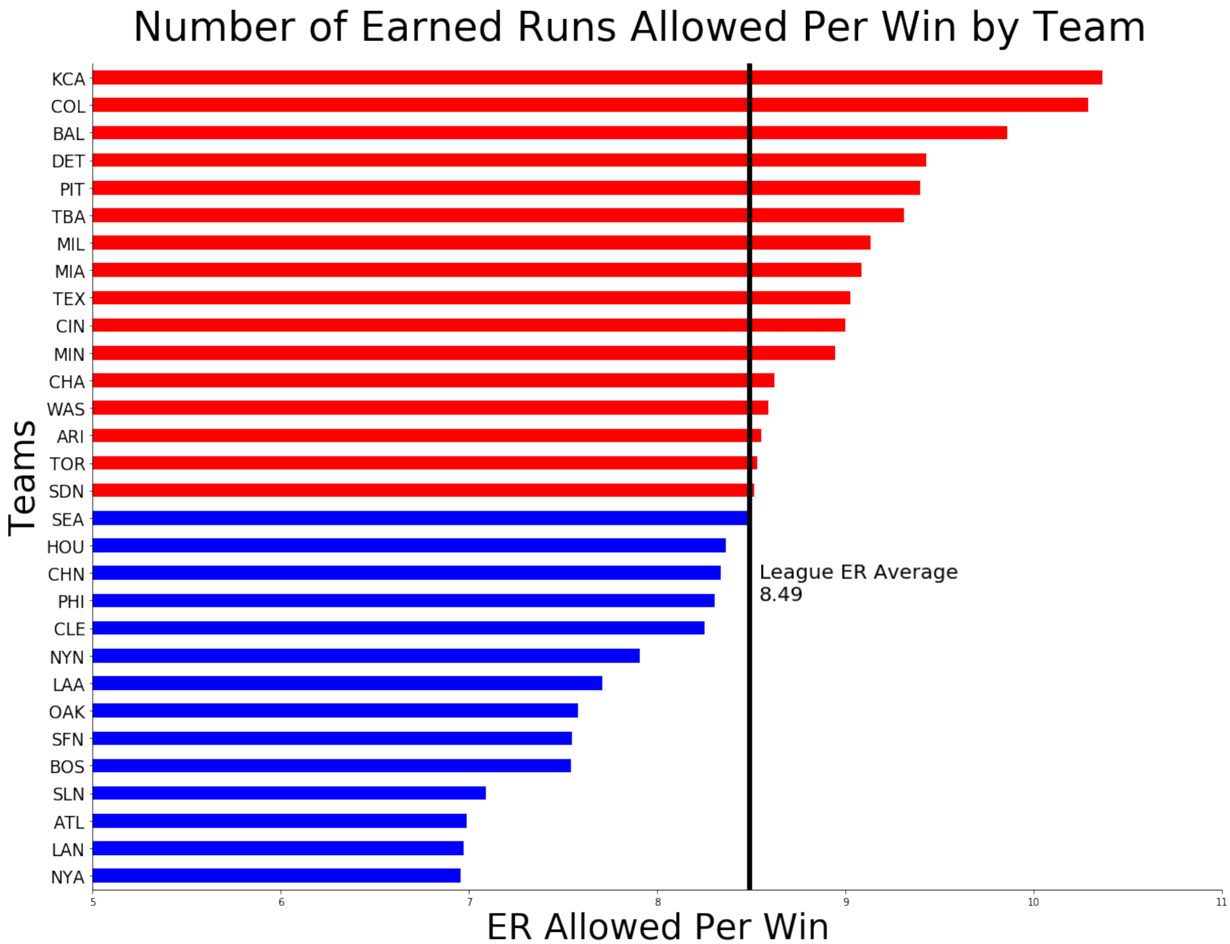
Out[14]:

	yearID	playerID	teamID	W	L	G	GS	CG	SHO	SV	...	GIDP	nameFirst	nameLa
0	1998	abbotji01	CHA	5	0	5	5	0	0	0	...	7.0	Jim	Abbott
1	1999	abbotji01	MIL	2	8	20	15	0	0	0	...	9.0	Jim	Abbott
2	1998	abbotpa01	SEA	3	1	4	4	0	0	0	...	3.0	Paul	Abbott
3	1999	abbotpa01	SEA	6	2	25	7	0	0	0	...	3.0	Paul	Abbott
4	2000	abbotpa01	SEA	9	7	35	27	0	0	0	...	20.0	Paul	Abbott

5 rows × 37 columns

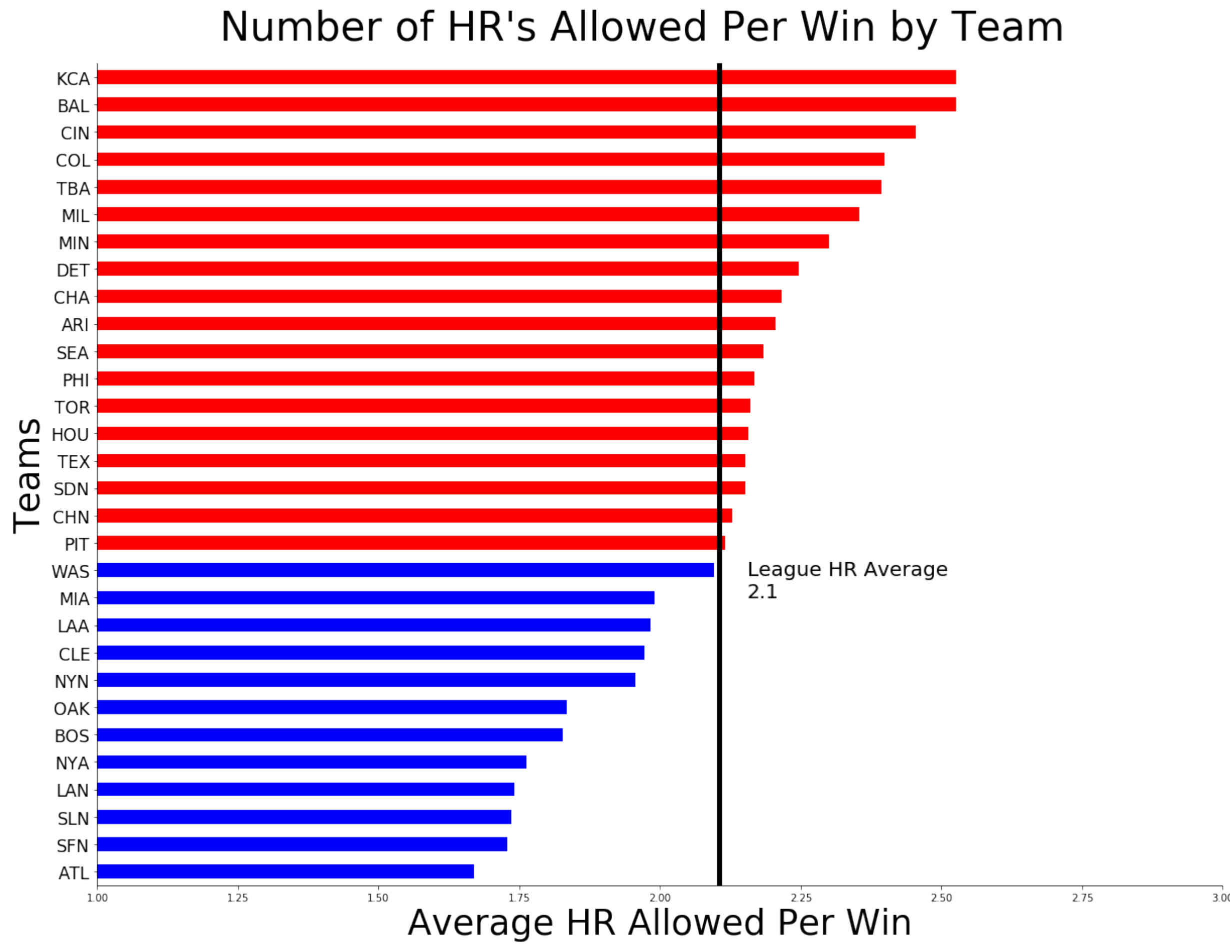
In [15]:
```
Team_Pitching=Pitching_Data.groupby("teamID")
Pitching_ER=Team_Pitching.ER.describe()
Pitching_HR=Team_Pitching.HR.describe()
Pitching_ER["ER_Sum"]=Team_Pitching.ER.sum()
Pitching_HR["HR_Sum"]=Team_Pitching.HR.sum()
Pitching_ER=Pitching_ER.join(Total_Wins,how="outer")
Pitching_HR=Pitching_HR.join(Total_Wins,how="outer")
Pitching_ER["ER/Win"]=Pitching_ER["ER_Sum"]/Pitching_ER["W"]
Pitching_HR["HR/Win"]=Pitching_HR["HR_Sum"]/Pitching_HR["W"]
```

In [40]:
```
fig,ax=plt.subplots(figsize=(20,15))

colors_3=[]
for item in Pitching_ER["ER/Win"]:
    if item>Pitching_ER["ER/Win"].mean():
        colors_3.append("r")
    else:
        colors_3.append("b")

Pitching_ER=Pitching_ER.sort_values("ER/Win")
Pitching_ER.plot(ax=ax,y="ER/Win",kind="barh",color=colors_3)


ax.spines["right"].set_visible(False)
ax.spines["top"].set_visible(False)

ax.set_ylabel("Teams",fontsize=35)
ax.set_xlabel("ER Allowed Per Win", fontsize=35)


avg_er=Pitching_ER["ER/Win"].mean()
ax.axvline(x=avg_er,
          color="k", label="Average",linewidth=5)
message_er= "League ER Average \n" + str(round(avg_er,2))

ax.text(avg_er+.05,10,message_er,fontsize=20)


ax.legend().set_visible(False)

ax.set_xlim(5,11)

ax.set_ymargin(0)

plt.yticks(fontsize=17)

fig.suptitle("Number of Earned Runs Allowed Per Win by Team",fontsize=
40,y=.93)

plt.show()
```



This graph gives each team's total Earned Runs allowed per win by their Pitchers. It indicates the league average of 8.49 and prints teams that give up more Earned Runs than average in Red and teams that give up fewer Earned Runs than average in blue. Much like RBI and HR production, Los Angeles gives up significantly below average Earned Runs per win and Colorado gives up significantly above average Earned Runs per win. The New York Yankees give up the lowest Earned Run per win in the MLB and the Kansas City Royals give up the most Earned Runs per win.

In [41]:
```
fig,ax=plt.subplots(figsize=(20,15))

colors_4=[]
for item in Pitching_HR["HR/Win"]:
    if item>Pitching_HR["HR/Win"].mean():
        colors_4.append("r")
    else:
        colors_4.append("b")

Pitching_HR=Pitching_HR.sort_values("HR/Win")
Pitching_HR.plot(ax=ax,y="HR/Win",kind="barh",color=colors_4)



ax.spines["right"].set_visible(False)
ax.spines["top"].set_visible(False)

ax.set_ylabel("Teams",fontsize=35)
ax.set_xlabel("Average HR Allowed Per Win", fontsize=35)


avg_hr=Pitching_HR["HR/Win"].mean()
ax.axvline(x=avg_hr,
          color="k", label="Average",linewidth=5)
message_hr= "League HR Average \n" + str(round(avg_hr,2))

ax.text(avg_hr+.05,10,message_hr,fontsize=20)


ax.legend().set_visible(False)

ax.set_xlim(1,3)

ax.set_ymargin(0)

plt.yticks(fontsize=17)

fig.suptitle("Number of HR's Allowed Per Win by Team",fontsize=40,y=.9
3)

plt.show()
```



This graph shows HR's allowed per win and shows the average of 2.1. Like the previous graph, teams in red gave up more HR's per win than the league average and teams in blue gave up fewer HR's than the average. Following the pattern, Los Angeles is among the bottom teams on the graph and Colorado is among the highest. Atlanta gave up the fewest HR's per win, while Kansas City gave up the most HR's per win. Kansas City gave up both the most Earned Runs and the most Home Runs per win in the League, suggesting that Pitchers who play their home games in Kansas City face increased offensive production.

Park Dimension Data

In [18]:
```
park="/my_first_repository/master/ParkConfig.csv"  ##read in dataset a
bout Parks
Park_Data=pd.read_csv(url+park)
Park_Data.set_index("Year",inplace=True)
Park_Data=Park_Data.loc[Years]
prk_names="/my_first_repository/master/Home%20Main%20Data%20With%20Par
ks%20Breakout.csv"
Park_Names=pd.read_csv(url+prk_names)
Park_Names.set_index("Year",inplace=True)
Park_Names=Park_Names.loc[Years]
Park_Names=Park_Names[["TeamID","Park_ID"]]
Park_Names.reset_index(inplace=True)
Park_Names.columns=["Year","TeamID","parkID"]
Park_Data=pd.merge(Park_Data,Park_Names,how="inner",
                   on="parkID",indicator=True)  ##merge first two park
s data set
```

In [19]:
```
pks="/my_first_repository/master/Parks.csv"  ## 3rd data set on parks
prks=pd.read_csv(url+pks)
prks.drop(["START","END","NOTES","AKA","Exact"],axis=1,inplace=True)
##cleaning up data
prks.drop(["CITY","STATE","NAME"],axis=1,inplace=True)
prks.columns=["parkID","League","Lat","Long","Alt"]
Parks_Data=pd.merge(Park_Data,prks,on="parkID",how="inner") ## merge t
his data set into existing merged dataframe
```

In [20]:
```
Parks_Data.drop(["Cover","SLF_Dim","LC_Dim","RC_Dim","LFA_Dim","LCC_Di
m","RCC_Dim","RFA_Dim","SRF_Dim"]
                ,axis=1,inplace=True)  ##cleaning up data
Parks_Data["AVG_Dim"]=((Parks_Data["LF_Dim"]+Parks_Data["CF_Dim"]
                        +Parks_Data["RF_Dim"])/3)  ## create a column
equal to the sum of dimensions to each part of
                                                  ##field and divide
by 3
Parks_Data.columns=['parkID', 'NAME', 'Capacity', 'Surface', 'Area_Fai
r', 'LF_Dim',
        'CF_Dim', 'RF_Dim', 'Backstop', 'Foul', 'LF_W',
       'LC_W', 'CF_W', 'RC_W', 'RF_W', 'Comments', 'Year', 'teamID', '
_merge',
       'League', 'Lat', 'Long', 'Alt', 'AVG_Dim']
Parks_Data["teamID"].replace({"MON":"WAS","FLO":"MIA",
                              "ANA":"LAA"},
                             inplace=True)
Parks_Data.head()
```

Out[20]:

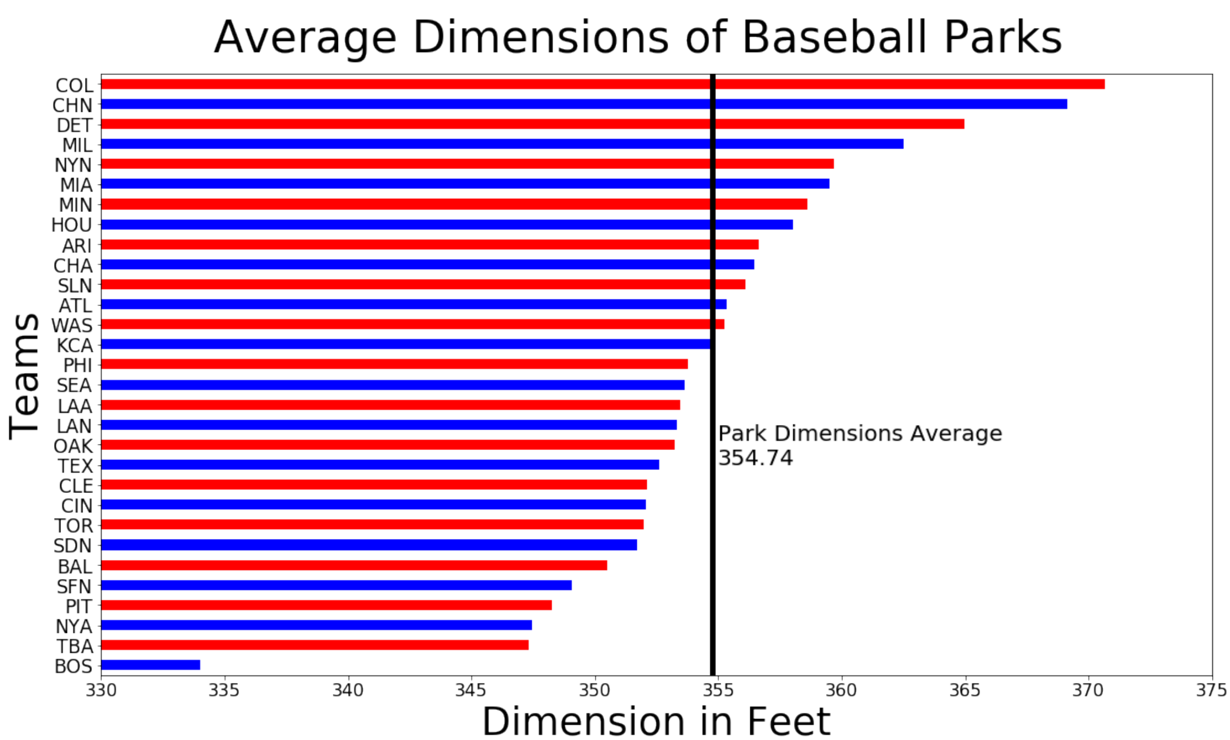
	parkID	NAME	Capacity	Surface	Area_Fair	LF_Dim	CF_Dim	RF_Dim	Backs
0	ANA01	Edison International Field of Anaheim	45054.0	N	110.0	330.0	408.0	330.0	60.0
1	ANA01	Edison International Field of Anaheim	45054.0	N	110.0	330.0	408.0	330.0	60.0
2	ANA01	Edison International Field of Anaheim	45054.0	N	110.0	330.0	408.0	330.0	60.0
3	ANA01	Edison International Field of Anaheim	45054.0	N	110.0	330.0	408.0	330.0	60.0
4	ANA01	Edison International Field of Anaheim	45054.0	N	110.0	330.0	408.0	330.0	60.0

5 rows × 24 columns

In [21]:

```
Team_Parks=Parks_Data.groupby("teamID")
Avg_Dimensions=pd.DataFrame(Team_Parks.AVG_Dim.mean())  ## creates a d
ataframe that gives the average value for average
                                                        ## dimension f
or each team.  I chose to use mean because some
                                                        ## teams have 
changed their stadium design since 1998
Avg_Dimensions["AVG_Dim"]=round(Avg_Dimensions["AVG_Dim"],2)  ## round
s avg dimension to 2 decimal points
```

In [22]:
```
fig,ax=plt.subplots(figsize=(18,10))

Avg_Dimensions=Avg_Dimensions.sort_values("AVG_Dim")
Avg_Dimensions.plot(ax=ax,kind="barh",color=[["b","r"]])


avg_dim=Avg_Dimensions["AVG_Dim"].mean()
ax.axvline(x=avg_dim,
          color="k", label="Average",linewidth=5)
message_hr= "Park Dimensions Average \n" + str(round(avg_dim,2))

ax.text(avg_dim+.23,10,message_hr,fontsize=20)

ax.set_xlim(330,375)

plt.yticks(fontsize=17)
plt.xticks(fontsize=16)
fig.suptitle("Average Dimensions of Baseball Parks",fontsize=40,y=.95)
ax.set_ylabel("Teams",fontsize=35)
ax.set_xlabel("Dimension in Feet", fontsize=35)

ax.legend().set_visible(False)

plt.show()
```



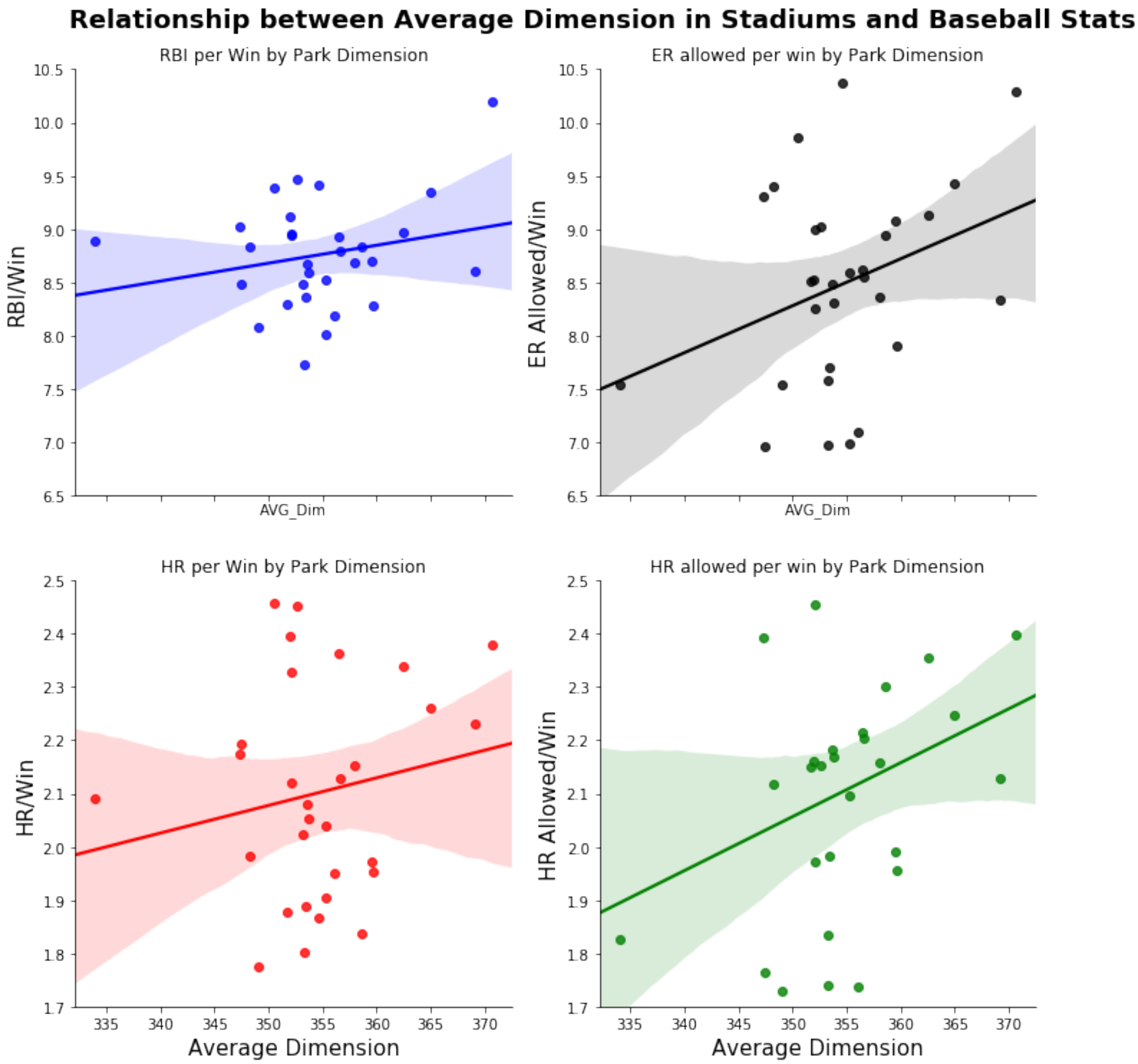
This graphs gives the Average Dimension of each team's stadium throughout the MLB. Average Dimension is defined as the sum of the distances to Left, Center, and Right Fields divided by 3. The graph also indicates that the average average dimension of an MLB stadium is 354.74 feet. Notably, Colorado has the biggest stadium and also had among the highest run scoring stats for its players. Colorado could be such a friendly environment to hitters both because of its high altitude and the fact that its field is very large, meaning that fielders have much more ground to cover. It might be that for a larger field, the probability that any given batted ball becomes a hit is higher. This is further supported by the fact that Boston's and San Francisco's (SFN) pitchers gave up below avereage Earend Runs and Home Runs per win and both teams have average stadium dimensions well below the League Average.

Plotting Run Production Stats versus Dimensions

In [23]:
```
Team_RBI=Team_RBI.join(Avg_Dimensions) ## this adds avg dimensions dat
aframe to stat summaries dataframes
Team_HR=Team_HR.join(Avg_Dimensions)
Pitching_ER=Pitching_ER.join(Avg_Dimensions)
Pitching_HR=Pitching_HR.join(Avg_Dimensions)
```

In [24]:
```
fig,[[ax1,ax2],[ax3,ax4]]=plt.subplots(ncols=2, nrows=2,figsize=(12,12
),sharex=True) ## create a figure with 4 axes
                                                ##delineating the axes
as ax1,..etc made it simpler to adjust them
                                                ## individually


sns.regplot(Team_RBI["AVG_Dim"],Team_RBI["RBI/Wins"],ax=ax1,color="b")
##I used Seaborn to plot scatter plot and line

## of best fit for each set of variables.  The

## variable listed shows up as x, the 2nd shows

## up as the y, the 3rd part indicates which

## axis and the last dictates color. Regplot

## also shades in a Confidence Interval for the

## line of best fit
sns.regplot(Team_HR["AVG_Dim"],Team_HR["HR/Wins"],ax=ax3, color="r")
sns.regplot(Pitching_ER["AVG_Dim"],Pitching_ER["ER/Win"],ax=ax2, color
="k")
sns.regplot(Pitching_HR["AVG_Dim"],Pitching_HR["HR/Win"],ax=ax4, color
```

```
="g")


ax1.set_ylabel("RBI/Win",fontsize=15)
ax2.set_ylabel("ER Allowed/Win",fontsize=15)
ax3.set_ylabel("HR/Win",fontsize=15)
ax4.set_ylabel("HR Allowed/Win",fontsize=15)

ax3.set_xlabel("Average Dimension",fontsize=15)
ax4.set_xlabel("Average Dimension",fontsize=15)

ax1.set_title("RBI per Win by Park Dimension",x=.5)
ax2.set_title("ER allowed per win by Park Dimension",x=.5)
ax3.set_title("HR per Win by Park Dimension",x=.5)
ax4.set_title("HR allowed per win by Park Dimension",x=.5)

ax1.spines["right"].set_visible(False)
ax2.spines["right"].set_visible(False)
ax3.spines["right"].set_visible(False)
ax4.spines["right"].set_visible(False)

ax1.spines["top"].set_visible(False)
ax2.spines["top"].set_visible(False)
ax3.spines["top"].set_visible(False)
ax4.spines["top"].set_visible(False)

ax4.set_ylim(1.7,2.5)
ax3.set_ylim(1.7,2.5)
ax1.set_ylim(6.5,10.5)
ax2.set_ylim(6.5,10.5)

fig.suptitle("Relationship between Average Dimension in Stadiums and B
aseball Stats",x=.55,y=.93,
             fontsize=18,fontweight="bold")
plt.show()
```

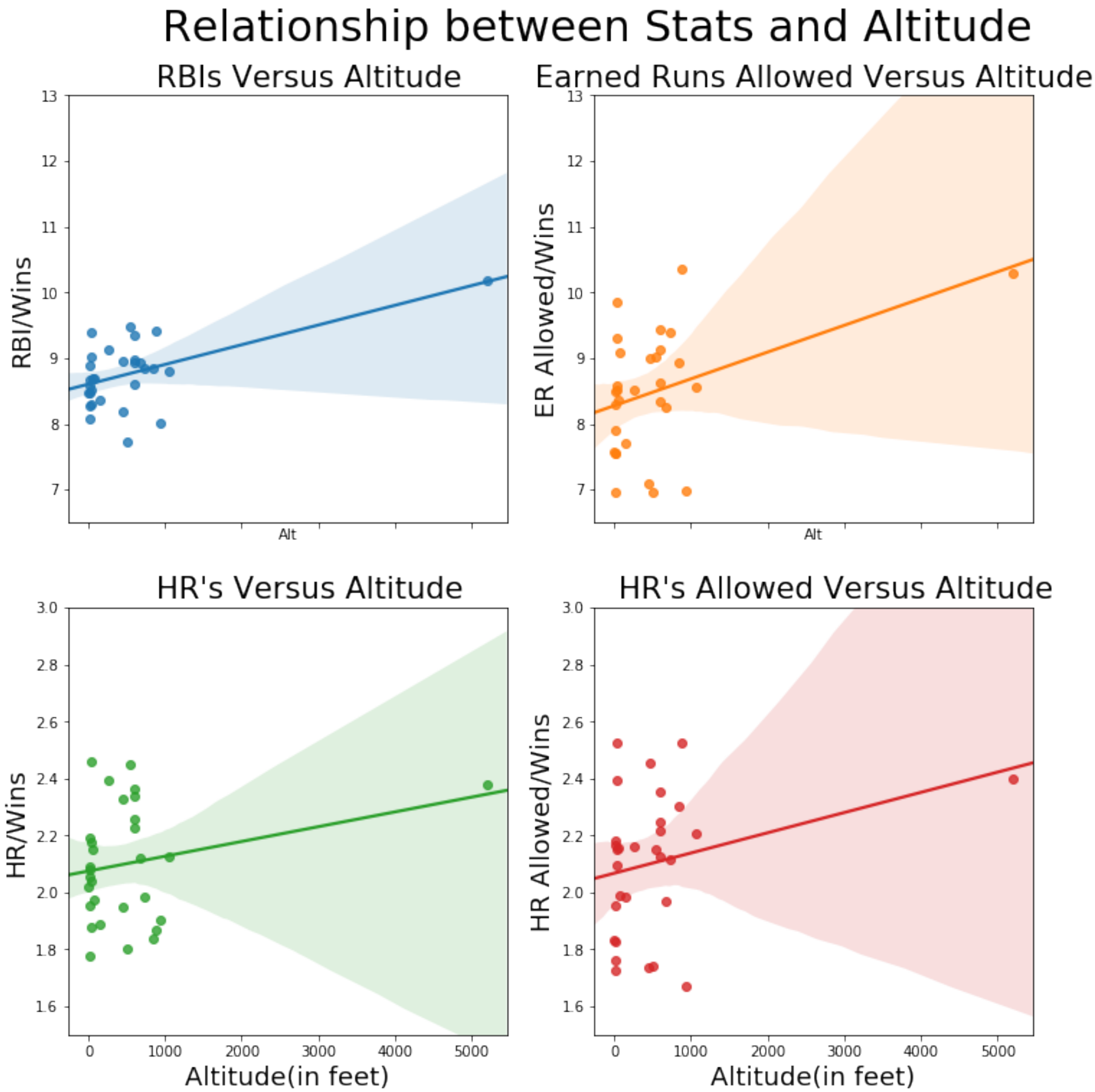


These 4 graphs plot the Average Dimensions of baseball stadiums versus the 4 stats (RBI/Win, ER Allowed/Win, HR/Win, and HR Allowed/Win) depicted in the bar graphs above. Average Dimension is on the x-axis while each stat consists of a y-axis on one of the plots. For RBI's, and ER Allowed per win, there seems to be some loose relationship between bigger stadiums and higher run production. As the average dimension of a stadium gets bigger, the total RBI/Win, and ER Allowed/Win seems to trend upward. The relationship is less clear for the Home Run stats, which seem more randomly scattered among stadiums of different sizes.

Plotting Run Production Stats against Stadium Altitudes

In [25]:
```
Altitude=pd.DataFrame(Team_Parks.Alt.mean())  ## Adding altitude data to dataframe
Pitching_ER=Pitching_ER.join(Altitude)
Team_HR=Team_HR.join(Altitude)
Pitching_HR=Pitching_HR.join(Altitude)
Team_RBI=Team_RBI.join(Altitude)
```

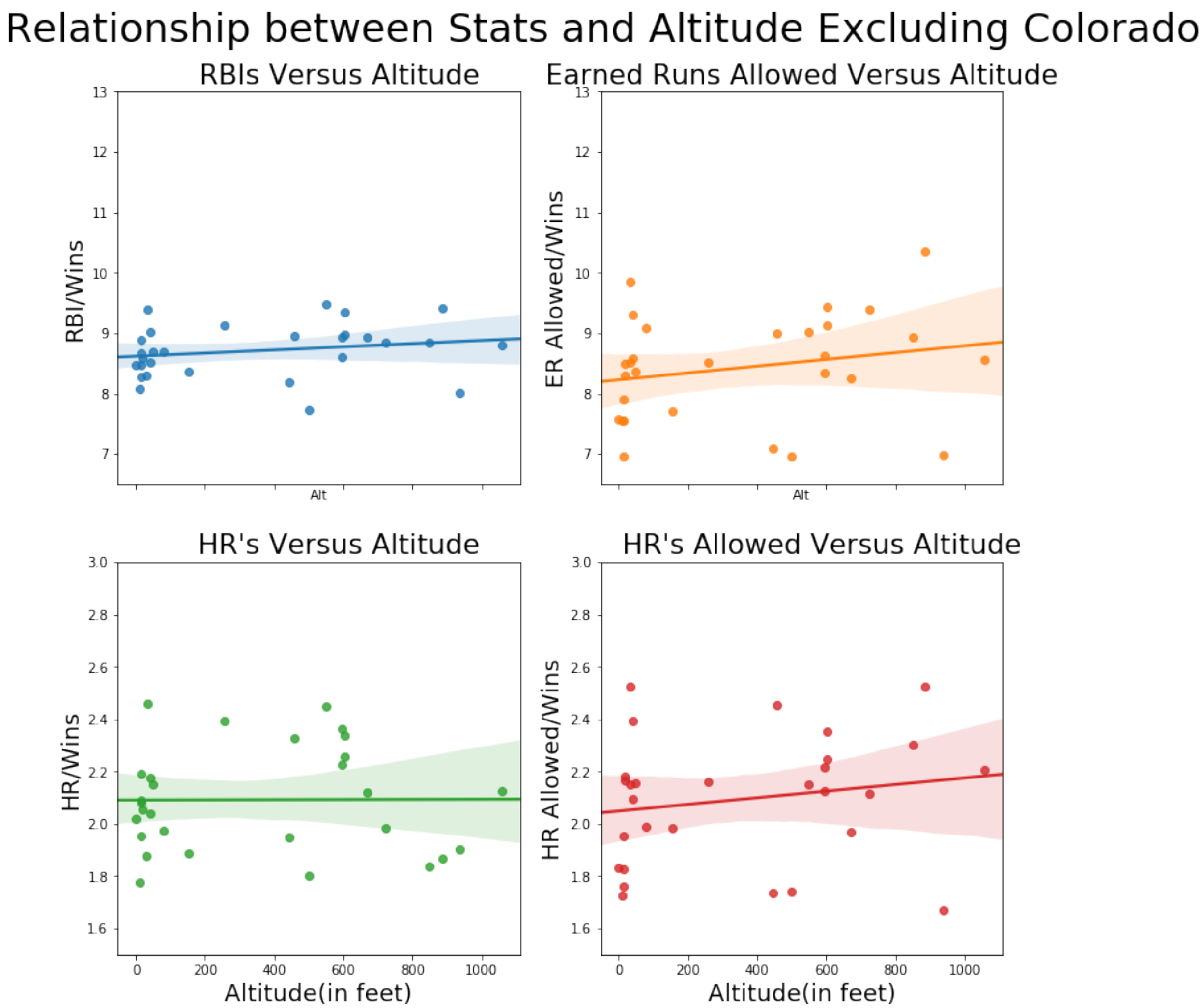
In [26]:
```
fig,[[ax1,ax2],[ax3,ax4]]=plt.subplots(ncols=2, nrows=2,figsize=(12,12),sharex=True)

sns.regplot(Team_RBI["Alt"],Team_RBI["RBI/Wins"],ax=ax1)
sns.regplot(Pitching_ER["Alt"],Pitching_ER["ER/Win"],ax=ax2)
sns.regplot(Team_HR["Alt"],Team_HR["HR/Wins"],ax=ax3)
sns.regplot(Pitching_HR["Alt"],Pitching_HR["HR/Win"],ax=ax4)


ax1.set_ylabel("RBI/Wins",fontsize=18)
ax2.set_ylabel("ER Allowed/Wins",fontsize=18)
ax3.set_ylabel("HR/Wins",fontsize=18)
ax4.set_ylabel("HR Allowed/Wins",fontsize=18)

ax3.set_xlabel("Altitude(in feet)",fontsize=18)
ax4.set_xlabel("Altitude(in feet)",fontsize=18)

ax1.set_title("RBIs Versus Altitude",fontsize=21,x=.55)
ax2.set_title("Earned Runs Allowed Versus Altitude",fontsize=21,x=.5)
ax3.set_title("HR's Versus Altitude",fontsize=21,x=.55)
ax4.set_title("HR's Allowed Versus Altitude",fontsize=21,x=.55)

ax4.set_ylim(1.5,3.0)
ax3.set_ylim(1.5,3.0)
ax2.set_ylim(6.5,13)
ax1.set_ylim(6.5,13)
fig.suptitle("Relationship between Stats and Altitude",fontsize=30,y=.95,x=.55)



plt.show()
```



These 4 graphs show the relationship between the Runs and Home Runs statistiscs and the altitudes of each stadium. Altitude is on the x-axis while each y-axis is one of the stats plotted earlier. The outlier point on the far right belongs to Colorado, who play at a substantially higher altitude than any other team in the League. I think these graphs are interesting, in that they show how abnormal Colorado's situation is compared to the rest of the League. Colorado plays at an altitude of greater than 5000 feet while almost the entire rest of the League plays at below 1000 feet. Furthermore, these graphs suggest a relationship between Colorado's altitude and their stats, since each graph suggests they are among the highest scoring teams in the league. Since Colorado is such an outlier, however, these graphs don't really communicate anything about the rest of the league clustered under 1200 feet high altitudes, so I decided to re-run these graphs excluding Colorado.

In [27]:
```
Team_List=list(Batting_Data.teamID.unique())  ## creates a list of all
teams
No_Col=list(Team_List)
No_Col.remove("COL")  ##creates new list called No_Col that removed CO
L
Team_HR_exc=Team_HR.loc[No_Col]  ##creates new dataframes using groupb
y dataframes without COL
Team_RBI_exc=Team_RBI.loc[No_Col]
Pitching_ER_exc=Pitching_ER.loc[No_Col]
Pitching_HR_exc=Pitching_HR.loc[No_Col]
```

In [28]:
```
fig,[[ax1,ax2],[ax3,ax4]]=plt.subplots(ncols=2, nrows=2,figsize=(12,12
),sharex=True)

sns.regplot(Team_RBI_exc["Alt"],Team_RBI_exc["RBI/Wins"],ax=ax1)
sns.regplot(Pitching_ER_exc["Alt"],Pitching_ER_exc["ER/Win"],ax=ax2)
sns.regplot(Team_HR_exc["Alt"],Team_HR_exc["HR/Wins"],ax=ax3)
sns.regplot(Pitching_HR_exc["Alt"],Pitching_HR_exc["HR/Win"],ax=ax4)


ax1.set_ylabel("RBI/Wins",fontsize=18)
ax2.set_ylabel("ER Allowed/Wins",fontsize=18)
ax3.set_ylabel("HR/Wins",fontsize=18)
ax4.set_ylabel("HR Allowed/Wins",fontsize=18)

ax3.set_xlabel("Altitude(in feet)",fontsize=18)
ax4.set_xlabel("Altitude(in feet)",fontsize=18)

ax1.set_title("RBIs Versus Altitude",fontsize=21,x=.55)
ax2.set_title("Earned Runs Allowed Versus Altitude",fontsize=21,x=.5)
ax3.set_title("HR's Versus Altitude",fontsize=21,x=.55)
ax4.set_title("HR's Allowed Versus Altitude",fontsize=21,x=.55)

ax4.set_ylim(1.5,3.0)
ax3.set_ylim(1.5,3.0)
ax2.set_ylim(6.5,13)
ax1.set_ylim(6.5,13)
fig.suptitle("Relationship between Stats and Altitude Excluding Colora
do",fontsize=30,y=.95,x=.55)



plt.show()
```



These are the same 4 graphs printed above just wihout Colorado. Although there seems to be a correlation between Colorado's altitude and their offensive production, that relationship does not hold true for the rest of the League's 29 teams. These graphs suggest that teams that play at marginally higher altitdues are not significantly more likely to score runs than teams playing at slightly lower altitudes. I think that this suggests that high altitudes can influence baseball scoring, but only when those altitudes become substantially higher than 1200 feet above sea level.

Handedness and Dimensions

The next thing I wanted to examine was to see if stadiums with short left field fences produce more RBI's and HR's for right handed hitters and whether short right field fences do the same for left handed hitters. Right-handed hitters are generally more likely to hit ball to left field, while left-handed hitters hit the ball to right field more often than any other part of the field. I suspected that stadiums with short distances to either corner field would produce better hitting stats for batters better positioned to take advantage. I examined this by adding a 2nd group (bats) to the group by and creating 4 dataframes one each for RBI's and HR's for Right-Handed Batters and Left-Handed Batters.

In [29]:
```
Handedness=Batting_Data.groupby(["teamID","bats"])  ## groups by team and which side player bats from
RHB=pd.DataFrame()  ##for loop adds all batters that bat right handed to RHB dataframe
for team in Team_List:
    t=Handedness.get_group((team,"R"))
    RHB=pd.concat([RHB,t])
RHB=RHB.groupby("teamID")
RHB_HR=RHB.HR.describe()  ##creates summary dataframe for each stat
RHB_RBI=RHB.RBI.describe()
RHB_HR["Sum"]=RHB.HR.sum()
RHB_RBI["Sum"]=RHB.RBI.sum()
RHB_HR.columns
```

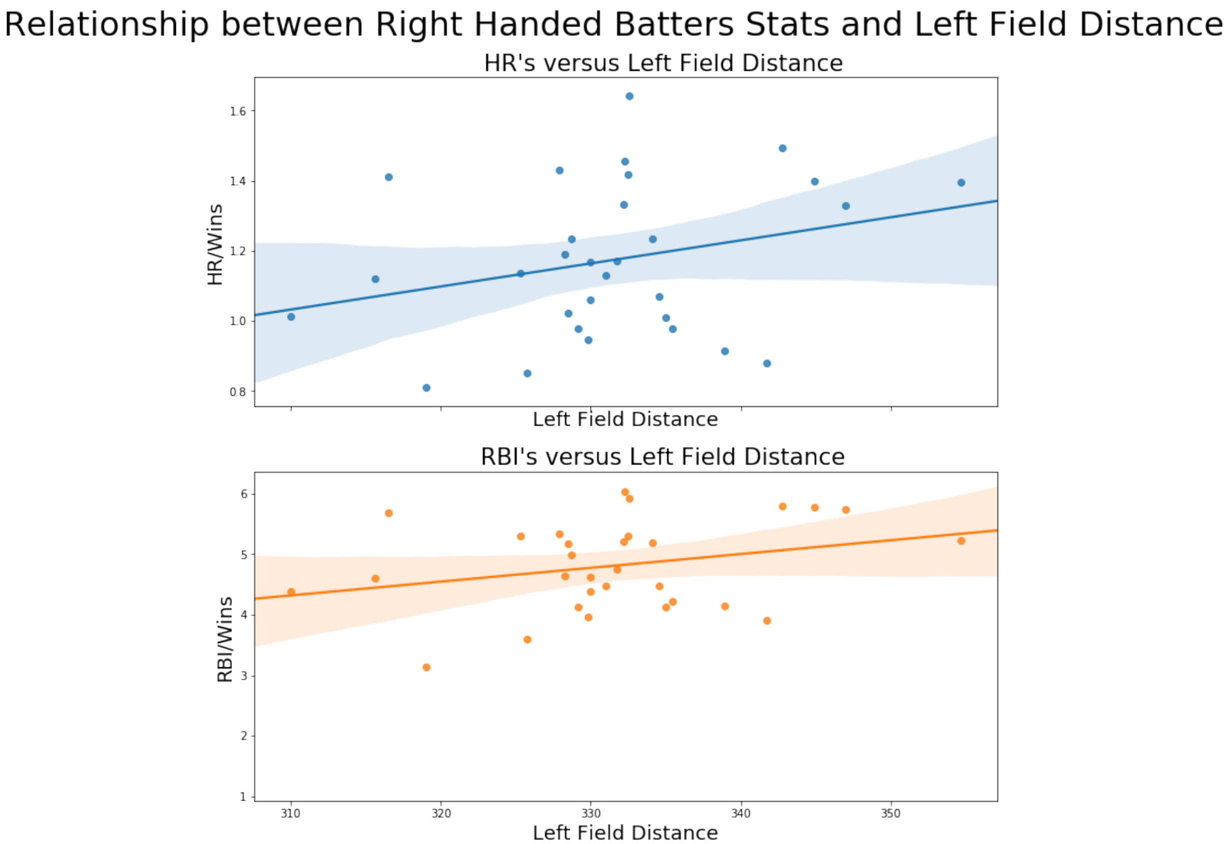
Out[29]:
```
Index(['count', 'mean', 'std', 'min', '25%', '50%', '75%', 'max', 'S
um'], dtype='object')
```

In [30]:
```
Left_Field=pd.DataFrame(round(Team_Parks.LF_Dim.mean(),2))  ##creates DataFrame for left field dimensions
RHB_HR=RHB_HR.join(Total_Wins)
RHB_HR["HR/Wins"]=RHB_HR["Sum"]/RHB_HR["W"]
RHB_HR=RHB_HR.join(Left_Field)
RHB_RBI=RHB_RBI.join(Total_Wins)
RHB_RBI["RBI/Wins"]=RHB_RBI["Sum"]/RHB_RBI["W"]
RHB_RBI=RHB_RBI.join(Left_Field)
```

In [31]:
```
LHB=pd.DataFrame()
for team in Team_List:  ##for loop adds all left handed batters to LHB dataframe
    l=Handedness.get_group((team,"L"))
    LHB=pd.concat([LHB,l])
LHB=LHB.groupby("teamID")
LHB_HR=LHB.HR.describe()  ##creates summary dataframe for each stat
LHB_RBI=LHB.RBI.describe()
LHB_HR["Sum"]=LHB.HR.sum()
LHB_RBI["Sum"]=LHB.RBI.sum()
```

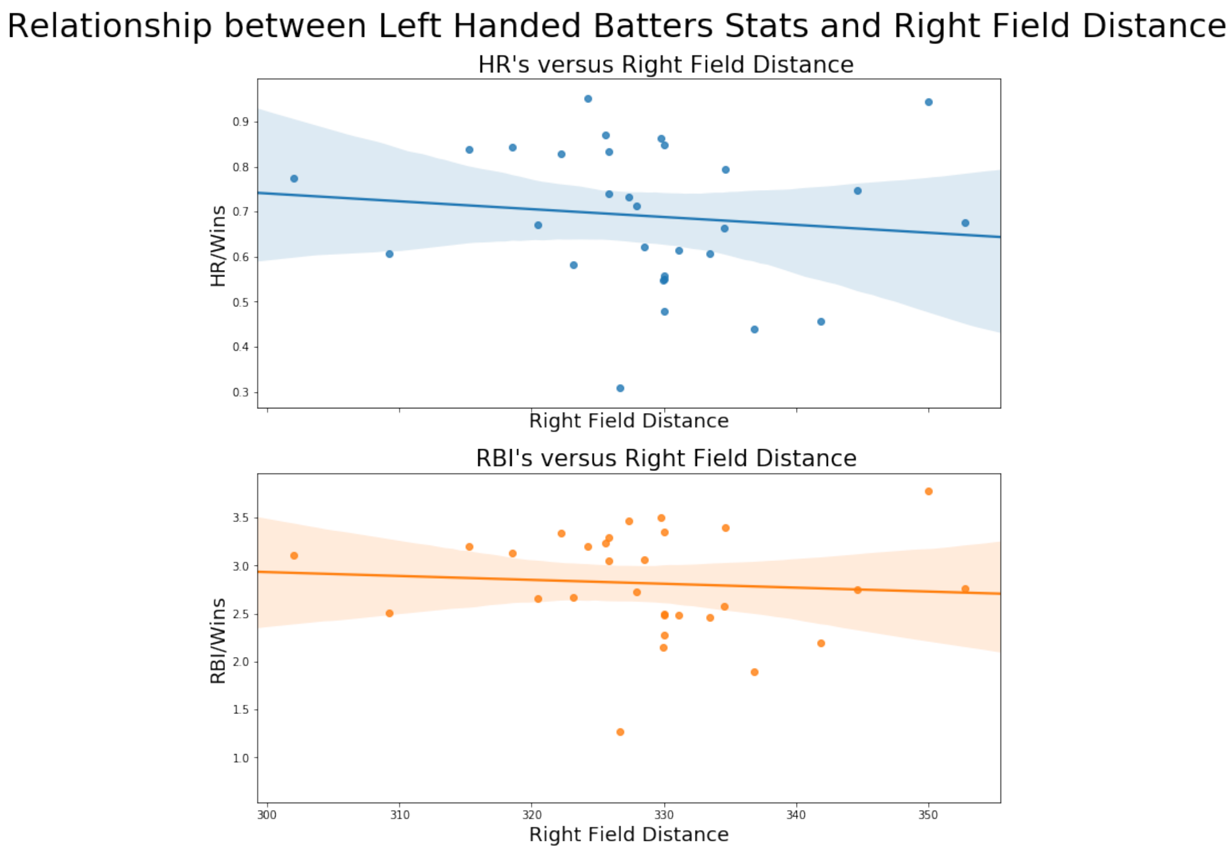
In [32]:
```
Right_Field=pd.DataFrame(round(Team_Parks.RF_Dim.mean(),2))  ##creates dataframe for Right Field Dimension
LHB_HR=LHB_HR.join(Total_Wins)
LHB_HR["HR/Wins"]=LHB_HR["Sum"]/LHB_HR["W"]
LHB_HR=LHB_HR.join(Right_Field)
LHB_RBI=LHB_RBI.join(Total_Wins)
LHB_RBI["RBI/Wins"]=LHB_RBI["Sum"]/LHB_RBI["W"]
LHB_RBI=LHB_RBI.join(Right_Field)
```

In [33]:
```
fig,ax=plt.subplots(ncols=1,nrows=2,figsize=(12,12),sharex=True)

sns.regplot(RHB_HR["LF_Dim"],RHB_HR["HR/Wins"],ax=ax[0])
sns.regplot(RHB_RBI["LF_Dim"],RHB_RBI["RBI/Wins"],ax=ax[1])

ax[0].set_ylabel("HR/Wins",fontsize=18)
ax[1].set_ylabel("RBI/Wins",fontsize=18)
ax[0].set_xlabel("Left Field Distance",fontsize=18)
ax[1].set_xlabel("Left Field Distance",fontsize=18)

fig.suptitle("Relationship between Right Handed Batters Stats and Left Field Distance",fontsize=30,y=.95)

ax[0].set_title("HR's versus Left Field Distance",fontsize=21,x=.55)
ax[1].set_title("RBI's versus Left Field Distance",fontsize=21,x=.55)



plt.show()
```



These graphs plot the relationship between HR/Win and RBI/Win for just Right Handed Batters against Left Field Distance. Interestingly, right handed batters seem to perform better in stadiums with longer left-field fences. This seems counter-intuitive to me and I don't know why that relationship might exist, or whether there is any meaning to it. The RBI/Win might be explained by the theory that longer fences means more ground for defenders to cover which leads to more hits.

In [34]:
```
fig,ax=plt.subplots(ncols=1,nrows=2,figsize=(12,12),sharex=True)

sns.regplot(LHB_HR["RF_Dim"],LHB_HR["HR/Wins"],ax=ax[0])
sns.regplot(LHB_RBI["RF_Dim"],LHB_RBI["RBI/Wins"],ax=ax[1])

ax[0].set_ylabel("HR/Wins",fontsize=18)
ax[1].set_ylabel("RBI/Wins",fontsize=18)
ax[0].set_xlabel("Right Field Distance",fontsize=18)
ax[1].set_xlabel("Right Field Distance",fontsize=18)

fig.suptitle("Relationship between Left Handed Batters Stats and Right
Field Distance",fontsize=30,y=.95)

ax[0].set_title("HR's versus Right Field Distance",fontsize=21,x=.55)
ax[1].set_title("RBI's versus Right Field Distance",fontsize=21,x=.55)


plt.show()
```



This graphs plots the relationship between HR/Win and RBI/Win for Left-Handed Batters agsinst Right Field Distance. Contrary to the Right Handed Batters, these graphs trend downward, suggesting that Left Handed Batters perform better in stadiums with shorter right fields. However, this relationship does not seem to be very strong

How Changing a Stadium Influences Run Production Stats

Finally, I decided to take an example of 2 teams, the New York Mets and the New York Yankes, who both opened new stadiums in the same year, and determine how the opening of a stadium influenced their offensive production. Citi Field (Mets) and the New Yankee Stadium both opened in 2009, which makes it easy to compare the differing impact of the 2 stadiums.

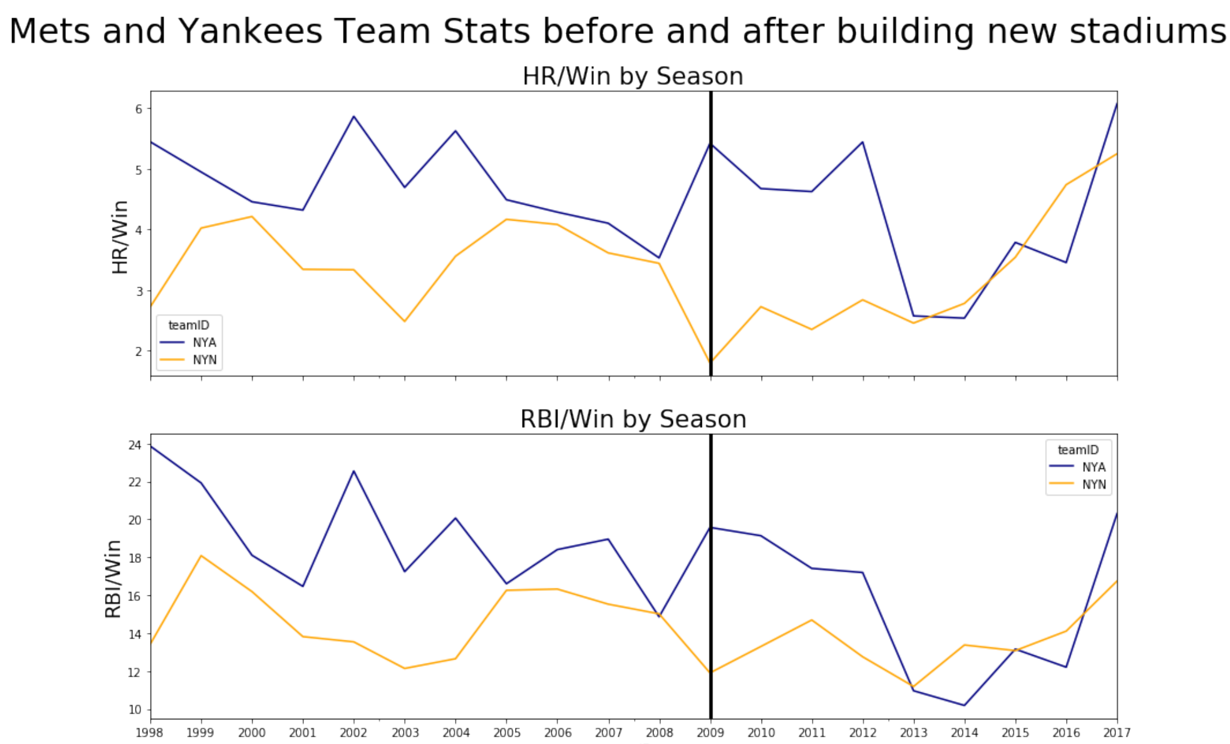
In [35]:
```
new_stad=["NYN","NYA"] ## list of teams I want to compare
New_Parks=Batting_Data.set_index("teamID").loc[new_stad]  ## pulled ou
t new team list
Batting_Parks=New_Parks.groupby(["teamID","yearID"])  ## grouped them
by both team and year
Batting_HR=Batting_Parks.HR.describe()  ##creates dataframe with summa
ry stats of HR and RBI
Batting_RBI=Batting_Parks.RBI.describe()
Batting_HR=Batting_HR.unstack(0) ##unstacking the index allows me to p
lot 2 lines, one for each team
Batting_RBI=Batting_RBI.unstack(0)
```

In [36]:
```
Batting_HR.head()
```

Out[36]:

	count		mean		std		min		25%		50
teamID	**NYA**	**NYN**	**NYA**	**NYN**	**NYA**	**NYN**	**NYA**	**NYN**	**NYA**	**NYN**	**NY**
yearID											
1998	38.0	50.0	5.447368	2.720000	9.048510	5.879886	0.0	0.0	0.0	0.0	0.0
1999	39.0	45.0	4.948718	4.022222	8.425990	8.907323	0.0	0.0	0.0	0.0	0.0
2000	46.0	47.0	4.456522	4.212766	7.799449	8.492800	0.0	0.0	0.0	0.0	0.0
2001	47.0	44.0	4.319149	3.340909	8.536638	6.914572	0.0	0.0	0.0	0.0	0.0
2002	38.0	48.0	5.868421	3.333333	10.825823	6.959865	0.0	0.0	0.0	0.0	0.0

In [37]:
```
fig,[ax1,ax2]=plt.subplots(ncols=1,nrows=2,figsize=(15,10),sharex=True
)

colors_6=["navy","orange"]

Batting_HR.plot(y="mean",kind="line",ax=ax1,color=colors_6)
Batting_RBI.plot(y="mean",kind="line",ax=ax2,color=colors_6)

new=ax1.axvline(x=2009.0,
          color="k", label="New Stadiums",linewidth=3)
new2=ax2.axvline(x=2009.0,color="k",label="New Stadium",linewidth=3)

ax1.set_xlim(1998,2017)
ax2.set_xticks(list(range(1998,2018)))

ax1.set_ylabel("HR/Win",fontsize=18)
ax2.set_ylabel("RBI/Win",fontsize=18)
ax1.set_xlabel("Seasons",fontsize=18)
ax1.set_title("HR/Win by Season",fontsize=21)
ax2.set_title("RBI/Win by Season",fontsize=21)

fig.suptitle("Mets and Yankees Team Stats before and after building ne
w stadiums",fontsize=30,y=.97)


plt.show()
```



These graphs plot the HR/Win by Season and RBI/Win by season for both the Mets and the Yankees from 1998 to 2017. The black vertical line on both graphs indicates the opening of new stadiums in 2009. The Mets are plotted in orange while the Yankees are plotted in blue. After opening their new stadium, the Mets have generally seen their offensive production trend upward. Although their was a brief slip in both HR/Win and RBI/Win for the Mets in 2013, they have generally seen an increase each year in both stats since 2009. This suggests that Citi Field might be a more offense friendly field than Shea Stadium, their previous field. The Yankees, on the other hand, saw a steep drop in both offensive stats from 2009 to 2013 followed by a steep increase from 2013 to 2017. It's not clear if anything changed in 2013 to trigger this change, but it could be that after a few seasons in their new stadium, the Yankees began to pursue players more likely to be successful given the new stadium's configuration.