Data Analysis of NBA Statistics

Topics Covered:

- #### A look into Undervalued, Underplayed, and Strong Performing Players
- #### Relationships Between Statistics/Correlation with Win Shares
- #### Valuation Model and Evaluating Players

Summary:

The purpose of this project is to analyze different NBA statistics to better understand players' values. I downloaded my data from Basketball Reference and Kaggle at the links below. I filtered my data for 2010 to 2019, eliminated duplicates within each year that came from trades and salary changes, and merged my 2019 data with the current salaries of the NBA players. Additionally, I filtered for different positions, minutes, and salaries to look more closely at the numbers and better compare players.

Throughout the project, I adjusted my dataframes to only include players who played an average of at least 2 minutes per 84 game season. This is because I continuously saw that different players who played minimal minutes had extremely high usage rates and efficiency ratings if they happened to, for example, score a three pointer in 1 minute played. I believe that this adjustment increases the reliability of my results by eliminating those skewed numbers. In analyzing player performances, I took into account the minutes played and salaries earned by each player to find those who may be undervalued or deserve more minutes. I discovered players who were most efficient with the minutes they were allocated, as well as those who gave the best return on their yearly salary. This information would help GMs and coaches make informed decisions on player personnel and usage.

In order to conduct my valuation, I first examined how different key statistics correlate with win shares. I used this stat because I believe that a player's value should be determined by how he influences his team and delivers them wins. However, strong talent within a team may disperse the win shares among the talented players, driving down each individual's statistic. Therefore, I used the correlation coefficients of key statistics over a 10 year period to determine the values of players, using the numbers to weigh the importance of each stat since win shares alone can be biased. While this is not a perfect fix for the potential dilemma, since other statistics are affected by strength of teammates, it helps diminish the flaw.

Finally, I created a valuation model by using the correlation coefficients and applying them to each player's stats. I multiplied each statistic by its coefficient, added them together, and divided the result by the number of stats used in order to average the win shares estimated for each player. This method proved to be effective, as the model showed 74% accuracy in predicting NBA all-stars over 5 years and identified potentially undervalued players. After discovering each player's value, I weighed the value of players in the top 50% of the league against their yearly salary. This analysis allowed me to discover players whose salaries are most valuable given their return. I also weighed the values against the minutes played to see which players perhaps deserve more time on the court. I repeated these methods, looking into the top performers at each position. I believe my findings would be useful to an NBA GM in deciding which players to target and carrying out different transactions.

While I believe this is a thorough analysis, I am always searching for new perspectives and ideas on how to improve my valuation. If you have any questions, comments, or concerns regarding my analysis, you may reach out to me via email at jeh606@stern.nyu.edu or phone at 610-509-1189. I am excited by any opportunity to

enhance this model, so please do not hesitate to contact me if you find anything you believe I can improve.

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Sources:

https://www.basketball-reference.com/leagues/NBA_2019_advanced.html
https://www.basketball-reference.com/leagues/NBA_2019_totals.html
https://www.basketball-reference.com/contracts/players.html
https://www.kaggle.com/drgilermo/nba-players-stats#Seasons_Stats.csv

In [1]:

```
%matplotlib inline 
import pandas as pd
pd.set_option('display.max_columns', 60)
import matplotlib.pyplot as plt
import datetime as dt
import os
import requests, io
import zipfile as zf
import shutil
import numpy as np
import statsmodels.formula.api as smf
from sklearn.linear_model import LinearRegression as reg
from patsy import dmatrices
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestRegressor as rf
from sklearn.neighbors import KNeighborsRegressor as knn
plt.style.use('seaborn')
pd.options.display.float_format = '{:,}'.format
```

In [2]:
```
# Import the statistics from 1950 through 2019
nbaStats = pd.read_csv('newstats.csv')

# Divide the statistics by year and drop duplicates that came from trade
s and signings
nbaStats10 = nbaStats.loc[nbaStats['Year'] == 2010]
nbaStats10 = nbaStats10.drop_duplicates(subset = 'Player', keep = 'firs
t')

nbaStats11 = nbaStats.loc[nbaStats['Year'] == 2011]
nbaStats11 = nbaStats11.drop_duplicates(subset = 'Player', keep = 'firs
t')

nbaStats12 = nbaStats.loc[nbaStats['Year'] == 2012]
nbaStats12 = nbaStats12.drop_duplicates(subset = 'Player', keep = 'firs
t')

nbaStats13 = nbaStats.loc[nbaStats['Year'] == 2013]
nbaStats13 = nbaStats13.drop_duplicates(subset = 'Player', keep = 'firs
t')
```

```
nbaStats14 = nbaStats.loc[nbaStats['Year'] == 2014]
nbaStats14 = nbaStats14.drop_duplicates(subset = 'Player', keep = 'firs
t')

nbaStats15 = nbaStats.loc[nbaStats['Year'] == 2015]
nbaStats15 = nbaStats15.drop_duplicates(subset = 'Player', keep = 'firs
t')

nbaStats16 = nbaStats.loc[nbaStats['Year'] == 2016]
nbaStats16 = nbaStats16.drop_duplicates(subset = 'Player', keep = 'firs
t')

nbaStats17 = nbaStats.loc[nbaStats['Year'] == 2017]
nbaStats17 = nbaStats17.drop_duplicates(subset = 'Player', keep = 'firs
t')

nbaStats18 = nbaStats.loc[nbaStats['Year'] == 2018]
nbaStats18 = nbaStats18.drop_duplicates(subset = 'Player', keep = 'firs
t')

nbaStats19 = nbaStats.loc[nbaStats['Year'] == 2019]
nbaStats19 = nbaStats19.drop_duplicates(subset = 'Player', keep = 'firs
t')
nbaStats19['USG'] = nbaStats19['USG%']
nbaStats19['eFGpct'] = nbaStats19['eFG%']
nbaStats19['TOVpct'] = nbaStats19['TOV%']
nbaStats19 = nbaStats19.drop(columns = (['Unnamed: 0','ORB%','DRB%','TR
B%','AST%','STL%','BLK%',
                                         '2P','2PA','2P%','OWS','DWS','OBPM'
,'DBPM','PF','USG%']))
# Create a dataframe for a ten year span to use when running regressions
nbaStats10yr = (nbaStats10.append(nbaStats11).append(nbaStats12).append(
nbaStats13).append(nbaStats14)
                .append(nbaStats15).append(nbaStats16).append(nbaStats17
).append(nbaStats18)
                .append(nbaStats19))
# Change title of usage column to avoid complications during regression
 and drop unused columns
nbaStats10yr['USG'] = nbaStats10yr['USG%']
nbaStats10yr['eFGpct'] = nbaStats10yr['eFG%']
nbaStats10yr['TOVpct'] = nbaStats10yr['TOV%']
nbaStats10yr = nbaStats10yr.drop(columns = (['Unnamed: 0','ORB%','DRB%',
'TRB%','AST%','STL%','BLK%','TOV%',
                                         '2P','2PA','2P%','OWS','DWS','OBPM'
,'DBPM','PF','USG%']))

# Import salary data for current NBA salaries and drop unused columns
salary = pd.read_excel("NBAcurrentSalaries.xls")
salary.drop(['Rk','Tm', '2020-21', '2021-22', '2022-23', '2023-24', '202
4-25', '2025-26', 'Signed Using'], axis=1, inplace=True) # drop unneeded
columns
salary['Salary/Year'] = salary['Salary/Year'].round(decimals=0)

# Merge salary data with statistics, matching by Player
nbaStats19 = nbaStats19.merge(salary[['Player','Guaranteed','Salary/Yea
r', 'Years Remaining']],on='Player',how='inner')
nbaStats19 = nbaStats19.drop_duplicates(subset = 'Player', keep = 'firs
```

```
t')

# Create datasets for each positon, first including all years, then only
including 2019
statsPG = nbaStats.loc[nbaStats['Pos'] == 'PG']
nbaStats19PG = nbaStats19.loc[nbaStats19['Pos'] == 'PG']
statsSG = nbaStats.loc[nbaStats['Pos'] == 'SG']
nbaStats19SG = nbaStats19.loc[nbaStats19['Pos'] == 'SG']
statsSF = nbaStats.loc[nbaStats['Pos'] == 'SF']
nbaStats19SF = nbaStats19.loc[nbaStats19['Pos'] == 'SF']
statsPF = nbaStats.loc[nbaStats['Pos'] == 'PF']
nbaStats19PF = nbaStats19.loc[nbaStats19['Pos'] == 'PF']
statsC = nbaStats.loc[nbaStats['Pos'] == 'C']
nbaStats19C = nbaStats19.loc[nbaStats19['Pos'] == 'C']
```

Abbreviation Key:

Pos: Position
Tm: Team
G: Games
GS: Games Started
MP: Minutes Played
PER: Player Efficiency Rating
TS%: True Shooting %
3PAr: 3-Point Attempt Rate
FTr: Free Throw Rate
ORB%: Offensive Rebound Percentage
DRB%: Defensive Rebound Percentage
TRB%: Total Rebound Percentage
AST%: Assist Percentage
STL%: Steal Percentage
BLK%: Block Percentage
TOV%: Turnover Percentage
USG%: Usage Percentage

Discovery of Special Performers and Undervalued Players

In this section, I will look at the statistics of players who are not receiving many minutes but are still putting up large numbers, players who are young but effective, players who have low salaries but strong statistics, and players with high BPM, USG%, and PER statistics. I will adjust for players who have high BPM, USG%, and PER due to low minutes played by ensuring all players average at least 2 minutes per game. I will compare players as a whole, as well as by minutes and salary.

Assists

Low Minutes, High Assists

In [3]:
```
# Identify players who have lower than the median amount of minutes but above the median amount of assists
LowMinHiAST = (nbaStats19.loc[nbaStats19['MP'] < nbaStats19['MP'].median()][nbaStats19['AST'] > nbaStats19['AST'].median()]
               [['Player','Pos','Age','MP','AST','Salary/Year','Years Remaining']])
# Sort and display the dataframe
Top10LowMinHiAST = LowMinHiAST.sort_values('AST', ascending = False).reset_index(drop = True).head(10)
Top10LowMinHiAST
```

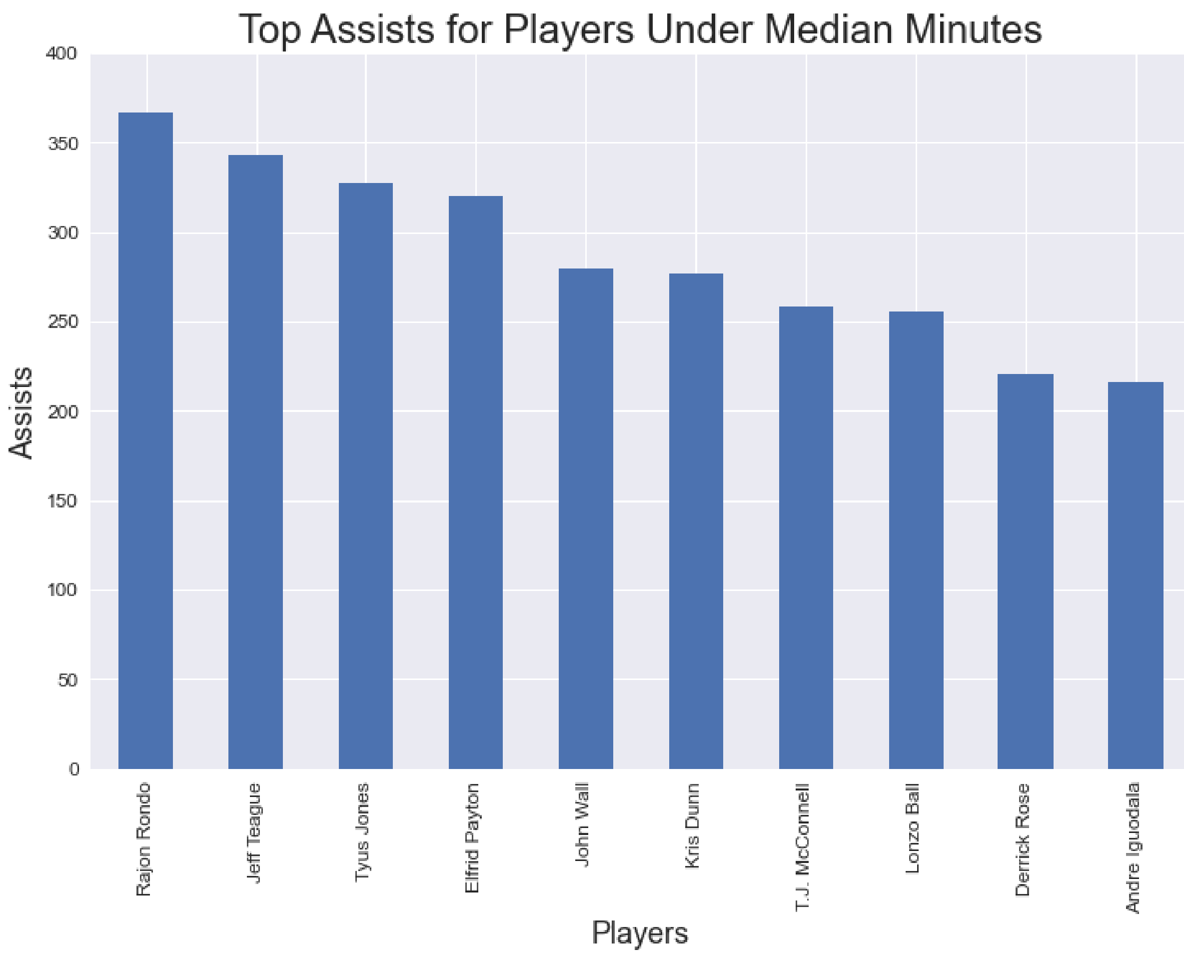
```
<ipython-input-3-1071ff9bf3fc>:2: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  LowMinHiAST = (nbaStats19.loc[nbaStats19['MP'] < nbaStats19['MP'].median()][nbaStats19['AST'] > nbaStats19['AST'].median()]
```

Out[3]:

	Player	Pos	Age	MP	AST	Salary/Year	Years Remaining
0	Rajon Rondo	PG	32.0	1,369.0	367.0	7,500,000.0	2
1	Jeff Teague	PG	30.0	1,264.0	343.0	2,564,753.0	1
2	Tyus Jones	PG	22.0	1,560.0	327.0	7,743,650.0	2
3	Elfrid Payton	PG	24.0	1,250.0	320.0	5,760,000.0	1
4	John Wall	PG	28.0	1,104.0	279.0	44,310,840.0	3
5	Kris Dunn	PG	24.0	1,389.0	277.0	4,886,175.0	2
6	T.J. McConnell	PG	26.0	1,470.0	258.0	3,500,000.0	1
7	Lonzo Ball	PG	21.0	1,423.0	255.0	11,003,782.0	1
8	Derrick Rose	PG	30.0	1,392.0	220.0	7,682,927.0	1
9	Andre Iguodala	SF	35.0	1,578.0	216.0	15,000,000.0	2

NOTES: This shows high value players who are potentially underplayed in terms of their production of Assists. *Kris Dunn* and *TJ McConnell* seem to be excellent potential targets, as they are under 27 years old and put up great numbers despite low minutes and low salary. These attributes make them extremely valuable, as they offer a high, long-term reward for a low cost.

In [4]:
```
fig,ax = plt.subplots()
Top10LowMinHiAST.plot.bar(x='Player',y='AST',ax=ax,figsize=(12,8), legen
d = False)
ax.set_ylim(0,400)
ax.set_title('Top Assists for Players Under Median Minutes',size=24)
ax.set_ylabel('Assists',size = 18)
ax.set_xlabel('Players',size = 18)
ax.tick_params(axis='both', which='major', labelsize=12)
```



Low Salary, High Assists

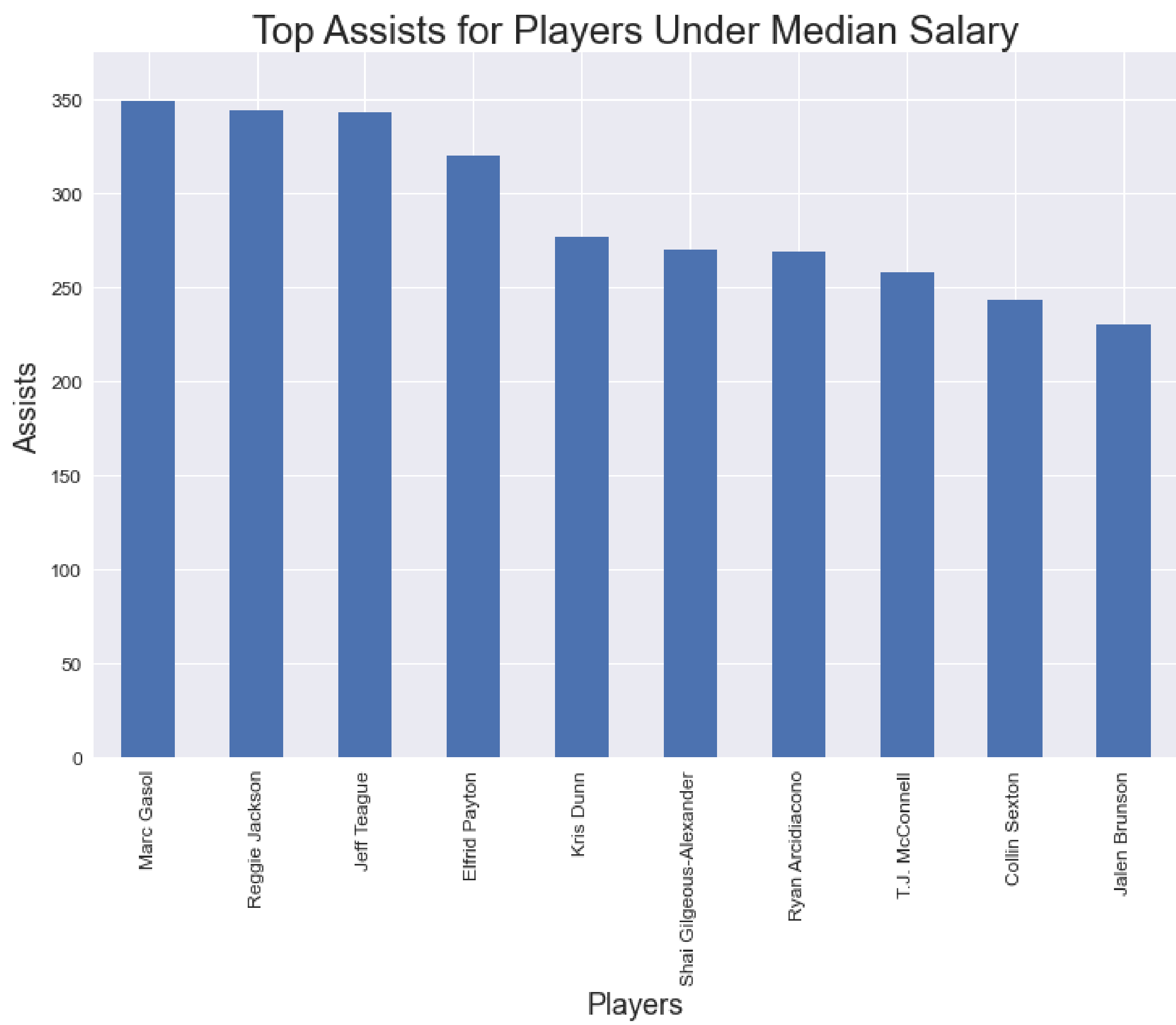
In [5]:
```
# Identify players with salaries in the lower 50% and discover the top a
ssist amounts of the group
LowSALHiAST = nbaStats19.loc[nbaStats19['Salary/Year'] < nbaStats19['Sal
ary/Year'].median()][['Player','Pos','Age','AST','Salary/Year','Years Re
maining']]
# Sort and display the dataframe
Top10LowSALHiAST = LowSALHiAST.sort_values('AST', ascending = False).res
et_index(drop = True).head(10)
Top10LowSALHiAST
```

Out[5]:

	Player	Pos	Age	AST	Salary/Year	Years Remaining
0	Marc Gasol	C	34.0	349.0	2,628,872.0	2
1	Reggie Jackson	PG	28.0	344.0	2,331,593.0	1
2	Jeff Teague	PG	30.0	343.0	2,564,753.0	1
3	Elfrid Payton	PG	24.0	320.0	5,760,000.0	1
4	Kris Dunn	PG	24.0	277.0	4,886,175.0	2
5	Shai Gilgeous-Alexander	PG	20.0	270.0	4,818,426.0	2
6	Ryan Arcidiacono	PG	24.0	269.0	3,000,000.0	2
7	T.J. McConnell	PG	26.0	258.0	3,500,000.0	1
8	Collin Sexton	PG	20.0	243.0	5,670,776.0	2
9	Jalen Brunson	PG	22.0	230.0	1,732,959.0	2

NOTES: This shows the assist numbers for low cost players which is extremely valuable to GMs because it provides a high performance for a minimal salary expense. *Ryan Arcidiacono* and *Jalen Brunson* seem to be excellent targets, as they are under 25, and they put up high assist totals while costing under $3 million per year for 2 more seasons.

In [6]:
```
fig,ax = plt.subplots()
Top10LowSALHiAST.plot.bar(x='Player',y='AST',ax=ax,figsize=(12,8), legen
d = False)
ax.set_ylim(0,375)
ax.set_title('Top Assists for Players Under Median Salary',size=24)
ax.set_ylabel('Assists',size = 18)
ax.set_xlabel('Players',size = 18)
ax.tick_params(axis='both', which='major', labelsize=12)
```



Assists per Minute (Assist Efficiency)

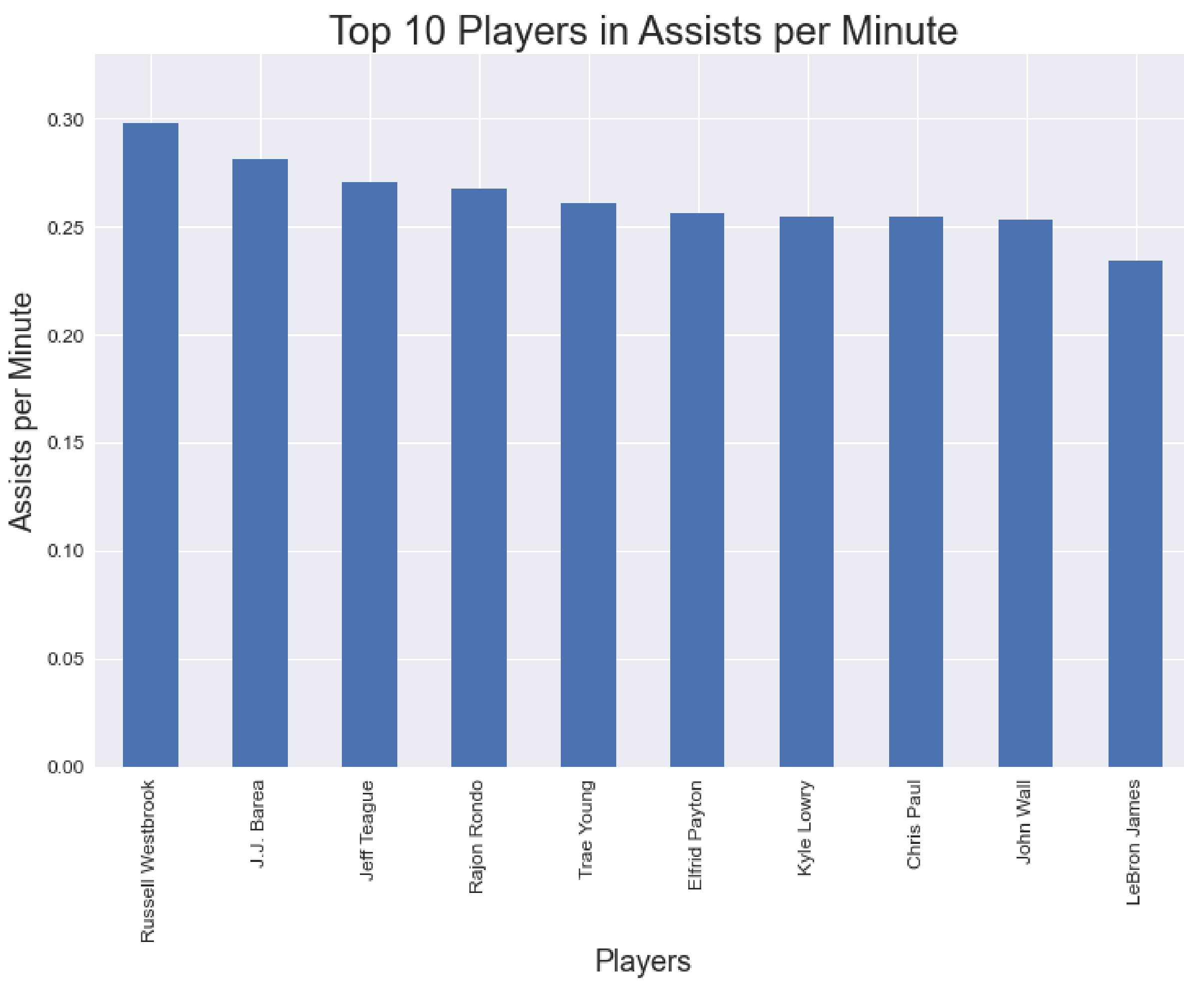
In [7]:
```
# Discover the assists each player gets per minute played and round to n
earest thousanth
nbaStats19['ASTperMP'] = nbaStats19['AST']/nbaStats19['MP']
nbaStats19['ASTperMP'] = nbaStats19['ASTperMP'].round(decimals=3)
# Filter the data to only include players with more than 2 minutes playe
d per game in order for the most accurate results.
ASTperMin = nbaStats19.loc[nbaStats19['MP'] > 164][['Player','Pos','Age'
,'AST','MP','ASTperMP','Salary/Year','Years Remaining']]
# Sort and display the dataframe
Top10ASTperMin = ASTperMin.sort_values('ASTperMP', ascending = False).re
set_index(drop = True).head(10)
Top10ASTperMin
```

Out[7]:

	Player	Pos	Age	AST	MP	ASTperMP	Salary/Year	Years Remaining
0	Russell Westbrook	PG	30.0	784.0	2,630.0	0.298	44,211,146.0	3
1	J.J. Barea	PG	34.0	211.0	752.0	0.281	2,564,753.0	1
2	Jeff Teague	PG	30.0	343.0	1,264.0	0.271	2,564,753.0	1
3	Rajon Rondo	PG	32.0	367.0	1,369.0	0.268	7,500,000.0	2
4	Trae Young	PG	20.0	653.0	2,503.0	0.261	7,449,136.0	2
5	Elfrid Payton	PG	24.0	320.0	1,250.0	0.256	5,760,000.0	1
6	Kyle Lowry	PG	32.0	564.0	2,213.0	0.255	30,000,000.0	1
7	Chris Paul	PG	33.0	473.0	1,857.0	0.255	42,784,980.0	2
8	John Wall	PG	28.0	279.0	1,104.0	0.253	44,310,840.0	3
9	LeBron James	SF	34.0	454.0	1,937.0	0.234	41,625,032.0	3

NOTES: *Elfrid Payton* appears to be of high value, as he is in the top ten for Assists per minute, costs under $6 million, and is 24 years old. It seems he is deserving of more minutes, as he has shown his efficiency during his time on the court.

In [8]:
```
fig,ax = plt.subplots()
Top10ASTperMin.plot.bar(x='Player',y='ASTperMP',ax=ax,figsize=(12,8), le
gend = False)
ax.set_ylim(0,0.33)
ax.set_title('Top 10 Players in Assists per Minute',size=24)
ax.set_ylabel('Assists per Minute',size = 18)
ax.set_xlabel('Players',size = 18)
ax.tick_params(axis='both', which='major', labelsize=12)
```



Low Salary, High Assists Per Minute

In [9]:
```
# Filter data to only include players with more than 2 minutes played pe
r game in order for the most accuracy
# Filter data to only include players with salary below the median
ASTperMin2= (nbaStats19.loc[nbaStats19['MP'] > 164][nbaStats19['Salary/Y
ear'] < nbaStats19['Salary/Year'].median()]
             [['Player','Pos','Age','AST','MP','ASTperMP','Salary/Year',
'Years Remaining']])
# Sort and display dataframe
Top10ASTperMin2 = ASTperMin2.sort_values('ASTperMP', ascending = False).
reset_index(drop = True).head(10)
Top10ASTperMin2
```

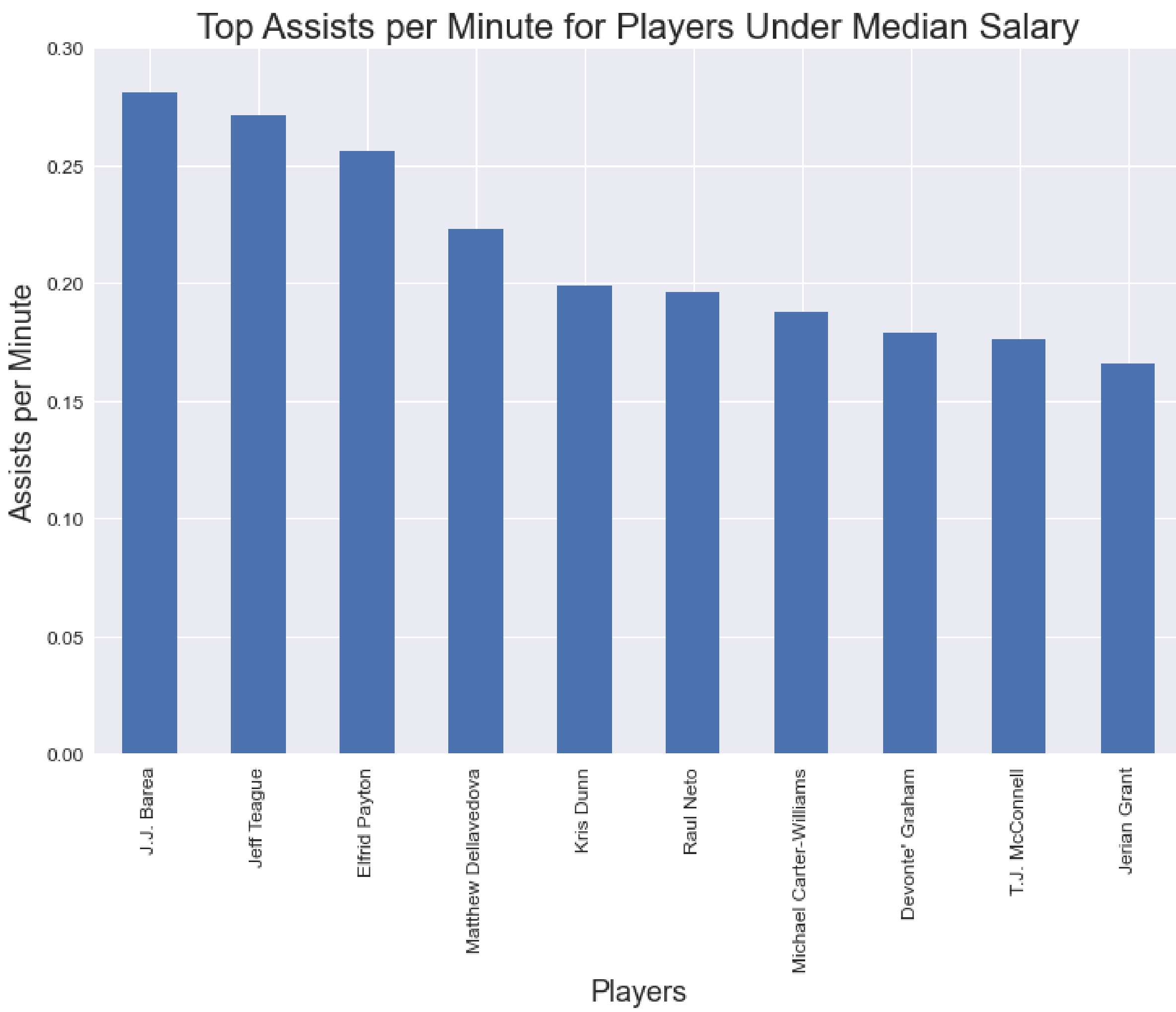
```
<ipython-input-9-5f0ed8ad5a6e>:3: UserWarning: Boolean Series key will 
be reindexed to match DataFrame index.
  ASTperMin2= (nbaStats19.loc[nbaStats19['MP'] > 164][nbaStats19['Salar
y/Year'] < nbaStats19['Salary/Year'].median()]
```

Out[9]:

	Player	Pos	Age	AST	MP	ASTperMP	Salary/Year	Years Remaining
0	J.J. Barea	PG	34.0	211.0	752.0	0.281	2,564,753.0	1
1	Jeff Teague	PG	30.0	343.0	1,264.0	0.271	2,564,753.0	1
2	Elfrid Payton	PG	24.0	320.0	1,250.0	0.256	5,760,000.0	1
3	Matthew Dellavedova	PG	28.0	181.0	812.0	0.223	2,174,318.0	1
4	Kris Dunn	PG	24.0	277.0	1,389.0	0.199	4,886,175.0	2
5	Raul Neto	PG	26.0	93.0	474.0	0.196	1,882,867.0	1
6	Michael Carter-Williams	PG	27.0	70.0	372.0	0.188	3,000,000.0	2
7	Devonte' Graham	PG	23.0	121.0	676.0	0.179	1,663,861.0	1
8	T.J. McConnell	PG	26.0	258.0	1,470.0	0.176	3,500,000.0	1
9	Jerian Grant	PG	26.0	156.0	939.0	0.166	1,882,867.0	1

NOTES: This shows the players who cost less than the median salary who provide the most efficiency in dishing out assists. *Raul Neto, Devonte Graham,* and *Jerian Grant* seem to be very valuable, as they cost less than $2 million per year, are 26 years old or younger, and put up high assist numbers for eacn minute played.

In [10]:
```
fig,ax = plt.subplots()
Top10ASTperMin2.plot.bar(x='Player',y='ASTperMP',ax=ax,figsize=(12,8),le
gend = False)
ax.set_ylim(0,.3)
ax.set_title('Top Assists per Minute for Players Under Median Salary',si
ze=22)
ax.set_ylabel('Assists per Minute',size = 18)
ax.set_xlabel('Players',size = 18)
ax.tick_params(axis='both', which='major', labelsize=12)
```



Points

Low Minutes, High Points

In [11]:

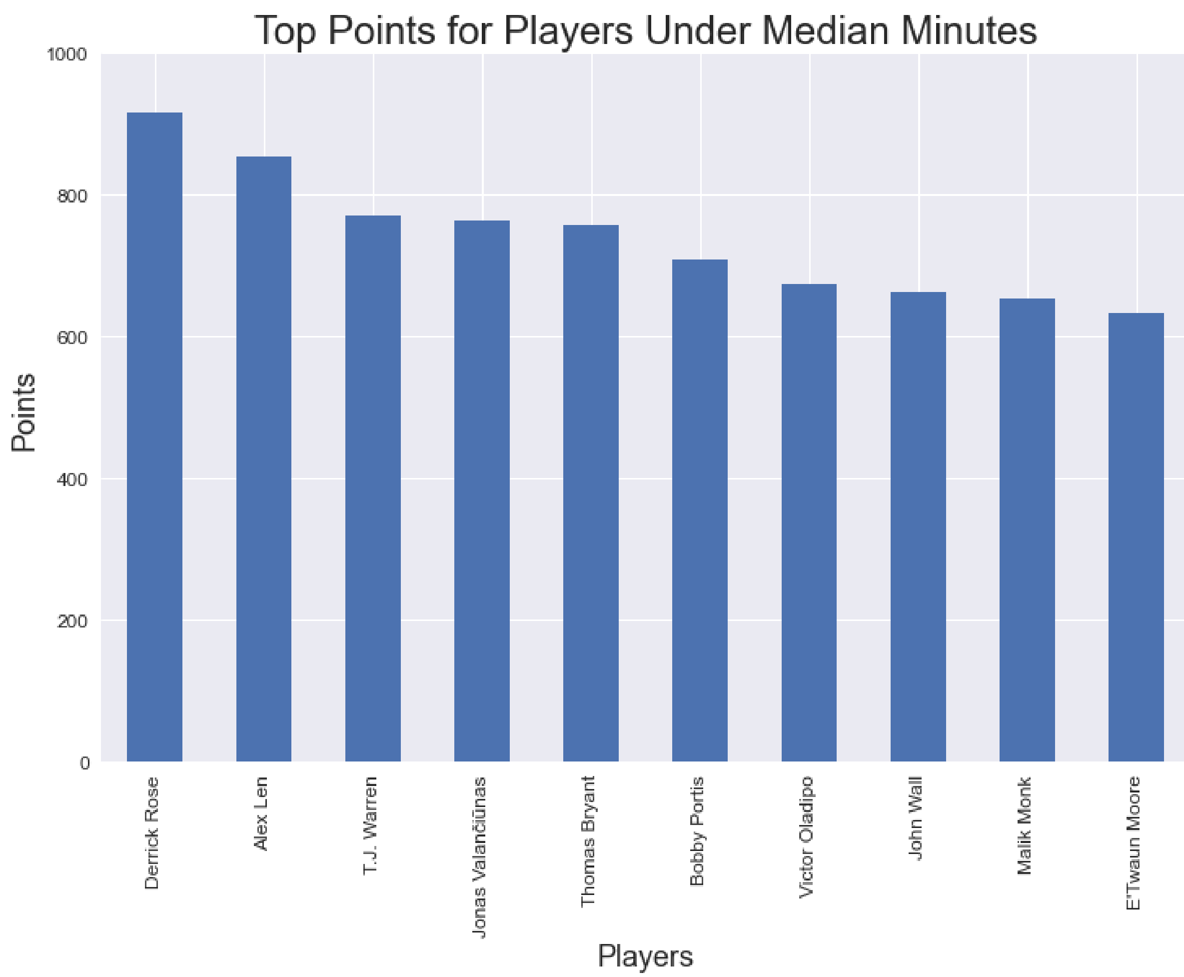
```
# Identify players who have below the median minutes played, but managed to put up high point totals
LowMinHiPTS = (nbaStats19.loc[nbaStats19['MP'] < nbaStats19['MP'].median()]
               [['Player','Pos','Age','PTS','MP','Salary/Year','Years Remaining']])
# Sort and display the dataframe
Top10LowMinHiPTS = LowMinHiPTS.sort_values('PTS', ascending = False).reset_index(drop = True).head(10)
Top10LowMinHiPTS
```

Out[11]:

	Player	Pos	Age	PTS	MP	Salary/Year	Years Remaining
0	Derrick Rose	PG	30.0	917.0	1,392.0	7,682,927.0	1
1	Alex Len	C	25.0	854.0	1,544.0	2,320,000.0	1
2	T.J. Warren	SF	25.0	772.0	1,360.0	12,220,000.0	2
3	Jonas Valančiūnas	C	26.0	763.0	1,091.0	14,500,000.0	2
4	Thomas Bryant	C	21.0	758.0	1,496.0	8,531,746.0	2
5	Bobby Portis	PF	23.0	710.0	1,299.0	3,713,575.0	2
6	Victor Oladipo	SG	26.0	675.0	1,147.0	21,000,000.0	1
7	John Wall	PG	28.0	663.0	1,104.0	44,310,840.0	3
8	Malik Monk	SG	20.0	653.0	1,258.0	5,345,687.0	1
9	E'Twaun Moore	SG	29.0	633.0	1,463.0	2,331,593.0	1

NOTES: This shows the players who receive less than the median minutes played who produce the most points. *Alex Len* and *Bobby Portis* seem to be undervalued players, as they score a large amount of points despite low minutes and cost under $4 million. They are also 25 years old and younger, providing good value for the future.

In [12]:
```
fig,ax = plt.subplots()
Top10LowMinHiPTS.plot.bar(x='Player',y='PTS',ax=ax,figsize=(12,8), legen
d = False)
ax.set_ylim(0,1000)
ax.set_title('Top Points for Players Under Median Minutes',size=24)
ax.set_ylabel('Points',size = 18)
ax.set_xlabel('Players',size = 18)
ax.tick_params(axis='both', which='major', labelsize=12)
```



Low Salary, High Points

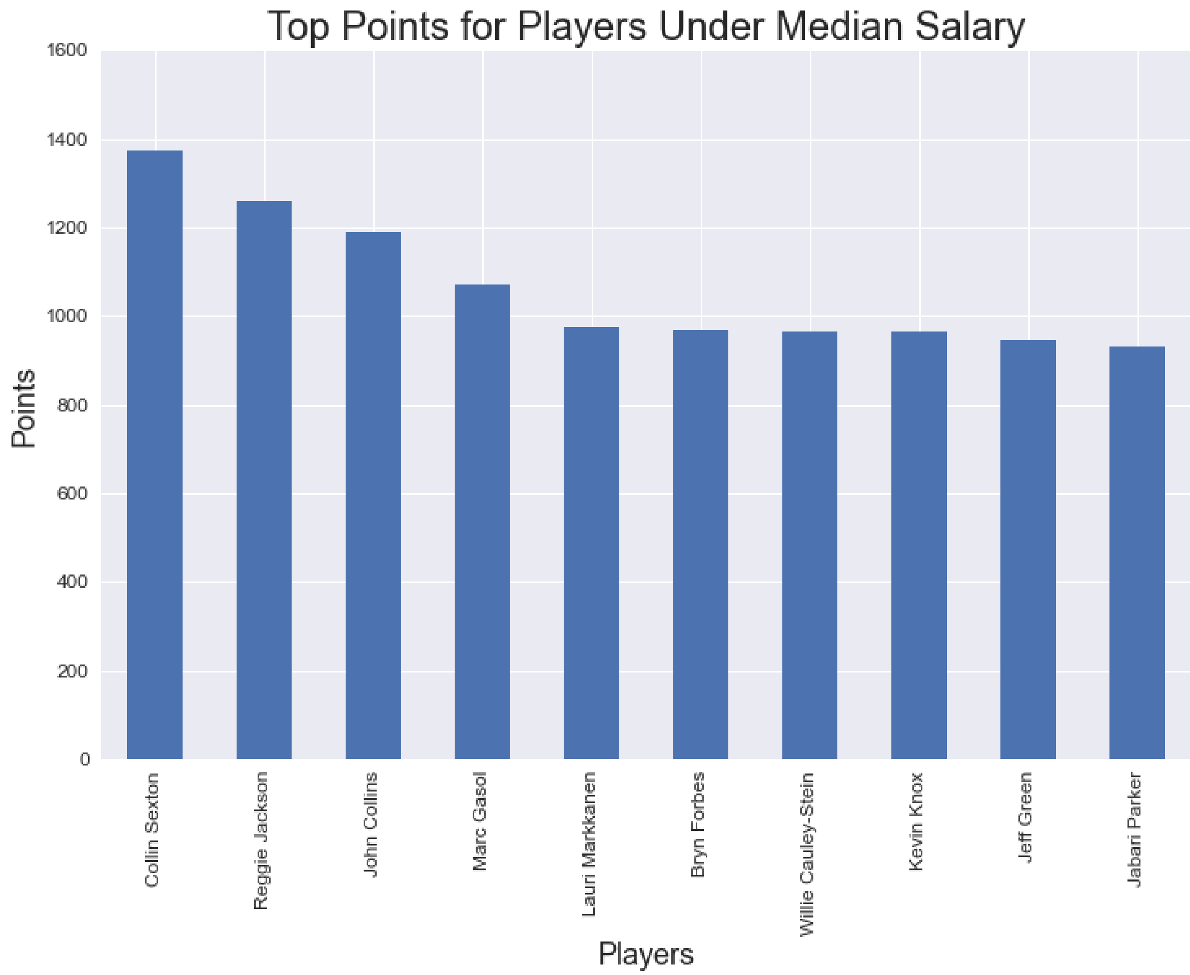
In [13]:
```
# Identify players with salaries in the lower 50% and discover the top point totals of the group
LowSALHiPTS = nbaStats19.loc[nbaStats19['Salary/Year'] < nbaStats19['Salary/Year'].median()][['Player','Pos','Age','PTS','Salary/Year','Years Remaining']]
# Sort and display the dataframe
Top10LowSALHiPTS = LowSALHiPTS.sort_values('PTS', ascending = False).reset_index(drop = True).head(10)
Top10LowSALHiPTS
```

Out[13]:

	Player	Pos	Age	PTS	Salary/Year	Years Remaining
0	Collin Sexton	PG	20.0	1,371.0	5,670,776.0	2
1	Reggie Jackson	PG	28.0	1,260.0	2,331,593.0	1
2	John Collins	PF	21.0	1,188.0	4,137,302.0	1
3	Marc Gasol	C	34.0	1,071.0	2,628,872.0	2
4	Lauri Markkanen	PF	21.0	974.0	6,731,508.0	1
5	Bryn Forbes	SG	25.0	967.0	2,395,574.0	2
6	Willie Cauley-Stein	C	25.0	965.0	4,100,000.0	2
7	Kevin Knox	PF	19.0	963.0	5,217,329.0	2
8	Jeff Green	PF	32.0	946.0	2,564,753.0	1
9	Jabari Parker	PF	23.0	930.0	6,500,000.0	1

NOTES: Bryn Forbes and Willie Cauley-Stein are good targets, as they score a lot of points while costing under $4.5 million per year and are 25 years old. Additionally, they have 2 more years on their contract, so their cost is not at risk to go up for a couple years.

In [14]:
```
fig,ax = plt.subplots()
Top10LowSALHiPTS.plot.bar(x='Player',y='PTS',ax=ax,figsize=(12,8), legen
d = False)
ax.set_ylim(0,1600)
ax.set_title('Top Points for Players Under Median Salary',size=24)
ax.set_ylabel('Points',size = 18)
ax.set_xlabel('Players',size = 18)
ax.tick_params(axis='both', which='major', labelsize=12)
```



Points per Minute (Scoring Efficiency)

In [15]:

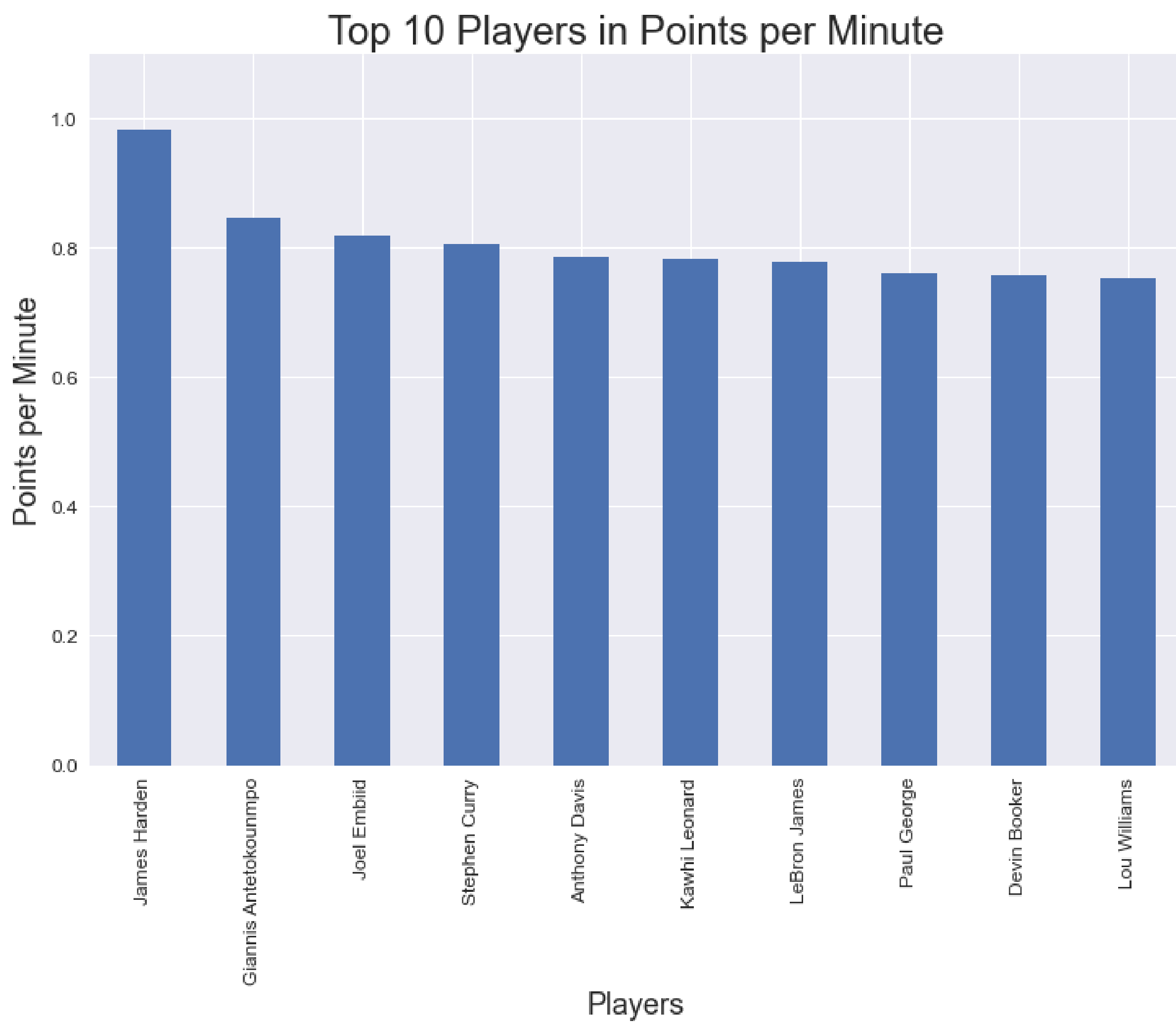
```
# Identify the number of points scored per minute played and round it to thousanths
nbaStats19['PTSperMP'] = nbaStats19['PTS']/nbaStats19['MP']
nbaStats19['PTSperMP'] = nbaStats19['PTSperMP'].round(decimals=3)
# Filter data to only include players with more than 2 minutes played per game in order for the most accuracy.
PTSperMin= nbaStats19.loc[nbaStats19['MP'] > 164][['Player','Pos','Age','PTS','MP','PTSperMP','Salary/Year','Years Remaining']]
#Sort and displaying the dataframe
Top10PTSperMin = PTSperMin.sort_values('PTSperMP', ascending = False).reset_index(drop = True).head(10)
Top10PTSperMin
```

Out[15]:

	Player	Pos	Age	PTS	MP	PTSperMP	Salary/Year	Years Remaining
0	James Harden	PG	29.0	2,818.0	2,867.0	0.983	43,848,000.0	3
1	Giannis Antetokounmpo	PF	24.0	1,994.0	2,358.0	0.846	42,621,486.0	6
2	Joel Embiid	C	24.0	1,761.0	2,154.0	0.818	31,579,390.0	3
3	Stephen Curry	PG	30.0	1,881.0	2,331.0	0.807	44,393,664.0	2
4	Anthony Davis	C	25.0	1,452.0	1,850.0	0.785	37,980,720.0	5
5	Kawhi Leonard	SF	27.0	1,596.0	2,040.0	0.782	35,197,650.0	2
6	LeBron James	SF	34.0	1,505.0	1,937.0	0.777	41,625,032.0	3
7	Paul George	SF	28.0	2,159.0	2,841.0	0.76	42,343,176.0	5
8	Devin Booker	SG	22.0	1,700.0	2,242.0	0.758	32,700,000.0	4
9	Lou Williams	SG	32.0	1,498.0	1,993.0	0.752	8,000,000.0	1

NOTES: This shows the players who score most efficiently. Not surprisingly, James Harden leads the league in this category, scoring about 1 point each minute played. Lou Williams is only $8 million and is an efficient scorer, but his age may turn GMs away. Nonetheless, he is a good target for a short term role player.

In [16]:
```
fig,ax = plt.subplots()
Top10PTSperMin.plot.bar(x='Player',y='PTSperMP',ax=ax,figsize=(12,8), le
gend = False)
ax.set_ylim(0,1.1)
ax.set_title('Top 10 Players in Points per Minute',size=24)
ax.set_ylabel('Points per Minute',size = 18)
ax.set_xlabel('Players',size = 18)
ax.tick_params(axis='both', which='major', labelsize=12)
```



Low Salary, High Points per Minute

In [17]:

```
# Identify the points per minute played for those below the median salar
y
# Filter data to only include players with more than 2 minutes played pe
r game in order for the most accuracy.
PTSperMin2= (nbaStats19.loc[nbaStats19['MP'] > 164][nbaStats19['Salary/Y
ear'] < nbaStats19['Salary/Year'].median()]
             [['Player','Pos','Age','PTS','MP','PTSperMP','Salary/Year',
'Years Remaining']])
# Sort and display the dataframe
Top10PTSperMin2 = PTSperMin2.sort_values('PTSperMP', ascending = False).
reset_index(drop = True).head(10)
Top10PTSperMin2
```

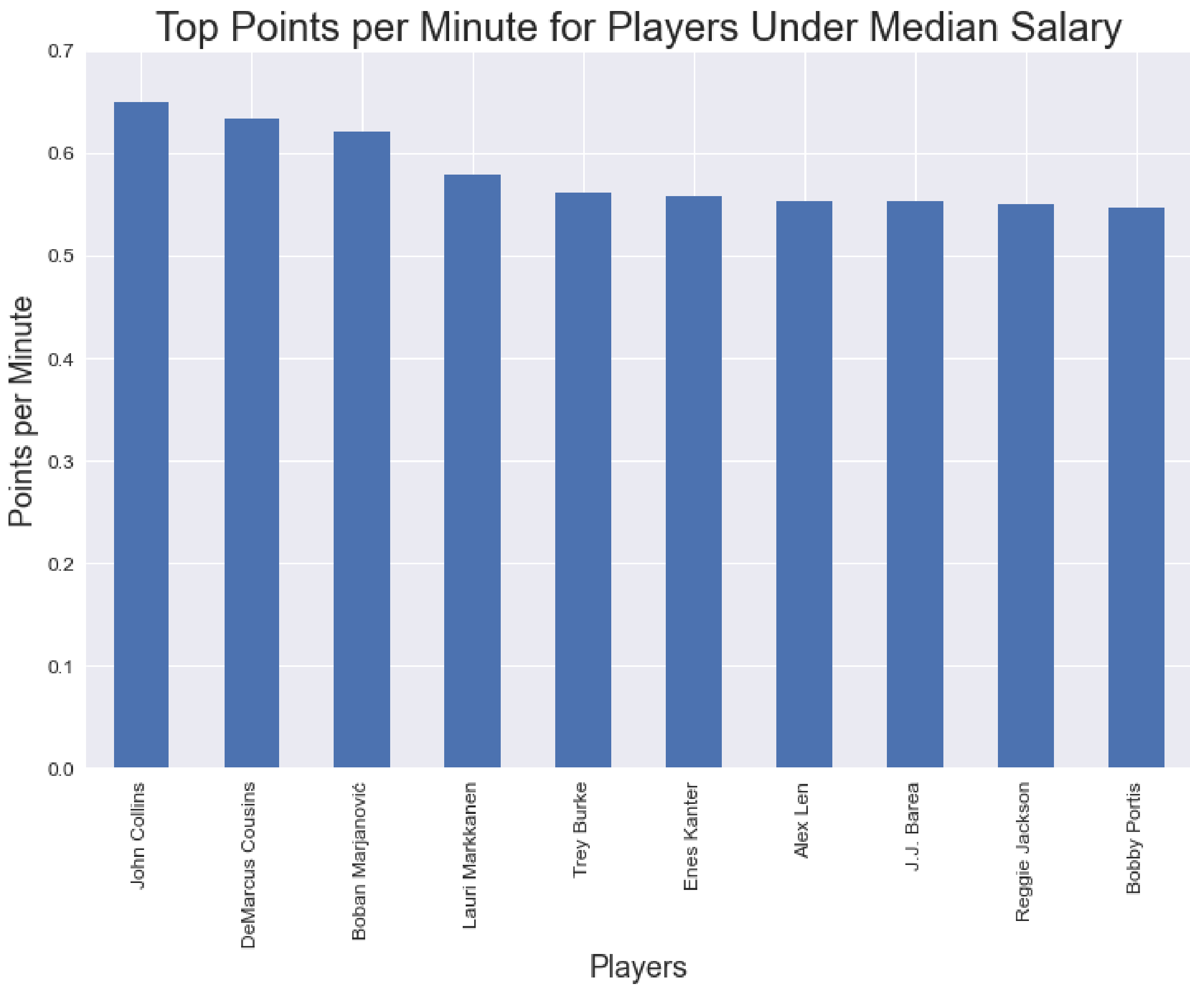
```
<ipython-input-17-dde186f19891>:3: UserWarning: Boolean Series key will
be reindexed to match DataFrame index.
  PTSperMin2= (nbaStats19.loc[nbaStats19['MP'] > 164][nbaStats19['Salar
y/Year'] < nbaStats19['Salary/Year'].median()]
```

Out[17]:

	Player	Pos	Age	PTS	MP	PTSperMP	Salary/Year	Years Remaining
0	John Collins	PF	21.0	1,188.0	1,829.0	0.65	4,137,302.0	1
1	DeMarcus Cousins	C	28.0	488.0	771.0	0.633	2,331,593.0	1
2	Boban Marjanović	C	30.0	422.0	681.0	0.62	3,500,000.0	1
3	Lauri Markkanen	PF	21.0	974.0	1,682.0	0.579	6,731,508.0	1
4	Trey Burke	PG	26.0	631.0	1,125.0	0.561	3,333,333.0	3
5	Enes Kanter	C	26.0	915.0	1,640.0	0.558	5,005,350.0	1
6	Alex Len	C	25.0	854.0	1,544.0	0.553	2,320,000.0	1
7	J.J. Barea	PG	34.0	415.0	752.0	0.552	2,564,753.0	1
8	Reggie Jackson	PG	28.0	1,260.0	2,289.0	0.55	2,331,593.0	1
9	Bobby Portis	PF	23.0	710.0	1,299.0	0.547	3,713,575.0	2

NOTES: *Trey Burke* and *Bobby Portis* average over half a point per minute and cost under $4 million for at least 2 more years. This signals that they could be excellent targets if a team is looking for a productive player for a low cost. Their young age also provides a positive future upside as well.

In [18]:
```
fig,ax = plt.subplots()
Top10PTSperMin2.plot.bar(x='Player',y='PTSperMP',ax=ax,figsize=(12,8), l
egend = False)
ax.set_ylim(0,.7)
ax.set_title('Top Points per Minute for Players Under Median Salary',siz
e=24)
ax.set_ylabel('Points per Minute',size = 18)
ax.set_xlabel('Players',size = 18)
ax.tick_params(axis='both', which='major', labelsize=12)
```



Rebounds

Low Minutes, High Rebounds

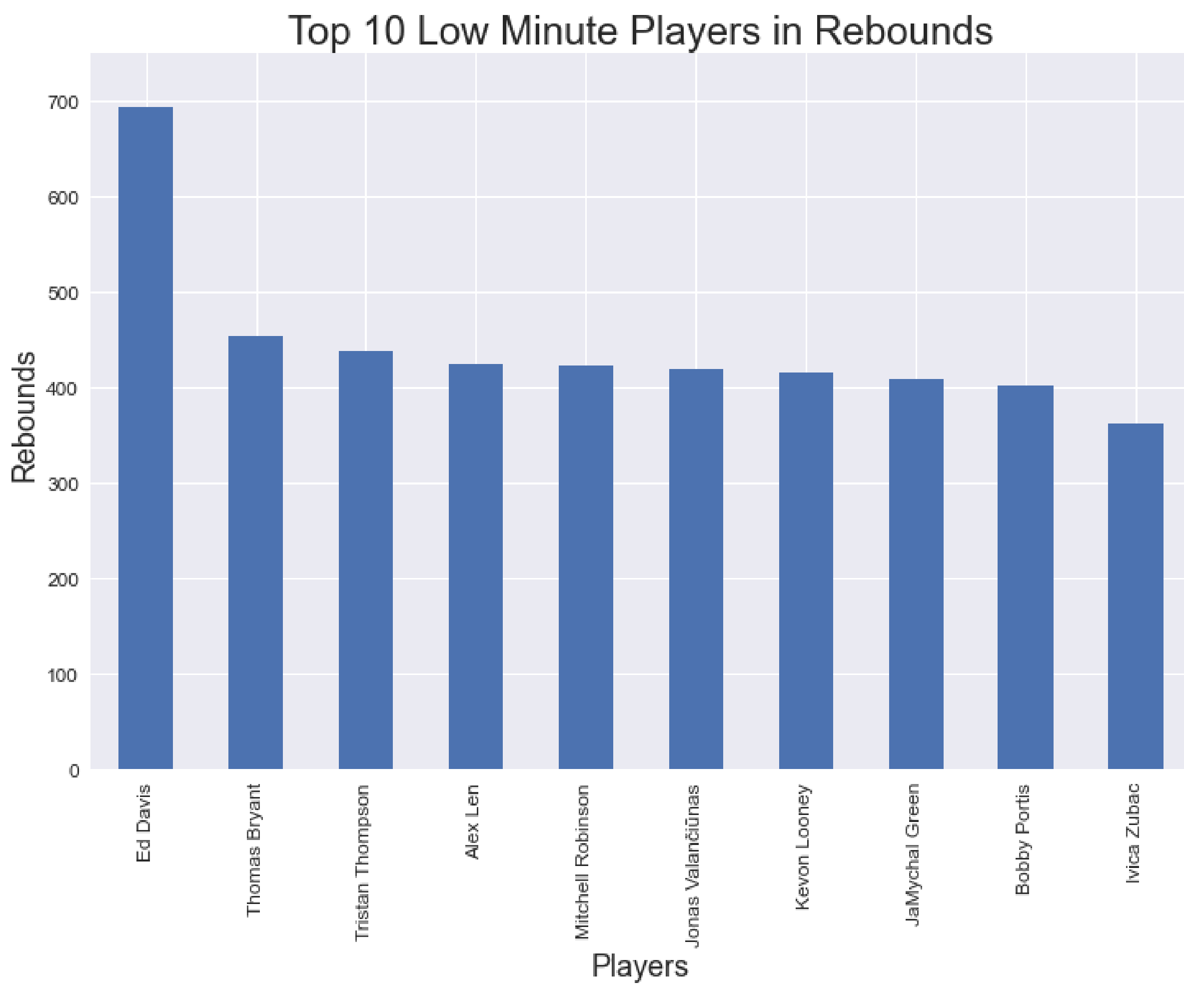
In [19]:
```
# Identify players who play fewer minutes than the median
LowMinHiTRB = (nbaStats19.loc[nbaStats19['MP'] < nbaStats19['MP'].median
()]
               [['Player','Pos','Age','Tm','TRB','MP','Salary/Year','Yea
rs Remaining']])
# Sort and display the dataframe
Top10LowMinHiTRB = LowMinHiTRB.sort_values('TRB', ascending = False).res
et_index(drop = True).head(10)
Top10LowMinHiTRB
```

Out[19]:

	Player	Pos	Age	Tm	TRB	MP	Salary/Year	Years Remaining
0	Ed Davis	C	29.0	BRK	694.0	1,446.0	5,005,350.0	1
1	Thomas Bryant	C	21.0	WAS	454.0	1,496.0	8,531,746.0	2
2	Tristan Thompson	C	27.0	CLE	438.0	1,198.0	9,489,450.0	2
3	Alex Len	C	25.0	ATL	424.0	1,544.0	2,320,000.0	1
4	Mitchell Robinson	C	20.0	NYK	423.0	1,360.0	1,732,959.0	2
5	Jonas Valančiūnas	C	26.0	TOT	419.0	1,091.0	14,500,000.0	2
6	Kevon Looney	C	22.0	GSW	417.0	1,481.0	5,000,000.0	2
7	JaMychal Green	PF	28.0	TOT	409.0	1,371.0	7,379,754.0	2
8	Bobby Portis	PF	23.0	TOT	403.0	1,299.0	3,713,575.0	2
9	Ivica Zubac	C	21.0	TOT	362.0	1,040.0	7,345,679.0	3

NOTES: *Bobby Portis, Mitchell Robinson,* and *Kevon Looney* seem to be undervalued and underplayed, as they put up high rebounding numbers despite few minutes and low salaries. Additionally, they are all under 24 years old, adding to their value by promising a potential future return.

In [20]:
```
fig,ax = plt.subplots()
Top10LowMinHiTRB.plot.bar(x='Player',y='TRB',ax=ax,figsize=(12,8), legen
d = False)
ax.set_ylim(0,750)
ax.set_title('Top 10 Low Minute Players in Rebounds',size=24)
ax.set_ylabel('Rebounds',size = 18)
ax.set_xlabel('Players',size = 18)
ax.tick_params(axis='both', which='major', labelsize=12)
```



Low Salary, High Rebounds

In [21]:

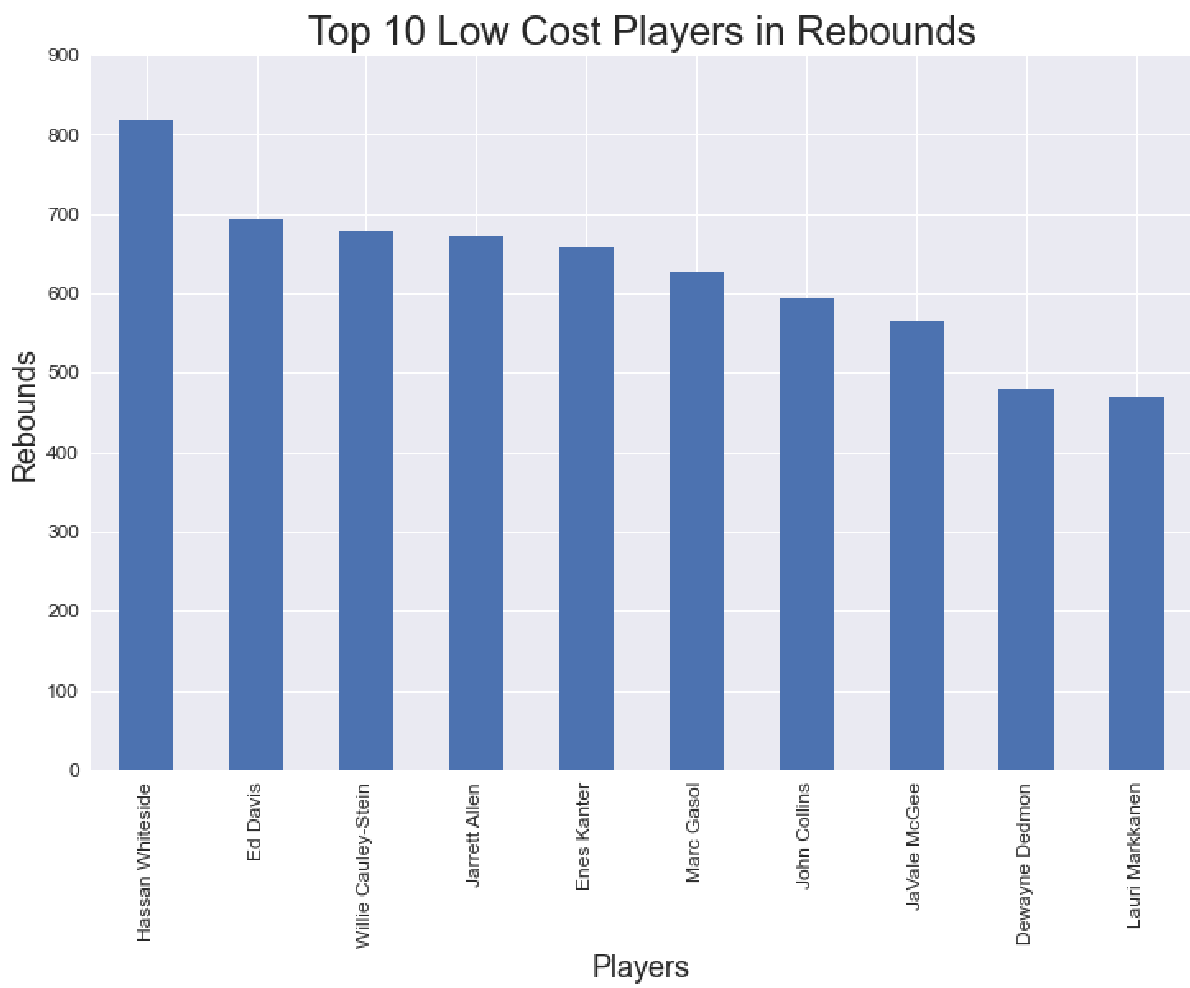
```
# Identify the rebounds total for players for those with salaries below
 the median
LowSALHiTRB = nbaStats19.loc[nbaStats19['Salary/Year'] < nbaStats19['Sal
ary/Year'].median()][['Player','Pos','Age','TRB','Salary/Year','Years Re
maining']]
# Sort and display the dataframe
Top10LowSALHiTRB = LowSALHiTRB.sort_values('TRB', ascending = False).res
et_index(drop = True).head(10)
Top10LowSALHiTRB
```

Out[21]:

	Player	Pos	Age	TRB	Salary/Year	Years Remaining
0	Hassan Whiteside	C	29.0	817.0	2,320,044.0	1
1	Ed Davis	C	29.0	694.0	5,005,350.0	1
2	Willie Cauley-Stein	C	25.0	678.0	4,100,000.0	2
3	Jarrett Allen	C	20.0	672.0	3,909,902.0	1
4	Enes Kanter	C	26.0	659.0	5,005,350.0	1
5	Marc Gasol	C	34.0	627.0	2,628,872.0	2
6	John Collins	PF	21.0	595.0	4,137,302.0	1
7	JaVale McGee	C	31.0	566.0	4,200,000.0	1
8	Dewayne Dedmon	C	29.0	480.0	2,866,667.0	5
9	Lauri Markkanen	PF	21.0	470.0	6,731,508.0	1

NOTES: *Hassan Whiteside* soars above all others in this category, showing how valuable he is despite his age and a salary under 2.5 million dollars. *Jarrett Allen* is also extremely valuable, as he is 20 years old, a top performer, and costs under 4 million dollars. Additionally, *Willie Cauley-Stein* also is highly valuable given 2 years remaining on his contract at 4.1 million dollars and his excellent performance.

In [22]:
```
fig,ax = plt.subplots()
Top10LowSALHiTRB.plot.bar(x='Player',y='TRB',ax=ax,figsize=(12,8), legen
d = False)
ax.set_ylim(0,900)
ax.set_title('Top 10 Low Cost Players in Rebounds',size=24)
ax.set_ylabel('Rebounds',size = 18)
ax.set_xlabel('Players',size = 18)
ax.tick_params(axis='both', which='major', labelsize=12)
```



Rebounds per Minute (Rebounding Efficiency)

In [23]:

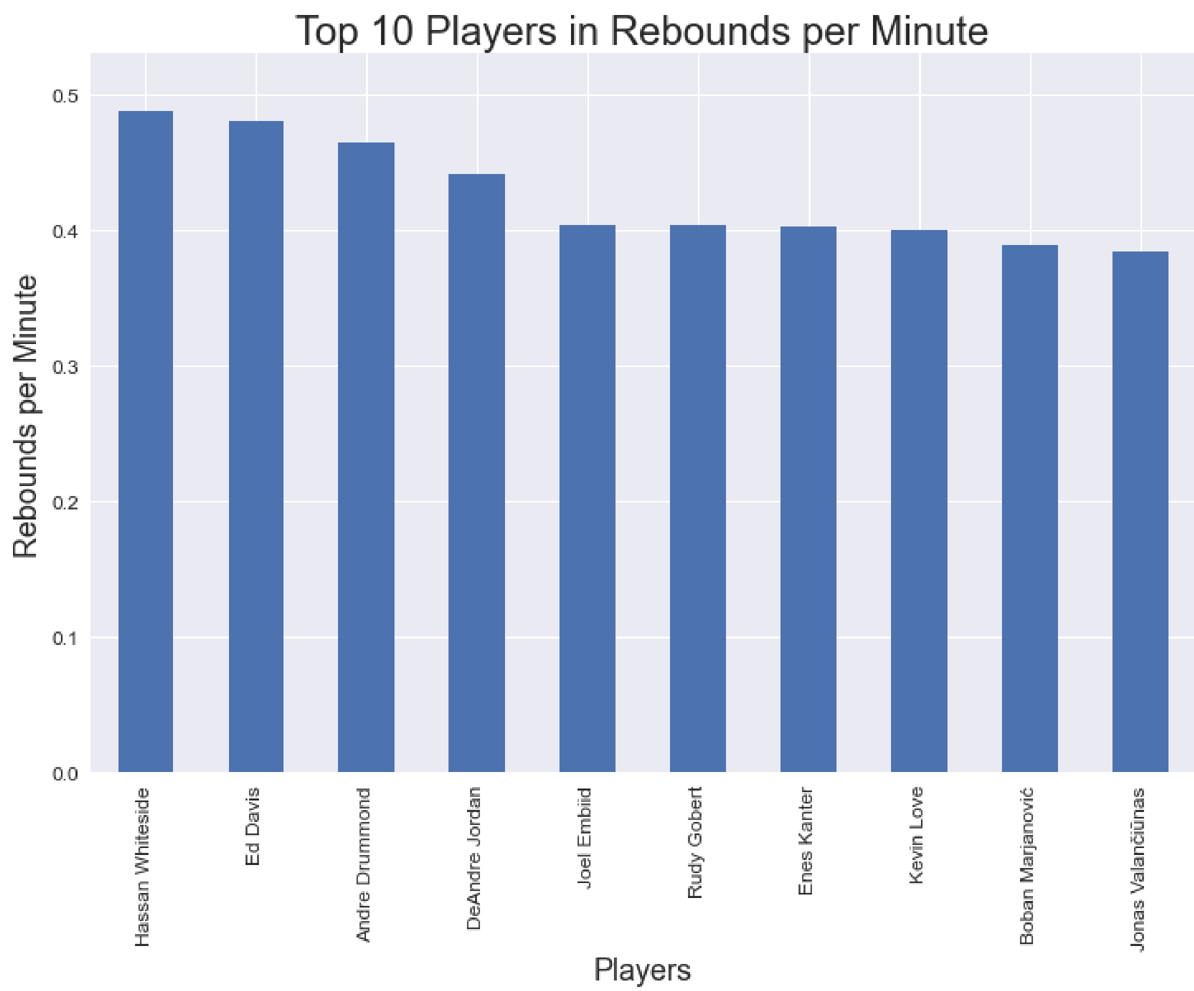
```
# Discover the rebounds per minute played and rounding to nearest thousa
nth
nbaStats19['TRBperMP'] = nbaStats19['TRB']/nbaStats19['MP']
nbaStats19['TRBperMP'] = nbaStats19['TRBperMP'].round(decimals=3)
# Filter data to only include players with more than 2 minutes played pe
r game in order for the most accuracy.
TRBperMin= nbaStats19.loc[nbaStats19['MP'] > 164][['Player','Pos','Age',
'Tm','TRB','MP','TRBperMP','Salary/Year','Years Remaining']]
# Sort and display the dataframe
Top10TRBperMin = TRBperMin.sort_values('TRBperMP', ascending = False).re
set_index(drop = True).head(10)
Top10TRBperMin
```

Out[23]:

	Player	Pos	Age	Tm	TRB	MP	TRBperMP	Salary/Year	Years Remaining
0	Hassan Whiteside	C	29.0	MIA	817.0	1,674.0	0.488	2,320,044.0	1
1	Ed Davis	C	29.0	BRK	694.0	1,446.0	0.48	5,005,350.0	1
2	Andre Drummond	C	25.0	DET	1,232.0	2,647.0	0.465	28,751,775.0	1
3	DeAndre Jordan	C	30.0	TOT	902.0	2,047.0	0.441	10,026,373.0	3
4	Joel Embiid	C	24.0	PHI	871.0	2,154.0	0.404	31,579,390.0	3
5	Rudy Gobert	C	26.0	UTA	1,041.0	2,577.0	0.404	38,587,547.0	6
6	Enes Kanter	C	26.0	TOT	659.0	1,640.0	0.402	5,005,350.0	1
7	Kevin Love	PF	30.0	CLE	239.0	598.0	0.4	30,500,000.0	3
8	Boban Marjanović	C	30.0	TOT	265.0	681.0	0.389	3,500,000.0	1
9	Jonas Valančiūnas	C	26.0	TOT	419.0	1,091.0	0.384	14,500,000.0	2

NOTES: *Enes Kanter* and *Ed Davis* seem to be extremely undervalued, as they are top 10 in rebounds per minute but cost under 5.1 million dollars and played under 700 minutes. Again, *Hassan Whiteside* provides incredible value in the rebounding category, as he leads in rebounding efficiency and is only 2.32 million dollars. These players could be valuable additions to an NBA roster.

In [24]:
```
fig,ax = plt.subplots()
Top10TRBperMin.plot.bar(x='Player',y='TRBperMP',ax=ax,figsize=(12,8), le
gend = False)
ax.set_ylim(0,0.53)
ax.set_title('Top 10 Players in Rebounds per Minute',size=24)
ax.set_ylabel('Rebounds per Minute',size = 18)
ax.set_xlabel('Players',size = 18)
ax.tick_params(axis='both', which='major', labelsize=12)
```



Low Salary, High Rebounds per Minute

In [25]:

```
# Discover the rebounds per minute played and round to nearest thousanth
nbaStats19['TRBperMP'] = nbaStats19['TRB']/nbaStats19['MP']
nbaStats19['TRBperMP'] = nbaStats19['TRBperMP'].round(decimals=3)
# Filter data to only include players with more than 2 minutes played pe
r game in order for the most accuracy.
# Filter data to only include players with salaries below the median
TRBperMin2= (nbaStats19.loc[nbaStats19['MP'] > 164][nbaStats19['Salary/Y
ear'] < nbaStats19['Salary/Year'].median()]
                [['Player','Pos','Age','PTS','MP','TRBperMP','Salary/Year',
'Years Remaining']])
# Sort and display the dataframe
Top10TRBperMin2 = TRBperMin2.sort_values('TRBperMP', ascending = False).
reset_index(drop = True).head(10)
Top10TRBperMin2
```

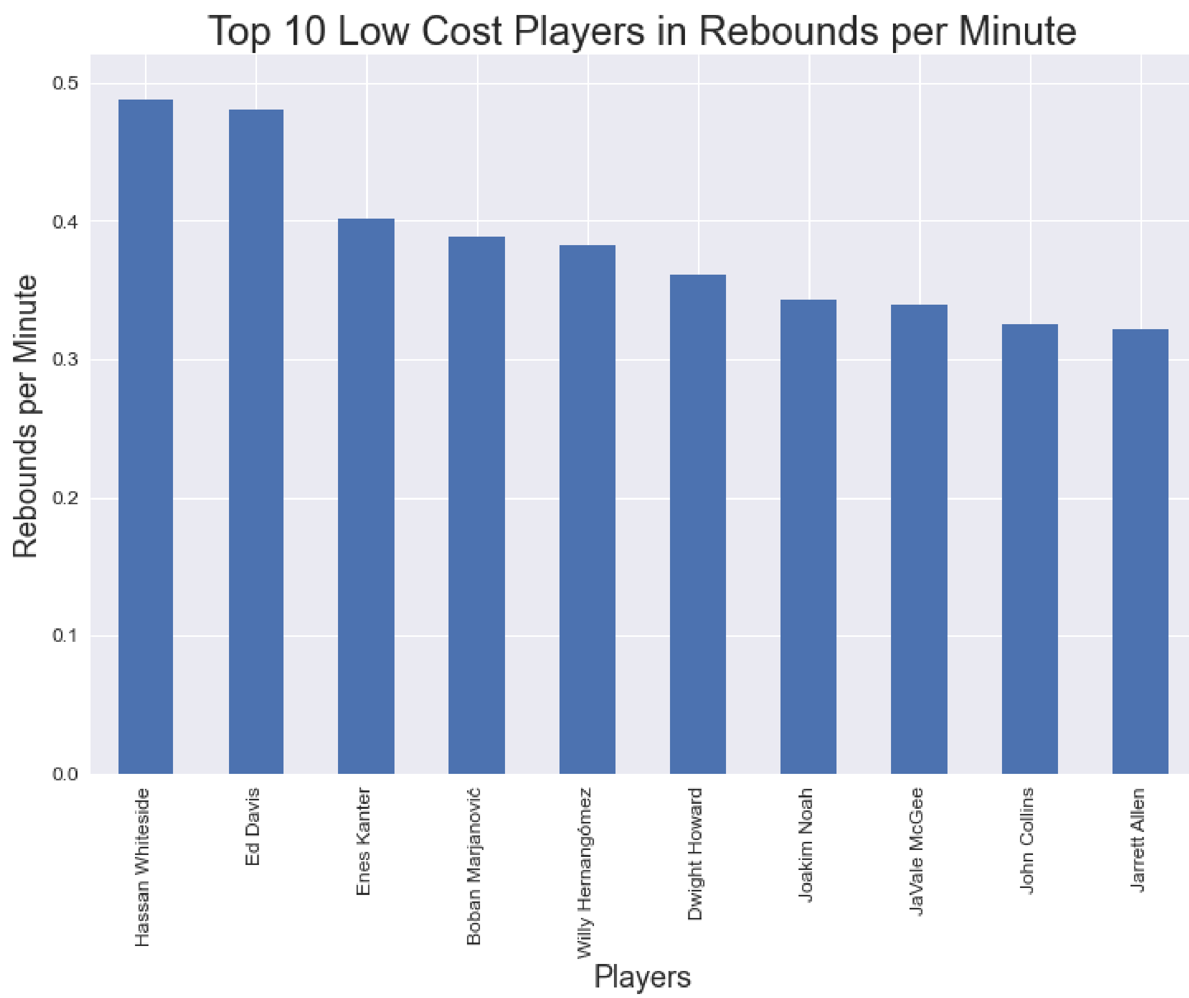
```
<ipython-input-25-4ebc645f4e81>:6: UserWarning: Boolean Series key will
be reindexed to match DataFrame index.
  TRBperMin2= (nbaStats19.loc[nbaStats19['MP'] > 164][nbaStats19['Salar
y/Year'] < nbaStats19['Salary/Year'].median()]
```

Out[25]:

	Player	Pos	Age	PTS	MP	TRBperMP	Salary/Year	Years Remaining
0	Hassan Whiteside	C	29.0	887.0	1,674.0	0.488	2,320,044.0	1
1	Ed Davis	C	29.0	472.0	1,446.0	0.48	5,005,350.0	1
2	Enes Kanter	C	26.0	915.0	1,640.0	0.402	5,005,350.0	1
3	Boban Marjanović	C	30.0	422.0	681.0	0.389	3,500,000.0	1
4	Willy Hernangómez	C	24.0	421.0	812.0	0.383	1,727,145.0	1
5	Dwight Howard	C	33.0	115.0	230.0	0.361	2,564,753.0	1
6	Joakim Noah	C	33.0	298.0	693.0	0.343	6,431,666.0	2
7	JaVale McGee	C	31.0	897.0	1,671.0	0.339	4,200,000.0	1
8	John Collins	PF	21.0	1,188.0	1,829.0	0.325	4,137,302.0	1
9	Jarrett Allen	C	20.0	873.0	2,096.0	0.321	3,909,902.0	1

NOTES: This chart shows very high value players, as they are able to put up impressive numbers while all costing less than $6.5 million. Teams should target these players to boost their rebounding numbers without spending much money and creating a long term value with young players.

In [26]:
```
fig,ax = plt.subplots()
Top10TRBperMin2.plot.bar(x='Player',y='TRBperMP',ax=ax,figsize=(12,8),legend = False)
ax.set_ylim(0,0.52)
ax.set_title('Top 10 Low Cost Players in Rebounds per Minute',size=24)
ax.set_ylabel('Rebounds per Minute',size = 18)
ax.set_xlabel('Players',size = 18)
ax.tick_params(axis='both', which='major', labelsize=12)
```



Usage %

Low Minutes, High USG%

In [27]:

```
# Discover USG% for players who play under the median number of minutes
# Adjust for players who barely played and saw high usage rate as a resu
lt
LowMinHiUSG = (nbaStats19.loc[nbaStats19['MP'] < nbaStats19['MP'].median
()][nbaStats19['MP'] > 164]
               [nbaStats19['USG'] > nbaStats19['USG'].median()][['Playe
r','Pos','Age','Tm','USG','MP','Salary/Year','Years Remaining']])
# Sort and display the dataframe
Top10LowMinHiUSG = LowMinHiUSG.sort_values('USG', ascending = False).res
et_index(drop = True).head(10)
Top10LowMinHiUSG
```

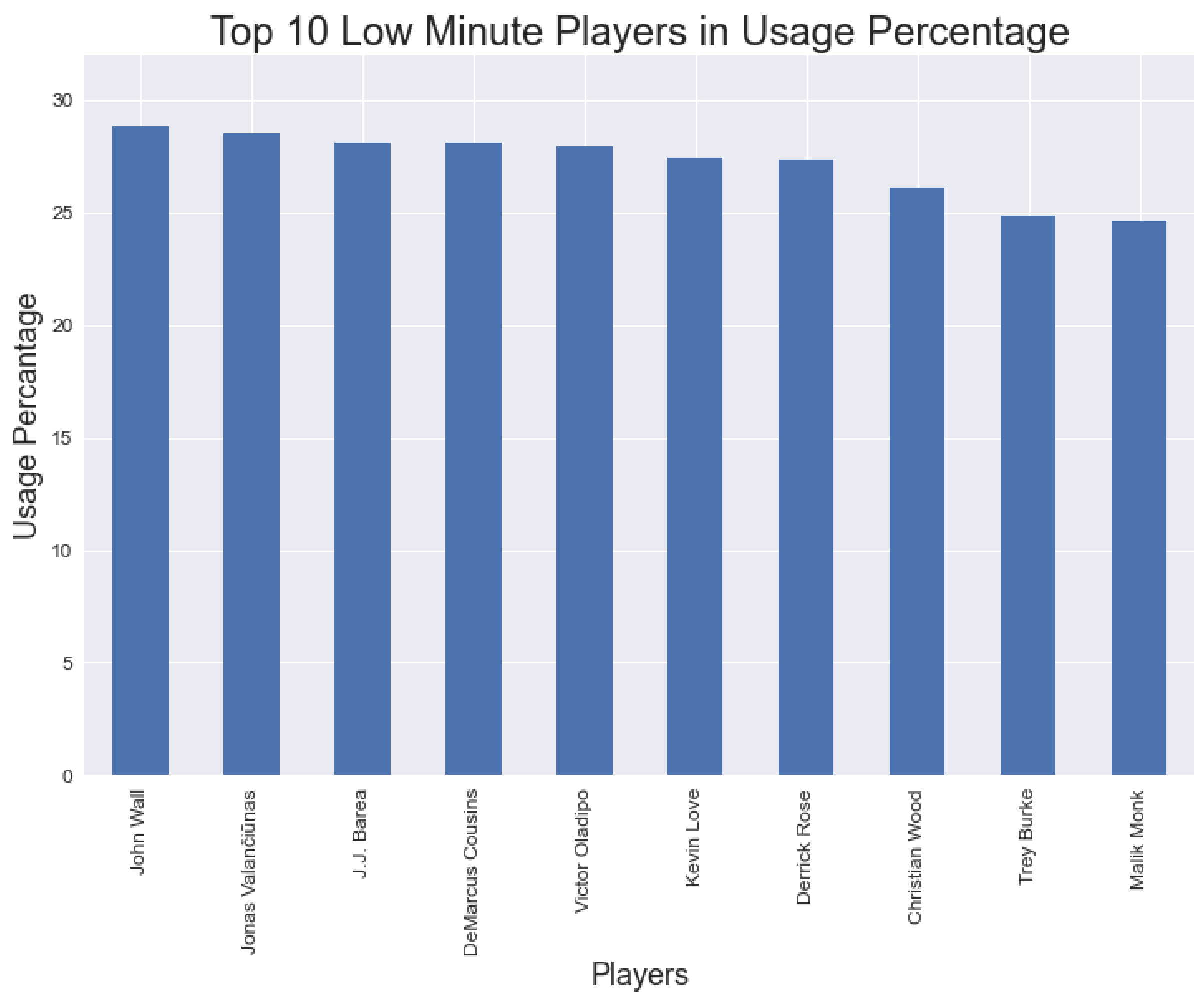
```
<ipython-input-27-13ef7134c89a>:3: UserWarning: Boolean Series key will 
be reindexed to match DataFrame index.
  LowMinHiUSG = (nbaStats19.loc[nbaStats19['MP'] < nbaStats19['MP'].med
ian()][nbaStats19['MP'] > 164]
```

Out[27]:

	Player	Pos	Age	Tm	USG	MP	Salary/Year	Years Remaining
0	John Wall	PG	28.0	WAS	28.8	1,104.0	44,310,840.0	3
1	Jonas Valančiūnas	C	26.0	TOT	28.5	1,091.0	14,500,000.0	2
2	J.J. Barea	PG	34.0	DAL	28.1	752.0	2,564,753.0	1
3	DeMarcus Cousins	C	28.0	GSW	28.1	771.0	2,331,593.0	1
4	Victor Oladipo	SG	26.0	IND	27.9	1,147.0	21,000,000.0	1
5	Kevin Love	PF	30.0	CLE	27.4	598.0	30,500,000.0	3
6	Derrick Rose	PG	30.0	MIN	27.3	1,392.0	7,682,927.0	1
7	Christian Wood	PF	23.0	TOT	26.1	251.0	13,666,667.0	3
8	Trey Burke	PG	26.0	TOT	24.8	1,125.0	3,333,333.0	3
9	Malik Monk	SG	20.0	CHO	24.6	1,258.0	5,345,687.0	1

NOTES: This chart shows the players who played fewer minutes than 50% of the league who were used the most by their respective teams while on the court, suggesting that they may deserve more minutes. John Wall and Victor Oladipo made this list, but only due to injury. Trey Burke is an excellent target, as he is 26 years old, costs under $3.4 million while holding a usage rate of 24.8%.

In [28]:
```
fig,ax = plt.subplots()
Top10LowMinHiUSG.plot.bar(x='Player',y='USG',ax=ax,figsize=(12,8),legend
=False)
ax.set_ylim(0,32)
ax.set_title('Top 10 Low Minute Players in Usage Percentage',size=24)
ax.set_ylabel('Usage Percantage',size = 18)
ax.set_xlabel('Players',size = 18)
ax.tick_params(axis='both', which='major', labelsize=12)
```



Low Salary, High Usage

In [29]:
```
# Filter for players with salaries below median
LowSALHiUSG = (nbaStats19.loc[nbaStats19['Salary/Year'] < nbaStats19['Salary/Year'].median()][nbaStats19['MP'] > 164]
               [['Player','Pos','Age','USG','Salary/Year','Years Remaining']])
# Sort and display the dataframe
Top10LowSALHiUSG = LowSALHiUSG.sort_values('USG', ascending = False).reset_index(drop = True).head(10)
Top10LowSALHiUSG
```

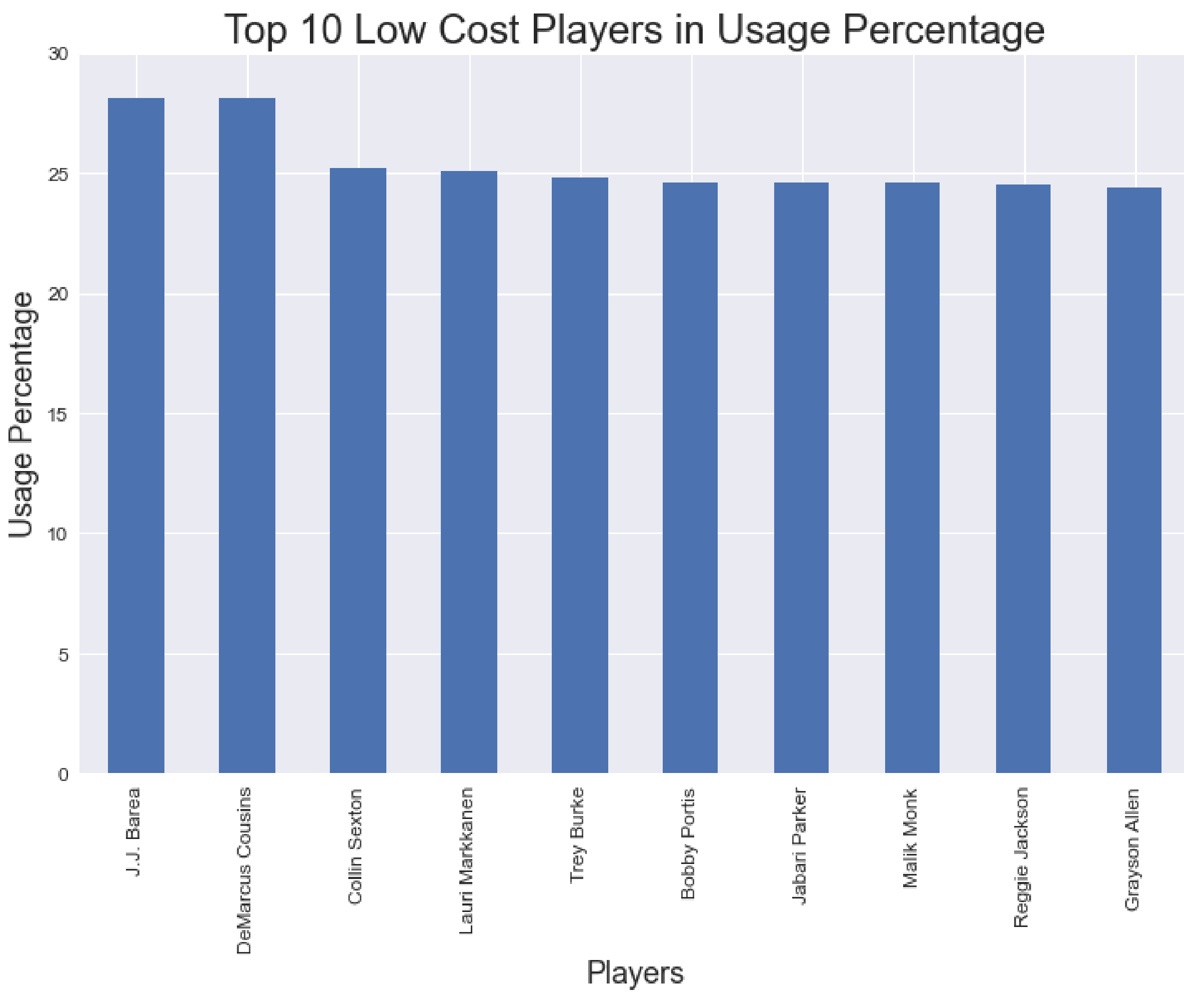
```
<ipython-input-29-596f36d85a71>:2: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  LowSALHiUSG = (nbaStats19.loc[nbaStats19['Salary/Year'] < nbaStats19['Salary/Year'].median()][nbaStats19['MP'] > 164]
```

Out[29]:

	Player	Pos	Age	USG	Salary/Year	Years Remaining
0	J.J. Barea	PG	34.0	28.1	2,564,753.0	1
1	DeMarcus Cousins	C	28.0	28.1	2,331,593.0	1
2	Collin Sexton	PG	20.0	25.2	5,670,776.0	2
3	Lauri Markkanen	PF	21.0	25.1	6,731,508.0	1
4	Trey Burke	PG	26.0	24.8	3,333,333.0	3
5	Bobby Portis	PF	23.0	24.6	3,713,575.0	2
6	Jabari Parker	PF	23.0	24.6	6,500,000.0	1
7	Malik Monk	SG	20.0	24.6	5,345,687.0	1
8	Reggie Jackson	PG	28.0	24.5	2,331,593.0	1
9	Grayson Allen	SG	23.0	24.4	3,300,008.0	2

NOTES: This chart shows the usage percentages for players below the median salary. All players on this chart are heavily used with usage rates over 24% and provide excellent value due to their low salary. *Bobby Portis* and *Grayson Allen* provide excellent additional value, as they are 23 years old, are under $4 million, and have 2 years remaining on their contracts.

In [30]:
```
fig,ax = plt.subplots()
Top10LowSALHiUSG.plot.bar(x='Player',y='USG',ax=ax,figsize=(12,8), legen
d = False)
ax.set_ylim(0,30)
ax.set_title('Top 10 Low Cost Players in Usage Percentage',size=24)
ax.set_ylabel('Usage Percentage',size = 18)
ax.set_xlabel('Players',size = 18)
ax.tick_params(axis='both', which='major', labelsize=12)
```



PER

Low Minutes, High PER

In [31]:
```
# Filter for players below median minutes played
# Adjust for players who barely played and saw high PER as a result
LowMinHiPER = (nbaStats19.loc[nbaStats19['MP'] < nbaStats19['MP'].median
()][nbaStats19['MP'] > 164]
               [nbaStats19['PER'] > nbaStats19['PER'].median()][['Playe
r','Pos','Age','Tm','PER','MP','Salary/Year','Years Remaining']])
# Sort and display the dataframe
Top10LowMinHiPER = LowMinHiPER.sort_values('PER', ascending = False).res
et_index(drop = True).head(10)
Top10LowMinHiPER
```

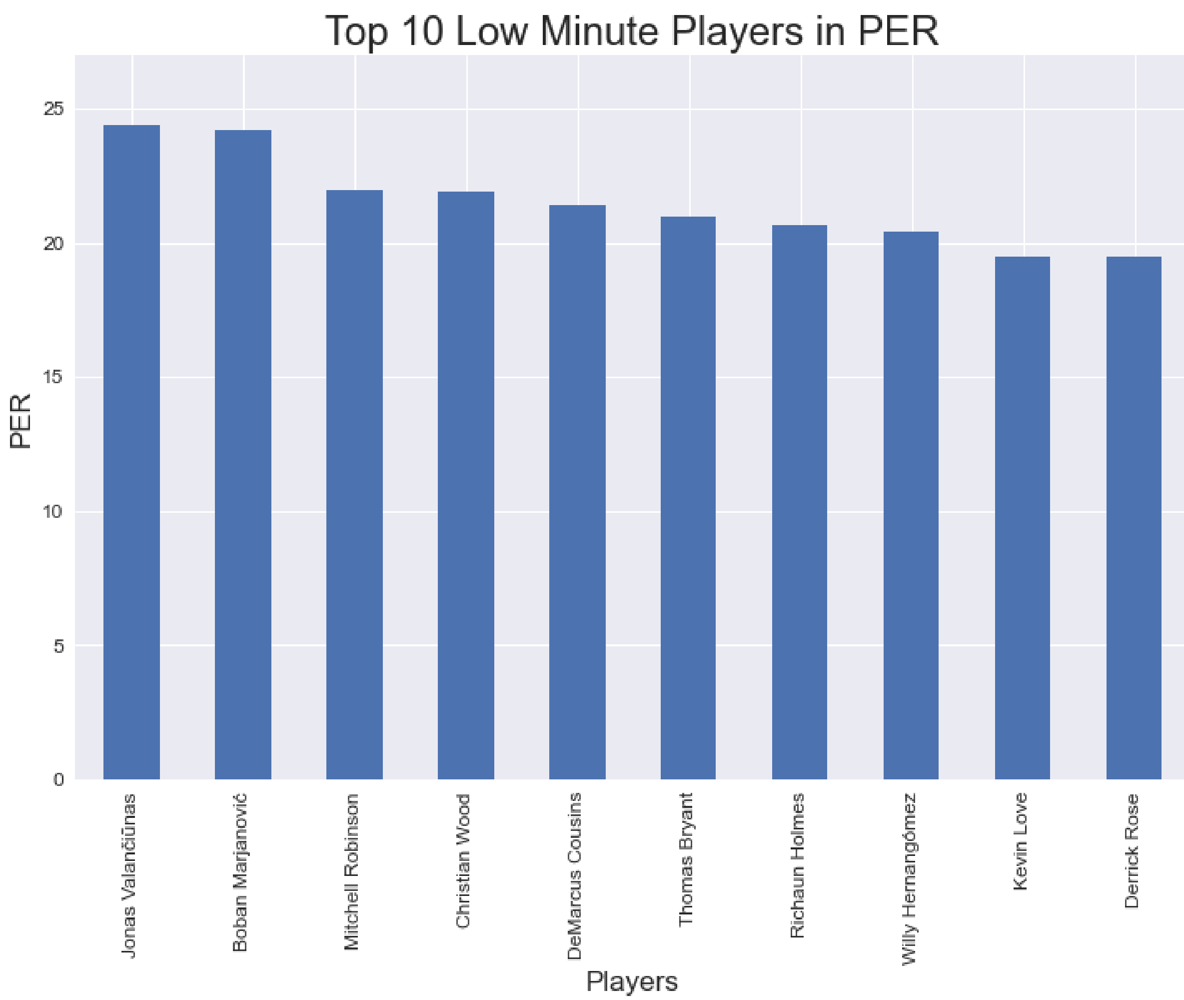
```
<ipython-input-31-db99c43ad968>:3: UserWarning: Boolean Series key will
be reindexed to match DataFrame index.
  LowMinHiPER = (nbaStats19.loc[nbaStats19['MP'] < nbaStats19['MP'].med
ian()][nbaStats19['MP'] > 164]
```

Out[31]:

	Player	Pos	Age	Tm	PER	MP	Salary/Year	Years Remaining
0	Jonas Valančiūnas	C	26.0	TOT	24.4	1,091.0	14,500,000.0	2
1	Boban Marjanović	C	30.0	TOT	24.2	681.0	3,500,000.0	1
2	Mitchell Robinson	C	20.0	NYK	22.0	1,360.0	1,732,959.0	2
3	Christian Wood	PF	23.0	TOT	21.9	251.0	13,666,667.0	3
4	DeMarcus Cousins	C	28.0	GSW	21.4	771.0	2,331,593.0	1
5	Thomas Bryant	C	21.0	WAS	21.0	1,496.0	8,531,746.0	2
6	Richaun Holmes	C	25.0	PHO	20.7	1,184.0	5,005,350.0	1
7	Willy Hernangómez	C	24.0	CHO	20.4	812.0	1,727,145.0	1
8	Kevin Love	PF	30.0	CLE	19.5	598.0	30,500,000.0	3
9	Derrick Rose	PG	30.0	MIN	19.5	1,392.0	7,682,927.0	1

NOTES: This chart shows players who played less than the median amount of minutes but provided a high PER during their time on the court. *Mitchell Robinson* and *Willy Hernangomez* seem to be excellent targets, as they are under 25 yers old, cost under $1.75 million, and have PER's over 20.

In [32]:
```
fig,ax = plt.subplots()
Top10LowMinHiPER.plot.bar(x='Player',y='PER',ax=ax,figsize=(12,8), legen
d = False)
ax.set_ylim(0,27)
ax.set_title('Top 10 Low Minute Players in PER',size=24)
ax.set_ylabel('PER',size = 17)
ax.set_xlabel('Players',size = 17)
ax.tick_params(axis='both', which='major', labelsize=12)
```



Low Salary, High PER

In [33]:
```
# Filter for players with salaries below the median
# Adjust for players who barely played and saw high PER as a result
LowSALHiPER = (nbaStats19.loc[nbaStats19['Salary/Year'] < nbaStats19['Salary/Year'].median()][nbaStats19['MP'] > 164]
               [nbaStats19['PER'] > nbaStats19['PER'].median()][['Player','Pos','Age','Tm','PER','MP','Salary/Year','Years Remaining']])
# Sort and display the dataframe
Top10LowSALHiPER = LowSALHiPER.sort_values('PER', ascending = False).reset_index(drop = True).head(10)
Top10LowSALHiPER
```

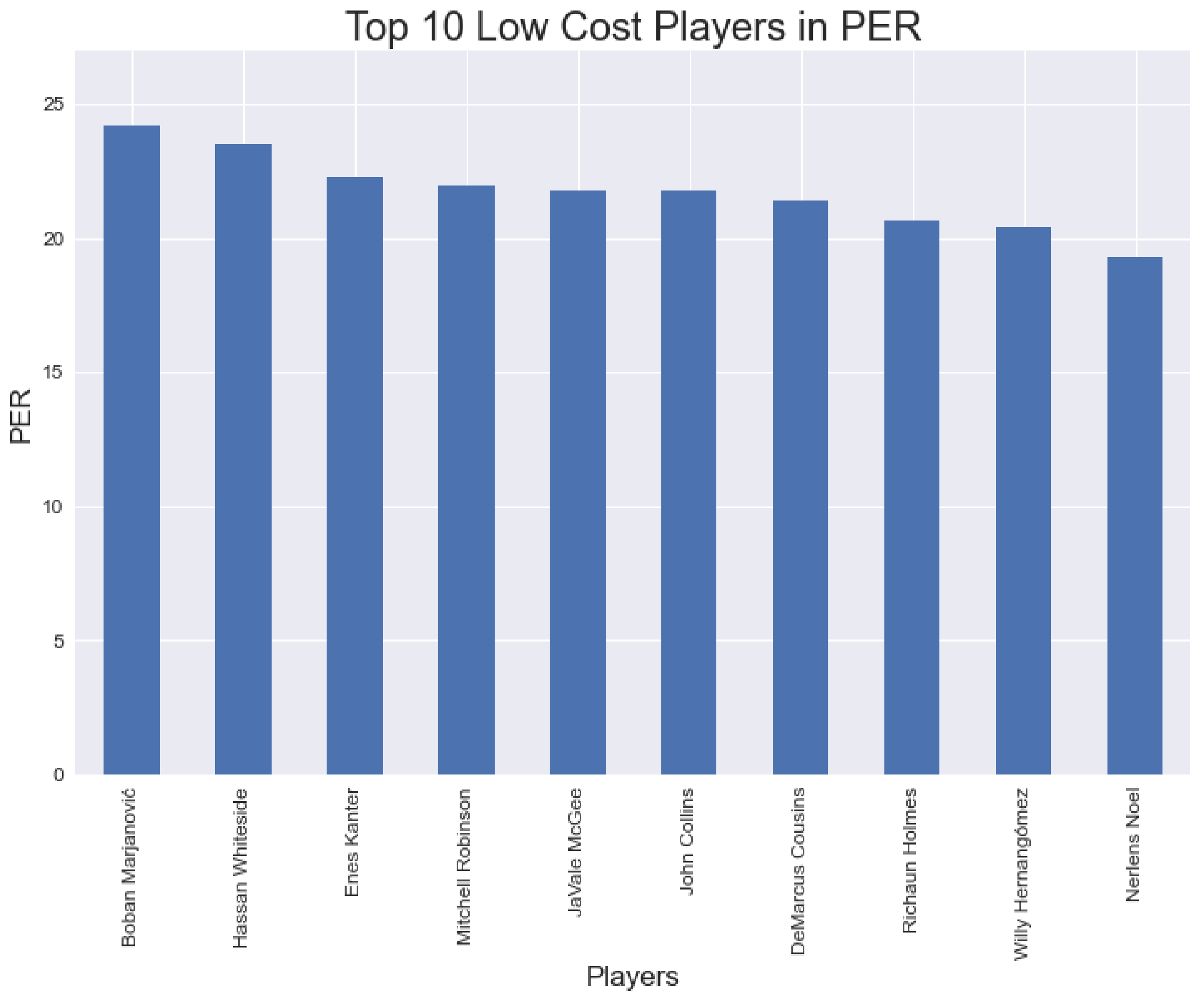
```
<ipython-input-33-bcb34cde15bb>:3: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  LowSALHiPER = (nbaStats19.loc[nbaStats19['Salary/Year'] < nbaStats19['Salary/Year'].median()][nbaStats19['MP'] > 164]
```

Out[33]:

	Player	Pos	Age	Tm	PER	MP	Salary/Year	Years Remaining
0	Boban Marjanović	C	30.0	TOT	24.2	681.0	3,500,000.0	1
1	Hassan Whiteside	C	29.0	MIA	23.5	1,674.0	2,320,044.0	1
2	Enes Kanter	C	26.0	TOT	22.3	1,640.0	5,005,350.0	1
3	Mitchell Robinson	C	20.0	NYK	22.0	1,360.0	1,732,959.0	2
4	JaVale McGee	C	31.0	LAL	21.8	1,671.0	4,200,000.0	1
5	John Collins	PF	21.0	ATL	21.8	1,829.0	4,137,302.0	1
6	DeMarcus Cousins	C	28.0	GSW	21.4	771.0	2,331,593.0	1
7	Richaun Holmes	C	25.0	PHO	20.7	1,184.0	5,005,350.0	1
8	Willy Hernangómez	C	24.0	CHO	20.4	812.0	1,727,145.0	1
9	Nerlens Noel	C	24.0	OKC	19.3	1,055.0	5,000,000.0	1

NOTES: This chart shows the players who are inexpensive, but offer a very high PER. All young players on this chart would be great targets, as they are inexpensive and provide excellent upside for the future. *Mitchell Robinson* is perhaps the most attractive target, as he is 20 years old and has a contract under $2 million for another 2 years.

In [34]:
```
fig,ax = plt.subplots()
Top10LowSALHiPER.plot.bar(x='Player',y='PER',ax=ax,figsize=(12,8), legen
d = False)
ax.set_ylim(0,27)
ax.set_title('Top 10 Low Cost Players in PER',size=24)
ax.set_ylabel('PER',size = 17)
ax.set_xlabel('Players',size = 17)
ax.tick_params(axis='both', which='major', labelsize=12)
```



BPM

Low Minutes, High BPM

In [35]:
```
# Filter for players with fewer minutes played than the median
# Adjust for players who barely played and saw high BPM as a result of l
ack of minutes
LowMinHiBPM = (nbaStats19.loc[nbaStats19['MP'] < nbaStats19['MP'].median
()][nbaStats19['MP'] > 164]
                [nbaStats19['BPM'] > nbaStats19['BPM'].median()][['Playe
r','Pos','Age','Tm','BPM','MP','Salary/Year','Years Remaining']])
# Sort and display the dataframe
Top10LowMinHiBPM = LowMinHiBPM.sort_values('BPM', ascending = False).res
et_index(drop = True).head(10)
Top10LowMinHiBPM
```

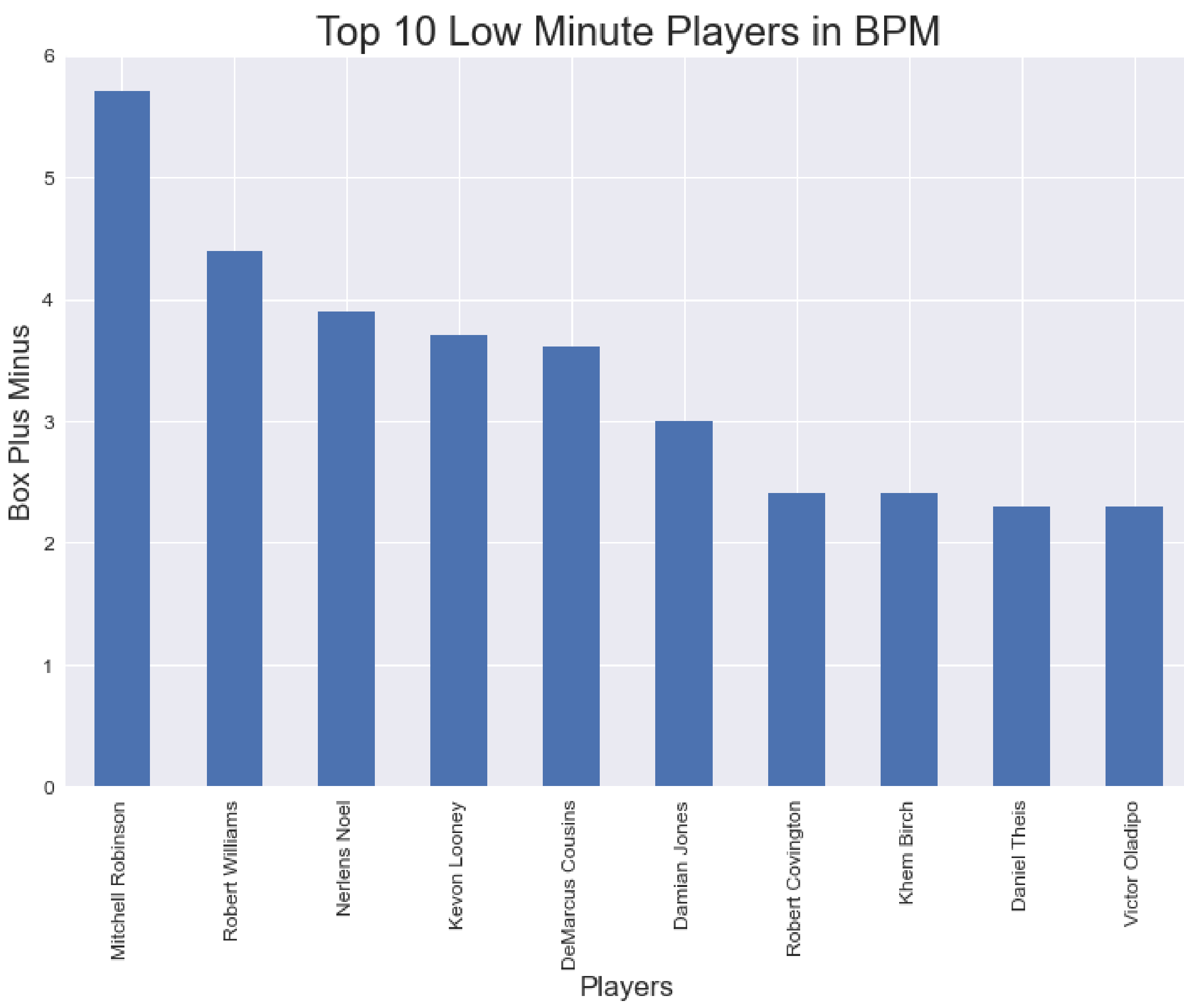
```
<ipython-input-35-8e67c60eb5be>:3: UserWarning: Boolean Series key will 
be reindexed to match DataFrame index.
  LowMinHiBPM = (nbaStats19.loc[nbaStats19['MP'] < nbaStats19['MP'].med
ian()][nbaStats19['MP'] > 164]
```

Out[35]:

	Player	Pos	Age	Tm	BPM	MP	Salary/Year	Years Remaining
0	Mitchell Robinson	C	20.0	NYK	5.7	1,360.0	1,732,959.0	2
1	Robert Williams	C	21.0	BOS	4.4	283.0	2,845,948.0	2
2	Nerlens Noel	C	24.0	OKC	3.9	1,055.0	5,000,000.0	1
3	Kevon Looney	C	22.0	GSW	3.7	1,481.0	5,000,000.0	2
4	DeMarcus Cousins	C	28.0	GSW	3.6	771.0	2,331,593.0	1
5	Damian Jones	C	23.0	GSW	3.0	410.0	1,857,078.0	2
6	Robert Covington	SF	28.0	TOT	2.4	1,203.0	12,556,908.0	2
7	Khem Birch	C	26.0	ORL	2.4	643.0	3,000,000.0	1
8	Daniel Theis	C	26.0	BOS	2.3	908.0	5,000,000.0	1
9	Victor Oladipo	SG	26.0	IND	2.3	1,147.0	21,000,000.0	1

NOTES: *Mitchell Robinson*, *Nerlens Noel*, and *Kevon Looney* are all excellent targets as they cost $5 million or less, are under 25 years old, and held a high BPM. Additionally, *Mitchell Robinson* and *Kevon Looney* still have 2 years remaining on their contract, providing low risk for an increase in cost in the near future.

In [36]:
```
fig,ax = plt.subplots()
Top10LowMinHiBPM.plot.bar(x='Player',y='BPM',ax=ax,figsize=(12,8), legen
d = False)
ax.set_ylim(0,6)
ax.set_title('Top 10 Low Minute Players in BPM',size=24)
ax.set_ylabel('Box Plus Minus',size = 17)
ax.set_xlabel('Players',size = 17)
ax.tick_params(axis='both', which='major', labelsize=12)
```



Low Salary, High BPM

In [37]:
```
# Filter data for players with salaries below the median
# Adjust for players who barely played and saw high BPM as a result of l
ack of minutes
LowSALHiBPM = (nbaStats19.loc[nbaStats19['Salary/Year'] < nbaStats19['Sa
lary/Year'].median()][nbaStats19['MP'] > 164]
               [nbaStats19['BPM'] > nbaStats19['BPM'].median()][['Playe
r','Pos','Age','Tm','BPM','MP','Salary/Year','Years Remaining']])
# Sort and display the dataframe
Top10LowSALHiBPM = LowSALHiBPM.sort_values('BPM', ascending = False).res
et_index(drop = True).head(10)
Top10LowSALHiBPM
```

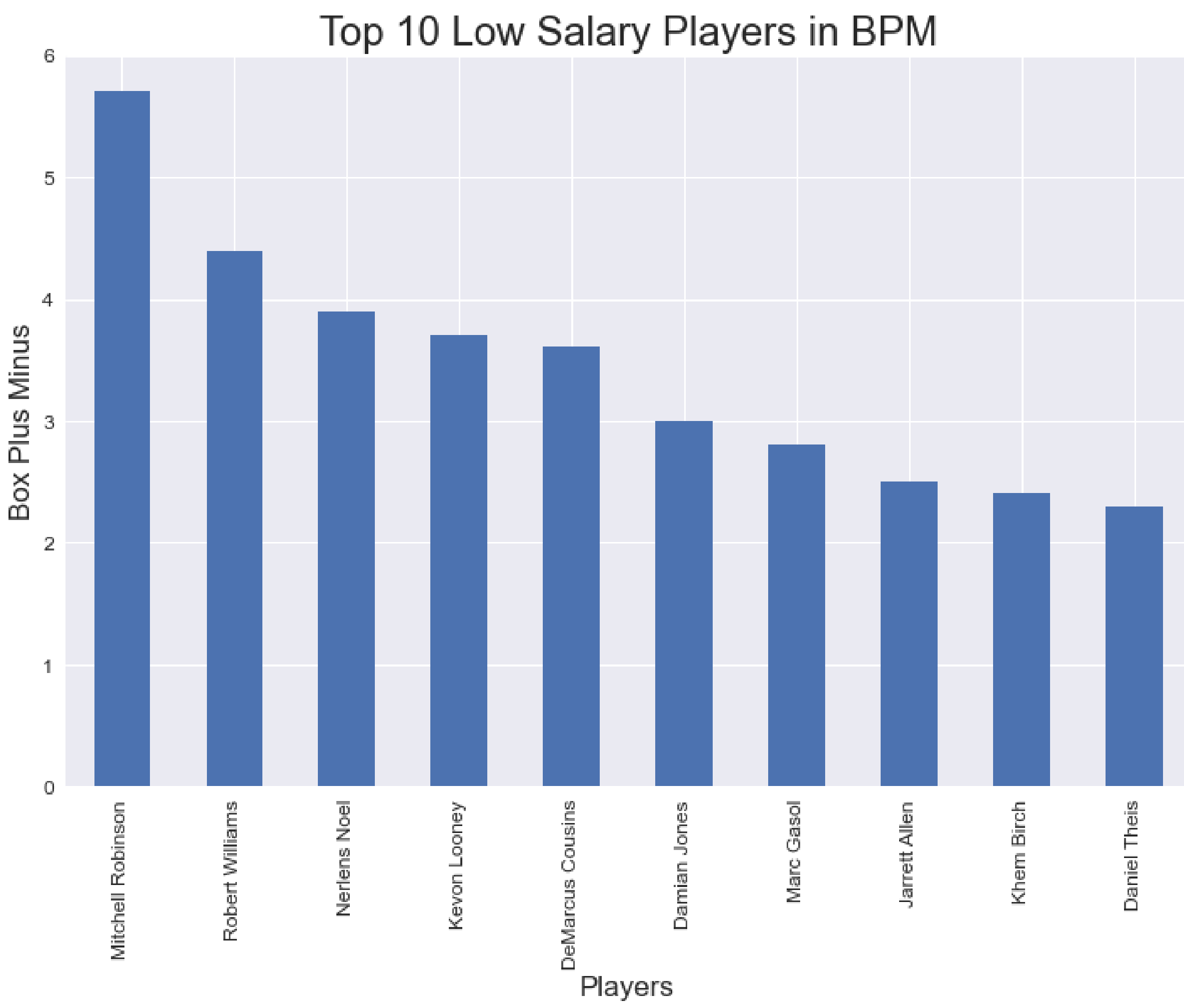
```
<ipython-input-37-c37184353a81>:3: UserWarning: Boolean Series key will
be reindexed to match DataFrame index.
  LowSALHiBPM = (nbaStats19.loc[nbaStats19['Salary/Year'] < nbaStats19
['Salary/Year'].median()][nbaStats19['MP'] > 164]
```

Out[37]:

	Player	Pos	Age	Tm	BPM	MP	Salary/Year	Years Remaining
0	Mitchell Robinson	C	20.0	NYK	5.7	1,360.0	1,732,959.0	2
1	Robert Williams	C	21.0	BOS	4.4	283.0	2,845,948.0	2
2	Nerlens Noel	C	24.0	OKC	3.9	1,055.0	5,000,000.0	1
3	Kevon Looney	C	22.0	GSW	3.7	1,481.0	5,000,000.0	2
4	DeMarcus Cousins	C	28.0	GSW	3.6	771.0	2,331,593.0	1
5	Damian Jones	C	23.0	GSW	3.0	410.0	1,857,078.0	2
6	Marc Gasol	C	34.0	TOT	2.8	2,436.0	2,628,872.0	2
7	Jarrett Allen	C	20.0	BRK	2.5	2,096.0	3,909,902.0	1
8	Khem Birch	C	26.0	ORL	2.4	643.0	3,000,000.0	1
9	Daniel Theis	C	26.0	BOS	2.3	908.0	5,000,000.0	1

NOTES: This chart shows low cost players with the highest BPMs. Again, *Mitchell Robinson, Nerlens Noel,* and *Kevon Looney* look to be excellent targets due to their high BPM, low salaries, and young ages.

In [38]:
```
fig,ax = plt.subplots()
Top10LowSALHiBPM.plot.bar(x='Player',y='BPM',ax=ax,figsize=(12,8), legen
d = False)
ax.set_ylim(0,6)
ax.set_title('Top 10 Low Salary Players in BPM',size=24)
ax.set_ylabel('Box Plus Minus',size = 17)
ax.set_xlabel('Players',size = 17)
ax.tick_params(axis='both', which='major', labelsize=12)
```



Relationships Between Key Statistics

In this section, I run regressions to determine how key statistics correlate with a player's win share. I will
look at BPM to Win Share, PER to Win Share, Assists to Win Share, Points to Win Share, Rebound to Win Share,
Steals to Win Share, and Blocks to Win Share, comparing the 10 year correlations I find to determine which
statistics make the largest positive impact on a player's team wins. I will later use the correllation
coefficients to determine a player's value (relating value to team wins for which the player is responsible).

BPM to Win Share

In [39]:
```
BPMvWS = nbaStats10yr.loc[nbaStats10yr['MP'] > 164][['Player','BPM','WS'
]]
BPM_to_WS = smf.ols('WS ~ BPM',data=BPMvWS).fit()
```

In [40]:
```
BPM_to_WS.rsquared
```

Out[40]:
```
0.6738143926161737
```

In [41]:
```
print(BPM_to_WS.summary())
```

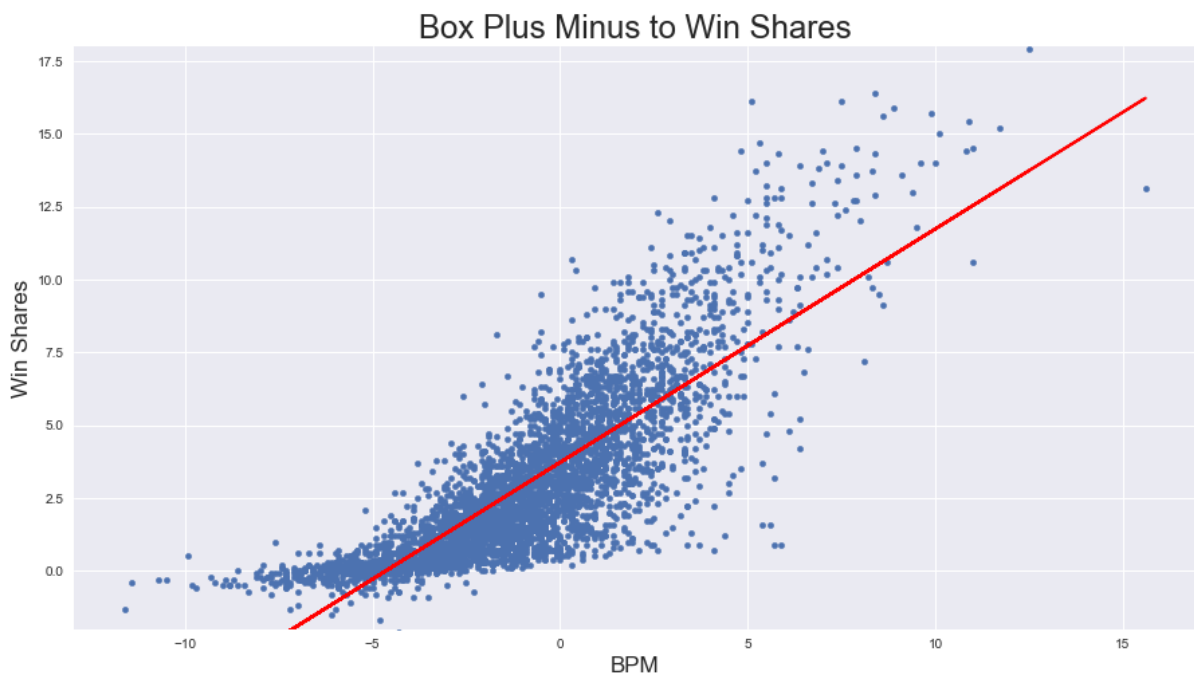
```
                            OLS Regression Results
==============================================================================
=======
Dep. Variable:                     WS   R-squared:
0.674
Model:                            OLS   Adj. R-squared:
0.674
Method:                 Least Squares   F-statistic:
8581.
Date:                Fri, 01 Jan 2021   Prob (F-statistic):
0.00
Time:                        23:08:12   Log-Likelihood:
-7955.1
No. Observations:                4156   AIC:                             1.
591e+04
Df Residuals:                    4154   BIC:                             1.
593e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
Intercept      3.7206      0.027    139.128      0.000       3.668
3.773
BPM            0.8013      0.009     92.634      0.000       0.784
0.818
==============================================================================
=======
Omnibus:                      288.356   Durbin-Watson:
1.960
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
693.814
Skew:                           0.420   Prob(JB):                        2.
19e-151
Kurtosis:                       4.817   Cond. No.
3.28
==============================================================================
=======

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

In [42]:
```
BPMvWS['yhat'] = BPM_to_WS.predict()
```

In [43]:
```
fig,ax = plt.subplots()
BPMvWS.plot.scatter(y='WS',x='BPM',ax=ax,alpha=1, figsize = (15,8))
ax.set_ylim(-2,18)
ax.set_title('Box Plus Minus to Win Shares',size=24)
ax.set_ylabel('Win Shares',size = 17)
ax.set_xlabel('Box Plus Minus',size = 17)
BPMvWS.set_index('BPM')['yhat'].plot(ax=ax,color='red',lw=2, legend=False)
```

Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd54d7c5c10>



NOTES: There is a very strong correlation between Bow Plus Minus and Win Shares. This shows that the more positive the point differential while a player is on the court, the more wins he will add for his team. This further shows the importance of the statistic BPM, as it has a high correlation with wins.

PER to Win Share

In [44]:
```
PERvWS = nbaStats10yr.loc[nbaStats10yr['MP'] > 164][['Player','PER','WS']]
PER_to_WS = smf.ols('WS ~ PER',data=PERvWS).fit()
```

In [45]:
```
PER_to_WS.rsquared
```

Out[45]: 0.6013549784390977

In [46]:
```
print(PER_to_WS.summary())
```

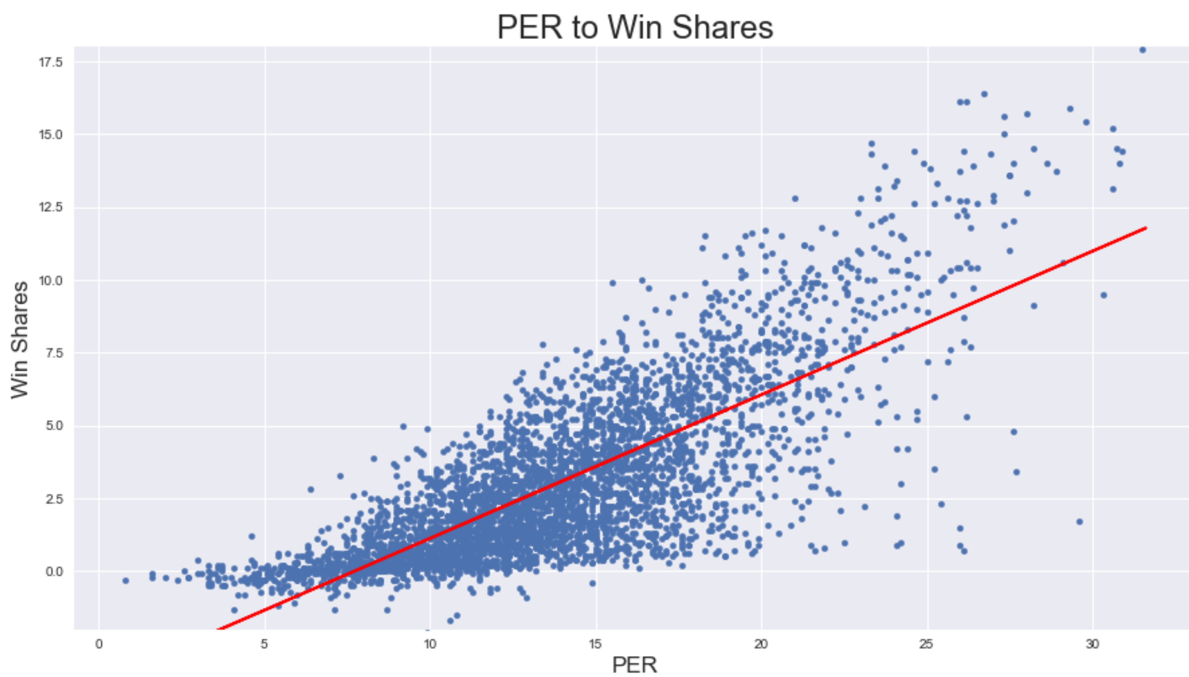
```
                            OLS Regression Results
==============================================================================
=======
Dep. Variable:                     WS   R-squared:
0.601
Model:                            OLS   Adj. R-squared:
0.601
Method:                 Least Squares   F-statistic:
6266.
Date:                Fri, 01 Jan 2021   Prob (F-statistic):
0.00
Time:                        23:08:15   Log-Likelihood:
-8371.9
No. Observations:                4156   AIC:                             1.
675e+04
Df Residuals:                    4154   BIC:                             1.
676e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
Intercept     -3.8088      0.090    -42.298      0.000      -3.985
-3.632
PER            0.4930      0.006     79.160      0.000       0.481
0.505
==============================================================================
=======
Omnibus:                      136.974   Durbin-Watson:
1.929
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
335.456
Skew:                           0.138   Prob(JB):
1.43e-73
Kurtosis:                       4.364   Cond. No.
46.5
==============================================================================
=======

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

In [47]:
```
PERvWS['yhat'] = PER_to_WS.predict()
```

In [48]:
```
fig,ax = plt.subplots()
PERvWS.plot.scatter(y='WS',x='PER',ax=ax,alpha=1, figsize = (15,8))
ax.set_ylim(-2,18)
ax.set_title('PER to Win Shares',size=24)
ax.set_ylabel('Win Shares',size = 17)
ax.set_xlabel('Player Efficiency Rating',size = 17)
PERvWS.set_index('PER')['yhat'].plot(ax=ax,color='red',lw=2, legend=False)
```

Out[48]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd54af84f70>



NOTES: There is a high correlation between PER and win shares, showing PER to be an extremely important statistic in determining a player's value. However, this correlation is lower than the correlation between BPM and Win shares, showing BPM to be a more valuable statistic in determining value.

USG to Win Shares

In [49]:
```
USGvWS = nbaStats10yr.loc[nbaStats10yr['MP'] > 164][['Player','USG','WS']].dropna()
USG_to_WS = smf.ols('WS ~ USG',data=USGvWS).fit()
```

In [50]:
```
USG_to_WS.rsquared
```

Out[50]: 0.15556328166862865

In [51]:
```
print(USG_to_WS.summary())
```

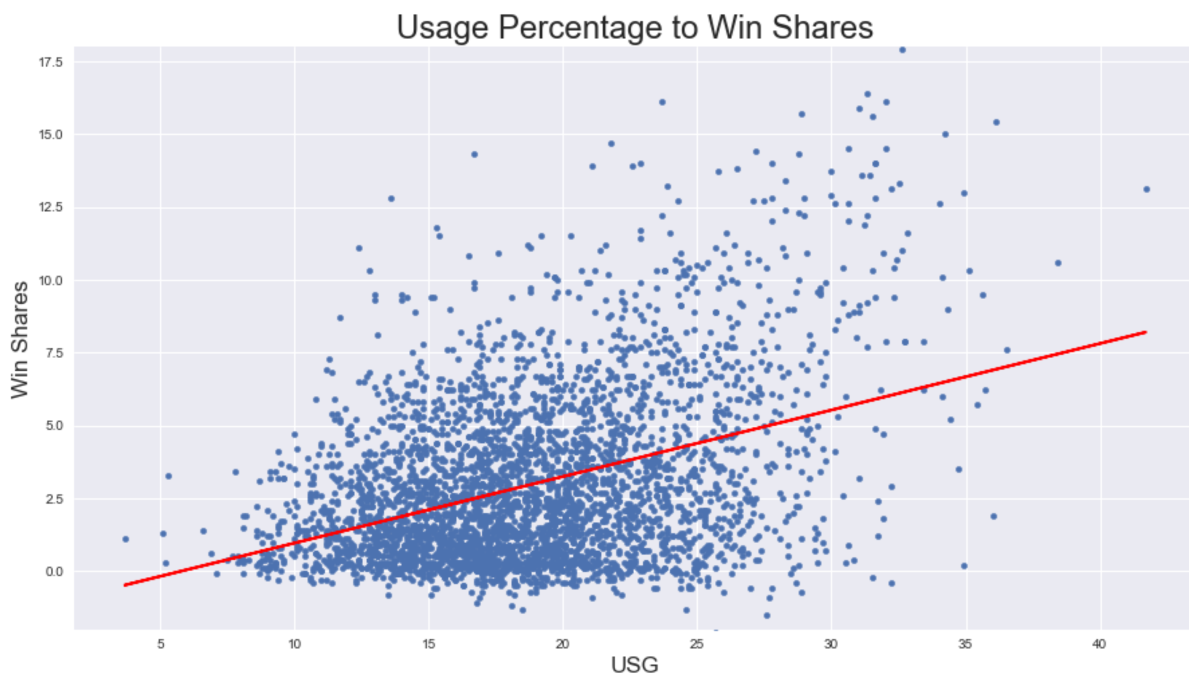
```
                            OLS Regression Results
==============================================================================
=======
Dep. Variable:                     WS   R-squared:
0.156
Model:                            OLS   Adj. R-squared:
0.155
Method:                 Least Squares   F-statistic:
684.9
Date:                Fri, 01 Jan 2021   Prob (F-statistic):          1.
02e-138
Time:                        23:08:17   Log-Likelihood:
-8904.2
No. Observations:                3720   AIC:                         1.
781e+04
Df Residuals:                    3718   BIC:                         1.
782e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
Intercept     -1.3231      0.170     -7.788      0.000      -1.656
-0.990
USG            0.2283      0.009     26.171      0.000       0.211
0.245
==============================================================================
=======
Omnibus:                      587.631   Durbin-Watson:
1.972
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               1
054.819
Skew:                           1.005   Prob(JB):                    8.
89e-230
Kurtosis:                       4.662   Cond. No.
76.3
==============================================================================
=======

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

In [52]:
```
USGvWS['yhat'] = USG_to_WS.predict()
```

In [53]:
```
fig,ax = plt.subplots()
USGvWS.plot.scatter(y='WS',x='USG',ax=ax,alpha=1, figsize = (15,8))
ax.set_ylim(-2,18)
ax.set_title('Usage Percentage to Win Shares',size=24)
ax.set_ylabel('Win Shares',size = 17)
ax.set_xlabel('Usage Percentage',size = 17)
USGvWS.set_index('USG')['yhat'].plot(ax=ax,color='red',lw=2, legend=False)
```

Out[53]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd54bb62e20>



NOTES: I found there was a positive correlation between Usage and Win Shares in 2017. However, its correlation was lower than both that of BPM and PER, showing it to be an inferior statistic in determining a player's value. Nevertheless, a player with a high usage rate does carry a higher value than a player with a low usage rate due to the positive correlation.

Assists to Win Share

In [54]:
```
ASTvWS = nbaStats10yr.loc[nbaStats10yr['MP'] > 164][['Player','AST','WS']]
AST_to_WS = smf.ols('WS ~ AST',data=ASTvWS).fit()
```

In [55]:
```
AST_to_WS.rsquared
```

Out[55]: 0.3383056529820492

In [56]:
```
print(AST_to_WS.summary())
```

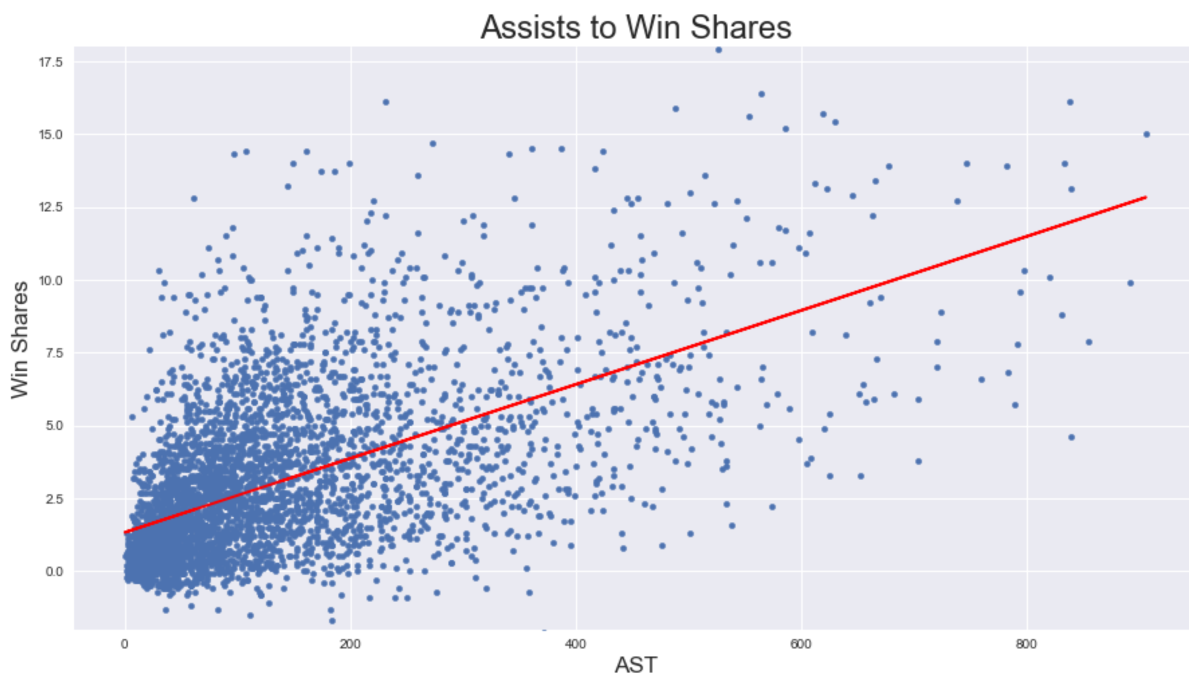
```
                            OLS Regression Results
==============================================================================
=======
Dep. Variable:                     WS   R-squared:
0.338
Model:                            OLS   Adj. R-squared:
0.338
Method:                 Least Squares   F-statistic:
2124.
Date:                Fri, 01 Jan 2021   Prob (F-statistic):
0.00
Time:                        23:08:20   Log-Likelihood:
-9424.9
No. Observations:                4156   AIC:                             1.
885e+04
Df Residuals:                    4154   BIC:                             1.
887e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
Intercept      1.3305      0.051     26.255      0.000       1.231
1.430
AST            0.0127      0.000     46.085      0.000       0.012
0.013
==============================================================================
=======
Omnibus:                      839.768   Durbin-Watson:
1.925
Prob(Omnibus):                  0.000   Jarque-Bera (JB):                 2
012.652
Skew:                           1.121   Prob(JB):
0.00
Kurtosis:                       5.568   Cond. No.
257.
==============================================================================
=======

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

In [57]:
```
ASTvWS['yhat'] = AST_to_WS.predict()
```

In [58]:
```
fig,ax = plt.subplots()
ASTvWS.plot.scatter(y='WS',x='AST',ax=ax,alpha=1, figsize = (15,8))
ax.set_ylim(-2,18)
ax.set_title('Assists to Win Shares',size=24)
ax.set_ylabel('Win Shares',size = 17)
ax.set_xlabel('Assists',size = 17)
ASTvWS.set_index('AST')['yhat'].plot(ax=ax,color='red',lw=2, legend=False)
```

Out[58]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd54bc255e0>



NOTES: Out of rebounds, points, and assists, assists had the lowest correlation to win shares, showing it to be the least valuable of the 3 statistics. Nevertheless, its positive correlation does show that it carries some value in a player's contribution, but not as high a value as rebounds and points.

Points to Win Share

In [59]:
```
PTSvWS = nbaStats10yr.loc[nbaStats10yr['MP'] > 164][['Player','PTS','WS']]
PTS_to_WS = smf.ols('WS ~ PTS',data=PTSvWS).fit()
```

In [60]:
```
PTS_to_WS.rsquared
```

Out[60]: 0.6839718477023737

In [61]:
```
print(PTS_to_WS.summary())
```

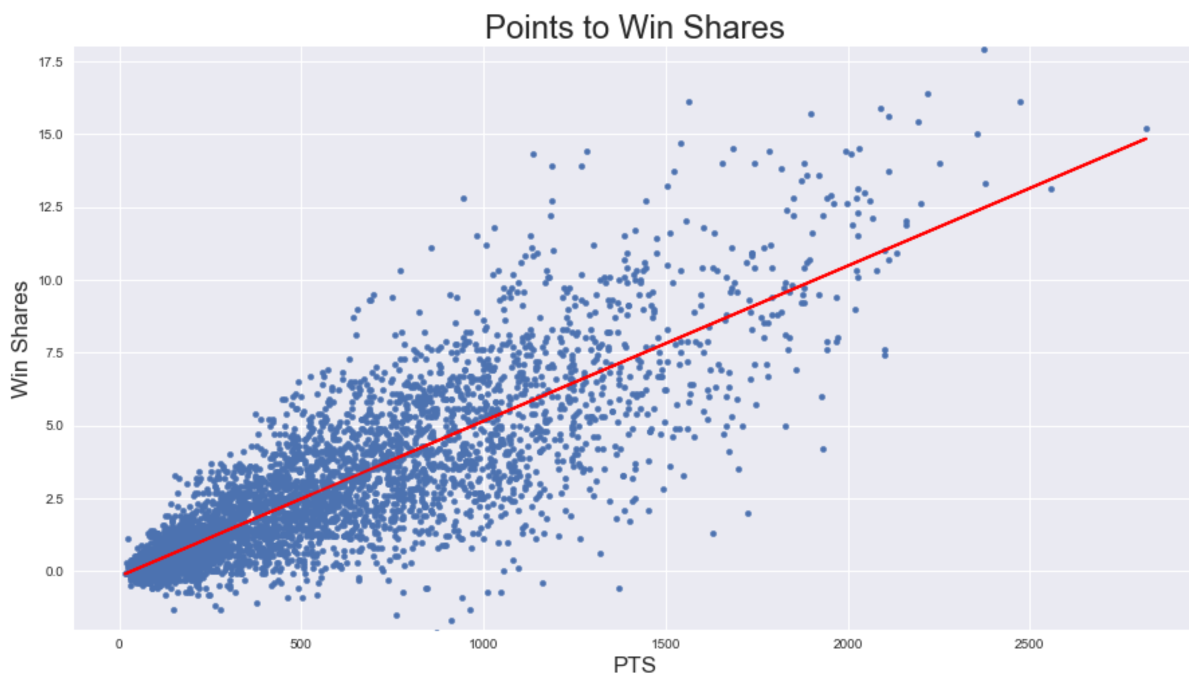
```
                            OLS Regression Results
==============================================================================
=======
Dep. Variable:                     WS   R-squared:
0.684
Model:                            OLS   Adj. R-squared:
0.684
Method:                 Least Squares   F-statistic:
8990.
Date:                Fri, 01 Jan 2021   Prob (F-statistic):
0.00
Time:                        23:08:24   Log-Likelihood:
-7889.3
No. Observations:                4156   AIC:                             1.
578e+04
Df Residuals:                    4154   BIC:                             1.
580e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
Intercept     -0.1813      0.042     -4.363      0.000      -0.263
-0.100
PTS            0.0053   5.62e-05     94.818      0.000       0.005
0.005
==============================================================================
=======
Omnibus:                      340.296   Durbin-Watson:
1.932
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               1
516.157
Skew:                           0.277   Prob(JB):
0.00
Kurtosis:                       5.907   Cond. No.
1.23e+03
==============================================================================
=======

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 1.23e+03. This might indicate that t
here are
strong multicollinearity or other numerical problems.
```

In [62]:
```
PTSvWS['yhat'] = PTS_to_WS.predict()
```

In [63]:
```
fig,ax = plt.subplots()
PTSvWS.plot.scatter(y='WS',x='PTS',ax=ax,alpha=1, figsize = (15,8))
ax.set_ylim(-2,18)
ax.set_title('Points to Win Shares',size=24)
ax.set_ylabel('Win Shares',size = 17)
ax.set_xlabel('Points',size = 17)
PTSvWS.set_index('PTS')['yhat'].plot(ax=ax,color='red',lw=2, legend=False)
```

Out[63]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd54d188850>



NOTES: Points had the highest correlation out of assists, rebounds, and points, showing that players with high point totals carry a higher value than players with high assist and rebound values. This is to be expected, as wins are determined by the team with more points, not necessarily more assists or rebounds.

Rebounds to Win Share

In [64]:
```
TRBvWS = nbaStats10yr.loc[nbaStats10yr['MP'] > 164][['Player','TRB','WS']]
TRB_to_WS = smf.ols('WS ~ TRB',data=TRBvWS).fit()
```

In [65]:
```
TRB_to_WS.rsquared
```

Out[65]: 0.5496005790709452

In [66]:
```
print(TRB_to_WS.summary())
```

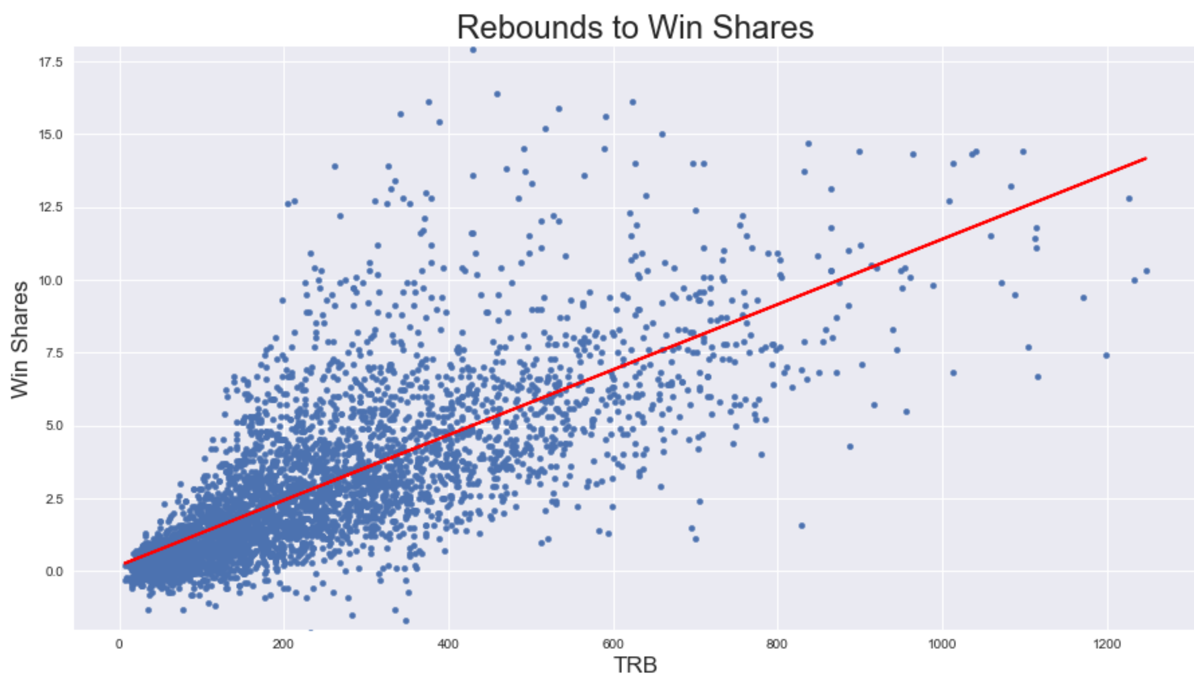
```
                            OLS Regression Results
==============================================================================
=======
Dep. Variable:                     WS   R-squared:
0.550
Model:                            OLS   Adj. R-squared:
0.549
Method:                 Least Squares   F-statistic:
5069.
Date:                Fri, 01 Jan 2021   Prob (F-statistic):
0.00
Time:                        23:08:27   Log-Likelihood:
-8625.6
No. Observations:                4156   AIC:                            1.
726e+04
Df Residuals:                    4154   BIC:                            1.
727e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
Intercept      0.1920      0.049      3.912      0.000       0.096
0.288
TRB            0.0112      0.000     71.196      0.000       0.011
0.012
==============================================================================
=======
Omnibus:                     1576.570   Durbin-Watson:
2.077
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               9
405.178
Skew:                           1.695   Prob(JB):
0.00
Kurtosis:                       9.543   Cond. No.
512.
==============================================================================
=======

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

In [67]:
```
TRBvWS['yhat'] = TRB_to_WS.predict()
```

In [68]:
```
fig,ax = plt.subplots()
TRBvWS.plot.scatter(y='WS',x='TRB',ax=ax,alpha=1, figsize = (15,8))
ax.set_ylim(-2,18)
ax.set_title('Rebounds to Win Shares',size=24)
ax.set_ylabel('Win Shares',size = 17)
ax.set_xlabel('Rebounds',size = 17)
TRBvWS.set_index('TRB')['yhat'].plot(ax=ax,color='red',lw=2, legend=False)
```

Out[68]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd54bcde7c0>



NOTES: I found that Rebounds had a stronger correlation to Win Shares than Assists, supporting an argument that it is a more important statistic than Assists. Therefore, one can conclude that rebounds should carry over more value than assists, and players who have a higher number of rebounds should be valued higher than players who have the same relative number of assists.

Steals to Win Share

In [69]:
```
STLvWS = nbaStats10yr.loc[nbaStats10yr['MP'] > 164][['Player','STL','WS']]
STL_to_WS = smf.ols('WS ~ STL',data=STLvWS).fit()
```

In [70]:
```
STL_to_WS.rsquared
```

Out[70]: 0.44928266757701607

In [71]:
```
print(STL_to_WS.summary())
```

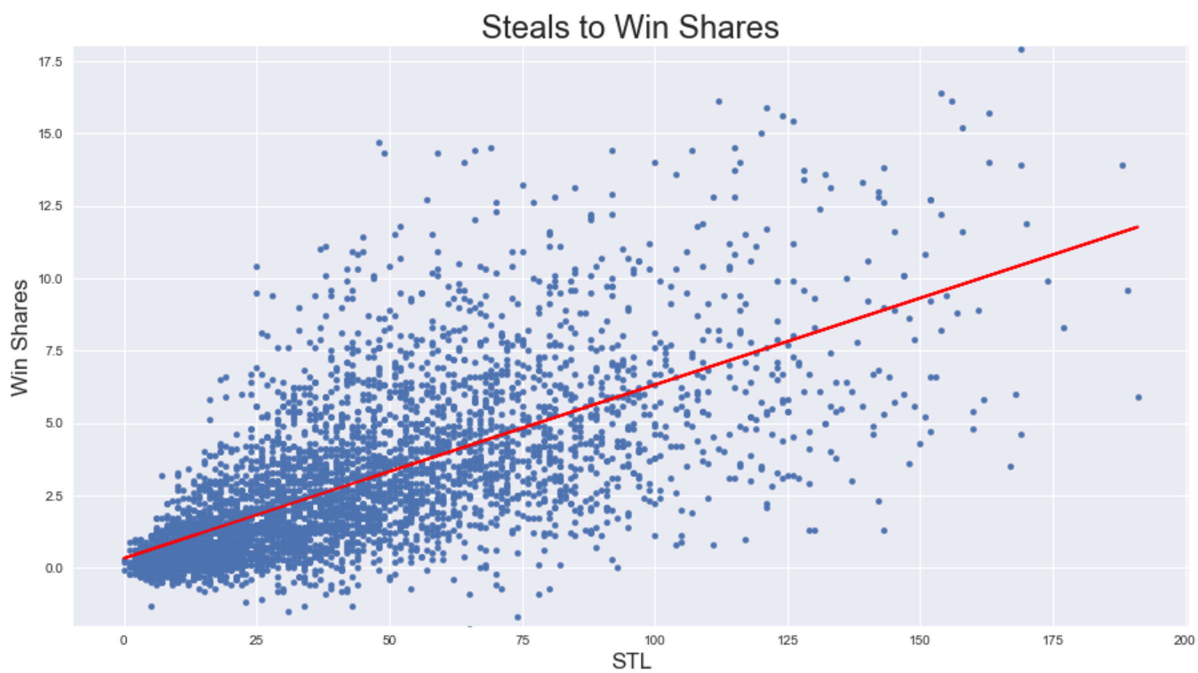
```
                            OLS Regression Results
==============================================================================
=======
Dep. Variable:                     WS   R-squared:
0.449
Model:                            OLS   Adj. R-squared:
0.449
Method:                 Least Squares   F-statistic:
3389.
Date:                Fri, 01 Jan 2021   Prob (F-statistic):
0.00
Time:                        23:08:30   Log-Likelihood:
-9043.4
No. Observations:                4156   AIC:                              1.
809e+04
Df Residuals:                    4154   BIC:                              1.
810e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
Intercept      0.3302      0.056      5.894      0.000       0.220
0.440
STL            0.0599      0.001     58.214      0.000       0.058
0.062
==============================================================================
=======
Omnibus:                      924.880   Durbin-Watson:
1.943
Prob(Omnibus):                  0.000   Jarque-Bera (JB):                  2
843.988
Skew:                           1.134   Prob(JB):
0.00
Kurtosis:                       6.359   Cond. No.
92.3
==============================================================================
=======

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

In [72]:
```
STLvWS['yhat'] = STL_to_WS.predict()
```

In [73]:
```
fig,ax = plt.subplots()
STLvWS.plot.scatter(y='WS',x='STL',ax=ax,alpha=1, figsize = (15,8))
ax.set_ylim(-2,18)
ax.set_title('Steals to Win Shares',size=24)
ax.set_ylabel('Win Shares',size = 17)
ax.set_xlabel('Steals',size = 17)
STLvWS.set_index('STL')['yhat'].plot(ax=ax,color='red',lw=2, legend=False)
```

Out[73]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd54ee33070>



NOTES: Out of the defensive statistics, I found that Steals had a stronger correlation to Win Shares than blocks. This makes sense because a steal translates to possession and a scoring opportunity for the team causing the steal, while blocks often do not change possession. (see next graph)

Blocks to Win Share

In [74]:
```
BLKvWS = nbaStats10yr.loc[nbaStats10yr['MP'] > 164][['Player','BLK','WS']]
BLK_to_WS = smf.ols('WS ~ BLK',data=BLKvWS).fit()
```

In [75]:
```
BLK_to_WS.rsquared
```

Out[75]: 0.2844218367667327

In [76]:
```
print(BLK_to_WS.summary())
```

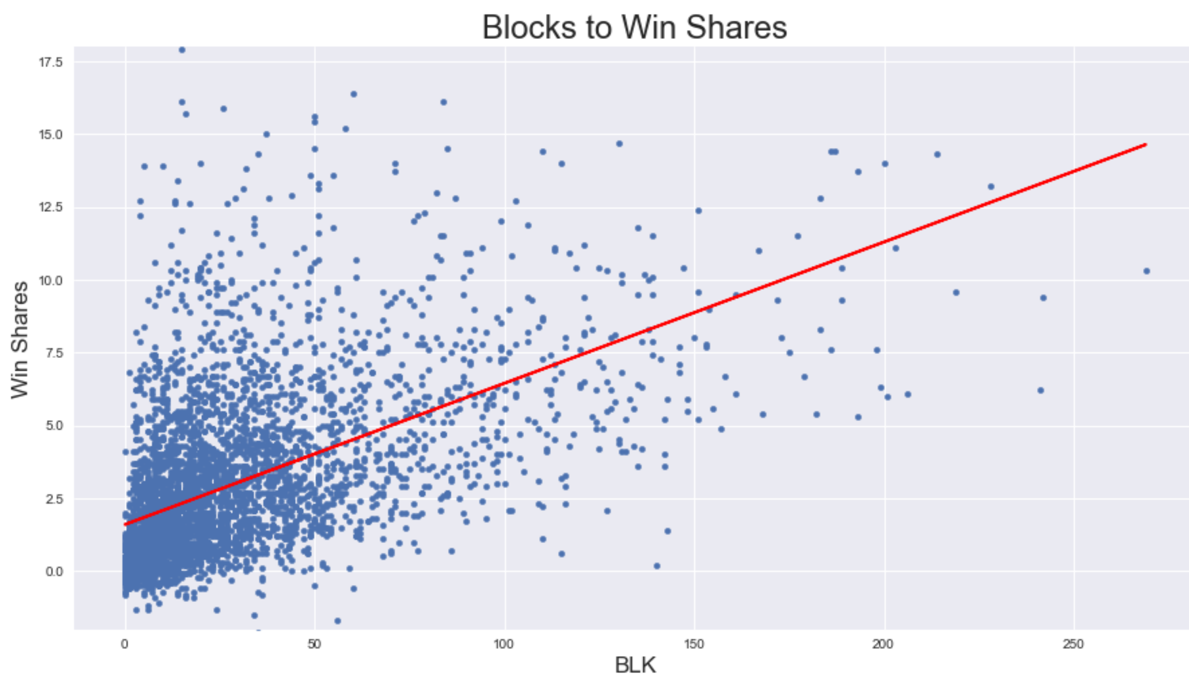
```
                            OLS Regression Results
==============================================================================
=======
Dep. Variable:                     WS   R-squared:
0.284
Model:                            OLS   Adj. R-squared:
0.284
Method:                 Least Squares   F-statistic:
1651.
Date:                Fri, 01 Jan 2021   Prob (F-statistic):          3.
08e-304
Time:                        23:08:33   Log-Likelihood:
-9587.6
No. Observations:                4156   AIC:                         1.
918e+04
Df Residuals:                    4154   BIC:                         1.
919e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
Intercept      1.5986      0.050     31.671      0.000       1.500
1.698
BLK            0.0485      0.001     40.634      0.000       0.046
0.051
==============================================================================
=======
Omnibus:                     1411.778   Durbin-Watson:
2.069
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            5
469.147
Skew:                           1.653   Prob(JB):
0.00
Kurtosis:                       7.544   Cond. No.
56.7
==============================================================================
=======

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is 
correctly specified.
```

In [77]:
```
BLKvWS['yhat'] = BLK_to_WS.predict()
```

In [78]:
```
fig,ax = plt.subplots()
BLKvWS.plot.scatter(y='WS',x='BLK',ax=ax,alpha=1, figsize = (15,8))
ax.set_ylim(-2,18)
ax.set_title('Blocks to Win Shares',size=24)
ax.set_ylabel('Win Shares',size = 17)
ax.set_xlabel('Blocks',size = 17)
BLKvWS.set_index('BLK')['yhat'].plot(ax=ax,color='red',lw=2, legend=False)
```

Out[78]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd54d7b98b0>



NOTES: There is a low, positive correllation between a player's blocks total and win share.

Model for Valuation of Players

In order to determine a player's value, I multiplied their different statistics to their given correlation
coefficient to win shares to determine the predicted win share for each stat. I then took added the products
together and divided by the number of statistics used to find the average win share predicted for each player.
By using the correllation coefficients from the 10 year dataframe, I am eliminating a large portion of the
penalty players' win share receives from the strength of their teammates by using a larger data pool.
Therefore, I am generating a more accurate estimation of the players' value.

Additionally, I look into the top valued players at each position and look into top valued players below the
median salary and below 26 years old. This allows someone to more easily identify potential targets. I
elaborate on the salaries of the different players and use rhetoric to discuss players who look to be of high
value due to their age or salary.

Finally compared the model to the all star teams in 5 previous years to assess its accuracy, and further
compared player values given salaries and positions. I found it to have 74% accuracy in predicting all star
teams. I believe some of the discrepencies come from strengths of teammates, an issue I attempted to diminish.
For example, Klay Thompson was an All Star in many of the seasons, but since Steph Curry and Kevin Durant were
his teammates, his win share was pushed lower, dropping him out of the top players. However, despite this
issue, I believe that my results are largely accurate and are useful in identifying valuable players, as well
as undervalued or underpaid players.

In [79]:
```
nbaStats19['Value'] = ((nbaStats19['BPM']*.8013 + nbaStats19['PER']*.4930 + nbaStats19['USG']*.2283
                               + nbaStats19['PTS']*.0053 + nbaStats19['AST']*.0127 + nbaStats19['BLK']*.0485
                               + nbaStats19['TRB']*.0112 + nbaStats19['STL']*.0599)/8)
nbaStats19['Value'] = nbaStats19['Value'].round(decimals=2)

nbaStats19['Value/$1M'] = (nbaStats19['Value']/nbaStats19['Salary/Year']) * 1000000
nbaStats19['Value/$1M'] = nbaStats19['Value/$1M'].round(decimals=2)
```

Top 26 Players 2019

In [80]:
```
nbaValuation19 = nbaStats19.loc[nbaStats19['MP'] > 164].sort_values('Val
ue', ascending = False).reset_index(drop = True)
nbaValuation19[['Player','Pos','Age','MP','Value']].head(26)
```

Out[80]:

	Player	Pos	Age	MP	Value
0	James Harden	PG	29.0	2,867.0	9.27
1	Giannis Antetokounmpo	PF	24.0	2,358.0	8.51
2	Nikola Jokić	C	23.0	2,504.0	7.69
3	Russell Westbrook	PG	30.0	2,630.0	7.58
4	Karl-Anthony Towns	C	23.0	2,545.0	7.38
5	Anthony Davis	C	25.0	1,850.0	7.29
6	Paul George	SF	28.0	2,841.0	7.12
7	Nikola Vučević	C	28.0	2,510.0	7.09
8	Andre Drummond	C	25.0	2,647.0	7.05
9	Rudy Gobert	C	26.0	2,577.0	6.92
10	Joel Embiid	C	24.0	2,154.0	6.81
11	Damian Lillard	PG	28.0	2,838.0	6.48
12	Kevin Durant	SF	30.0	2,702.0	6.46
13	LeBron James	SF	34.0	1,937.0	6.4
14	Bradley Beal	SG	25.0	3,028.0	6.31
15	Ben Simmons	PG	22.0	2,700.0	6.31
16	Kyrie Irving	PG	26.0	2,214.0	6.22
17	Kemba Walker	PG	28.0	2,863.0	6.2
18	Stephen Curry	PG	30.0	2,331.0	6.18
19	Jusuf Nurkić	C	24.0	1,974.0	5.98
20	Kawhi Leonard	SF	27.0	2,040.0	5.88
21	Blake Griffin	PF	29.0	2,622.0	5.82
22	LaMarcus Aldridge	C	33.0	2,687.0	5.8
23	D'Angelo Russell	PG	22.0	2,448.0	5.79
24	Luka Dončić	SG	19.0	2,318.0	5.7
25	Montrezl Harrell	C	25.0	2,158.0	5.64

Top Value Under Median Salary

In [81]:
```
nbaValuationLoSal = nbaStats19.loc[nbaStats19['Year'] == 2019][nbaStats19['MP'] > 164][nbaStats19['Salary/Year'] < nbaStats19['Salary/Year'].median()].sort_values('Value', ascending = False).reset_index(drop = True)
nbaValuationLoSal[['Player','Pos','Age','MP','Value','Salary/Year','Years Remaining']].head(26)
```

```
<ipython-input-81-d684562d8091>:1: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  nbaValuationLoSal = nbaStats19.loc[nbaStats19['Year'] == 2019][nbaStats19['MP'] > 164][nbaStats19['Salary/Year'] < nbaStats19['Salary/Year'].median()].sort_values('Value', ascending = False).reset_index(drop = True)
```

Out[81]:

	Player	Pos	Age	MP	Value	Salary/Year	Years Remaining
0	Marc Gasol	C	34.0	2,436.0	5.19	2,628,872.0	2
1	Hassan Whiteside	C	29.0	1,674.0	5.16	2,320,044.0	1
2	JaVale McGee	C	31.0	1,671.0	4.83	4,200,000.0	1
3	Willie Cauley-Stein	C	25.0	2,213.0	4.73	4,100,000.0	2
4	Mitchell Robinson	C	20.0	1,360.0	4.61	1,732,959.0	2
5	Jarrett Allen	C	20.0	2,096.0	4.59	3,909,902.0	1
6	John Collins	PF	21.0	1,829.0	4.37	4,137,302.0	1
7	Enes Kanter	C	26.0	1,640.0	4.27	5,005,350.0	1
8	DeMarcus Cousins	C	28.0	771.0	3.89	2,331,593.0	1
9	Nerlens Noel	C	24.0	1,055.0	3.83	5,000,000.0	1
10	Dewayne Dedmon	C	29.0	1,609.0	3.81	2,866,667.0	5
11	Reggie Jackson	PG	28.0	2,289.0	3.76	2,331,593.0	1
12	Richaun Holmes	C	25.0	1,184.0	3.66	5,005,350.0	1
13	Shai Gilgeous-Alexander	PG	20.0	2,174.0	3.65	4,818,426.0	2
14	Kevon Looney	C	22.0	1,481.0	3.58	5,000,000.0	2
15	Alex Len	C	25.0	1,544.0	3.52	2,320,000.0	1
16	Lauri Markkanen	PF	21.0	1,682.0	3.48	6,731,508.0	1
17	Jabari Parker	PF	23.0	1,724.0	3.42	6,500,000.0	1
18	Boban Marjanović	C	30.0	681.0	3.37	3,500,000.0	1
19	Justin Holiday	SG	29.0	2,607.0	3.36	6,006,420.0	3
20	Ed Davis	C	29.0	1,446.0	3.31	5,005,350.0	1
21	Mikal Bridges	SF	22.0	2,417.0	3.29	4,958,362.0	2
22	DeAndre' Bembry	SG	24.0	1,931.0	3.25	1,857,078.0	2
23	Kent Bazemore	SG	29.0	1,643.0	3.18	2,320,044.0	1
24	Josh Jackson	SG	21.0	1,988.0	3.13	4,886,175.0	2
25	Jeff Green	PF	32.0	2,097.0	3.06	2,564,753.0	1

Top Value per Dollar for Players in Top 50%

In [82]:
```
nbaValuationPdollar = nbaValuation19.loc[nbaValuation19['Value'] > nbaValuation19['Value'].median()]
nbaValuationPdollar[['Player','Pos','Age','MP','Value','Value/$1M','Salary/Year','Years Remaining']].sort_values('Value/$1M', ascending = False).reset_index(drop = True).head(26)
```

Out[82]:

	Player	Pos	Age	MP	Value	Value/$1M	Salary/Year	Years Remaining
0	Mitchell Robinson	C	20.0	1,360.0	4.61	2.66	1,732,959.0	2
1	Hassan Whiteside	C	29.0	1,674.0	5.16	2.22	2,320,044.0	1
2	Marc Gasol	C	34.0	2,436.0	5.19	1.97	2,628,872.0	2
3	DeAndre' Bembry	SG	24.0	1,931.0	3.25	1.75	1,857,078.0	2
4	DeMarcus Cousins	C	28.0	771.0	3.89	1.67	2,331,593.0	1
5	Reggie Jackson	PG	28.0	2,289.0	3.76	1.61	2,331,593.0	1
6	Alex Len	C	25.0	1,544.0	3.52	1.52	2,320,000.0	1
7	Kent Bazemore	SG	29.0	1,643.0	3.18	1.37	2,320,044.0	1
8	Dewayne Dedmon	C	29.0	1,609.0	3.81	1.33	2,866,667.0	5
9	Jeff Green	PF	32.0	2,097.0	3.06	1.19	2,564,753.0	1
10	Jarrett Allen	C	20.0	2,096.0	4.59	1.17	3,909,902.0	1
11	Willie Cauley-Stein	C	25.0	2,213.0	4.73	1.15	4,100,000.0	2
12	JaVale McGee	C	31.0	1,671.0	4.83	1.15	4,200,000.0	1
13	John Collins	PF	21.0	1,829.0	4.37	1.06	4,137,302.0	1
14	Boban Marjanović	C	30.0	681.0	3.37	0.96	3,500,000.0	1
15	Enes Kanter	C	26.0	1,640.0	4.27	0.85	5,005,350.0	1
16	Maurice Harkless	SF	25.0	1,415.0	3.05	0.84	3,623,000.0	1
17	Nerlens Noel	C	24.0	1,055.0	3.83	0.77	5,000,000.0	1
18	Shai Gilgeous-Alexander	PG	20.0	2,174.0	3.65	0.76	4,818,426.0	2
19	Richaun Holmes	C	25.0	1,184.0	3.66	0.73	5,005,350.0	1
20	Kevon Looney	C	22.0	1,481.0	3.58	0.72	5,000,000.0	2
21	Ed Davis	C	29.0	1,446.0	3.31	0.66	5,005,350.0	1
22	Mikal Bridges	SF	22.0	2,417.0	3.29	0.66	4,958,362.0	2
23	Trae Young	PG	20.0	2,503.0	4.86	0.65	7,449,136.0	2
24	Josh Jackson	SG	21.0	1,988.0	3.13	0.64	4,886,175.0	2
25	Luka Dončić	SG	19.0	2,318.0	5.7	0.63	9,111,876.0	2

Top Value per Dollar Under Median Age, Top 50% Value

In [83]:
```
nbaValuationPdollarYoung = nbaValuation19.loc[nbaValuation19['Value'] > nbaValuation19['Value'].median()][nbaValuation19['Age'] < nbaValuation19['Age'].median()]
nbaValuationPdollarYoung[['Player','Pos','Age','MP','Value','Value/$1M','Salary/Year','Years Remaining']].sort_values('Value/$1M', ascending = False).reset_index(drop = True).head(26)
```

```
<ipython-input-83-b13aede58124>:1: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  nbaValuationPdollarYoung = nbaValuation19.loc[nbaValuation19['Value'] > nbaValuation19['Value'].median()][nbaValuation19['Age'] < nbaValuation19['Age'].median()]
```

Out[83]:

	Player	Pos	Age	MP	Value	Value/$1M	Salary/Year	Years Remaining
0	Mitchell Robinson	C	20.0	1,360.0	4.61	2.66	1,732,959.0	2
1	DeAndre' Bembry	SG	24.0	1,931.0	3.25	1.75	1,857,078.0	2
2	Alex Len	C	25.0	1,544.0	3.52	1.52	2,320,000.0	1
3	Jarrett Allen	C	20.0	2,096.0	4.59	1.17	3,909,902.0	1
4	Willie Cauley-Stein	C	25.0	2,213.0	4.73	1.15	4,100,000.0	2
5	John Collins	PF	21.0	1,829.0	4.37	1.06	4,137,302.0	1
6	Maurice Harkless	SF	25.0	1,415.0	3.05	0.84	3,623,000.0	1
7	Nerlens Noel	C	24.0	1,055.0	3.83	0.77	5,000,000.0	1
8	Shai Gilgeous-Alexander	PG	20.0	2,174.0	3.65	0.76	4,818,426.0	2
9	Richaun Holmes	C	25.0	1,184.0	3.66	0.73	5,005,350.0	1
10	Kevon Looney	C	22.0	1,481.0	3.58	0.72	5,000,000.0	2
11	Mikal Bridges	SF	22.0	2,417.0	3.29	0.66	4,958,362.0	2
12	Trae Young	PG	20.0	2,503.0	4.86	0.65	7,449,136.0	2
13	Josh Jackson	SG	21.0	1,988.0	3.13	0.64	4,886,175.0	2
14	Luka Dončić	SG	19.0	2,318.0	5.7	0.63	9,111,876.0	2
15	Montrezl Harrell	C	25.0	2,158.0	5.64	0.59	9,489,450.0	2
16	Jabari Parker	PF	23.0	1,724.0	3.42	0.53	6,500,000.0	1
17	Lauri Markkanen	PF	21.0	1,682.0	3.48	0.52	6,731,508.0	1
18	Jusuf Nurkić	C	24.0	1,974.0	5.98	0.5	12,000,000.0	2
19	Monte Morris	PG	23.0	1,970.0	3.38	0.47	7,165,965.0	4
20	Thomas Bryant	C	21.0	1,496.0	3.83	0.45	8,531,746.0	2
21	Ivica Zubac	C	21.0	1,040.0	3.08	0.42	7,345,679.0	3
22	Deandre Ayton	C	20.0	2,183.0	4.74	0.42	11,325,575.0	2
23	Cedi Osman	SF	23.0	2,444.0	3.01	0.39	7,700,000.0	4
24	Josh Richardson	SG	25.0	2,539.0	3.96	0.35	11,200,000.0	2
25	Kyle Kuzma	PF	23.0	2,314.0	3.52	0.33	10,640,544.0	4

Top Players By Position:

```
This section is designed for an easy view of top players by position for GMs 
to review and use in making
transactional decisions. It also looks into low cost players and young_playe
rs with high value at each 
position.
```

Point Guard

Top 10 PG

In [84]:
```
nbaValuation19.loc[nbaValuation19['Pos'] == 'PG'][['Player','Pos','Age',
'Value','Value/$1M','Salary/Year','Years Remaining']].reset_index(drop = 
True).head(10)
```

Out[84]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	James Harden	PG	29.0	9.27	0.21	43,848,000.0	3
1	Russell Westbrook	PG	30.0	7.58	0.17	44,211,146.0	3
2	Damian Lillard	PG	28.0	6.48	0.14	45,525,391.0	5
3	Ben Simmons	PG	22.0	6.31	0.19	33,930,000.0	5
4	Kyrie Irving	PG	26.0	6.22	0.18	34,916,200.0	3
5	Kemba Walker	PG	28.0	6.2	0.17	36,016,200.0	3
6	Stephen Curry	PG	30.0	6.18	0.14	44,393,664.0	2
7	D'Angelo Russell	PG	22.0	5.79	0.19	30,013,500.0	3
8	De'Aaron Fox	PG	21.0	5.48	0.19	28,516,703.0	6
9	Mike Conley	PG	31.0	5.3	0.15	34,504,132.0	1

NOTES: This chart shows the top 10 valued Point Guards, led heavily by *James Harden*. As the only player under $30 million with a contract lasting 6 years at age 21, *De'Aaron Fox* is an excellent target for a GM focused on the future and looking for a star at PG.

Top 10 PG in Value Per $1M in Salary

In [85]:
```
nbaValuation19.loc[nbaValuation19['Pos'] == 'PG'][nbaValuation19['Value'] > 2][['Player','Pos','Age','Value','Value/$1M','Salary/Year','Years Remaining']].sort_values('Value/$1M', ascending = False).reset_index(drop = True).head(10)
```

```
<ipython-input-85-dabde52c3d9d>:1: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  nbaValuation19.loc[nbaValuation19['Pos'] == 'PG'][nbaValuation19['Value'] > 2][['Player','Pos','Age','Value','Value/$1M','Salary/Year','Years Remaining']].sort_values('Value/$1M', ascending = False).reset_index(drop = True).head(10)
```

Out[85]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	Shaquille Harrison	PG	25.0	2.8	1.67	1,678,854.0	1
1	Reggie Jackson	PG	28.0	3.76	1.61	2,331,593.0	1
2	Jalen Brunson	PG	22.0	2.44	1.41	1,732,959.0	2
3	Tyler Johnson	PG	26.0	2.68	1.32	2,028,594.0	1
4	Jeff Teague	PG	30.0	2.72	1.06	2,564,753.0	1
5	J.J. Barea	PG	34.0	2.61	1.02	2,564,753.0	1
6	Ryan Arcidiacono	PG	24.0	2.55	0.85	3,000,000.0	2
7	T.J. McConnell	PG	26.0	2.76	0.79	3,500,000.0	1
8	Trey Burke	PG	26.0	2.57	0.77	3,333,333.0	3
9	Shai Gilgeous-Alexander	PG	20.0	3.65	0.76	4,818,426.0	2

NOTES: *Shaquille Harrison* leads PGs in value per $1M of salary and is of high value. *Jalen Brunson* is another player who shows to be an excellent target, as he is ranked third and has 2 years remaining on his inexpensive contract.

Top 10 Low Cost PG

In [86]:
```
(nbaValuation19.loc[nbaValuation19['Pos'] == 'PG'][nbaValuation19['Salar
y/Year'] < nbaValuation19['Salary/Year'].median()]
 [nbaValuation19['MP'] > 164][['Player','Pos','Age','Value','Value/$1M',
'Salary/Year','Years Remaining']].reset_index(drop = True).head(10))
```

```
<ipython-input-86-10c0af044b47>:1: UserWarning: Boolean Series key will
be reindexed to match DataFrame index.
  (nbaValuation19.loc[nbaValuation19['Pos'] == 'PG'][nbaValuation19['Sa
lary/Year'] < nbaValuation19['Salary/Year'].median()]
```

Out[86]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	Reggie Jackson	PG	28.0	3.76	1.61	2,331,593.0	1
1	Shai Gilgeous-Alexander	PG	20.0	3.65	0.76	4,818,426.0	2
2	D.J. Augustin	PG	31.0	3.43	0.49	7,000,000.0	3
3	Monte Morris	PG	23.0	3.38	0.47	7,165,965.0	4
4	Collin Sexton	PG	20.0	2.93	0.52	5,670,776.0	2
5	Kris Dunn	PG	24.0	2.84	0.58	4,886,175.0	2
6	Elfrid Payton	PG	24.0	2.84	0.49	5,760,000.0	1
7	Shaquille Harrison	PG	25.0	2.8	1.67	1,678,854.0	1
8	T.J. McConnell	PG	26.0	2.76	0.79	3,500,000.0	1
9	Jeff Teague	PG	30.0	2.72	1.06	2,564,753.0	1

NOTES: This chart shows the top Point Guards priced below the median salary. *Shai Gilgeous-Alexander, Monte Morris, Colin Sexton*, and *Kris Dunn* are excellent options for a GM, as they are all under 25 and cost under $7.2 million for at least 2 more years.

Top 10 PG Under 26

In [87]:
```
(nbaValuation19.loc[nbaValuation19['Pos'] == 'PG'][nbaValuation19['Age'] < nbaValuation19['Age'].median()]
 [nbaValuation19['MP'] > 164][['Player','Pos','Age','Value','Value/$1M','Salary/Year','Years Remaining']].reset_index(drop = True).head(10))
```

```
<ipython-input-87-8c1d46a80e5d>:1: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  (nbaValuation19.loc[nbaValuation19['Pos'] == 'PG'][nbaValuation19['Age'] < nbaValuation19['Age'].median()]
```

Out[87]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	Ben Simmons	PG	22.0	6.31	0.19	33,930,000.0	5
1	D'Angelo Russell	PG	22.0	5.79	0.19	30,013,500.0	3
2	De'Aaron Fox	PG	21.0	5.48	0.19	28,516,703.0	6
3	Trae Young	PG	20.0	4.86	0.65	7,449,136.0	2
4	Jamal Murray	PG	21.0	4.3	0.13	33,930,000.0	5
5	Shai Gilgeous-Alexander	PG	20.0	3.65	0.76	4,818,426.0	2
6	Spencer Dinwiddie	PG	25.0	3.58	0.3	11,878,272.0	2
7	Derrick White	PG	24.0	3.5	0.24	14,303,257.0	5
8	Dennis Schröder	PG	25.0	3.44	0.22	15,500,000.0	1
9	Monte Morris	PG	23.0	3.38	0.47	7,165,965.0	4

NOTES: *Ben Simmons* is the top ranked PG under 26 and is extremely valuable at age 22. However, perhaps the best budget option on the board is *Monte Morris*, who costs under $7.2 million for the next 4 years. Therefore, he would make a great target, along with *Trae Young* and *Shai Gildeous-Alexander*, who are also low cost for the next 2 years at age 20.

Shooting Guard

Top 10 SG

In [88]:
```
nbaValuation19.loc[nbaValuation19['Pos'] == 'SG'][['Player','Pos','Age',
'Value','Value/$1M','Salary/Year','Years Remaining']].reset_index(drop =
True).head(10)
```

Out[88]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	Bradley Beal	SG	25.0	6.31	0.19	33,505,402.0	3
1	Luka Dončić	SG	19.0	5.7	0.63	9,111,876.0	2
2	Jrue Holiday	SG	28.0	5.58	0.21	26,575,556.0	2
3	DeMar DeRozan	SG	29.0	5.44	0.2	27,739,975.0	1
4	Donovan Mitchell	SG	22.0	5.17	0.18	28,032,682.0	6
5	Devin Booker	SG	22.0	4.95	0.15	32,700,000.0	4
6	Lou Williams	SG	32.0	4.71	0.59	8,000,000.0	1
7	Buddy Hield	SG	26.0	4.56	0.21	21,500,000.0	4
8	Zach LaVine	SG	23.0	4.48	0.23	19,500,000.0	2
9	Klay Thompson	SG	28.0	4.41	0.11	39,290,400.0	4

NOTES: This chart rates the Shooting Guards around the league and provides a top 10. *Luca Doncic* ranks second at 19 years old, and this along with his low cost contract for the next 2 years makes him perhaps the top prospect on this board.

Top 10 SG in Value Per $1M in Salary

In [89]:
```
nbaValuation19.loc[nbaValuation19['Pos'] == 'SG'][nbaValuation19['Value'
] > 2][['Player','Pos','Age','Value','Value/$1M','Salary/Year','Years Re
maining']].sort_values('Value/$1M', ascending = False).reset_index(drop
= True).head(10)
```

```
<ipython-input-89-11cb14a1eb0a>:1: UserWarning: Boolean Series key will
be reindexed to match DataFrame index.
  nbaValuation19.loc[nbaValuation19['Pos'] == 'SG'][nbaValuation19['Val
ue'] > 2][['Player','Pos','Age','Value','Value/$1M','Salary/Year','Year
s Remaining']].sort_values('Value/$1M', ascending = False).reset_index
(drop = True).head(10)
```

Out[89]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	DeAndre' Bembry	SG	24.0	3.25	1.75	1,857,078.0	2
1	Kent Bazemore	SG	29.0	3.18	1.37	2,320,044.0	1
2	Damyean Dotson	SG	24.0	2.52	1.26	2,000,000.0	2
3	Bryn Forbes	SG	25.0	2.78	1.16	2,395,574.0	2
4	Langston Galloway	SG	27.0	2.13	1.05	2,028,594.0	1
5	E'Twaun Moore	SG	29.0	2.09	0.9	2,331,593.0	1
6	Wayne Ellington	SG	31.0	2.3	0.77	3,005,225.0	1
7	Kevin Huerter	SG	20.0	2.68	0.76	3,507,638.0	2
8	Landry Shamet	SG	21.0	2.2	0.75	2,929,191.0	2
9	Josh Okogie	SG	20.0	2.53	0.75	3,369,472.0	2

NOTES: *Deandre Bembry* is the clear most valuable target at the SG position, as he leads this group in both value and value per 1 million in salary, at age 24 and with 2 years remaining on his contract. He is also the cheapest player, with a salary under 2 million dollars.

Top 10 Low Cost SG

In [90]:
```
(nbaValuation19.loc[nbaValuation19['Pos'] == 'SG'][nbaValuation19['Salary/Year'] < nbaValuation19['Salary/Year'].median()]
 [nbaValuation19['MP'] > 164][['Player','Pos','Age','Value','Value/$1M','Salary/Year','Years Remaining']].reset_index(drop = True).head(10))
```

```
<ipython-input-90-eb7436ba30a7>:1: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  (nbaValuation19.loc[nbaValuation19['Pos'] == 'SG'][nbaValuation19['Salary/Year'] < nbaValuation19['Salary/Year'].median()]
```

Out[90]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	Justin Holiday	SG	29.0	3.36	0.56	6,006,420.0	3
1	DeAndre' Bembry	SG	24.0	3.25	1.75	1,857,078.0	2
2	Kent Bazemore	SG	29.0	3.18	1.37	2,320,044.0	1
3	Josh Jackson	SG	21.0	3.13	0.64	4,886,175.0	2
4	Bryn Forbes	SG	25.0	2.78	1.16	2,395,574.0	2
5	Kevin Huerter	SG	20.0	2.68	0.76	3,507,638.0	2
6	Pat Connaughton	SG	26.0	2.61	0.49	5,333,333.0	3
7	Josh Okogie	SG	20.0	2.53	0.75	3,369,472.0	2
8	Damyean Dotson	SG	24.0	2.52	1.26	2,000,000.0	2
9	Josh Hart	SG	23.0	2.45	0.7	3,491,159.0	1

NOTES: Each of these players is extremely valuable, as most are very young, and all are rated excellently. However, *Deandre Bembry* stands out among the group, with the highest Value/$1M at 1.75 and a salary of 1.86 million for the next 2 years at age 24. Therefore, he appears to be an outstanding target.

Top 10 SG Under 26

In [91]:
```
(nbaValuation19.loc[nbaValuation19['Pos'] == 'SG'][nbaValuation19['Age'] < nbaValuation19['Age'].median()]
 [nbaValuation19['MP'] > 164][['Player','Pos','Age','Value','Value/$1M','Salary/Year','Years Remaining']].reset_index(drop = True).head(10))
```

```
<ipython-input-91-d668be190ecb>:1: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  (nbaValuation19.loc[nbaValuation19['Pos'] == 'SG'][nbaValuation19['Age'] < nbaValuation19['Age'].median()]
```

Out[91]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	Bradley Beal	SG	25.0	6.31	0.19	33,505,402.0	3
1	Luka Dončić	SG	19.0	5.7	0.63	9,111,876.0	2
2	Donovan Mitchell	SG	22.0	5.17	0.18	28,032,682.0	6
3	Devin Booker	SG	22.0	4.95	0.15	32,700,000.0	4
4	Zach LaVine	SG	23.0	4.48	0.23	19,500,000.0	2
5	Josh Richardson	SG	25.0	3.96	0.35	11,200,000.0	2
6	Marcus Smart	SG	24.0	3.95	0.28	13,892,856.0	2
7	DeAndre' Bembry	SG	24.0	3.25	1.75	1,857,078.0	2
8	Jaylen Brown	SG	22.0	3.2	0.12	25,750,000.0	4
9	Josh Jackson	SG	21.0	3.13	0.64	4,886,175.0	2

NOTES: This chart shows the top SGs under 26 years old. *Luka Doncic* is an extremely valuable player who costs under 9.2 million with 2 years remaining on his contract at age 19. Therefore, he is an excellent option for any GM. Additionally, *DeAndre Bembry* is, again, an excellent option. He is 24 years old, high value, and costs under 1.9 million for the next 2 years. His Value/1M is 1.75, by far the highest of the group, combining with the other factors to make *DeAndre Bembry* an awesome target.

Small Forward

Top 10 SF

In [92]:
```
nbaValuation19.loc[nbaValuation19['Pos'] == 'SF'][['Player','Pos','Age',
'Value','Value/$1M','Salary/Year','Years Remaining']].reset_index(drop =
True).head(10)
```

Out[92]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	Paul George	SF	28.0	7.12	0.17	42,343,176.0	5
1	Kevin Durant	SF	30.0	6.46	0.16	40,918,900.0	3
2	LeBron James	SF	34.0	6.4	0.15	41,625,032.0	3
3	Kawhi Leonard	SF	27.0	5.88	0.17	35,197,650.0	2
4	Jimmy Butler	SF	29.0	5.06	0.14	36,016,200.0	3
5	Khris Middleton	SF	27.0	4.56	0.12	36,724,138.0	4
6	Danilo Gallinari	SF	30.0	4.53	0.22	20,475,000.0	3
7	Jayson Tatum	SF	20.0	4.21	0.15	28,816,285.0	6
8	Bojan Bogdanović	SF	29.0	3.84	0.21	18,700,000.0	3
9	Andrew Wiggins	SF	23.0	3.65	0.12	31,579,390.0	3

NOTES: This chart shows the top 10 valued SFs. Since all are either expensive or veterans, it is tough to find a player that truly sticks out from the pack. *Jayson Tatum* would have to be the noted player here, as he is under $30 million with 6 years remaining on his contract and the 8th best SF at age 20.

Top 10 SF in Value Per $1M in Salary

In [93]:
```
nbaValuation19.loc[nbaValuation19['Pos'] == 'SF'][nbaValuation19['Value'] > 2][['Player','Pos','Age','Value','Value/$1M','Salary/Year','Years Remaining']].sort_values('Value/$1M', ascending = False).reset_index(drop = True).head(10)
```

```
<ipython-input-93-c580fc5d2119>:1: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  nbaValuation19.loc[nbaValuation19['Pos'] == 'SF'][nbaValuation19['Value'] > 2][['Player','Pos','Age','Value','Value/$1M','Salary/Year','Years Remaining']].sort_values('Value/$1M', ascending = False).reset_index(drop = True).head(10)
```

Out[93]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	Torrey Craig	SF	28.0	2.31	1.38	1,678,854.0	1
1	Rodions Kurucs	SF	20.0	2.2	1.21	1,820,610.0	2
2	Bruno Caboclo	SF	23.0	2.03	0.94	2,155,814.0	2
3	Maurice Harkless	SF	25.0	3.05	0.84	3,623,000.0	1
4	Dorian Finney-Smith	SF	25.0	2.93	0.73	4,000,000.0	2
5	Wesley Matthews	SF	32.0	2.55	0.7	3,623,000.0	1
6	Mikal Bridges	SF	22.0	3.29	0.66	4,958,362.0	2
7	Jake Layman	SF	24.0	2.42	0.63	3,850,634.0	2
8	Miles Bridges	SF	20.0	2.89	0.62	4,677,906.0	2
9	Stanley Johnson	SF	22.0	2.16	0.57	3,801,000.0	1

NOTES: *Rodions Kurucs* seems to be a very good prospect, as he is 2nd in this category, is 20 years old, and has a salary under $2 million for the next 2 years. Therefore, it appears that he would make an excellent target for a GM.

Top 10 Low Cost SF

In [94]:
```
(nbaValuation19.loc[nbaValuation19['Pos'] == 'SF'][nbaValuation19['Salar
y/Year'] < nbaValuation19['Salary/Year'].median()]
 [nbaValuation19['MP'] > 164][['Player','Pos','Age','Value','Value/$1M',
'Salary/Year','Years Remaining']].reset_index(drop = True).head(10))
```

```
<ipython-input-94-1b54fc5fa7c8>:1: UserWarning: Boolean Series key will
be reindexed to match DataFrame index.
  (nbaValuation19.loc[nbaValuation19['Pos'] == 'SF'][nbaValuation19['Sa
lary/Year'] < nbaValuation19['Salary/Year'].median()]
```

Out[94]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	Mikal Bridges	SF	22.0	3.29	0.66	4,958,362.0	2
1	Maurice Harkless	SF	25.0	3.05	0.84	3,623,000.0	1
2	Dorian Finney-Smith	SF	25.0	2.93	0.73	4,000,000.0	2
3	Miles Bridges	SF	20.0	2.89	0.62	4,677,906.0	2
4	Wesley Matthews	SF	32.0	2.55	0.7	3,623,000.0	1
5	Jake Layman	SF	24.0	2.42	0.63	3,850,634.0	2
6	Torrey Craig	SF	28.0	2.31	1.38	1,678,854.0	1
7	Rodions Kurucs	SF	20.0	2.2	1.21	1,820,610.0	2
8	Stanley Johnson	SF	22.0	2.16	0.57	3,801,000.0	1
9	Justin Jackson	SF	23.0	2.1	0.42	5,029,650.0	1

NOTES: All players on this chart are excellent options, as they cost under 5.1 million and provide excellent value at the SF position. However, *Rodions Kurucs* again appears to be an excellent option, as he is 20 years old and costs less than $2 million.

Top 10 SF Under 26

In [95]:
```
(nbaValuation19.loc[nbaValuation19['Pos'] == 'SF'][nbaValuation19['Age'] < nbaValuation19['Age'].median()]
 [nbaValuation19['MP'] > 164][['Player','Pos','Age','Value','Value/$1M','Salary/Year','Years Remaining']].reset_index(drop = True).head(10))
```

```
<ipython-input-95-2e84e90bf430>:1: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  (nbaValuation19.loc[nbaValuation19['Pos'] == 'SF'][nbaValuation19['Age'] < nbaValuation19['Age'].median()]
```

Out[95]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	Jayson Tatum	SF	20.0	4.21	0.15	28,816,285.0	6
1	Andrew Wiggins	SF	23.0	3.65	0.12	31,579,390.0	3
2	Otto Porter	SF	25.0	3.52	0.12	28,489,239.0	1
3	Justise Winslow	SF	22.0	3.52	0.27	13,000,000.0	2
4	Mikal Bridges	SF	22.0	3.29	0.66	4,958,362.0	2
5	Maurice Harkless	SF	25.0	3.05	0.84	3,623,000.0	1
6	Cedi Osman	SF	23.0	3.01	0.39	7,700,000.0	4
7	Dorian Finney-Smith	SF	25.0	2.93	0.73	4,000,000.0	2
8	T.J. Warren	SF	25.0	2.9	0.24	12,220,000.0	2
9	Miles Bridges	SF	20.0	2.89	0.62	4,677,906.0	2

NOTES: *Jason Tatum* is the highest valued SF under age 26. While he is obviously a great option for a team with a lot of money left to spend, a solid target for a GM would be *Cedi Osman*, who is 23 years old, a high value player, and holds a salary of 7.7 million dollars for 4 more years. *Mikal Bridges* and *Miles Bridges* are other excellent budget options due to being under 23 years old and under $5 million for 2 remaining years.

Power Forward

Top 10 PF

In [96]:
```
nbaValuation19.loc[nbaValuation19['Pos'] == 'PF'][['Player','Pos','Age',
'Value','Value/$1M','Salary/Year','Years Remaining']].reset_index(drop =
True).head(10)
```

Out[96]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	Giannis Antetokounmpo	PF	24.0	8.51	0.2	42,621,486.0	6
1	Blake Griffin	PF	29.0	5.82	0.15	37,776,512.0	2
2	Julius Randle	PF	24.0	5.18	0.27	19,350,000.0	2
3	Pascal Siakam	PF	24.0	5.01	0.15	32,480,000.0	4
4	Tobias Harris	PF	26.0	4.72	0.13	37,241,379.0	4
5	Thaddeus Young	PF	30.0	4.68	0.34	13,867,500.0	2
6	Aaron Gordon	PF	23.0	4.51	0.26	17,272,728.0	2
7	Paul Millsap	PF	33.0	4.37	0.44	10,000,000.0	1
8	John Collins	PF	21.0	4.37	1.06	4,137,302.0	1
9	Joe Ingles	PF	31.0	4.23	0.34	12,431,818.0	2

NOTES: This shows the top 10 valued Power Forwards with *Giannis Antetokuonmpo* leading the pack, followed by *Blake Griffin*. *Aaron Gordon* seems to be an extremely valuable option, as he is 23 years old, about $17 million, and has 2 years remaining on his contract.

Top 10 PF in Value Per $1M in Salary

In [97]:
```
nbaValuation19.loc[nbaValuation19['Pos'] == 'PF'][nbaValuation19['Value'] > 2][['Player','Pos','Age','Value','Value/$1M','Salary/Year','Years Remaining']].sort_values('Value/$1M', ascending = False).reset_index(drop = True).head(10)
```

```
<ipython-input-97-2a44ded8fc4f>:1: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  nbaValuation19.loc[nbaValuation19['Pos'] == 'PF'][nbaValuation19['Value'] > 2][['Player','Pos','Age','Value','Value/$1M','Salary/Year','Years Remaining']].sort_values('Value/$1M', ascending = False).reset_index(drop = True).head(10)
```

Out[97]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	Harry Giles	PF	20.0	2.42	1.44	1,678,854.0	1
1	Jeff Green	PF	32.0	3.06	1.19	2,564,753.0	1
2	Luke Kornet	PF	23.0	2.44	1.06	2,304,878.0	1
3	John Collins	PF	21.0	4.37	1.06	4,137,302.0	1
4	Markieff Morris	PF	29.0	2.25	0.97	2,331,593.0	1
5	Mike Muscala	PF	27.0	2.16	0.95	2,283,034.0	1
6	Bobby Portis	PF	23.0	2.94	0.79	3,713,575.0	2
7	DeMarre Carroll	PF	32.0	2.52	0.68	3,710,007.0	2
8	Jabari Parker	PF	23.0	3.42	0.53	6,500,000.0	1
9	Nemanja Bjelica	PF	30.0	3.71	0.52	7,150,000.0	1

NOTES: Among this group, *Bobby Portis* is an excellent target, as he ranks 7th in value per million dollars of salary, is 23 years old, and has 2 years remaining on his contract.

Top 10 Low Cost PF

In [98]:
```
(nbaValuation19.loc[nbaValuation19['Pos'] == 'PF'][nbaValuation19['Salary/Year'] < nbaValuation19['Salary/Year'].median()]
 [nbaValuation19['MP'] > 164][['Player','Pos','Age','Value','Value/$1M','Salary/Year','Years Remaining']].reset_index(drop = True).head(10))
```

```
<ipython-input-98-f5e407973da2>:1: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  (nbaValuation19.loc[nbaValuation19['Pos'] == 'PF'][nbaValuation19['Salary/Year'] < nbaValuation19['Salary/Year'].median()]
```

Out[98]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	John Collins	PF	21.0	4.37	1.06	4,137,302.0	1
1	Nemanja Bjelica	PF	30.0	3.71	0.52	7,150,000.0	1
2	Lauri Markkanen	PF	21.0	3.48	0.52	6,731,508.0	1
3	Jabari Parker	PF	23.0	3.42	0.53	6,500,000.0	1
4	Jeff Green	PF	32.0	3.06	1.19	2,564,753.0	1
5	Bobby Portis	PF	23.0	2.94	0.79	3,713,575.0	2
6	DeMarre Carroll	PF	32.0	2.52	0.68	3,710,007.0	2
7	Luke Kornet	PF	23.0	2.44	1.06	2,304,878.0	1
8	Harry Giles	PF	20.0	2.42	1.44	1,678,854.0	1
9	Trey Lyles	PF	23.0	2.33	0.42	5,500,000.0	1

NOTES: *John Collins* leads the low cost Centers with the highest value. He is an excellent target, as he is also 21 years old. Additionally, *Bobby Portis* also is an excellent option, as he has 2 years left of his contract and costs under $3.72 million. Therefore, GMs should look into adding these players.

Top 10 PF Under 26

In [99]:
```
(nbaValuation19.loc[nbaValuation19['Pos'] == 'PF'][nbaValuation19['Age'] < nbaValuation19['Age'].median()]
 [nbaValuation19['MP'] > 164][['Player','Pos','Age','Value','Value/$1M','Salary/Year','Years Remaining']].reset_index(drop = True).head(10))
```

```
<ipython-input-99-f1f907f16c66>:1: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  (nbaValuation19.loc[nbaValuation19['Pos'] == 'PF'][nbaValuation19['Age'] < nbaValuation19['Age'].median()]
```

Out[99]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	Giannis Antetokounmpo	PF	24.0	8.51	0.2	42,621,486.0	6
1	Julius Randle	PF	24.0	5.18	0.27	19,350,000.0	2
2	Pascal Siakam	PF	24.0	5.01	0.15	32,480,000.0	4
3	Aaron Gordon	PF	23.0	4.51	0.26	17,272,728.0	2
4	John Collins	PF	21.0	4.37	1.06	4,137,302.0	1
5	Jerami Grant	PF	24.0	3.81	0.19	20,000,000.0	3
6	Kyle Kuzma	PF	23.0	3.52	0.33	10,640,544.0	4
7	Jonathan Isaac	PF	21.0	3.49	0.23	15,392,513.0	5
8	Lauri Markkanen	PF	21.0	3.48	0.52	6,731,508.0	1
9	Jabari Parker	PF	23.0	3.42	0.53	6,500,000.0	1

NOTES: This shows the top 10 PF's under 26 years old. *Giannis Antetokounmpo* leads the group, but *John Collins* provides the most value for his salary, with a Value/$1M of 1.06. Additionally, he is 21 years old and makes a great option for a GM. However, *Kyle Kuzma* and *Jonathan Isaac* are extremely valuable due to their youth, low salary, and years remaining at such a low price.

Center

Top 10 C

In [100]:
```
nbaValuation19.loc[nbaValuation19['Pos'] == 'C'][['Player','Pos','Age',
'Value','Value/$1M','Salary/Year','Years Remaining']].reset_index(drop =
True).head(10)
```

Out[100]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	Nikola Jokić	C	23.0	7.69	0.25	30,510,423.0	3
1	Karl-Anthony Towns	C	23.0	7.38	0.23	32,700,000.0	4
2	Anthony Davis	C	25.0	7.29	0.19	37,980,720.0	5
3	Nikola Vučević	C	28.0	7.09	0.3	24,000,000.0	3
4	Andre Drummond	C	25.0	7.05	0.25	28,751,775.0	1
5	Rudy Gobert	C	26.0	6.92	0.18	38,587,547.0	6
6	Joel Embiid	C	24.0	6.81	0.22	31,579,390.0	3
7	Jusuf Nurkić	C	24.0	5.98	0.5	12,000,000.0	2
8	LaMarcus Aldridge	C	33.0	5.8	0.24	24,000,000.0	1
9	Montrezl Harrell	C	25.0	5.64	0.59	9,489,450.0	2

NOTES: This shows the top Centers in the league, as estimated by the valuation. Jokic led the league, but Nurkic and Montrezl Harrell made the top 10 and are $12 million and under

Top 10 C in Value Per $1M in Salary

In [101]:

```
nbaValuation19.loc[nbaValuation19['Pos'] == 'C'][nbaValuation19['Value'] > 2][['Player','Pos','Age','Value','Value/$1M','Salary/Year','Years Remaining']].sort_values('Value/$1M', ascending = False).reset_index(drop = True).head(10)
```

```
<ipython-input-101-6ff7f6ad5026>:1: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  nbaValuation19.loc[nbaValuation19['Pos'] == 'C'][nbaValuation19['Value'] > 2][['Player','Pos','Age','Value','Value/$1M','Salary/Year','Years Remaining']].sort_values('Value/$1M', ascending = False).reset_index(drop = True).head(10)
```

Out[101]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	Mitchell Robinson	C	20.0	4.61	2.66	1,732,959.0	2
1	Hassan Whiteside	C	29.0	5.16	2.22	2,320,044.0	1
2	Marc Gasol	C	34.0	5.19	1.97	2,628,872.0	2
3	Willy Hernangómez	C	24.0	2.92	1.69	1,727,145.0	1
4	DeMarcus Cousins	C	28.0	3.89	1.67	2,331,593.0	1
5	Alex Len	C	25.0	3.52	1.52	2,320,000.0	1
6	Dewayne Dedmon	C	29.0	3.81	1.33	2,866,667.0	5
7	Jahlil Okafor	C	23.0	2.57	1.28	2,006,445.0	2
8	Jarrett Allen	C	20.0	4.59	1.17	3,909,902.0	1
9	JaVale McGee	C	31.0	4.83	1.15	4,200,000.0	1

NOTES: Among this group, *Mitchell Robinson* is clearly the best target. Not only is his value the highest relative to his salary, but he also is 20 years old and has 2 more years remaining on his contract. Therefore, teams should very pleased to add him to their roster if possible. Additionally, *Dewayne Dedmon* is another good option, as he provides a solid value while costing under $3 million for the next 5 years.

Top 10 Low Cost C

In [102]:
```
(nbaValuation19.loc[nbaValuation19['Pos'] == 'C'][nbaValuation19['Salary/Year'] < nbaValuation19['Salary/Year'].median()]
 [nbaValuation19['MP'] > 164][['Player','Pos','Age','Value','Value/$1M','Salary/Year','Years Remaining']].reset_index(drop = True).head(10))
```

```
<ipython-input-102-8071bc1375e3>:1: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  (nbaValuation19.loc[nbaValuation19['Pos'] == 'C'][nbaValuation19['Salary/Year'] < nbaValuation19['Salary/Year'].median()]
```

Out[102]:

	Player	Pos	Age	Value	Value/$1M	Salary/Year	Years Remaining
0	Marc Gasol	C	34.0	5.19	1.97	2,628,872.0	2
1	Hassan Whiteside	C	29.0	5.16	2.22	2,320,044.0	1
2	JaVale McGee	C	31.0	4.83	1.15	4,200,000.0	1
3	Willie Cauley-Stein	C	25.0	4.73	1.15	4,100,000.0	2
4	Mitchell Robinson	C	20.0	4.61	2.66	1,732,959.0	2
5	Jarrett Allen	C	20.0	4.59	1.17	3,909,902.0	1
6	Enes Kanter	C	26.0	4.27	0.85	5,005,350.0	1
7	DeMarcus Cousins	C	28.0	3.89	1.67	2,331,593.0	1
8	Nerlens Noel	C	24.0	3.83	0.77	5,000,000.0	1
9	Dewayne Dedmon	C	29.0	3.81	1.33	2,866,667.0	5

NOTES: This shows the Centers who cost below the median salary and are top performers. *Willie Cauley-Stein, Mitchell Robinson*, and *Jarrett Allen* are extremely valuable, as they are under 26, have a high value, and cost under $4.2 million.

Top 10 C Under 26

In [103]:
```
(nbaValuation19.loc[nbaValuation19['Pos'] == 'C'][nbaValuation19['Age'] < nbaValuation19['Age'].median()]
 [nbaValuation19['MP'] > 164][['Player','Pos','Age','Value','Salary/Year','Years Remaining']].reset_index(drop = True).head(10))
```

```
<ipython-input-103-63b81562651a>:1: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  (nbaValuation19.loc[nbaValuation19['Pos'] == 'C'][nbaValuation19['Age'] < nbaValuation19['Age'].median()]
```

Out[103]:

	Player	Pos	Age	Value	Salary/Year	Years Remaining
0	Nikola Jokić	C	23.0	7.69	30,510,423.0	3
1	Karl-Anthony Towns	C	23.0	7.38	32,700,000.0	4
2	Anthony Davis	C	25.0	7.29	37,980,720.0	5
3	Andre Drummond	C	25.0	7.05	28,751,775.0	1
4	Joel Embiid	C	24.0	6.81	31,579,390.0	3
5	Jusuf Nurkić	C	24.0	5.98	12,000,000.0	2
6	Montrezl Harrell	C	25.0	5.64	9,489,450.0	2
7	Clint Capela	C	24.0	5.3	17,103,448.0	3
8	Myles Turner	C	22.0	5.24	18,000,000.0	3
9	Steven Adams	C	25.0	5.21	20,842,697.0	3

NOTES: These players excelled despite their young age. *Jusuf Nurkic, Montrezl Harrell, Clint Capela*, and *Myles Turner* are extremely valuable players, as not only are they younger than 26 with a high value, but they also cost under $20 million.

Historic Top Players, by year and number of All Stars

In this section, I look at the past years and compare my results to the all star teams in each year. I found that my top players correllated with the all star teams 74% of the time. While predicting all stars was never the goal, it shows the reliability of my results.

Top 28 Players 2018

In [104]:
```
nbaStats18['Value'] = ((nbaStats18['BPM']*.8013 + nbaStats18['PER']*.4930 + nbaStats18['USG%']*.2283
                          + nbaStats18['PTS']*.0053 + nbaStats18['AST']*.0127 + nbaStats18['BLK']*.0485
                          + nbaStats18['TRB']*.0112 + nbaStats18['STL']*.0599)/8)
nbaStats18['Value'] = nbaStats18['Value'].round(decimals=2)
```

In [105]:
```
nbaValuation18 = nbaStats18.loc[nbaStats18['MP'] > 164].sort_values('Value', ascending = False).reset_index(drop = True)
nbaValuation18[['Player','Pos','Age','MP','Value']].head(28)
```

Out[105]:

	Player	Pos	Age	MP	Value
0	LeBron James	PF	33.0	3,026.0	8.59
1	Russell Westbrook	PG	29.0	2,914.0	8.31
2	James Harden	SG	28.0	2,551.0	8.2
3	Anthony Davis	PF	24.0	2,727.0	8.03
4	Giannis Antetokounmpo	PF	23.0	2,756.0	7.57
5	Andre Drummond	C	24.0	2,625.0	7.09
6	Karl-Anthony Towns	C	22.0	2,918.0	6.8
7	Nikola Jokic	C	22.0	2,443.0	6.72
8	Victor Oladipo	SG	25.0	2,552.0	6.65
9	Ben Simmons	PG	21.0	2,732.0	6.62
10	Kevin Durant	PF	29.0	2,325.0	6.54
11	Damian Lillard	PG	27.0	2,670.0	6.36
12	DeMarcus Cousins	C	27.0	1,737.0	5.98
13	Stephen Curry	PG	29.0	1,631.0	5.88
14	LaMarcus Aldridge	C	32.0	2,509.0	5.85
15	Joel Embiid	C	23.0	1,912.0	5.84
16	Paul George	SF	27.0	2,891.0	5.78
17	Chris Paul	PG	32.0	1,847.0	5.6
18	Jrue Holiday	SG	27.0	2,927.0	5.58
19	Dwight Howard	C	32.0	2,463.0	5.55
20	Clint Capela	C	23.0	2,034.0	5.54
21	Kyle Lowry	PG	31.0	2,510.0	5.46
22	Jimmy Butler	SG	28.0	2,164.0	5.45
23	Kemba Walker	PG	27.0	2,736.0	5.42
24	DeMar DeRozan	SG	28.0	2,711.0	5.41
25	Kyrie Irving	PG	25.0	1,931.0	5.41
26	Eric Bledsoe	PG	28.0	2,322.0	5.39
27	Bradley Beal	SG	24.0	2,977.0	5.36

Top 25 Players 2017

In [106]:

```
nbaStats17['Value'] = ((nbaStats17['BPM']*.8013 + nbaStats17['PER']*.4930 + nbaStats17['USG%']*.2283
                          + nbaStats17['PTS']*.0053 + nbaStats17['AST']*.0127 + nbaStats17['BLK']*.0485
                          + nbaStats17['TRB']*.0112 + nbaStats17['STL']*.0599)/8)
nbaStats17['Value'] = nbaStats17['Value'].round(decimals=2)
nbaValuation17 = nbaStats17.loc[nbaStats17['MP'] > 164].sort_values('Value', ascending = False).reset_index(drop = True)
nbaValuation17[['Player','Pos','Age','MP','Value']].head(25)
```

Out[106]:

	Player	Pos	Age	MP	Value
0	Russell Westbrook	PG	28.0	2,802.0	10.06
1	James Harden	PG	27.0	2,947.0	8.71
2	Giannis Antetokounmpo	SF	22.0	2,845.0	7.96
3	Anthony Davis	C	23.0	2,708.0	7.59
4	LeBron James	SF	32.0	2,794.0	7.53
5	DeMarcus Cousins	C	26.0	2,465.0	7.52
6	John Wall	PG	26.0	2,836.0	7.15
7	Karl-Anthony Towns	C	21.0	3,030.0	7.06
8	Kawhi Leonard	SF	25.0	2,474.0	6.96
9	Stephen Curry	PG	28.0	2,638.0	6.93
10	Jimmy Butler	SF	27.0	2,809.0	6.78
11	Kevin Durant	SF	28.0	2,070.0	6.61
12	Rudy Gobert	C	24.0	2,744.0	6.51
13	Nikola Jokic	C	21.0	2,038.0	6.31
14	Isaiah Thomas	PG	27.0	2,569.0	6.21
15	Chris Paul	PG	31.0	1,921.0	6.17
16	Draymond Green	PF	26.0	2,471.0	6.01
17	Damian Lillard	PG	26.0	2,694.0	6.0
18	Andre Drummond	C	23.0	2,409.0	5.91
19	Hassan Whiteside	C	27.0	2,513.0	5.87
20	DeAndre Jordan	C	28.0	2,570.0	5.78
21	Marc Gasol	C	32.0	2,531.0	5.66
22	Paul George	SF	26.0	2,689.0	5.65
23	Kemba Walker	PG	26.0	2,739.0	5.61
24	DeMar DeRozan	SG	27.0	2,620.0	5.55

Top 25 Players 2016

In [107]:

```
nbaStats16['Value'] = ((nbaStats16['BPM']*.8013 + nbaStats16['PER']*.4930 + nbaStats16['USG%']*.2283
                          + nbaStats16['PTS']*.0053 + nbaStats16['AST']*.0127 + nbaStats16['BLK']*.0485
                          + nbaStats16['TRB']*.0112 + nbaStats16['STL']*.0599)/8)
nbaStats16['Value'] = nbaStats16['Value'].round(decimals=2)
nbaValuation16 = nbaStats16.loc[nbaStats16['MP'] > 164].sort_values('Value', ascending = False).reset_index(drop = True)
nbaValuation16[['Player','Pos','Age','MP','Value']].head(25)
```

Out[107]:

	Player	Pos	Age	MP	Value
0	Stephen Curry	PG	27.0	2,700.0	8.49
1	Russell Westbrook	PG	27.0	2,750.0	8.39
2	James Harden	SG	26.0	3,125.0	7.75
3	LeBron James	SF	31.0	2,709.0	7.46
4	Kevin Durant	SF	27.0	2,578.0	7.18
5	Chris Paul	PG	30.0	2,420.0	6.95
6	Paul Millsap	PF	30.0	2,647.0	6.84
7	Draymond Green	PF	25.0	2,808.0	6.66
8	John Wall	PG	25.0	2,784.0	6.6
9	DeMarcus Cousins	C	25.0	2,246.0	6.58
10	Kyle Lowry	PG	29.0	2,851.0	6.56
11	Kawhi Leonard	SF	24.0	2,380.0	6.55
12	Paul George	SF	25.0	2,819.0	6.47
13	Hassan Whiteside	C	26.0	2,125.0	6.33
14	Andre Drummond	C	22.0	2,666.0	6.17
15	Karl-Anthony Towns	C	20.0	2,627.0	6.1
16	Pau Gasol	C	35.0	2,291.0	6.0
17	Anthony Davis	C	22.0	2,164.0	5.99
18	Kemba Walker	PG	25.0	2,885.0	5.91
19	DeAndre Jordan	C	27.0	2,598.0	5.78
20	Damian Lillard	PG	25.0	2,676.0	5.77
21	Giannis Antetokounmpo	PG	21.0	2,823.0	5.72
22	Isaiah Thomas	PG	26.0	2,644.0	5.56
23	Al Horford	C	29.0	2,631.0	5.52
24	Brook Lopez	C	27.0	2,457.0	5.46

Top 25 Players 2015

In [108]:
```
nbaStats15['Value'] = ((nbaStats15['BPM']*.8013 + nbaStats15['PER']*.4930 + nbaStats15['USG%']*.2283
                          + nbaStats15['PTS']*.0053 + nbaStats15['AST']*.0127 + nbaStats15['BLK']*.0485
                          + nbaStats15['TRB']*.0112 + nbaStats15['STL']*.0599)/8)
nbaStats15['Value'] = nbaStats15['Value'].round(decimals=2)
nbaValuation15 = nbaStats15.loc[nbaStats15['MP'] > 164].sort_values('Value', ascending = False).reset_index(drop = True)
nbaValuation15[['Player','Pos','Age','MP','Value']].head(25)
```

Out[108]:

	Player	Pos	Age	MP	Value
0	Russell Westbrook	PG	26.0	2,302.0	7.97
1	James Harden	SG	25.0	2,981.0	7.91
2	Anthony Davis	PF	21.0	2,455.0	7.67
3	Stephen Curry	PG	26.0	2,613.0	7.58
4	Chris Paul	PG	29.0	2,857.0	7.18
5	LeBron James	SF	30.0	2,493.0	6.92
6	DeMarcus Cousins	C	24.0	2,013.0	6.62
7	John Wall	PG	24.0	2,837.0	6.32
8	DeAndre Jordan	C	26.0	2,820.0	6.25
9	Marc Gasol	C	30.0	2,687.0	6.14
10	Pau Gasol	PF	34.0	2,681.0	6.04
11	Tim Duncan	C	38.0	2,227.0	6.02
12	Damian Lillard	PG	24.0	2,925.0	5.88
13	Andre Drummond	C	21.0	2,502.0	5.78
14	Paul Millsap	PF	29.0	2,390.0	5.68
15	Rudy Gobert	C	22.0	2,158.0	5.65
16	Kawhi Leonard	SF	23.0	2,033.0	5.62
17	Eric Bledsoe	PG	25.0	2,800.0	5.58
18	Blake Griffin	PF	25.0	2,356.0	5.56
19	Draymond Green	PF	24.0	2,490.0	5.5
20	Kyrie Irving	PG	22.0	2,730.0	5.41
21	LaMarcus Aldridge	PF	29.0	2,512.0	5.38
22	Al Horford	C	28.0	2,318.0	5.35
23	Gordon Hayward	SF	24.0	2,618.0	5.31
24	Tyreke Evans	SG	25.0	2,690.0	5.28