Who Should An MLB GM Take With Their First Pick?

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https://github.com/ablansdowne/Who-Should-A-MLB-GM_Draft

Before data science was a prominent force in GM offices everywhere, MLB scouts used to have to rely on their intuition and basic stats to decide who was worth drafting. Intuition included checking whether a player had a weak handshake, small hands or square shoulders. They also avoided players who hit and threw with opposite hands, who had duck feet or who had a less than ideal physique. I hope to instead use data science techniques to decide who is worth drafting. I will be looking at picks from the June Amateur Draft and not the Rule V Draft. I will also be assuming that the ultimate goal of a GM is to win and not to increase ticket sales. I will also be assuming that a player is drafted to play on that team and not to be traded. Finally, I will not be considering intangibles as there are no stats for this and will be assuming that a team could benefit from either a bat or an arm.

The first question I hope to solve is whether it is more beneficial to draft a pitcher or a position player with the first pick. In the past 5 years 3 position players have been taken first (Mickey Moniak, Dansby Swanson, Carlos Correa) and 2 pitchers have been taken first (Brady Aiken and Mark Appel). So is a team more likely to find a Bryce Harper or a Stephen Strasburg with the 1st pick? And who is more likely to bring a championship to the organization? My first step was to find a database that contained the data I needed. Baseball-reference.com listed the history of first picks and their stats to 1965 so I created a Python script to put this data into a csv file. This is how the data looked before I did any tidying:

	Year	Rnd	DT	FrRnd	RdPck	Tm	Signed	Name	Pos	WAR	...	BA	OPS	G.1	W	L	ERA	WHIP	SV	Type
0	2016	1	NaN	FrRnd	1	Phillies	Y	Mickey Moniak (minors)	OF	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	HS
1	2015	1	NaN	FrRnd	1	Diamondbacks	Y	Dansby Swanson (minors)\swansda01	SS	0.9	...	0.302	0.803	NaN	NaN	NaN	NaN	NaN	NaN	4Yr

The first thing I did to clean up this database was to take out any players who had a "N" in the "Signed" column. This is because I want to analyze players who sign with the team who drafts them. For example Brady Aiken was drafted first in 2014 by the Astros but did not sign so I took him out of the data. The next thing I did was to split my data into pitchers and position players. Then with all 3 data sets I took out unnecessary columns including what school they were drafted out of and what round they were picked in because this was the first round for everyone.

From the original data I took out all stats besides WAR because this is the primary stat I want to look at. WAR stands for Wins Above Replacement and can be compared between pitchers and field players. It is harder to compare batting average and ERA for example. The WAR I am using is technically bWAR because WAR does not have a specific calculation and bWAR is the WAR calculated by Baseball Reference. For the pitcher and position player I took out the data that is not relevant to them. So my 3 (original, pitcher and position in order) sets of data now look like this:

	Year	Tm	Name	Pos	WAR	Type
0	2016	Phillies	Mickey Moniak (minors)	OF	NaN	HS
1	2015	Diamondbacks	Dansby Swanson (minors)\swansda01	SS	0.9	4Yr
3	2013	Astros	Mark Appel (minors)	RHP	NaN	4Yr
4	2012	Astros	Carlos Correa (minors)\correca01	SS	10.1	HS
5	2011	Pirates	Gerrit Cole (minors)\colege01	RHP	9.4	4Yr

	Year	Tm	Name	Pos	WAR	G.1	W	L	ERA	WHIP	SV	Type
3	2013	Astros	Mark Appel (minors)	RHP	NaN	NaN	NaN	NaN	NaN	NaN	NaN	4Yr
5	2011	Pirates	Gerrit Cole (minors)\colege01	RHP	9.4	94.0	47.0	30.0	3.23	1.20	0.0	4Yr
7	2009	Nationals	Stephen Strasburg (minors)\strasst01	RHP	18.2	156.0	69.0	41.0	3.17	1.09	0.0	4Yr
9	2007	Devil Rays	David Price (minors)\priceda01	LHP	31.9	253.0	121.0	65.0	3.21	1.14	0.0	4Yr
10	2006	Royals	Luke Hochevar (minors)\hochelu01	RHP	3.1	279.0	46.0	65.0	4.98	1.34	3.0	NaN

	Year	Tm	Name	Pos	WAR	G	AB	HR	BA	OPS	Type
0	2016	Phillies	Mickey Moniak (minors)	OF	NaN	NaN	NaN	NaN	NaN	NaN	HS
1	2015	Diamondbacks	Dansby Swanson (minors)\swansda01	SS	0.9	38.0	129.0	3.0	0.302	0.803	4Yr
4	2012	Astros	Carlos Correa (minors)\correca01	SS	10.1	252.0	964.0	42.0	0.276	0.829	HS
6	2010	Nationals	Bryce Harper (minors)\harpebr03	OF	21.5	657.0	2336.0	121.0	0.279	0.883	JC
8	2008	Rays	Tim Beckham (minors)\beckhti01	SS	1.3	151.0	408.0	14.0	0.238	0.720	HS

The next thing I did was get basic stats about the types of players. First I compared the mean of the WAR of the pitchers against the mean of the WAR of the position players. The average WAR of a pitcher taken first overall is 14.29 and the average WAR of a position player taken first overall is 24.36:

```
In [18]: df_Pitchers['WAR'].mean()
Out[18]: 14.292307692307691

In [19]: df_Position['WAR'].mean()
Out[19]: 24.35625
```

I also want to ask the question should a GM pick a player from High School or College? Going back to the past 5 picks, 3 have been from High School (Mickey Moniak, Brady Aiken, Carlos Correa) and 2 have been from College (Dansby Swanson and Mark Appel). So I compared the mean of the WAR of players from a 4-year institution against the mean of the WAR of players from a High School. The average WAR of a player taken first overall out of a 4-year institution was 16.32 and the average WAR of a player taken first overall out of a high school was 27.69:

```
In [26]: df[(df.Type == 'HS')].mean()

Out[26]: Year     1988.500000
         WAR        27.690476
         dtype: float64
```

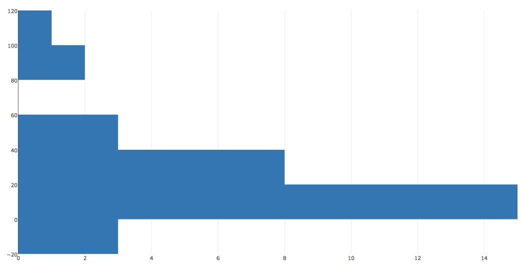
```
In [54]: df[(df.Type == '4Yr') | (df.Type == 'JC')].mean()

Out[54]: Year     1992.000000
         WAR        16.547826
         dtype: float64
```

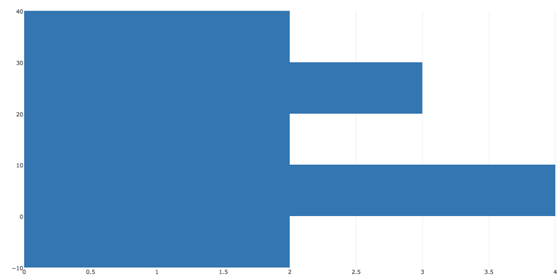
To examine these numbers further I took the means of the WARs from pitchers from High School, position players from High School, pitchers from 4-year institutions and position players from 4-year institutions. The results were:

Type	**WAR**
Pitcher from HS	0.70
Position Player from HS	29.04
Pitcher from 4Yr	16.55
Position Player from 4Yr or JC	16.55

Because we are comparing two different populations (pitchers vs. position players), I wanted to check the significance of the means that I had previously calculated. The first means I compared were just all position players vs. all pitchers.



Position Players



Pitchers

```
In [41]: from scipy.stats import ttest_ind

         position = df_Position.WAR
         pitchers = df_Pitchers.WAR

         ttest_ind(position, pitchers, nan_policy='omit')

Out[41]: Ttest_indResult(statistic=1.2424590601379675, pvalue=0.22080051149262181)
```

Using a two-sided t test I was able to calculate that the p-value was 0.22, which is less than 0.5 meaning the difference in means is significant. From this we can conclude that it is more likely that drafting a position player with the first pick in the draft will give you a player that brings more Wins Above Replacement.

The next thing I did in order to analyze my data was create an odds ratio. I wanted to see what the odds were of drafting a franchise player with the first pick. For this odds ratio I decided that a truly impactful position player would have a WAR of over 40. I decided upon this number because according to Baseball Reference in order to have an all-star quality year a player should have a WAR above 8 and I thought an impactful player should have at least 5 years where they are an all-star. For a truly impactful pitcher I lowered the number to 30 because pitchers tend to have more injuries and be more inconsistent so they might not have as many all-star quality seasons. So I wanted to see what the odds were of drafting an impactful player. The odds ratio formula is:

$$\text{Odds ratio} = \frac{PG_1 / (1 - PG_1)}{PG_2 / (1 - PG_2)}$$

PG1 (The odds of drafting an impactful position player): 6/34 = 3/17

```
In [24]: df_Position[(df_Position.WAR > 40.0)].count()

Out[24]: Year     6
         Tm       6
         Name     6
         Pos      6
         WAR      6
         G        6
         AB       6
         HR       6
         BA       6
         OPS      6
         Type     6
         dtype: int64

In [26]: df_Position.count()

Out[26]: Year     34
         Tm       34
         Name     34
         Pos      34
         WAR      32
         G        32
         AB       32
         HR       32
         BA       31
         OPS      31
         Type     34
         dtype: int64
```

PG2 (The odds of drafting an impactful pitcher): 2/15

```
In [28]: df_Pitchers[(df_Pitchers.WAR > 30.0)].count()

Out[28]: Year     2
         Tm       2
         Name     2
         Pos      2
         WAR      2
         G.1      2
         W        2
         L        2
         ERA      2
         WHIP     2
         SV       2
         Type     2
         dtype: int64

In [29]: df_Pitchers.count()

Out[29]: Year     15
         Tm       15
         Name     15
         Pos      15
         WAR      13
         G.1      13
         W        13
         L        13
         ERA      13
         WHIP     13
         SV       13
         Type     14
         dtype: int64
```

So the odds ratio would be (3/17 / 14/17) / (2/15 / 13/15) =

1.39

It's important to note that if the odds were equal the odds ratio would be 1 and not 0. I wanted to use a Fisher's Exact Probability Test to see if this was significant. When I ran this test I got a p value of 1 which is greater than 0.5 and we can conclude this is not significant.

```
In [30]: import scipy.stats as stats

In [31]: oddsratio, pvalue = stats.fisher_exact([[3, 14], [2, 13]])

In [32]: pvalue

Out[32]: 1.0
```

From this calculation we can conclude that drafting a very good pitcher or player as the first pick is equally likely, (that is not so likely).