Data Management

Culminating Project

NBA/NFL Draft Picks

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<u>Question:</u>

What effects, short-term and long-term, do draft picks in both the NFL and NBA have on their team?

NBA/NFL Draft Picks

In my project I was looking for trends between sports draft picks and many other attributes. For this investigation I focused only on the top ten draft picks in both the NFL and NBA. I used the range of years from 1993-1997. This was so I could look at the draft picks at a minimum of five years down the road and observe the effects. I focused mainly on three things: salaries, winning percentage and attendance. All of the attributes had observable effects, although some had more than others.

Question: What effects, short-term and long-term, do draft picks in both the NFL and NBA have on their team?

National Basketball Association (NBA)

The following is a portion of the data that I was able to obtain and calculate regarding NBA draft picks in the last five years:

97-93 NBA

	Pick	Name	Year	S5	Position	Team	A1	A5	W1	W5
1	1	Tim Duncan	97	10865250	PF	San Anto...	10.87	28.27	179.92	189.75
2	1	Allen Iverson	96	10130000	SG	Philadelp...	28.03	64.65	21.82	210.91
3	1	Chris Webber	93	9000000	PF	Orlando	0.92	12.95	95.31	114.45
4	1	Glenn Robinson	94	3890000	SF	Milwaukee	5.77	-1.22	70.08	129.51
5	1	Joe Smith	95	2100000	PF	Golden S...	0	-17.35	38.49	-26.81
6	2	Keith Van Horn	97	10865250	SF	Philadelp...	4.62	34.55	41.04	95.52
7	2	Antonio McDyess	95	9900000	PF	LA Clippe...	-5.41	45.12	71.01	-11.59
8	2	Shawn Bradley	93	5940000	C	Philadelp...	-1.15	-2.38	-3.79	19.24
9	2	Marcus Camby	96	5750000	PF	Toronto	-21.19	-16.53	42.97	123.83
10	2	Jason Kidd	94	3683000	PG	Dallas	28.88	13.04	176.1	138.99

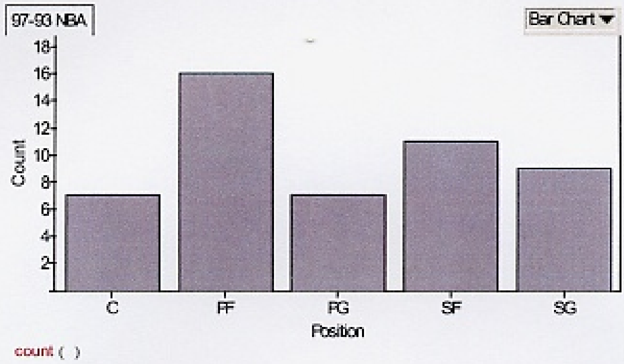
First is the pick number, I only carried picks from 1-10. Second is the player who was drafted. The next is the year that they begun their NBA playing career. For example, Tim Duncan was drafted in 1997 and played in the 97-98 season. Next is their salary after five years. The reason that I did it after five years was because the NBA has set salaries for every distinct draft position. For example, a first overall pick can only make a maximum of \$1 million after one year and \$1.3 million after three years. After that, the draft picks salary greatly increases. Next is their position that they currently play. I stress this because a player doesn't necessarily play the same position in college. The positions are Center (C), Power Forward (PF), Small Forward (SF), Shooting Guard (SG) and Point Guard (PG). Next is the team that drafted the player. Not all players necessarily stay with the team that drafted them, but these can be removed as outliers. Also, there are enough with the correct team that the results are still accurate. Next is the attendance change after one year. I made this as a percentage based on the previous years attendance, that way a team with a smaller stadium wouldn't be at a disadvantage. The next year column is attendance change after five years. This is to focus more on the long-term effects of a basketball draft pick, rather than short-term. Next is the change in winning percentage (as a percentage) after one year. The final column is looking at change in winning percentage, but again, I focus on long-term, five years from drafting.

Pick Summary Tables:

97-93 NBA	Summary Table				
	Salaryafter5	Attendance1	Attendance5	Winning1	Winning5
A	5	5	5	5	5
	7197050	9.118	17.46	81.124	123.562
	9000000	5.77	12.95	70.08	129.51
	2100000	0	-17.35	21.82	-26.81
	10865250	28.03	64.65	179.92	210.91
	3890000	0.92	-1.22	38.49	114.45
	10130000	10.87	28.27	95.31	189.75
	3944141.7	11.426805	31.323996	62.085595	93.194246
Column Summary	50	50	50	50	50
	5702846.2	2.1574	8.7562	24.3674	64.3126
	4437446	0	-0.935	14.215	53.65
	0	-21.19	-21.48	-54.48	-69.48
	16806300	60.51	84.74	179.92	226.78
	2960000	-3.56	-11.26	-6.56	7.87
	9675000	5.77	22.49	42.97	114.45
	3794471.5	12.80249	24.996832	53.541127	73.052378

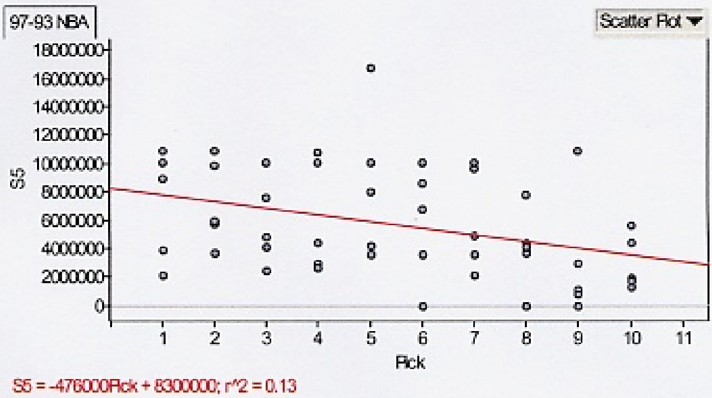
I created tables for the years 93-97 picks 1-10. I assigned the numbers corresponding letters so that I would be able to perform a series of calculations to all pick numbers in a single, combined chart. This was to observe both the short and long term effects of different picks on the team and themselves. I dealt with all of the columns that were in our chart and perform a series of calculations to all of them. I calculated: mean, median, min, max, Q1, Q3 and standard deviation. Seeing as the category that I put the most emphasis on was salary after five years, I decided to focus on the calculations based in this category. From this I learned that the largest mean was the fifth overall pick, the largest median was first and the smallest standard deviation was tenth. The highest mean was misleading because of one pick, Kevin Garnett. His salary was almost $17 million compared to the mean of eight. Without him the mean would be $6.48 million, although still high it fits more the trends observed. The standard deviation was smallest with tenth and that number was also misleading due to three picks: Sharone Wright, Shawn Respert and Ed O'Bannon. All of these players, picks 6, 8 & 9, were out of the league within five years. If these players are removed as outliers, the eighth pick then has the lowest standard deviation at $1.89 million, just below the tenth. Focusing just at the total medians of the other remaining categories, you can observe the trend that I expected to see. There is a slight increase in winning percentage and attendance after the first year. The second year, however, experienced a greater increase in both winning percentage and attendance. This is what I expected as a player needs time to develop and their effect can't be totally appreciated until a few years down the line. There is a large improvement in NBA as many players are drafted out of high school or as a freshman so players must mature and learn to gel with their teammates in order to accumulate a fan base and have a substantial improvement in record.

Position Breakdowns:



This histogram is just to show how teams use their top ten picks in the last few years. The most of one position picked is the power forward with sixteen being picked in those five years. The least are center and point guard with only seven being picked.

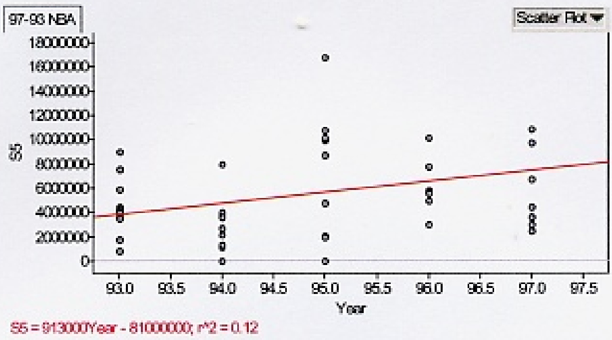
Pick vs. Salary:



This was to observe a trend between the positions someone was picked and the salary made by that player five years later. I used the salary as an indicator for the pick effectiveness. Although, its not always true, generally a salary would show how good the player is. I observed that as the pick number decreased so did the salary. The slope is not dramatic, but it is there. There were a few exceptions, including four mentioned earlier: Kevin Garnett, Sharone Wright, Shawn Respert and Ed O'Bannon. One other was Tracy McGrady who was picked ninth, but makes $10.87 million compared to the approximate $ 5 million that should be made by a ninth pick according to interpolation.

Extrapolation: By extrapolation outside my pick range, I predict that an 11th pick should make somewhere around three million dollars after five years. Allan Houston, selected in 1993 with the 11th pick made $3.05 million after five years. Unfortunately, this trend is flawless because the numbers diminish at a much larger margin than they should. If I continued to plot data points past 10th pick I'm sure a curve of best fit would be seen.

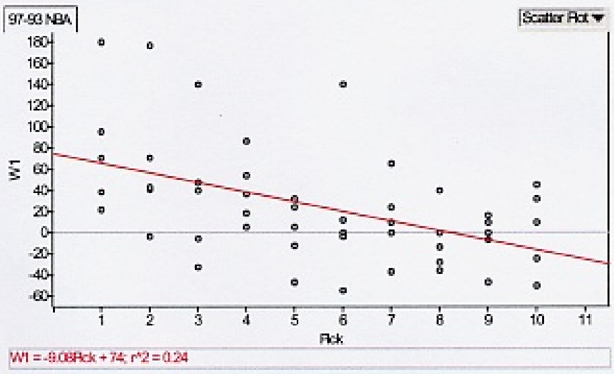
Year vs. Salary:



This graph is to observe how salaries, on average, have changed during each year that I focused on (93-97). I grouped each pick in the top ten into one group listed under the year. I noticed that as the year increased, so did the salary, which is a sign of rising costs, payrolls, ticket prices, etc. Again, the outlier would be Kevin Garnett who according to his year should be making around \$5 million as opposed to the almost \$17 million he is making.

Extrapolation: By extrapolating, I've been able to observe that the line of best fit seems to go through 1998 around \$8 million. When finding the mean of all of the 1998 players salaries after five years, I had found it to be just that, \$7.899 million. This graph seems to be a good indication of the change in average salaries.

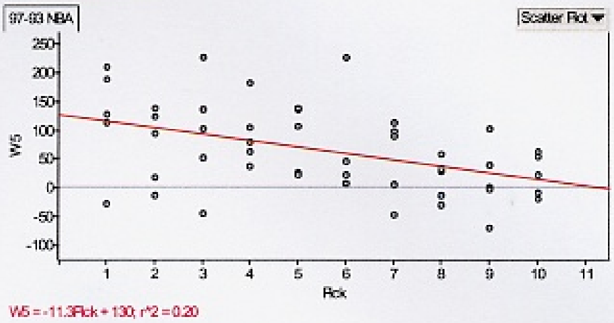
Pick vs. Winning Percentage One:



This was to observe the short-term effect that a player had on his team's winning percentage after only one year. I wanted to see if a lower numbered pick created a bigger improvement for the team. The trend I observed was that a lower numbered pick gives a higher improvement in teams winning percentage. Outliers were Tim Duncan, Jason Kidd and Ron Mercer who's teams all observed a huge improvement the next year as the first, second and sixth pick.

Extrapolation: According to my graph a team with the 11th pick could anticipate a decrease in winning percentage of 40%. Using the same 11th pick, Allan Houston, I discovered that his team, the Detroit Pistons, underwent a decrease in winning percentage of 50%, similar to the trend in my graph. Again, this is not a trend that can be carried on much further because higher picks would expect to decrease much more than possible. If you think about it, the graph would probably be seen more as a parabola as later picks would probably remain around the same winning percentage.

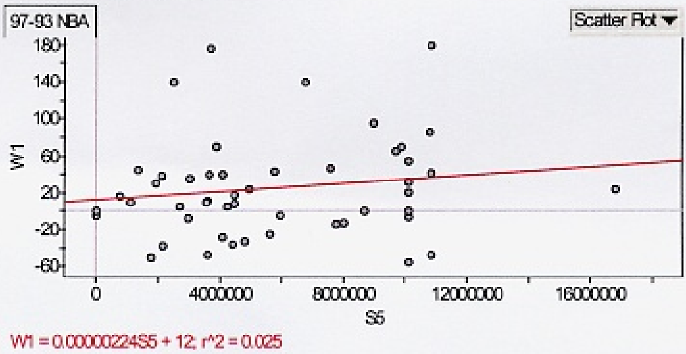
Pick vs. Winning Percentage Five:



This had the same intention, but to observe the long term effect of draft picks (five years). The same trend was observed with the same outliers and the addition of Chauncey Billups who played for the same team as Ron Mercer. According to the slope, the picks have a larger impact on winning percentage after five years as opposed to after one. *The problem with this graph is that some players are not still on their drafted team within five years, so some results may be incorrect. *The problem with both pick vs. winning percentage graphs is that as the pick number grows so does the winning percentage of the team that year. That means that it's that much harder for the teams to improve their winning percentage the next year.

Extrapolation: Using the same example with 11th pick, Allan Houston, I can see that his team should remain even after five years. In a span of five years, his team, experienced an increase of winning percentage of 1.89%, similar to the graph.

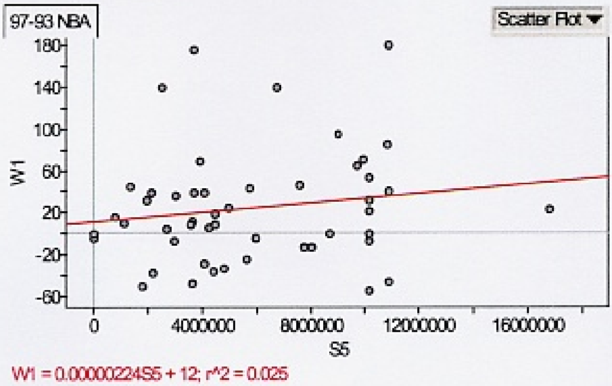
Salary vs. Winning Percentage One:



This graph was to observe the trend between salary, or "pick effectiveness" and short-term winning percentage. The trend is as expected with the higher the salary, the higher the winning percentage, thereby proving my theory that a higher salary represents a more effective pick. The two biggest outliers are Jason Kidd and Tim Duncan whose teams both experienced huge winning percentage increases after one year. Both are extremely talented players today so it makes sense that they create such an effect on the team's record, although both are moderately paid. Another outlier on the opposite end: Antoine Walker, a player highly paid five years from drafting, had a negative effect on his team within one year.

Extrapolation: To interpolate on this graph, I picked a random draft pick, my personal favourite, Vince Carter, and tried to see if he fit the trend. The reason I didn't extrapolate was because there is no way I could find a salary outside the range of the graph (Kevin Garnett). After five years Vince earns $10.07 million. According to the graph he should have an increase on the Raptors' winning percentage by approximately 20-25%. He increased the Raptors' winning percentage by 19.34% in the first year. He fits the trend.

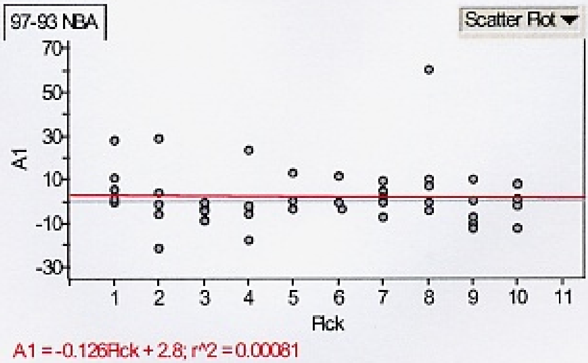
<u>Salary vs. Winning Percentage Five:</u>



This was the same as the previous graph, but was to observe the long term effects on "effective picks". This followed the same trend as the previous graph with the similar outliers, but this graph was even more effective in showing the trend with a larger slope and a better correlation. A new outlier is Anfernee Hardaway whose Golden State team experienced a downfall in winning percentage over five years. The reason he is an outlier is because he was traded within a year of drafted so could have little effect on his old team's performance.

Extrapolation: Again, it was too difficult to interpolate on the graph, so I again choose Vincent Lamar Carter. If you interpolate on the graph, an increase of 25-30% would be expected. In five years he increased the Raptors' winning percentage 24.6%.

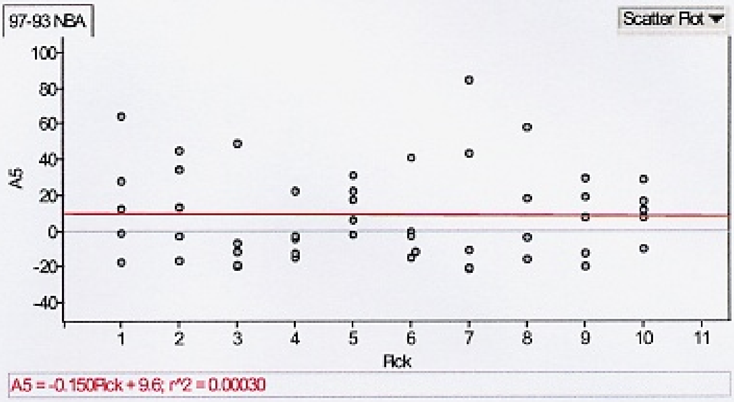
<u>Pick vs. Attendance One:</u>



This was to see if a lower numbered pick would increase a team's attendance. Although creating a very slight slope, the graph did not show what I had anticipated. Basically, this graph showed there is no correlation. Although, if you remove the largest outlier, Shawn Respect, there is a more substantial trend, with a slope of –0.49 as opposed to –0.125.

Extrapolation: By looking at the graph, the 11th overall pick should keep the attendance around the same for the following year. Again, I'm using Allan Houston as an example. He created an increase in attendance of 1.6% in one year. By using further extrapolation, I can see that a 25th pick should keep the attendance exactly the same. The 25th pick, in the same year as Houston, Corey Blount, created an increase of his teams' attendance of 0.02% (4 people).

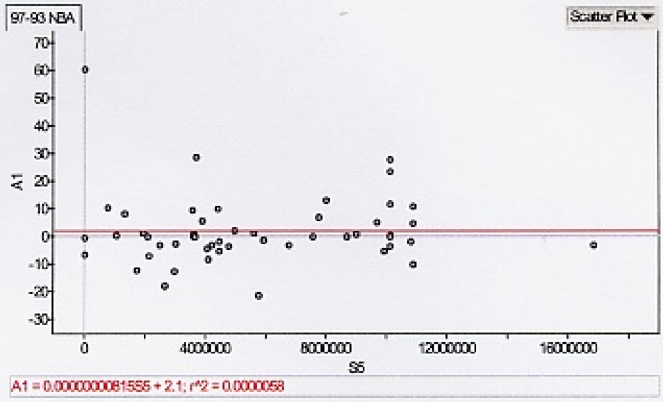
<u>Pick vs. Attendance Five:</u>



This was searching for a similar trend to the last one, but as a long-term effect. Again, little to no correlation is observed. There are far too many outliers to this trend to name, but one whose removal makes a substantial difference is Lorezen Wright whose team's attendance increased largely over five years. This team had more exciting players drafted in these five years who would increase attendance. Also, the Clippers (his team) changed to a new arena two years later, gathering more interest from the community. If these outliers are removed (3 of them) the slope becomes –0.741 instead of –0.147, creating an observable trend.

Extrapolation: Looking at this graph, you would expect the 11th pick to create an increase of approximately 10-15% after five years. After five years, Allan Houston created a 10.5% increase in attendance.

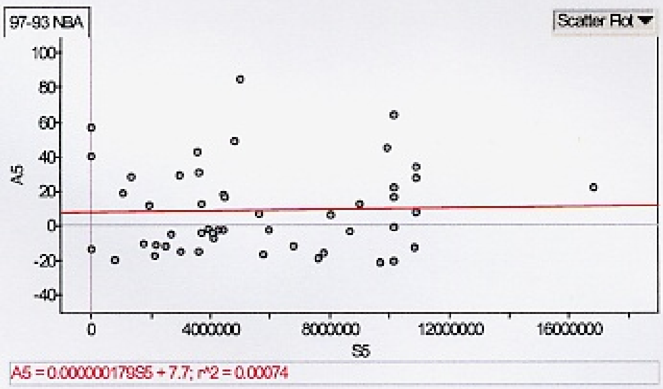
Salary vs. Attendance One:



This was to observe trends between pick effectiveness and attendance changes in the short term. There isn't a large observable trend, but there are outliers that create somewhat of a trend. Two outliers are Jason Kidd whose team's attendance increased a lot over one year and Marcus Camby for the Raptors. Their attendance decreased significantly because it was the second year of the team and the draw had diminished somewhat for Toronto. If these two are removed a larger trend is observed that the more effective the pick, the greater the increase in attendance.

Extrapolation: Because of Kevin Garnett, I again must interpolate and I again choose Vince Carter. His $10+ million would expect an increase in attendance of approximately 5%. Vince created an increase of 5.03% for the Raptors in his first year.

Salary vs. Attendance Five:



This had the same purpose as the previous, but to observe long-term effects. Again, there was little trend observed, but the removal of the outliers does create an observable trend. The outliers in the graph are Sharone Wright, Jerry Stackhouse and Allen Iverson. All of these players were drafted by the Philadelphia 76ers, a team that improved greatly through the 90s. This improvement greatly improved attendance and threw of the results of this graph. Another is Shareef Adbur-Rahim who was drafted by the Vancouver Grizzles. Their attendance significantly lowered due to the same theory as Marcus Camby. The removal of these outliers creates a far more logical graph with more observable trends.

Extrapolation: Again, I must interpolate, rather than extrapolate and I will use Vince Carter. It looks that a player making around $10 million should create an increase of attendance around 10% after five years. Vince being the exciting basketball player that he is sparked an increase of 12.75%.

Position vs. Salary:

97-93 NBA		Summary Table S5
Position	C	7 4184238
	PF	16 6632347.6
	PG	7 4959285.7
	SF	11 5666166.7
	SG	9 5854694.4
Column Summary		50 5702846.2

S1 = count ( )
S2 = mean ( )

The purpose of this was to observe which picks, by position, turn out to be more effective, as determined by salary. According to the mean, its PF, but this is again due to Kevin Garnett. The removal of Kevin Garnett creates a mean of just under $6 million, although still the highest, much closer to the others. The highest median is SG, which shows that there are some extreme highs, and some extreme lows, but overall is the best pick available. Shawn Respert, a SG is listed at making 0, so the removal of him creates the highest mean by far at $6.58 million. The smallest standard deviation belongs to C, which shows that the safest pick would be C, although the mean is the lowest.

Position vs. Winning Five:

97-93 NBA		Summary Table W5
Position	C	9.47 7
	PF	50.836875 16
	PG	101.25286 7
	SF	73.636364 11
	SG	90.797778 9
Column Summary		64.3126 50

S1 = mean ( )
S2 = count ( )

This was to see if any specific position had a larger increase on a team's performance. The largest mean was PG, which was actually pretty accurate as most picks were consistent with the exception of Lindsey Hunter with the change of –7.58. The highest median was SG because for the most part they were high with the exception of Anfernee Hardaway at –44.1. So the removal of him would create the highest mean by far at 107.66 as opposed to 90.79. The lowest standard deviation was again center meaning that C's had a consistent impact on winning percentage, although it was low. This is generally because C's are picked later meaning a winning percentage is higher and harder to change.

Position vs. Attendance:

97-93 NBA — Summary Table

		A5
Position	C	7 16.041429
	PF	16 11.575625
	PG	7 3.2371429
	SF	11 -4.7263636
	SG	9 18.848889
Column Summary		50 8.7562

S1 = count ( )
S2 = mean ( )

This was to determine if any specific position was able to draw more fans out to the teams' games. The highest mean was SG even though Anfernee Hardaway's –18.8 had a large impact on the numbers. But the largest median was C with consistent values all around the 18.58 median. Because of this C also had the second lowest standard deviation, with SF being the most consistent, but consistently bad with a mean and median of –4.73 and –7.14 respectively. This means that if you're an owner who wants the best chance to have an increase in attendance, draft a C!!!

National Football League (NFL)

The following is a portion of the data that I was able to obtain and calculate on NFL draft picks in the last five years (As there are 50 rows, I only am able to show the first ten picks):

97-93 NFL

	Pick	Name	Year	Position	Team	S5	A1	A5	W1	W5
1	1	Keyshawn John...	96	WR	NY Jets	2358100	39.14	39.5	793.65	992.06
2	1	Drew Bledsoe	93	QB	New Engl...	5298900	30.24	24.09	99.68	99.68
3	1	Ki-Jana Carter	95	RB	Cincinnati	2531800	-0.6	6.55	14.16	32.98
4	1	Dan Wilkinson	94	DL	Cincinnati	2500000	-7.35	7.37	132.98	87.65
5	1	Orlando Pace	97	OL	St.Louis	4254866	-21.67	41.98	10.13	116.8
6	2	Darrell Russel	97	DL	Oakland	3874455	2.77	35.04	69.43	42.69
7	2	Rick Mirer	93	QB	Seattle	2673000	-4.23	20.89	0	33.33
8	2	Marshall Faulk	94	RB	Indianapo...	2701000	11.14	14.03	12.6	225.2
9	2	Tony Boselli	95	OL	Jacksonv...	4085500	-3.84	-2.45	125.2	250
10	2	Kevin Hardy	96	LB	Jacksonv...	2880000	4.61	-3.57	89.23	75.2

First is the pick number, I only carried picks from 1-10. Second is the player who was drafted. The next is the year that they begun their NFL playing career. For example, Keyshawn Johnson was drafted in 1996 and played in the 96-97 season. Next is their salary after five years. The reason that I did it after five years was because players in the NFL don't necessarily have a large effect in the first few years. Therefore a large contract, that is able to represent their performance, won't be given until the second contract year. Next is their position that they currently play. I stress this because a player doesn't necessarily play the same position in college. Possible positions are Quarterback (QB), Running Back (RB), Wide Receiver (WR), Tight End (TE), Offensive Linemen (OL), Defensive Linemen (DL), Linebackers (LB), and Cornerbacks (CB). Next is the team that drafted the player. Not all players necessarily stay with the team that drafted them, but these can be removed as outliers. Also, there are enough with the correct team that the results are still accurate. Next is the attendance change after one year. I made this as a percentage based on the previous years attendance, that way a team with a smaller stadium wouldn't be at a disadvantage. This is much more relevant in the NFL compared to the NBA, as sizes of NFL stadiums range from 35,000 to 80,000. The next column is attendance change after five years. This is to focus more on the long-term effects of a football draft pick, rather than short-term. Next is the change in winning percentage (as a percentage) after one year. The final column is looking at change in winning percentage, but again, I focus on long-term, five years from drafting.

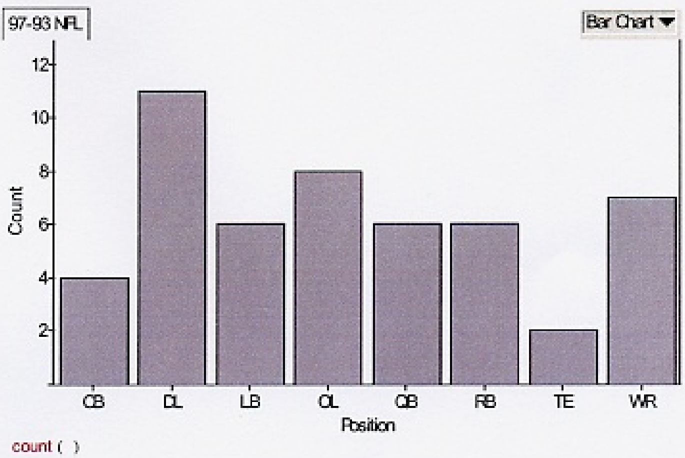
*All of the graphs are the same as located in the NBA section, so instead of explaining each graph I will only state outliers and trends observed.

Pick Summary Tables:

97-93 NFL	Summary Table				
	Salaryafter5	Attendance1	Attendance5	Winning1	Winning5
A	5	5	5	5	5
	3388733.2	7.952	23.898	210.12	265.834
	2531800	-0.6	24.09	99.68	99.68
	2358100	-21.67	6.55	10.13	32.98
	5298900	39.14	41.98	793.65	992.06
	2500000	-7.35	7.37	14.16	87.65
	4254866	30.24	39.5	132.98	116.8
	1321486.8	25.75945	16.915569	330.54922	407.18332
	3388733.2	7.952	23.898	210.12	265.834
Column Summary	50	50	50	50	50
	2274602.3	4.5884	19.8808	42.8012	93.6766
	2271850	0.745	12.75	16.8	50
	0	-23.53	-23.88	-54.51	-69.32
	6075200	39.71	256.81	793.65	992.06
	1300000	-4.06	0.36	0	16.8
	3000640	11.14	27.23	71.12	132.98
	1341013.9	15.304669	40.564433	117.85896	166.30365
	2274602.3	4.5884	19.8808	42.8012	93.6766

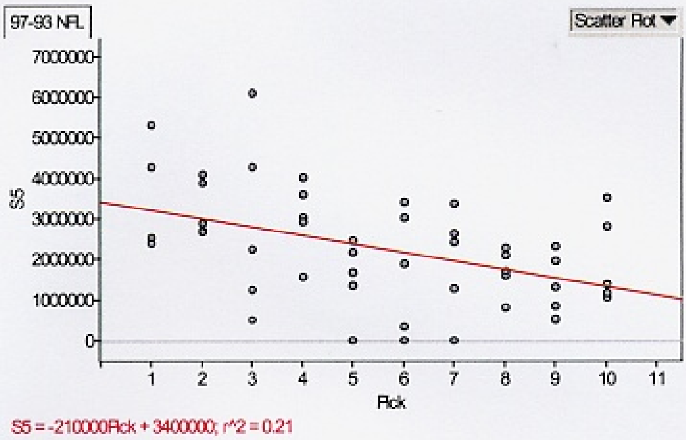
The highest mean was first overall pick, but Drew Bledsoe's $5.3 million had a large effect on that. Without him the mean would have been $2.91 million as opposed to $3.4 lower than both second and forth pick. The highest median is pick four which is low because of Marvin Jones whose salary was only $1.5 million. Without him the forth pick's mean would've been $3.4 million, much higher than all others. The lowest standard deviation was eighth, meaning that the eighth pick was most consistent around $1.7 million. Surprisingly, the second most consistent was second pick with all picks making around $3.2 million. Again, my predictions were shown to be correct. There were increases in all categories and much larger increases in long-term. The mean for attendance change jumped up over 15% from year one to year five compared to the NBA, whose only increased 6%. The big surprise was in winning percentage change. The mean of all draft picks was 42% in year one. In year five is was 94%, an increase of over 50%! This is partly because of the smaller NFL schedule, meaning that a change in one win would greatly increase the percentage. Even so, the great increase from year one to year five shows what I anticipated.

Position Breakdowns:



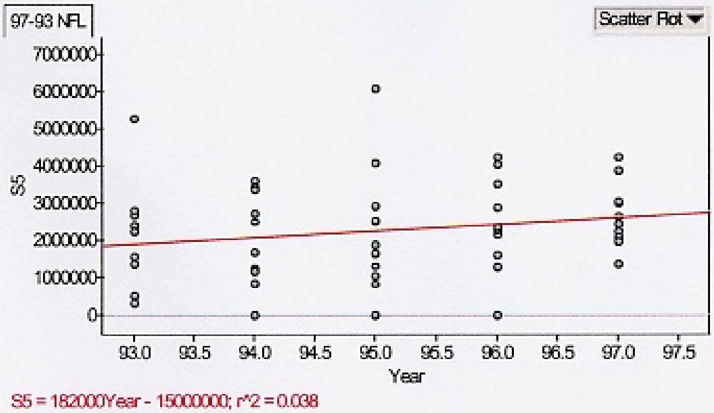
The majority of players picked in the draft were DL with eleven of the 50 picks playing that position. The least amount of picks belonged to TE only two being picked compared to the second lowest; four CB's.

Pick vs. Salary:



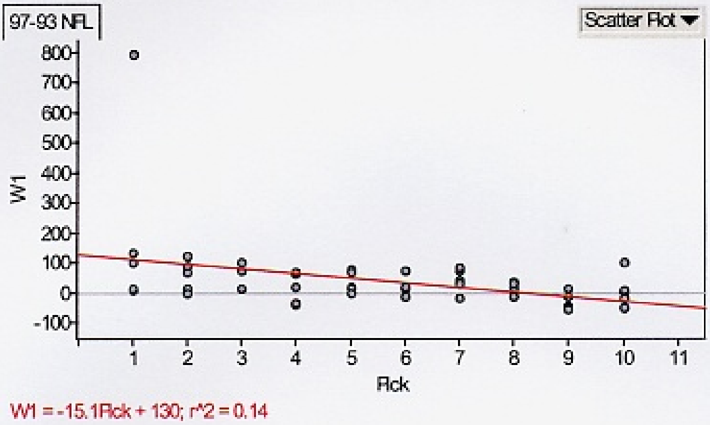
The trend shows that the salary decreases as the picks get later. Four outliers are the three people not in the league anymore: Trev Alberts, Mike Mumula and Lawrence Phillips, none of which fit the typical draft pick patterns. The other being Steve McNair who is making just over $6 million when interpolation shows he should be making around $3 million.

Year vs. Salary:



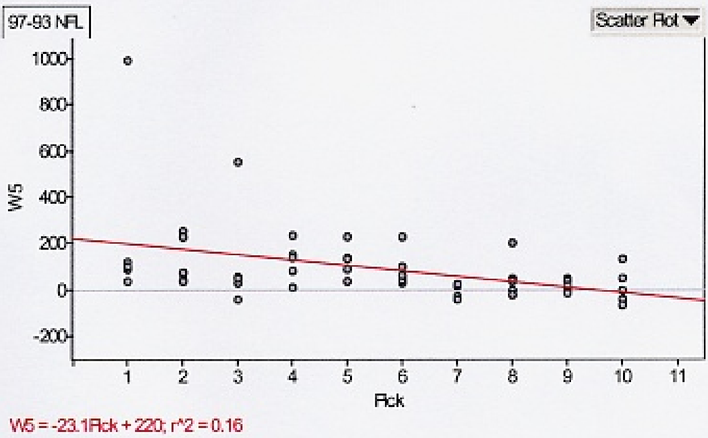
The trend shows that as the years increase, so does the salary. Again, the three not in the league anymore are outliers as well as Drew Bledsoe who was signed to a huge contract after the completion of his rookie contract. Steve McNair is also way above the line of best fit again.

Pick vs. Winning Percentage One:



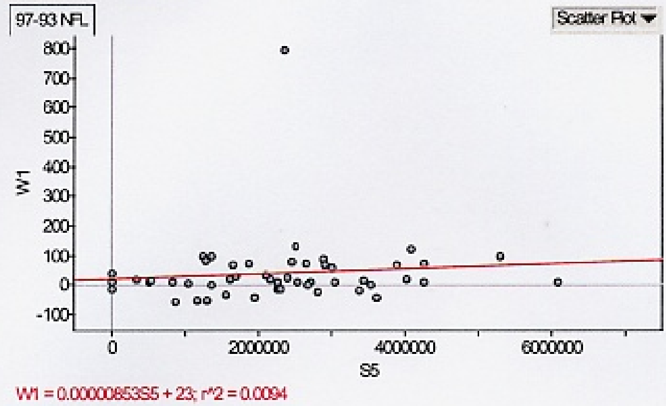
The trends is that as the pick increases, the winning percentage short term decreases. One giant outlier is Keyshawn Johnson whose team increased its winning percentage by about 800%. If he is removed, a normal graph is created where the same trend is visible and the correlation is very close at 0.19 as opposed to 0.14 from the original graph.

Pick vs. Winning Percentage Five:



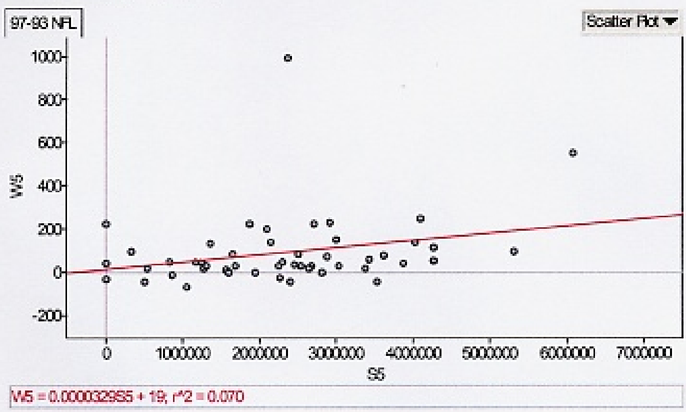
The same trends are visible in the long-term and again Keyshawn Johnson is an outlier. There is no reason that I can state for the reason of such a significant increase, other than the Jets had a horrible season when he was picked and a great season the next year. The next outlier is Steve McNair whose team became much better when moving to Tennessee with a new city, stadium and opportunity. With these two removed, the slope is less severe, but the correlation is much stronger.

Salary vs. Winning Percentage One:



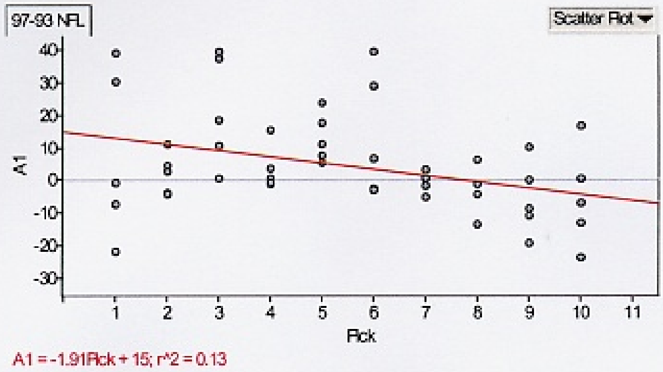
As the pick effectiveness increases so does the short-term team improvement. The biggest outlier is again Keyshawn Johnson, but once removed a more accurate graph is obtained. In that one, Dan Wilkinson is an outlier with his team's improvement being higher than it should be too. A common trend between the outliers is that they were picked number one, meaning that the team that took them was horrible, so improvement is easy.

Salary vs. Winning Percentage Five:



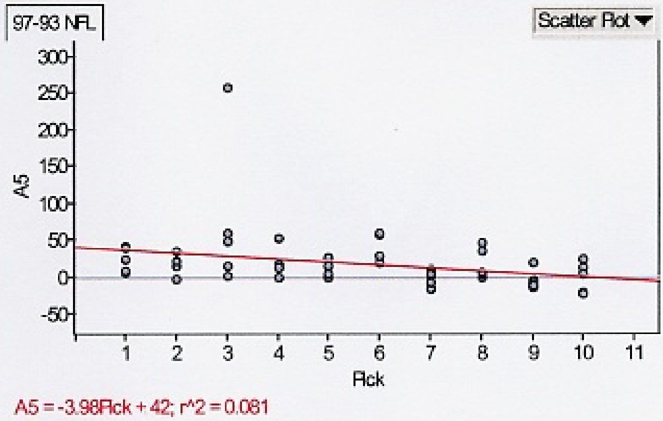
The same trend as short-term is observed long-term with similar outliers. Again, the largest is Keyshawn with the second biggest being Steve McNair whose team experienced a huge increase in winning percentage over five years due to reasons mentioned earlier. Removal of these two creates a regression of 0.14 as opposed to 0.07.

Pick vs. Attendance One:



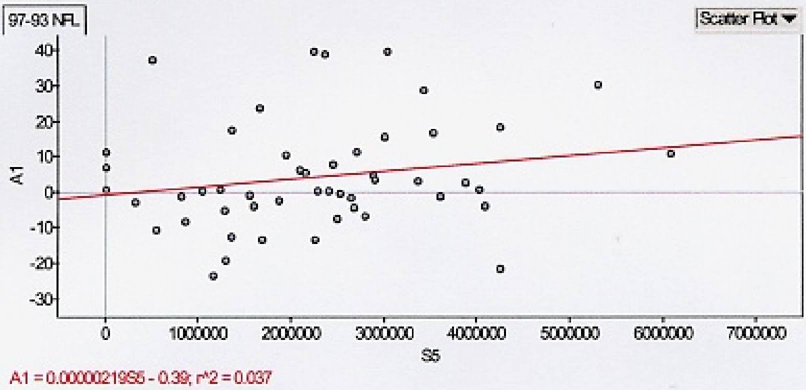
This graph shows that the lower the pick, the lower the attendance changes the next year. Many picks were far above or below the line of best fit, but a few are: Orlando Pace, Walter Jones and Shawn Springs. Pace was below the line, while Jones and Springs were above the trend, possibly because their teams all improved the next season, drawing out more fans.

Pick vs. Attendance Five:



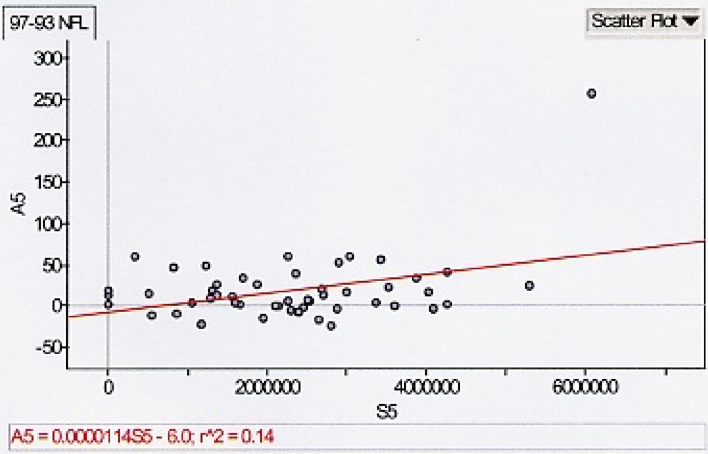
This graph shows the same as the last, but on a long-term scale. The only real outlier in this graph is Steve McNair. His team's attendance is way higher than the trend. This is because his team changed cities in between these five years and far more fans came out to a Tennessee Titans game then a Houston Oilers game.

Salary vs. Attendance One:



This graph plots effectiveness against attendance increase after one year. Two outliers are Garrison Hearst, far about the line of best fit, and Orlando Pace, far below the line. For attendance it's hard to know what creates an increase or decrease in attendance, but I doubt that Orlando Pace an OL could create enough spite for people not to come to games. It's probably because the Rams were a last place team when they got him, so it was hard drawing fans back. Arizona experienced an increase in winning percentage in the first year, possibly drawing out more fans.

Salary vs. Attendance Five:



This graph shows that the more effective the draft pick, the higher the increase in long-term attendance. The biggest outlier in this graph is again Steve McNair, for the same reason I've mentioned earlier, change of city. After the graph is rescale there are many outliers, the biggest being Eric Curry, who played for Tampa Bay. The attendance increase is above what it should be for one simple reason: the Bucs were so bad they had nowhere to go but up in every aspect.

Position vs. Salary:

97-93 NFL		Summary Table
		S5
Position	CB	4 1873275.8
	DL	11 2269750.5
	LB	6 1781569.3
	OL	8 2883262.8
	QB	6 3392116.7
	RB	6 1688716.7
	TE	2 1795000
	WR	7 1919868.6
Column Summary		50 2274602.3

S1 = count ( )
S2 = mean ( )

These results aren't as definitive as the NBA ones because the picks are more scattered and there are less in each position. The highest mean is QB and so is the highest median, but their standard deviation is also the highest by far. This is because two of the six QB's, Steve McNair and Drew Bledsoe both make way more than the average. The lowest standard deviation is TE, but this might be because there are only two who are both around the same mediocre salary. Basically, all positions other than QB's are close, so standard deviation seems to go in order by the number in each position.

Position vs. Winning Five:

97-93 NFL		Summary Table
		W5
Position	CB	4 12.6925
	DL	11 80.662727
	LB	6 118.67833
	OL	8 77.1025
	QB	6 146.6
	RB	6 42.991667
	TE	2 41.665
	WR	7 170.85714
Column Summary		50 93.6766

S1 = count ( )
S2 = mean ( )

The position with the highest mean is WR with a mean 50 above LB. This is somewhat due to Keyshawn's 793 which has a large impact on the results. Without Keyshawn WR would just have a mean of 66.17. The real indication of best effect on wins is the median, which is LB with a median of 112.6. The lowest standard deviation is CB, but although the consistency is good the effect of winning is low at only a median of 14.27.

<u>Position vs. Attendance:</u>

97-93 NFL — Summary Table

		A5
Position	CB	8.94 4
	DL	18.113636 11
	LB	3.075 6
	OL	18.54125 8
	QB	68.42 6
	RB	6.2466667 6
	TE	7.195 2
	WR	18.551429 7
Column Summary		19.8808 50

S1 = mean ( )
S2 = count ( )

The highest mean is QB by far. Although there are some high number changing the results, its obvious that QB's have the largest impact as shown by median as well. Not only is the mean highest by 40+, but median is highest by 20+. This shows that a QB can have a huge impact on your teams' attendance. The most consistent is LB, but a message to owners, it's worth the risk, pick a QB!!

Conclusion:

These results showed me a lot of things, although not all of the trends were as strongly correlated as I thought they would be. A few of my graphs do not look like they have any trends, but the removal of outliers show the trends that I expected. The best correlation seemed to be between salaries and a second variable as opposed to pick number. Since salaries are correlated to pick number, picks are still obviously correlated with attendance and winning, but just not as strongly. An interesting thing that I observed was the difference in trends between the NFL and NBA. The NFL seemed to have larger outliers, mainly because of larger stadiums and smaller season lengths. The larger stadiums make attendances capable of increasing or decreasing less. The smaller season lengths make one game that much more important, playing a bigger role on the winning percentage change. In addition to larger first year increases compared to the NBA, the NFL has larger long-term impacts. This shows the opposite of my prediction: that a single NFL player can become a franchise player, one who attracts fans/money/wins, much easier and to a larger degree than an NFL player. Although I only extrapolated for one league, the NBA, due to an easier access to information and more consistent numbers, I was able to view trends. Picking random players and testing them on all of my graphs proved that the trends do fit draft picks outside the top ten, but generally not much higher than 15. Overall, there are a lot of interesting trends I observed and the key is to draft a player who will make lots of money (and deserve it), if you can figure out how to do that.

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