

# TALENT EVALUATION AND ROSTER BUILDING FOR NBA EXPANSION

Michael Mistarz

Northwestern University, MSDS457: Sports Management Analytics

Github: [https://github.com/mistmr7/MSDS457\\_NBA-Expansion-Draft](https://github.com/mistmr7/MSDS457_NBA-Expansion-Draft)

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## 1. Introduction

NBA expansion has been a constant in a league that has grown since its inception, with 10 expansion drafts occurring between the years of 1966 with the introduction of the Chicago Bulls all the way to 2004 in the re-launch of a Charlotte franchise (NBA 2004). In fact, this is the longest drought of an expansion draft since the initial one. Commissioner Adam Silver has repeatedly spoken of impending expansion in the last few years, with Seattle and Las Vegas named as two of the likeliest cities for the next round (Buller-Ross 2025). This paper will focus on creating an expansion team for the city of Seattle, which recently lost a team to relocation during the Great Recession.

Besides being named as a likely destination, Seattle has a rich basketball history, with Seattle becoming the 11<sup>th</sup> team added to the NBA in the 1967 Expansion draft (NBA 2004). Their previous owner, Howard Schultz, sold the team in 2006 to Oklahoma-native Clay Bennett with a clause that Bennett would keep the team in the Greater Seattle Area (AP 2008). Bennett eventually sued the city of Seattle for not helping build an arena and moved the team to Oklahoma City. Schultz filed a counter lawsuit to try to nullify the sale, eventually withdrawing the suit, and has since apologized for the sale. Schultz called it one of his biggest professional regrets and a public wound he would not be able to heal (Grabar 2019). Seattle has proven that it can support an NBA franchise, supporting a franchise that achieved an NBA title in 1979, and it should be given the chance to do so again.

NBA expansion teams face a difficult road to success, as the last five expansion franchises have a total of one NBA title between them from the 2019 Raptors (NBA 2004). That includes 36 seasons for the Orlando Magic and Minnesota Timberwolves, 30 seasons for the

Toronto Raptors and Vancouver/Memphis Grizzlies, and 21 seasons for the Charlotte Bobcats/Hornets. In 153 seasons, they have managed just a single championship combined. Maximizing talent on the initial roster should be a priority for the team, and this paper will be an analytical-based prioritization of the suspected expansion-eligible draft pool.

## **2. Literature Review**

Researchers from the International Hellenic University in Thessaloniki, Greece attempted to discern what existing performance metrics help discern team and player success on the basketball court using machine learning and data mining techniques. The researchers aimed to analyze these metrics to better forecast players to help improve team composition choices. They created a comparison chart for many existing metrics, charted different metrics using logarithmic normalization for some of the league's top players. They used these charts to create an Aggregated Performance Indicator using the formula shown in Figure 1. They concluded that basketball is becoming more of a team sport than it ever has been, and full team composition, including how players fit alongside one another, is necessary to maximize performance. They suggest that future work should combine statistical modeling, player and team statistics, social commentary, visual tracking data, and exercise and gym statistics along with wearable metric data should all be utilized in creating the best predictive metrics (Sarlis, Vangelis and Tjortjis 2020).

$$\begin{aligned}
\text{API} = & [\text{RPM}(+/-) + \% \text{PER} + \% \text{PIE} + \% \text{4Factors} + \% \text{NETRTG} + \% \text{EFF} + \% \text{PIR} + \% \text{Tendex} + \\
& \% \text{BPM} + \% \text{PIPM} + \% \text{GmSc} + \% \text{FP} + \% \text{WS/48} + \% \text{TeamELO} + \% \text{EFG\%} + \% \text{TS\%} + \\
& \% \text{VORP} + \% \text{WinsRPM} + \% \text{WAR} + \% \text{EWA} + \% \text{Deflections} + \% \text{PACE} + \% \text{USG\%} + \\
& \% \text{AST/TO} + \% \text{ScreenAssistsPTS} + \% \text{PRA} + \% \text{REB\%} + \% \text{LooseBallsRecovered} + \% \text{PPP} + \\
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\end{aligned}$$

**Figure 1:** Aggregated Performance Indicator formula derived by researchers at International Hellenic University

Joseph Rozier III of the United States Sports Academy published a study on the feasibility of a hypothetical expansion team to Seattle for the NBA in *The Sport Journal* in 2018. He examined the issue from a public support and public opposition perspective, showing overall more positive public support, a positive corporate sponsorship outlook, and a positive community revitalization outcome. Opponents proposed insignificant economic progression since the team was relocated to Oklahoma City, the expense of a new arena, and too many professional sports franchises in one city as the main arguments. The author provided arguments from both sides, noting that the community is likely to obtain an NHL and NBA team in the near future and the long-term financial and social success is uncertain (Rozier III 2018).

Researchers at MIT published a study exploring the return on investment of investing money into analytics. They studied the causal relationship between analytics team head count and wins over a 12-year period. They found through a two-way fixed model approach that increased analytics headcount does have a statistically significant positive effect on regular season wins. They normalized the data by collecting player-games injured, roster continuity, coaching experience, roster experience, analyst headcount, and roster salary for each team. Through this, they were able to see how roster experience, roster salary, coaching experience,

and roster continuity all had positive effects on team wins while player-games injured and new coach had a negative effect, allowing them to normalize the data to focus on analyst headcount (Wang, Sarker, and Hosoi 2025).

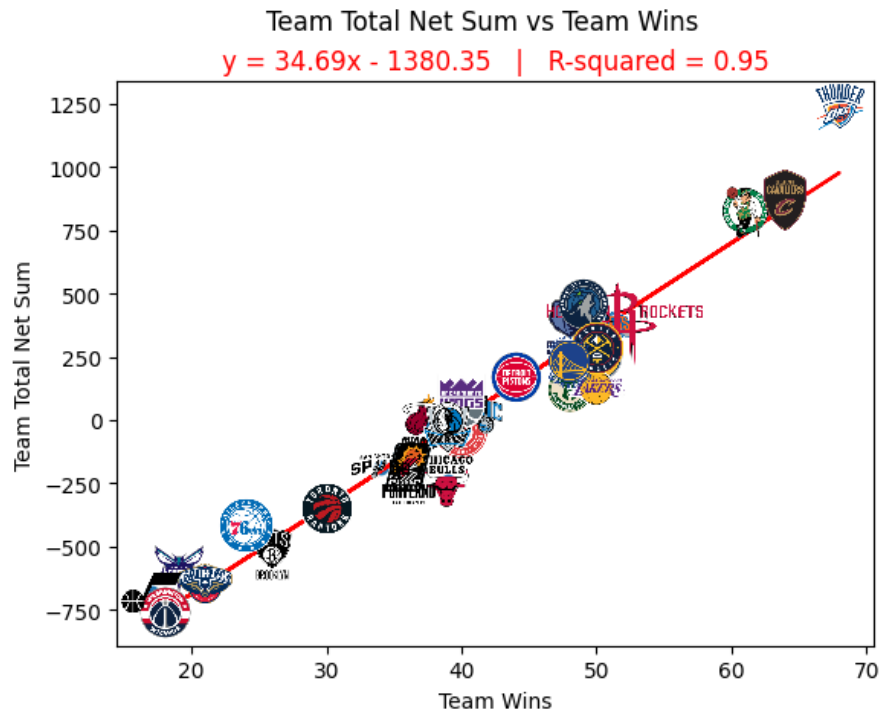
### **3. Methods**

In preparation for the expansion draft, public NBA data tables were aggregated using Python along with many Python libraries, notably among them were Requests, BeautifulSoup, Selenium, Pandas, Matplotlib, and NumPy. ESPN was scraped to build a table of the total net points for each player in the league (ESPN 2025). Spotrac was scraped to determine player salaries for each player in the league, to determine which players had player options and which players would become restricted free agents during the 2025 offseason (Spotrac 2025).

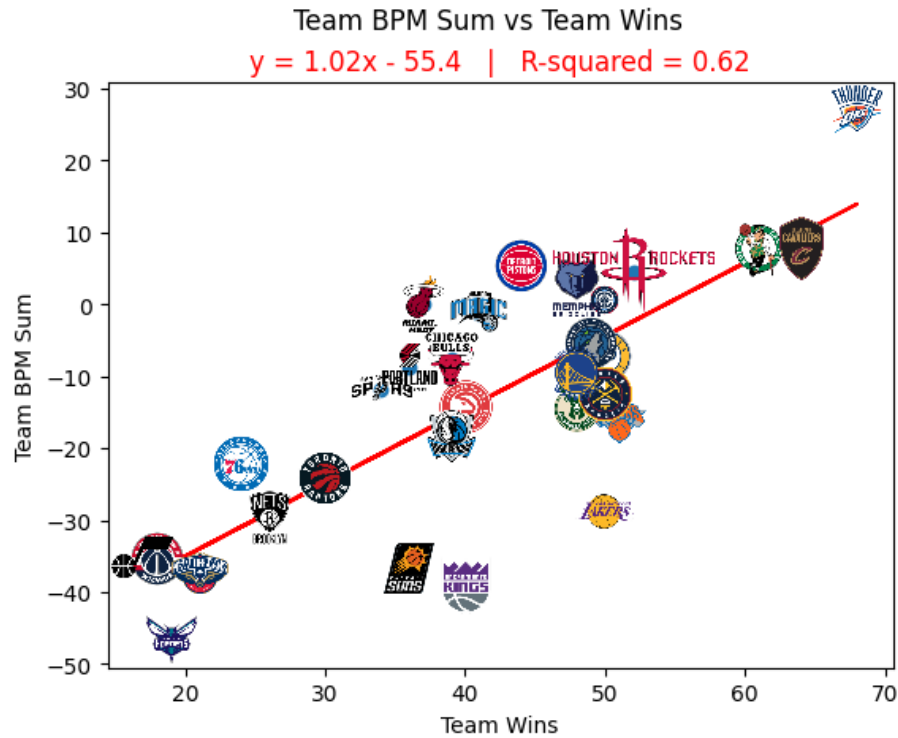
Basketball reference was scraped to get the advanced analytics table for each team in the league (Basketball Reference 2025). Each of these tables was joined together on players, ensuring each player's name matched the names from the other databases through a customized dictionary as players were left off of the list. This created one large Pandas DataFrame for analysis, including values for Total Net Points, Box Plus-Minus (BPM), and Value Over Replacement Player (VORP).

Total Net Points, BPM, and VORP were evaluated for each team in the NBA, with graphical representations of each plotted against wins, shown in Figures 2, 3, and 4. As can be seen from the plots, Total Net Points and VORP both correlate highly with team wins, meaning they are good metrics to choose to analyze. To check to ensure they correlate with each other as well, VORP was plotted against team Total Net Points, and these correlated highly as well. The main question becomes, how does being on a good team versus a bad team affect their analytical

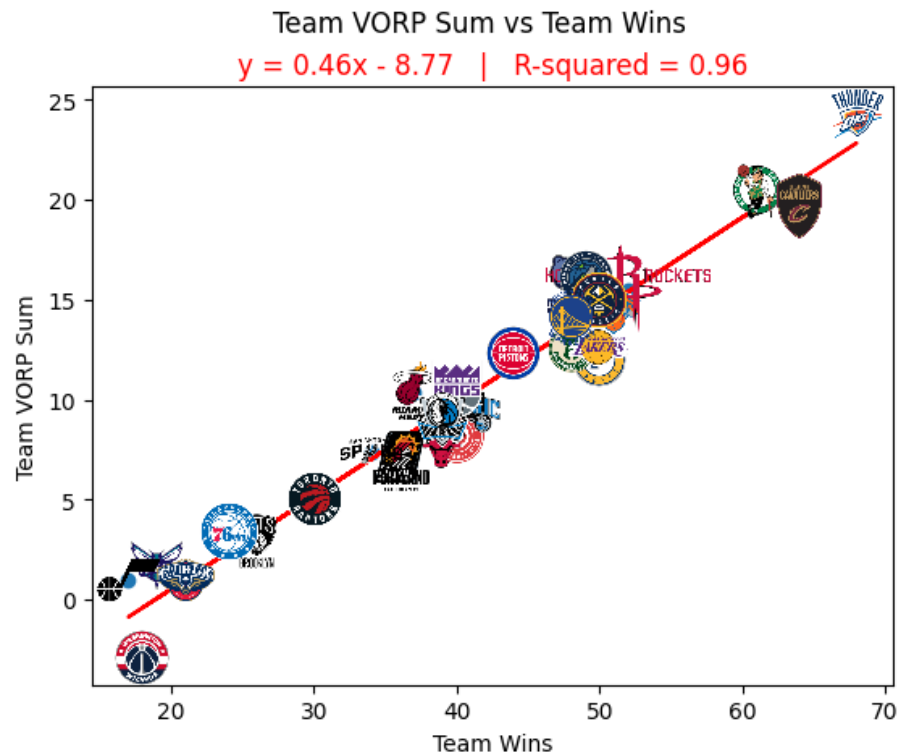
statistics? Does being on a good team naturally raise your analytical statistics, while being on a bad team naturally lowers them?



**Figure 2:** Sum of Total Net Points for each NBA franchise, plotted against total team wins.



**Figure 3:** Sum of player BPM for each NBA franchise, plotted against team wins



**Figure 4:** Sum of player VORP for each NBA franchise, plotted against team wins.

For an anecdotal look at these questions, we could look at the issue from both offensive and defensive perspectives. One could imagine playing defense with a good defensive support group and a poor defensive support group. A player with a good defensive support group could miss a defensive assignment and be covered for the mistake, while a player with a poor defensive support group could miss a defensive assignment and cost their team points. On the offensive end, a poor offensive player could benefit from getting a more favorable defender playing against him due to the offensive strength of his teammates. It is important to try to work through this noise of uneven support groups in order to better discern a player's value towards winning and losing.

In order to normalize team performance within player analysis, subtracting out some portion of team performance seems pertinent. To do this, the total minutes played for each team were summed, and each player's individual minutes played was divided by total team minutes to represent a minute played fraction for each player. This number was multiplied by the difference of team total net and player total net, and the full equation can be visualized below in Figure 5.

$$Net\ Minus\ Team\ Ind = Player\ Net - \left( \frac{Player\ Mins\ Played}{Team\ Mins\ Played} \times (Team\ Net - Player\ Net) \right)$$

**Figure 5:** Calculation for Net Minus Team Individual, where total net is normalized by team performance

Total Net Points is an analytical statistic developed by ESPN that uses play-by-play data, box score data, and optical tracking technology to credit or fault players on the court for every event that happens in a game (ESPN 2025). The Total Net Points value is equal to the points above average created on offense and defense, and this value adds up to the net score of each game. For example, if the NY Knicks beat the Boston Celtics 120-100, the NY Knicks roster will have a team Total Net Points of +20 and the Boston Celtics would have a team Total Net Points



of -20. These values also correspond to the sum of the individual net points of each player that played in the game (Oliver 2025).

To try to see how individual Total Net Points correlated with Team Net Points, Net Minus Team Individual attempts to adjust player net rating for the players that they are sharing the court with. The table in Figure 6 below allows us to look at six examples of how this adjusts players towards the mean for a more even analysis by analyzing Shai Gilgeous-Alexander, Kevin Durant, Victor Wembanyama, Jordan Poole, Trey Murphy III, and Luguentz Dort. Shai Gilgeous-Alexander won the MVP this year as the best player on the 68-win Oklahoma City Thunder. His Total Net Points for the season were 480 points, but his Net Minus Team Individual drops to just below 381 points due to the fact he played on the league's best team. Jordan Poole, whose Total Net Points for the season were -57, played on the league-worst Washington Wizards. His Total Net Rank is 442<sup>nd</sup> in the league, but adjusting team performance bumps his Net Minus Team Individual points to just over +39, with his rank jumping to 81<sup>st</sup> in the league. This more closely matches what NBA GMs think he is worth, measured by his salary of having the 52<sup>nd</sup> highest contract in the league for the year, and also much closer to his BPM and VORP. Net Minus Team Individual will be the metric chosen for further analysis, and a similar table to Figure 6 shows the top 25 and bottom 25 players in the league sorted by Net Minus Team Individual in Appendix A.

PLAYER	MIN FRACTION	TOTAL NET	TEAM NET POINTS	NET MINUS TEAM IND	NMTI Rank	TOTAL NET Rank	BPM Rank	VORP Rank	BPM	VORP
Shai Gilgeous-Alexander	0.135957	480.0	1209.0	380.887435	2	2	2	2	11.5	8.9
Kevin Durant	0.117840	128.0	-323.0	181.145778	12	25	50	27	3.2	3.0
Victor Wembanyama	0.077908	141.0	-219.0	169.046939	13	22	7	22	6.5	3.3
Jordan Poole	0.120397	-57.0	-919.0	46.782310	81	442	161	99	0.4	1.2
Trey Murphy III	0.104498	-35.0	-746.0	39.297937	93	392	135	90	0.8	1.3
Luguentz Dort	0.108483	24.0	1209.0	-104.552253	484	119	183	109	0.2	1.2

**Figure 6:** Selected players to show how Net Minus Team Individual compares to other major metrics, including how it adjusts players to the mean based on team.

After determining to use Net Minus Team Individual, the aggregated analysis DataFrame was filtered to include only unprotected players. NBA teams are allowed to protect 8 players signed to their roster for 2025-2026, not including player options. Unrestricted free agents are also not allowed to be drafted in an expansion draft. The list of NBA players protected for each franchise was taken from *The Ringer* article on what a potential expansion draft would look like (Pina 2025). The author collaborated with the rest of the NBA staff at *The Ringer* and attempted to put each GM's hat on to make the decisions, prioritizing the current championship window and roster construction when making each choice. Therefore, contending teams would likely hold onto a more valuable veteran than a potentially promising rookie, and vice versa for rebuilding teams. These players were scraped from the article and removed from the analytic DataFrame. Then, Spotrac was scraped of all player options and upcoming unrestricted free agents, with each of these players removed from the DataFrame as well (Spotrac 2025). This filtering resulted in a DataFrame of 116 unique players who were split into bigs, wings, and guards. These tables were further filtered to remove any player playing less than 500 minutes on the season to remove any small sample size outliers, and each of the three resulting tables can be seen in Appendix A.3-A.5.

The other rules for NBA expansion helped guide the process from this point. The NBA salary cap for 2025-2026 will be set to \$154.6 million (Marks 2025). The NBA CBA states that expansion teams will have a salary cap of 2/3 of the league salary cap for year 1 and 80 percent of the league salary cap for year 2 (NBA 2023). This makes the salary cap for the first year \$103.07 million. They must spend at least 90 percent of this cap to reach the league salary floor, so at least \$92.76 million. In the NBA, spending above the salary cap is acceptable, though there is a luxury tax ceiling where teams pay into a league tax pot to try to balance revenues for small

market teams, as well as further punishments for going over higher salary levels of the first and second apron. For this study's purposes, only the luxury tax will be necessary and will be set as the salary ceiling, as expansion teams likely would avoid paying into the tax until they are competitive, with a luxury tax cap set to \$187.9 million (Marks 2025). This gives a target salary of between \$92.76 million and \$187.9 million. Teams may also only select one player from each NBA team, so attrition is kept to a minimum for protecting teams.

To find the best roster, Python PuLP library was used to create a linear programming problem trying to maximize Net Minus Team Individual. The problem involved limiting players selected to one player per team for the roster and ensuring the salary of the players falls within the target salary range of \$92.76 million to \$187.9 million. The number of bigs the team carried was set to between 3 and 5, the number of wings the team carried was set to between 4 and 8, and the number of guards the team carried was set to between 4 and 8. Each unprotected player was set as a PuLP linear programming variable with a binary option of 1 or 0, and this binary variable was multiplied by the salary, an analytical variable, in this case Net Minus Team Individual, and the team to ensure only one player per team, and a linear programming problem was solved. A linear programming problem was also solved using Total Net, VORP, and BPM to look at the rosters those variables could create as well. Total roster tables for each analytical variable can be seen in Appendix C.

These results were plotted against salary to visualize how the players on the team performed analytically versus their respective salaries along with a plot against team wins to see how the roster performed analytically versus their respective team performance. This was expanded to view the roster against the entire league in visualizations, and these plots will be reviewed and analyzed in the results section.

#### 4. Results

After scraping publicly available NBA data tables, aggregating them together for further analysis, creating a normalized metric and filtering out protected players, a pool of 116 players was left to sort through to pick the best roster. Using Python's PuLP library, rosters were selected prioritizing maximizing Net Minus Team Individual, VORP, BPM, and Total Net Points while fitting into salary restrictions, only picking a single player from each team and ensuring that a certain number of players from each position were chosen. The resulting table of all four teams can be seen in Figure 7. Net Minus Team Individual results are broken down further in Figures 8, 9, and 10 showing salary plotted against Net Minus Team Individual for the position groups as well as Team Net Points plotted against Net Minus Team Individual, highlighting the players chosen by the algorithm.

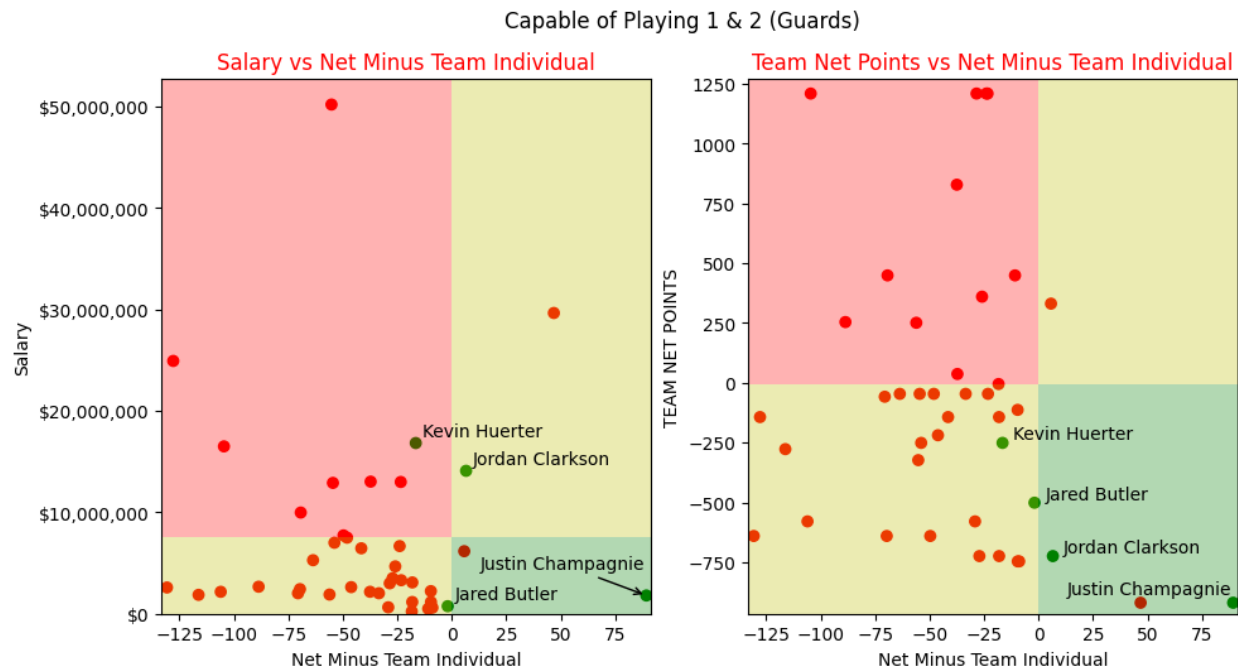
BPM_Roster	VORP_Roster	Total_Net_Roster	NMTI_Roster
Jay Huff	Santi Aldama	Santi Aldama	Santi Aldama
Moritz Wagner	Moritz Wagner	Moritz Wagner	Moritz Wagner
Neemias Queta	Deandre Ayton	Neemias Queta	Karlo Matkovic
Zach Collins	Neemias Queta	Kelly Olynyk	Jusuf Nurkic
Obi Toppin	Obi Toppin	Obi Toppin	Obi Toppin
Jaylin Williams	Trayce Jackson-Davis	Richaun Holmes	Jaylin Williams
Trayce Jackson-Davis	Cam Whitmore	Jae'Sean Tate	Jae'Sean Tate
Cam Whitmore	Brice Sensabaugh	Mouhamed Gueye	Mouhamed Gueye
Richaun Holmes	Mouhamed Gueye	Jabari Walker	Jabari Walker
Mouhamed Gueye	Mike Conley	Gui Santos	Gui Santos
Jabari Walker	Isaiah Joe	Moussa Diabate	Moussa Diabate
Mike Conley	Jordan Poole	Isaiah Joe	Justin Champagnie
Sam Merrill	Sam Merrill	Sam Merrill	Kevin Huerter
Bradley Beal	Bradley Beal	Jaylen Clark	Jordan Clarkson
Davion Mitchell	Davion Mitchell	Kevin Huerter	Jared Butler

**Figure 7:** Analytically optimized expansion teams chosen for each analytical measurement.

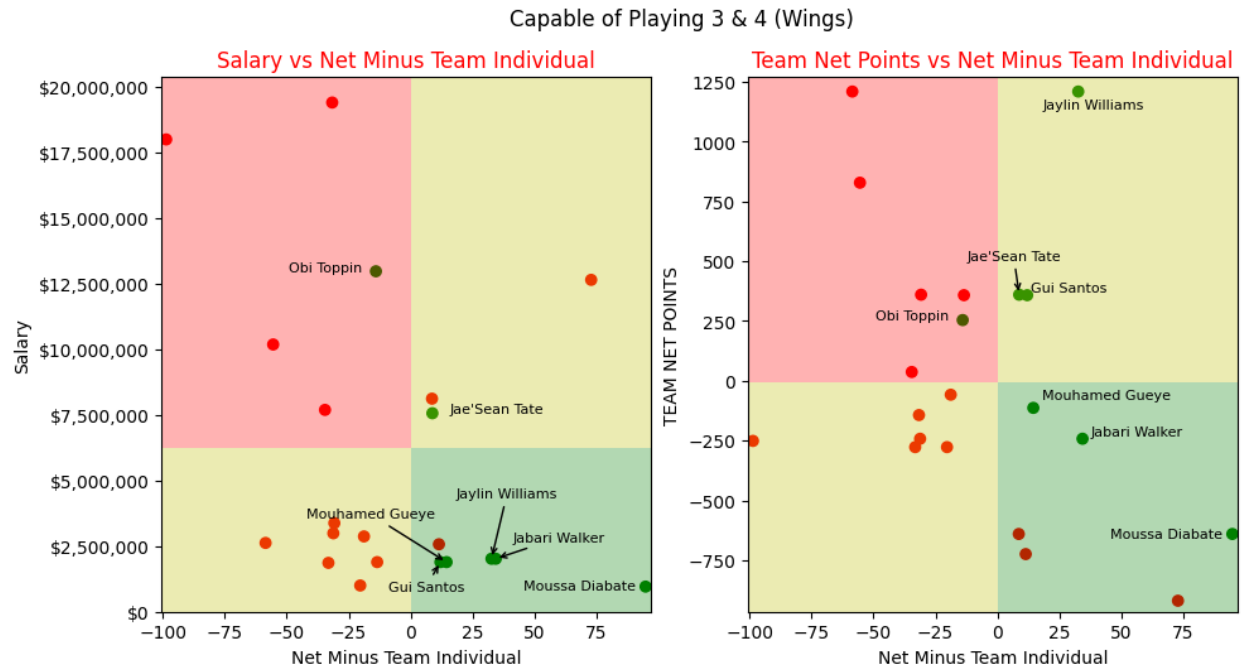
Teams were chosen with all expansion draft rules in place.

As can be seen in Figures 8, 9, and 10, players in the top left corner of the left chart show players with high salaries and negative Net Minus Team Individual points. The top right and lower left-hand corners correlate to average Net Minus Team Individual players as they relate to salary. Players in the top left-hand corners are players that are paid more than their on-court production predicts, and players in the lower right-hand corners are players that are outperforming their contracts analytically. The split in the vertical axis in this chart refers to the average of the analytical measurement, and the split in the horizontal axis refers to the average

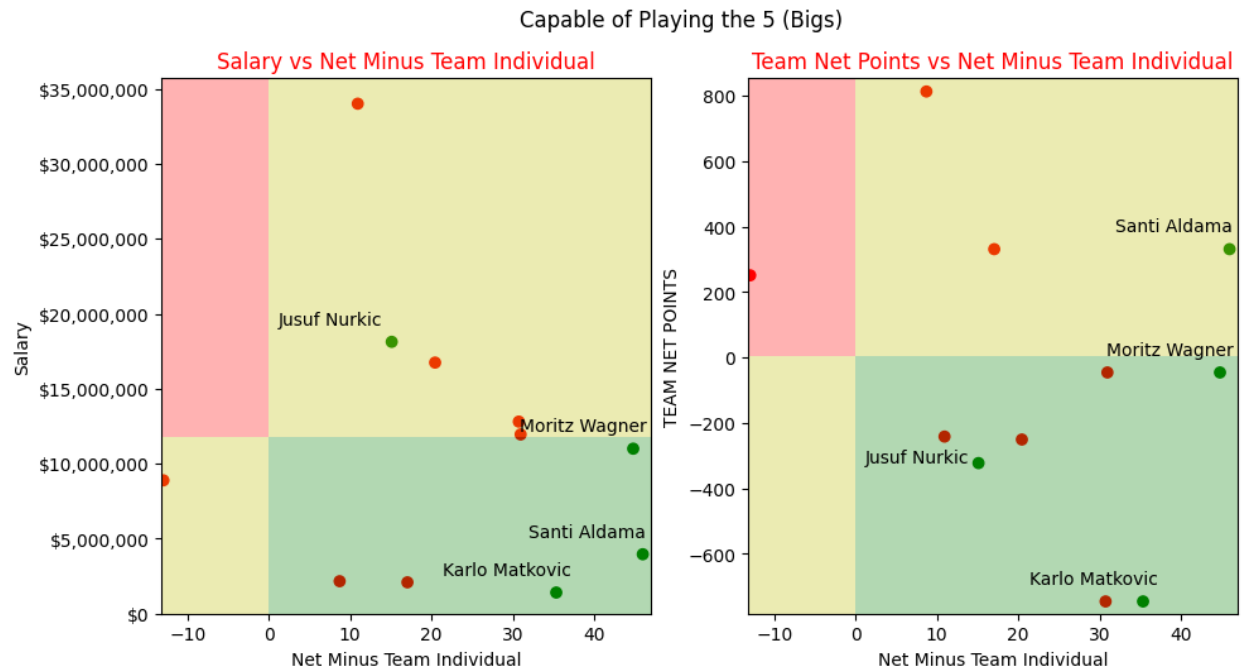
salary per slot on the team to reach the salary floor. In the right-hand chart in each figure, the trends remain the same but players in the top left performed poorly on a good team, players in the top right and bottom left-hand corners had average performance for their team, and players in the bottom right-hand corners performed well despite being on a bad team. The vertical axis in the right-hand charts refers to the average of the analytical measurement, and the horizontal axis on the right-hand charts refers to a team that had a net rating of 0 for the season. Similar plots for position four all four analytical measurements can be found in Appendix B.



**Figure 8:** Salary and Team Net Points plotted against Net Minus Team Individual for all guards chosen by the algorithm.



**Figure 9:** Salary and Team Net Points plotted against Net Minus Team Individual for all wings chosen by the algorithm.

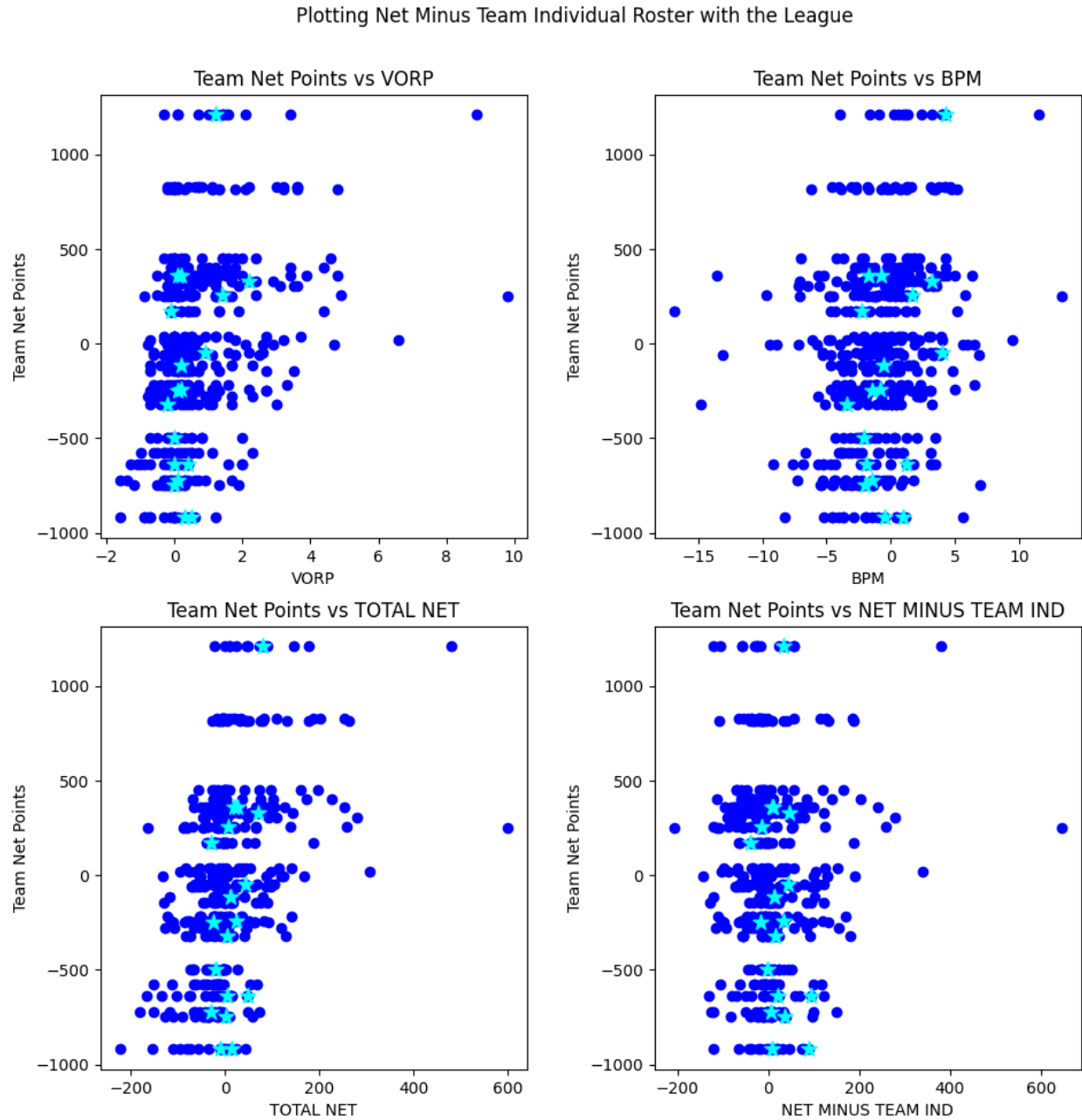


**Figure 10:** Salary and Team Net Points plotted against Net Minus Team Individual for all guards chosen by the algorithm.

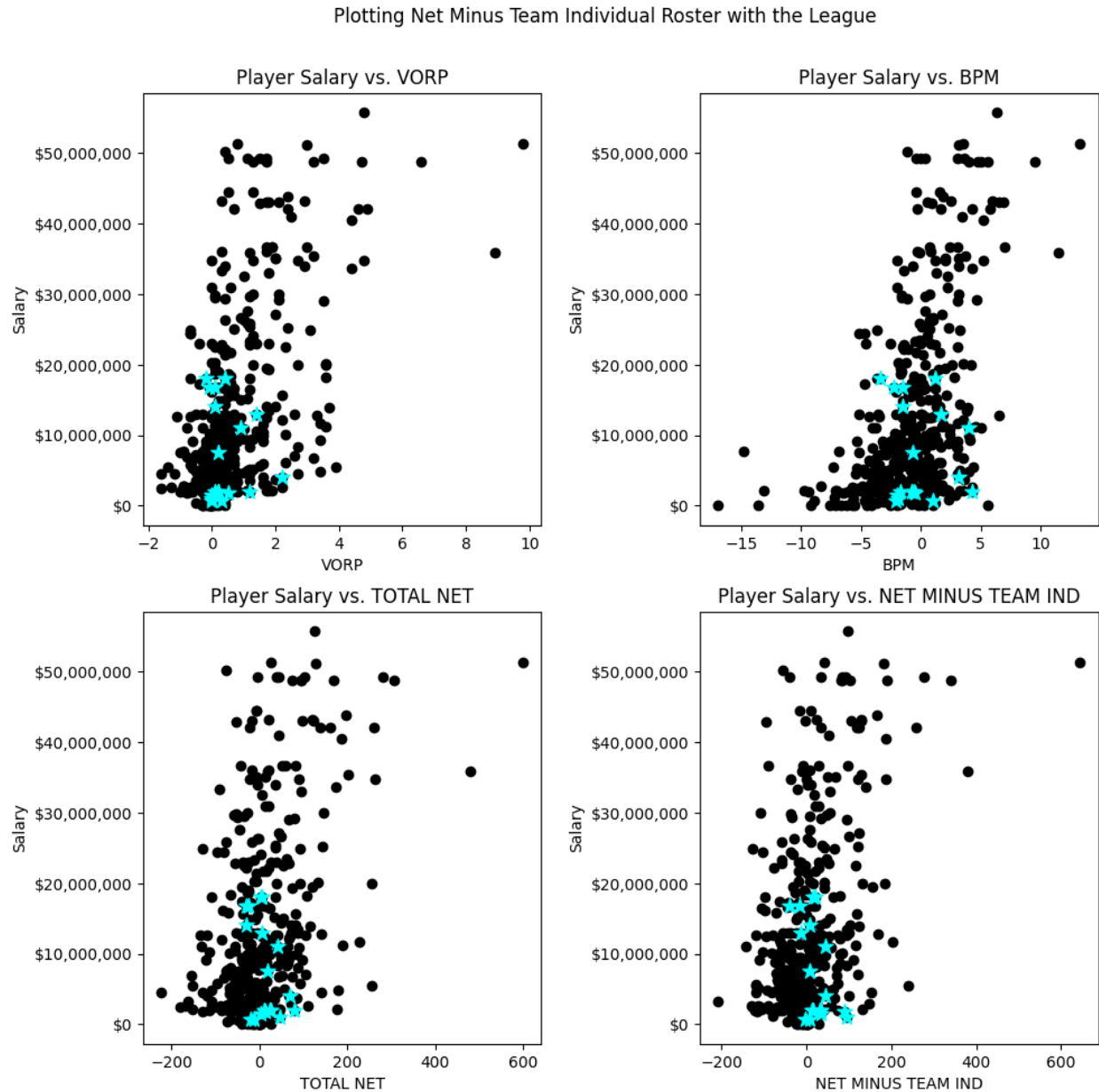
After visualizing the players within the unprotected players pool, the same players for the Net Minus Team Individual roster were plotted against the rest of the league for each of the four analytical measurements, with the Net Minus Team Individual roster highlighted in cyan. These plots feature both Team Net Points and salary to help visualize what teams they came from, how they compared to the rest of the players on the team, and how they performed compared to their salary. These can be found in Figure 11 and Figure 12. For each of the team net points versus analytical measurement plots in Figure 11, teams are organized along the vertical axis, with the Washington Wizards comprising the bottom row of data points on the plots and the Oklahoma City Thunder comprising the top row of data points on the plots.

From the position of each Net Minus Team Individual player in Figure 11, it can be seen that many of the players selected performed at least average analytically on their team for the given metric, and one could hypothesize that this roster would create around an average NBA team. Figure 12 helps visualize the roster from a salary perspective against the rest of the league. Starting with a constrained salary cap offered to expansion teams kept the roster on the bottom half of each graph, painting the players selected as low risk players at worst. At best, these players may prove to be bargain finds when coupled with above average analytical measurements for most of the team.





**Figure 11:** Team net points for each player in the NBA plotted against four different analytical measurements. Players chosen by the Net Minus Team Individual maximizing algorithm are highlighted in cyan.



**Figure 12:** Salary for each player in the NBA plotted against four different analytical measurements. Players chosen by the Net Minus Team Individual maximizing algorithm are highlighted in cyan.

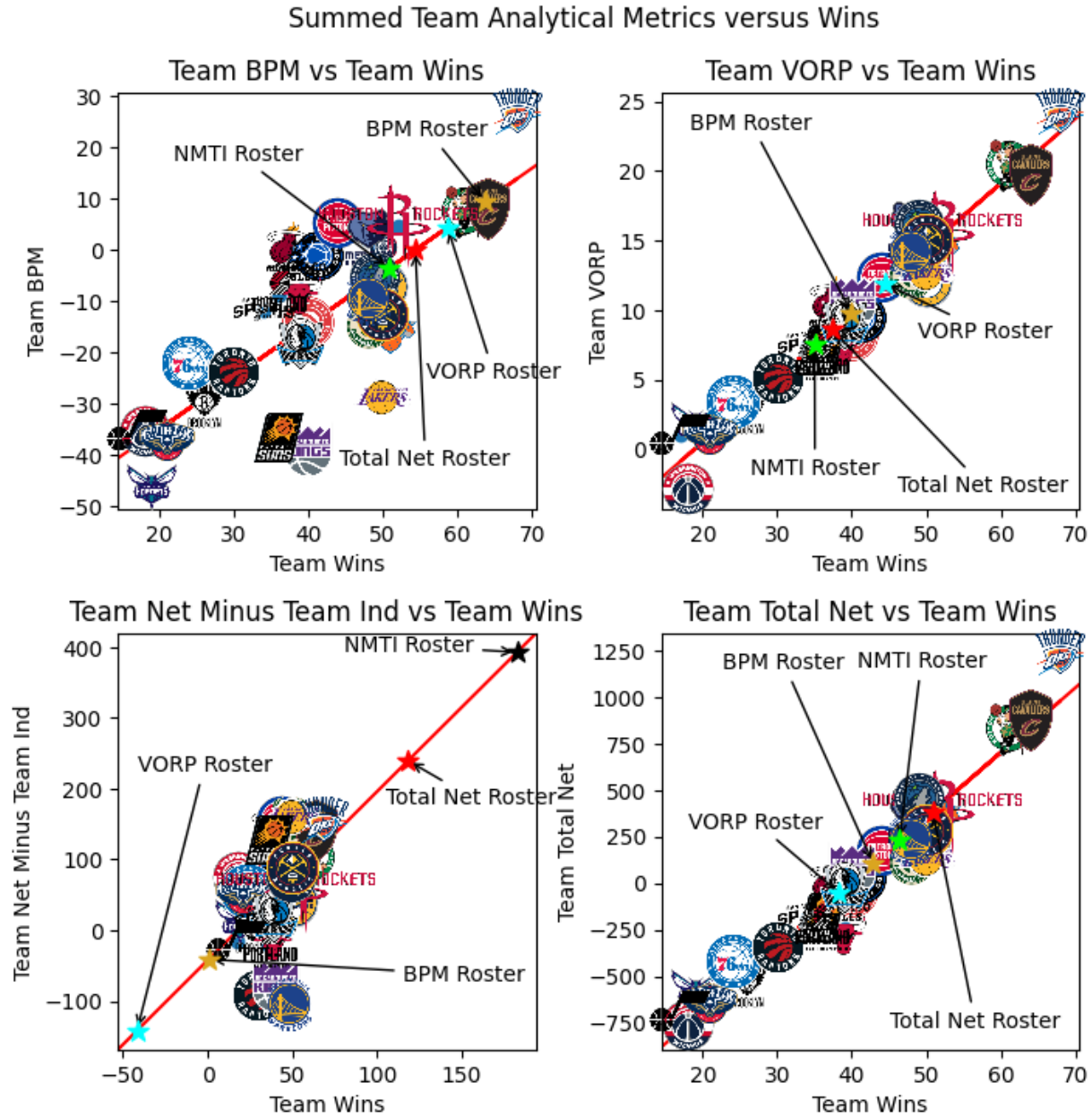
After visualizing the players within the expansion player pool and within the entire NBA, each roster had the four analytical measurements (BPM, VORP, Net Minus Team Individual,

Total Net Points) summed for the team. This was also done for each NBA team, and the sum of each NBA team's analytical measurement was plotted against team wins for the league, in a similar fashion to Figures 2, 3, and 4. Each analytically optimized roster was fitted through linear regression to these league tables to attempt to forecast wins. The projected wins for each analytical team across each of the four metrics can be seen in tabular form in Figure 14 along with the league plots and fitted rosters in Figure 13.

As can be seen in the figure, BPM, VORP, and Total Net all correlate well with team wins and each of the rosters would perform at least around league average based on these metrics, with many teams forecasting to be playoff teams. Net Minus Team Individual was created in an attempt to normalize team performance and player performance, and it does not correlate well as a statistic against the league due to this. For this reason, the plot on the bottom left-hand corner serves little value. This can be seen with win predictions between -42 and 183 wins despite neither of these outcomes being possible. The other three charts feature metrics used by NBA teams and analysts, and each team except the BPM roster fitted to the VORP regression line projects to have win totals allowing them to have a shot to compete in the playoffs.

	BPM Roster	VORP Roster	NMTI Roster	Total Net Roster
<b>BPM Wins Projected</b>	50.82	63.68	58.67	54.35
<b>VORP Wins Projected</b>	35.02	39.97	44.49	37.38
<b>NMTI Wins Projected</b>	182.56	0.53	-41.69	118.23
<b>Total Net Wins Projected</b>	46.42	42.87	38.29	50.86

**Figure 13:** Projected win totals for each roster when fitted to the regression line for the measurement plotted against team wins for the league.

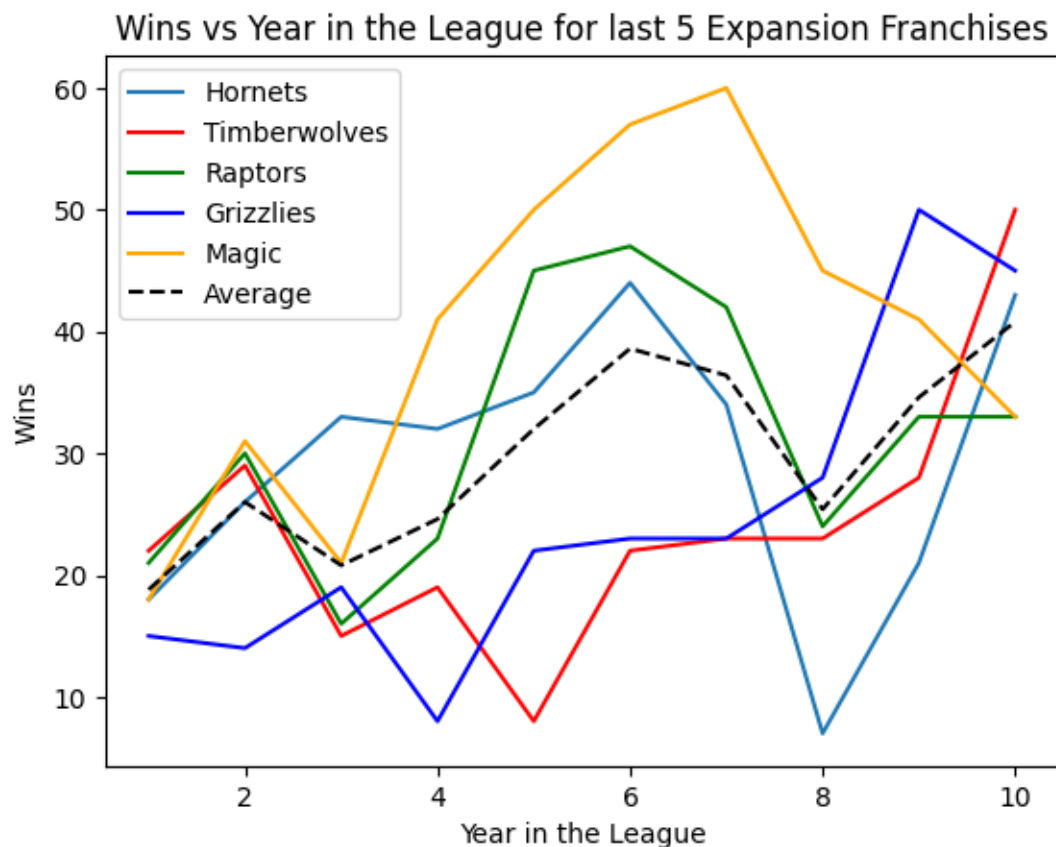


**Figure 14:** The team sum of four analytical measurements plotted against Team Wins for each team in the NBA. Linear regression was performed on the analysis versus team wins and each analytically optimized expansion roster was fit to the linear regression line to approximate wins.

## 5. Conclusions, Recommendations, and Discussion

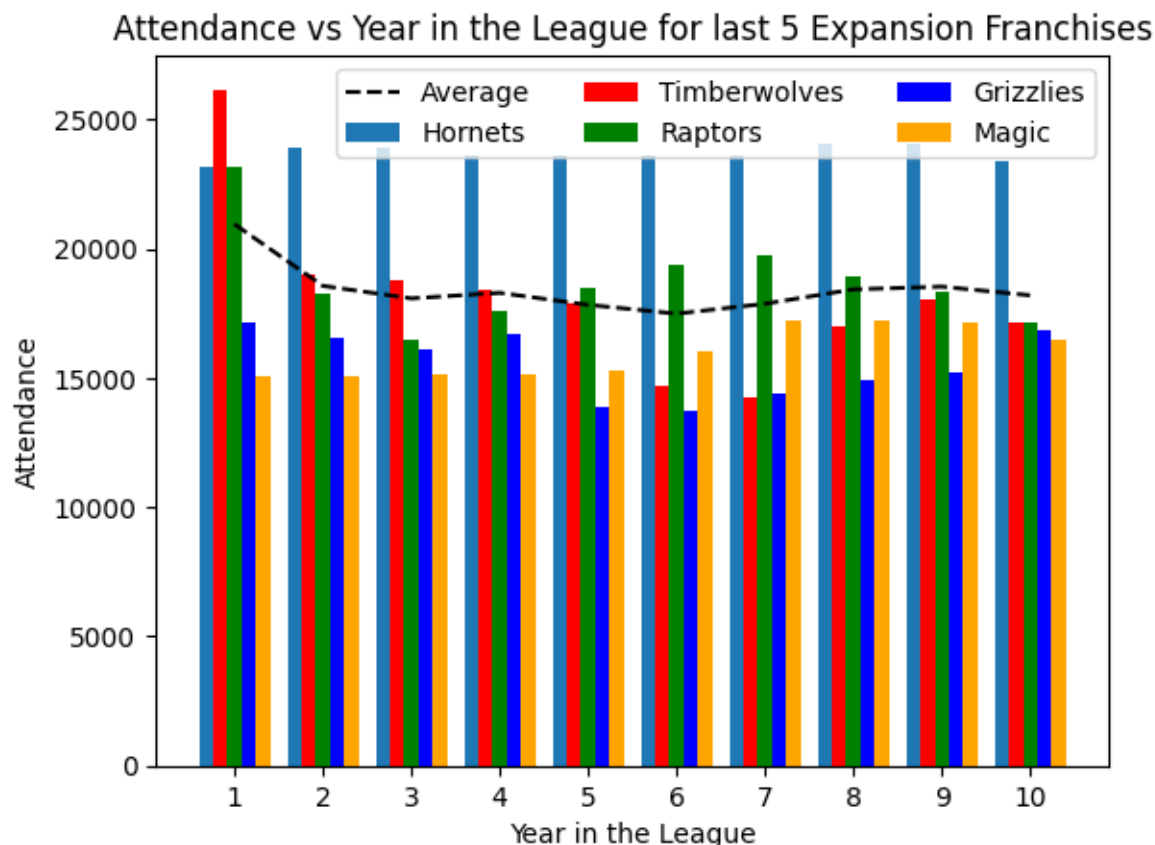
It would be easy to take the results of the analysis and conclude that creating a competent NBA team through an expansion draft is possible with the right tools. However, I would urge management to present the four rosters from Figure 7 to each coaching candidate and ask the coaches how many wins they could expect from each team and to pick the roster they would like to coach. I would predict each of the teams to receive interest from different coaches, but I would venture to guess that none of the candidates would present management with an optimistic picture for the first year. I can also say pretty confidently that none of them would make playoff promises. Does that make the above analysis null and void? It could, but I would like to argue the evidence presented in this paper should prove to management that trying to draft the best team is a fool's errand, and better strategies are available.

Taking a look at the last five expansion teams, all five are in the bottom ten for winning percentage since entering the league (NBA 2025). Plotting each of these five teams' win totals over the first ten years of NBA basketball reveals a visualization of teams that mostly struggled to succeed until at least year five, as can be seen in Figure 15. No team crossed the 40-win threshold until year 4 and only one team achieved 50 wins in the first nine seasons. But do expansion teams need to win to be successful? Most owners would offer a picture of success that marries success on the court with success as a business. From the on-court perspective, teams are unlikely to succeed early. Does this mean that they also are struggling to succeed financially?



**Figure 15:** Number of wins plotted by year in the league for the last 5 NBA expansion teams

While there are many income streams in the NBA, selling tickets seems to be the one sought out for maximization by most teams. Figure 16 shows attendance by year for each of the last 5 NBA expansion franchises. Some, like the Timberwolves playing in the larger Metrodome, had their highest attendance in year 1 due to the venue. Taking this into account along with the Grizzlies relocating to Memphis and a new arena after year 6, you can see from the chart most of the teams do pretty well attendance wise for their first decade despite the lack of wins. New NBA fanbases seem to come out to support their new team whether they're winning or not, so winning in the first year might not be the best strategic goal.



**Figure 16:** Average attendance by year for each of the last 5 NBA expansion franchises.

If teams shouldn't prioritize winning immediately, what should they do? Looking back at NBA expansion franchises, just the Miami Heat and Dallas Mavericks have career winning percentages in the top 15 in the league (NBA 2025). They both achieved faster and more long-lasting success through a series of backdoor deals before the expansion draft started (Kram 2025). Dallas decided that the expansion players list could not help them build a competent team, so they started calling each team and asking them if they would trade any future picks in exchange for drafting and then trading an expansion player they could pick from the pool. They realized that the unprotected NBA veterans and young players from the expansion pool would hold more value to many teams than a future pick. This worked in cases where bad teams coveted a promising expansion player, and competing teams coveted a veteran who could bolster

their title chances. Through this, they received a stockpile of future picks that they used to build a competent franchise (Kram 2025).

The Miami Heat followed a similar model, but instead of offering expansion players to different teams they offered to take a big contract or a worse player as long as the team would attach a future pick to the player. For example, if a contender had a large contract for a player who wasn't contributing, that player would be placed on the list of potential players to be drafted. An expansion team looking to succeed both on and off the court would obviously avoid picking such a player. However, the Heat would agree to take such a player as long as the team attached draft assets to this player. This prevented teams from losing more valuable players and opened up priceless cap space to make moves along the margins. The Heat used this strategy to build a competent contender as well (Kram 2025).

The Seattle SuperSonics expansion franchise should follow both of these examples and see if they can maximize their future draft capital. NBA franchises can only trade picks 7 years out, and with the Stepien rule must retain their own pick at least every other year (NBA 2023). With data showing that expansion franchises can fill stadiums despite not fielding a competent team in the first decade, this gives plenty of runway to use these picks to be profitable by the time fans start expecting success.

One last recommendation I would have for the Seattle Super Sonics expansion franchise would be the pursuit of Kevin Durant for this year's first round pick. The Phoenix Suns have been actively shopping Durant this offseason, and their asking price has reportedly been lowered due to the restrictions of being a second apron team (Iko 2025). Kevin Durant was originally selected by the Seattle Super Sonics as the number 2 pick in the 2007 draft before they moved to Oklahoma City in 2008. Durant said he would like to be a part of a Seattle team if the city



received another team, either as a player or part owner (Friedell 2018). What better way to show the city how committed you are than to bring in one of the greatest scorers in NBA history and the last high pick that the franchise selected? Yes, Durant would not fit the timeline of the team, but he would more than make up for it in sales, veteran leadership, and marketing. Also, he would be an extremely attractive asset to flip for future draft capital if he desires to compete for a title during his last years.

In conclusion, the analysis done in this study bolsters the historical evidence that competing with an expansion-drafted team faces long odds. Sports analytics provides some tools in the toolbox in order to evaluate the game of basketball, but as Brian Kalbrosky found through interviewing NBA experts and team executives, there is no metric that everyone trusts (Kalbrosky 2021). Basketball does not have distinct time stops like baseball and football, and the continuous nature of the game along with 5 players playing on each team at once has made finding an analytical catch-all metric nearly impossible. As technology expands, maybe this gap will shrink, but I do not expect that will lead to putting together a group of expansion players to legitimately strive for an NBA title. NBA GMs and front offices should use every avenue to expand future draft capital and build a team akin to this year's Oklahoma City Thunder, who stockpiled draft equity to build a lasting contender. If history is a proper guide, expecting to win early is fraught with folly, and much patience and human interaction with front offices will lead to the best team building strategy.

## Appendix A

PLAYER	MIN FRACTION	TOTAL NET	TEAM NET	POINTS	NET MINUS TEAM IND	NMTI Rank	TOTAL NET Rank	BPM Rank	VORP Rank	BPM	VORP
Nikola Jokic	0.13	599.00		251.00	644.77	1	1	1	1	13.30	9.80
Shai Gilgeous-Alexander	0.14	480.00		1209.00	380.89	2	2	2	2	11.50	8.90
Giannis Antetokounmpo	0.12	307.00		21.00	340.81	3	3	3	3	9.50	6.60
Karl-Anthony Towns	0.13	281.00		303.00	278.19	4	4	34	18	3.60	3.50
Tyrese Haliburton	0.13	259.00		254.00	259.64	5	6	10	4	5.80	4.90
Alperen Sengun	0.12	254.00		360.00	241.08	6	8	20	11	4.40	3.90
Ivica Zubac	0.14	226.00		400.00	202.37	7	9	56	19	3.10	3.40
LeBron James	0.13	168.00		-5.00	190.88	8	17	12	7	5.60	4.70
Domantas Sabonis	0.12	186.00		172.00	187.73	9	13	13	9	5.20	4.40
Jayson Tatum	0.14	262.00		813.00	187.39	10	5	14	6	5.20	4.80
Jarrett Allen	0.12	254.00		828.00	184.53	11	7	25	13	4.20	3.60
Kevin Durant	0.12	128.00		-323.00	181.15	12	25	50	27	3.20	3.00
Victor Wembanyama	0.08	141.00		-219.00	169.05	13	22	7	22	6.50	3.30
Rudy Gobert	0.12	196.00		449.00	165.41	14	11	88	39	1.90	2.40
Jakob Poeltl	0.09	119.00		-277.00	155.07	15	29	81	69	2.00	1.70
Jalen Duren	0.11	141.00		37.00	152.60	16	21	57	32	3.10	2.70
Walker Kessler	0.10	73.00		-724.00	148.88	17	60	92	70	1.80	1.70
James Harden	0.14	173.00		400.00	140.24	18	16	22	10	4.30	4.40
Luke Kornet	0.07	177.00		813.00	132.33	19	15	45	64	3.30	1.80
Nikola Vucevic	0.12	92.00		-251.00	131.96	20	41	64	33	2.60	2.70
Luka Doncic	0.05	122.93		-5.00	129.74	21	27	6	49	6.50	2.10
Anthony Davis	0.08	119.86		-5.00	129.59	22	28	9	30	6.00	2.90
Donovan Mitchell	0.12	202.00		828.00	128.35	23	10	33	25	3.70	3.20
Cade Cunningham	0.13	114.00		37.00	124.35	24	30	31	12	3.90	3.70
Pascal Siakam	0.13	139.00		254.00	123.71	25	23	93	38	1.70	2.40

**A.1:** NBA Analytic DataFrame sorted by Net Minus Team Individual showing the top 25 players

PLAYER	MIN FRACTION	TOTAL NET	TEAM NET	POINTS	NET MINUS	TEAM IND	NMTI Rank	TOTAL NET Rank	BPM Rank	VORP Rank	BPM	VORP
Russell Westbrook	0.11	-163.00	251.00		-207.31	501		498	275	183	-1.10	0.50
Gabe Vincent	0.08	-132.00	-5.00		-142.49	500		493	433	489	-4.00	-0.80
Nick Smith Jr	0.08	-167.00	-640.00		-130.68	499		499	479	498	-5.70	-1.30
Terry Rozier	0.09	-129.00	-143.00		-127.81	498		492	421	485	-3.70	-0.70
Isaiah Collier	0.10	-181.00	-724.00		-126.36	497		500	470	500	-5.30	-1.60
Andrew Nembhard	0.10	-87.00	254.00		-120.47	496		475	355	410	-2.30	-0.10
Bub Carrington	0.15	-223.00	-919.00		-120.07	495		501	454	501	-4.60	-1.60
Cody Williams	0.06	-153.00	-724.00		-119.88	494		496	491	499	-7.30	-1.40
Cason Wallace	0.10	-1.00	1209.00		-119.79	493		205	123	82	1.00	1.50
Zaccharie Risacher	0.10	-119.00	-113.00		-119.59	492		487	415	483	-3.50	-0.70
Jamal Shead	0.08	-128.00	-277.00		-116.19	491		491	438	488	-4.10	-0.80
Julian Strawther	0.07	-89.00	251.00		-113.07	490		476	451	491	-4.50	-0.90
Kris Dunn	0.09	-69.00	400.00		-112.27	489		458	151	111	0.60	1.20
Stephon Castle	0.11	-122.00	-219.00		-111.30	488		489	400	475	-3.20	-0.60
Jrue Holiday	0.10	-27.00	813.00		-109.18	487		369	147	98	0.70	1.30
Peyton Watson	0.08	-81.00	251.00		-109.13	486		470	322	277	-1.80	0.10
Keon Johnson	0.11	-151.00	-579.00		-106.03	485		495	407	476	-3.30	-0.60
Luguentz Dort	0.11	24.00	1209.00		-104.55	484		119	183	109	0.20	1.20
Kyle Kuzma	0.05	-96.99	21.00		-103.38	483		478	459	480	-4.70	-0.70
Scout Henderson	0.09	-115.00	-242.00		-103.37	482		486	350	405	-2.20	-0.10
Patrick Williams	0.08	-110.00	-251.00		-98.63	481		483	420	482	-3.70	-0.70
Tim Hardaway Jr	0.12	-83.00	37.00		-97.16	480		473	343	335	-2.10	0.00
Fred VanVleet	0.11	-52.00	360.00		-96.26	479		429	132	84	0.90	1.50
Jalen Green	0.14	-41.00	360.00		-96.04	478		409	158	73	0.50	1.70
Gradey Dick	0.09	-108.00	-277.00		-93.51	477		481	401	469	-3.20	-0.50

## A.2: NBA Analytics DataFrame sorted by Net Minus Team Individual of the bottom 25 players

	PLAYER	TEAM	AGE	MP	SALARY	POSITION	NET MINUS	TEAM IND	TOTAL NET	TEAM NET	POINTS	BPM	VORP	MIN FRACTION	NMTI Rank	BPM Rank	VORP Rank	TOTAL NET Rank
	Santi Aldama	MEM	24	1660	\$3,960,531	F-C		45.99	69.00		331.00	3.20	2.20	0.09	83	48	44	64
	Moritz Wagner	ORL	27	564	\$11,000,000	F-C		44.81	42.00		-46.00	4.00	0.90	0.03	85	28	131	93
	Karlo Matkovic	NOP	23	791	\$1,407,153	F-C		35.35	2.00		-746.00	-2.00	0.00	0.04	97	335	349	184
Wendell Carter Jr	ORL	25	1758	\$11,950,000	C-F		30.97	24.00			-46.00	-1.20	0.30	0.10	107	276	223	118
	Kelly Olynyk	NOP	33	508	\$12,804,878	F-C		30.74	9.12		-746.00	-1.40	0.10	0.03	108	290	290	153
	Zach Collins	CHI	27	552	\$16,741,200	F-C		20.45	12.99		-251.00	0.10	0.30	0.03	131	191	244	142
	Jay Huff	MEM	26	748	\$2,088,033	C		17.05	29.00		331.00	3.50	1.10	0.04	137	40	116	111
	Jusuf Nurkic	PHO	30	592	\$18,125,000	C		15.11	5.01		-323.00	-3.40	-0.20	0.03	140	409	433	166
	Deandre Ayton	POR	26	1206	\$34,005,126	C		10.94	-4.00		-242.00	-0.70	0.40	0.06	154	246	204	224
	Neemias Queta	BOS	25	863	\$2,162,606	C		8.71	43.00		813.00	-0.70	0.30	0.04	166	244	243	91
	Zeke Nnaji	DEN	24	608	\$8,888,889	F-C		-12.96	-5.00		251.00	-1.30	0.10	0.03	292	288	278	234

## A.3: NBA analytics DataFrame for unprotected bigs available for selection in NBA expansion

PLAYER	TEAM	AGE	MP	SALARY	POSITION	NET MINUS	TEAM IND	TOTAL NET	TEAM NET	POINTS	BPM	VORP	MIN FRACTION	NMTI Rank	BPM Rank	VORP Rank	TOTAL NET Rank
Moussa Diabate	CHO	23	1241	\$957,763	F		94.82	47.00	-640.00	-1.90	0.00		0.07	46	329	347	84
Richaun Holmes	WAS	31	534	\$12,648,321	F		72.88	42.00	-919.00	1.10	0.40		0.03	60	120	218	95
Santi Aldama	MEM	24	1660	\$3,960,531	F-C		45.99	69.00	331.00	3.20	2.20		0.09	83	48	44	64
Moritz Wagner	ORL	27	564	\$11,000,000	F-C		44.81	42.00	-46.00	4.00	0.90		0.03	85	28	131	93
Karlo Matkovic	NOP	23	791	\$1,407,153	F-C		35.35	2.00	-746.00	-2.00	0.00		0.04	97	335	349	184
Jabari Walker	POR	22	749	\$2,019,699	F		34.37	24.00	-242.00	-0.80	0.20		0.04	101	253	264	117
Jaylin Williams	OKC	22	784	\$2,019,699	F		32.64	79.00	1209.00	4.30	1.20		0.04	105	23	103	55
Kelly Olynyk	NOP	33	508	\$12,804,878	F-C		30.74	9.12	-746.00	-1.40	0.10		0.03	108	290	290	153
Zach Collins	CHI	27	552	\$16,741,200	F-C		20.45	12.99	-251.00	0.10	0.30		0.03	131	191	244	142
Mouhamed Gueye	ATL	22	533	\$1,891,857	F		14.51	11.00	-113.00	-0.60	0.20		0.03	142	238	258	148
Gui Santos	GSW	22	762	\$1,891,857	F		12.04	25.00	358.00	-1.70	0.10		0.04	151	320	303	115
Brice Sensabaugh	UTA	21	1432	\$2,571,480	F		11.44	-42.00	-724.00	-1.20	0.30		0.08	153	279	233	413
Jae'Sean Tate	HOU	29	588	\$7,565,217	F		8.80	19.00	360.00	-0.70	0.20		0.03	164	243	256	128
Cody Martin	CHO	29	967	\$8,120,000	F		8.64	-24.73	-640.00	-1.20	0.20		0.05	168	278	271	355
Zeke Nnaji	DEN	24	608	\$8,888,889	F-C		-12.96	-5.00	251.00	-1.30	0.10		0.03	292	288	278	234
Trayce Jackson-Davis	GSW	24	967	\$1,891,857	F		-13.49	4.00	358.00	1.20	0.80		0.05	294	117	134	173
Obi Toppin	IND	26	1545	\$12,975,000	F		-14.00	6.00	254.00	1.70	1.40		0.08	297	96	88	164
Olivier-Maxence Prosper	DAL	22	584	\$2,870,400	F		-18.81	-20.00	-58.00	-2.10	0.00		0.03	330	339	366	327
Jamison Battle	TOR	23	1042	\$1,000,000	F		-20.32	-34.00	-277.00	-2.30	-0.10		0.06	342	353	368	387
Cam Whitmore	HOU	20	827	\$3,379,080	F		-30.78	-15.00	360.00	0.30	0.50		0.04	377	174	176	299
Kris Murray	POR	24	1040	\$2,990,040	F		-31.18	-42.00	-242.00	-3.00	-0.30		0.05	378	394	443	414
Duncan Robinson	MIA	30	1785	\$19,406,000	F		-31.63	-41.00	-143.00	-1.70	0.10		0.09	379	312	285	408
Jonathan Mogbo	TOR	23	1286	\$1,862,265	F		-33.16	-49.00	-277.00	-1.90	0.00		0.07	385	327	337	424
Simone Fontecchio	DET	29	1237	\$7,692,308	F		-34.54	-30.00	37.00	-2.90	-0.30		0.07	392	390	442	377
Isaac Okoro	CLE	24	1053	\$10,185,186	F-G		-55.46	-9.00	828.00	-0.50	0.40		0.06	434	232	199	261
Dillon Jones	OKC	23	551	\$2,622,360	F		-58.52	-23.00	1209.00	-4.00	-0.30		0.03	443	435	445	346
Patrick Williams	CHI	23	1576	\$18,000,000	F		-98.63	-110.00	-251.00	-3.70	-0.70		0.08	481	420	482	483

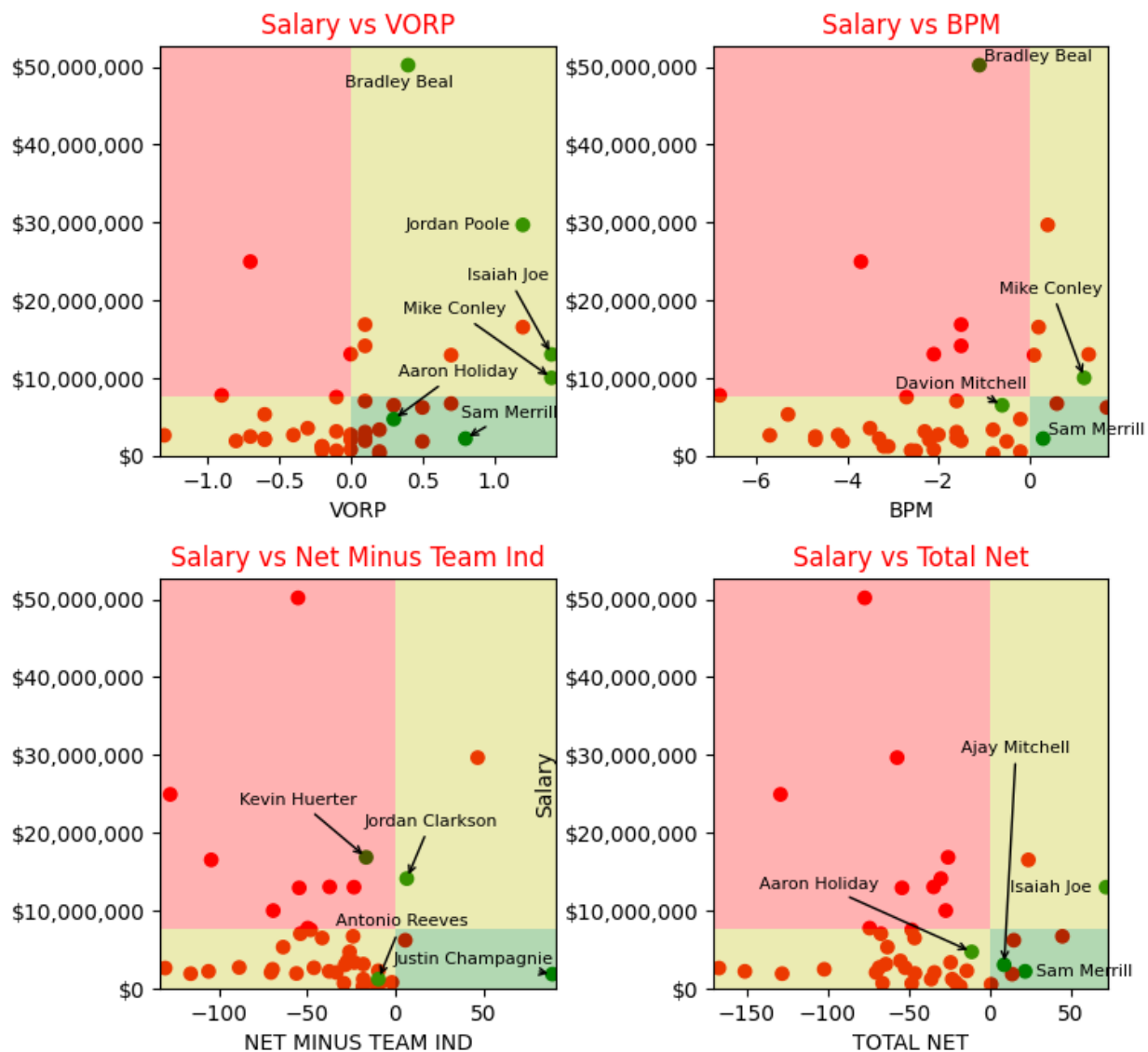
#### A.4: NBA analytics DataFrame for unprotected wings available for selection in NBA expansion

PLAYER	TEAM	AGE	MP	SALARY	POSITION	NET MINUS	TEAM IND	TOTAL NET	TEAM NET	POINTS	BPM	VORP	MIN	FRACTION	NMTI Rank	BPM Rank	VORP Rank	TOTAL NET Rank
Justin Champagnie	WAS	23	1340	\$1,800,000	G-F	89.22	14.00	-919.00	-0.50	0.50	0.08	49	235	191	138			
Jordan Poole	WAS	25	2001	\$29,651,786	G	46.78	-57.00	-919.00	0.40	1.20	0.12	81	161	99	442			
Jordan Clarkson	UTA	32	962	\$14,092,577	G	6.53	-30.00	-724.00	-1.50	0.10	0.05	177	296	313	378			
John Konchar	MEM	28	558	\$6,165,000	G	5.67	15.00	331.00	1.70	0.50	0.03	181	95	180	135			
Jared Butler	PHI	24	682	\$745,726	G	-1.91	-20.90	-501.00	-2.10	0.00	0.04	218	341	325	331			
Brandon Boston Jr	NOP	23	993	\$596,581	G	-8.93	-48.00	-746.00	-2.50	-0.10	0.06	272	367	413	423			
Antonio Reeves	NOP	24	660	\$1,157,153	G	-9.59	-36.00	-746.00	-3.20	-0.20	0.04	274	404	425	393			
Garrison Mathews	ATL	28	830	\$2,230,253	G	-9.64	-14.00	-113.00	-1.60	0.10	0.04	275	301	305	290			
Jaylen Clark	MIN	23	522	\$492,323	G	-10.84	1.00	449.00	-0.20	0.20	0.03	281	214	252	189			
Dennis Schroder	BRK	31	772	\$13,025,250	G	-14.97	-37.77	-579.00	0.00	0.40	0.04	305	196	207	398			
Kevin Huerter	CHI	26	780	\$16,830,357	G-F	-16.56	-25.55	-251.00	-1.50	0.10	0.04	315	294	292	360			
Johnny Juzang	UTA	23	1270	\$3,087,519	G	-18.13	-64.00	-724.00	-2.30	-0.10	0.07	326	354	402	449			
Pelle Larsson	MIA	23	782	\$1,157,153	G	-18.17	-23.00	-143.00	-3.10	-0.20	0.04	327	399	423	348			
Jordan Goodwin	LAL	26	543	\$223,718	G	-18.38	-18.00	-5.00	-0.80	0.20	0.03	328	251	260	315			
Cory Joseph	ORL	33	612	\$3,303,771	G	-23.24	-24.00	-46.00	-0.80	0.20	0.03	355	249	249	352			
Isaiah Joe	OKC	25	1604	\$12,991,650	G	-23.44	72.00	1209.00	1.30	1.40	0.08	356	105	86	61			
Kenrich Williams	OKC	30	1132	\$6,669,000	G-F	-23.95	45.00	1209.00	0.60	0.70	0.06	359	154	150	87			
Aaron Holiday	HOU	28	792	\$4,668,000	G	-25.95	-11.00	360.00	-0.20	0.30	0.04	366	215	246	273			
Svi Mykhailiuk	UTA	27	760	\$3,500,000	G-F	-27.18	-55.00	-724.00	-3.50	-0.30	0.04	368	414	447	438			
Ajay Mitchell	OKC	22	597	\$3,000,000	G	-28.49	9.00	1209.00	-1.60	0.10	0.03	373	304	299	154			
Tyrese Martin	BRK	25	1315	\$635,853	G	-29.18	-66.00	-579.00	-2.60	-0.20	0.07	374	376	421	450			
Caleb Houston	ORL	22	788	\$2,019,699	G	-33.46	-34.00	-46.00	-2.20	0.00	0.04	388	349	321	389			
Dennis Schroder	DET	31	705	\$13,025,250	G	-37.26	-34.50	37.00	-2.10	0.00	0.04	401	345	361	391			
Sam Merrill	CLE	28	1401	\$2,164,993	G	-37.52	22.00	828.00	0.30	0.80	0.07	403	173	141	124			
Kevin Huerter	SAC	26	899	\$16,830,357	G-F	-38.64	-29.45	172.00	-2.30	-0.10	0.05	406	356	418	376			
Davion Mitchell	TOR	26	1080	\$6,451,077	G	-39.66	-52.75	-277.00	-4.30	-0.60	0.06	408	445	473	431			
Davion Mitchell	MIA	26	947	\$6,451,077	G	-41.54	-46.25	-143.00	-0.60	0.30	0.05	411	240	230	421			
Dennis Schroder	GSW	31	628	\$13,025,250	G	-43.20	-30.73	358.00	-5.20	-0.50	0.03	415	468	467	380			
Blake Wesley	SAS	21	683	\$2,624,280	G	-46.18	-52.00	-219.00	-4.20	-0.40	0.03	421	442	463	428			
Gary Harris	ORL	30	711	\$7,500,000	G	-48.08	-48.00	-46.00	-2.70	-0.10	0.04	424	382	389	422			
Vasilije Micic	CHO	31	764	\$7,723,000	G	-49.71	-73.97	-640.00	-6.80	-0.90	0.04	428	485	493	463			
Ayo Dosunmu	CHI	25	1394	\$7,000,000	G	-53.88	-67.00	-251.00	-1.60	0.10	0.07	429	302	309	453			
Cole Anthony	ORL	24	1234	\$12,900,000	G	-54.56	-54.00	-46.00	0.10	0.70	0.07	430	189	144	434			
Bradley Beal	PHO	31	1702	\$50,203,930	G	-55.22	-77.00	-323.00	-1.10	0.40	0.09	433	273	198	468			
Jalen Pickett	DEN	25	666	\$1,891,857	G	-56.12	-46.00	251.00	-1.50	0.10	0.03	437	297	279	418			
Jett Howard	ORL	21	701	\$5,278,320	G	-63.67	-63.00	-46.00	-5.30	-0.60	0.04	452	471	477	447			
Mike Conley	MIN	37	1756	\$9,975,962	G	-69.32	-27.00	449.00	1.20	1.40	0.09	462	110	85	368			
DaQuan Jeffries	CHO	27	1071	\$2,425,404	G-F	-69.68	-102.00	-640.00	-4.70	-0.70	0.06	463	460	484	480			
Jaden Hardy	DAL	22	907	\$2,019,699	G	-70.58	-70.00	-58.00	-4.70	-0.60	0.05	464	461	474	459			
Ben Sheppard	IND	23	1228	\$2,663,880	G	-88.64	-68.00	254.00	-2.00	0.00	0.06	475	334	318	457			
Luguentz Dort	OKC	25	2073	\$16,500,000	G	-104.55	24.00	1209.00	0.20	1.20	0.11	484	183	109	119			
Keon Johnson	BRK	22	1925	\$2,162,606	G	-106.03	-151.00	-579.00	-3.30	-0.60	0.11	485	407	476	495			
Jamal Shead	TOR	22	1467	\$1,862,265	G	-116.19	-128.00	-277.00	-4.10	-0.80	0.08	491	438	488	491			
Terry Rozier	MIA	30	1658	\$24,924,126	G	-127.81	-129.00	-143.00	-3.70	-0.70	0.09	498	421	485	492			
Nick Smith Jr	CHO	20	1369	\$2,587,200	G	-130.68	-167.00	-640.00	-5.70	-1.30	0.08	499	479	498	499			

## A.5: NBA analytics DataFrame of unprotected guards available for selection in NBA expansion

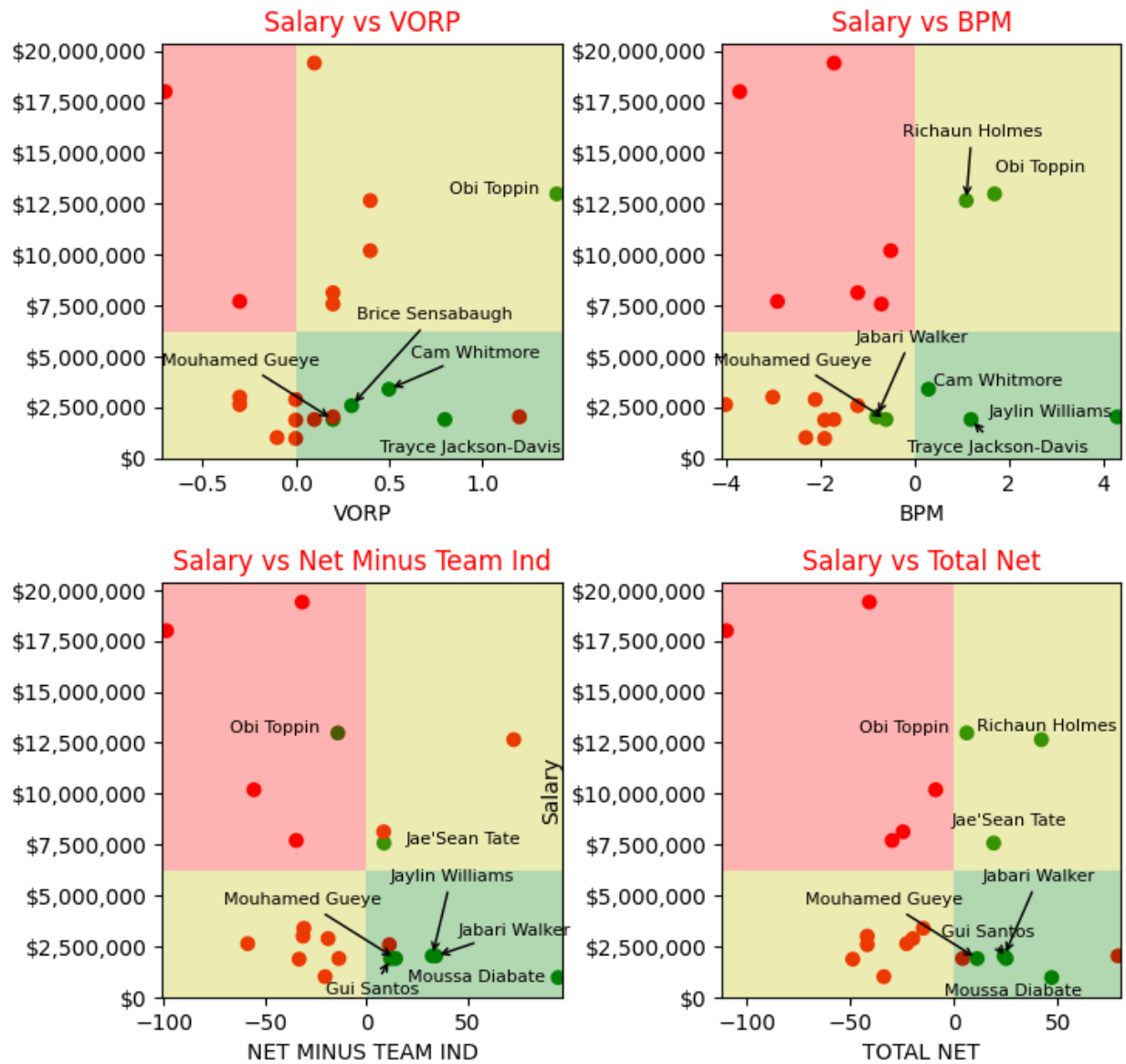
## Appendix B

### Capable of Playing 1 & 2 (Guards)



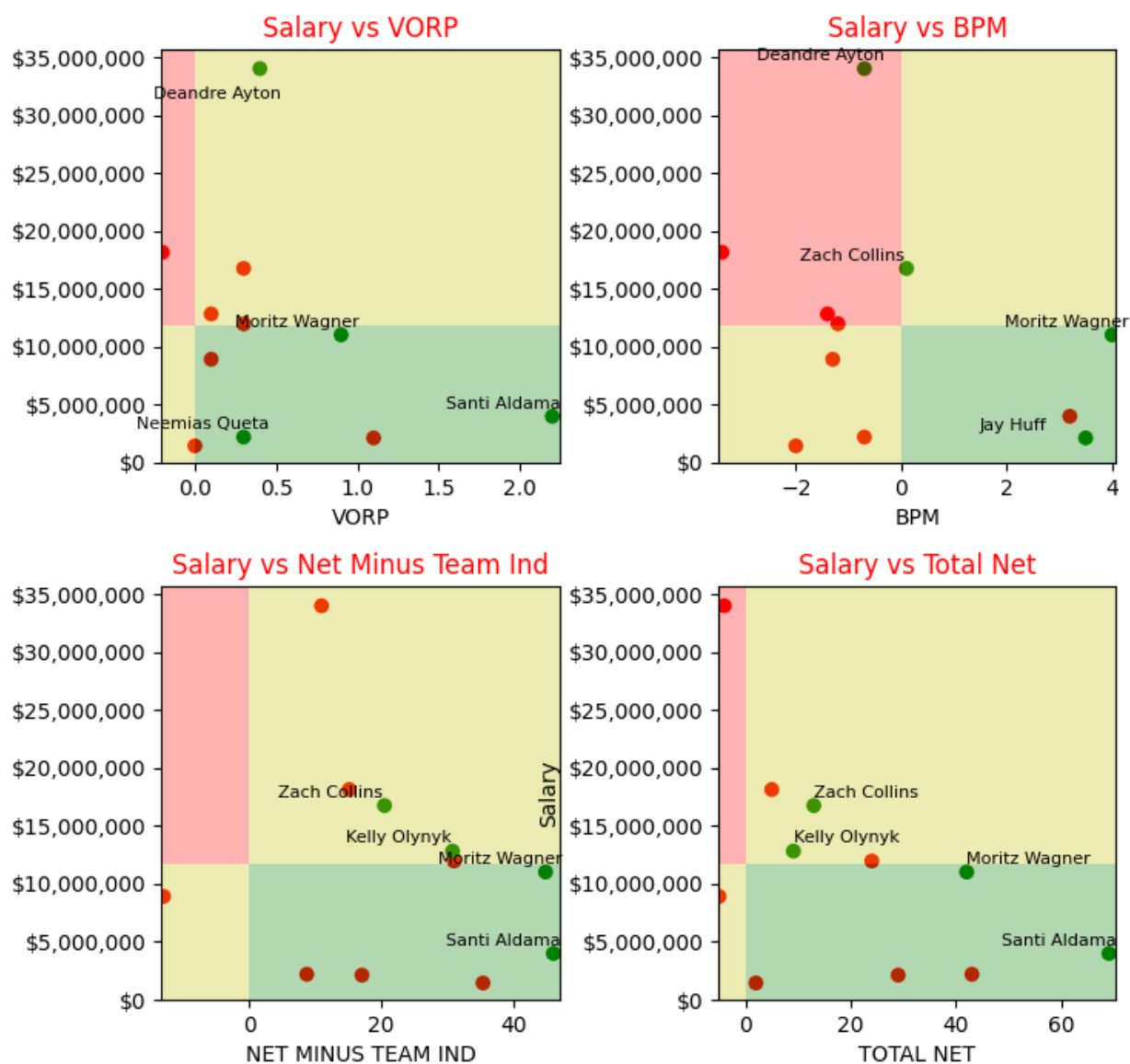
**B.1:** Analytically optimized backcourt players using VORP, BPM, Net Minus Team Individual, and Total Net Points. Each graph is split into 4 quadrants where the average salary per roster slot splits the y axis and the average analytical metric splitting the x axis.

### Capable of Playing 3 & 4 (Wings)



**B.2:** Analytically optimized wing players using VORP, BPM, Net Minus Team Individual, and Total Net Points. Each graph is split into 4 quadrants where the average salary per roster slot splits the y axis and the average analytical metric splitting the x axis.

### Capable of Playing the 5 (Bigs)



**B.3:** Analytically optimized frontcourt players using VORP, BPM, Net Minus Team Individual, and Total Net Points. Each graph is split into 4 quadrants where the average salary per roster slot splits the y axis and the average analytical metric splitting the x axis.



## Appendix C

	PLAYER	AGE	TEAM	POSITION	TOTAL NET	TEAM NET POINTS	SALARY	BPM	VORP	NET MINUS	TEAM IND	NMTI Rank	BPM Rank	VORP Rank	TOTAL NET Rank
	Moussa Diabate	23	CHO	F	47.000000	-640.0	\$957,763	-1.9	0.0		94.821797	46	329	347	84
Justin	Champagnie	23	WAS	G-F	14.000000	-919.0	\$1,800,000	-0.5	0.5		89.223827	49	235	191	138
	Santi Aldama	24	MEM	F-C	69.000000	331.0	\$3,960,531	3.2	2.2		45.987142	83	48	44	64
	Moritz Wagner	27	ORL	F-C	42.000000	-46.0	\$11,000,000	4.0	0.9		44.810260	85	28	131	93
	Karlo Matkovic	23	NOP	F-C	2.000000	-746.0	\$1,407,153	-2.0	0.0		35.348439	97	335	349	184
	Jabari Walker	22	POR	F	24.000000	-242.0	\$2,019,699	-0.8	0.2		34.368131	101	253	264	117
	Jaylin Williams	22	OKC	F	79.000000	1209.0	\$2,019,699	4.3	1.2		32.638600	105	23	103	55
	Jusuf Nurkic	30	CHO	C	3.987770	-640.0	\$18,125,000	1.2	0.4		21.001358	130	118	200	174
Mouhamed	Gueye	22	ATL	F	11.000000	-113.0	\$1,891,857	-0.6	0.2		14.508999	142	238	258	148
	Gui Santos	22	GSW	F	25.000000	358.0	\$1,891,857	-1.7	0.1		12.035917	151	320	303	115
	Jae'Sean Tate	29	HOU	F	19.000000	360.0	\$7,565,217	-0.7	0.2		8.796031	164	243	256	128
	Jared Butler	24	WAS	G	-11.095785	-919.0	\$745,726	1.0	0.3		8.679264	167	125	241	276
Jordan	Clarkson	32	UTA	G	-30.000000	-724.0	\$14,092,577	-1.5	0.1		6.532312	177	296	313	378
	Jared Butler	24	PHI	G	-20.904215	-501.0	\$745,726	-2.1	0.0		-1.906517	218	341	325	331
	Obi Toppin	26	IND	F	6.000000	254.0	\$12,975,000	1.7	1.4		-13.995825	297	96	88	164
	Kevin Huerter	26	CHI	G-F	-25.550923	-251.0	\$16,830,357	-1.5	0.1		-16.556944	315	294	292	360

### C.1: Expansion roster when maximizing Net Minus Team Individual

	PLAYER	AGE	TEAM	POSITION	TOTAL NET	TEAM NET POINTS	SALARY	BPM	VORP	NET MINUS	TEAM IND	NMTI Rank	BPM Rank	VORP Rank	TOTAL NET Rank
	Jaylin Williams	22	OKC	F	79.000000	1209.0	\$2,019,699	4.3	1.2		32.638600	105	23	103	55
	Moritz Wagner	27	ORL	F-C	42.000000	-46.0	\$11,000,000	4.0	0.9		44.810260	85	28	131	93
	Jay Huff	26	MEM	C	29.000000	331.0	\$2,088,033	3.5	1.1		17.047198	137	40	116	111
	Obi Toppin	26	IND	F	6.000000	254.0	\$12,975,000	1.7	1.4		-13.995825	297	96	88	164
	Mike Conley	37	MIN	G	-27.000000	449.0	\$9,975,962	1.2	1.4		-69.317537	462	110	85	368
Trayce	Jackson-Davis	24	GSW	F	4.000000	358.0	\$1,891,857	1.2	0.8		-13.489296	294	117	134	173
	Richaun Holmes	31	WAS	F	42.000000	-919.0	\$12,648,321	1.1	0.4		72.876895	60	120	218	95
	Sam Merrill	28	CLE	G	22.000000	828.0	\$2,164,993	0.3	0.8		-37.519608	403	173	141	124
	Cam Whitmore	20	HOU	F	-15.000000	360.0	\$3,379,080	0.3	0.5		-30.782443	377	174	176	299
	Zach Collins	27	CHI	F-C	12.994882	-251.0	\$16,741,200	0.1	0.3		20.448093	131	191	244	142
Mouhamed	Gueye	22	ATL	F	11.000000	-113.0	\$1,891,857	-0.6	0.2		14.508999	142	238	258	148
	Davion Mitchell	26	MIA	G	-46.252097	-143.0	\$6,451,077	-0.6	0.3		-41.537908	411	240	230	421
	Neemias Queta	25	BOS	C	43.000000	813.0	\$2,162,606	-0.7	0.3		8.709789	166	244	243	91
	Jabari Walker	22	POR	F	24.000000	-242.0	\$2,019,699	-0.8	0.2		34.368131	101	253	264	117
	Bradley Beal	31	PHO	G	-77.000000	-323.0	\$50,203,930	-1.1	0.4		-55.216950	433	273	198	468
	Davion Mitchell	26	TOR	G	-52.747903	-277.0	\$6,451,077	-4.3	-0.6		-39.663502	408	445	473	431

### C.2. Expansion roster when maximizing BPM

PLAYER	AGE	TEAM	POSITION	TOTAL NET	TEAM NET	POINTS	SALARY	BPM	VORP	NET MINUS	TEAM IND	NMTI	Rank	BPM Rank	VORP Rank	TOTAL NET Rank
Santi Aldama	24	MEM	F-C	69.000000		331.0	\$3,960,531	3.2	2.2		45.987142		83	48	44	64
Mike Conley	37	MIN	G	-27.000000		449.0	\$9,975,962	1.2	1.4		-69.317537		462	110	85	368
Isaiah Joe	25	OKC	G	72.000000		1209.0	\$12,991,650	1.3	1.4		-23.439217		356	105	86	61
Obi Toppin	26	IND	F	6.000000		254.0	\$12,975,000	1.7	1.4		-13.995825		297	96	88	164
Jordan Poole	25	WAS	G	-57.000000		-919.0	\$29,651,786	0.4	1.2		46.782310		81	161	99	442
Moritz Wagner	27	ORL	F-C	42.000000		-46.0	\$11,000,000	4.0	0.9		44.810260		85	28	131	93
Trayce Jackson-Davis	24	GSW	F	4.000000		358.0	\$1,891,857	1.2	0.8		-13.489296		294	117	134	173
Sam Merrill	28	CLE	G	22.000000		828.0	\$2,164,993	0.3	0.8		-37.519608		403	173	141	124
Cam Whitmore	20	HOU	F	-15.000000		360.0	\$3,379,080	0.3	0.5		-30.782443		377	174	176	299
Bradley Beal	31	PHO	G	-77.000000		-323.0	\$50,203,930	-1.1	0.4		-55.216950		433	273	198	468
Deandre Ayton	26	POR	C	-4.000000		-242.0	\$34,005,126	-0.7	0.4		10.936928		154	246	204	224
Davion Mitchell	26	MIA	G	-46.252097		-143.0	\$6,451,077	-0.6	0.3		-41.537908		411	240	230	421
Brice Sensabaugh	21	UTA	F	-42.000000		-724.0	\$2,571,480	-1.2	0.3		11.440438		153	279	233	413
Neemias Queta	25	BOS	C	43.000000		813.0	\$2,162,606	-0.7	0.3		8.709789		166	244	243	91
Mouhamed Gueye	22	ATL	F	11.000000		-113.0	\$1,891,857	-0.6	0.2		14.508999		142	238	258	148
Davion Mitchell	26	TOR	G	-52.747903		-277.0	\$6,451,077	-4.3	-0.6		-39.663502		408	445	473	431

### C.3. Expansion roster when maximizing VORP

PLAYER	AGE	TEAM	POSITION	TOTAL NET	TEAM NET	POINTS	SALARY	BPM	VORP	NET MINUS	TEAM IND	NMTI	Rank	BPM Rank	VORP Rank	TOTAL NET Rank
Isaiah Joe	25	OKC	G	72.000000		1209.0	\$12,991,650	1.3	1.4		-23.439217		356	105	86	61
Santi Aldama	24	MEM	F-C	69.000000		331.0	\$3,960,531	3.2	2.2		45.987142		83	48	44	64
Moussa Diabate	23	CHO	F	47.000000		-640.0	\$957,763	-1.9	0.0		94.821797		46	329	347	84
Neemias Queta	25	BOS	C	43.000000		813.0	\$2,162,606	-0.7	0.3		8.709789		166	244	243	91
Moritz Wagner	27	ORL	F-C	42.000000		-46.0	\$11,000,000	4.0	0.9		44.810260		85	28	131	93
Richaun Holmes	31	WAS	F	42.000000		-919.0	\$12,648,321	1.1	0.4		72.876895		60	120	218	95
Gui Santos	22	GSW	F	25.000000		358.0	\$1,891,857	-1.7	0.1		12.035917		151	320	303	115
Jabari Walker	22	POR	F	24.000000		-242.0	\$2,019,699	-0.8	0.2		34.368131		101	253	264	117
Sam Merrill	28	CLE	G	22.000000		828.0	\$2,164,993	0.3	0.8		-37.519608		403	173	141	124
Jae'Sean Tate	29	HOU	F	19.000000		360.0	\$7,565,217	-0.7	0.2		8.796031		164	243	256	128
Mouhamed Gueye	22	ATL	F	11.000000		-113.0	\$1,891,857	-0.6	0.2		14.508999		142	238	258	148
Kelly Olynyk	33	NOP	F-C	9.122334		-746.0	\$12,804,878	-1.4	0.1		30.743468		108	290	290	153
Kelly Olynyk	33	TOR	F-C	6.877666		-277.0	\$12,804,878	0.2	0.2		12.751525		149	187	273	163
Obi Toppin	26	IND	F	6.000000		254.0	\$12,975,000	1.7	1.4		-13.995825		297	96	88	164
Jaylen Clark	23	MIN	G	1.000000		449.0	\$492,323	-0.2	0.2		-10.839611		281	214	252	189
Kevin Huerter	26	CHI	G-F	-25.550923		-251.0	\$16,830,357	-1.5	0.1		-16.556944		315	294	292	360

### C.4. Expansion roster when maximizing Total Net Points

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