

Analyzing the Value of NBA Rookie Contracts

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Abstract

This paper quantifies the value of an NBA player on a rookie contract by creating a model predicting veteran salary and using that to predict the true market value for players on a rookie contract. From there, a team surplus is calculated by subtracting the actual salary of a player from their market value. We find that nearly all players on a rookie contract have a positive team surplus, meaning that their on-court performance is better than their salary would indicate. We create a second model that predicts team surplus from overall draft pick and years of experience. This model finds that, as draft pick increases, team surplus increases indicating that the most valuable draft picks are at the end of the first round.

JEL Classification: Z22, Z23

Key words and phrases: NBA, draft, team surplus, market value

Introduction

Over the past decade, the competitive landscape of the National Basketball Association (NBA) has changed dramatically. Due to increased youth and foreign participation, the mass of basketball talent has never been greater. With every NBA team having a trove of quality players, teams can no longer rely on a single star player to carry them to contention. Now, to compete for a title, franchises do everything within their capabilities to chase after a second or third star. Over the past few years, many superstar players have requested trades, resulting in a bidding war with teams sending out most of their future draft picks to land one of the league's best players. This paper analyzes the cost of these trades by determining the value of recently drafted players and discerning if their fixed starting salary is appropriate to their performance output.

The NBA draft occurs once a year after the season has finished with teams selecting from the pool of eligible college, domestic, and international players. It consists of two rounds with every team having one pick per round unless a team traded away their pick or acquired another team's pick. The draft order is based on a lottery system, where the fourteen teams that failed to reach the playoffs are all granted odds of landing any given pick. The team with the worst regular season record has the best odds of landing the top pick and so on. The draft serves as a mechanism for creating leaguewide parity. If a team has a poor season, it acquires talent through the draft to be more competitive the following season. Every season, a handful of teams trade away their better players to avoid mediocrity and gain a more valuable draft pick. Therefore, a natural inequity materializes with better older players being traded to winning teams from losing teams in exchange for draft picks. Since the league began, this has always been a strategy for building a successful team.

What has changed in the modern NBA is the increased scale of this player for draft pick style of trade. Recently, franchises have mortgaged their entire future to land a star by trading away nearly all their draft equity. One example of such a trade is the Phoenix Suns trading for Kevin Durant last year. Phoenix traded their unprotected first round pick in 2023, 2025, 2027, and 2029 along with two promising young players for Durant, one of the best players in the league. Phoenix created a three- or four-year window to win a championship but put themselves at an extreme disadvantage in the later 2020s. The Phoenix trade is not an isolated incident; teams are making increasingly risky moves by placing an extreme discount rate on the future in the hope of competing in the present.

Other franchises have chosen to develop their team through the draft by keeping and using their picks rather than trading them for players. The Oklahoma City Thunder and Boston Celtics are two of the favorites to win the 2024 NBA championship while still maintaining control of nearly all their future first-round picks. This strategy is difficult to accomplish and requires skillful drafting, but it has many advantages over building a team through trade. This paper focuses on the benefit of gaining short-run value by adding recently drafted players at a discounted cost relative to their production.

The NBA places restrictions on the amount of spending by a team in the form of a salary cap. If a team exceeds this cap, they are penalized with a tax and, with the signing of the 2023 collective bargaining agreement, restricted freedom in acquiring players. The best teams normally have three or four players that consume most of that team's available spending. Therefore, teams must fill out the rest of their roster with relatively inexpensive players. Teams that previously traded away their draft picks can only fill their roster by signing players in free agency or acquiring

them by trade. However, this paper argues that the far more lucrative strategy is to find players through the draft.

All NBA first-round draft picks are signed to a rookie-scale contract. The first overall pick earns a set proportion of the salary cap. The amount earned by all other players drafted is scaled to what the first overall pick earns and decreases by draft pick. For instance, in the 2023 draft, the first overall pick had a first-year salary of \$12,160,680, the second overall pick had a salary of \$10,880,400, the third overall pick had a salary of \$9,770,880, and so on. Rookie contracts are guaranteed for two seasons with a team option for the third and fourth seasons. Generally, teams opt to keep players on rookie contracts signed for all four years.

This paper hypothesizes that drafting players and signing them to a rookie contract is advantageous to signing players through free agency. In free agency, a team must pay the market price for a player at their level of production. Rookie contracts, however, are normally lower than if that player were to sign a standard contract at market value. Because of this, well drafting teams can find players that strongly outproduce their salary. The Oklahoma City Thunder, who are set to finish the 2023-24 season with one of the three best records, are a perfect example of the benefits of rookie contracts. Six of the top ten players in minutes per game for Oklahoma City are on a rookie contract which allows the team to have only the 19th most expensive payroll in the NBA despite being one of the best teams. Rookie contract players Anthony Edwards, Paulo Banchero, Tyrese Maxey, and Scottie Barnes all made the 2024 All-Star game while only being paid \$4.3 million to \$13.5 million, \$20 million less than the contracts of other All-Stars. Having rookie contract players allows teams to pursue players in free agency they would not be able to afford if they had to pay rookie contract players their market value. In the coming sections, we will further explore the extent to which this market failure aids teams that draft well.

We begin by looking at past literature on draft and salary analysis and explain how this paper changes and expands on previously established models. Then we describe the source, format, and variables in the data used for the model. Next, we explain the models used, their validity, and the econometric principles behind them. Finally, we display our findings in graphical and numeric form along with interpretations of the model results and their broader meaning.

Literature Review

This paper most closely falls in the lineage of Massey and Thaler (2005), who analyzed drafting in sports through an econometric lens. In their paper, Massey and Thaler examine National Football League (NFL) draft history to determine if it is beneficial or harmful for teams to trade away assets to move up in the draft selection order. Our paper adapts their idea of a team surplus to the NBA, using player performance to estimate the dollar value of a player and then subtracting their actual salary. However, we calculate team surplus using a slightly different model. Massey and Thaler estimate the value of a player by using binary indicators that designate the quality of the player. This model leaves little room for discrepancy between two players in the same group. For instance, LeBron James and D'Angelo Russell would both fall into the all-star indicator group, which would assign them equal value using Massey and Thaler's model. However, the actual gap between the values of James and Russell is greater than the difference between the values of Russell and some non-all-star players. We allow for more fluidity in our model by using summary performance metrics to estimate value rather than binary indicators.

Other papers have applied Massey and Thaler's framework to the NBA before ours. Like Massey and Thaler, Adhiraj Watave (2016) finds that the largest team surplus comes from late first-

round draft picks. Watave calculates team surplus by comparing summary performance metrics for rookie contract players to their actual compensation. Our methodology differs in that team surplus is calculated using a model to predict the market value of a player in their first four years if he were not preordained to a rookie contract.

Most of the existing literature on NBA contracts is about which statistics are most predictive of salary. For instance, Papadaki and Tsagris (2022), Cabarkapa et al. (2022), and Wu et al. (2022) attempt to measure player salary based on various performance statistics including field goal attempts and points scored. Similarly, Sigler and Compton (2018) find that points, rebounds, personal fouls, and assists have a significant effect on salary. These papers are only indirectly related to ours. We could use the most accurate model from the models established in previous literature to estimate veteran player salaries. However, we instead use summary metrics in our model. One of these metrics is player efficiency rating (PER), which is used by Rosen and Kimbrough (2016) to try and determine the worth of a player from the difference between predicted wins if the team has that player versus if they did not sign the player. They conclude that superstar players are being overpaid, whereas bench players are underpaid.

There is preexisting literature on the NBA draft that provides insight into potential biases in our study. Staw and Hoang (1995) analyze the psychological aspect of playing time for young players. They find that highly drafted players tend to receive more playing time than lower drafted players no matter their performance due to the sunk cost fallacy. Win shares, one of the summary statistics used in our model, is a counting statistic meaning it increases with playing time. According to Staw and Hoang's findings, there may be bias in that a highly drafted player could have a larger value for win shares than their actual performance warrants due to them receiving unearned playing time.

Another potential bias in our study is teams incorrectly drafting players. Certain players are bound to be over or under-drafted, but we assume general efficiency in the drafting process. If teams consistently fail to correctly identify and select the best available player, draft pick will have little effect on player performance. Berger and Daumann (2021) analyze the flaws in NBA teams' draft selection process. They find that teams too easily succumb to consensus player rankings. To formulate this conclusion, Berger and Daumann look at player rankings out of high school to see how closely they align with the order of players drafted a year later. They conclude that general managers default to solidified rankings too easily and should consider college performance more in their selections. Berger and Daumann's hypothesis would lead to players being drafted incorrectly, which could alter the effect of draft pick on the performance value of the player drafted.

Data and Methodology

The data used for this project spans from the 2003-04 season to the most recent full season, 2022-23. We collected the player statistics and draft history data from the website [basketballreference.com](https://www.basketballreference.com), which has basic and advanced statistics for all players and seasons. The player salary data comes from HoopsHype. We chose to only analyze first round picks because their contracts are guaranteed for two years, whereas the contracts for second round picks are not guaranteed. Because of this, we removed all players drafted in the second round or undrafted from the data.

The model we develop uses two widely accepted summary statistics, PER and win shares. Both metrics estimate the overall performance of a player using formulas that consider standard

and advanced statistics. PER and win shares are more advanced than raw statistics because they adjust for other factors that are more difficult to quantify, such as the quality of opponent. It should be noted that both PER and win shares have shortcomings. John Hollinger, who created PER, has said it fails to capture a player's full defensive proficiency. The win share value for a player is affected by the quality of their team, so players on very good or bad teams may have disproportionate win shares.

To adjust for the rise of the NBA salary cap over the years, we chose to transform player salary to be a percentage of the salary cap for that year. As the salary cap has increased, the pay of superstars, average players, and rookies has generally increased at a proportional rate, so it is appropriate to judge salary as a percentage of the cap equivalently across years.

We set an arbitrary minimum of games played at thirty to remove players that have outlier values for PER and win shares. Because we are only interested in players who are paid their market value, we removed all maximum contract players from the data. Maximum contracts are capped at a certain amount, so it does not reflect the actual market value of that player. Then we split the data into players in their first four seasons, indicating they are on a rookie contract, and players beyond their fourth season, labeled as veterans. We removed one observation from the veteran data set due to an error in reading in the data, and three observations from the rookie data set due to being strong outliers. Finally, we randomly set aside 20% of the observations from each data set for model validation.

To estimate the true value of a draft pick, we must find a predicted team surplus that the team expects to gain from a given pick. To do this, we first create a model to determine the effect of PER and win shares, our chosen performance metrics, on player salary. Because rookie contracts are scaled by draft selection, not output, it is not appropriate to include them in the model. The

veteran data set only contains players who have played four seasons in the NBA already. Therefore, teams have a large sample size of their performance, so we can expect their salary to be accurate to their market value. Some players are certainly paid above or below their market value because they improve or worsen after signing a contract. Still, we can assume general market efficiency, and that players are paid close to their true value. The following model is estimated using only the veteran data set:

$$\text{Model 1: } \sqrt{\text{salary}} = \beta_0 + \beta_1 \text{winshares} + \beta_2 \text{PER} + \epsilon$$

Win shares and PER have low variance inflation factors, so we can assume they are not collinear. There is also no evidence of autocorrelation in the model. We did a square root transformation on salary to address normality and heteroskedasticity concerns. After the transformation, the QQ plot and the residuals vs fitted plot are much improved. However, we must note that the Breusch-Pagan test for heteroskedasticity and the Shapiro-Wilk test for normality state that both assumptions are violated. No transformations we performed improved the results of the tests. Because the plots do not reveal violations of normality or homoskedasticity, we will proceed in our analysis and use cross validation to indicate the validity of model one.

To ascertain the market value of rookie-scale players, we predict their salaries using model one for each of their first four seasons. This provides a prediction of what the rookie contract players are worth to their team at market value. Then, we calculated a team surplus value for each of the first four seasons for all rookie contract players by subtracting their actual salary from their true market value. Team surplus can be thought of as the added performance of a player extrinsic to their salary. We then created a second model using the rookie dataset, which contains players in their first four seasons, to determine the effect of draft position on team surplus. The model

includes experience, which is the number seasons a player has already played prior to the season being observed, as a blocking variable.

$$\text{Model 2: } \log(\text{team surplus}) = \beta_0 + \beta_1(\text{overall pick}) + \beta_2(\text{experience}) + \epsilon$$

To address issues of normality and heteroskedasticity, we performed a logarithmic transformation of team surplus based on the results of a Box-Cox procedure. To allow for a logarithmic transformation, we adjusted team surplus by adding a constant so that no values are negative. All values in the results section are after the constant has been removed from team surplus. After the logarithmic transformation, the homoskedasticity and normality assumptions appear to be met, judging by the QQ plot and the residuals vs fitted plot. There is no apparent violation of structure and the variance inflation factors for overall pick and experience are small, so there is no issue of multicollinearity in model two.

Model two predicts the amount of team surplus a team can expect to receive on average from a draft pick for each of the players first four seasons. This provides the extra predicted short-run value a team gains by drafting a player and signing them to a rookie contract compared to spending the equivalent salary on a player in free agency. We expect experience to have a positive effect on team surplus because players improve greatly in skill over their first few years despite their salary only increasing slightly.

Intuition would imply that higher draft picks provide a larger team surplus than later picks because they are better players. However, this may not be the case. Massey and Thaler (2005) used a similar approach and found that team surplus increases with draft pick. This effect may be even stronger in the NBA versus the NFL. The NBA draft is not an exact ranking of the players' estimated immediate impact. Top picks are often drafted for their upside rather than their current

skill level. Contending teams at the end of the draft look to select players who can play in their rotation instantly. These players are normally slightly older and more developed players but lack the maximum potential of earlier drafted players. A second reason for a positive effect of overall pick could be that the pay scale of drafted players decreases at a sharper rate than their performance. Figure one and figure two show that, for the first seven picks, salary and win shares decrease at about the same rate. However, figure one shows very little change in win shares for players drafted between pick seven and thirty. In that same range, the average salary decreases by approximately \$2 million. Therefore, the difference in rate of decline for salary and performance may be strong enough to make overall pick have a positive effect on team surplus.

Results

Model one indicates that both PER and win shares have a significant effect on salary. We tested the model using robust standard errors due to the potential issues with our model assumptions. For every one-point increase in PER, the average predicted square root of salary increases by 0.67% of the salary cap after adjusting for win shares. This effect is significant at a 0.0001 level with a t-value of 10.36. Win shares has a slightly more significant effect. For every one-win increase in win shares, the average predicted square root of salary increases by 1.56% of the salary cap after adjusting for PER. The effect of win shares is also significant at a 0.0001 level with a t-value of 15.61. Unsurprisingly, model one only accounts for 35.32% of the variation in salary. Extrinsic factors such as a player's reputation, injury risk, or maximum potential also impact salary. As was mentioned earlier, PER and win shares have flaws, so other performance metrics, specifically defensive statistics, could also have a significant effect on salary. We chose to limit the model to two predictors to avoid issues with multicollinearity. Finally, players can

unexpectedly improve or worsen after signing a contract, which leads to their contract being too expensive or cheap given the player's level of performance, further increasing the total variance in salary.

Cross validating model one results in an MSE of 0.0082 and an MSPE of 0.0030. These values are close to zero, which indicates good predictive ability of the model. Model one has a predictive R^2 of 0.3510, meaning we can expect the model to account for 35.10% of the variation in salary when predicting new observations. Model one has a PRESS of 16.19 and an SSE of 16.13. From these statistics, we can be moderately confident in model one predicting accurate values for salary.

Using model one, we found team surplus values for each player in each of their first four seasons. Overwhelmingly, the predicted market value of a player is greater than his actual salary. Team surplus for a single season of a player is positive 94.94% of the time. This means that teams can be extremely confident when drafting a player that their contract will be less than their performance level would demand. The mean team surplus for the data is \$3,700,223 which means that, on average, rookie contract players should be making \$3.7 million more than their current salary. The average team surplus allows a team to sign a player in free agency worth \$3.7 million more than if they had to pay their rookie contract player proportionately to their performance. We are 95% confident that the true average team surplus of a draft pick for a single season is between \$3.54 million and \$3.86 million. Unsurprisingly, a significance test on team surplus resulted in an extremely large t-value of 44.57. Therefore, we can conclude that the average team surplus is significantly greater than zero. This is a massive incentive for teams to retain their draft picks. Often, recently drafted players are only considered beneficial years into the future after they have

developed experience in the league. Our findings, however, indicate that players have an immediate positive impact in their first four years in the NBA.

We further examine team surplus using model two, which predicts team surplus from the overall draft pick and years of experience for a player. Once again, we used robust standard errors to calculate the following effects. For every one pick increase in overall draft selection, the average predicted team surplus increases by 1.05% after adjusting for experience. This effect is significant at the 0.0001 level with a t-value of 8.30. As we surmised is a possibility, overall pick has a positive effect on team surplus. This means that the later the draft pick falls in the first round, the more valuable the pick in terms of team surplus. Here, we must reiterate that this result does not mean that later drafted players are better than earlier drafted players, or that the last pick is more valuable overall than the first. PER and win shares both have a negative correlation with overall pick. Additionally, the top players drafted have a greater long-term benefit because, once a player's rookie contract expires, teams would always prefer to have the opportunity to re-sign better performing players to a more expensive contract than worse players to a smaller contract. Still, our results from model two indicate that, for their first four seasons, players at the tail end of the first round are more valuable than players drafted earlier.

The predictive power of model two is not as strong as model one. After cross validating model two, we found an MSE of 0.11, an MSPE of 0.0075, a PRESS of 143.55 and an SSE of 142.76. We can expect model two to account for 11.92% of the variation in team surplus when predicting new observations. These are poor but expected results. Team surplus contains a lot of variation simply due to the difficulty of accurately drafting the best player available. It is important to note that, although it is extremely likely that a team gains a surplus by drafting a player, the amount of that surplus varies greatly based on the accuracy of their selection.

To fully understand team surplus, we must analyze its trend graphically. Figure 3 shows that team surplus increases from the second to final draft pick. However, team surplus is highest for the first overall draft pick before a sharp decline to the second pick. This trend is to be expected given the nature of the NBA draft. Occasionally, a player enters the league who is considered a generational prospect and insurmountably better than the other players drafted. LeBron James in the 2003 draft and Victor Wembanyama in the 2023 draft are examples of such a player. Generational prospects will have such strong performance metrics as to raise the average team surplus significantly for the first overall draft position.

Even with the effect of generational prospects, the first overall pick still has a similar average team surplus than the last overall pick in the first round. The most likely reason for this effect is that salary for first round draft picks decreases at a sharper rate than performance. Later drafting teams can benefit from this market inefficiency by retaining their draft picks and selecting intelligently.

Finally, let us reconsider the initial prompt for this paper: is trading away future draft picks for current players the optimal strategy for contention? Based on our findings, the answer is no. The added value of a player on a rookie contract is too significant to trade away. Contending teams generally devalue their own draft picks because they are projected to be late in the first round and young players are not considered to be immediately helpful in pursuing a championship. Our findings reject both theories. Model two procures that the short-run benefit of later draft picks is preferred to early draft picks. Therefore, to contending teams who are competing for a championship immediately, draft picks at the end of the first round may even be preferable due to their high team surplus. Table one, at the end of this paper, indicates the predicted team surplus for

each combination of draft pick and experience. By trading away their future draft picks, NBA franchises essentially omit the predicted total team surplus value of their projected pick.

Conclusion

This paper argues that, for contending teams, drafting players to perform immediately is a superior strategy to trading away picks and signing players in free agency. Teams gain an average of \$3.7 million in surplus by drafting a player in the first round. Specifically, our model finds that draft pick has a significant positive effect on predicted team surplus. Therefore, in terms of team surplus, the most valuable picks are at the end of the first round. Contending teams, who are close to their salary cap, can utilize the draft to add cheap players whose performance is greater than their contract would indicate. By trading away their picks, franchises lose this luxury and hinder their team's chance of winning a championship both immediately and years in the future.

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Table 1

Draft Pick	Experience				Total
	1	2	3	4	
1	\$ 4,365,146	\$ 7,910,252	\$ 10,439,268	\$ 11,503,730	\$ 34,218,396
2	\$ 383,969	\$ 1,048,186	\$ 4,690,794	\$ 5,255,593	\$ 11,378,542
3	\$ 3,339,374	\$ 5,551,893	\$ 6,435,125	\$ 9,084,874	\$ 24,411,266
4	\$ 2,609,101	\$ 3,298,619	\$ 5,311,693	\$ 8,175,755	\$ 19,395,168
5	\$ 1,137,407	\$ 4,134,065	\$ 6,472,241	\$ 9,143,654	\$ 20,887,367
6	\$ 3,616,842	\$ 4,454,409	\$ 7,368,631	\$ 8,669,725	\$ 24,109,607
7	\$ 4,265,059	\$ 4,709,764	\$ 7,128,980	\$ 6,681,499	\$ 22,785,302
8	\$ 3,219,731	\$ 4,337,183	\$ 4,673,125	\$ 2,399,898	\$ 14,629,937
9	\$ 4,700,161	\$ 5,276,134	\$ 8,984,075	\$ 7,838,456	\$ 26,798,826
10	\$ 3,296,684	\$ 4,595,801	\$ 7,632,574	\$ 7,521,069	\$ 23,046,128
11	\$ 3,407,023	\$ 5,107,727	\$ 8,634,845	\$ 7,865,770	\$ 25,015,365
12	\$ 5,451,098	\$ 5,512,573	\$ 6,862,838	\$ 5,362,414	\$ 23,188,923
13	\$ 5,046,228	\$ 5,060,575	\$ 7,032,236	\$ 7,400,914	\$ 24,539,953
14	\$ 4,786,196	\$ 5,292,016	\$ 7,820,164	\$ 6,371,967	\$ 24,270,343
15	\$ 4,965,174	\$ 5,501,227	\$ 7,995,211	\$ 10,750,708	\$ 29,212,320
16	\$ 4,641,836	\$ 5,465,049	\$ 5,150,659	\$ 5,825,141	\$ 21,082,685
17	\$ 4,869,336	\$ 5,903,477	\$ 7,454,436	\$ 8,119,087	\$ 26,346,336
18	\$ 4,309,490	\$ 5,316,939	\$ 7,728,901	\$ 6,765,683	\$ 24,121,013
19	\$ 4,631,179	\$ 5,640,091	\$ 7,212,224	\$ 7,698,237	\$ 25,181,731
20	\$ 5,703,302	\$ 6,160,731	\$ 6,242,468	\$ 6,040,403	\$ 24,146,904
21	\$ 6,333,141	\$ 6,830,670	\$ 9,710,926	\$ 10,382,872	\$ 33,257,609
22	\$ 7,844,717	\$ 8,058,727	\$ 9,645,302	\$ 9,120,657	\$ 34,669,403
23	\$ 5,695,825	\$ 6,178,745	\$ 8,756,874	\$ 6,671,504	\$ 27,302,948
24	\$ 5,109,791	\$ 6,234,206	\$ 8,957,645	\$ 9,650,016	\$ 29,951,658
25	\$ 5,582,257	\$ 6,828,276	\$ 7,900,452	\$ 6,303,856	\$ 26,614,841
26	\$ 5,749,025	\$ 6,603,627	\$ 8,981,242	\$ 8,577,130	\$ 29,911,024
27	\$ 6,772,452	\$ 7,069,956	\$ 10,289,701	\$ 9,953,348	\$ 34,085,457
28	\$ 3,693,591	\$ 5,958,239	\$ 7,791,993	\$ 8,177,800	\$ 25,621,623
29	\$ 5,438,915	\$ 6,760,813	\$ 7,551,953	\$ 7,702,474	\$ 27,454,155
30	\$ 5,512,065	\$ 7,454,868	\$ 11,055,807	\$ 9,724,726	\$ 33,747,466

Table 1 shows the mean team surpluses for all draft pick and experience combinations. All dollar values are in terms of the 2023 salary cap.

Figure 1

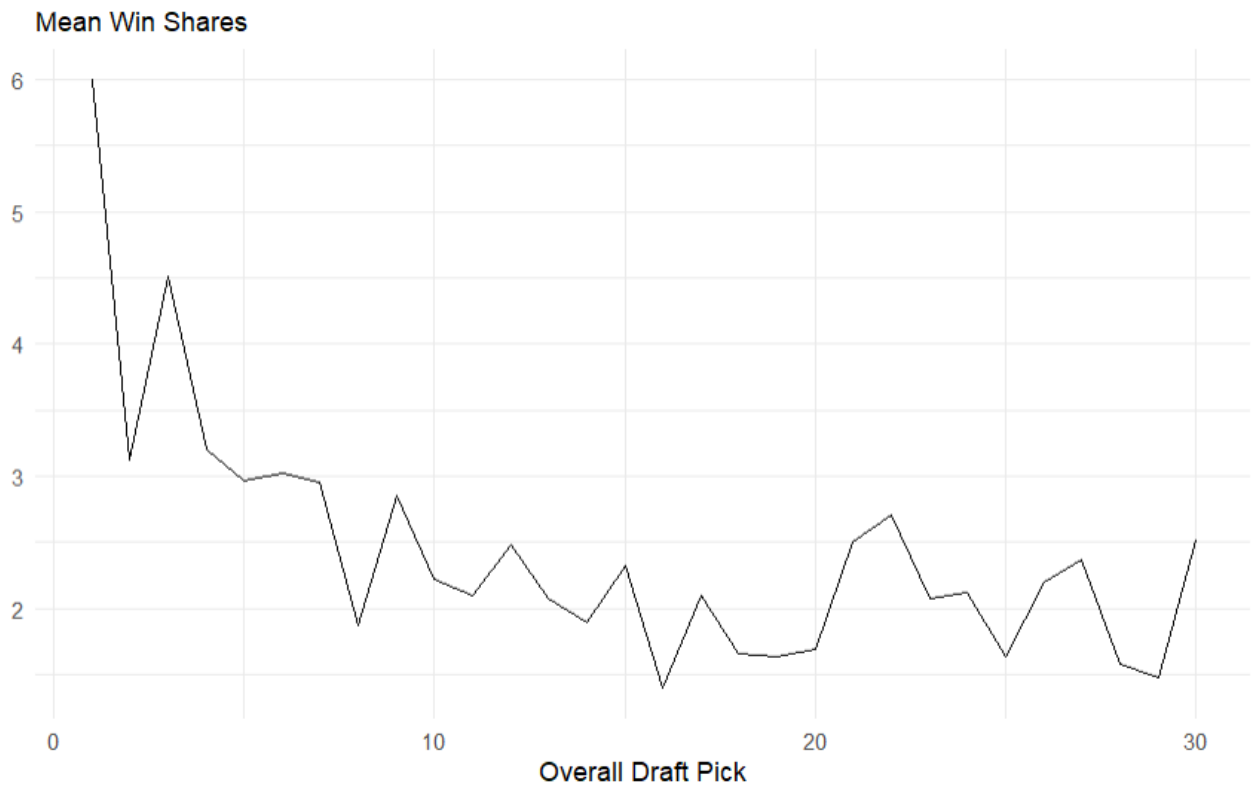
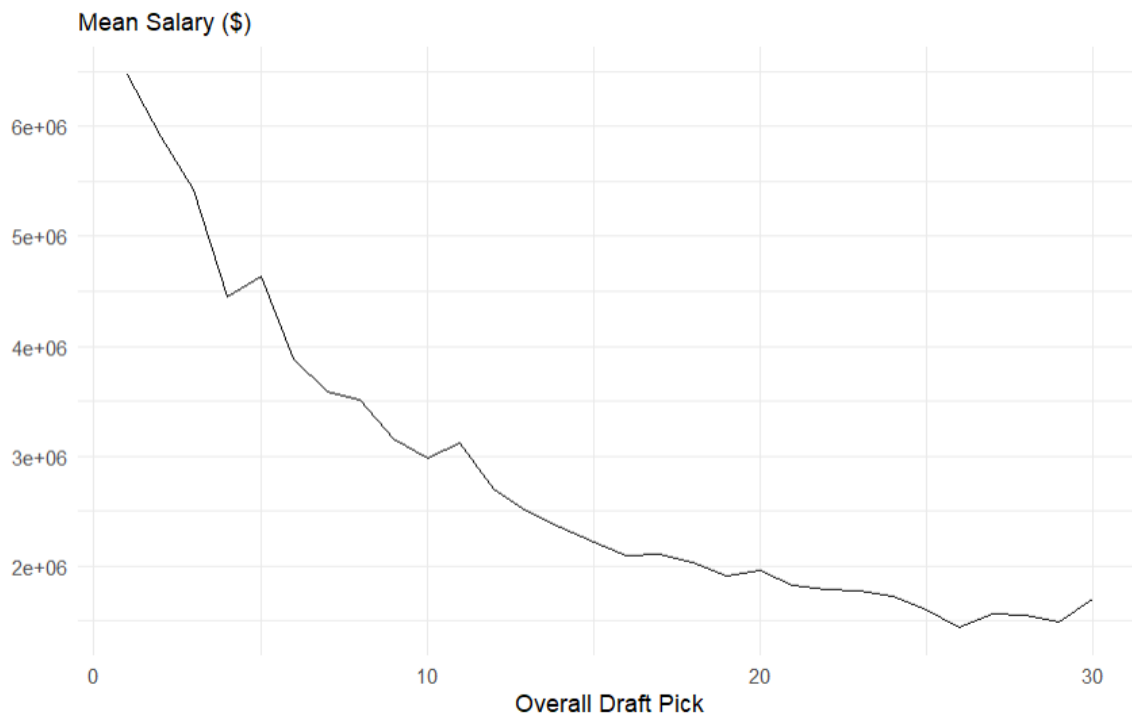
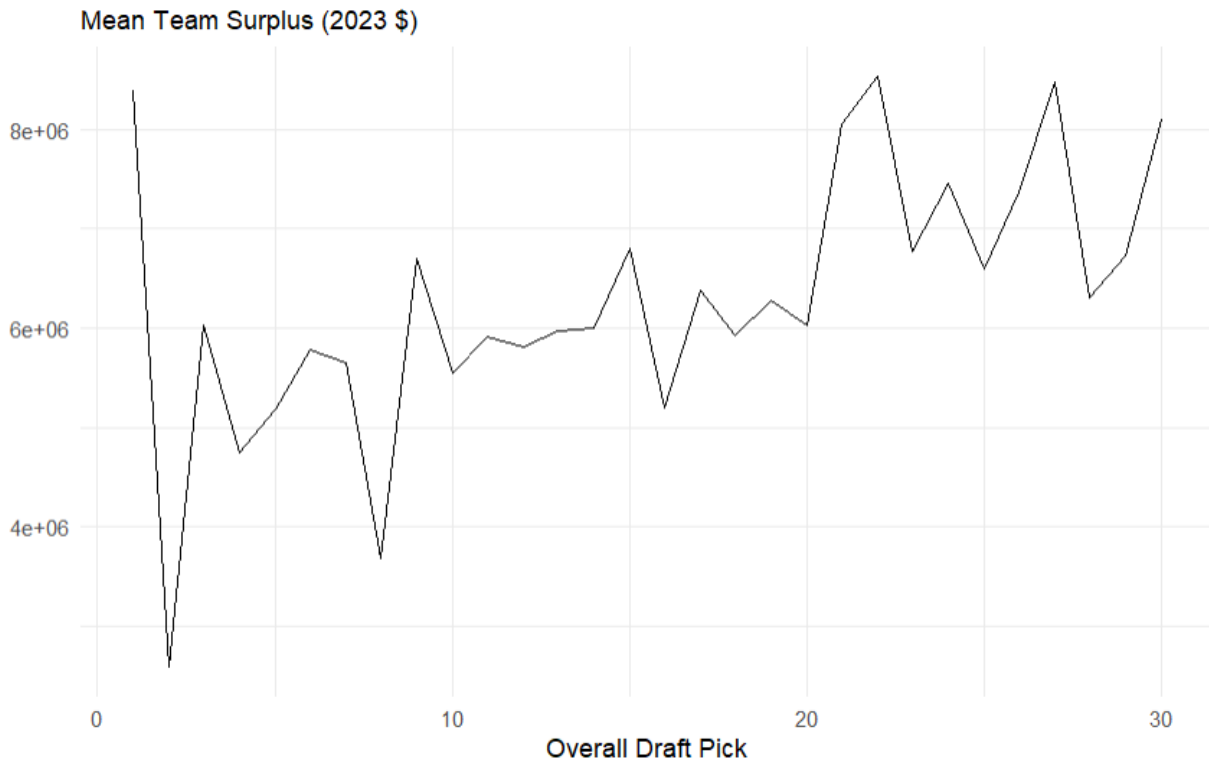


Figure 2



All dollar values are in their original values.

Figure 3



All dollar values are in terms of the 2023 salary cap.