League and Draft Pick Effect on Player Success: NBA

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1 Introduction

Every year, the NBA hosts an amateur player draft selecting top professional basketball talent all over the world. Naturally, as avid fans, we become curious about the future outcome of the players selected by our favorite team. While these speculations by the general public are based purely on emotion and vibes. For my project, I'll try to take a more analytical approach to projecting an NBA player's career outcome. Specifically, I'll focus my analysis on where a player played their amateur ball, their age entering the draft, and which pick they were selected with. Using these factors, I'll try to predict the player's peak player value through the stat BPM.

Drafting is one of the most consequential decisions an organization can make, as it shapes the future outlook of a team for many years to come. Making any improvement in this phase of roster construction a real competitive advantage. The results from this paper can help organizations make smarter decisions and take more calculated risks in the draft room. Hopefully, leading to long-term success.

2 Data

Since I'm interested in looking at the maximum potential an NBA player can reach in their career, I need to quantify how valuable a player is to a team. Luckily, there is an all-in-one metric by Basketball Reference called Box Plus Minus[1] (BPM) that quantifies how good a basketball player is relative to others in the league. With 0 being a league-average player. I wanted to run my analysis on players who played in the last decade, so I pulled the BPM leaders starting from 2014-15 to 2024-25[2]. Due to BPM being highly inflated for players with low playing time, I filtered this dataset to those who played more than 250 minutes over the course of a season. This resulted in 1,028 unique players to pull data for.

My analysis was focused on a player's peak BPM, which required me to pull the BPM values throughout a player's entire career. To do this, I brought in additional data starting from the year the oldest player in my dataset was drafted into the league. Once I had these values, I then took the average of a player's top 3 highest BPM seasons to get a more stable estimate of a player's true value. In cases where a player had fewer than 3 seasons, I would take the average over the number of seasons they had played.

To gather the league and draft pick information for each player I used the NBA API[3] on Python. The following info was stored as a dictionary and added as a column to my merged dataset.

When analyzing the counts by league I realized there was a big data sparsity issue. To work around this and get more stable MCMC chains, I grouped leagues with small samples (fewer than 10) into a larger group. Table 6 in my Appendix shows the final league groupings I used in my dataset.

The level of competition between these leagues is also vastly different. In order to capture the disparity in talent between the leagues I added a league difficulty feature to my dataset. For this, I ranked all the leagues individually based on different ranking websites, and took the average if they were grouped with others in my reduced league groupings. The rankings for each league individually can be seen in Table 7, with the grouped league rankings seen in Table 8 of the Appendix. These ranking values were then converted into standard deviations to quantify the difficulty in respect to

[1] https://www.basketball-reference.com/about/bpm2.html

[2] https://www.basketball-reference.com/leagues/NBA_2025_advanced.html

[3] https://github.com/swar/nba_api

the other leagues in my dataset.

The final dataset stored League, League difficulty, Age Entering Draft, and their Draft Pick for each player.

I was later interested in running my model on the up incoming NBA prospects. For this dataset, I referenced NBA Draft.Net's Mock Draft[4] to get a list of players to pull data from and used their projected picks as the draft hasn't taken place just yet. I then pulled an additional 5 names from various mock draft websites to be my "Undrafted" examples. The total list came out to 65 players, which I manually pulled their necessary information using Google.

3 Methodology

I used a Bayesian Regression model to predict a player's Top 3 Average BPM value given their League, League difficulty, age, and draft pick. To help decide which of these factors I wanted to add as fixed or mixed effects, I drew my attention to the data to aid with these decisions.

3.1 Assumptions

League was the first factor I analyzed. I assumed that more difficult leagues would result in higher-quality talent. To analyze this, I plotted the proportions of player tiers, with the cut-offs specified in Table 1, across different Leagues, with it decreasing in difficulty across the x-axis.

Tier	Cut Off
All Time Great (ATG)	> 10
MVP	7.5 - 10
All-NBA (AN)	5 - 7.5
All-Star (AS)	3.7 - 5
Good Starter (GS)	2 - 3.7
Role Player (RP)	0 - 2
Replacement Level (RL)	-2 - 0
Benchwarmer (B)	< -2

Table 1: Player Tiers

In Figure 1, we can see that the distribution of talent generally varies by league, especially in the number of elite level players (All-Star and above) as leagues become less difficult. Although in my dataset high school is a biased group which skews this relationship. This is due to the NBA removing high school players from being draft eligible in the early 2000's making those who survived till the last decade to be top of the line talent. From this plot it feels that league has a varying relationship with player talent which we can fit with its own intercepts.

My assumptions for draft pick was similar, in that, players selected with high picks should result in high quality talent. When looking at Figure's 2 and 3 we can see that this relationship holds even as we specify it for a specific league when we have enough samples. In Figure 4, we can see that while a bit nosier, due to the much smaller sample size of 48 compared to 714 the trend seems to hold. For this reason it feels relatively safe to assume that the draft pick relationship is fixed regardless of league.

Lastly, I assumed that Age would have a similar fixed effect regardless of league due to its high correlation with draft pick. Generally, we see that younger players are selected with higher overall picks due to their higher potential.

3.2 Model

My final model came out to the following:

$$BPM \sim 1 + Age + Difficulty + DP + (1|L)$$

Since I already created a league difficulty variance in my dataset I added this as a fixed effect as I didn't want it to change for leagues. After running for 4 chains, with 10,000 iterations I checked its model fit on my data and later tested it on the incoming draft class.

3.3 Model Fit

How well did our model fit with our data? After converting our raw BPM values into tiers using the same cut offs as in Table 1 I checked to see if figures I previously made still held true. When looking at Figure 5 we can see that it follows a very similar pattern that we saw in Figure 1 with some smoothing in Leagues with small sample sizes. The same holds true when looking at Figures 6 and 7 as they follow a similar trend that we saw in Figure 2 and 3. These checks give us some confidence that our model is fitting well to the data at hand!

4 Results

Using these posterior samples I looked into what kind of effect leagues and picks have on the trajectory of an NBA player. I ran a similar analysis first on my current NBA player dataset and next on the NBA prospects. For both datasets I was curious on the probability of a player meeting their draft day expectations, and the probabilities of ending up in each of my tier bins.

For such an analysis I created a new categorical variable that considered what pick they were selected with and their projected player outcome. The logic followed that of Table 9 in the Appendix. For Undrafted players, I set the Bust Rate to be zero as there is no expectation for that player to even make it onto the active roster. I similarly, created another categorical variable that grouped some of the tiers into larger bins. The new groupings followed that of Table 2.

4.1 Current Players

Using the current player dataset I looked into the overall group rate effects. Starting with just league rate effects. When

[4] https://www.nbadraft.net/nba-mock-drafts/

Label	Tier
Elite	ATG, MVP, AN, AS
Floor	GS, RP
Bum	RL, B

Table 2: Player Expectation Categories

grouping by league, the league with greatest proportions of Elite players came out to High School with 21%, Other European Lower with 11%, and European Elite with 9%. What's interesting to note is that the two easiest leagues came out to have the best players. This is largely due to a combination of sampling bias in High School players, and a small sample size (23 and 14 respectively). This results in an enlarging effect in these leagues. The leagues with the greatest proportion in the Bum category came out to, Australian Top with 72%, Developmental League with 70% and Spain Top with 61%. The full table can be seen in Table 10 in the Appendix. The two worse performing leagues are also the youngest in our dataset which might hint at what the true hit rate might be for high school players. The lowest bust rate group wasn't High School but was Other D1 with a rate of 26% but was followed closely by High School with a rate of 29%.

Unsurprisingly, when grouping by Pick Bin we got that those selected with higher picks ended up to be better players on average. The full results can be seen in Table 11 in the Appendix. Lastly, I then grouped Pick Bin by League. The top was again dominated by High School players but surprisingly, South America jumped up to the 3rd best group with an Elite rate of 17%. After controlling for Pick Bin France Top jumped up to three with a rate of 83%. Top D1 also jumped up 2 slots for the highest rate of Bum players after controlling for Pick Bin with a rate of 80%. The full results can be seen in Table 12.

4.2 Prospects

I then looked at the projected outcomes using the prospects dataset. When sorting by Elite rate the top 5 nearly fell in the same order as the draft picks which fits with our intuition.

Player	Pick	Elite Rate
AJ Dybantsa	1	0.122
Darryn Peterson	2	0.121
Mikel Brown	4	0.119
Cameron Boozer	3	0.117
Caleb Wilson	6	0.115

Table 3: 2026 NBA Prospects: Most Likely Elite Players

The most likely Bums had a strong bias towards Undrafted players making up 4 of the 5. Interestingly, the 5th most likely Bum came with Malique Lewis 83.9%, the projected 42 pick coming from the Australian league. Although, he was closely followed by the last Undrafted player in my prospects dataset in Flory Bidunga from Kansas with a rate of 83.7%. When looking at the Bust rates for the prospects there was a clear negative bias towards the Australian league (NBL) with the 3 players from this league making up the top 3 highest bust rates.

From the Table above we can see that our model thinks that players from this league aren't worth the risk that they come with with a near 10% jump in risk between Thomas (Top D1 player) and the Lewis (NBL).

The top 5 value picks, disregarding our projected Undrafted players were:

Player	Pick	Bust Rate
Dash Daniels	13	0.902
Karim Lopez	8	0.881
Malique Lewis	42	0.839
Meleek Thomas	11	0.763
Chris Cenac	10	0.763

Table 4: 2026 NBA Prospects: Most Likely Busts

Player	Pick	Exceed Rate
Zuby Ejiofor	31	0.151
Richie Saunders	37	0.149
PJ Haggerty	35	0.138
Karter Knox	34	0.136
JT Toppin	33	0.135

Table 5: 2026 NBA Prospects: Best Value Picks

From this table it seems our model learned that the early 2nd round offers a good mix of opportunity and minimal risk. The full prospects rates will be attached as a csv due to it being too large to fit in this report.

5 Conclusion

From this project, I've learned that league and draft pick have some association with an NBA player's future outcome. While our league estimates are a bit noisy due to a lack of sample size, we've shown that historically, NBL players aren't worth the risk, especially with a high lottery pick (1-5). In addition, International leagues have proven to create players with higher peaks, but US programs have a safer floor.

This project has also shown that higher overall picks tend to have higher peaks on average, with some leagues generally producing better overall talent. In my case, due to the selection bias in my dataset, High School players were the best producers of top-tier talent, followed by Other European Lower, European Elite, and South America. It seems Age has some interaction with these rankings, as the younger leagues in the NBL and Developmental Leagues were worse at producing elite-level talent. Our results seem to suggest that, in general, jumping into the league can be overwhelming to younger athletes. While the transition for older and more seasoned players coming overseas is better equipped for the change in pace between leagues. For future work, I'm curious to see how much of this analysis holds as we increase our sample size and if it changes over time.

A Appendix

Table 6: League Groupings

Group	Leagues
Top D1	Top D1 US conferences (ACC, SEC, Big 10, Big 12, Big East)
Other D1	any other D1 US conference
Developmental League	G League, International Prep, Overtime Elite
Europe Elite	Any team with in Euroleague (top European tournament)
Spain Top	Liga ACB
France Top	LNB Pro A
Eastern Europe Top	ABA
Other Europe Top	Serie A, Bundesliga, Super Ligi
Other Europe Lower	Primera FEB, Serie B, Nationale Masculine 1, LNB Pro B
Australian Top	NBL
High School	All HS US
South America	NBB, LUB
Other	CBA, Premier League, JUCO, Super League 1, VTB

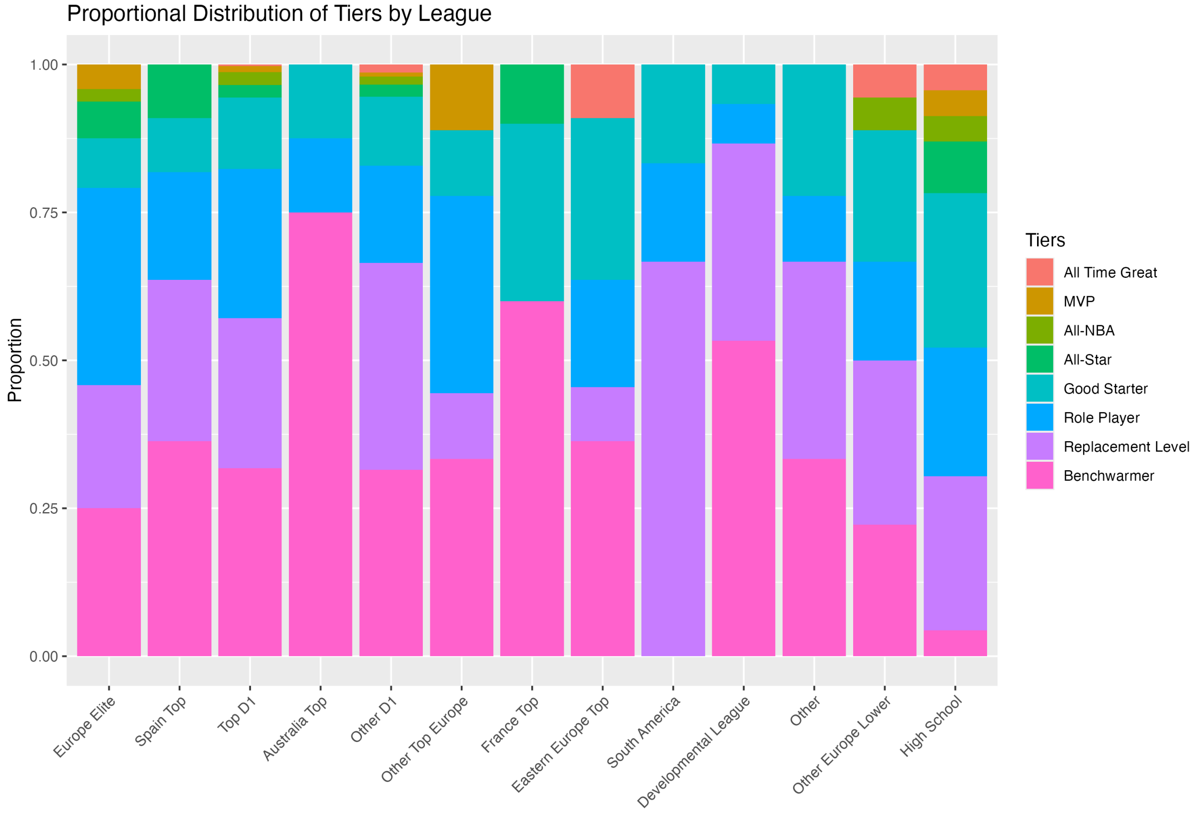
Table 7: Rankings

League	Rank
Euroleague	1
Liga ACB	2
Top D1	3
NBL	4
Super Ligi	5
Serie A	6
VTB United League	7
Other D1	8
LNB Pro A	9
Bundesliga	10
G League	11
CBA	12
ABA	13
LKL	14
NBB	15
Israeli Premier League	16
LNB Pro B	17
Greek B	18
Primera FEB	19
Serie B	20
LUB	21
Super League 1	22
BSL	23
Overtime	24
Nationale Masculine 1	25
International Prep	26
JUCO	27
High School	28

Table 8: New Group Rankings

League	Rank
Europe Elite	1
Spain Top	2
Top D1	3
Australian Top	4
Other D1	5
Other Top European	6
France Top	7
Eastern European Top	8
South America	9
Developmental League	10
Other	11
Other Europe Lower	11
High School	12

Figure 1: Distributions of Player Tiers by League



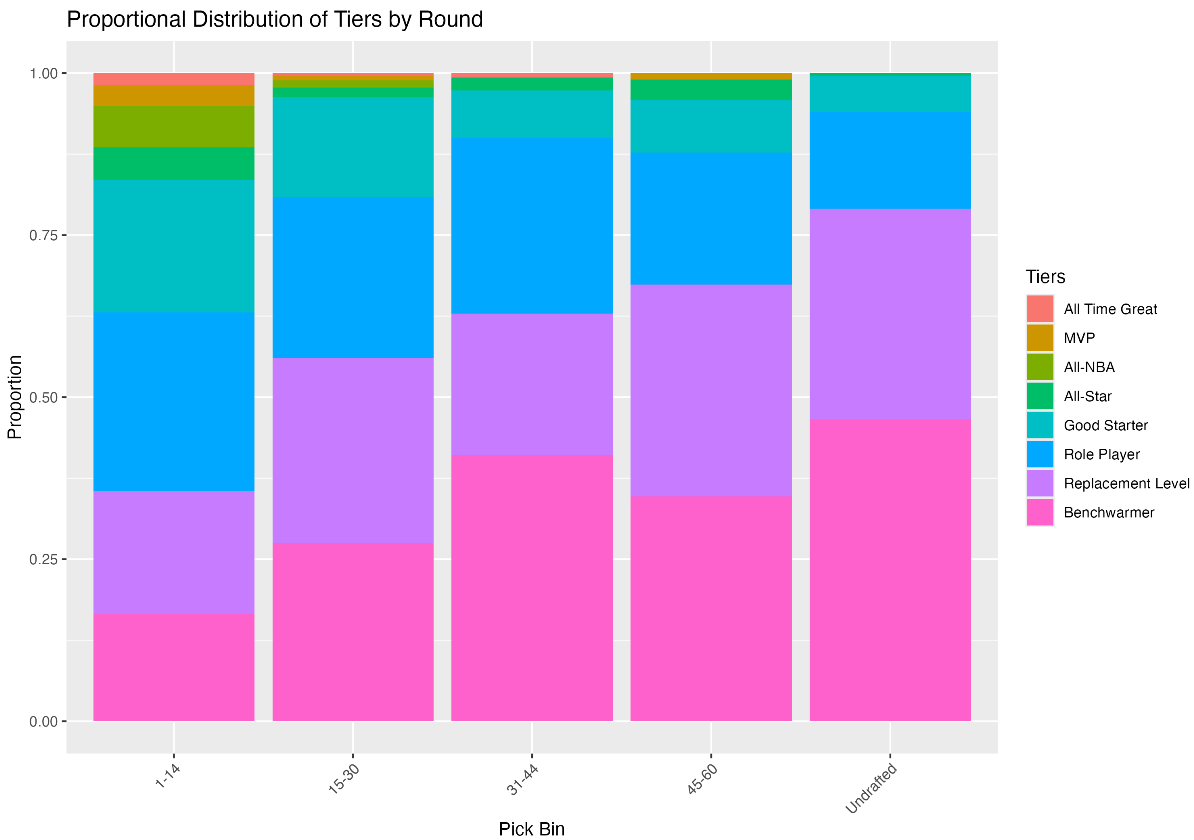
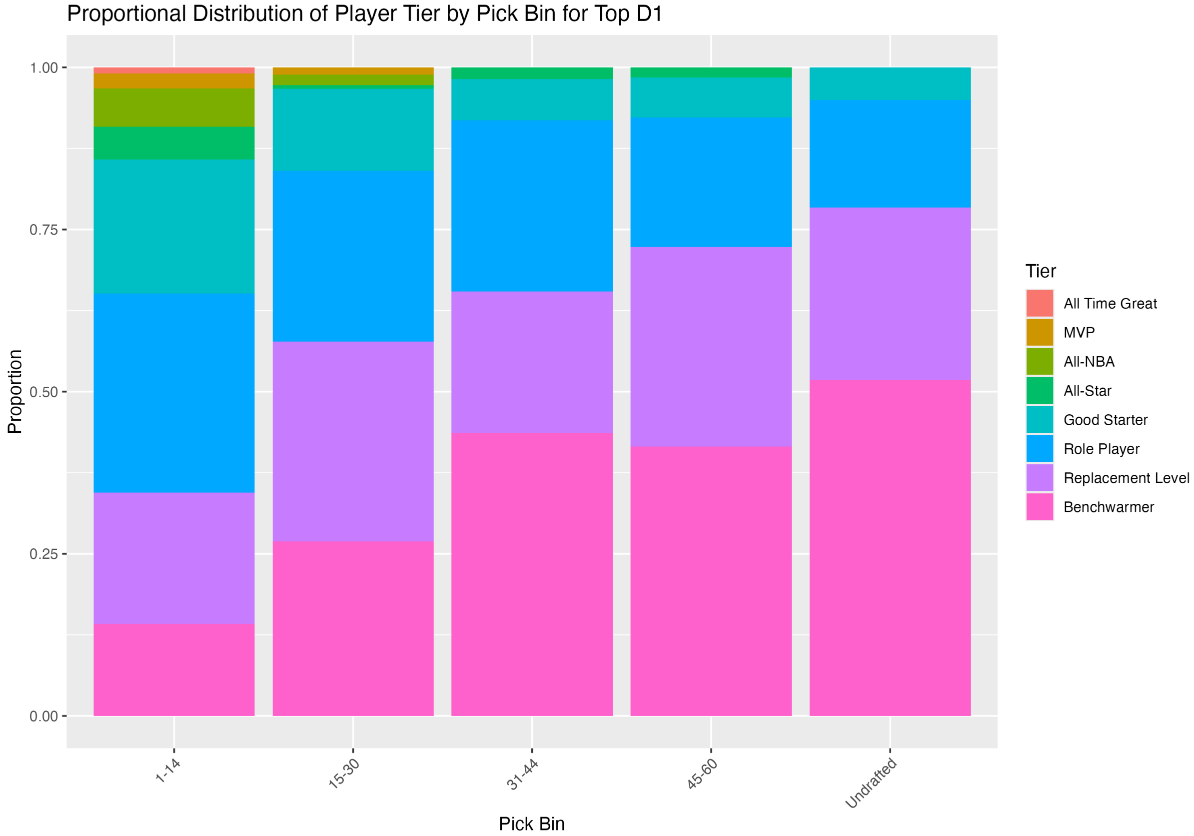


Figure 2: Distributions of Player Tiers by Draft Pick Bin.

Figure 3: Distributions of Player Tiers by Draft Pick Bin for Top D1



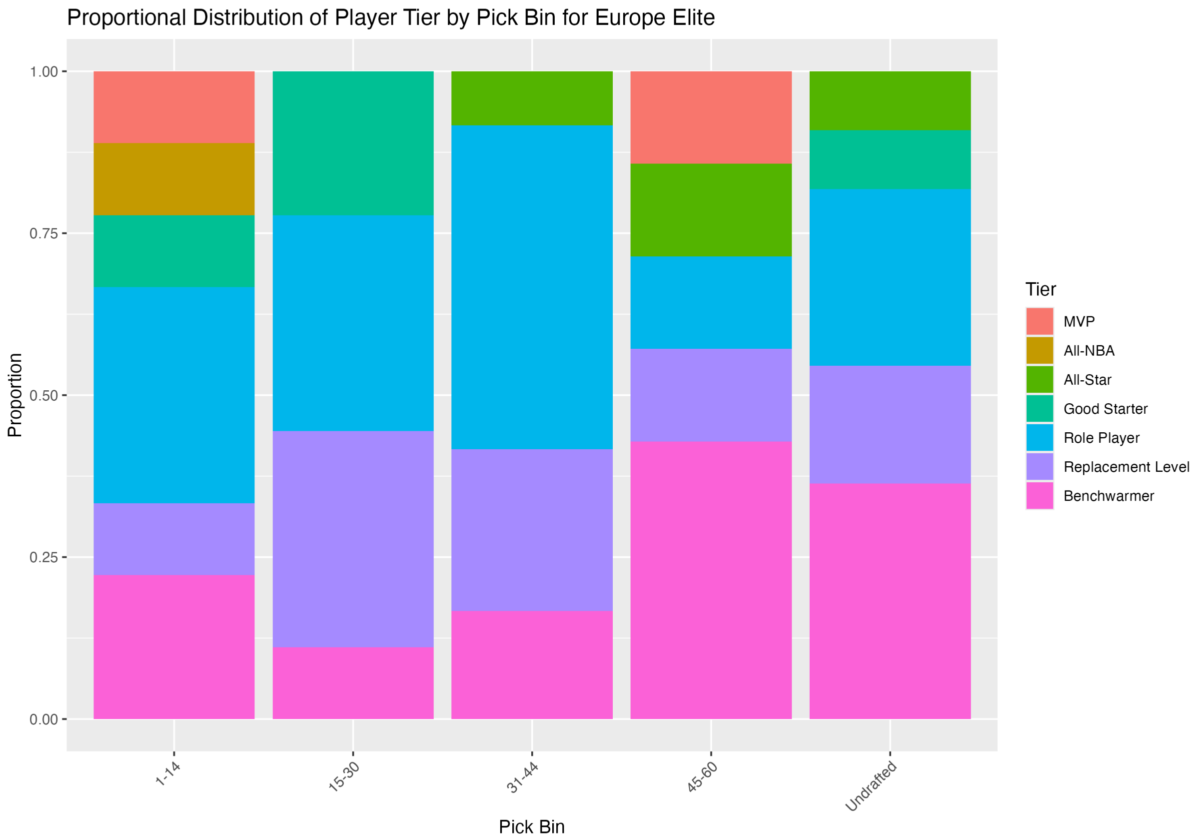
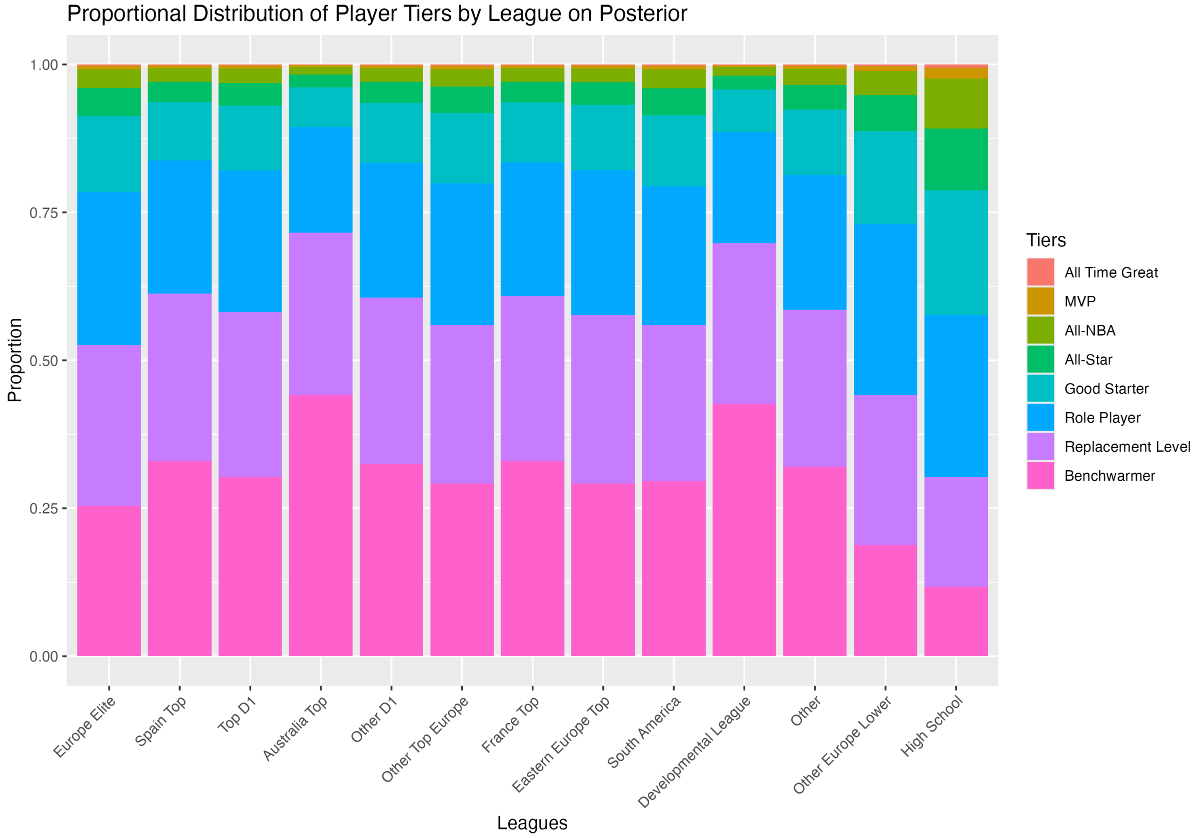


Figure 4: Distributions of Player Tiers by Draft Pick Bin for Euroleague

Figure 5: Distributions of Player Tiers by League on Posterior



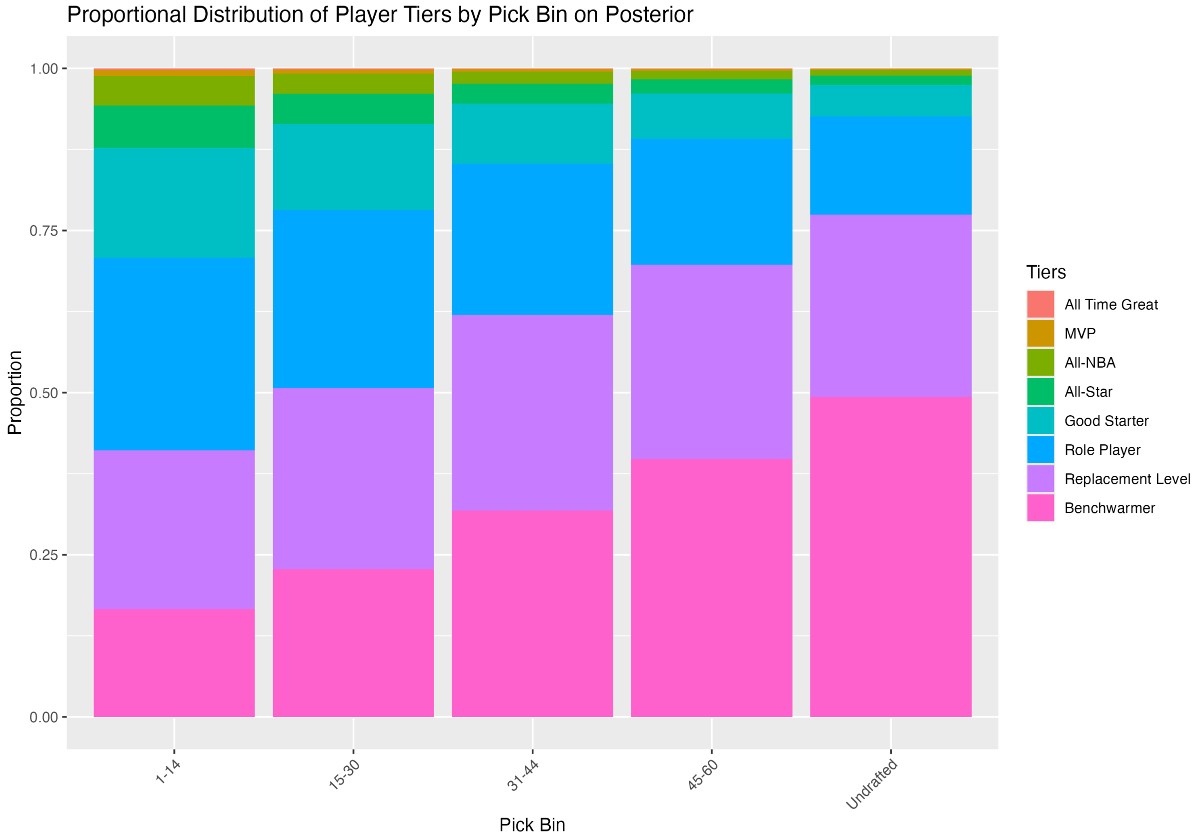


Figure 6: Distributions of Player Tiers by Draft Pick Bin on Posterior

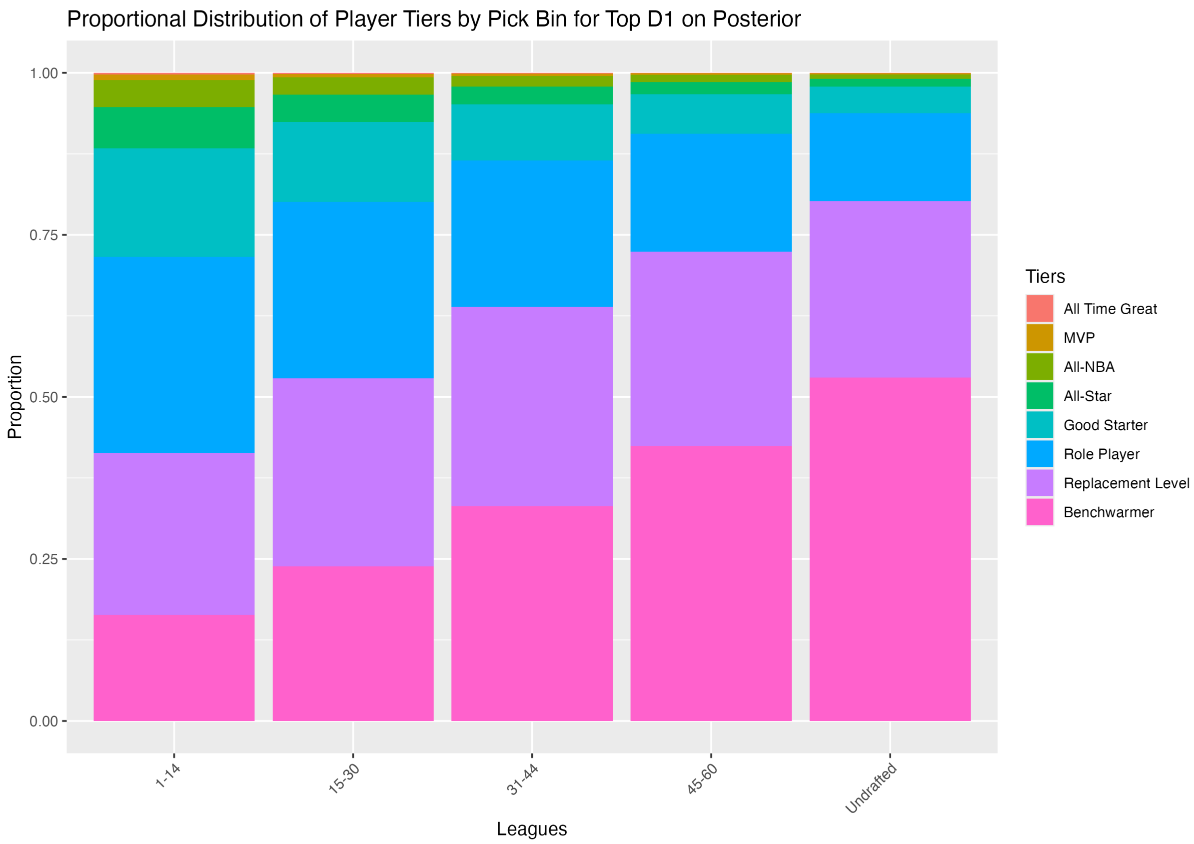


Figure 7: Distributions of Player Tiers by Draft Pick Bin for Top D1 on Posterior

Pick	Label	Formula
>14	Exceeded	$\frac{ATG+MVP+AN}{Total}$
	Met	$\frac{AS+GS}{Total}$
	Bust	$\frac{RP+RL+B}{Total}$
14-30	Exceeded	$\frac{ATG+MVP+AN+AS}{Total}$
	Met	$\frac{GS+RP}{Total}$
	Bust	$\frac{RL+B}{Total}$
31-44	Exceeded	$\frac{ATG+MVP+AN+AS+GS}{Total}$
	Met	$\frac{RP}{Total}$
	Bust	$\frac{RL+B}{Total}$
45-60	Exceeded	$\frac{ATG+MVP+AN+AS+GS}{Total}$
	Met	$\frac{RP+RL}{Total}$
	Bust	$\frac{B}{Total}$
Undrafted	Exceeded	$\frac{ATG+MVP+AN+AS+RP+GS}{Total}$
	Met	$\frac{RL+B}{Total}$
	Bust	$\frac{0}{Total}$

Table 9: Player Expectation Categories

Table 10: Outcome Rates by League

League	Age	Elite Rate	Floor Rate	Bum Rate	Exceed Rate	Met Rate	Bust Rate
Australian Top	19.12	0.039	0.245	0.712	0.028	0.149	0.823
Developmental League	19.60	0.042	0.260	0.698	0.034	0.243	0.723
Eastern Europe Top	21.45	0.068	0.355	0.577	0.107	0.396	0.497
Europe Elite	23.67	0.087	0.386	0.526	0.178	0.439	0.383
France Top	20.10	0.0643	0.327	0.609	0.0695	0.324	0.607
High School	19.96	0.213	0.484	0.303	0.233	0.472	0.294
Other	21.89	0.0761	0.338	0.586	0.128	0.478	0.394
Other D1	22.88	0.065	0.329	0.606	0.187	0.555	0.258
Other Europe Lower	21.06	0.112	0.446	0.442	0.100	0.358	0.542
Other Top Europe	21.22	0.082	0.358	0.560	0.134	0.440	0.426
South America	22.00	0.086	0.355	0.560	0.161	0.525	0.314
Spain Top	23.91	0.0632	0.324	0.613	0.150	0.466	0.384
Top D1	21.75	0.070	0.350	0.581	0.103	0.406	0.490

Table 11: Outcome Rates by Round

Pick Bin	Age	Elite Rate	Floor Rate	Bum Rate	Exceed Rate	Met Rate	Bust Rate
1-14	20.38	0.123	0.466	0.411	0.057	0.235	0.708
15-30	21.24	0.086	0.406	0.507	0.086	0.406	0.507
31-44	21.85	0.054	0.326	0.620	0.147	0.233	0.620
45-60	22.89	0.0385	0.264	0.697	0.108	0.495	0.397
Undrafted	24.073	0.0258	0.200	0.774	0.226	0.774	0.00

League	Pick Bin	Age	Elite Rate	Floor Rate	Bum Rate	Exceed Rate	Met Rate	Bust Rate
Australia Top	1-14	19.00	0.051	0.302	0.647	0.022	0.116	0.862
	15-30	19.33	0.030	0.211	0.759	0.030	0.211	0.759
	31-44	19.00	0.015	0.123	0.862	0.043	0.095	0.862
Developmental League	1-14	19.50	0.053	0.312	0.635	0.024	0.118	0.858
	15-30	20.50	0.035	0.247	0.717	0.035	0.247	0.717
	31-44	20.00	0.0185	0.156	0.826	0.056	0.119	0.826
	Undrafted	19.00	0.008	0.066	0.926	0.074	0.926	0.00
Eastern Europe Top	15-30	20.33	0.085	0.399	0.516	0.085	0.399	0.516
	31-44	19.50	0.050	0.308	0.642	0.137	0.221	0.642
	45-60	25.00	0.048	0.296	0.656	0.1301	0.506	0.363
Europe Elite	1-14	20.22	0.166	0.507	0.327	0.079	0.291	0.630
	15-30	21.78	0.106	0.450	0.443	0.106	0.450	0.443
	31-44	22.50	0.074	0.384	0.542	0.195	0.263	0.542
	45-60	25.43	0.053	0.326	0.621	0.146	0.536	0.318
	Undrafted	28.18	0.042	0.277	0.681	0.319	0.6801	0.00
France Top	1-14	19.00	0.098	0.418	0.484	0.045	0.197	0.758
	15-30	20.40	0.059	0.323	0.618	0.059	0.323	0.618
	31-44	19.00	0.0404	0.256	0.704	0.107	0.189	0.704
	Undrafted	23.00	0.017	0.145	0.839	0.161	0.839	0.00
High School	1-14	19.43	0.314	0.506	0.180	0.169	0.398	0.433
	15-30	20.11	0.223	0.518	0.259	0.223	0.518	0.259
	31-44	19.50	0.136	0.484	0.380	0.317	0.303	0.380
	45-60	20.00	0.094	0.415	0.491	0.233	0.548	0.219
	Undrafted	21.50	0.066	0.357	0.577	0.423	0.577	0.00
Other	1-14	19.33	0.128	0.461	0.411	0.060	0.239	0.701
	15-30	21.00	0.0923	0.407	0.501	0.092	0.407	0.501
	45-60	23.00	0.036	0.237	0.727	0.099	0.463	0.438
	Undrafted	24.67	0.027	0.203	0.770	0.230	0.770	0.00
Other D1	1-14	20.87	0.159	0.510	0.331	0.075	0.286	0.640
	15-30	21.57	0.107	0.454	0.4340	0.107	0.454	0.440
	31-44	22.35	0.068	0.375	0.556	0.183	0.261	0.556
	45-60	22.60	0.043	0.291	0.666	0.120	0.520	0.359
	Undrafted	24.087	0.0306	0.232	0.737	0.263	0.737	0.00
Other Europe Lower	1-14	20.00	0.141	0.485	0.374	0.066	0.258	0.675
	15-30	21.60	0.105	0.441	0.454	0.105	0.441	0.454
	31-44	21.50	0.066	0.353	0.581	0.173	0.246	0.581
Other Top Europe	1-14	19.50	0.139	0.471	0.389	0.067	0.253	0.680
	15-30	19.67	0.101	0.417	0.483	0.101	0.417	0.483
	31-44	20.00	0.055	0.326	0.618	0.150	0.231	0.618
	45-60	24.00	0.040	0.261	0.700	0.112	0.479	0.408
	Undrafted	24.50	0.031	0.222	0.747	0.253	0.747	0.00
South America	1-14	20.00	0.170	0.497	0.334	0.082	0.290	0.628
	15-30	22.00	0.117	0.444	0.438	0.117	0.444	0.438
	45-60	22.00	0.0421	0.282	0.676	0.118	0.500	0.382
	Undrafted	23.00	0.0340	0.230	0.736	0.264	0.736	0.00
Spain Top	1-14	20.00	0.141	0.476	0.383	0.069	0.253	0.679
	15-30	23.33	0.087	0.403	0.510	0.087	0.403	0.510
	31-44	21.500	0.056	0.324	0.622	0.150	0.228	0.622
	45-60	23.00	0.043	0.273	0.684	0.116	0.495	0.389
	Undrafted	28.00	0.0323	0.228	0.739	0.261	0.739	0.00
Top D1	1-14	20.50	0.116	0.470	0.414	0.053	0.231	0.716
	15-30	21.27	0.076	0.396	0.528	0.0758	0.396	0.528
	31-44	21.89	0.049	0.313	0.639	0.135	0.227	0.639
	45-60	22.71	0.033	0.243	0.724	0.094	0.482	0.424
	Undrafted	23.77	0.0215	0.177	0.802	0.198	0.802	0.00

Table 12: League Pick Outcome Rates