How Rare Is It to Be Average in the NBA?

A Statistical Exploration of Player Balance in Points, Rebounds, Assists, Steals, and Blocks

Prepared by:

Michael Nguyen

Course/Instructor:

Probability and Applied Statistics

Byron Hoy

Institution:

Stockton University

Date:

May 2025

Introduction

The NBA is a league that is built around theatrics and outliers. The media will talk endlessly back and forth on the all time greats like Michael Jordan and Lebron. Countless highlight dunks, buzzer beaters, outrageously high point total games; these are the moments that define a player's legacy and shape their perception in the public eye. But underneath the surface of this lies a more subtle, stable foundation for the league; statistical averageness. This report is an examination of how truly rare it is to be a statistically average NBA player. We will explore past the outliers, both good and bad. What lies beneath dominance? What rises above mediocrity? This report aims to answer these questions by looking across the 5 major statistical categories in the NBA. These are points, assists, rebounds, blocks, and steals. These will all be analyzed on a per game basis. Contrary to what may be intuition for some, being "average" across the board for an NBA player is not common. In fact, it is a statistical anomaly. The data shows that players tend to stand out in some way, either positively or negatively. Few players maintain a consistent middle ground profile. Through the use of probability theory, statistical modeling, and the stats from the 2024-2025 NBA regular season we investigate how rare it is to be statistically average in the NBA.

To avoid skewed conclusions, it's important that we evaluate players that had a meaningful impact throughout the regular season. There are players that play very brief minutes, or those that play only a few games that can heavily impact our statistical analysis. To combat this, we used set theory to define what makes a player eligible to be considered in our analysis.

Two sets were defined :

Set A : These are players that averaged more than 20 minutes per game. This is 268 total players.

Set B : These are players that played in at least 41 games (exactly half of the amount of games in the regular season). This is a total of 340 players.

We then took the intersection of these two sets A and B to achieve our set S.

$S = A \cap B = 226\, players$

These 226 players form the pool of qualified players for our analysis. These players are the regular contributors whose statistics represent sustained performance across the course of the entire season. Using this framework will ensure that we are avoiding outliers or small-sample anomalies in our definition of what it means to be average.

Set theory provides an intuitive and powerful way to define inclusion criteria. By using the intersection of these well-defined sets, we apply a strict mathematical layer to what would otherwise be subjective thresholds. With a qualified player pool established, the next step was to define what we mean by "statistically average." This required a consistent, mathematically sound definition across all five core statistical categories.

What does it mean to be average for our purposes?

In this report, statistical averageness is defined using a flexible range; a player is considered average in a major statistical category if they fall within 15% of the league mean for that stat.

For example, since the mean PPG (points per game) was 14.18, then a player would be considered average in scoring if they scored between 12.05 and 16.31 points per game.

We applied this definition across all 5 major statistical categories :

-Points (PPG)

-Rebounds (RPG)

-Assists (APG)

-Steals (SPG)

-Blocks (BPG)

Next, we counted how many of these five categories each player was average in. The distribution is laid out as follows :

-0 categories : 32.3%

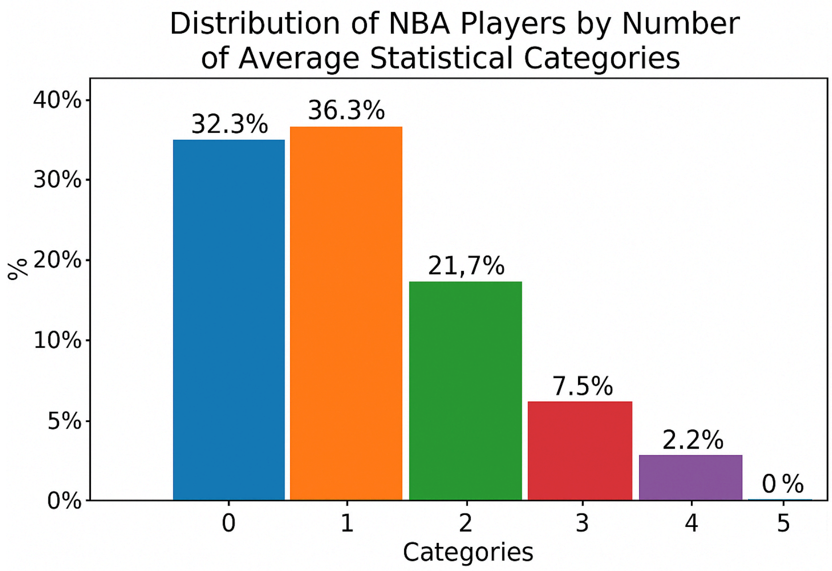
-1 category : 36.3%

-2 categories : 21.7%

-3 categories : 7.5%

-4 categories : 2.2%

-5 categories : 0%



The takeaway from these statistics is that nearly 7 out of every 10 NBA players

P(0)32.2% + P(1)36.3% = 68.6%

are average in either one or zero statistical categories. This result is counterintuitive. Most people tend to think of being "average" as a common quality, but in reality, most players are far from average in at least one area either due to their strengths or weaknesses. Even more surprisingly, there are 0 players that are average across all five statistical categories by our definition.

In an effort to put some names and context to these statistics and percentages here are some players from each section.

Average in 1 Category

Aaron Nesmith

Aaron Wiggins

Alperen Şengün

Average in 2 Categories

Al Horford

Andrew Wiggins

Kelly Oubre Jr.

Average in 3 Categories

Aaron Gordon

Cade Cunningham

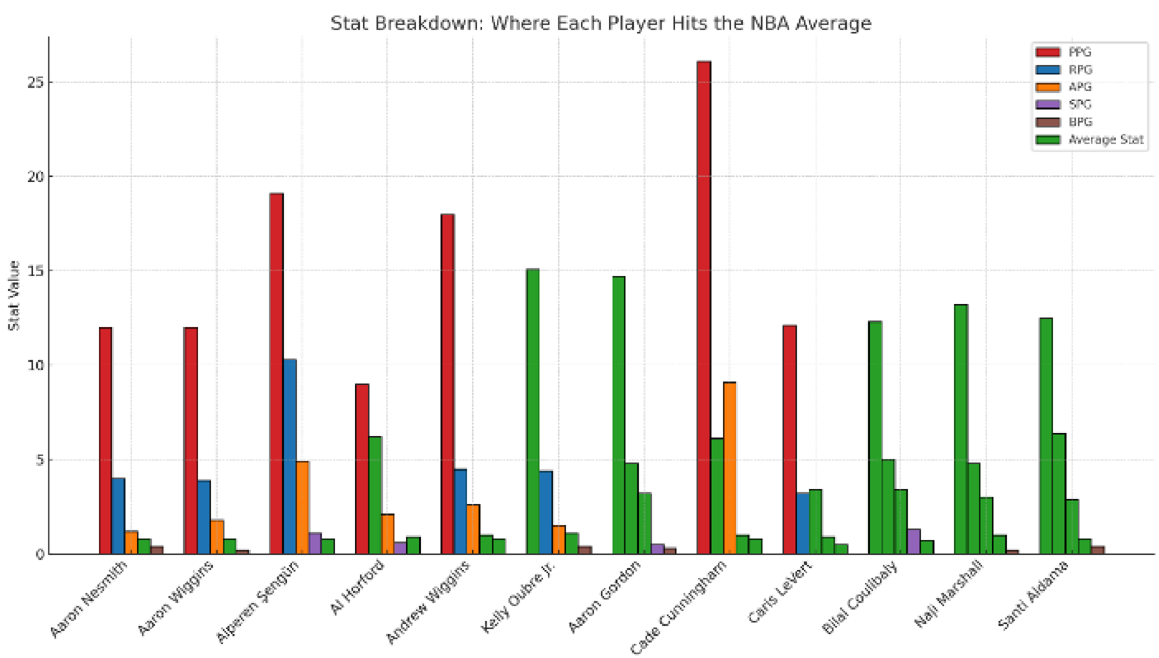
Caris LeVert

Average in 4 Categories

Bilal Coulibaly

Naji Marshall

Santi Aldama



Once we identified which players met our criteria for averageness in each category, we tallied how many players were average in multiple categories. This distribution revealed just how uncommon statistical balance really is.

We calculated the expected value (mean) for number of average stats per player using weighted probabilities :

$E|X| = 1.11$

This means that, on average, players are only statistically average in slightly more than one category out of the five we are analyzing. A truly balanced stat line is very rare. While raw counts are useful, deeper insight can be gained by exploring relationships between categories. Do average scorers tend to also be average in other stats? This led to our examination of conditional and joint probabilities.

Are stats related to each other? (conditional and joint probabilities)

Being average in one stat does not guarantee one to be average in another. But does it increase the likelihood?

We calculated conditional probabilities against PPG for the other four categories :

- P(TRB | PPG) = 41.4%
- P(AST | PPG) = 27.6%

- P(STL | PPG) = 25.9%
- P(BLK | PPG) = 19.0%

So, even if a player is average in points, they are not likely to be average in blocks or steals. The strongest correlation is between scoring and rebounding. This may be a reflection of the role that bigs (Power forwards and Centers) play in the grand scheme of the NBA.

Curious whether statistical balance is influenced by position, we applied Bayes' Theorem to evaluate the relationship between player position and scoring consistency.

Does Playing a Certain Position Make You More or Less Likely to be average?

Next we used Bayes' Theorem to answer the question : if a player is average in scoring, what is the probability that they are a big man? Again, for our purposes a "Big" is referring to either a Center or Power Forward

- P(PPG) = 58 / 226 = 0.257
- P(Big) = 84 / 226 = 0.372

- P(PPG | Big) = 19 / 84 = 0.226

Using Bayes' Rule:

P(Big | PPG) = (0.226 * 0.372) / 0.257 = 0.327

This data shows that approximately 32.7% of all average scorers are bigs. This is useful information : big men are not resigned to just playing defense, protecting the rim, or fighting for a rebound. A decent portion of them also contribute balanced, middle-of-the-pack scoring. This tells us that averageness spans many positions and not just one specific one.

While this positional insight was centered on scoring, we expanded our analysis to include how many statistical categories players from each role were average in. We grouped players into three archetypes based on their listed position:

- **Ball Handlers**: Point Guards
- **Wings**: Shooting Guards and Small Forwards
- **Bigs**: Power Forwards and Centers

Then, for every player who was average in 1, 2, 3, or 4 categories (out of the 5 total), we counted how often each role appeared. Here are the results:

# of Categories Average In	Ball Handlers	Wings	Bigs
1 Category	15	44	24
2 Categories	7	21	21

3 Categories	2	4	11
4 Categories	0	2	2
Total (1–4)	**24**	**71**	**58**

This breakdown reveals a surprising trend: wings are most likely to land in the "average" zones, dominating the 1-category group and remaining steady across 2 to 4. Bigs make up the majority of players in the 3- and 4-category range, suggesting they're the most well-rounded contributors statistically. Ball handlers, on the other hand, are the least likely to reach multiple statistical averages, highlighting the specialized and assist-heavy role most point guards play in modern basketball.

To model and quantify the rarity of statistical balance, we applied several discrete probability distributions. These mathematical tools help estimate how likely it is to find players with average stats in multiple categories.

Probability Distributions That Model Rarity

To further investigate how unlikely it is for players to be statistically average, we applied several probability distributions. Each model offers a different lens on how "rare" this kind of balance truly is, especially when selecting players at random from the league.

Binomial Distribution – The Odds of Hitting 5-for-5

The binomial distribution helps answer: *What are the chances that a player randomly ends up being average in all five categories — points, rebounds, assists, steals, and blocks — if the average* *probability for each is around 22.2%(found by adding % of average players in each category and dividing by 5)?*

$$P(X = 5) = \binom{5}{5}(0.222)^5(1 - 0.222)^0 \approx 0.00054$$

There's about a 0.05% chance (1 in ~1,850) that a randomly selected player would be average in all five categories. That aligns perfectly with our data, where **zero players** fit this profile.

Geometric Distribution – Waiting for an Average Player

The geometric distribution is ideal for modeling how long we might expect to wait before encountering a player that is average in at least one category.

If 22.2% of qualified players are average in any given category, what's the chance the first average player appears on the 5th trial?

$$P(X = 5) = (1 - 0.222)^4 \cdot 0.222 \approx 0.06449$$

There's about a **6.4% chance** that it would take until the 5th player to find an average one — not very likely, but certainly not impossible. This reflects the moderate rarity of averageness even in a single stat.

Negative Binomial Distribution – Reaching a Target

Suppose you're trying to build a team with 3 players who are each average in at least one stat. The negative binomial distribution can tell us how many players you'd need to sample, on average, before hitting that quota.

Using the same average probability of 22.2%, the expected number of trials is:

$$E(X) = \frac{r}{p} = \frac{3}{0.222} \approx 13.5$$

You'd need to evaluate about 13–14 players just to get 3 average performers — reinforcing how skewed the league is toward specialization.

Hypergeometric Distribution – Drawing from a Small Pool

Let's say a team is selecting **4 players from a pool of 226 qualified players**, and you want to know the chances **all 4 are average scorers** (where 58 of the 226 are average in PPG).

Using the hypergeometric formula:

$$P(X = 4) = \frac{\binom{58}{4}\binom{168}{0}}{\binom{226}{4}} \approx 0.01806$$

Even under generous assumptions, there's only a 1.8% chance that 4 randomly selected players will all be average in scoring. That's rarer than many would expect, showing just how clustered scoring tends to be around extremes.

Using these models we reinforce just how rare statistical balance really is in the NBA. whether selecting a handful of players or simulating a large number of trials, the odds of finding someone that is average across the board is incredibly slim.

Of course, some stats — especially those like points per game — are best modeled as continuous variables. We shifted our focus to continuous distributions to explore how traits like scoring are spread across the league.

---

7. Continuous Distributions and Real-World Shapes

For continuous data like PPG, we used a normal distribution: Mean = 14.18, Std Dev = 5.96

- Using this model: P(12.05 X 16.31) = 27.9%

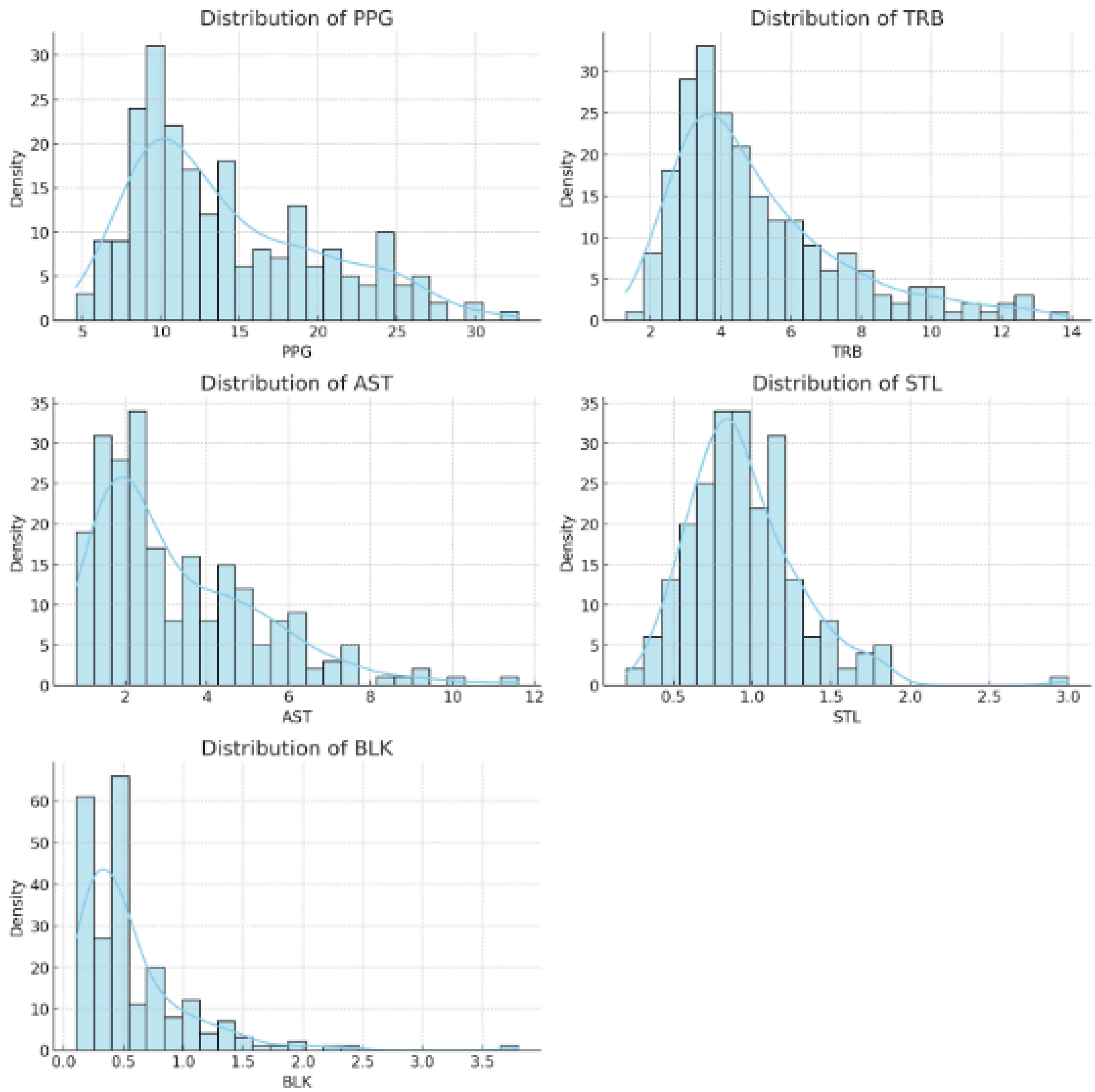
So fewer than 3 in 10 players fall in the 'average' range for scoring.

Tchebysheff's Theorem also supported the observation that most players fall close to the mean:

At 1.5 standard deviations, at least 55.6% should fall in that range — we observed 87.2%.

However, not all stat categories follow a normal distribution. In fact, many exhibit **right-skewed behavior**, meaning that a majority of players post low values, while a small minority produce extremely high numbers. This is most visible in stats like **blocks, steals, and assists**, where rare high-end performances skew the overall distribution.

We found that **gamma distributions** fit these stat categories well due to their positive skew and long right tail. To illustrate this point, we visualized the distributions of each of the five major statistical categories:



We also challenged one assumption head-on: what if certain stats followed a uniform distribution? Assists provided a compelling case study.

---

8. The Case of Assists and Uniformity

To challenge our assumptions, we applied a uniform distribution model to assists: U(0, 10)

- The average AST range was between 2.77 and 3.75
- Width of this range: 0.98
- Probability under uniform: 0.98 / 10 = 9.8%

However, actual data showed 20.8% of players fell in this range. This reveals that assists cluster more than expected, a sign of role specialization and team strategy.

While the findings in this report are compelling, it's important to acknowledge what this report does and does not cover. The following section outlines the limitations of this analysis and opportunities for deeper exploration.

Limitations & Further Research

While this report provides a data-driven exploration of statistical averageness in the NBA, several limitations are worth noting. First, the analysis focuses exclusively on traditional box score statistics — points, rebounds, assists, steals, and blocks — and does not include advanced metrics such as Player Efficiency Rating (PER), Box Plus-Minus (BPM), or on/off impact. This report also doesn't take efficiency stats such as Field Goal Percentage (FG%), 3-Point Percentage (3P%), Free Throw Percentage (FT%) into account when defining the 'average' player. These advanced and efficiency statistics would do a lot to help better shape the mold of the average NBA player than just the counting stats that we have provided.

Second, all statistics are measured on a per-game basis, which may not account for fluctuations in usage, team role, or game context. A player who averages near the mean in several categories might achieve those numbers through inconsistent or streaky performance, rather than true balance.

Additionally, the classification of "average" as within ±15% of the league mean is a defensible but somewhat arbitrary threshold. Slight changes in that window could materially affect who qualifies.

Lastly, this report is a cross-sectional analysis of a single season. Future research could explore longitudinal consistency in averageness, player trajectories, or correlations with team success.

Conclusion :

The NBA is often viewed through the lens of extremes — the highest scorers, the most dominant defenders, the flashiest playmakers. But this report set out to explore a different angle: what does it mean to be average in a league built around outliers, and how common is that statistical balance?

After analyzing five major statistical categories — points, rebounds, assists, steals, and blocks — across qualified players from the 2024–2025 NBA season, the answer is clear: being average is surprisingly rare. Nearly 70% of players were average in zero or only one category. None were average across all five. The expected number of average stats per player? Just a little over one.

The data doesn't just show rarity; it reveals how NBA roles are deeply specialized. Players don't settle in the middle — they gravitate toward strengths or struggle in certain areas. Even tools from probability theory and statistical modeling reinforced this, whether through binomial, geometric, Poisson, or normal distributions. Each lens pointed to the same truth: statistical balance is the exception, not the norm.

So while the league celebrates its stars — and rightly so — it's worth recognizing that the quiet, balanced contributor isn't just underappreciated. They're statistically extraordinary.

Category	Mean	±15% Range	# Avg Players	% Avg Players
PPG	14.18	12.05–16.31	58	25.7%
TRB	5.65	4.80–6.50	65	28.8%
AST	3.26	2.77–3.75	47	20.8%
STL	0.89	0.76–1.02	39	17.3%
BLK	0.79	0.67–0.91	33	14.6%

This report uses player statistics from the 2024–2025 NBA regular season. Only players who played at least 41 games and averaged more than 20 minutes per game were included, resulting in a qualified sample of 226 players. All statistics are measured on a per-game basis and sourced from official NBA records and Basketball Reference. A player is considered “average” in a category if their per-game stat lies within ±15% of the league mean among the qualified player pool.

Works Cited

Basketball-Reference.com. (2025). *2024–25 NBA player stats*. Sports Reference LLC. https://www.basketball-reference.com/leagues/NBA_2025_totals.html