Offensive Putbacks, Why Bother?

The Art of Exploiting the Extra Possession

By Christian Hanish

Introduction

On February 21st, the Lakers erased a 19-point second half deficit against the Houston Rockets en route to their largest comeback victory of the season. Aside from LeBron James' near triple-double and Brandon Ingram's season-high 13 rebounds, a deeper dive into the game film affirmed that the driving force behind LA's come from behind win was actually their second chance scoring and 3PT shooting efficiency. Not only did the Lakers capitalize on 12 offensive boards to the tune of 21 second chance points, but they did so by knocking down 3-of-4 second chance three-pointers and resetting their offense 42% of the time following an offensive rebound. Similarly, just six weeks earlier, the Lakers used 20 more second chance points to fuel yet another double-digit second half comeback over the Kings. Comparable to their victory against Houston, the Lakers reset their offense a staggering 58% of time following offensive rebounds versus Sacramento, and connected on 4-of-6 second chance three-pointers - including two in the final 4 minutes - to ignite a resurgent 18-4 run to close the game. Subsequently, this pair of improbable comebacks got me thinking: what is the optimal strategy for scoring on extra posessessions, and just how efficient are second chance 3PA?

Objectives & Datasets

Throughout this study, we will be exploring league-wide statistical trends and tendencies associated with extra possessions, comparing efficiency margins between putbacks and resets, as well as, assessing three-point shooting percentages following offensive rebounds in order to determine the optimal strategy for capitalizing on second chance opportunities. To conduct this analysis, we will be drawing upon three primary datasets that have been customized and extracted from Second Spectrum, Synergy, and Basketball Reference. Among these datasets, the first is comprised of a randomly selected sample of 82 games encompassing all 30 teams during the 2018-19 season. This will be referred to as the "NBA Dataset" and its purpose will be to provide league-wide statistical context for the study. The second dataset is composed of all 82 Lakers games during the 2018-19 season. This will be referred to as the "Lakers Dataset" and used to juxtapose the Lakers' tendencies with league averages. The third dataset consists of the 55 Lakers games in which LeBron James played this season. This will be referred to as the "Lakers Dataset w/ LeBron" and used to highlight the differences in Lakers efficiency and second chance tendencies when he takes the court.

Trends & Tendencies

According to the NBA Dataset, putbacks occurred 16% more often than resets yet yielded 2% fewer second chance points around the league during the 2018-19 season. As displayed in Figure 1 below, 58% of the league's offensive rebounds resulted in putbacks while 51% of second chance points were scored by resetting the offense. The Lakers, also shown below in Figure 1, posted nearly identical numbers, attempting putbacks 58% of the time while scoring 52% of their second chance points via offensive resets. Therefore, while it is evident that offensive resets produce points at a more efficient rate than offensive putbacks, the question now becomes just how large is the margin?

Figure 1

Breakdown of Second Chance Possessions

Outer Circle: % of PTS vs. Inner Circle: % of POSS

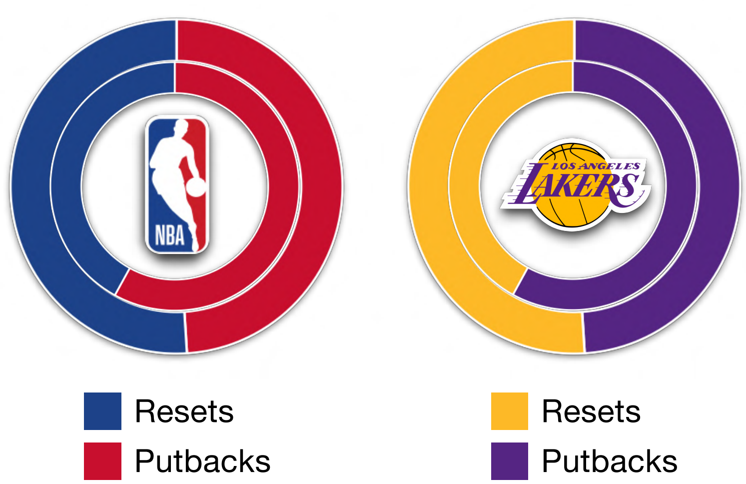
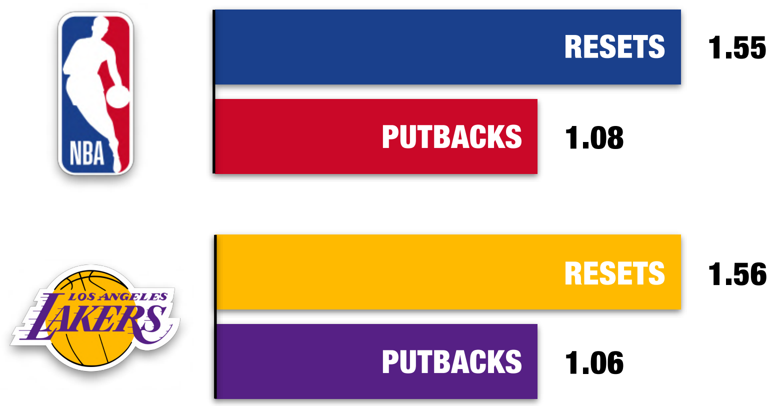


Figure 2

Scoring Efficiency via Offensive Rebounds

Play Type w/ Points Per Possesion (PPP)



Putbacks vs. Resets

According to the NBA Dataset, offensive resets produced 43% more points per possession than offensive putbacks during the 2018-19 season. Specifically, offensive resets yielded 1.55 PPP - an astonishingly efficient amount that ranks considerably higher than the league-wide efficiency of any other team play or shot type tracked on the Synergy platform. The Lakers Dataset exhibited similarly staggering results, as the purple and gold poured in 1.56 PPP via offensive resets during the 2018-19 campaign. This amount is 47% higher than the 1.06 PPP they scored via offensive putback attempts.

Upon first glance, the efficiency of offensive putbacks was remarkably lower than anticipated. However, after further consideration and film evaluation, it became evident that offensive putbacks are not your ordinary, high-percentage attempt around the basket. Rather, putbacks are subject to an array of variables - including frenzied play and awkward shot angles, hesitation and middling scoring acumen by the offensive rebounders, even stifling double or triple teams given the close proximity to the basket - that dramatically diminish the shot's quality. To further support this point, the league-wide efficiency of shots around the basket was 1.18 PPP this season - 8% higher than the efficiency of putbacks. Thus, supporting the notion that there is more to offensive putbacks than meets the eye.

Alternatively, while the efficiency of offensive resets was substantially higher than expected, its justification is far simpler to pinpoint and revolves around the emergence of the three-point shot. To illustrate, catch and shoot threes are among the most efficient shot attempts in the game due to their combination of increased value while minimizing the shooter's movements. But what if we could streamline the player's shooting mechanics even further? This is essentially what is happening on second chance three-point attempts. Because the majority of offensive rebounds and ensuing kick-outs occur directly under the basket, the perimeter shooters receiving the passes are able to eliminate the need to turn their body and face the rim, thus isolating their catch and shoot motions even further. That said, just how efficient are second chance threes and why don't teams shoot them more often?

Second Chance 3PA

According to the NBA Dataset, teams shot 10.4% higher and scored 32% more points per shot (PPS) on three-point attempts following offensive rebounds than they did on all other three-point attempts combined during the 2018-19 season. Specifically, teams knocked down a blistering 43.8% of three-point attempts following offensive rebounds and cashed in 1.32 PPS on such attempts. In contrast, teams shot a rather pedestrian 33.4% and netted just 1.00 PPS on all other 3PA this season.

Likewise, both Lakers datasets also demonstrated notable improvements in 3P% and PPS efficiency on second chance three-pointers. Accoring to the Lakers Dataset w/ LeBron, the team shot 4.3% higher and scored 13% more PPS on three-point attempts following offensive rebounds than on all other attempts. Similarly, the Lakers Dataset revealed that LA shot 3.0% higher and scored 9% more PPS on second chance three-point attempts throughout the season as a whole. For contextual purposes, it's worth nothing that while the Lakers' second chance 3PT efficiency margins may pale in comparison to the rest of the league, it is indeed representative of the team's season-long struggle from beyond the arc that rendered them 29th in the league in 3P%. Nonetheless, the data confirms the eye test that second chance, kick-out 3PA are among the most efficient shots in today's game.

Now that we have effectively established the statistical advantages of resets over putbacks, as well as, highlighted the impressive levels of efficiency associated with second chance threes, let's calculate the frequency with which both plays occur and explore their effects on LA winning games.

Figure 3

Advantage of Shooting Second Chance Threes

3P% Following ORBs vs. 3P% All Other Attempts

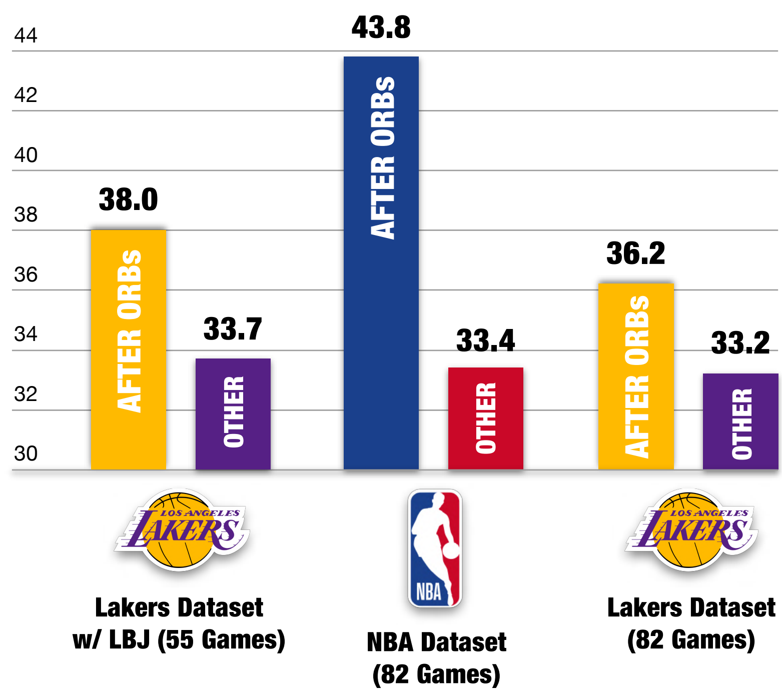


Figure 4

Detailed View: Resets Following ORBs

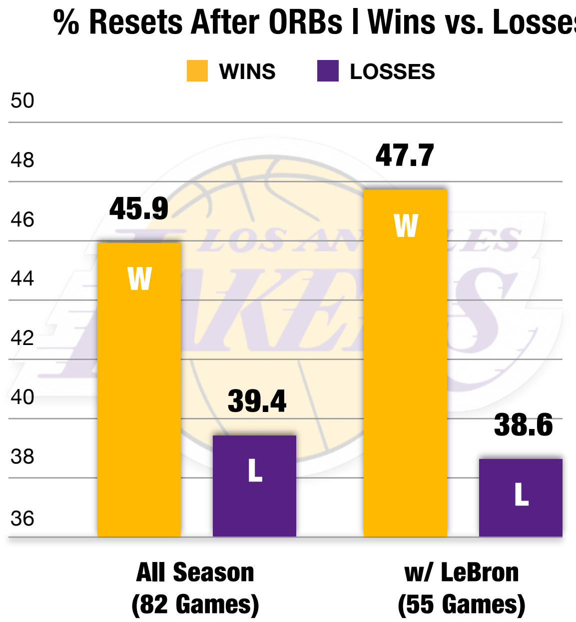
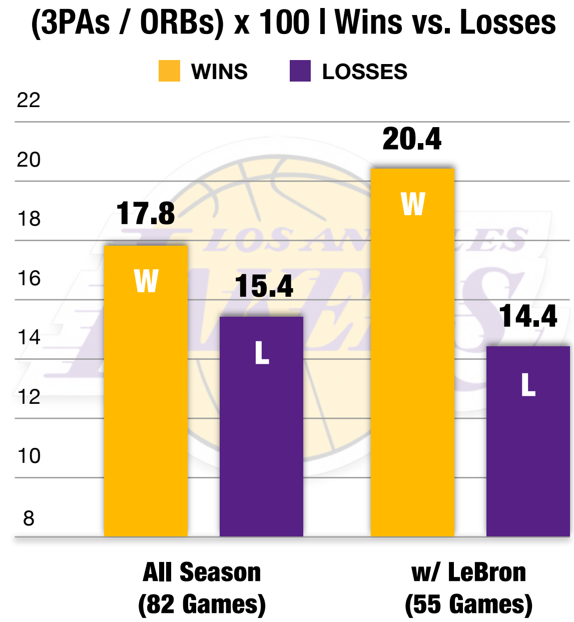


Figure 5

Detailed View: 3PAs Following ORBs



Correlation to Winning

According to the Lakers datasets visualized above in Figure 4, Los Angeles reset their offense 6.5% more often during their 37 wins than during their 45 losses this season - including 9.1% more often during their 28 wins than during their 27 losses with LeBron James. Even more eye-opening, when the Lakers reset their offense at least 45% of the time following an offensive rebound, their record was 20-19 (51.3% win percentage) overall and 17-10 (63.0% win percentage) with LeBron. Conversely, when the Lakers reset their offense less than 45% of the time, their record was just 17-26 (39.5% win percentage) overall and 11-17 (39.3% win percentage) with LeBron this season.

Furthermore, according to the Lakers datasets exhibited above in Figure 5, Los Angeles attempted second chance three-pointers 2.4% more often during their 37 wins than during their 45 losses this season - including 6.0% more often during their 28 wins than during their 27 losses with LeBron James. Also noteworthy, when the Lakers attempted second chance three-pointers at least 20% of the time following an offensive board, their record was 15-16 (48.4% win percentage) overall and 13-8 (61.9% win percentage) with LeBron. Meanwhile, when the Lakers attempted second chance three-pointers less than 20% of the time following an offensive board, their record was just 22-29 (43.1% win percentage) overall and 15-19 (44.1% win percentage) with LeBron this season.

Thus, as outlined above, the Lakers winning percentage was markedly higher when the team reset their offense and attempted second chance three-pointers with greater frequency following offensive rebounds. Furthermore, the correlation was underscored even more dramatically during the 55 games in which LeBron James donned the purple and gold during the 2018-19 NBA season.

Conclusion

In summary, the primary takeaways of this research are threefold. The first conclusion involves the counterintuitive relationship between the efficiency and frequency of offensive resets and offensive putbacks around the league during the 2018-19 season. Specifically, according to the NBA and Lakers Datasets, we determined that resets resulted in 43-47% greater efficiency yet were utilized 16% less frequently than putback attempts following offensive rebounds. We also concluded that offensive putbacks involve a greater degree of difficulty than was presupposed, and determined that they produce 8% fewer points per possession than the league's average shot around the basket.

Second, we analyzed the factors sparking such high-levels of reset efficiency by quantifying the remarkable statistical advantages associated with second chance 3PA. Particularly, the NBA Dataset observed second chance 3PA falling at a near 44% clip and producing 32% more points per shot than the league's average attempt from beyond the arc. We also demonstrated the positive impact that LeBron's presence had on the Lakers' second chance 3PT efficiency by showing that LA connected on 38% of such attempts and poured in 1.14 points per shot when The King took the court this year.

Third, we thoroughly illustrated the overwhelmingly positive effects that offensive resets and second chance 3PA had on the Lakers winning games during the 2018-19 season. Specifically, according to the Lakers Dataset w/ LeBron, the Lakers increased their team winning percentage by 23.7% and played like a 52-win team when they reset their offense at least 45% of the time following an offensive rebound. Moreover, also according to the Lakers Dataset w/ LeBron, LA improved their team winning percentage by 17.8% and played like a 51-win team when they attempted second chance threes at least 20% of the time following an offensive rebound.

In parting, I challenge anyone reading this to evaluate these findings from the perspective of the efficiency renaissance currently sweeping through the league. If the objective of every trip down the court is to find the most efficient attempt available, then why should the strategy change when second chance possessions present themselves? The statistical evidence is undeniable and the analytical awareness is becoming ingrained within the players. Now, the opportunity is ripe for the taking.

About the Author

Christian Hanish is a recent graduate of Pepperdine University, where he just earned his Master of Science (M.S.) in Applied Analytics. During the 2018-19 season, he performed quantitative analysis & research for the UCLA Bruins. In addition, he also served as the Graduate Assistant & Director of Analytics & Strategy for the Pepperdine Waves. This project has been completed as a series of post-graduate research & designed to aid the Lakers analytics department.

The Golden Age of Backup PGs

Identifying Point Gods in the NBA Draft

By Christian Hanish

Introduction

Thanks to him, Kawhi Leonard received his second all-but-unanimous NBA Finals MVP award on Thursday night. No, I'm not talking about the one media member who failed to vote for Leonard (we're looking at you Hubie Brown), but rather the player who stole that one lonesome tally. His name is Fred VanVleet, the Raptors' diminutive backup point guard who provided elite playmaking abilities for Toronto's bench mob and took center stage during Game 6 of the NBA Finals. Ironically, nearly three years to the day prior to his national coming out party, VanVleet was overlooked by all 30 teams *(twice)* in the 2016 NBA Draft. To the casual observer, Fred VanVleet came out of nowhere to provide a jolt of energy at the tailend of the Raptors' epic playoff run. But, to those who followed Canadian basketball closer this season, they were well-aware of the consistent and reliable presence that FVV provided Toronto's second-unit all year long. During the 2018-19 NBA season, there were many backup point guards across the league who demonstrated similarly effective, multidimensional value for their respective organizations. From VanVleet to Tyus Jones to Monte Morris, backup PGs have quietly become one of the most critically important positions in the NBA. So, who's got next?

Objectives & Datasets

Throughout this study, we will be exploring statistical trends and tendencies associated with successful backup point guard play, analyzing how effectively key performance metrics such assist-to-turnover ratio translate from college to the NBA, as well as, combining advanced analytics with film evaluation in order to identify the most promising backup point guard prospect in the 2019 NBA Draft. To conduct this analysis, we will be drawing upon a robust dataset of traditional statistics and advanced metrics pertaining to the playmaking efficiencies of rising draft prospects and current NBA point guards. For the purposes of this research, we will be valuing ball-control, decision-making, and playmaking abilities as the foundational characteristics of successful, backup NBA point guards.

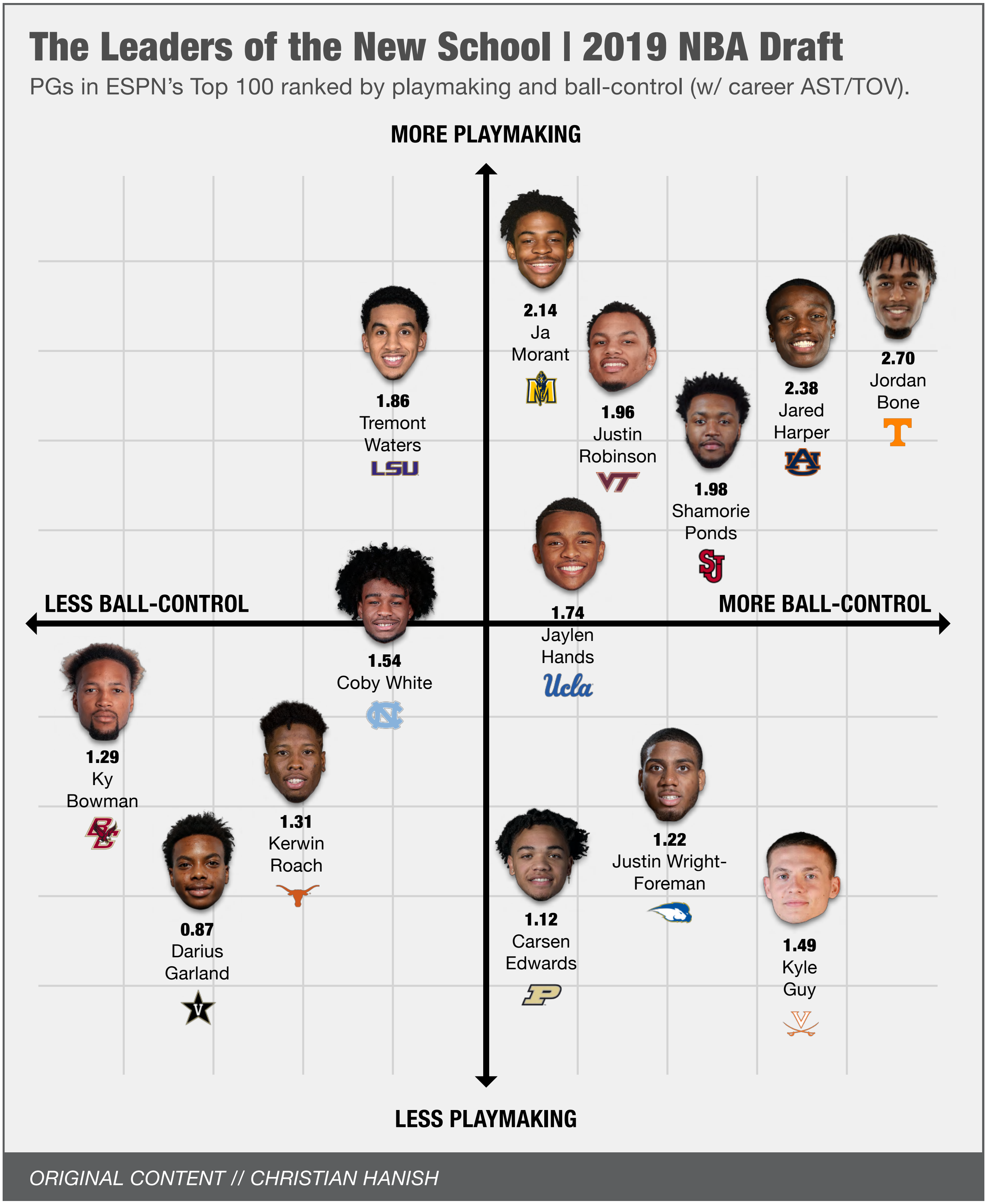
Trends & Tendencies

During the 2018-19 NBA season, the Top 5 leaders in assist-to-turnover ratio were all backup point guards for their respective teams. In fact, Minnesota Timberwolves backup floor general Tyus Jones broke the NBA's all-time single season record for assist-to-turnover ratio by racking up 327 assists and turning it over just 47 times this season for an overall ratio of 6.96. Other notable names atop the leaderboard included Denver's Monte Morris (2nd, 5.71 ratio) and none other than Game 6 hero himself Fred VanVleet (5th, 3.74 ratio). Besides the fact that all three players were widely slept on before successfully carving out their niche as backup ball-handlers in the league, they possess one notable similarity that should have given teams an indication of the success that was to come at the next-level. The common attribute is that all three players boasted remarkably high assist-to-turnover ratios throughout their collegiate careers, and, as a matter of fact, each player ranked first or second amongst their respective draft classes in that particular statistical category. But just how well does collegiate assist-to-turnover ratio translate to the NBA? The answer is overwhelmingly favorable. According to my dataset of every point guard who qualified for the NBA's assist-to-turnover metric last season, the average PG's career NBA assist-to-turnover ratio (2.44) is 35% higher than their career assist-to-turnover ratio was in college (1.81). While collegiate point guards are frequently manuevering thru tight windows and crowded spaces due to stagnant defensive schemes and sluggish paces-of-play, the NBA's rule changes open up the floor and present refreshingly wide open spaces for PGs to orchestrate their team's offense more freely. Subsequently, this bodes well for strong ball-handlers entering the league, especially those who possessed high assist-to-turnover ratios in college.

How Does Career NCAA Assist-to-Turnover Ratio Translate to the NBA?

Analysis of NBA Point Guards to Play in College & Qualify for AST/TOV in 2018-19

COUNT	NCAA AST / TOV	AVG NBA IMPROVEMENT	NOTABLE PLAYERS
6	> 2.50	+0.52 (16%)	M. Morris, F. VanVleet, T. Jones
5	2.50 - 2.00	+1.08 (50%)	C. Paul, R. Arcidiacono, C. Joseph
23	2.00 - 1.50	+0.62 (36%)	K. Irving, R. Westbrook, K. Lowry
12	1.50 - 1.00	+0.93 (71%)	D. Lillard, B. Simmons, S. Curry
2	< 1.00	+0.86 (91%)	Eric Bledsoe, Jamal Murray



The visualization showcased above provides an analytically-driven illustration of the top point guard prospects in Thursday's NBA Draft. Using a combination of assist-to-turnover ratio, as well as, AST%, TOV%, and USG%, the prospects have been arranged according to their playmaking and ball-control skills at the collegiate-level. While my positioning formula is still undergoing refinement, the results exhibited above should offer an intriguing perspective for evaluating this year's PG class.

Assist-to-turnover ratio has led us to Tennessee's **Jordan Bone**. The Volunteers' floor general showcased elite ball-control and pinpoint passing instincts during his three seasons in Knoxville. During the 2018-19 campaign, Bone led the SEC with an eye-popping 3.03 AST/TOV ratio and captained Tennessee's offense to the 3rd highest efficiency in the nation. Additionally, Bone's career 2.70 AST/TOV ratio is unparalleled amongst this year's draft class and the highest amongst draft prospects since Monte Morris' time at Iowa State. To put his consistency into perspective, Bone is the only guard in this year's class to possess an AST/TOV ratio greater than 2.00 during each of his collegiate seasons. Not only do his career AST/TOV numbers trump every prospect in this year's class, but Bone measures up favorably to several aforementioned, star PGs from previous drafts, as well. Now that we've identified our prospect of interest, let's explore Jordan's game in further detail.

COMPARISON OF COLLEGE STATISTICS:				
DRAFT POSITION	Rd 1 / Pk 24	Rd 2 / Pk 51	Undrafted	**?**
CAREER ASSISTS	217	768	637	**405**
CAREER TURNOVERS	76	165	207	**150**
AST / TOV RATIO	2.86	4.65	3.08	**2.70**
STRENGTH OF SCHEDULE*	9.9	10.3	3.9	**10.2**

**Higher numbers correspond to stronger competition.*

Analytical Breakdown

Bone's unique combination of tantalizing athleticism, supreme ball-control, and clairvoyant court vision allowed him to thrive within a variety of situations while orchestrating Tennessee's offense during his time in Knoxville. According to Synergy, the Volunteers' point guard ranked in the 95th percentile in half-court playmaking, as well as, the 82nd percentile in transition playmaking during the 2018-19 campaign. Furthermore, Bone was the only major conference player to rank Top 20 in the nation in both half-court (2.94) and transition (2.72) assist-to-turnover ratio last season.

Per Synergy, Bone was also the single most efficient major conference playmaker within the pick-and-roll (min. 100 possessions) during the 2018-19 season, as his passes yielded 1.31 points per possession. Moreover, the Volunteers scored 55.4% of the time and shot 68.6% eFG via Bone's pick-and-roll passes last year, while just 11.9% of such passes resulted in turnovers. Specifically, Bone excelled at utilizing the pick-and-roll to find spot-up perimeter shooters, as he ranked in the 96th percentile in this category and again led all major conference players in efficiency by creating 1.37 points per possession on such passes. Altogether, Bone dished out 215 assists and committed just 50 passing turnovers during his junior season, good for an elite assist-to-passing turnover ratio of 4.30.

Part of the reason why Bone is able to excel within such a wide array of in-game scenarios is due to his extraordinary athleticism and physical capabilities. During last month's NBA Combine in Chicago, Bone dazzled onlookers with his lightning-quick agility and jaw-dropping leaping abilities en route to one of the most impressive pound-for-pound performances in recent combine history. In addition to winning the shuttle run (2.78 sec) and finishing 4th in the three-quarter court sprint (3.08 sec), Bone recorded the highest standing vertical leap (36.0 inches) since Donovan Mitchell in 2017 and posted the 2nd fastest lane agility (9.97 sec) since the NBA began tracking combine data in 2000. Now that we've showcased Bone's physical and statistical proficiencies, let's analyze him in action.

Jordan Bone's 2018-19 Season

Playmaking Efficiency | By Play Type

AST / Overall TOV vs. AST / Passing TOV

PLAY TYPE	AST / TOV	AST / PTOV*
Overall	2.91	4.30
Half Court	2.94	4.46
Transition	2.72	3.77
Pick-&-Roll	2.82	4.00
Other	2.93	4.68

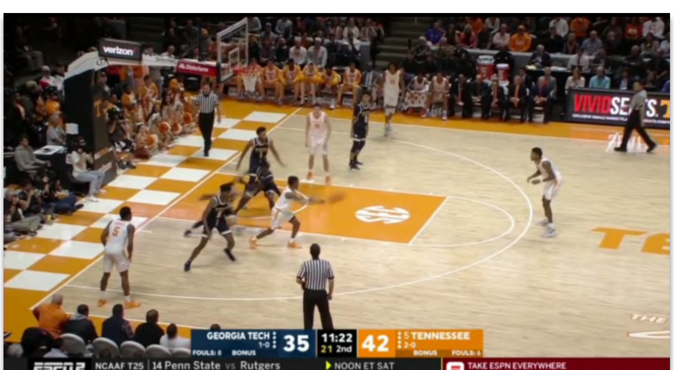
**AST / PTOV represents assist-to-passing turnover ratio.*

Video Breakdown

In the first two clips below, Bone utilizes his lightning-quick first step to attack the pick-and-roll and aggressively accelerate into the teeth of the defense. In torching the switch, Jordan expands his passing lanes by collapsing the defense and attracting the helpside-defenders. He then uses his leaping ability and court vision to elevate over the defense and find shooters for matching wide-open threes.

In the next set of clips, Jordan dribbles off the Grant Williams screens and is instantly smothered by defenders. Similar to a quarterback looking off a free safety, Bone sets up the defense by averting his eyes from his intended receiver. This subtle (yet advanced) disguise momentarily freezes the help-defenders and gives Jordan time to whip no-look passes to the cutting Williams for wide-open layups.

In the final pair of clips, Bone catches the defense off-guard by refusing the screens. In the first clip, Jordan flashes his speed off-the-dribble and creates tremendous airspace for the popping screener to catch-and-shoot. Though against Gonzaga, he exhibits outstanding composure by intentionally side-stepping the play and waiting for both defenders to engage before orchestrating the pick-and-pop 3PA.



Conclusion: Does Bone Fit in Los Angeles?

Absolutely. With the recent departure of guards Lonzo Ball and Josh Hart, as well as, the 4th overall selection in Thursday's NBA Draft that was widely rumored to belong to Vanderbilt PG Darius Garland, the Lakers find themselves in an untimely predicament. Specifically, the purple and gold covet competent, backcourt playmakers but have limited funds to expend… Enter Jordan Bone.

At the moment, Tennessee's PG is ranked 56th on ESPN's big board of the Top 100 prospects in the 2019 NBA Draft, and projected to be selected at the backend of the second round (if at all). While the Lakers do not presently possess any further draft picks, there are six teams with multiple second round selections (Hawks, Hornets, Clippers, Pelicans, 76ers, Kings) who might be persuaded to unload one in exchange for Moritz Wagner, Jemerrio Jones, Isaac Bonga, or cash considerations.

The acquisition of Jordan Bone would not only satisfy the intricate financial requirements that Los Angeles must meet in order to create $32 million-plus in salary cap space by the time the NBA's free agent moratorium concludes on July 6th, but it could also provide the Lakers with inexpensive playmaking abilities that seamlessly complement the current composition of their roster. With the impending addition of pick-and-roll savant Anthony Davis, the purple and gold's offense will be in dire need of dependable ball-handlers capable of threading the needle and feeding their brand new, multidimensional offensive weapon. In addition to Bone's innate ability to hit rolling or popping big men in stride, his proficiency at utilizing the pick-and-roll to feed spot-up perimeter shooters would be the perfect companion for the sharp-shooting prowess of Kyle Kuzma, as well.

What's more, new Lakers Head Coach Frank Vogel is no stranger to the importance of players cut from the same cloth as Jordan Bone, as backup playmakers with high assist-to-turnover ratios were foundational elements of some of his most successful Pacers teams (where he played a hand in developing point guards such as George Hill, D.J. Augustin, and C.J. Watson). Given the vast number of personnel changes and new players the Lakers will be incorporating next season, the playmaking consistency, ball-handling stability, and affordable efficiency that an experienced floor general of Bone's caliber would bring to Los Angeles presents an incredibly unique and alluring opportunity.

About the Author

Christian Hanish is a recent graduate of Pepperdine University, where he just earned his Master of Science (M.S.) in Applied Analytics. During the 2018-19 season, he performed quantitative analysis & research for the UCLA Bruins. In addition, he also served as the Graduate Assistant & Director of Analytics & Strategy for the Pepperdine Waves. This project has been completed as a series of post-graduate research & designed to aid the Lakers analytics department.

College Stats: The Good, Bad & Ugly

Analyzing Point Guards & Playmaking Metrics w/ Predictive Modeling & Machine Learning

By Christian Hanish

Introduction

In our last report, we analyzed the incoming crop of collegiate point guards from the 2019 NBA Draft. Specifically, we utilized career assist-to-turnover ratio to determine which prospects projected as the best floor generals at the next-level. Our rationale for using assist-to-turnover ratio was that it conveniently combined insights about each prospects' playmaking and ball-control skills into one concise metric. Moreover, assist-to-turnover ratio proved to translate quite positively from college to the NBA, as 94% of the players observed in our dataset improved upon their collegiate ratios in the pros. However, upon further consideration we concluded that such NCAA-to-NBA improvement does not necessarily indicate strength as a predictor of future performance, nor does it inherently imply that it's the best metric available. Subsequently, the purpose of this study will be to sift through a variety of playmaking metrics in order to determine which collegiate statistics provide the most valuable insights into evaluating PG prospects and forecasting future NBA performance. Furthermore, we will also identify alternative metrics that are less mainstream yet provide more accurate insights into the players' on-court abilities and instinctive tendencies that will determine their fate at the NBA level.

Objectives & Datasets

Throughout this study, we will be utilizing regression analysis to evaluate the predictive power of various playmaking metrics, employing machine learning techniques to forecast the future NBA contributions of top draft prospects, as well as, using powerful Python programming frameworks and compelling data visualizations to effectively illustrate our findings. To conduct this research, we will be drawing upon a robust dataset of traditional, advanced, and customized statistics pertaining to the playmaking, ball-control, and decision-making abilities of recent draft prospects and current NBA point guards. To illustrate, our dataset is comprised of the four-dozen point guards who qualified for the league's assist-to-turnover leaderboard during the recent 2018-19 NBA season, and include an array of variables ranging from collegiate production to NBA efficiencies to combine measurables. Moreover, each individual players' statistics are based upon their career averages at both the NCAA and NBA levels. To reiterate the notions put forth in the introduction, the primary objectives of this report will be to pinpoint which college metrics are most indicative of sustainable growth at the next-level, as well as, which college prospects project as the most well-rounded point guards in the NBA.

Trends & Tendencies

During the 2018-19 NBA season, more than 50 point guards qualified for the league's assist-to-turnover statistic, which requires at least 200 assists for consideration. From this list, 48 of the players had collegiate careers before transitioning to the NBA, thus rendering themselves suitable for this study. The advantage of drafting our dataset based upon criterion as flexible as assist-to-turnover ratio was that it does not discriminate against non-starters, instead providing valuable insights into players from all walks of the NBA. Subsequently, our dataset is composed of a wide variety of talent, including lottery-picks turned superstars like Russell Westbrook and James Harden, four-year starters turned undrafted backups like T.J. McConnell and Ryan Arcidiacono, as well as, mid-round draftees turned late bloomers like Spencer Dinwiddie and Derrick White. Moreover, we have put together a list of variables that should provide diversified insights into each players' career arcs and styles of play. Before jumping into analysis, let's explore the descriptive statistics to get a better feel for our dataset.

Descriptive Statistics of Our Study's Dataset

Analysis of NBA Point Guards to Play in College & Qualify for AST/TOV in 2018-19

	MEAN		STDEV		MIN		MAX	
VARIABLES	NCAA	NBA	NCAA	NBA	NCAA	NBA	NCAA	NBA
APG	4.4	5.0	1.4	1.9	1.8	2.3	8.7	9.7
AST%	27%	28%	7%	7%	12%	15%	49%	46%
TPG	2.5	2.1	0.8	0.9	1.1	0.6	5.2	4.1
TOV%	16%	15%	3%	3%	10%	7%	23%	22%
AST / TOV	1.81	2.44	0.64	0.78	0.94	1.31	4.65	5.74
AST% / USG%	1.16	1.30	0.32	0.34	0.45	0.61	1.83	2.17

Assists Per Game vs. Assist Percentage

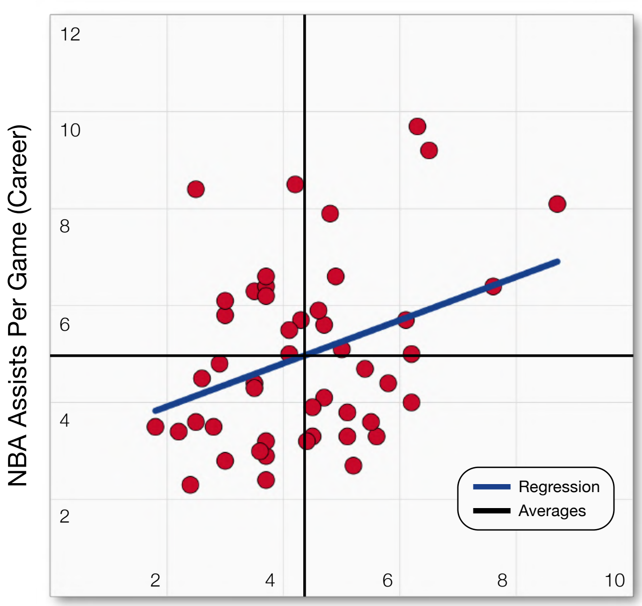
Let's kick things off by utilizing bivariate regression analysis to investigate how well several of the most frequently used playmaking metrics translate from college to the NBA. Using the players' career collegiate statistics as independent variables and career NBA statistics as dependent variables, we can quickly construct an ordinary least squares (OLS) regression model and implement the ggplot2 package within R to generate two-way scatter plot visualizations for evaluating our model.

The first metric that we will investigate is assists per game (APG). While APG is arguably the most commonly used statistic for referencing collegiate playmaking ability, this popular passing metric proves to be a poor indicator of future NBA performance. Specifically, the model's correlation coefficient (R) is just 0.35 while the coefficient of determination (R-Squared) is only 0.12. Thus, despite being statistically significant at the 95% confidence interval, the NCAA-to-NBA correlation for APG is very weak and the model is quite poor. Surely, there must be a stronger metric available.

Alternatively, let's consider assist percentage (AST%). By measuring assists on a possession-by-possession basis rather than a game-by-game basis, we can minimize the effects of endogeneity created by average playing time in the APG equation. The effects of using AST% include stronger models results, greater correlation between our variables, as well as, statistical signficance at the 99.9% confidence interval. Thus, AST% clearly translates more effectively from college to the NBA than does APG, yet there remains much room for improvement. Next, let's examine turnover metrics.

Assists Per Game (APG)
Correlation Between NBA & NCAA

R = 0.345 | P-Value = 0.0162 | R-Squared = 0.119

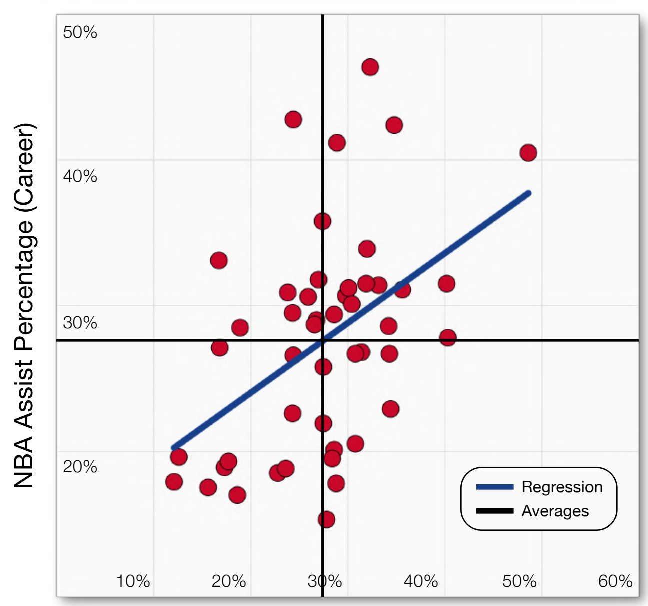


NCAA Assists Per Game (Career)

NBA APG = 3.02 + 0.45(NCAA APG)

Assist Percentage (AST%)
Correlation Between NBA & NCAA

R = 0.466 | P-Value = 0.0009 | R-Squared = 0.217

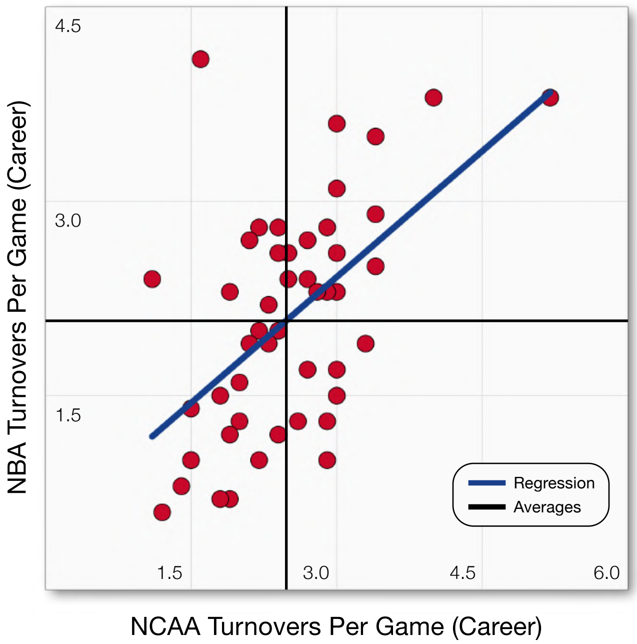


NCAA Assist Percentage (Career)

NBA AST% = 0.14 + 0.48(NCAA AST%)

Turnovers Per Game (TPG)
Correlation Between NBA & NCAA

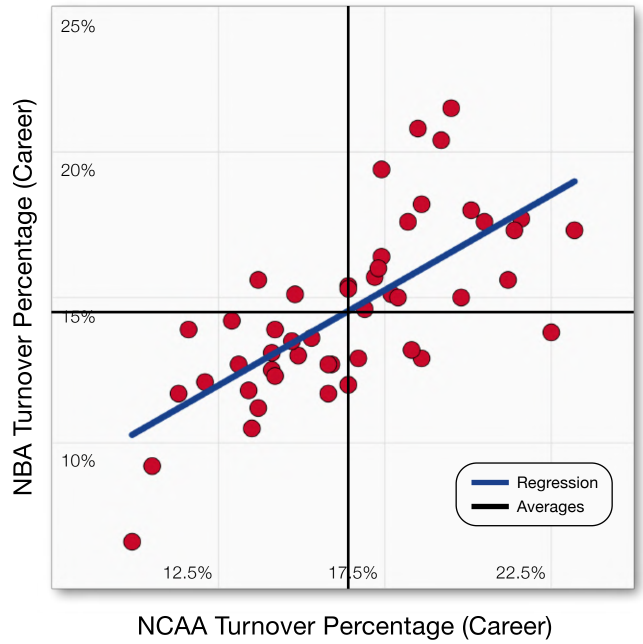
R = 0.551 | P-Value = 5.03E-5 | R-Squared = 0.303



NBA TPG = 0.47 + 0.65(NCAA TPG)

Turnover Percentage (TOV%)
Correlation Between NBA & NCAA

R = 0.700 | P-Value = 3.04E-8 | R-Squared = 0.490



NBA TOV% = 0.04 + 0.65(NCAA TOV%)

Turnovers Per Game vs. Turnover Percentage

According to the regression model showcased above, turnovers per game (TPG) translates from college to the NBA more strongly than APG or AST%. Specifically, the correlation coefficient for the TPG data is 0.55, thus indicating a moderately strong, positive relationship between NCAA TPG and NBA TPG. For added perspective, if NCAA TPG increases by one standard deviation (σ), we can expect NBA TPG to increase by R = 0.55 standard deviations. Moreover, in terms of the slope of the regression line, if NCAA TPG increases by 1.0, we can expect NBA TPG to increase by $\beta = 0.65$.

While the regression analysis for TPG is promising, there is indeed a stronger metric available: turnover percentage (TOV%). Similar to assist percentage, TOV% measures how many turnovers a player commits per 100 possessions and thus corrects for endogeneity otherwise created by average playing time. As demonstrated by the model's surprisingly large correlation coefficient of 0.70, there exists a strong, positive relationship between NCAA TOV% and NBA TOV%. In fact, by using the model's p-value and calculating the margin of error, we can assert with 99.9% confidence that a 1.0% increase in NCAA TOV% will yield an expected increase between 0.3% and 1.0% in NBA TOV%.

It's important to note that the slope of the TOV% regression equation is expressed in terms of percentages. In other words, the traditional 1-unit increase of the explanatory variable's value is now equivalent to a 100% rise. Therefore, we must first determine how much we'd like the explanatory variable to increase before reasonably interpreting the slope. For example, a 1.0% increase in NCAA TOV% yields an expected 0.65% rise in NBA TOV%. Next, let's examine assist-to-turnover ratio.

Assist-to-Turnover Ratio

In order to sufficiently analyze how effectively assist-to-turnover ratio (AST/TOV) translates from college to the NBA, we will need to create and compare two different regression models. The first (Model A) contains all 48 observations from our dataset, while the second (Model B) excludes any outliers that create significant association between our variables resulting in skewed statistical results.

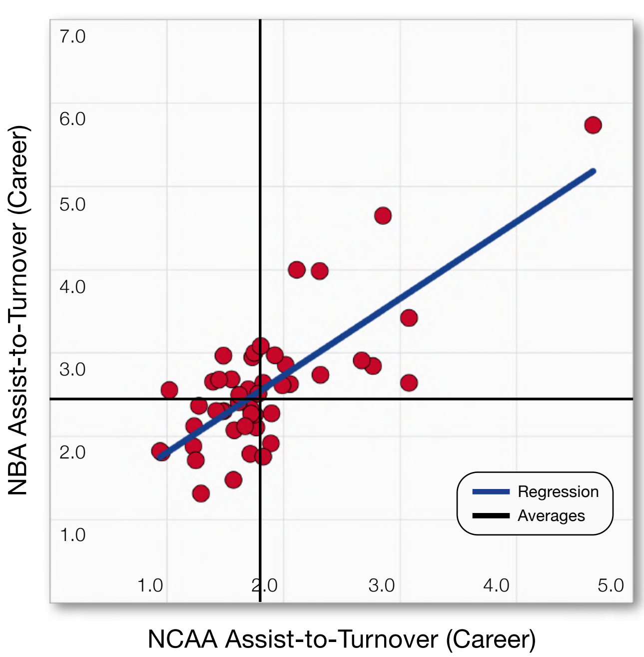
According to Model A, assist-to-turnover ratio translates very effectively from college to the NBA. Specifically, the model's correlation coefficient (0.76) and coefficient of determination (0.58) are the largest of any metric we have studied to this point, thus indicating legitimate variable association and model strength. However, one possible issue exists with this model: Monte Morris. The former Iowa State Cyclone and current Nuggets PG has posted such remarkably high AST/TOV ratios at both levels that an exaggerated association between the two variables may result from his extreme efficiency. Subsequently, an additional model (excluding the outlier) is necessary for proper analysis.

According to Model B, the association between variables remains moderately strong yet the strength of the model becomes noticeably weaker upon the exclusion of Morris. As a result, the decision of whether or not to exclude Morris from our analysis is tricky. On one hand, his NBA and NCAA ratios lie approximately 4.1 and 4.3 standard deviations away from their respective means. However, on the other hand, the slopes of each models' regression lines are not very far apart, thus insinuating that Morris' numbers fall within the directional pattern established by the overall dataset.

Nonetheless, whether you prefer Model A or Model B, you cannot ignore the fact that 45 of the 48 players in the dataset increased their AST/TOV ratios from college to the NBA by an average margin of 35%. Now that we have thoroughly examined AST/TOV ratio, let's explore an intriguing alternative.

Assist-to-Turnover (Model A)
Correlation Between NBA & NCAA

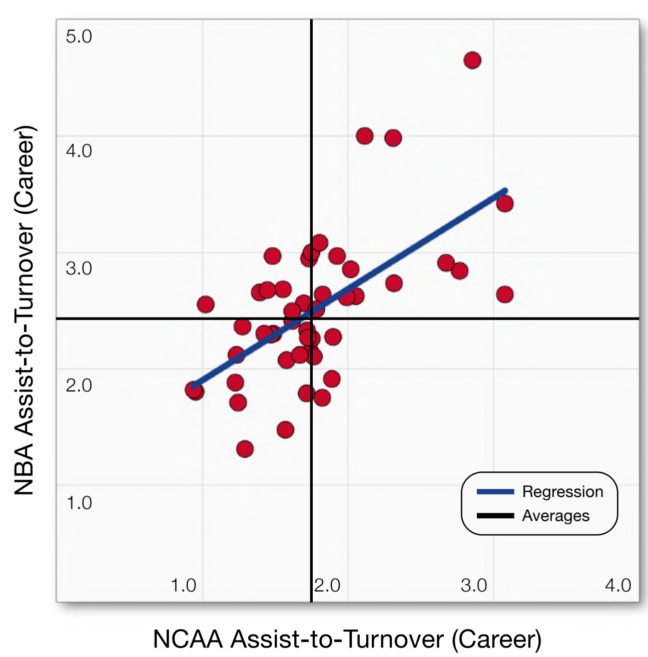
R = 0.760 | P-Value = 1.14E-9 | R-Squared = 0.577



NBA AST/TOV = 0.95 + 0.88(NCAA AST/TOV)

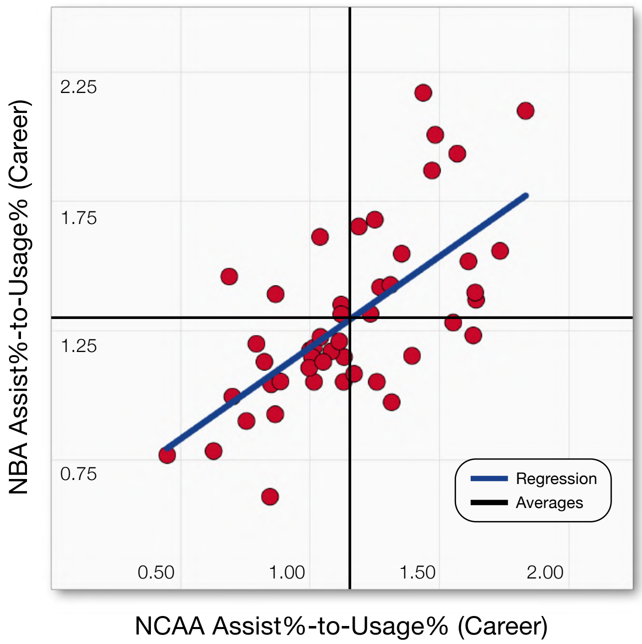
Assist-to-Turnover (Model B)
Correlation Between NBA & NCAA

R = 0.612 | P-Value = 1.17E-5 | R-Squared = 0.375



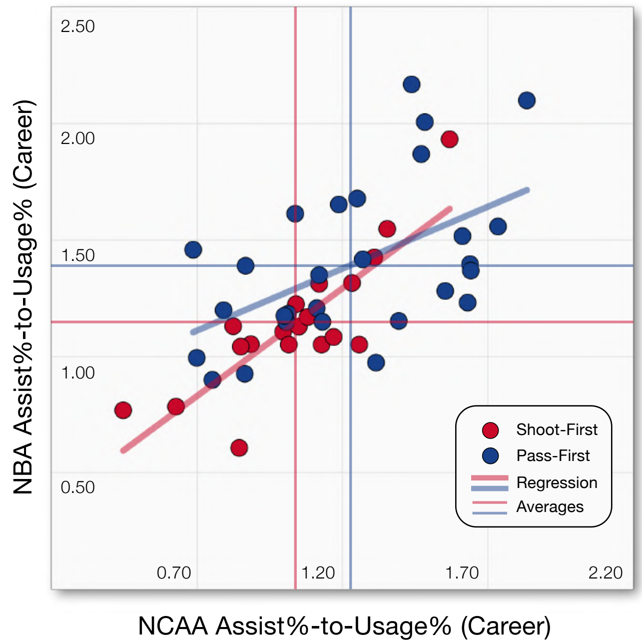
NBA AST/TOV = 1.20 + 0.74(NCAA AST/TOV)

Assist%-to-Usage% (Model A)
Correlation Between NBA & NCAA
R = 0.660 | P-Value = 4.45E-7 | R-Squared = 0.436



NBA AST%/USG% = 0.48 + 0.71(NCAA AST%/USG%)

Assist%-to-Usage% (Model B)
Correlation Between NBA & NCAA
$R = 0.831$ | $R^2 = 0.691$ || $R = 0.526$ | $R^2 = 0.277$

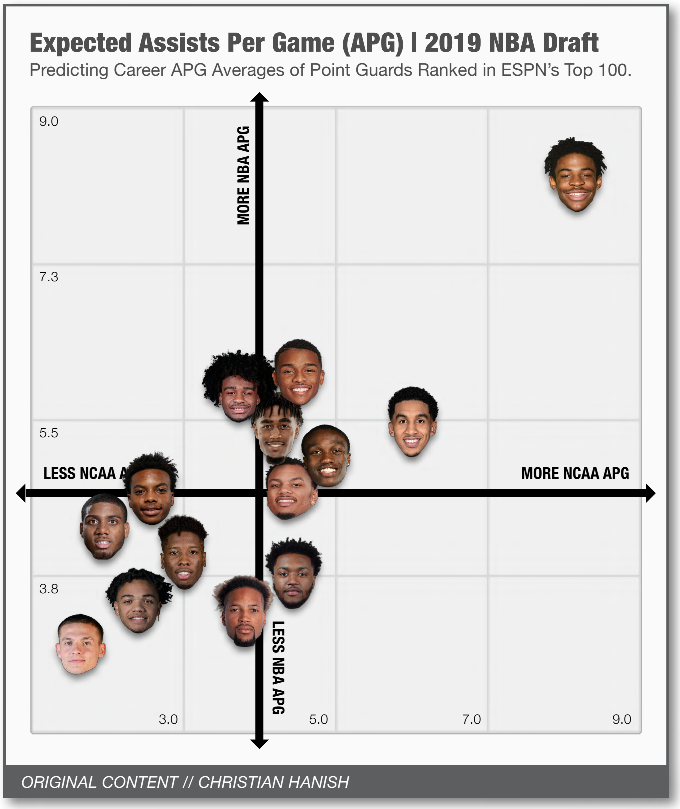


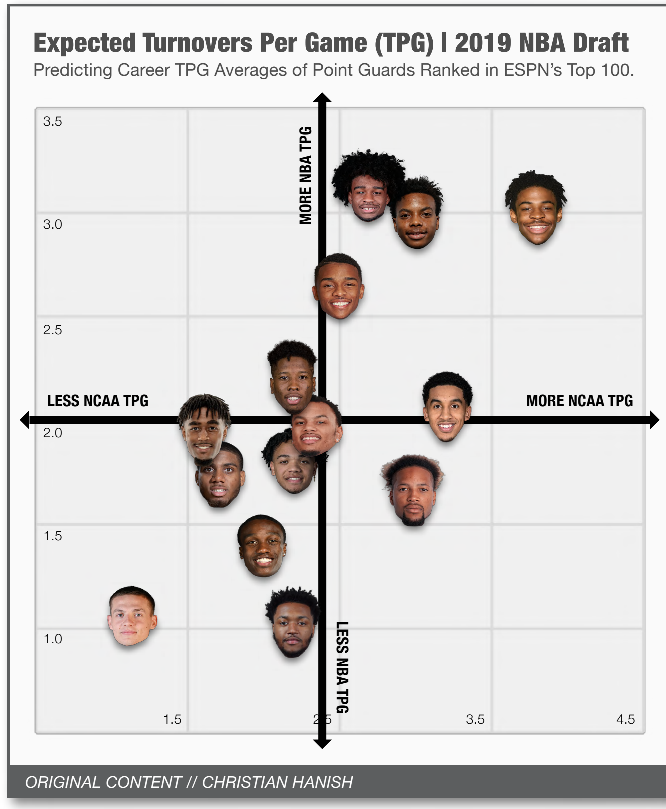
NBA AST%/USG% = 0.18 + 0.93(NCAA AST%/USG%)
NBA AST%/USG% = 0.74 + 0.53(NCAA AST%/USG%)

Assist Percentage-to-Usage Percentage Ratio

Thus far throughout our study, we have evaluated point guards from two primary perspectives: playmaking and decision-making. While playmaking ability intuitively goes hand-in-hand with setting up one's teammates and can be effectively measured most accurately (as we've established) with assist percentage, decision making ability is more complicated to quantify. While the decision-making prowess of primary ball-handlers is most readily assessed by how well the player takes care of the ball and limits turnovers, there are other ways in which a player can end their team's possession in negative fashion (most notably via missed shots). Subsequently, I'd like to challenge us to think outside the box and employ an alternative metric - one that takes into account turnovers committed and missed field goal attempts - in order to more accurately evaluate the decision-making abilities of true point guards. Thus, our final metric of interest is assist percentage-to-usage percentage ratio (AST%/USG%).

In order to effectively illustrate the functionality of the AST%/USG% metric, we will once again employ two models for our evaluation. The first (Model A) showcases the association between the two variables amongst our entire dataset, while the second (Model B) simply divides that dataset into two categories based upon style of play. According to Model A, AST%/USG% actually translates from college to the NBA better than AST/TOV (excluding outliers) and upon first glance appears to be a viable alternative. Upon undergoing an exploratory data analysis, I noticed a fascinating trend amongst the residuals pertaining to a particular type of PG. Specifically, it appeared that AST%/USG% of shoot-first PGs translated much more cleanly from college to the NBA. So, I built a quick model and my suspicions were confirmed. According to Model B, the AST%/USG% of shoot-first PGs (i.e. Stephen Curry, Kyrie Irving, or Trae Young) is significantly more predictable than pass-first PGs (i.e. Lonzo Ball, Ben Simmons, or Rajon Rondo). In fact, AST%/USG% amongst shoot-first point guards yields the greatest variable association (R = 0.83) and model strength (R-Squared = 0.69) of any metric exhibited in the study. This discovery is valuable because it provides us with reliable insights towards a very niche crop of prospects during the evaluation processes. Now that we have successfully identified this new metric, as well as, performed our due diligence in assessing the validity of several other popular statistics, let's get rolling with some player analysis.





Predictions w/ Multivariate Regression Analysis (1/3)

Now that we have successfully evaluated the individual strength of these playmaking statistics, it's time to put them to good use and make some predictions. However, while the metrics offer a legitimate starting point, they are not strong enough to adequately predict future performance on their own. As a result, we will need to upgrade our modeling efforts to multivariate regression analysis and augment our previous models with additional valuable insights - including age, height, games played (GP), minutes per game (MPG), and strength of schedule (SOS).

According to our APG model showcased above, Ja Morant leads all recent draft prospects with an expected career average of 8.2 assists per game. While Morant's position atop our leaderboard comes as no surprise, the rest of the model presents several fascinating insights. In terms of expected improvements, the model's biggest risers include Darius Garland (+1.9 APG), Coby White (+1.6 APG), and Jaylen Hands (+1.4 APG). While Garland and White were Top 10 picks, Hands did not hear his name called until the late-second round and came out of nowhere to finish with the model's second-highest expected career APG (5.8). By examining variable coefficients and replacing the prospects' actual numbers with dataset averages, we can pinpoint the specific root causes of the statistical fluctuations. To illustrate, it appears that the model has most notably rewarded the former UCLA point guard due to his combination of above average size (6-3), relative youth (20 years old) and fewer MPG (28.3).

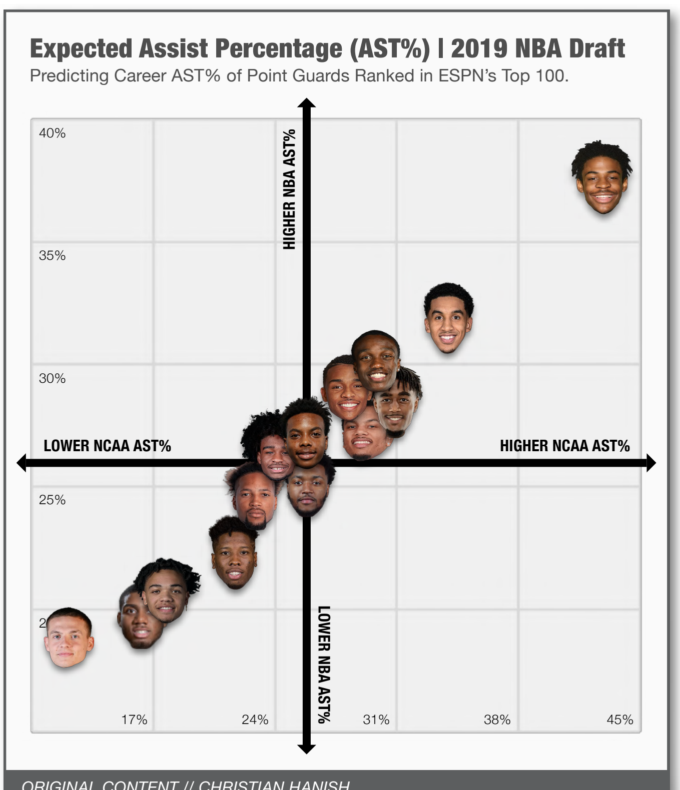
According to our TPG model also shown above, Coby White is expected to lead all draft prospects with 3.1 career turnovers per game, just edging out Darius Garland and Ja Morant (3.0 TPG, apiece). While there are not many surprises here, the associations between our explanatory variables and expected TPG are quite fascinating. Specifically, the most intriguing include expected TPG's direct relationship with height and inverse relationships with age and strength of schedule. When you think about it, these make sense and provide statistical reinforcement for some commonly occurring trends and assumptions: for instance, the notion that older prospects with more experience against high-level competition will be better prepared for the rigors of ball-handing in the NBA, while taller players may have looser handles and greater difficulty adjusting to elite ball-hawks at the professional level.

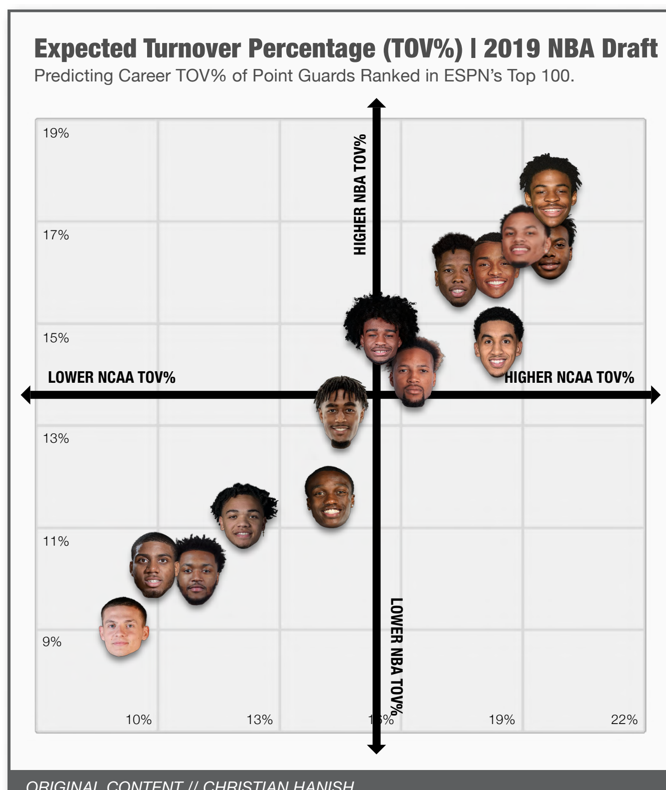
Predictions w/ Multivariate Regression Analysis (2/3)

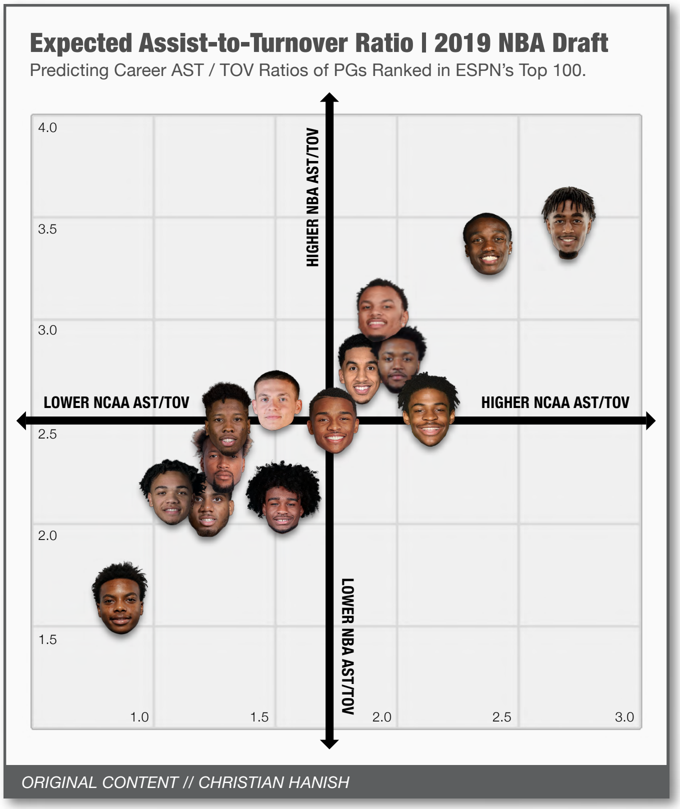
While APG and TPG are the sexiest metrics to predict given their mainstream appeal, we have proven throughout our study that these statistics are difficult to project because they are predicated upon an array of unknown variables. To explain, raw counting stats (such as assists and turnovers) are highly dependent upon the situation into which the prospect is drafted. In other words, prospects are subject to the skillsets of their teammates, the philosophies of their coaches, as well as, their team's style of play. Subsequently, let's brush such raw counting stats to the side for a moment and focus our attention upon advanced metrics that measure the prospects' output as percentages of their time spent on the court. As proven earlier, doing so will provide us with more accurate insights into the prospects' true on-court abilities and natural tendencies rather than skewing our results in favor of players who amass more playing time or benefit more from their environment.

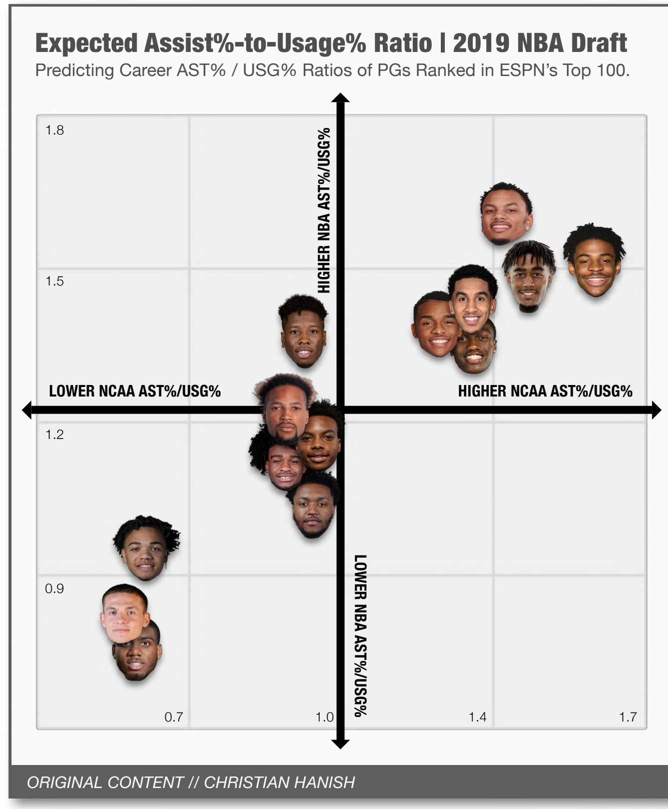
According to our AST% model showcased below, Ja Morant leads all prospects with an expected 37% career assist percentage, more than 5% higher than Celtics-signee Tremont Waters. Curiously, the trend in our AST% model is considerably more linear (R-Squared = 0.98) than the APG model (R-Squared = 0.68). This can be attributed to the models' margins of error and prediction interval (PI) widths. For context, the APG model's margin of error at the 95% PI is roughly 3.7 APG. This is relatively massive when considering that several prospects are expected to average fewer APG than this in the NBA. Alternatively, the AST% model's margin of error for the same 95% PI is just over 15%, which is still not ideal yet substantially more palatable.

According to our TOV% model also shown below, it's no surprise that Morant is expected to lead this year's class of prospects with an expected 17% career turnover percentage, as well. Similar to the TPG model, prospect height is once again statistically significant at the 95% confidence interval. In fact, if you look closely at the chart below, you'll notice something curious. In terms of expected NBA TOV%, the top-seven prospects are on average 2-inches taller than the bottom-seven prospects. Additionally, the average height of the top quartile is 74.5 inches, the middle quartile is 74 inches, and the bottom quartile is 73.5 inches. Thus, it appears that prospect height and expected turnovers possess a strong, linear relationship. And, furthermore, it's evident that when evaluating prospects' turnover tendencies, the pecking order of metrics that are most worthwhile to take into account are their college turnovers, height, and age (which was significant for TPG but not TOV%).









Predictions w/ Multivariate Regression Analysis (3/3)

Through our projections of per game averages and possession-based percentages, we have unearthed an array of thought-provoking correlations and identified several promising prospects of interest. While these statistics paint an incredibly valuable perspective about each prospects' NBA potential, these particular metrics are indeed highly-conditional and awkward to make heads or tails of given their isolated nature. Subsequently, let's avert our attention to our final pair of metrics which utilize proportionable measurements to more accurately assess prospects' skillsets.

According to our assist-to-turnover model exhibited above, Jordan Bone is expected to lead all prospects with a career AST/TOV ratio of 3.40 at the next-level. The former Tennessee floor general's position atop our model is very encouraging because it substantiates much of our previous report, which employed heavy video and statistical analysis yet lacked the appropriate modeling needed to yield more definitive conclusions. In addition to leading all prospects in career collegiate AST/TOV ratio, the model rewarded Bone handsomely for possessing the draft class' lowest usage percentage (21%) and competing against the third-strongest collegiate schedule (10.15). Other notable risers included Justin Robinson (+1.06 AST/TOV) and Jared Harper (+0.98 AST/TOV), whom the model looked favorably upon due to their low USG% (21% and 23%) and wealth of collegiate experience (125 GP and 106 GP).

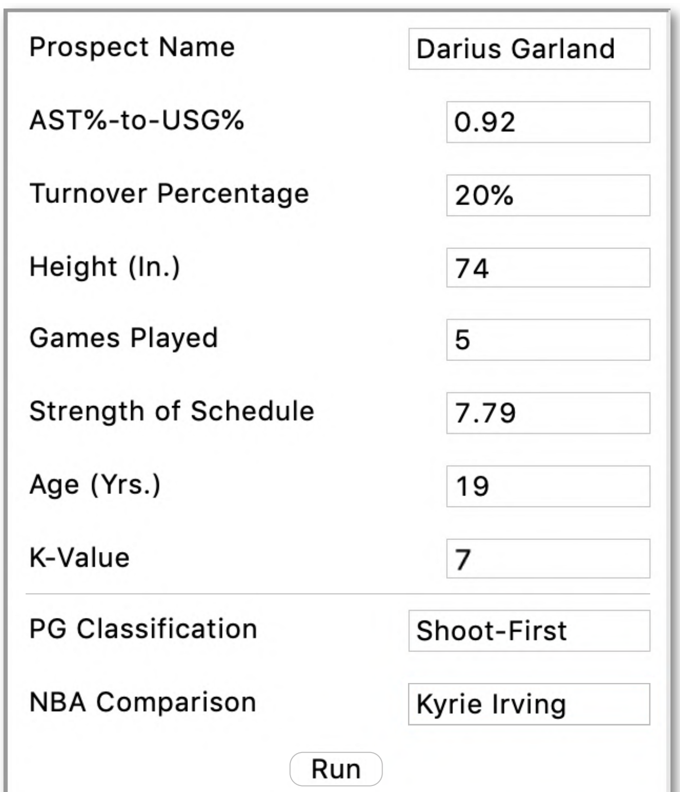
According to our assist percentage-to-usage percentage model also detailed above, Robinson is expected to lead this year's point guard class with a career AST%/USG% ratio of 1.60 in the NBA. To reiterate the notions from earlier in the study, AST%/USG% is a functional alternative to the more traditional AST/TOV metric. Once again, its purpose is to provide valuable insights into the players' inherent play-style tendencies by specifically pinpointing their ability to effectively involve teammates at the expense of their own scoring opportunities. Curiously, upon evaluating the expected results of our above model, the data appears to be noticeably segmented and capable of being divided into at least two distinct classes: pass-first PGs (who will likely tend to own higher ratios) and shoot-first PGs (who will likely tend to possess lower ratios). That being said, it would be fascinating to determine the classifications for each prospect and to project their precise player comparisons (in terms of play-style) in the NBA.

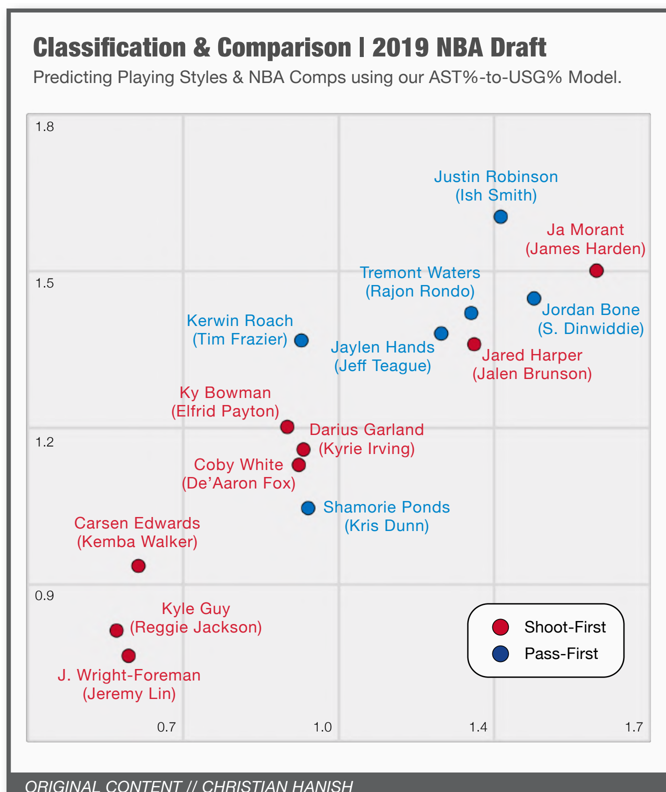
Classification & Comparison w/ Machine Learning

In building upon our predictive modeling efforts, the final step of our analysis will involve utilizing one of the popular machine learning techniques to classify our prospects and make statistically-driven comparisons. The method that we will employ is the *k*-nearest neighbors algorithm (kNN), which combines pattern recognition with instance-based learning and uses the Euclidean distance formula to classify our draft prospects according to their expected play-style tendencies (pass-first or shoot-first) in the NBA. After prepping and normalizing our dataset of NBA PGs in RStudio, we will split the data into training and testing sets using the 75:25 ratio in order to assess the predictive accuracy of our model. For the purposes of this study, our k-value will equal 7 since that is the square-root of our sample size. Using the CrossTable function within the gmodels package, we can determine that our kNN model is 82% accurate, as it correctly predicted the play-style tendency for 9 of the 11 players in the testing set. Thus, it appears that we have chosen an appropriate k-value and can begin classifying our prospects.

Rather than using our kNN model from RStudio to classify the recent draft prospects, I wanted to think outside the box and challenge myself to devise a more user-friendly solution. As a result, I have taken to Python and created an easy-to-use graphical user interface (GUI) that utilizes our kNN algorithm to classify each prospect in addition to using the Euclidean distance formula to specify their closest statistical NBA player comparison. To illustrate, I have provided a screenshot of the GUI below along with the user-input data for Darius Garland. Upon entering his collegiate statistics and running the model, the algorithm determined that Garland projects as a shoot-first PG in the NBA and that his statistical comparison (in terms of exp. playmaking tendencies) is Kyrie Irving. Ironically, Garland and Irving were often linked by scouts throughout the draft process due to their shiftiness and ability to create off the dribble, so it's curious that our statistical model reinforces their film-driven comparisons.

Beyond Darius Garland, I have determined the classifications and comparisons for each of our recent draft prospects within the model below. During your evaluation of each prospects' projected results, keep in mind that the play-style classifications and resulting comparisons are offensively-driven and rooted in playmaking tendencies. Now that we have put the final touch on our analysis, let's summarize our findings and visualize our projections.



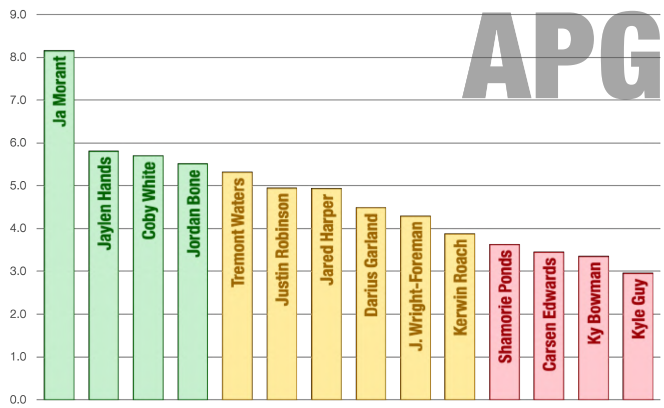


Visualizing Expected NBA Performance

Quartile 1 Quartile 2 Quartile 3

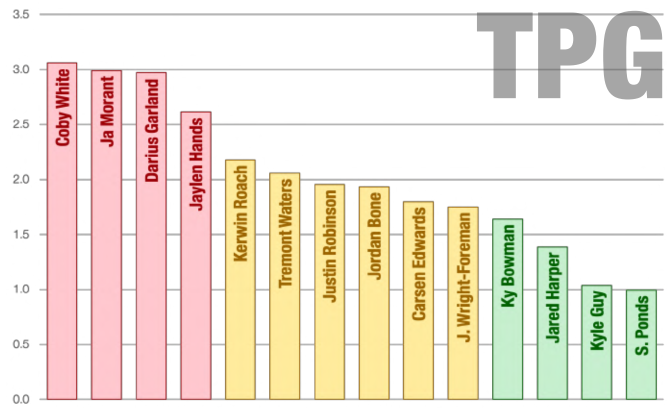
Assists Per Game

x̄ = 4.7 | σ = 1.4 | MIN = 3.0 | MAX = 8.2



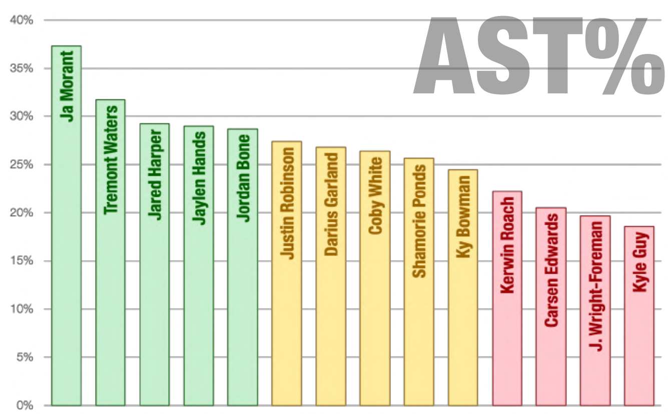
Turnovers Per Game

x̄ = 2.0 | σ = 0.7 | MIN = 1.0 | MAX = 3.1



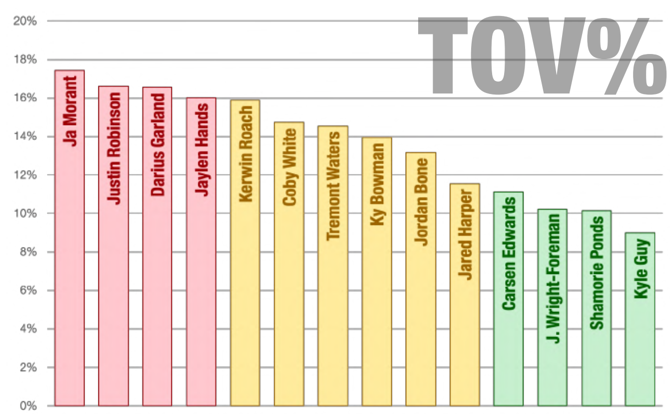
Assist Percentage

x̄ = 26% | σ = 5% | MIN = 19% | MAX = 37%



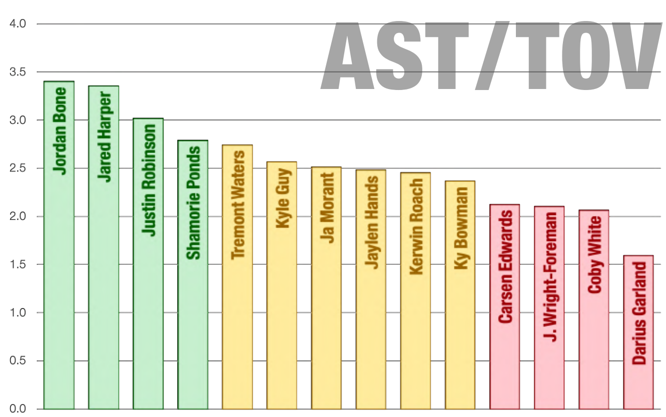
Turnover Percentage

x̄ = 14% | σ = 3% | MIN = 9% | MAX = 17%



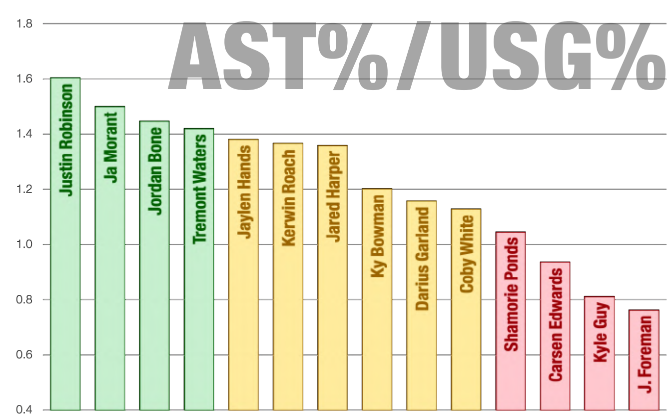
Assist-to-Turnover

x̄ = 2.5 | σ = 0.5 | MIN = 1.6 | MAX = 3.4



Assist%-to-Usage%

x̄ = 1.2 | σ = 0.3 | MIN = 0.8 | MAX = 1.6



Conclusion

Prospect	Composite Rank	APG	TPG	AST%	TOV%	AST / TOV	AST% / USG%
Jordan Bone	1	5.5	1.9	29%	13%	3.4	1.4
Jared Harper	2	4.9	1.4	29%	12%	3.4	1.4
Tremont Waters	3	5.3	2.1	32%	15%	2.7	1.4
Justin Robinson	4	5.0	2.0	27%	17%	3.0	1.6
Ja Morant	5	8.2	3.0	37%	17%	2.5	1.5
Shamorie Ponds	6	3.6	1.0	26%	10%	2.8	1.0
Jaylen Hands	7	5.8	2.6	29%	16%	2.5	1.4
Kyle Guy	8	3.0	1.0	19%	9%	2.6	0.8
Ky Bowman	9	3.4	1.6	24%	14%	2.4	1.2
Kerwin Roach	10	3.9	2.2	22%	16%	2.5	1.4
J. Wright-Foreman	11	4.3	1.7	20%	10%	2.1	0.8
Coby White	12	5.7	3.1	26%	15%	2.1	1.1
Carsen Edwards	13	3.4	1.8	21%	11%	2.1	0.9
Darius Garland	14	4.5	3.0	27%	17%	1.6	1.2

To further illustrate the statistical projections outlined throughout our study, take a look at the heat map visualization that I have built and showcased above using Tableau. The chart details each prospects' expected performance across all six-playmaking metrics, color codes them from best (green) to worst (red) within each category, and then compiles their individual scores into one overarching, composite ranking. According to our predictive analyses, Jordan Bone possesses the best composite ranking amongst all prospects and ranks Top 7 in all six-playmaking categories. While Bone's composite ranking benefitted greatly from his exceptional ball-control, expected turnovers proved to be the Achilles heel for the draft's Top 3 PGs (Morant, Garland, White).

In summary, the primary takeaways of this research are threefold. The first conclusion is that prospects' per game statistics are extraordinarily difficult to forecast (even within multivariate models) due to their strong dependence upon the environments into which they are drafted. Secondly, possession-based percentages prove to be more-effective indicators of future performance, as they do an excellent job of normalizing the data and accounting for variations in playing time. Thirdly, we justified that AST%-to-USG% is a functional alternative to the traditional AST-to-TOV metric as it possesses legitimate predictive power and offers incredibly valuable insights into the prospects' inherent playing-style tendencies… And lastly, if there was ever a fourth takeaway from all of this exhaustive research, it'd have to be: "How on earth did Jordan Bone slip all the way to 57th?"

About the Author

Christian Hanish is a recent graduate of Pepperdine University, where he just earned his Master of Science (M.S.) in Applied Analytics. During the 2018-19 season, he performed quantitative analysis & research for the UCLA Bruins. In addition, he also served as the Graduate Assistant & Director of Analytics & Strategy for the Pepperdine Waves. This project has been completed as a series of post-graduate research & designed to aid the Lakers analytics department.