

The Dwight Effect: A New Ensemble of Interior Defense Analytics for the NBA

Kirk Goldsberry¹ and Eric Weiss²

¹Harvard University,
Cambridge, MA, USA, 02138
kgoldsberry@fas.harvard.edu

²Sports Aptitude, LLC
eweiss@sportsaptitude.com

Abstract

Basketball is a dualistic sport: all players compete on both offense and defense, and the core strategies of basketball revolve around scoring points on offense and preventing points on defense. However, conventional basketball statistics emphasize offensive performance much more than defensive performance. In the basketball analytics community, we do not have enough metrics and analytical frameworks to effectively characterize defensive play. However, although measuring defense has traditionally been difficult, new player tracking data are presenting new opportunities to understand defensive basketball. This paper introduces new spatial and visual analytics capable of assessing and characterizing the nature of interior defense in the NBA. We present two case studies that each focus on a different component of defensive play. Our results suggest that the integration of spatial approaches and player tracking data promise to improve the status quo of defensive analytics but also reveal some important challenges associated with evaluating defense.

Introduction

Basketball is a dualistic sport. Players compete on both offense and defense, and the two core objectives of all basketball stratagems are scoring points and preventing points. Although it is self-evident that the final score of every basketball game depends equally on these two facets, this basic tenet is not properly represented in contemporary basketball statistics. A quick reading of even the most “advanced” basketball statistics would suggest that basketball success hinges more on offensive factors and less on defensive factors. Few of the sport’s most common metrics quantify key defensive aspects. Basketball’s most common statistics are related to events that are most obviously attributable to one individual action at one moment; defensive prowess in basketball fails to meet this basic criterion.

Contemporary basketball expertise is significantly hindered by the inability to properly assess defensive play; current evaluations of a player or team’s defensive tendencies are constrained by a lack of proper reasoning artifacts. Most defensive analytics remain guided by the simple tallying of disparate event types including “steals,” “blocks,” and “defensive rebounds,” which does little to characterize either the nature or the effectiveness of defensive performance. Effective defensive play requires a cohesive assembly of structured actions converging upon a simple objective: keep your opponent from scoring points. With this in mind, as the NBA enters its “big data” era and new kinds of basketball analytics emerge, advancing defensive understanding presents one of our biggest challenges.

This paper explores defensive evaluations in the NBA and examines emerging opportunities and challenges associated with measuring defense using optical tracking data. The paper presents a new methodology designed to characterize the interior defensive effectiveness of NBA “big men”. The core objectives of this paper are 1) to improve the characterization and understanding of interior defense in the NBA, and 2) expose key challenges associated with measuring defense as new forms of performance data emerge. We present case studies that 1) use spatial analyses to extract new defensive metrics from optically tracked game data (SportVu data) and 2) use visual analytics to present results.

The paper also introduces a new ensemble of spatially minded metrics that present a novel and simple means to characterize basketball performance. One key and recurring limitation of many basketball statistics is their relatively limited explanatory abilities. For example, even the most effective “advanced” metrics like “defensive rating” (points allowed per 100 possessions) may provide valuable insight into overall performance ability, but simultaneously they often fail to offer any additional explanatory insight as to *why* a performance may be good or bad. We introduce “spatial splits” - a concept inspired by baseball’s “triple-slash” lines - as a means to address this shortcoming; in tandem with other metrics, we contend spatial splits provide additional insight into the nature of how players and teams are performing within court space, therein providing analysts with a more powerful set of reasoning artifacts.

The paper contains three main sections: a brief background section is followed by an explanation of our

methodology, which in turn is followed by a discussion of our results and conclusions. We also append thorough listings of detailed results at the end of the paper.

Background

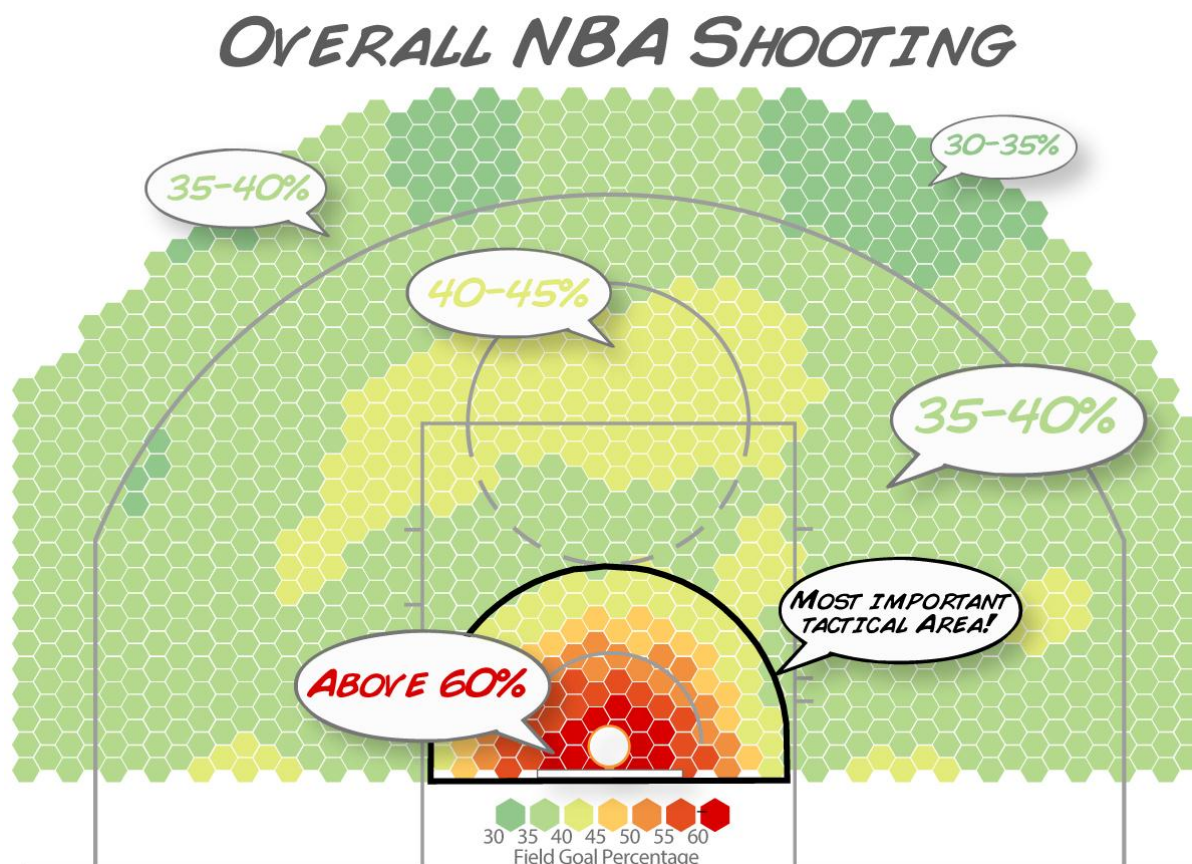


Figure 1: Overall shooting efficiencies in the NBA. The only shots that go in over half the time occur close to the basket. For this reason, this relatively small area remains the most important tactical space - and the most vigorously defended space in the NBA. Graphic by Kirk Goldsberry.

NBA shooters only make about 39% of their field goals from everywhere outside of 7 feet. The only shots that go in more than half the time occur very close to the rim. Despite the rapidly growing importance of the 3-point shot, good shots close to the basket remain the best shots on the floor; not only do they result in points at a higher rate, when missed they have a much greater chance of being rebounded by the shooting team. Over 70% of shots near the rim either result in points, a shooting foul or an offensive rebound. Good shots near the rim are clearly advantageous. For this reason, the league shoots over 1/3rd of its shots from the tiny portion of the court close to the basket, and defenders protect this area with more vigor than any other real estate on the court. Although the vitality of this strategic space is self-evident, few if any contemporary analytics effectively characterize the ability of players or teams to defend basketball's most sacred real estate. The problem is obvious: interior defense is critical to basketball success, but our ability to measure or characterize players' interior defensive abilities remains undeveloped. Consider these two basic questions:

- 1) Who is the best interior defender in the NBA?
- 2) What metrics would you use to answer that question?

The NBA's most prominent defensive metrics can be misleading, but this is not a problem unique to basketball. Until very recently, the dominant conventional defensive metrics in baseball were "errors" and "fielding percentage," which do not frequently correlate with a player's true defensive value. In the NFL, the best cornerbacks never lead the league in any conventional stats because quarterbacks are too afraid to even throw in their direction; they don't even get chances to defend passes. Basketball exhibits similar issues; our conventional defensive metrics fail to accurately reveal the NBA's most dominant defenders.

Last season, Oklahoma City's Serge Ibaka led the NBA in blocks by averaging an incredible 6.46 blocks per 48 minutes, but what does that really reveal? Does that mean he is an "elite defender," or even the "best shot blocker" in the NBA? Shot blocks are relatively infrequent events that have an ambiguous relationship with defensive effectiveness. In many cases, for a shot block event to occur a shooter has to believe that his shot will not be blocked. In other words, the shot blocker has to "come out of nowhere" or has to somehow deceive the shooter; at the point of the shot's release the shooter believes the path is clear, but that turns out not to be the case.

Dwight Howard, who is commonly referred to as the NBA's "most dominant" interior defender, only averaged 2.69 blocks per 48 minutes, almost 4 fewer than Ibaka; however, it could be argued that Howard's mere presence "blocks" shots before they happen. The presence of a truly dominant interior force can augment the spatial behavior of the offense in the same way that a dominant cornerback changes the behavior of a quarterback. While it is easy to tally up things like blocks, rebounds, and steals, it's much harder to measure the kind of disruption or the strategic augmentations that dominant interior defenders like Dwight Howard create. We define "The Dwight Effect" as the ability of an interior defender to reduce the efficiency of an opponent's shooting behavior.

Perhaps the most logical method to evaluate this disruption is to measure the spatial shooting patterns and efficiencies of NBA teams in the presence of different interior defenders. Using emerging data sets from SportVu, it's now possible – although still not easy – to look at defense in new ways. In the case of interior defense, we can evaluate how NBA offenses behave differently depending on which NBA "big" is on the floor; furthermore, we can evaluate how offenses behave when a given NBA interior defender is "protecting the rim" or near a shot event.

Methodology, Data, and Case Studies

We conducted two separate case studies of interior defense in the NBA. Using player tracking data provided by STATS (SportVu) we evaluated player positions, shooting tendencies, and shot outcomes for over 75,000 NBA shots during the 2011-2012 and 2012-2013 seasons. We evaluated the spatial structures and efficiencies of NBA shooting in the presence of the 52 NBA interior defenders who faced at least 500 shot attempts during the study period. Each case study monitors a different aspect of defensive effectiveness and introduces new metrics.

We introduce "spatial splits" as a means to communicate our results. Since NBA scoring efficiency is clearly dependent on spatial factors, we contend spatial splits offer a mechanism to detect, understand, and communicate key aspects of NBA scoring efficiency. Presented in a manner meant to mimic baseball's "slash line" or "triple-slash line" these sequences of three numbers not only offer a basic quantification of a player or opponent's shooting, they also present an inherent explanatory characterization as well. Figure 2 depicts the 3 zones represented in the spatial splits.

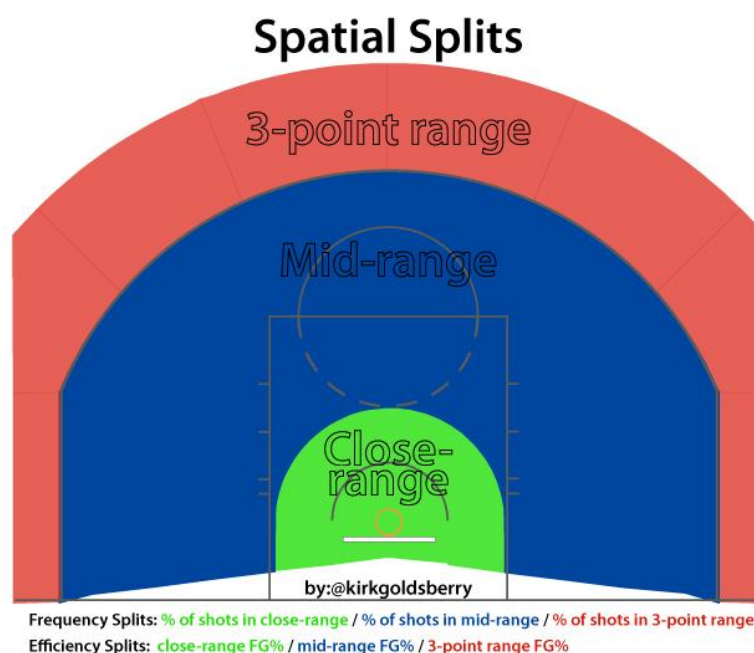


Figure 2: The 3 zones associated with spatial splits: close-range in green, mid-range in blue, and 3-point range in red. Splitting offensive performance data using these zones can help characterize the nature of scoring behaviors in the NBA.

We introduce two kinds of spatial splits: frequency splits and efficiency splits. Both reflect percentage values in the following sequence: Close-range value / Mid-range value / 3-point range value. Frequency splits focus on shot distribution; each number corresponds to the percentage of shots that come from the corresponding zone. The three numbers in the frequency splits should sum to 100 (barring any rounding errors). Efficiency splits characterize how well a player or teams shoots from each zone; each value represents the field goal percentage in the corresponding zone. As an example, consider the spatial splits of the NBA as a whole, and two NBA players from the previous two NBA seasons: Kevin Durant and Josh Smith.

NBA League Average: Frequency 35/41/24 Efficiency 53/39/36

Kevin Durant: Frequency 27/46/27 Efficiency 65/44/37

Josh Smith: Frequency 45/43/12 Efficiency 61/37/30

The above examples illustrate the ability of spatial splits to quickly summarize key differences in scoring tendencies. These splits quickly communicate a few facts: 1) In terms of shot distribution, Kevin Durant shot 27% of his shots close to the basket, 46% of his shots in the mid-range, and 27% of his shots from three-point range, 2) In terms of shot efficiency, Durant shot 65% close to the basket, 44% in the mid-range, and 37% from beyond the arc – above league averages in each zone, while Smith is only above average close to the basket. They also enable comparison across players. In this case we can quickly note that Durant is less active close to the basket than Smith, they are both active in the midrange, Durant is more active beyond the arc, and Durant is a more efficient shooter in every area. We contend that this contribution is a valuable new way to characterize NBA scoring behaviors.

Although spatial splits present an effective way to characterize the nature of an individual player's offensive tendencies and abilities, in this paper we use them to evaluate defense. More specifically, within the context of spatial splits, effective interior defense should manifest in two ways. The most obvious is perhaps reduced shooting *efficiencies* close to the basket. The second is less apparent but perhaps more important: reduced shooting *frequencies* close to the basket, and increased frequency in the mid-range and three-point areas. Taken together, reduced close-range efficiency and reduced close-range frequency translate to fewer easy shots, fewer points, and fewer offensive rebounding opportunities for the offense.

Case Study 1: The Basket Proximity Condition

The objective of the first case study was to examine the ability of interior defenders to “protect the basket.” This case study considered shot attempts that occurred when there was an interior defender within 5 feet of the basket and was designed to measure two aspects of point prevention: the ability to prevent shots near the basket, and the ability to reduce the shooting efficiency of opponents near the basket. We evaluated shooting patterns using spatial splits. As a means to characterize the opponents' shooting tendencies, we calculated both the frequency and efficiency of shooting in each zone, but placed primary emphasis on close range shooting.

Case Study 2: The Shot Proximity Condition

The second case study evaluates the ability of interior defenders to defend shots in their immediate proximity. This study has two objectives: to determine how frequently an interior defender is proximate to a shot attempt, and to determine how effective an interior defender is when they are proximate to a shot attempt. In this case we place a reduced emphasis on shot locations and instead evaluate two other aspects of defending; each aspect is evaluated via a new metric:

A) Shots Defended: the relative frequencies in which the defender finds himself within 1, 3, or 5 feet of shot attempts.

B) Proximal FG%: the relative efficiencies of shooters in the proximity of the defender.

Results

Case Study 1: Basket Proximity

Overall more than 1/3rd of shots in our superset of 76,000 shots occurred with an interior defender within 5 feet of the basket. We assert that “dominant” interior defense can manifest in two ways: reducing the shooting efficiency of opponents, and also reducing the shooting frequency of opponents. In terms of reducing efficiency, we found that Indiana's Roy Hibbert and Milwaukee's Larry Sanders (Figure 3) were by far the most effective. We evaluated this by measuring the field goal percentage of close range shots when a qualifying interior defender was within 5 feet of the basket. Overall, NBA shooters make 49.7% of their field goal attempts when qualifying interior defender is within 5 feet of the basket; however, this number drops to 38% when either Hibbert or Sanders are within 5 feet. In contrast, we found that Phoenix's Luis Scola and Golden State's David Lee (Figure 3) were the worst defenders in these situations; opponents made 63% of their close-range field goals when Scola was within 5 feet of the basket. See Appendices 1 and 1A for a full list of qualifying defenders.

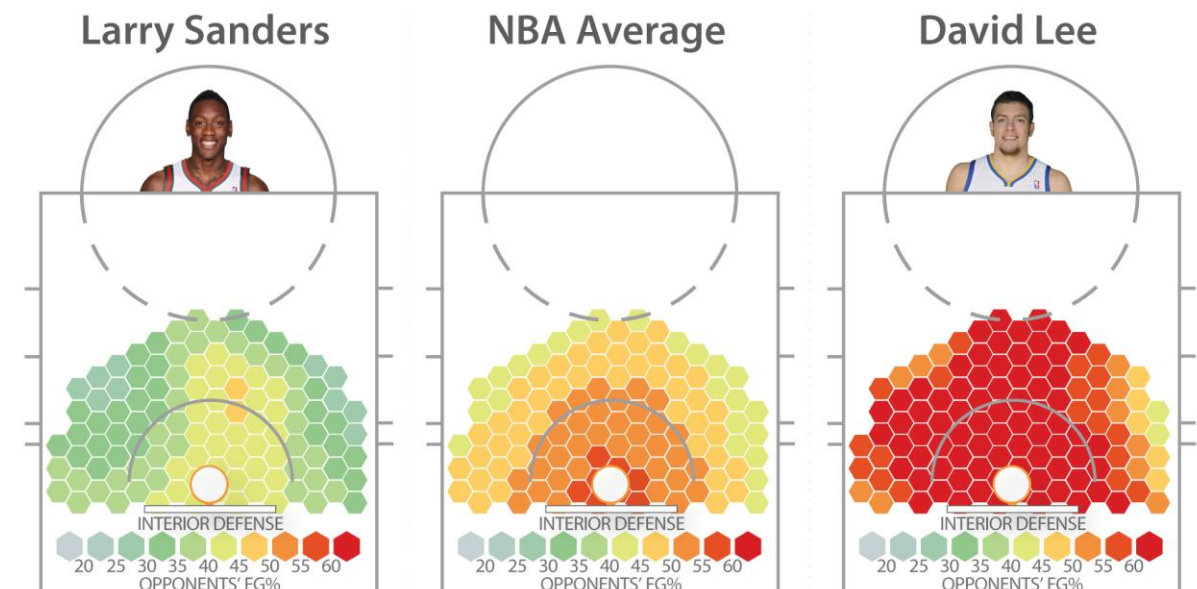


Figure 3: Opponents' field goal percentages vary widely depending on which interior defender is close to the basket. Milwaukee's Larry Sanders is one of the most effective interior defenders in the league; opponents struggle to score when he is near the basket. This is not the case with Golden State's David Lee; when he is close to the basket, opponents score at very high efficiencies.

We also contend that dominant interior defenders often deter shots from even happening. Many NBA players will be reluctant to “challenge” a dominant interior player or be more likely to “settle” for a jump shot further from the basket. We evaluated this effect by examining the percentage of field goal attempts that occur near the basket when a qualifying interior defender is within 5 feet of the rim. We found that the most deterrent interior defender in this sense was Dwight Howard. Overall, when a qualifying defender is within 5 feet of the basket, the NBA shoots 57.2% of its attempts close to the basket; however, when Dwight Howard was the interior defender this number dropped to 48.2% (Appendix 1A). This is what we call the “Dwight Effect” – the most effective way to defend close range shots is to prevent them from even happening. Although Howard does not lead the league in blocks, he does lead the league in “invisible blocks,” which may prove to be markedly more significant. When Howard is protecting the basket, opponents shoot many fewer close range shots than average, and settle for many more mid-range shots, which are the least productive shots in the NBA. Furthermore, out of centers who have faced at least 100 total shots in the basket proximity study, Serge Ibaka ranked last; when he is within 5 feet of the basket, opponents shot 74% of their shots in the close range area. This means that Ibaka is likely to be around any shot near the basket and suggests that while Ibaka leads the NBA in blocks per game, part of the reason is that he has many more “potential blocks” than almost any other defender. Full results for Case Study 1 are presented in Appendix 1. We also discuss the challenges and limitations associated with this study in the Discussion section.

Case Study 2: Shot Proximity

Overall 27.8% of NBA shots occur within 5 feet of a qualifying interior defender. We evaluated 21,042 shots that met this criterion and examined two separate aspects of defensive tendencies: Shots Defended, and Proximal FG%. The results for each are presented below.

A) Shots Defended: the relative frequencies in which the defender is located within 1, 3, or 5 feet of shot attempts. We calculated these frequencies for 93 qualifying defenders that faced at least 200 shots while playing defense. Tyler Hansbrough had the lowest frequency of being close to shots; he was within 5 feet of shots only 20.7% of the time. Only 3 defenders were within 5 feet of shots more than 35% of the time: Josh Harrellson, Kosta Koufos, and Jordan Hill. Serge Ibaka was fourth at 34.5%. The full set of results is available in Appendix 2.

B) Proximal FG%: the relative efficiencies of shooters in the proximity of the defender. Overall, when there is a qualifying interior defender within 5 feet of a shot attempt, the NBA shoots 45.6% from the field; however this value varies considerably depending on which defender that is. The most effective proximate defender in our study was Larry Sanders; opponents shot only 34.9% when he was within 5 feet of their shot. Conversely, Anderson Varejao was found to be the least effective proximate defenders with a proximal FG% value of 54.2%. Table 1 summarizes the best and worst players according to proximal FG%, but a complete list of proximal FG% values can be found in Appendix 2.

Top 5	Proximal FG%	Bottom 5	Proximal FG%
1. Larry Sanders	34.9%	48. Kevin Love	52.1%
2. Andrea Bargnani	35.2%	49. Jonas Valanciunas	52.8%
3. Kendrick Perkins	37.3%	50. David Lee	53.0%
4. Elton Brand	38.0%	51. Jordan Hill	53.9%
5. Roy Hibbert	38.7%	52. Anderson Varejao	54.2%

Table 1: The top and bottom 5 interior defenders according to proximal FG%, which is defined as the opponent's FG% when the qualifying defender is within 5 feet of the shot attempt.

Discussion and Limitations

In a league that is both teeming with new data sources as well as desperate for better diagnostics, the application of spatial and visual approaches to optical tracking data represents a vital new corridor to new kinds of basketball expertise. Furthermore, perhaps no aspect of basketball is as important and as under-studied as defense. Our case studies were designed to show how new data and emerging approaches can be integrated to help analysts better characterize defense in the NBA. While we contend it is clear that these studies effectively demonstrated the potential of spatial/visual analytics to expose new insights about defense, we also assert that the paper's methods only represent a small first step in a multi-step progression towards the core objective of better defensive analytics.

Evaluating defense in the NBA is very difficult. Despite the new analytical opportunities introduced by player tracking data, our current ability to extract meaningful defensive analytics from these data remains undeveloped. This fundamental notion manifests in multiple ways within our evaluation of interior defense. Perhaps the biggest limitation in our study involves the sample; player-tracking data is only being collected in a subset of NBA arenas. More specifically, as of January 2013, only 15 NBA arenas are equipped with SportVu systems. This obviously biases the sample and is likely to introduce error into our results. But our goal was not to generate the "be-all end-all" ensemble of defensive analytics; instead our goal was to demonstrate the viability of spatial approaches as they relate to making sense of defensive performance data.

Another key limitation is the lack of context associated with the data. Optical tracking data enables us to track player movements in fascinating new ways, but it also reduces players to geometric primitives that frequently obscure the nature of an action. In reality we know players are not coordinate pairs, they are athletic human beings. When we reduce Serge Ibaka to a simple x,y pair, we lose key information. In reality, Serge Ibaka is a 3-dimensional creature with arms that stretch and legs that jump. While this is painfully obvious, even our most sophisticated player tracking systems model NBA players as discrete locations on a plane. This dramatic abstraction of reality introduces infinite issues relating to uncertainty and error. Although we contend there is a vast amount of value in optical tracking data, more research is needed to evaluate uncertainty and reliability in these kinds of investigations.

Conclusion

This paper has sought to accomplish two main objectives: 1) demonstrate that the combination of spatial analyses, visual analytics, and optical tracking data presents a potent new mechanism to understand defensive effectiveness in the NBA, and 2) expose important challenges associated with measuring defensive performances in the NBA. Despite some relevant limitations, we contend that our results suggest that interior defensive abilities vary considerably across the league; simply stated, some players are more effective interior defenders than others. In terms of affecting shooting, we evaluated interior defense in 2 separate case studies. Each study focused on important aspects of interior defense, and as a result each study both answers and provokes important questions about defensive analytics. Although we acknowledge that neither study clearly identifies the best and worst interior defenders, we also contend that 1) each study effectively reveals important characteristics of good defensive play, and 2) advancing defensive analytics will be an long-term iterative process that will require several investigations and multiple new approaches. Lastly, due to his outstanding performance in both case studies, we conclude by suggesting Larry Sanders is the best interior defender in the NBA.

Acknowledgements

The authors would like to acknowledge the help and support of Brian Kopp, Ryan Warkins, Ryan Shea, and David Sherman of STATS. Thank you!

Appendix 1: Expanded Results from Case Study 1: Basket Proximity Shots faced when defender was within 5 feet of basket.

Rank	Defender	Shots Faced	% Close Range	% Mid-range	% 3-point range	Close FG%	Mid FG%	3-point FG%
1	Roy Hibbert	419	54.4	29.6	14.8	38.2	37.9	30.7
2	Larry Sanders	622	61.9	22.2	15.4	38.4	32.6	30.2
3	Elton Brand	198	57.1	26.8	14.1	39.8	32.1	46.4
4	Serge Ibaka	104	74.0	16.3	9.6	41.6	35.3	10.0
5	LaMarcus Aldridge	221	58.8	24.9	14.5	43.9	38.2	46.9
6	Jermaine O'Neal	392	56.9	28.1	14.0	44.0	32.7	32.7
7	Kosta Koufos	200	60.0	23.5	15.5	45.0	31.9	25.8
8	Kendrick Perkins	745	59.3	24.3	16.1	45.5	37.0	36.7
9	Joakim Noah	334	56.6	27.8	14.4	45.5	44.1	31.3
10	Dwight Howard	409	48.2	32.0	19.1	45.7	38.2	43.6
11	JaVale McGee	401	53.6	30.2	16.0	46.1	40.5	40.6
12	Amir Johnson	207	56.5	25.1	17.4	46.2	44.2	41.7
13	Ekpe Udoh	468	65.2	20.1	14.1	46.2	42.6	34.9
14	Andris Biedrins	317	49.8	28.7	20.5	46.8	42.9	36.9
15	Tim Duncan	930	57.3	28.6	13.7	47.1	41.4	46.5
16	Emeka Okafor	310	52.3	24.5	22.6	47.5	43.4	32.9
17	Jeremy Tyler	177	60.5	29.4	10.2	47.7	38.5	50.0
18	Nick Collison	273	52.0	27.8	18.7	47.9	35.5	37.3
19	Kevin Seraphin	475	55.6	28.4	14.9	48.1	40.7	35.2
20	DeMarcus Cousins	279	48.4	29.7	20.1	48.2	38.6	44.6
21	Marcus Camby	204	57.8	28.4	13.7	48.3	41.4	39.3
22	Kevin Garnett	772	54.4	28.6	16.2	48.3	37.6	41.6
23	Tiago Splitter	687	58.8	27.2	13.5	48.5	38.0	35.5
24	Samuel Dalembert	777	56.4	30.4	12.9	48.6	38.6	41.0
25	Nene Hilario	212	56.1	25.9	17.9	48.7	36.4	29.0
26	Aaron Gray	275	54.5	29.5	15.6	49.3	39.5	44.2
27	Ed Davis	391	61.6	23.3	14.8	49.4	40.7	34.5
28	Nazr Mohammed	260	51.9	28.1	18.8	49.6	41.1	28.6
29	Chris Bosh	263	55.9	23.2	19.8	49.7	32.8	40.4
30	Marcin Gortat	679	60.2	27.0	12.5	50.4	42.6	37.7
31	Al Jefferson	340	52.9	29.7	16.8	50.6	38.6	33.3
32	Jonas Valanciunas	239	59.4	26.8	13.4	50.7	43.8	37.5
33	Omer Asik	578	58.8	25.8	14.0	51.2	39.6	29.6
34	Greg Stiemsma	407	56.0	31.2	12.5	51.3	41.7	33.3
35	Tyson Chandler	794	57.6	25.6	16.5	51.4	40.4	34.4
36	Nikola Vucevic	421	64.4	24.0	11.6	51.7	37.6	26.5
37	Marc Gasol	344	52.6	26.5	19.5	51.9	33.0	32.8
38	Spencer Hawes	185	61.1	29.7	8.6	52.2	32.7	25.0
39	Nikola Pekovic	669	55.5	27.5	16.9	52.6	46.2	38.1
40	Greg Smith	207	65.2	26.1	8.2	52.6	35.2	35.3
41	Tristan Thompson	174	67.2	18.4	14.4	53.0	56.3	32.0
42	Chris Wilcox	217	65.9	21.2	12.4	53.2	45.7	40.7
43	Robin Lopez	201	61.2	22.4	14.9	53.7	31.1	33.3
44	Jordan Hill	195	60.5	17.9	20.5	54.2	51.4	27.5
45	Tyler Zeller	298	53.4	30.5	16.1	54.7	40.7	33.3
46	Chris Kaman	445	51.2	25.6	22.5	54.8	42.1	42.0
47	Drew Gooden	562	61.6	23.3	14.9	54.9	37.4	36.9
48	Anderson Varejao	224	56.7	23.2	19.2	55.9	42.3	37.2
49	Kevin Love	357	55.2	24.6	20.2	57.9	36.4	31.9
50	Greg Monroe	302	57.0	25.2	17.5	58.7	55.3	35.9
51	David Lee	400	60.3	23.3	15.3	61.0	33.3	29.5
52	Luis Scola	199	62.8	22.6	14.6	62.4	28.9	27.6

Appendix 1A: Same data as Appendix 1, but sorted according to % of shots occurring close to the basket

Rank	Defender	Shots Faced	% Close Range	% Mid-range	% 3-point range	Close FG%	Mid FG%	3-point FG%
1	Dwight Howard	409	48.2	32	19.1	45.7	38.2	43.6
2	DeMarcus Cousins	279	48.4	29.7	20.1	48.2	38.6	44.6
3	Andris Biedrins	317	49.8	28.7	20.5	46.8	42.9	36.9
4	Chris Kaman	445	51.2	25.6	22.5	54.8	42.1	42
5	Nazr Mohammed	260	51.9	28.1	18.8	49.6	41.1	28.6
6	Nick Collison	273	52	27.8	18.7	47.9	35.5	37.3
7	Emeka Okafor	310	52.3	24.5	22.6	47.5	43.4	32.9
8	Marc Gasol	344	52.6	26.5	19.5	51.9	33	32.8
9	Al Jefferson	340	52.9	29.7	16.8	50.6	38.6	33.3
10	Tyler Zeller	298	53.4	30.5	16.1	54.7	40.7	33.3
11	JaVale McGee	401	53.6	30.2	16	46.1	40.5	40.6
12	Roy Hibbert	419	54.4	29.6	14.8	38.2	37.9	30.7
13	Kevin Garnett	772	54.4	28.6	16.2	48.3	37.6	41.6
14	Aaron Gray	275	54.5	29.5	15.6	49.3	39.5	44.2
15	Kevin Love	357	55.2	24.6	20.2	57.9	36.4	31.9
16	Nikola Pekovic	669	55.5	27.5	16.9	52.6	46.2	38.1
17	Kevin Seraphin	475	55.6	28.4	14.9	48.1	40.7	35.2
18	Chris Bosh	263	55.9	23.2	19.8	49.7	32.8	40.4
19	Greg Stiemsma	407	56	31.2	12.5	51.3	41.7	33.3
20	Nene Hilario	212	56.1	25.9	17.9	48.7	36.4	29
21	Samuel Dalembert	777	56.4	30.4	12.9	48.6	38.6	41
22	Amir Johnson	207	56.5	25.1	17.4	46.2	44.2	41.7
23	Joakim Noah	334	56.6	27.8	14.4	45.5	44.1	31.3
24	Anderson Varejao	224	56.7	23.2	19.2	55.9	42.3	37.2
25	Jermaine O'Neal	392	56.9	28.1	14	44	32.7	32.7
26	Greg Monroe	302	57	25.2	17.5	58.7	55.3	35.9
27	Elton Brand	198	57.1	26.8	14.1	39.8	32.1	46.4
28	Tim Duncan	930	57.3	28.6	13.7	47.1	41.4	46.5
29	Tyson Chandler	794	57.6	25.6	16.5	51.4	40.4	34.4
30	Marcus Camby	204	57.8	28.4	13.7	48.3	41.4	39.3
31	LaMarcus Aldridge	221	58.8	24.9	14.5	43.9	38.2	46.9
32	Tiago Splitter	687	58.8	27.2	13.5	48.5	38	35.5
33	Omer Asik	578	58.8	25.8	14	51.2	39.6	29.6
34	Kendrick Perkins	745	59.3	24.3	16.1	45.5	37	36.7
35	Jonas Valanciunas	239	59.4	26.8	13.4	50.7	43.8	37.5
36	Kosta Koufos	200	60	23.5	15.5	45	31.9	25.8
37	Marcin Gortat	679	60.2	27	12.5	50.4	42.6	37.7
38	David Lee	400	60.3	23.3	15.3	61	33.3	29.5
39	Jeremy Tyler	177	60.5	29.4	10.2	47.7	38.5	50
40	Jordan Hill	195	60.5	17.9	20.5	54.2	51.4	27.5
41	Spencer Hawes	185	61.1	29.7	8.6	52.2	32.7	25
42	Robin Lopez	201	61.2	22.4	14.9	53.7	31.1	33.3
43	Ed Davis	391	61.6	23.3	14.8	49.4	40.7	34.5
44	Drew Gooden	562	61.6	23.3	14.9	54.9	37.4	36.9
45	Larry Sanders	622	61.9	22.2	15.4	38.4	32.6	30.2
46	Luis Scola	199	62.8	22.6	14.6	62.4	28.9	27.6
47	Nikola Vucevic	421	64.4	24	11.6	51.7	37.6	26.5
48	Ekpe Udoh	468	65.2	20.1	14.1	46.2	42.6	34.9
49	Greg Smith	207	65.2	26.1	8.2	52.6	35.2	35.3
50	Chris Wilcox	217	65.9	21.2	12.4	53.2	45.7	40.7
51	Tristan Thompson	174	67.2	18.4	14.4	53	56.3	32
52	Serge Ibaka	104	74	16.3	9.6	41.6	35.3	10

Appendix 2: Expanded Results from Case Study 2: Shot Defended: Shots faced when defender was close to shooter.

A) **Shots defended:** The results are presented as:

(% of shots where defenders was within 1 foot) / (% within 3-feet) / (% within 5-feet)

5-ft Rank	Defender	Shots Faced	Within 1ft	Within 3ft	Within 5ft
1	Josh Harrellson	206	1.5	22.3	35.9
2	Kosta Koufos	447	3.8	21.3	35.6
3	Jordan Hill	519	1.9	22.4	35.1
4	Serge Ibaka	223	1.8	21.1	34.5
5	Chris Wilcox	616	1.6	17.9	34.4
6	Greg Smith	613	1.6	16.6	34.3
7	Jermaine O'Neal	925	1.6	17.6	34.1
8	Cole Aldrich	364	0.8	14.0	33.8
9	Greg Stiemsma	910	1.9	18.6	33.7
10	Jonas Valanciunas	536	2.1	18.1	33.6
11	Ekpe Udoh	1321	2.0	17.6	32.6
12	Larry Sanders	1482	2.4	17.3	32.5
13	Spencer Hawes	553	1.4	16.3	32.2
14	Jason Collins	207	1.9	16.9	31.9
15	Jeremy Tyler	502	2.4	18.1	31.7
16	Marcin Gortat	1745	1.7	17.3	31.4
17	Elton Brand	547	1.3	17.0	31.3
18	Gustavo Ayon	437	0.9	16.5	31.1
19	Robin Lopez	540	0.7	16.9	31.1
20	Tim Duncan	2353	1.4	17.5	31.1
21	Kevin Love	922	1.8	15.2	31.0
22	Amir Johnson	488	2.9	17.4	30.5
23	Drew Gooden	1513	1.2	13.4	30.3
24	Tiago Splitter	2022	1.6	15.4	30.1
25	Anthony Randolph	284	0.4	15.5	29.9
26	Andray Blatche	389	1.5	14.4	29.8
27	Jon Leuer	239	1.3	15.5	29.7
28	Lavoy Allen	239	1.7	17.6	29.7
29	Amar'e Stoudemire	253	2.8	13.0	29.6
30	Chris Kaman	1095	2.5	17.4	29.5
31	Kurt Thomas	235	2.1	13.2	29.4
32	Nikola Vucevic	1352	1.7	14.1	29.0
33	Tyson Chandler	2186	1.3	15.7	29.0
34	Kevin Garnett	2067	0.8	13.0	28.7
35	Andrew Bogut	248	1.2	13.3	28.6
36	Roy Hibbert	1094	1.9	16.5	28.6
37	Jason Smith	221	1.8	15.4	28.5
38	Brandan Wright	435	0.9	13.8	28.5
39	Andris Biedrins	783	1.9	15.2	28.4
40	Al Jefferson	947	1.6	14.3	28.3
41	Ian Mahinmi	532	2.1	16.4	28.2
42	Ed Davis	1171	1.2	14.6	28.2
43	Tyler Zeller	741	1.1	13.5	27.9
44	Samuel Dalembert	1765	1.9	15.2	27.8
45	Anderson Varejao	603	0.7	12.9	27.5
46	Kevin Seraphin	1141	1.5	16.7	27.5
47	Tristan Thompson	611	1.3	14.1	27.5
48	Darko Milicic	420	1.0	13.8	27.4
49	Patrick Patterson	280	1.8	13.9	27.1
50	Nick Collison	854	1.4	12.6	27.0
51	Jared Jeffries	281	1.1	13.5	27.0
52	Brook Lopez	337	2.4	12.8	27.0
53	Omer Asik	1571	1.5	15.1	27.0
54	Joakim Noah	1017	1.3	13.0	26.8
55	Andre Drummond	210	1.4	10.5	26.7
56	Luis Scola	629	1.3	13.8	26.6
57	David Lee	1269	1.2	11.3	26.5
58	Kwame Brown	242	0.8	12.8	26.4
59	Pau Gasol	227	0.0	0.0	26.4
60	Jamaal Magloire	228	2.6	16.2	26.3
61	Jason Thompson	289	1.4	11.1	26.3
62	Chris Bosh	810	0.6	10.5	26.0
63	Kendrick Perkins	2605	1.3	12.6	25.9
64	Ryan Hollins	337	1.5	11.9	25.5
65	Marc Gasol	1071	1.5	13.7	25.5
66	Nazr Mohammed	699	1.3	13.2	25.5
67	Hasheem Thabeet	444	0.9	11.7	25.5
68	Byron Mullens	442	0.5	13.3	25.3
69	Festus Ezeli	487	1.4	12.9	25.3



7TH ANNUAL
MIT SLOAN
SPORTS ANALYTICS CONFERENCE
 MARCH 1-2, 2013 BOSTON CONVENTION AND EXHIBITION CENTER

presented by **ESPN**

70	Marcus Camby	674	0.4	11.1	25.2
71	Nene Hilario	598	2.2	11.2	25.1
72	Aaron Gray	836	0.8	11.4	25.0
73	Emeka Okafor	818	1.2	13.3	24.9
74	Greg Monroe	853	2.2	11.5	24.7
75	Meyers Leonard	211	0.9	12.3	24.6
76	Zaza Pachulia	492	1.8	13.6	24.6
77	Ryan Anderson	387	0.8	11.6	24.5
78	DeMarcus Cousins	802	1.5	11.5	24.4
79	DeAndre Jordan	566	0.5	10.6	24.4
80	DeJuan Blair	353	0.8	9.1	24.4
81	JaVale McGee	928	1.6	11.7	24.4
82	Nikola Pekovic	1980	1.0	13.4	24.0
83	Dwight Howard	1071	1.2	10.0	23.6
84	Al Horford	269	1.9	10.8	23.0
85	LaMarcus Aldridge	732	0.7	10.9	23.0
86	Enes Kanter	318	2.8	12.3	22.6
87	Boris Diaw	285	1.1	7.7	22.5
88	Andrew Bynum	614	0.5	9.8	22.3
89	Blake Griffin	256	0.8	9.0	21.9
90	Andrea Bargnani	727	1.0	9.8	21.9
91	Brandon Bass	271	1.1	11.8	21.8
92	Brendan Haywood	404	1.0	10.4	21.0
93	Tyler Hansbrough	381	1.3	9.2	20.7

B) Proximal FG%: The results summarize the FG% of opponents when each defender was within 5 feet.

Rank	Defender	FG%
1	Larry Sanders	34.9%
2	Andrea Bargnani	35.2%
3	Kendrick Perkins	37.3%
4	Elton Brand	38.0%
5	Roy Hibbert	38.7%
6	Kosta Koufos	39.0%
7	Nene Hilario	40.0%
8	Andris Biedrins	41.0%
9	Greg Stiemsma	41.7%
10	Jermaine O'Neal	42.2%
11	JaVale McGee	42.5%
12	Nazr Mohammed	43.3%
13	Ian Mahinmi	43.3%
14	Tim Duncan	43.4%
15	Dwight Howard	43.5%
16	Marc Gasol	43.6%
17	Kevin Seraphin	43.6%
18	Jeremy Tyler	44.0%
19	LaMarcus Aldridge	44.1%
20	Aaron Gray	44.5%
21	Kevin Garnett	44.9%
22	DeMarcus Cousins	44.9%
23	Marcus Camby	45.3%
24	Ekpe Udoh	45.4%
25	Nick Collison	45.5%
26	Chris Bosh	45.5%
27	Tiago Splitter	45.6%
28	Tyson Chandler	45.7%
29	Samuel Dalembert	45.7%
30	Joakim Noah	45.8%
31	Omer Asik	46.0%
32	Emeka Okafor	46.6%
33	Tyler Zeller	46.9%
34	Chris Wilcox	47.2%
35	Marcin Gortat	47.5%
36	Spencer Hawes	47.8%
37	Nikola Pekovic	48.0%
38	Al Jefferson	48.5%
39	Ed Davis	48.8%
40	Nikola Vucevic	49.0%
41	Greg Smith	49.1%
42	Robin Lopez	49.4%
43	Chris Kaman	49.5%
44	Greg Monroe	50.2%
45	Tristan Thompson	50.6%
46	Luis Scola	51.5%
47	Drew Gooden	51.8%
48	Kevin Love	52.1%
49	Jonas Valanciunas	52.8%
50	David Lee	53.0%
51	Jordan Hill	53.9%
52	Anderson Varejao	54.2%