Do In-Game Runs Increase the Probability of Winning in Professional Basketball? A Data-Driven Approach

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In professional basketball, an in-game run can be defined as a set of consecutive points that one team scores in a relatively short time frame. This study's goal was to determine whether an in-game run increases a team's probability of winning a game above and beyond a baseline value, which is calculated as the probability of winning observed for the same score advantage without a run. Data collected from 8,370 U.S. professional basketball games show that in-game runs rarely provide an additional increase in probability of winning above the baseline. In certain cases, in-game runs are associated with lower probabilities of winning despite their score advantage. Our analysis enables fans, sports enthusiasts, bettors, and TV networks to determine how in-game runs affect the probability of winning in real time.

Keywords: probability of winning, baseline probability, professional basketball, in-game runs

INTRODUCTION

Professional basketball is a fast-paced game with frequent scoring. One of the most closely watched metrics during game play is an in-game run, which is a set of unanswered points scored by one team in a relatively short time frame. While broadcasting games, TV networks usually overlay this metric on the screen such as Team A's 10-0 run in the past 3 minutes.

Most fans and sports enthusiasts entertain the notion that a team that makes an in-game run has a higher chance of winning not only because of the resulting point difference, but also the psychological damage inflicted on the opposing team by the end of the run. For example, teams that concede a run usually experience a loss of morale, which might further lead to panic and bad decisions, such as retaliatory fouls, premature shots, risky passes, or untimely timeouts. The effects can be more devastating when a run creates a double-digit deficit in a relatively short time frame. Holmes (2018, p.54) refers to this as "the most frightening 3 minutes" in professional basketball, especially when a team concedes 10 or more points in 3 minutes or less. Holmes further describes the state of the opposing players at the end of these types of runs using familiar scenes: players start to stare at the floor, their shoulders start to sag, and they droop onto the bench, while the energized fans for the other team start their raucous chanting.

In this paper, we examined the prevailing notion of these runs, or unanswered points, and how they influenced a team's probability of winning. We specifically analyzed whether an in-game run increased the probability of winning above and beyond a baseline probability, which is based on the same score advantage obtained without a run. To this end, we extracted data on in-game runs and analyzed their effects in two different scenarios, namely runs that break ties and runs that lead to ties. Fans and sports enthusiasts can use our results to determine whether an in-game run can change a game's outcome beyond the score advantage obtained at the end of the run. This might help them set their expectations for the game more realistically without getting caught up in the excitement that runs generate. Bettors also can use our findings to determine their in-game betting strategies specifically after runs. If they can determine how runs contribute to teams' winning probabilities, they can reduce their risks or take more risks, depending on how many points are scored during a run and when the run is made. Finally, understanding the effects of in-game runs can be important for TV networks that might want to provide predictive statistics on the screen while broadcasting games.

This paper is organized as follows. In the next section, we discuss previous work on in-game runs. In the subsequent section, we discuss our data set. We then describe our data analysis approach. After presenting our results, we conclude by discussing our findings and implications.

RELATED WORK

An in-game run can be defined as a set of consecutive and unanswered points that one team scores during a game (Schilling 2019). Runs also are viewed as the team version of the *hot hand* phenomenon, though in this case, a team scores a set of points in a relatively short amount of time without allowing the opponent to score any points during that time. Even though most fans and sports enthusiasts view a run as a sign of one team's dominance over another—and an early indication of a rout—a recent in-depth analysis shows that the occurrence of in-game runs is a random process (Schilling 2019). Accordingly, runs occur naturally during a game, with fans creating an illusion of dominance in their minds. Similar findings have been reported for the player version of the hot hand phenomenon, which concerns whether an individual player's scoring streak leads him/her to score more consecutive points. Findings show that there is no such thing as a hot hand because there is no correlation between successive shots' outcomes (Gilovich, Vallone, and Tversky 1985). Furthermore, extant work suggests that the hot hand phenomenon is more of a perception wherein one wants to believe that a player is on a scoring streak (e.g., Carlson and Shu 2007).

Even though these studies assert that in-game runs occur naturally in any given game, they do not provide insights into whether in-game runs determine game outcomes. Despite a lack of studies to address this question, it has been shown that the number of in-game runs that one team achieves during one season is positively correlated to the percentage of games that the team wins during that season (Partnow 2015). We also know that teams that make a last-ditch-effort run to come back from a deficit and tie their games at the end of regulation do not necessarily win these games (Morgulev, Azar, and Bar-Eli 2019).

It also has been suggested that in-game runs might change game outcomes because of their psychological effects on players, though the evidence is mostly anecdotal. For instance, players often speak of "embarrassment" after conceding a run, and fans usually attribute game losses to players' loss of morale after a run by the other team (c.f. Holmes 2018). One line of research that provides insights into these psychological effects is the concept of momentum. This line of work investigates whether a team's winning streak during one season leads to more wins during that season because of the streak's positive psychological effects. However, the findings are rather inconsistent. While certain studies demonstrate that success begets more success in professional basketball (e.g., Iso-Ahola and Dotson 2014; Arkes 2011; Arkes and Martinez 2011), others show no such effect (e.g., Vergin 2000).

In summary, the above studies do not provide a definitive answer to the question that this study examines. We still do not know whether an in-game run can increase a team's probability of winning above and beyond a baseline, which is the probability value observed for the same score difference generated without a run. One can argue that an in-game run is a natural occurrence in any given game and, thus, should not provide an advantage above the baseline. However, one also can argue that a run can exert significant scoring or psychological effects on teams and, thus, should generate a probability of winning higher than the baseline. In the sections that follow, we describe our data analysis strategy to investigate these arguments. Specifically, we examine how an in-game run changes a team's probability of winning compared with a baseline probability of winning while the game is underway.

DATA SET

Our data set comprises 8,370 National Basketball Association (NBA) professional games played between the 2011 and 2017 seasons. After downloading the play-by-play data from these games, we wrote a script to identify each team's in-game runs during each game. We only identified runs with 6 or more points. Focusing on 6-point runs as the minimum point total was motivated by the fact that 6 points can be achieved through two back-to-back 3-point goals or three back-to-back 2-point goals, which could signal the beginning of a run. Note that a typical NBA game lasts 48 minutes in regulation, but we excluded the first and last 6 minutes from the analysis because teams might not be able to find their rhythm in the first 6 minutes, and runs observed in the last 6 minutes might determine a winner because there is not enough time for the other team to respond. As a result, we performed analysis on the remaining 36 minutes of each game.

Considering that a team can make numerous runs during a game, we identified each run made by home and away teams separately for every game. For each run, we extracted the following information: points scored during the run; whether the home or away team executed the run; the time on the clock at the end of the run; and the point difference between the home and away teams before and after the run.

DATA ANALYSIS

In our preliminary analysis, we conducted a separate analysis for each second of these 36 minutes. First, we focused on home teams' 6-point runs that enabled them to take the lead by 6 points (i.e., the scores were tied before the run). For any given second, we identified all games in which a 6-point run was underway during that second. Among these games, we selected only those in which the home and away teams' scores were tied before the run. Next, we calculated the proportion of games that home teams won among these games. This generated the probability of winning as a result of a 6-point run (and a 6-point lead) at that second. To calculate a baseline probability, we identified all other games in which home teams had a 6-point lead that was achieved without a run. We calculated the baseline as the proportion of games that these teams won during this second. We compared this baseline probability with the probability of winning as a result of the run. We then repeated this analysis for up to 10-point runs. We further repeated the same analyses for the away teams.

Consider the following example: The time on the game clock shows 5 min 0 sec during the first quarter (i.e., 7 minutes have passed in the first quarter). We focus on home teams' 6-point runs that are underway at this second (i.e., home teams already have scored 6 points without conceding any goals at the 5 min 0 sec mark). We also focus on the games in which the point difference between home and away teams is 6 points at this second (i.e., the scores were tied before home teams started the 6-point runs.) Imagine that there is a total of 100 such games, with the home teams winning 60 of them. Therefore, the probability of winning is calculated as 60% for the home team under the following conditions: 1) Home teams made a 6-point run; 2) home teams have a 6-point advantage over away teams; and 3) the time on the clock shows 5 min 0 sec. Also imagine that in 300 more games, the home teams have a 6-point advantage over away teams without any runs (or runs that are less than 6 points) at the 5 min 0 sec mark. If home teams win 150 of these games, the baseline accuracy is calculated as 50% (which is 150÷300×100) for home teams. In this case, we posit that a 6-point run observed at 5 min 0 sec that creates a 6-point advantage for a home team provides an additional 10% chance of winning over the baseline probability of winning. We then move the time on the game clock ahead by 1 second (to 4 min 59 sec) and calculate the new baseline and new probability of winning. Repeating this until the end of the game shows how a 6-point run that provides a 6-point advantage for a home team changes the home team's probability of winning throughout the game timeline, compared with a baseline probability of winning. We then repeat this analysis for the away teams.

Note that conducting this analysis was challenging because there were not enough observations during certain parts of the game timeline that satisfied the three conditions discussed above: 1) a specific run (e.g., 6-points); 2) a specific point difference observed between the teams (e.g., a 6-point difference in favor of home teams); 3) a specific second on the game timeline (e.g., the 5 min 0 sec mark). In some cases, we could not calculate the probability because no runs occurred. In other cases, the probability of winning was calculated using only a few observations or outliers, which generated unreliable values. For this reason, we relaxed the last two conditions as follows: Instead of conducting a second-by-second analysis, we created a sliding window of 60 seconds that moved in 1-second increments. Therefore, we included all runs that occurred during this 60-second window in the analysis. Also, we allowed the point difference between the teams to fluctuate by 2 points in both directions. For example, instead of identifying those games in which home teams had a 6-point advantage over away teams in this sliding window, we identified all games in which home teams' point advantage ranged from 4 points to 8 points in the sliding window. Please note that we did not relax the first condition; therefore, our analysis still focused on a specific run, such as a 6-point run, to determine its effects on game outcomes. Despite these changes, we observed that the probability values still were being calculated using a few observations during certain parts of the game. As a result, we also created a rule to stop calculating probability values if a sliding window contained less than 10 observations.

As a result, the above example took the following form. The time on the game clock shows between 5 min 30 sec and 4 min 30 sec. We still focused on home teams' 6-point runs. We identified all games in which home teams' point advantage ranges from 4 to 8 points (i.e., 6 ± 2) over away teams.

After calculating the corresponding probability values for each sliding window, we plotted them on the game timeline and generated the chart presented in Figure 1. In this chart, the y-axis is the probability of winning, and the x-axis is the time on the game clock (in seconds passed). In the chart, the black line shows a home team's probability of winning after a 6-point run. For example, if a home team makes a 6-point run at the end of the second quarter (i.e., the 1,440-second mark on the x-axis), its probability of winning the game is 68%. On the other hand, the gray line on the same chart shows the baseline probability of winning for the same point difference without a run. For example, if another home team has the same point advantage at the 1,440-second mark—achieved without a run—then its probability of winning is 69.5%. This means that at this second of the game, a 6-point run made by a home team does not necessarily increase the team's probability of winning above the baseline. On the contrary, this run leads to a lower probability of winning compared with the baseline. To put it differently, a home team that makes a 6-point run during this second is less likely to win the game compared with another home team that has the same point advantage without a run.

As seen in the figure, a 6-point run gives a home team a higher probability of winning than the baseline at certain intervals of the game, but a lower probability of winning at other intervals. To reconcile the two probability values, we calculated two metrics: a) area above the baseline (AAB), which is the region where a run has a higher probability than the baseline, and b) area below the baseline (ABB), which is the region where a run has a lower probability than the baseline. For example, in Figure 2, the black-shaded area shows the AAB, while the gray-shaded area shows the ABB. The difference between these two areas can be viewed as the net effect from a 6-point run. For example, the difference between these areas corresponds to -0.5% for the first quarter, -2.5% for the second quarter, -0.3% for the third quarter, and -3.4% for the fourth quarter. This means that a 6-point run that generates a 6-point advantage for a home team, on average, does not necessarily increase the team's chances of winning above the baseline in any quarter of the game, despite some episodic increases at certain intervals during each quarter. Overall, one can say that the net effect, on average, is negative; thus, these types of runs reduce the probability of winning compared with the baseline.

FIGURE 1
PROBABILITY OF WINNING COMPARED WITH BASELINE—HOME TEAMS' 6-POINT RUNS

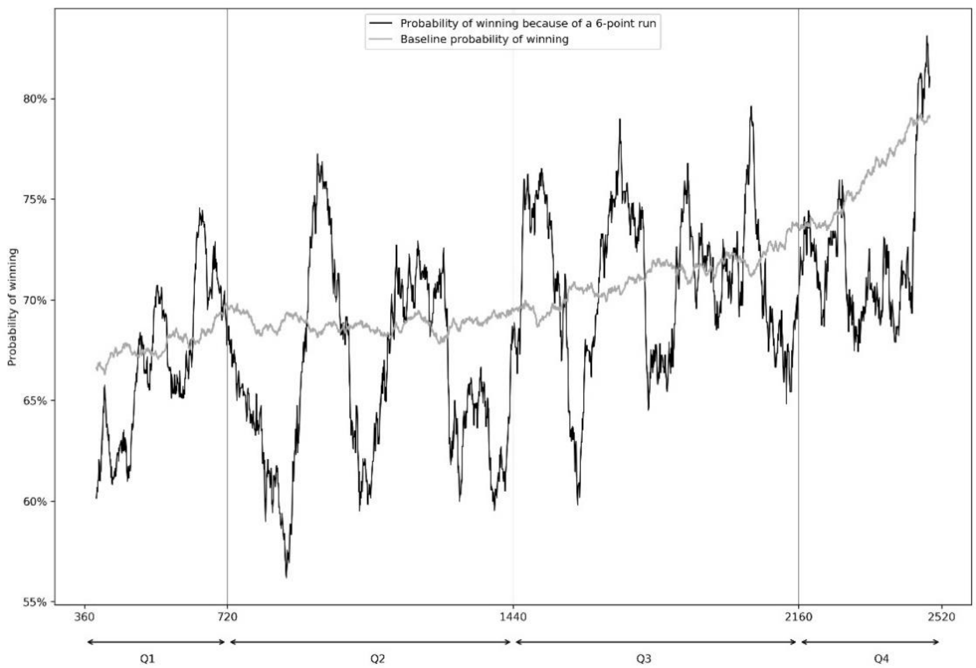
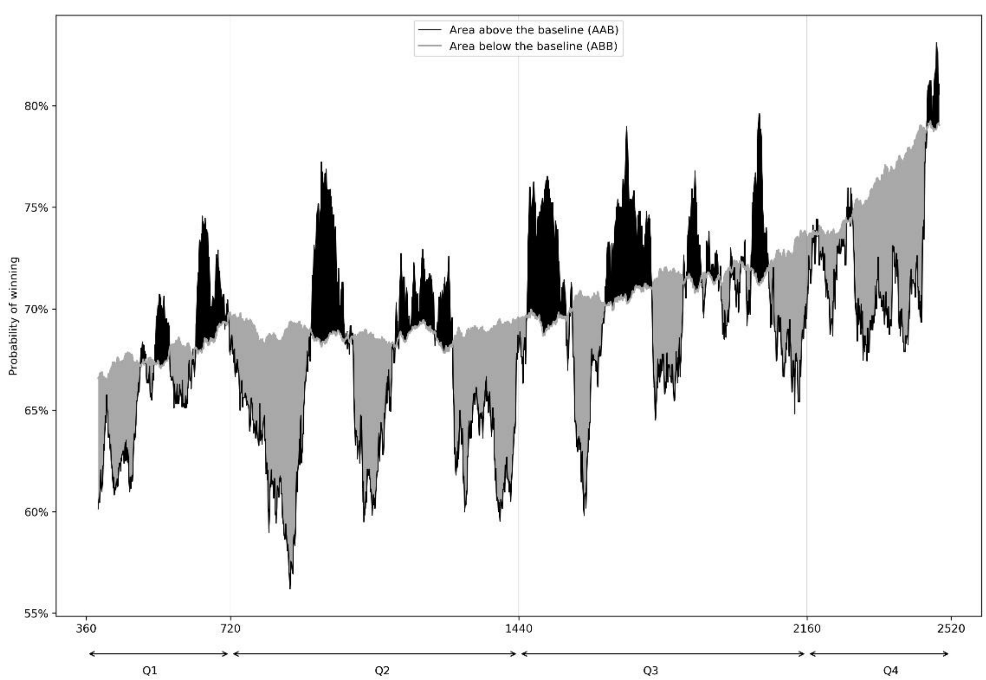


FIGURE 2
PROBABILITY OF WINNING COMPARED WITH BASELINE—HOME TEAMS' 6-POINT RUNS



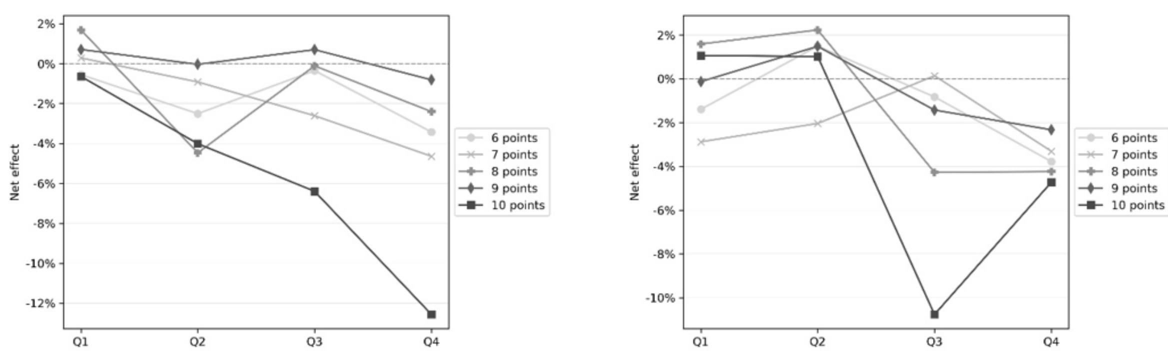
Note that the above analysis is for 6-point runs made by home teams that produce a 6-point advantage. We repeated this analysis for up to 10-point runs, including for the away teams. However, analyses of more than 10 points were based on so few observations that the probability values became unstable; therefore, we did not conduct analyses of runs that had more than 10 points.

RESULTS

Runs That Break a Tie

In the first analysis, we focused on runs in tied games, in which the home and away teams have the same point totals before a run. This analysis allowed us to see whether runs made during tied games generated a higher probability of winning compared with the baseline. We analyzed all runs between 6 and 10 points. For each run, we conducted the analysis described in the previous section and calculated the AAB and ABB values for each quarter.

FIGURE 1
SUMMARY OF FINDINGS FOR RUNS THAT BREAK TIES



Panel 3A. Home teams' runs—net effect

Panel 3B. Away teams' runs—net effect

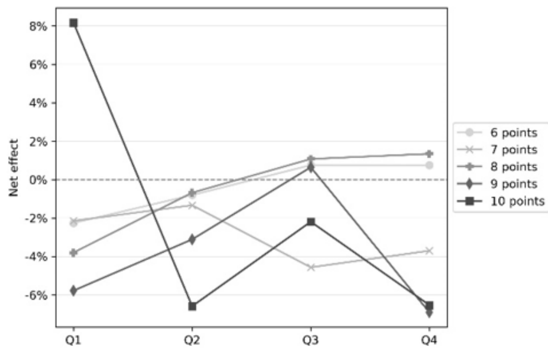
As seen in Panel 3B of the same figure, away teams' runs do not necessarily increase the probability of winning above the baseline either. The highest net effect is 2.2% for an 8-point run in the second quarter, while the lowest net effect is -10.8% for a 10-point run in the third quarter. The trend is similar such that the net effect decreases toward the end of the games. This indicates that when games are tied, away teams' runs generate lower probabilities of winning than the baselines toward the end of the games. The detailed results are presented in Table 1.2 of Appendix 1.

Runs That Lead to Ties

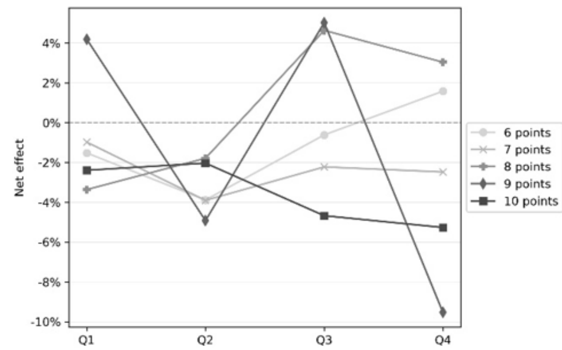
In the second analysis, we focused on runs that allowed teams to come back from deficits and tie the score. This analysis allowed us to examine whether these types of runs generate enough momentum for trailing teams to help them win games. Like before, we analyzed all runs between 6 and 10 points. For each run, we conducted the analysis described earlier and calculated the AAB and ABB values for each quarter.

The summary of findings is presented in Figure 4, in which Panels 4A and 4B show the results for the home and away teams, respectively. As seen in Panel 4A, the highest net effect was observed as 8.2% for a 10-point run in the first quarter. The lowest net effect was -6.9% for a 9-/point run in the **FOURTH** quarter. With a few exceptions, the net effect increases from the first quarter to the third quarter. However, most of the net effects are negative, indicating that home teams' runs that tie games, on average, do not necessarily generate higher probabilities of winning than the corresponding baselines. Detailed results that show the AAB and ABB values of each run for each quarter are provided in Table 2.1 of Appendix 2.

FIGURE 2
SUMMARY OF FINDINGS FOR RUNS THAT BREAK TIES



Panel 4A. Home teams' runs—net effect



Panel 4B. Away teams' runs—net effect

As seen in Panel 4B of the same figure, away teams' runs generate mixed results as well. The highest net effect is 5.0% for a 9-point run in the third quarter, while the lowest net effect is -9.5% for a 9-point run in the fourth quarter. With a few exceptions, most of the net effects are negative, indicating that away teams' runs that tie games usually generate lower probabilities of winning than the corresponding baselines. Detailed results that show the AAB and ABB values of each run for each quarter are provided in Table B2 of Appendix 2.

DISCUSSION

Summary of Results

In this study, we examined how in-game runs change a team's probability of winning a game compared with a baseline probability. The findings from our analyses are summarized in Table 1, in which Panels (a) and (b) show runs that break a tie and runs that lead to a tie, respectively. For each run in each quarter, we show whether it increases a team's probability of winning compared with the corresponding baseline, and if it does, by how much. If the increase is between 0.1% and 1.9%, we label it a "small" effect; if it is between 2.0% and 3.9%, we label it a "medium" effect; and if it is larger than 4.0%, we label it a "large" effect on the table.

As seen in Panel (a), most runs that break a tie do not increase either home teams' or away teams' probabilities of winning above the baseline. When they do, the increase is usually small. There is only one medium effect, on away teams' 8-point runs in the second quarter.

Panel (b) also shows that there are few instances in which runs that lead to a tie increase a team's probability of winning above the baseline. While most effects are small, runs that are 8 points or higher lead to larger increases above baselines, especially during the first and third quarters.

TABLE 1
SUMMARY OF FINDINGS—INCREASE IN WINNING PROBABILITY COMPARED WITH BASELINE

	Points	Q1 Home	Q1 Away	Q2 Home	Q2 Away	Q3 Home	Q3 Away	Q4 Home	Q4 Away
(a)	6 points	-	-	-	Small	-	-	-	-
	7 points	Small	-	-	-	-	Small	-	-
	8 points	Small	Small	-	Medium	-	-	-	-
	9 points	Small	-	-	Small	Small	-	-	-
	10 points	-	Small	-	Small	-	-	-	-
(b)	6 points	-	-	-	-	Small	-	Small	Small
	7 points	-	-	-	-	-	-	-	-
	8 points	-	-	-	-	Small	Large	Small	Medium
	9 points	-	Large	-	-	Small	Large	-	-
	10 points	Large	-	-	-	-	-	-	-

- : No increase above baseline
Small : 0.1% - 1.9% increase above baseline
Medium : 2.0% - 3.9% increase above baseline
Large : >4.0% increase above baseline

(a) Runs that break a tie
(b) Runs that lead to a tie

Limitations

A major limitation of this study is that we do not account for team strength while making predictions. Therefore, we cannot distinguish between a run made by the strongest team in the league and a run made by the weakest team. This is important because the psychological and/or score effects from a run made by the strongest team are likely to be more significant than those made by the weakest team. However, team strength cannot be considered easily in the analysis because team strength not only changes from one season to the next, but also changes from one game to the next due to various factors, such as team chemistry, injuries, fatigue, and roster. Therefore, it is not easy to break down the results using a strength index unless such a value can be measured for each game before the game starts using the roster, injuries, and other game-day variables. This is a challenging task (c.f. Manner 2016) that is outside this study's scope.

Implications

In-game runs are purported to be natural occurrences in professional basketball even though fans, sports enthusiasts, and even TV networks closely watch them to declare an early winner in a game. Our goal in this study was to see whether in-game runs that specifically break ties or lead to ties increase a team's probability of winning above the baseline probability of winning. Understanding the effects from these runs is important. Without knowing how in-game runs change game outcomes, many stakeholders, such as fans and bettors, make a naïve assumption that the team that makes one of these runs gains an advantage over the opponent because of the run's score advantage, as well as a psychological advantage. However, our analyses show that these runs do not necessarily provide an advantage above and beyond the baseline probability in many instances. In fact, in most cases, runs generate a lower probability of winning than the baseline probability. Even though this sounds counterintuitive, it might have two plausible explanations. The first concerns the randomness of runs and the fallacy of the hot hand phenomenon (Carlson and Shu 2007; Gilovich, Vallone, and Tversky 1985; Schilling 2019). Accordingly, temporal advantages gained through runs might not necessarily be the result of one team's dominance over the other, but rather these runs' stochasticity during any game. Therefore, it is likely that advantages gained from a run will be lost during subsequent minutes to the opposing team's runs.

The second explanation concerns the stability of the score advantage generated through runs. By *stability*, we mean how well the score advantage can be maintained. It might be the case that score advantages obtained from runs have less stability—and, thus, erode faster—than those obtained without runs, i.e., a score difference obtained without a run might be more stable because one team can be truly better than the other during a specific interval of the game. Therefore, score advantages obtained without runs might be built on a stronger foundation than those obtained with runs.

However, it should be noted that our findings do not necessarily indicate that a run does not increase a team's likelihood of winning a game. On the contrary, we find that they do increase winning probabilities, though in small amounts and in few instances. Therefore, runs still might help boost probabilities of winning, but not as much as the hype surrounding them would suggest.

The above insights are particularly important for bettors while placing in-game bets. Instead of making impulsive decisions, bettors can compare each run against the corresponding baseline probability to determine its effects on a game's outcome. This might prevent them from taking additional risks by adjusting their expectations of the resulting score advantage that runs generate. Furthermore, TV networks can use the insights gained from this study to show teams' winning probabilities after in-game runs while games are being played. This is important, as leagues and TV networks are trying to increase viewer engagement through the use of in-depth statistics during games (Ross 2020).

CONCLUSION

This study's goal was to determine whether in-game runs lead to a higher probability of winning above a baseline probability. Our analyses showed that most runs that break ties or lead to ties, on average, do not increase a team's probability of winning above and beyond a baseline probability.

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APPENDIX 1

TABLE 1.1
HOME TEAMS' RUNS THAT BREAK TIES

Points	Quarter	AAB*	ABB**	Net effect***
6 points	Q1	2.6%	3.1%	-0.5%
	Q2	2.9%	5.4%	-2.5%
	Q3	3.4%	3.7%	-0.3%
	Q4	1.5%	4.9%	-3.4%
7 points	Q1	2.8%	2.6%	0.3%
	Q2	3.4%	4.3%	-0.9%
	Q3	3.3%	5.9%	-2.6%
	Q4	1.7%	6.3%	-4.6%
8 points	Q1	3.6%	1.9%	1.7%
	Q2	3.6%	8.1%	-4.5%
	Q3	4.6%	4.7%	-0.1%
	Q4	1.6%	4.0%	-2.4%
9 points	Q1	6.1%	5.4%	0.7%
	Q2	2.9%	2.9%	0.0%
	Q3	6.0%	5.3%	0.7%
	Q4	7.5%	8.3%	-0.8%
10 points	Q1	5.0%	5.6%	-0.6%
	Q2	3.7%	7.7%	-4.0%
	Q3	4.9%	11.3%	-6.4%
	Q4	3.6%	16.1%	-12.6%

* Area above the baseline (AAB)
** Area below the baseline (ABB)
*** Net effect = AAB - ABB

TABLE 1.2
AWAY TEAMS' RUNS THAT BREAK TIES

Points	**Quarter**	**AAB***	**ABB****	**Net effect*****
6 points	Q1	1.9%	3.3%	-1.4%
	Q2	4.2%	2.7%	1.5%
	Q3	3.8%	4.6%	-0.8%
	Q4	2.5%	6.3%	-3.8%
7 points	Q1	2.1%	5.0%	-2.9%
	Q2	3.7%	5.8%	-2.0%
	Q3	5.5%	5.3%	0.1%
	Q4	3.6%	6.9%	-3.3%
8 points	Q1	8.0%	6.4%	1.6%
	Q2	7.7%	5.5%	2.2%
	Q3	3.6%	7.9%	-4.3%
	Q4	3.1%	7.4%	-4.2%
9 points	Q1	9.7%	9.8%	-0.1%
	Q2	6.1%	4.6%	1.5%
	Q3	4.3%	5.7%	-1.4%
	Q4	5.9%	8.2%	-2.3%
10 points	Q1	5.7%	4.7%	1.1%
	Q2	8.6%	7.6%	1.0%
	Q3	3.0%	13.8%	-10.8%
	Q4	6.6%	11.3%	-4.7%

* Area above the baseline (AAB)
** Area below the baseline (ABB)
*** Net effect = AAB = ABB

APPENDIX 2

TABLE 2.1
HOME TEAMS' RUNS THAT LEAD TO TIES

Points	Quarter	AAB*	ABB**	Net effect***
6 points	Q1	3.6%	5.9%	-2.3%
	Q2	3.5%	4.3%	-0.8%
	Q3	3.4%	2.6%	0.8%
	Q4	3.5%	2.7%	0.8%
7 points	Q1	2.1%	4.3%	-2.1%
	Q2	4.7%	6.0%	-1.3%
	Q3	3.0%	7.6%	-4.6%
	Q4	1.8%	5.5%	-3.7%
8 points	Q1	6.9%	10.7%	-3.8%
	Q2	7.4%	8.1%	-0.7%
	Q3	5.5%	4.5%	1.1%
	Q4	8.6%	7.3%	1.3%
9 points	Q1	2.6%	8.4%	-5.8%
	Q2	5.6%	8.7%	-3.1%
	Q3	7.3%	6.6%	0.6%
	Q4	2.4%	9.3%	-6.9%
10 points	Q1	12.0%	3.8%	8.2%
	Q2	6.6%	13.2%	-6.6%
	Q3	7.7%	9.9%	-2.2%
	Q4	3.0%	9.5%	-6.5%

* Area above the baseline (AAB)
** Area below the baseline (ABB)
*** Net effect = AAB - ABB

TABLE 2.2
AWAY TEAMS' RUNS THAT LEAD TO TIES

Points	Quarter	AAB*	ABB**	Net effect***
6 points	Q1	1.8%	3.3%	-1.5%
	Q2	1.9%	5.7%	-3.9%
	Q3	3.4%	4.0%	-0.6%
	Q4	4.6%	3.0%	1.6%
7 points	Q1	3.0%	4.0%	-1.0%
	Q2	1.9%	5.8%	-3.9%
	Q3	1.4%	3.7%	-2.2%
	Q4	4.1%	6.6%	-2.5%
8 points	Q1	3.7%	7.1%	-3.4%
	Q2	5.9%	7.7%	-1.8%
	Q3	9.2%	4.6%	4.6%
	Q4	6.7%	3.7%	3.0%
9 points	Q1	7.4%	3.2%	4.2%
	Q2	5.7%	10.6%	-4.9%
	Q3	13.0%	8.0%	5.0%
	Q4	3.2%	12.8%	-9.5%
10 points	Q1	11.3%	13.7%	-2.4%
	Q2	3.9%	5.9%	-2.0%
	Q3	7.7%	12.3%	-4.7%
	Q4	10.5%	15.8%	-5.3%

* Area above the baseline (AAB)
** Area below the baseline (ABB)
*** Net effect = AAB - ABB