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Research Paper

When is an NBA Lead Truly Safe?

A Mathematical Model of Win Probability Based on Score Differential and Time Remaining

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Abstract
A lead in a National Basketball Association (NBA) game does not have a fixed value. A 10-point deficit can still be overcome early in the fourth quarter, but the same margin is largely decisive in the closing minutes of a game. Using the play-by-play dataset pbp2023.csv for the 2022-23 NBA season, this paper uses quantitative modeling to examine how the security of a lead changes over time. Raw event records were processed into game snapshots sampled every 30 seconds throughout the fourth quarter. Each snapshot, referred to as a game state, recorded the point differential and remaining game time and was linked to whether the team ultimately won or lost the game. The final sample consists of 30,657 fourth-quarter game states across 1,320 games.
According to the sample statistics, teams with a positive point differential—that is, teams leading by at least 1 point—during the fourth quarter of an NBA game have an overall observed win rate of 86.64%. However, a lead does not guarantee a win, and the likelihood of winning depends on both the size of the lead and the amount of time remaining. Therefore, this study estimates win probability as a function of point differential and remaining game time.
This study constructs a logistic-regression win-probability model using current lead margin, remaining fourth-quarter time, and the interaction between these two variables as predictors. On the test set, the model achieves an AUC of 0.83974, which measures how well the model distinguishes winning game states from losing ones. It also achieves a Brier score of 0.091447 and a log loss of 0.28834, two measures of the accuracy of predicted probabilities, where lower values indicate better performance. The model can then be used to define thresholds for a secure lead. Using a 90%-win probability as the security criterion, a team must lead by at least 13 points at the start of the fourth quarter. The required lead then decreases to 11 points with 10 minutes remaining, 7 points with 5 minutes remaining, and 6 points with 2 minutes remaining. These results indicate that lead security depends jointly on lead margin and remaining game time rather than on the point differential alone.

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I. Introduction

Basketball coaches, sports analysts, and fans often debate whether a lead is surmountable. Although the notion of a "secure lead" is widely used in sports commentary, it has long lacked a clear, quantifiable definition. A 6-point lead may allow a team to breathe easy when there is only 30 seconds left on the clock; however, the same 6-point advantage is vulnerable at the start of the fourth quarter.

Although terms such as "secure lead" or "game over" are widely used, no single quantitative standard exists for comparing such situations at different times in a game[1]. Therefore, this study aims to translate an informal basketball term into a quantifiable statistical measure. The value of a lead changes as time runs down. As the game clock winds down, the trailing team has fewer offensive possessions, fewer opportunities to force turnovers, draw fouls for free throws, and call timeouts for tactical adjustments[2]. This report treats lead security as a probability-estimation problem: estimating the probability that the leading team will win, given the point differential and remaining time at any point in the fourth quarter[3]. To define a "secure lead," three win-probability thresholds are considered: 90%, 95%, and 99%.

This analysis focuses exclusively on the fourth quarter, when lead security is most relevant. While point differentials from the first three quarters provide context, they correlate less to a secure lead in the final minutes or seconds of play. By examining game-state snapshots from the fourth quarter, this study develops a simple, interpretable statistical model that directly addresses the core research question.

Data Source and Preprocessing

The source file for this study is *pbp2023.csv*, which contains complete play-by-play data for all NBA games of the 2022–23 season. Play-by-play data have been used in previous basketball research to model game states using information such as game time and point differential[4]. The raw dataset consists of 646,971 game-event records across 16 variables, corresponding to 1,320 games. Core fields include game identifier, quarter, remaining game time, home-team score, away-team score, team responsible for the event, event type, and event outcome. Many entries in the raw data do not reflect score changes, which is a common feature of play-by-play data. Rebounds, fouls, timeouts, and turnovers do not alter the game score alone. After filtering for entries with valid scores for both teams, 171,832 records remained.

Raw remaining-time values were stored as character strings such as "PT11M38.00S". These string-formatted timestamps were first converted to remaining seconds within the quarter, then transformed into remaining minutes for subsequent modeling. For each game, the final home-team and away-team scores were extracted to identify the winner. The dataset included 84 games that went into overtime. Nevertheless, the model used state-level data exclusively from the final minutes of regulation time. Overtime affected only the final outcome: a team leading late in the fourth quarter may lose its lead, enter overtime, and ultimately lose the game.

To avoid overweighting games with many late-game events and possessions, fixed time points rather than individual events were adopted as the sampling unit. For the fourth quarter of each game, game states were sampled at 30-second intervals from 12:00 down to 0:30 remaining on the clock. At each sampling timestamp, the most recent score recorded before or at that point in the game was used. Observations with tied scores at sampling moments were discarded. The final analytical sample comprised 30,657 fourth-quarter game-state observations covering all 1,320 games.

Table 1. Source data and modeling sample

Item	Value
Raw play-by-play rows	646,971
Variables in raw file	16
Games	1,320
Valid scoring records	171,832
Fourth-quarter non-tied states	30,657
Games represented in state sample	1,320
Current leader final win rate	86.64%
Overtime games	84

Descriptive Analysis

Based on the fixed-interval state samples, most fourth-quarter lead margins are relatively modest. Across all 30,657 observations, the mean lead margin is 11.115 points, with a median of 9 points and a standard deviation of 8.4531 points. The first, second, and third quartiles are 5 points, 9 points, and 16 points, respectively. After excluding tie scenarios, the minimum observed lead margin in the sample is 1 point, while the maximum reaches 59 points. Because the mean exceeds the median, the distribution of lead margins is positively skewed. Most games remain competitively close, and a relatively small number of large leads increases the overall mean.

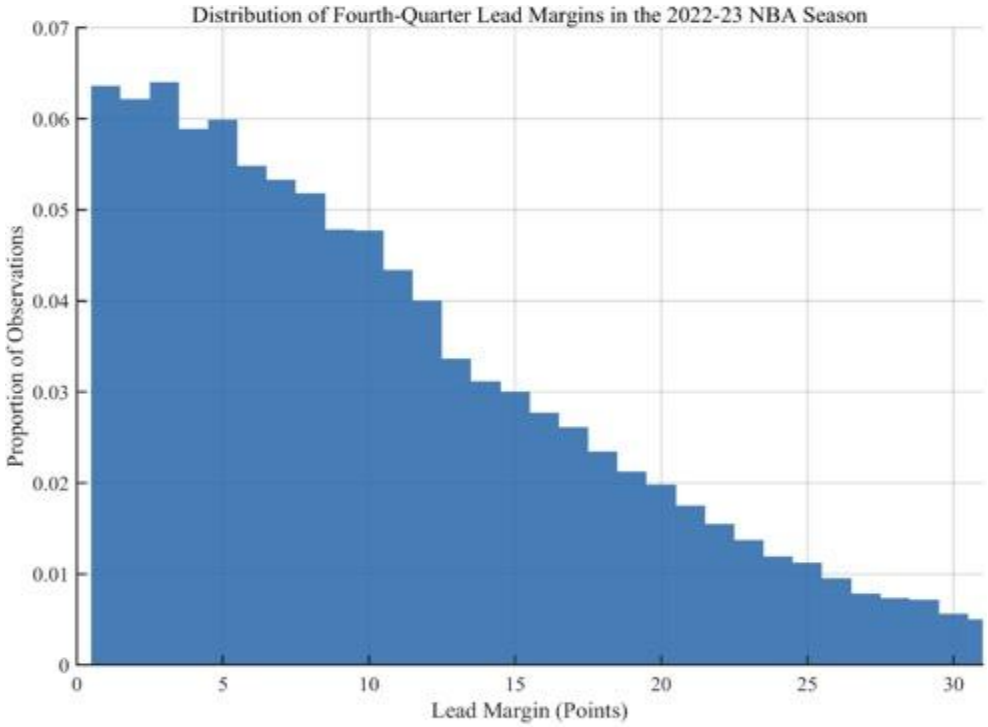


Figure 1. Distribution of fourth-quarter lead sizes in the 2022-23 NBA season

Across all non-tied fourth-quarter game states in the sample, the team leading at the sampled moment ultimately won 86.64% of the time. This indicates that holding a lead during the fourth quarter is a strong signal of eventual victory; however, it does not guarantee a win, since 13.36% of these game states were associated with eventual losses. Phrases such as "the leading team usually wins" are too broad; this report instead distinguishes between game situations with substantially different outcomes, such as leading by 1 point with 10 minutes remaining versus leading by 12 points with 1 minute remaining.

Table 2. Lead-size descriptive statistics for fourth-quarter states

Statistic	Value
Sample N	30,657
Game N	1,320
Mean lead	11.115
Median lead	9
Standard deviation	8.4531
Minimum lead	1
Maximum lead	59
First quartile	5
Second quartile	9
Third quartile	16

Leader win percentage	86.639%

Empirical Win Rates

Before constructing the regression model, empirical win rates were examined to identify basic data patterns. Table 3 groups observations by remaining game time and intervals of lead margin. It then reports the win rate for the leading team within each subgroup. The data show that with 10 minutes remaining, teams holding a 1- to 3-point lead have an empirical win rate of 61.05%, which rises to 89.41% for teams with a 10- to 12-point lead. When only 2 minutes remain, teams with a 4- to 6-point lead achieve a 90.19% win rate, and those holding a 10- to 12-point lead have a win rate of 99.39%.

Several subgroups in the table exhibit an observed win rate of 100%. This figure suggests that no comebacks occurred in the current-season sample. Given the limited sample size of a single-season dataset, certain extreme game scenarios contain no instances of losses, yet future games may still produce comebacks even when none occurred in that subgroup during this season. This motivates using a smoothed probabilistic model rather than relying solely on empirical win-rate tables.

Table 3. Empirical leader win rates by time remaining and lead range

Time	1-3	4-6	7-9	10-12	13-15	16-20	21+
10 min	61.05%	70.98%	81.25%	89.41%	97.44%	100%	100%
5 min	61.16%	77.25%	89.05%	95.38%	98.44%	99.35%	100%
3 min	68.29%	86.36%	96.34%	97.66%	99.08%	100%	100%
2 min	71.60%	90.19%	95.56%	99.39%	100%	100%	100%
1 min	76.40%	95.69%	98.89%	100%	100%	100%	100%
30 sec	77.57%	98.43%	99.45%	100%	100%	100%	100%

Logistic Win Probability Model

Logistic regression has also been applied to NBA data to model the relationship between game characteristics and winning probability[5]. The response variable is *leader_win*, which takes a value of 1 if the team leading at the sampling time point ultimately wins the game, and 0 otherwise. The explanatory variables consist of three components: L (current point lead), T (remaining minutes in the fourth quarter), and LT (the interaction term between L and T). Inclusion of this interaction term is essential, as the marginal value of an additional point tends to be higher in the later stages of a game than in earlier stages of the fourth quarter. Parameter estimation was performed after partitioning the samples by full games rather than individual observational states; consequently, similar states within the same game do not appear in both the training and test datasets. The training set comprises 24,475 states from 1,056 games, while the test set comprises 6,182 states from 264 games. The proportion of states in which the leading team ultimately won was similar in the two datasets: 86.472% in the training set and 87.302% in the test set. The fitted model is given by:

$$\mathbf{logit}(p) = 0.284413 + 0.389329L - 0.052826T - 0.015235LT$$

where p represents the predicted probability that the team currently leading will ultimately win the game.

Similar logistic-regression approaches have been used in basketball prediction models and evaluated using probability-based measures such as log loss[6]. The coefficient of lead margin is positive, indicating that a larger lead increases the probability of winning; the coefficient of remaining time is negative, indicating that, given a fixed lead margin, the longer the remaining time, the less secure the lead becomes; the negative interaction term implies that the positive effect of each additional point of lead margin intensifies as the remaining time decreases.

Table 4. Logistic regression coefficient estimates

Variable	Estimate	SE	t statistic	p value
Intercept	0.28441	0.07940	3.582	0.000341

Lead Margin (*L*)	0.38933	0.015893	24.496	1.61e-132
Remaining Time (*T*)	-0.052826	0.010056	-5.253	1.50e-7
Lead Margin × Remaining Time (*LT*)	-0.015235	0.001821	-8.367	5.94e-17

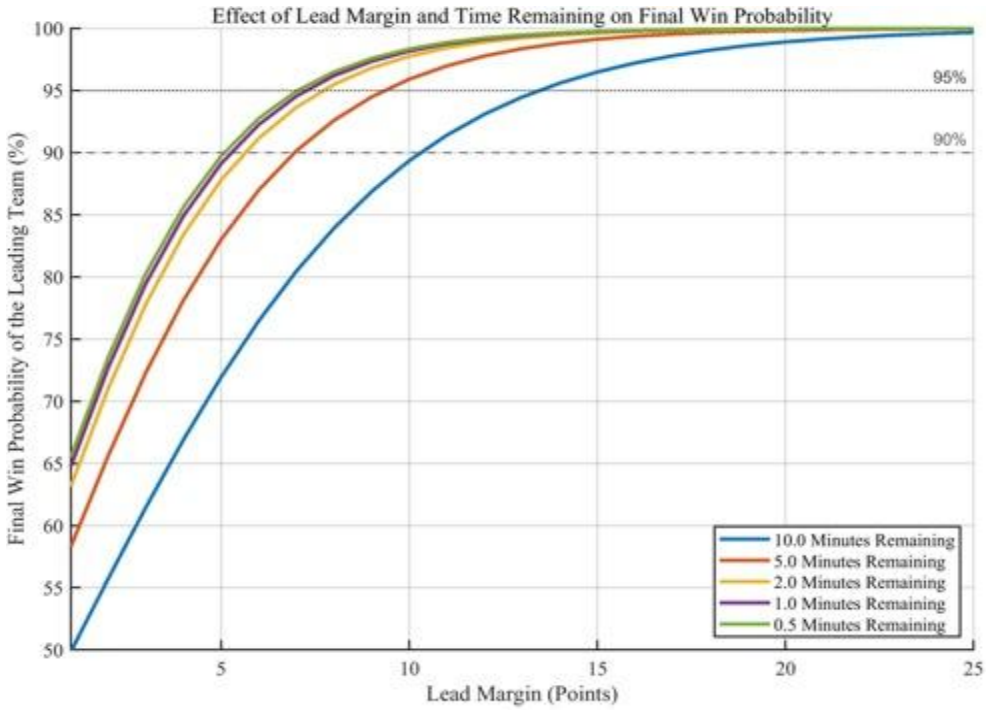


Figure 2. Model-predicted win probability curves by score differential and time remaining

The prediction curves illustrate why phrases such as "leading by 6 points" can be misleading: With 10 minutes remaining, the model-predicted win probability for a 6-point lead is 76.46%; with 5 minutes remaining, it rises to 86.98%; with 2 minutes remaining, it reaches 91.15%; and with 30 seconds remaining, it further increases to 92.75%. These results show that the same point differential can represent very different levels of game security depending on the time remaining.

Table 5. Model-predicted win probabilities for the leading team in common game states

Lead Margin (points)	10 min	5 min	3 min	2 min	1 min	30 sec
1	49.83%	58.26%	61.53%	63.13%	64.70%	65.47%
2	55.73%	65.62%	69.28%	71.02%	72.71%	73.52%
3	61.47%	72.31%	76.08%	77.82%	79.48%	80.27%
4	66.91%	78.12%	81.76%	83.40%	84.92%	85.63%
5	71.93%	83.01%	86.34%	87.79%	89.11%	89.72%
6	76.46%	86.98%	89.91%	91.15%	92.25%	92.75%
8	83.92%	92.59%	94.66%	95.48%	96.17%	96.48%

10	89.34%	95.90%	97.24%	97.74%	98.15%	98.33%
12	93.09%	97.76%	98.59%	98.88%	99.12%	99.21%
15	96.48%	99.11%	99.49%	99.62%	99.71%	99.75%
20	98.90%	99.81%	99.91%	99.94%	99.96%	99.96%

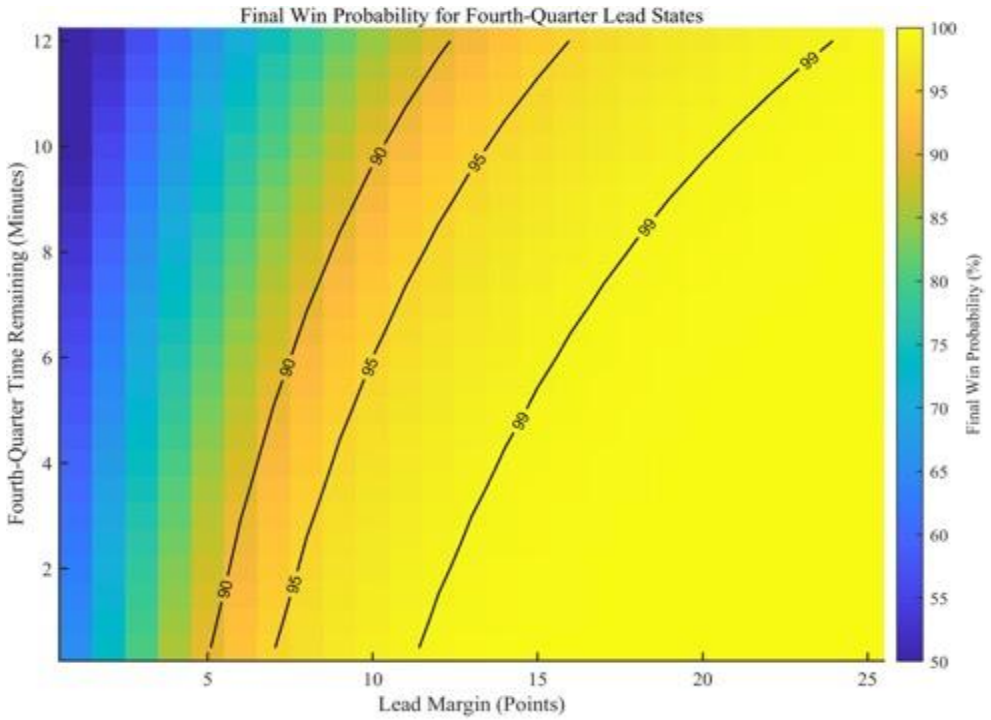


Figure 3. Two-dimensional win probability surface for lead size and remaining time

Model Performance, ROC, and Calibration

The held-out test set evaluates the model's performance on games not used for parameter estimation. At a probability threshold of 0.5, predicted probabilities are converted into binary win-or-loss classifications: probabilities of 0.5 or greater are classified as wins, while probabilities below 0.5 are classified as losses. Accuracy measures the overall proportion of correct classifications; precision measures how often predicted wins are actual wins; recall measures how many actual wins are correctly identified; specificity measures how many actual losses are correctly identified; and the F1-score summarizes the balance between precision and recall. At this threshold, the model yields an accuracy of 0.87253, a precision of 0.87859, a recall of 0.99092, a specificity of 0.058599, and an F1-score of 0.93138. The corresponding confusion matrix consists of 46 true-negative observations, 739 false-positive observations, 49 false-negative observations, and 5,348 true-positive observations.

The model's low specificity should be interpreted in the context of this study. Because teams with a positive point differential during the fourth quarter win a large majority of the observed game states, the 0.5 classification threshold causes the model to classify most observations as wins. As a result, the model identifies relatively few eventual losses among teams that are currently leading, which contributes to its low specificity. This limitation is less important for probability estimation than for detecting rare upsets. The model achieves an AUC of 0.83974, meaning that it assigns a higher predicted win probability to a randomly selected winning state than to a randomly selected losing state about 84% of the time. The Brier score and log loss evaluate the quality of predicted probabilities, with lower values indicating better performance[7]. The model achieves a Brier score of 0.091447 and a log loss of 0.28834.

Table 6. Test-set classification and probability metrics

Metric	Value
Accuracy	0.87253
Precision	0.87859
Recall	0.99092
Specificity	0.058599
F1-score	0.93138
AUC	0.83974
Brier score	0.091447
Log loss	0.28834

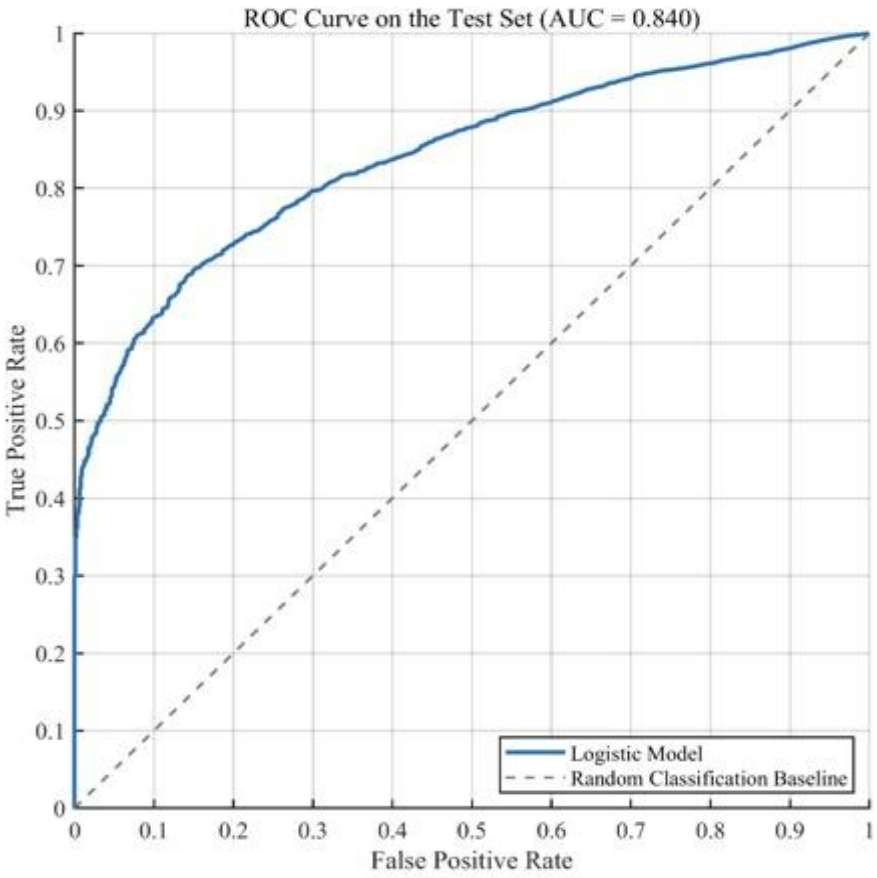


Figure 4. ROC curve for the logistic win-probability model

Probability calibration, which measures how closely predicted probabilities correspond to observed win frequencies, is particularly important because the secure-lead thresholds in this study are defined using model-predicted probabilities. Within intervals with sufficient data density, model-predicted probabilities closely align

with empirically observed win rates. For the predicted-probability bin ranging from 0.7 to 0.8, the mean predicted probability and observed win rate are 74.88% and 74.71%, respectively. For the 0.8-to-0.9 bin, the corresponding values are 85.45% and 84.93%. For the 0.9-to-1.0 bin, they reach 97.50% and 97.66%. By contrast, no observations fall into bins with predicted probabilities below 0.4, which is consistent with the dataset being restricted to fourth-quarter states in which one team is already leading.

Table 7. Calibration table for predicted probabilities

Predicted bin	Sample N	Mean predicted probability	Observed win rate
0.0-0.1	0	NaN	NaN
0.1-0.2	0	NaN	NaN
0.2-0.3	0	NaN	NaN
0.3-0.4	0	NaN	NaN
0.4-0.5	95	48.23%	51.58%
0.5-0.6	368	55.50%	57.07%
0.6-0.7	539	65.11%	66.98%
0.7-0.8	680	74.88%	74.71%
0.8-0.9	989	85.45%	84.93%
0.9-1.0	3,511	97.50%	97.66%

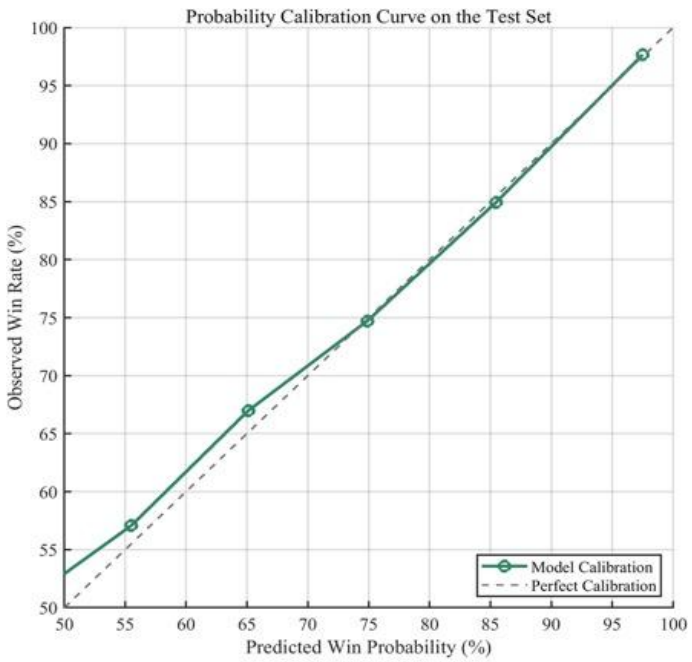


Figure 5. Calibration of predicted win probabilities against observed win rates

Safe Lead Thresholds

This model translates the abstract concept of a "secure lead" into concrete numerical values. Specifically, a target win probability q is first specified. For a given remaining time T, the minimum lead margin L that satisfies the target win probability is identified. This report adopts three target probability levels: 90%, 95%, and 99%. Among these, 90% represents a relatively lenient standard for a "secure lead," whereas 99% represents a much stricter one.

Table 8 summarizes the secure-lead thresholds for the three target win probabilities. At the beginning of the fourth quarter, a 13-point lead is required to achieve a 90%-win probability, 16 points for 95%, and 24 points for 99%. When 5 minutes remain, these thresholds drop to 7 points, 10 points and 15 points, respectively. At the 2-minute mark, they further decline to 6 points, 8 points and 13 points. In the final 30 seconds of play, the threshold for 90%-win probability remains 6 points, while the thresholds for 95% and 99% stand at 8 points and 12 points.

Table 8. Safe-lead thresholds by target win probability

Time remaining	90% threshold	95% threshold	99% threshold
12 min	13	16	24
10 min	11	14	21
8 min	9	12	18
6 min	8	10	16
5 min	7	10	15
4 min	7	9	14
3 min	7	9	14
2 min	6	8	13
1 min	6	8	12
30 sec	6	8	12

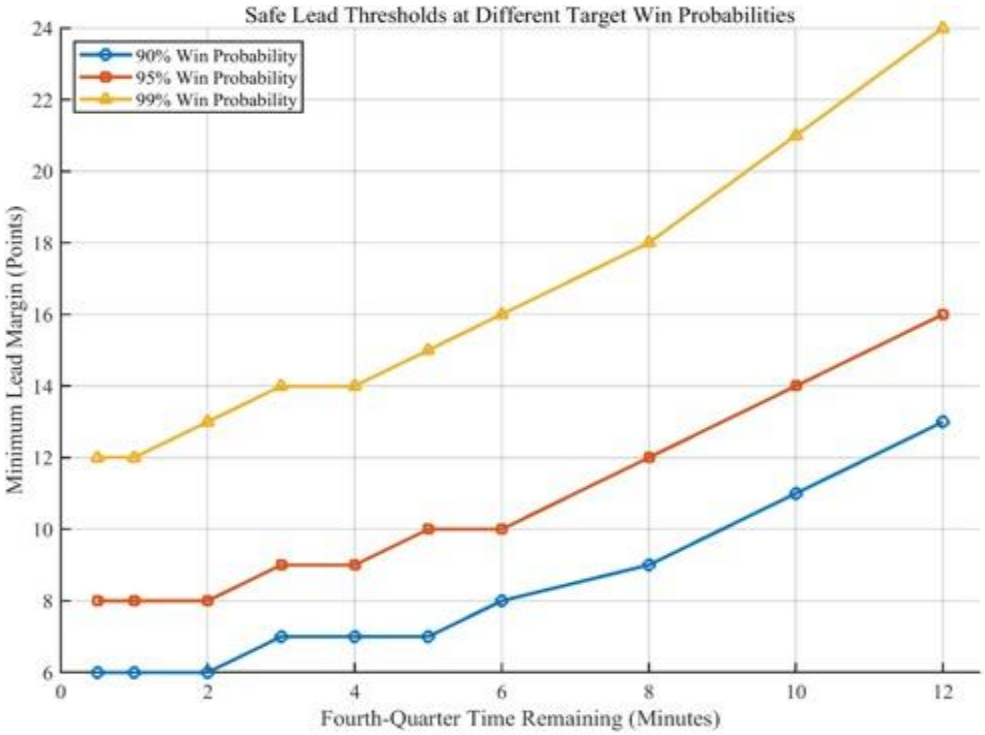


Figure 6. Safe-lead thresholds under 90 percent, 95 percent, and 99 percent win-probability definitions

This research model should not be treated as a rigid rule for every game. Rather, it should be considered a general reference. For instance, an 8-point lead with 2 minutes left yields a win probability above 95%, yet comebacks cannot be entirely ruled out. A turnover, a 3-point field goal, a missed free throw, or an intentional foul can still alter the course of the contest[8]. These thresholds provide a common probabilistic scale for comparing different game situations. They also show that each additional point becomes more valuable as less time remains.

As the fourth quarter unfolds, the lead margin required to reach a predefined win probability gradually decreases. A lead that appears unsafe earlier in the quarter can become much more secure in the final few minutes.

These findings also show that lead margin must be interpreted in relation to remaining game time. A 10-point lead with 10 minutes remaining falls slightly below the 90% win-probability threshold. By contrast, the same 10-point advantage exceeds the threshold for 95%-win probability when only 5 minutes remain. A 6-point lead is far from secure early in the fourth quarter, yet the same margin can meet the threshold for a 90%-win probability once the final 2 minutes arrive.

II. Limitations

This model is intentionally simple: it includes only the lead margin, remaining time, and their interaction as variables, while excluding factors such as ball possession, team strength, home-court advantage, player injuries, number of timeouts, number of fouls, point spread, or starting lineups. These factors may be important in individual games. For example, leading by 6 points while in possession may provide a greater advantage than leading by 6 points while the opponent is in possession. Likewise, a stronger team may protect a lead differently from a weaker team. This analysis uses data from a single NBA season, encompassing 1,320 games. However, NBA styles of play evolve: 3-point attempt rates, foul strategies, pace of play, and the frequency of timeout usage may all alter the practical value of a lead. Building the model on multi-season data would produce more reliable estimates, particularly for rare comebacks and the 99% win-probability threshold[9]. The fixed 30-second sampling interval also simplifies the analytical workflow: while this setup facilitates cross-game comparisons, it does not capture every possession. Other event-based sports models have shown that incorporating preceding event sequences can preserve additional context and improve probability estimates. Consequently, the model is best viewed as a simplified summary of fourth-quarter game dynamics during the 2022–23 NBA season, rather than a comprehensive real-time win-probability system.

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