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Computational Analysis of Komi and Fairness in Go: An AI-Based Approach Using KataGo

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Abstract—Go, a stimulating board game conquered by AI with the advancement of reinforcement learning, has attracted increasing attention. In Go, komi offsets the first-move advantage of Black so that the game can be considered fair. However, the theoretical basis for standard values such as 6.5 or 7.5 remains obscure, and the intrinsic fairness of these settings has not been tested. Using high-quality self-play iterations, we model the relationship between komi and the expected final score under optimal play. Our evaluation shows that this relationship follows a logistic distribution, which can determine a fair komi. We further investigate the trend of komi under Chinese or AGA area scoring versus Japanese territory scoring, and across different board sizes and AI strengths. We find that the fair komi for 7×7 boards is 9.0, while for 9×9, 13×13, and 19×19 boards it is 7.0 under Chinese or AGA rules. Under Japanese rules, the fair komi is consistently 1.0 point lower. Our findings challenge the long-standing assumption that komi must include a half-point and invite re-examination of how fairness should be defined. This work demonstrates how modern AI can act as scientific tools for testing the mathematical structure of complex board games such as Go.

Index Terms—Fairness, KataGo, Komi, Reinforcement Learning, Score-based Self-play

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I. INTRODUCTION

Go has long been one of the most intellectually challenging strategy games, with very simple rules and unmatched strategic complexity. Apart from its sportive appeal, considerable research has been conducted in psychology, cognitive neuroscience, and education regarding Go and other strategy games with increased strategic complexity as high-level cognitive tasks [1–3].

Given its intellectually demanding nature, to use Go as a competitive brain game, fair rule application becomes paramount, with each player seeking to triumph by virtue of their intellect, as opposed to rule-favoring advantages [4].

The first move inherently favors Black, and not White, due to Go's rule that Black goes first. To ensure adherence to "Victory by intellect, not by structure," modern versions of Go tournaments therefore involve komi, whereby white has points added to their score at game end to compensate for their first-move disadvantage [5].

The development of komi has been practice-driven, with the Go community evolving rules and game settings over time based more on experience with actual games than mathematical or computational analysis [4]. The original professional game format involved no komi at all, with the Black first-move lead merely considered part of the game and not something that led to any need to compensate for fairness reasons [4]. But with the build-up of statistical evidence regarding first-move bias, organizers introduced komi values such as 4.5 and 5.5 points, and later national Go organizations specified modern values such as 6.5 points for Japan and Korea, and 7.5 points in Chinese versions, all based on empirical win rate distributions in masters-level games and not due to theoretically supported values or logic [6]. Thus, while today komi has occupied center stage in competitive play, its role has been and continues to be a game tradition and based on empirical results, not a theoretically supported game parameter [6]. Prior theoretical discussions have also considered how komi fairness depends on the underlying scoring system, but these analyses have remained largely conceptual rather than based on large-scale AI-driven evaluation.[7]

The presence of such powerful Go-playing AI, such as AlphaGo, AlphaZero, Leela Zero, and others, could make one think that calculating "fair komi" has suddenly become easy. However, the classical win-loss-based architectures do not make this readily feasible. For

example, in systems like AlphaZero and Leela Zero, the value networks estimate the probability of winning as Black with a fixed komi, and Monte Carlo tree search conducts its searches with this fixed komi throughout the process [8]. This means that after such learning, it is not feasible to ask such a model to assess game advantages at another fixed value of komi, as its winning and losing conditions are already determined with respect to the komi at which it was trained [8],[9]. Recent advances, particularly in KataGo, brought multi-komi training and scoring learning, making it possible to analyze game positions with respect to several komi settings at once and behave identically with regard to various rules and playing sizes [10]. This really does provide new grounds to research komi fairness scientifically, although by far these abilities have applied primarily in enhancing playing strength and not in obtaining an exact estimate of fair komi values.

Even within the AI research literature, we are still left with gaps. Systematic comparisons across rulesets are rare. Further, we do not know how dependent K^* is on board size (9×9 , 13×13 , 19×19) or engine strength [11]. Most prior studies have treated Go engines as black-box evaluators of win probability, analyzing komi effects primarily through changes in win-rate estimates [11],[12]. These methods typically do not model komi in terms of expected score differences and most of them used win-probability-based methods such as AlphaZero or LeelaZero [12]. In fact, what is absent is a rigorous, data-rich, and theory-driven framework, one that uses modern multi-komi engines to characterize the full functional relationship between komi and expected final score in the context of AI-generated self-play. This is exactly what this study aims to address.

II. BACKGROUND & RELATED WORK

Playing complex strategy games such as Go has long been regarded as a demanding cognitive activity. Prior research has found that engaging in games with high strategic complexity can positively influence sustained attention, spatial reasoning, long-term planning, and working memory [1–3]. Neuroimaging studies of expert Baduk players further reveal distinctive patterns of brain activation and connectivity associated with high-level strategic reasoning [1–3].

In addition to these cognitive effects, Go-based activities have also been explored in clinical and educational contexts. Participation in demanding strategy games has been associated with delayed cognitive decline in older adults with normal cognition

and improved executive functioning in children with ADHD participating in Go-related training programs [1–3].

Historically, Go games were played without komi, and the advantage of the first move was regarded as an inherent feature of the game rather than something requiring compensation [4]. As competitive play developed and statistical analyses of professional games became more widely available, researchers began to observe a systematic advantage for Black associated with moving first [6].

To mitigate this imbalance, tournament organizers gradually introduced komi values as a compensatory mechanism. Early implementations adopted values such as 4.5 and 5.5 points, primarily based on empirical observations of game outcomes. Over time, as more professional game data accumulated, national Go organizations converged on larger komi values, including 6.5 points in Japanese and Korean rules and 7.5 points in Chinese rules, which remain widely used today [6]. These values were determined largely through empirical adjustment rather than theoretical derivation.

Estimating fair komi values from historical human games remains challenging. Professional game records contain multiple confounding factors, including differences in player strength, changes in opening theory over time, and varying tournament conditions [6]. In addition, different scoring systems—such as Japanese territory scoring and Chinese area scoring—can produce different effective komi values, further complicating attempts to infer a universally fair komi directly from human game datasets [6]. These factors introduce substantial noise into statistical analyses based solely on historical games.

To formalize the concept of fairness in Go, we consider the relationship between komi and the expected final score difference between Black and White. If komi is set too low, Black retains a systematic advantage because of the first move. Conversely, if komi is set too high, White gains an advantage. A fair komi value can therefore be defined as the equilibrium point at which the expected score difference between the two players is zero [4]. We denote this equilibrium komi value as K^* , representing the komi that produces balanced outcomes between Black and White under a given board size and ruleset.

Computer Go has long been regarded as one of the major challenges in artificial intelligence because of the

game’s enormous search space and strategic complexity. A major breakthrough occurred with the development of AlphaGo, which combined deep neural networks with Monte Carlo tree search to achieve superhuman performance against professional players [12]. Subsequent systems such as AlphaZero demonstrated that reinforcement learning through self-play could produce similarly strong performance without relying on human game databases [8].

Open-source projects such as Leela Zero later replicated many of these ideas using distributed self-play training. However, most of these systems were trained using a single fixed komi value during reinforcement learning, meaning that their internal evaluations of positions were calibrated specifically to the komi used during training [8]. As a result, these engines are not well suited for systematically studying how game outcomes vary under different komi settings.

More recent Go engines have introduced new capabilities that make systematic komi analysis possible. In particular, KataGo extends earlier reinforcement-learning architectures by incorporating score-based value networks and multi-komi training [10]. Rather than predicting only the probability of winning, KataGo can estimate the expected final score difference between the two players. This allows the engine to evaluate the same board position under different komi settings within a single model.

In addition, KataGo supports multiple rulesets, including Chinese and Japanese scoring, and can operate across different board sizes. These features make it particularly suitable for studying how komi influences game outcomes under controlled experimental conditions [10].

Several previous studies have attempted to investigate the fairness of komi using different approaches. Some analyses rely on statistical studies of professional game records to estimate the advantage associated with the first move and to infer appropriate compensation values [6]. However, such analyses are limited by the variability of human play, evolving opening strategies, and differences in tournament conditions.

Other work has explored fairness on smaller board sizes such as 5×5 or 9×9, where near-optimal play can sometimes be analyzed computationally. Although these studies provide useful insights into how board geometry affects first-move advantage, results obtained on small boards do not necessarily generalize to the standard

19×19 board used in professional play.

More recent studies have used AI engines to examine how win probabilities change as komi varies. While these approaches demonstrate that AI can provide useful evaluations of positional advantage, most analyses rely primarily on win-probability outputs and therefore lack a direct connection to expected score differences [11],[12]. Consequently, a systematic framework for estimating fair komi values using modern score-based AI engines remains largely absent.

III. METHODS

A. Area Scoring versus Territory Scoring: Differences between Japanese, Chinese, and AGA Rules

To quantify komi fairness under near-optimal play, we adopt a game-theoretic formalization of territorial value that agrees with modern area-scoring rules and the outputs of KataGo’s evaluation. Let a position of Go be denoted by s , and assume it is Black to move unless otherwise specified. The final score of a completed game is defined as the difference between Black’s points and White’s points, including komi. Under Chinese (area) scoring, a player’s final points equal the number of stones placed plus the number of controlled empty intersections; under Japanese (territory) scoring, points correspond to controlled territory plus captured stones.

Under the Japanese rules, the game enters the scoring phase once both players have passed. Japanese endgame scoring counts only the surrounded territory and does not include the players’ stones on the board. In addition, captured stones are placed inside the opponent’s surrounded territory. Therefore, in this game, White has 19 points of territory and Black has 25 points. Black leads by 6 points under the Japanese rules before applying komi. In contrast, according to the Chinese rules, endgame scoring counts both the surrounded territory and the players’ stones on the board, whereas captured stones do not count towards the final scoring. As a result, in this game, White has 19 points of territory plus 18 stones (37 points) and Black have 26 points of territory plus 18 stones (44 points). Black has a point margin of 7 points. For the AGA ruleset, the game enters the scoring phase only after alternating passes that must end with a final pass by White. Each pass gives the opponent a pass stone, which is treated as a captured stone for scoring. In Fig. 1, the required sequence, White

via maximum likelihood or Bayesian inference. We further define Expected White Success Rate as $E_{White}(K^*) = P_{White\ win}(K^*) + 0.5P_{Draw}(K^*)$, which is the expected outcome under a scoring rule with komi K^* , whereby Win = 1, Draw = 0.5, and Loss = 0. Thereby, the fairness of K^* can be defined as $E_{White}(K^*) = 50\%$, where $K^* = K^*(N, R, M)$ is the fair komi value for the board size of N under ruleset R with model of play M . Here, a model of play M is a stochastic or deterministic policy that assigns a probability distribution over legal moves for every board position. In this study, M corresponds to the KataGo engine operating with a fixed neural network, ruleset, search budget, and temperature settings. All estimated fairness values, $K^*(N, R, M)$, should therefore be interpreted as komi values that achieves $E_{White}(K^*) = 50\%$ (i.e., equalizing outcomes) under this specific model of play.

D. KataGo Engine Configuration

Our experiments use KataGo's score-based neural network evaluation and self-play engine (Fig. 2), which is identically configured for all board sizes to ensure reproducibility. Unless otherwise stated, all experiments use the Chinese area-scoring ruleset and the same engine settings for 7×7 , 9×9 , 13×13 , and 19×19 boards. The configuration can be summarized as follows.

1) Ruleset and Game Parameters: We adopt modern Chinese rules, implemented in KataGo as:

Ko Rule: SIMPLE(Prohibits immediate recapture of the last stone; applies only to one-move Ko)

Scoring: AREA(Score is based on territory plus own stones on the board)

Tax: NONE (In KataGo, tax means points subtracted from Black's score estimate)

This ruleset ensures deterministic scoring, eliminates special-case rule interactions, and aligns with prior Go AI research on komi evaluation.

Additional parameters include:

Maximum game length: 1000 (Limits the game to 1000 moves to prevent infinite loops)

Resignation: false (Ensures all games reach terminal scoring)

komi randomness: false (Uses a fixed komi value for consistency)

Neural network randomness: false (Makes inference fully deterministic and reproducible)

Maxvisit:6000 (Limits KataGo to 6000 search visits per move)

2) Neural Networks: For each board size, we employ KataGo's strongest publicly available neural network, kata1-b28c512nbt-adam-s11165M-d5387M, a 28-

block, 512-channel residual architecture trained on more than 11.1 billion positions and 5.3 billion policy samples. This high-capacity model provides stable score predictions, precise ownership estimation, and robust multi-komi conditioning, making it suitable for the fine-grained komi-fairness analysis conducted in this study.

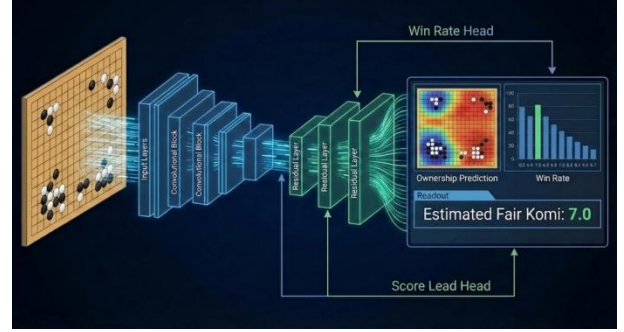


Fig. 2. Overview of KataGo's Neural Network Architecture.

3) Move Selection Policy: To balance exploration with strength, we use a temperature-based move policy:

For the opening, chosenMoveTemperatureEarly = 0.60, which introduces moderate stochasticity to diversify openings; for midgame and endgame, chosenMoveTemperature = 0.20, which encourages play closer to engine-optimal choices. This temperature schedule was found to reliably generate diverse yet high-quality self-play trajectories.

E. Estimating Fair komi

For each board size, in determining the fair komi, we carry out self-play experiments over a variety of candidate komi values, running 100 games for every komi setting. All experiments run at a fixed search strength of 6000 visits per move to ensure that conditions are consistent across different komi settings. In order to adequately cover the region in which the game is expected to be balanced, we use different komi ranges depending on the board size: 8.0–10.0 for 7×7 and 6.0–8.0 for 9×9 , 13×13 , and 19×19 . We estimate the empirical relationship between komi and win probability from the win rates obtained for the 100-game sample at each komi value in these ranges, identifying the komi value where the Black–White win rate approaches 50%. This value is taken as the fair komi for the corresponding board size.

F. Robustness and Sensitivity Analysis

We perform a robustness analysis here for the 9×9 board, as the representative case, in order to ensure that

the estimated fair komi K^* is not an artefact of engine stochasticity or variations in search depth. In this analysis, the same set of komi values is tested under four different search budgets-500, 1600, 5000, and 8000 visits per move-and the resulting komi-winrate curves are compared. Consistency of the estimated winrates across these search strengths indicates that the inferred fair komi is not sensitive to search-depth limitations.

We also perform a sensitivity check on the result with respect to temperature parameters, first by slightly altering the opening and midgame temperature settings and then by verifying if such variations greatly affect the winrate predictions around the equilibrium region. Neural-network randomization is disabled in all experiments so that uncontrolled variance is not introduced.

These checks taken together demonstrate that the estimated fair komi is stable and reflects reality for this engine, rather than noise because of specific settings of search or temperature.

G. Board-Size and Rule-Dependent Considerations

In general, the strategic value of the first move depends both on board size and on scoring rules; our komi estimation methodology includes these factors explicitly. Smaller boards, such as 7×7 and 9×9 , are spatially constraining, and severely limit Black's long-term initiative. This results in relatively low fair values of komi. Larger boards, such as 13×13 and 19×19 , provide more strategic latitude, within which Black can effectively exploit the advantage of the first move, and higher komi is required for balance. Considering multiple board sizes helps illustrate how komi fairness scales with geometric game structure.

Of course, komi is further influenced by differences among the various scoring rules. Under Chinese rules of area scoring, each stone placed adds one point to the final score, slightly expanding score differentials and thus also the komi-score relationship. Japanese rules of territory scoring count only secured territory and subtract captured stones, rendering the stone count itself irrelevant. The AGA rules clearly stand in an intermediate position: although the stones do not directly score, players must fill all remaining neutral points, yielding numerical outcomes that approximate closely to the area score while conceptually retaining a framework of territory scoring. For this reason, the typical komi values under AGA rules fall between the Chinese and Japanese systems.

By conducting self-play with all three sets of rules under identical configuration for the engines, we isolate rule-dependent effects on the estimated fair komi K^* and

ensure that any differences observed cannot be the result of inconsistencies in the experiment but are, in fact, due to the rules themselves.

H. Hardware Configuration

All experiments in this study were conducted on a system equipped with an NVIDIA RTX 4080 Super GPU and an NVIDIA Tesla T4 GPU. We used KataGo version 1.16.3 with a TensorRT backend, running under CUDA 12.8.

IV. AI Self-Play Experiments

A. Experimental Design Overview

This section describes the procedure for evaluating fair komi values across board sizes, rulesets, and engine strengths. The experiments follow the methodology described in Section III and rely on AI self-play data generated by KataGo under controlled komi conditions. The primary objective is to obtain robust win-rate estimates as a function of komi and use this information to infer the fair komi for each setting.

B. Data Generation and Summary Statistics

Self-play games data were generated using KataGo across four board sizes: 7×7 , 9×9 , 13×13 , and 19×19 , and multiple fixed komi values for each ruleset. For each condition, 100 self-play games were produced using a search budget of 6000 visits per move. Resignation was disabled in all experiments. KataGo output the final game result, score margin from white's perspective. These values form the basis of the statistical analysis.

For each experimental condition, we compute the following summary statistics: White win rate, 95% confidence interval for the win rate, draw rate, expected white score, average final score margin, and standard deviation of margin.

Following the formal definition in Section III, the fair komi K^* is defined as the komi value that yields an expected white score as close as possible to 0.5.

$$E_{\text{White}}(K^*) \approx 0.5$$

These statistics form the foundation for estimating the fair komi in the rest of this section, and for evaluating robustness to search strength and engine asymmetry.

C. Fair Komi Estimation

1) 7×7 board size

The detailed results for the 7×7 board under the Chinese, Japanese, and AGA rulesets are provided in Appendix Table A1. For the Chinese and AGA rulesets, the expected white score increases from near zero at komi 8.0 to balanced outcomes at komi 9.0, indicating that komi 9.0 satisfies the fairness criterion within the tested range. Under the Japanese ruleset, balanced outcomes occur at komi 8.0. Thus, on the 7×7 board, the estimated fair komi values are 9.0 for the Chinese and AGA rulesets and 8.0 for the Japanese ruleset.

TABLE I

STATISTICS OF GO GAMES ON A 7×7 BOARD ACROSS KOMI VALUES

Komi	Ruleset	White Win Rate	95% CI, White Win Rate	Draw Rate	Total Games	E_{White}	Avg Margin, points	Std. Dev. of Margin, points
8.0	Chinese	0.00	[0.000, 0.037]	0.00	100	0.000	-1.08	0.39
8.0	Japanese	0.00	[0.000, 0.037]	1.00	100	0.500	0.00	0.00
8.0	AGA	0.00	[0.000, 0.037]	0.00	100	0.000	-1.16	0.55
9.0	Chinese	0.00	[0.000, 0.037]	1.00	100	0.500	0.00	0.00
9.0	Japanese	1.00	[0.963, 1.000]	0.00	100	1.000	1.00	0.00
9.0	AGA	0.00	[0.000, 0.037]	1.00	100	0.500	0.00	0.00

2) 9×9 board size

The experimental results for the 9×9 board are summarized in Appendix Table A2. Under the Chinese ruleset, the expected white score increases as komi increases from 6.0 to 7.0 and reaches balanced outcomes at komi 7.0. The AGA ruleset shows a similar pattern, with balanced outcomes also occurring at komi 7.0. In contrast, under the Japanese ruleset, balanced outcomes occur at komi 6.0. These results indicate that the estimated fair komi values on the 9×9 board are 7.0 for the Chinese and AGA rulesets and 6.0 for the Japanese ruleset.

TABLE II

STATISTICS OF GO GAMES ON A 9×9 BOARD ACROSS KOMI VALUES

Komi	Ruleset	White Win Rate	95% CI, White Win Rate	Draw Rate	Total Games	E_{White}	Avg Margin, points	Std. Dev. of Margin, points
6.0	Chinese	0.16	[0.101, 0.244]	0.00	100	0.160	-1.44	2.74
6.0	Japanese	0.00	[0.000, 0.037]	1.00	100	0.500	0.00	0.00
6.0	AGA	0.01	[0.002, 0.054]	0.00	100	0.010	-2.66	1.82
7.0	Chinese	0.01	[0.002, 0.054]	0.98	100	0.500	0.06	0.83
7.0	Japanese	0.92	[0.850, 0.959]	0.07	100	0.955	1.58	1.00
7.0	AGA	0.00	[0.000, 0.037]	0.99	100	0.495	-0.02	0.20

3) 13×13 board size

The detailed statistics for the 13×13 board are provided in Appendix Table A3. Under the Chinese and AGA rulesets, the expected white score remains below 0.5 at komi 6.0 and 6.5 and exceeds 0.5 at komi 7.0, indicating that komi 7.0 is closest to the fairness criterion within the tested range. Under the Japanese ruleset, komi 6.0 produces outcomes closest to balance, with an expected white score near 0.5. These observations suggest that the estimated fair komi is 7.0 for the Chinese and AGA rulesets and 6.0 for the Japanese ruleset.

TABLE III

STATISTICS OF GO GAMES ON A 13×13 BOARD ACROSS KOMI VALUES

Komi	Ruleset	White Win Rate	95% CI, White Win Rate	Draw Rate	Total Games	E_{White}	Avg Margin, points	Std. Dev. of Margin, points
6.5	Chinese	0.30	[0.219, 0.396]	0.00	100	0.300	-0.56	3.88
6.0	Japanese	0.30	[0.241, 0.367]	0.36	200	0.480	0.12	3.40
6.5	AGA	0.31	[0.228, 0.406]	0.00	100	0.310	-0.56	3.88
7.0	Chinese	0.32	[0.208, 0.458]	0.62	50	0.630	0.76	2.94
7.0	Japanese	0.60	[0.502, 0.691]	0.27	100	0.735	1.69	3.47
7.0	AGA	0.38	[0.291, 0.478]	0.48	100	0.620	-0.84	5.10

4) 19×19 board size

The experimental results for the 19×19 board are reported in Appendix Table A4. Under the Chinese and AGA rulesets, the expected white score at komi 7.0 is closest to the fairness target of 0.5. Under the Japanese ruleset, the expected score at komi 6.0 is closest to balance. Therefore, the estimated fair komi values on the 19×19 board are 7.0 for the Chinese and AGA rulesets and 6.0 for the Japanese ruleset.

D. Search Strength (MaxVisit Sensitivity)

TABLE IV

STATISTICS OF GO GAMES ON A 19×19 BOARD ACROSS KOMI VALUES

Komi	Ruleset	White Win Rate	95% CI, White Win Rate	Draw Rate	Total Games	E_{White}	Avg Margin, points	Std. Dev. of Margin, points
6.0	Chinese	0.40	[0.309, 0.498]	0.00	100	0.400	-0.72	8.58
6.0	Japanese	0.39	[0.300, 0.488]	0.24	100	0.510	0.50	7.16
6.0	AGA	0.41	[0.319, 0.508]	0.01	100	0.415	-0.69	7.07
7.0	Chinese	0.32	[0.237, 0.417]	0.33	100	0.485	-0.03	7.72
7.0	Japanese	0.30	[0.219, 0.396]	0.19	100	0.395	0.72	5.24
7.0	AGA	0.33	[0.246, 0.427]	0.33	100	0.495	0.35	7.06

1) Single-Engine MaxVisit Sensitivity

To assess whether the estimated fair komi depends on the strength of the search, we evaluate how outcomes vary when the per-move search budget (maximum-visit settings) is changed. This test uses the 9×9 board under

the Chinese ruleset at komi 7.0, which was identified in Section IV-C as the empirically fair komi. We generate self-play games using four search budgets: 500, 1600, 5000, and 8000 visits per move. Each condition consists of 800 games.

Table V reports the outcome statistics for these configurations (see Appendix Table A5). Overall, the results show very limited dependence on the search budget. The fairness assessment at komi 7.0 therefore remains stable across MaxVisit levels.

TABLE V
SENSITIVITY AT KOMI 7.0

Visit	White Win Rate	95% CI, White Win Rate	Draw Rate	Total Games	E_{White}	Avg. Margin, Points	Std. Dev. of Margin, Points
500	0.00	[0.000, 0.005]	1.00	800	0.500	0.00	0.00
1600	0.00	[0.000, 0.005]	1.00	800	0.500	0.00	0.00
5000	0.00	[0.000, 0.005]	1.00	800	0.500	0.00	0.00
8000	0.02	[0.012, 0.032]	0.98	800	0.510	2.00	0.00

2) Cross-Strength Matches Between 1600 and 6000 Visits

To examine whether differences in search strength affect game outcomes, we conduct additional experiments in which a 1600-visit engine plays against a 6000-visit engine. Black and White are randomly assigned to avoid potential color bias. The detailed results are provided in Appendix Tables A6–A8.

Overall, matches between the two engines do not show a dominant advantage under the Japanese ruleset, while the Chinese and AGA rulesets show a modest advantage for the stronger engine. Nevertheless, draw rates remain high and expected scores stay close to 0.5, indicating that the estimated fair komi values remain broadly stable across the two engine strengths.

TABLE VI
OUTCOME OF 1600 VS. 6000 VISITS MATCHES AT KOMI 6.0 (JAPANESE RULESET)

MaxVisit	Win Rate	95% CI, Win Rate	Draw Rate	Total Games	E_{White}	Avg. Margin, Points
1600	0.000	[0.000, 0.008]	1.000	500	0.499	-0.01
6000	0.002	[0.000, 0.011]	0.998	500	0.501	0.01

TABLE VII
OUTCOME OF 1600 VS. 6000 VISITS MATCHES AT KOMI 7.0 (CHINESE RULESET)

MaxVisit	Win Rate	95% CI, Win Rate	Draw Rate	Total Games	E_{White}	Avg. Margin, Points
1600	0.002	[0.000, 0.011]	0.824	500	0.414	-0.94
6000	0.174	[0.143, 0.210]	0.824	500	0.586	0.94

TABLE VIII
OUTCOME OF 1600 VS. 6000 VISITS MATCHES AT KOMI 7.0 (AGA RULESET)

MaxVisit	Win Rate	95% CI, Win Rate	Draw Rate	Total Games	E_{White}	Avg. Margin, Points
1600	0.004	[0.001, 0.014]	0.844	500	0.426	-0.77
6000	0.152	[0.123, 0.186]	0.844	500	0.574	0.77

E. Validation at Fair Komi

To verify that the komi values identified in Section IV-C yield balanced outcomes, we conduct high-sample evaluations at the fair komi for each ruleset and board size. For each condition, 1000 self-play games are generated using a 6000-visit search budget, with resignation disabled.

The detailed statistics for these evaluations are provided in Appendix Tables A9–A11. Across board sizes and rulesets, the resulting win rates and expected scores remain close to the theoretical balance point of 0.5, confirming that the estimated fair komi values produce near-balanced outcomes.

TABLE IX
STATISTICS OF SELF-PLAY GAMES UNDER FAIR KOMI FOR EACH RULESET ON THE 7×7 BOARD

Ruleset	White Win Rate	95% CI, Win Rate	Draw Rate	Total Games	E_{White}	Avg. Margin, Points	Std. Dev. of Margin, Points
Japanese	0.000	[0.000, 0.004]	1.000	1000	0.5000	0.000	0.000
AGA	0.000	[0.000, 0.004]	1.000	1000	0.5000	0.000	0.000
Chinese	0.000	[0.000, 0.004]	1.000	1000	0.5000	0.000	0.000

Table X summarizes the corresponding results for the 9×9 board at fair komi (Japanese: 6.0, AGA and Chinese: 7.0). White’s win rate remains low across all rulesets, with values of 0.001, 0.003, and 0.068 for Japanese, AGA, and Chinese scoring, respectively. The expected white score remains close to 0.5 for all three rulesets (0.4995, 0.4830, and 0.4965), and score margins remain small.

TABLE X
STATISTICS OF SELF-PLAY GAMES UNDER FAIR KOMI FOR EACH RULESET ON THE 9×9 BOARD

Ruleset	White Win Rate	95% CI, Win Rate	Draw Rate	Total Games	E_{White}	Avg. Margin, Points	Std. Dev. of Margin, Points
Japanese	0.001	[0.000, 0.006]	0.997	1000	0.4995	-0.001	0.005
AGA	0.003	[0.001, 0.009]	0.960	1000	0.4830	-0.068	0.394
Chinese	0.068	[0.054, 0.085]	0.857	1000	0.4965	-0.014	2.036

Table XI reports the outcomes on the 13×13 board at the empirically determined fair komi for the Japanese and Chinese rulesets. Under Japanese rules, white’s win rate is 0.268, while under Chinese rules it is slightly higher at 0.314. Despite this difference in win rates, the expected white score remains close to the fairness benchmark for both rulesets, with E-White values of 0.479 and 0.606, respectively. Score margins remain small in both cases, indicating that games are generally competitive around the fair komi point.

TABLE XI
STATISTICS OF SELF-PLAY GAMES UNDER FAIR KOMI FOR EACH RULESET ON THE 13×13 BOARD

Ruleset	White Win Rate	95% CI, Win Rate	Draw Rate	Total Games	E-White	Avg. Margin, Points	Std. Dev. of Margin, Points
Japanese	0.268	[0.231, 0.308]	0.422	500	0.479	0.03	3.45
Chinese	0.314	[0.271, 0.361]	0.584	401	0.606	0.64	5.47

Overall, the results support the earlier fair komi estimates for the 7×7, 9×9 and 13×13 boards across all rulesets.

Win-Rate curve fitting: For each combination of board size and ruleset, the self-play outcomes collected under different komi values are converted into empirical white win rates. Let k denote the komi and $p(k)$ the observed proportion of games won by White at komi k . Since the relationship between komi and win probability is expected to be monotonic and smooth, we model $p(k)$ using a logistic (sigmoid) function:

$$\hat{w}(k) = \frac{1}{1 + \exp(-(ak + b))} \quad (6)$$

where a and b are parameters fitted via nonlinear least squares.

The fair komi for each condition is defined as the value of k at which the fitted curve reaches a 50% white win rate:

$$\hat{w}(K^*) = 0.5 \quad (7)$$

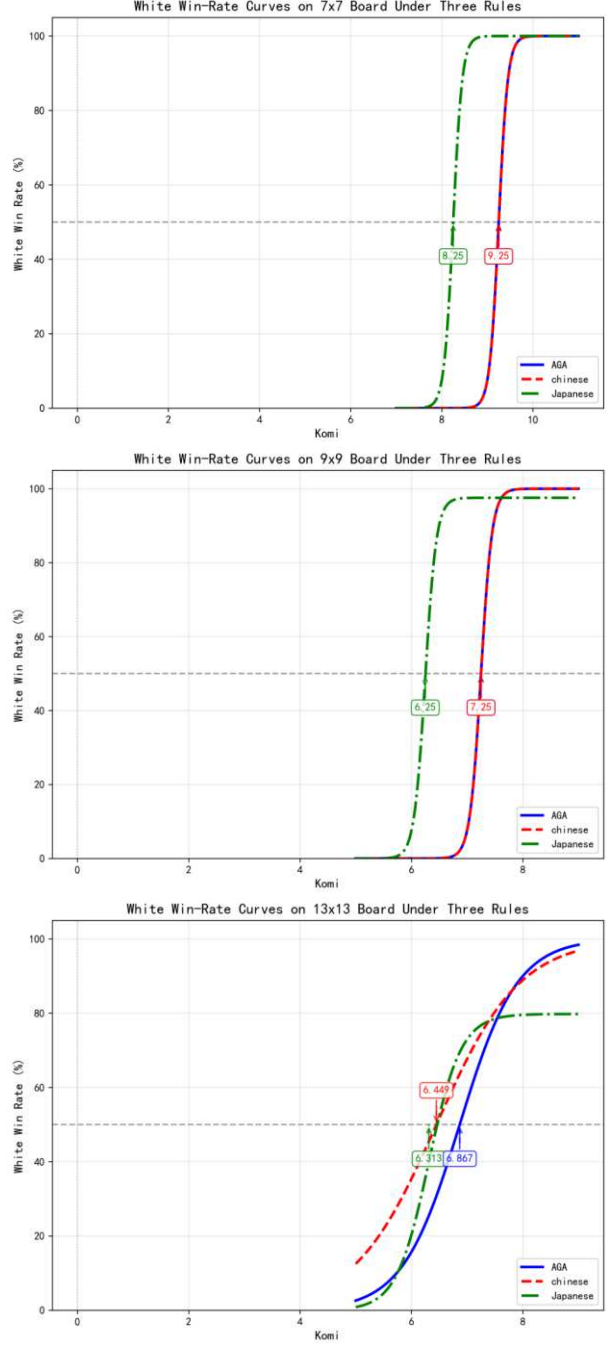
This yields a closed-form solution:

$$K^* = -\frac{b}{a} \quad (8)$$

The fitted curves provide a noise-reduced estimate of fair komi and allow comparison of rulesets through horizontal shifts in the transition region.

Figures 3(a) and (b) present the fitted win-rate curves for the 7×7 and 9×9 boards. On both board sizes, the Chinese and AGA curves nearly overlap, while the Japanese curve is consistently shifted left, indicating a lower fair komi under territory scoring.

A further theoretical interpretation of the observed komi values, including a parity-based analysis and conjectures for larger board sizes, is provided in Appendix B.



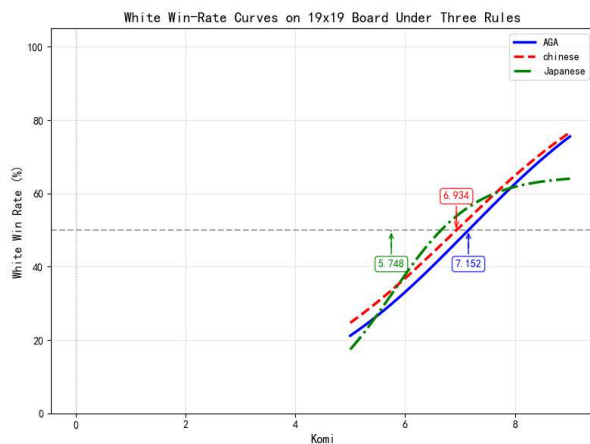


Figure 3. Fitted white win-rate curves under three rulesets.
(a) 7×7 board (b) 9×9 board (c) 13×13 board (d) 19×19 board

V. Discussion

A. Rule-dependent fairness

While AGA rules, Chinese rules, and Japanese rules have all been introduced in an effort to establish a hopefully fair scoring system for Go, the foundational scoring philosophy of two major styles is fundamentally different, resulting in unique natural baselines for komi. The substantial difference lies between scoring by area (AGA and Chinese rules) versus scoring by territory (Japanese rules). Area-based scoring counts stones played on the board and points controlled, while territory scoring counts empty points surrounded as territory. This in itself has different effects. For instance, area-based scoring does not impose a penalty for reinforcing or filling points, while Japanese territory scoring does. Under area-based scoring, playing inside one's own territory does not diminish the final score. Therefore, reinforcing a group, filling a liberty, or terminating a seki does not carry a point penalty. On the other hand, Japanese territory scoring deducts a point of territory for each play that takes place inside of one's own territory, creating an arbitrary penalty that is not relative to the actual strategic value of the inferred movement. This penalty applied to the rules typically leads to a slight extension of an effective edge for Black, because Black frequently controls many of the later endgame direct forcing movements. Consequently, to offset this small structural bias introduced by the scoring method, territory-scoring systems such as Japanese rules require a komi baseline that differs from the one used under area-scoring systems.

As a result, when fairness is defined as the ability of komi to equalize win rates between players of equal strength, the structural properties of Chinese rules yield a more stable and symmetric framework, whereas the Japanese rules introduce non-strategic scoring irregularities that can subtly bias outcomes, especially in the event that the players have close-to-equal strengths.

B. Philosophical considerations

A more nuanced question is what “fairness” means in Go. From one simple view of fairness, one can understand fairness to mean obtaining a 50% expected rate of winning between players of equal strength. In this case, any rule system or komi value that, across a large number of games, approximately evens out the Black advantage can be thought to be fair.

Fairness, however, can be more than simply obtaining equal outcomes. Some academics and game theorists have suggested that a fair game has, in addition to equal outcomes, some forms of symmetry; for example, the rules should not give more or less strategic one player an advantage over the other, nor should a structural disadvantage rest entirely with one side for the entirety of the game. Others emphasize “robustness,” and argue that a fair rule should be fair for a large number of possible options for play – styles, opening strategies, board sizes, and skill levels – and should not be fine-tuned to a narrow portion of competitive play.

C. Implications on competitive go games

The findings from this research have a number of important implications for competitive Go as played now. The standard komi values for 19×19 boards (7.5 points under Chinese rules, 6.5 points under Japanese or Korean rules) have not changed at all for almost twenty years, but have drawn more complaints and challenges than before. As an example, at this time there are still essentially no professional players willing to choose Black under these komi values. And while the komi for the LG Cup games was set to 6.5 points, still no one was willing to choose Black, indicating that professional players came to agree that the komi was unfair in some way. While the komi values were marks set in part from studies of professional games, these parameterizations now appear to not represent true balance when deviations from play are restricted to high quality or optimal-lines of play; that was also consistent with the intuition of many professional players.

First, the observation that the fair komi for Chinese

and AGA area-scoring rules seems to gravitate around 7.0 (as opposed to the more popular 7.5) implies that tournaments, perhaps, give White a slight advantage when played at the highest levels. In a sense, by including a half a point you are converting what would be split score margin into a White victory and biasing the results in a fashion that disproportionately favors White, during the types of positions where ideal play yields an extremely narrow score margin or jigo-like state. If it is true that ideal play is tending toward an expected balanced score of Black +7 points before komi, then a komi of 7.5 is actually providing White 0.5 points free of anything deducted that would offset that very first move advantage for Black.

Second, we provided a new perspective on the consistent disagreement between Chinese komi of 7.5 and Japanese (AGA) komi of 6.5. These have existed historically, developed when the rules and culture were both independent of one another. The results of this study show that these values are systematically higher than what appears to be fair under controlled AI play: the fair komi under Chinese rules appears closer to 7.0, and under Japanese rules closer to 6.0, reflecting the consistent offset inherent in territory scoring. This suggests that the conventional difference of one point between Chinese and Japanese komi is directionally correct but may be uniformly shifted upward relative to optimal-play estimates, again consistent with the intuition of most professional players who are reluctant to choose Black.

Third, the findings suggest that komi fairness may fluctuate from epoch to epoch. As playing ability rises - whether that means increases among peak professionals, or the proliferation of AI-driven applications - it will become increasingly obvious that small komi imbalances matter. A game between two near error-free professionals might hinge on a half-point. A half-point overcompensation will matter more so when one also accounts for the assumption that near-perfect play produces end-game scores closer to zero, compared with beginning a game where komi is imbalanced. Tournaments may be forced to rethink their komi value to fight against unintentional impacts on the nature of competitive outcomes. In fact, assuming that a fair komi (under area scoring rulesets) is 7.0 points, rather than the traditionally used 6.5 or 7.5, numerous professional games that ended with a 0.5-point margin would instead have resulted in jigo (draws).

Fourth, these findings might weigh on the continuing discussion regarding the future of competitive Go

structures. As an example, some recent professional analysis presented the notion that the current komi value was unfair to Black and should be reduced. This is consistent with evidence like winning percentage trends by top players such as Ke Jie, who achieved way higher winning rates when playing White. Moreover, AI versus human matches and multi-purpose tournaments recently experimented with variable komi and/or dual komi analysis. Our findings support the idea that fixed komi values may need reevaluation, especially if tournaments aim to maintain fairness as strategic understanding of Go evolves while making sure it does not end in draws. Organizations such as the Chinese Weiqi Association, Nihon Ki-in, and Korea Baduk Association could consider using AI-assisted large-scale self-play to revalidate their komi choices.

Last, and perhaps most importantly, it should be pointed out that while AI estimates can provide a clearer picture of fairness in terms of optimal play, competitive Go for humans is more complicated than objective score expectations. Psychological comfort, historical continuity, and differences in styles of play all affect the lived experience of fairness. A Go association may prefer to retain 7.5 or 6.5 as the fair komi in optimal play, even if the mathematically fair komi is 7.0 or 6.0, for potential reasons such as discouraging draws, the ups and downs of human strategic logic, or just tradition. With that being said, it remains arguable whether we should care more about the fairness of the game or the odds of draws happening. After all, draws should be allowed in this game and having draws doesn't necessarily reduce the charm of Go being an enjoyable, intellectually challenging, competitive brain game. With this in mind, the readers should interpret this article as an invitation to further discuss the topics presented, not as a recommendation for immediate change.

D. Handicaps and komi

In Go, handicaps are used when players of unequal skill face each other, helping to balance the game [13]. Go accommodates handicaps far better than most other board games. These adjustments come in two main forms: extra stones and komi (compensation points). For a small handicap—typically a one-rank difference—the weaker player simply takes Black and plays first without giving komi to White. For larger gaps in skill, Black receives additional free handicap stones placed on the board before the game begins to make sure that the win rates of two players would be closer to 50% for both fairness and better enjoyment of the game.

In most amateur Go ranking systems, the difference

in rank between two players is a useful indicator of how many handicap stones should be used to balance a match. A common guideline is that each rank corresponds to the value of one handicap stone. Thus, a 2-kyu player would typically give a 5-kyu player three stones. When using the standard fixed handicap placements, nine stones is usually considered the upper limit; going beyond this tends to produce unusual games.

This rank-to-stone relationship applies well to kyu and amateur dan levels (1d–7d). However, it does not translate cleanly to professional dan ranks. Professional rankings, awarded by Go associations, reflect tournament accomplishments rather than direct strength differences. As a result, the skill gap between adjacent professional dan levels is much smaller—often less than one-third of a handicap stone. However, what is the equivalence of handicapped games and komi points remains to be studied and we expect that the approach adopted in this study can be applied to address this type of unanswered questions related to the fairness and enjoyability of this challenging brain game.

Smaller Go boards are commonly used by beginners (especially double-digit kyu players) who are just learning the basics of the game, or for fast, casual play—most often on 13×13 or 9×9 boards. Because games on smaller boards contain far fewer moves, White has fewer opportunities to compensate for the advantage granted by handicap stones. As a result, each handicap stone is effectively stronger, and a smaller numerical handicap is appropriate for the same rank difference compared with a standard 19×19 board.

The handicap-per-rank therefore scales downward based on board size. Estimates of the appropriate scaling factor for 13×13 vary—from roughly 2.5 to about 4. Available evidence suggests that for timed games, a factor closer to 2.5 or 3 is more realistic than 4. Determining the corresponding factor for 9×9 is more difficult. In practice, a full handicap stone on a 13×13 board is roughly equivalent to 2.5–3 ranks, while a full stone on a 9×9 board corresponds to approximately 6 ranks. For example, if two players would normally play with nine stones on a 19×19 board, the equivalent handicap on a 13×13 board is about four stones ($3.5 \times 2.5 \approx 8.75$), and on a 9×9 board about two stones ($1.5 \times 6 = 9$). However, a more accurate estimate of these numbers would need to be obtained through this type of AI-based approach in order to maximize fairness and improve the user experiences for these handicapped games [14].

VI. Conclusion

This research employs top Go AI, KataGo, as a scientific tool instead of a black-box opponent, to analyze the fairness of Go and measure komi. Using KataGo’s score-based method, we modeled the relationship between komi and outcome of games under different board sizes and rulesets, which allows us to derive the “fair komi” K^* —the value at which White’s expected win rate approaches 50% under near-optimal play. Self-play experiments on 7×7 and 9×9 boards indicate that the komi-winrate relationship is approximately logistic, confirming previous qualitative impressions and forming a principled basis for estimating komi with statistical certainty. For the playing configurations considered here, komi 9.0 on 7×7 and komi 7.0 on 9×9 brings the game very close to the scoring equilibrium with near-zero margins and very high draw rates under Chinese and AGA rules. Although our results support the internal coherence of KataGo’s multi-komi training, they also demonstrate that the fair komi on small boards can be estimated with precision from AI self-play.

Instead of using a traditional half-points komi rule to guarantee a winner in a Go game, our perspective on fairness in Go has a simpler integer komi value. It appears that on a 7×7 board using Chinese (or AGA) rules, a fair komi should be 9.0, while under Japanese rules it is 8.0. In addition, we find that on 9×9 and 13×13 boards using Chinese (or AGA) rules, a fair komi should be 7.0. We also showcase that fairness is dependent on rules, for example the fair komi for Japanese rules are often 1.0 less than that of Chinese or AGA rules. Although AGA and Chinese rules share an area-scoring foundation and yield essentially identical komi baselines in our experiments, Japanese territory scoring leads to systematically shifted komi–winrate curves. This shift can be traced to structural features of territory scoring—most notably the fact that playing inside one’s own territory incurs a point penalty, even when such moves are required only to clarify life and death or achieve seki. In terms of structural fairness, area scoring provides a more symmetric mapping of strategic advantage to final score. Conversely, the Japanese rules introduce small, but systematic, distortions that we need to absorb into our effective komi. A cross-ruleset comparison makes this intuition explicit: small differences in scoring philosophy can lead to measurable differences in fair komi, and this was our goal. Given the observations thus far, we propose the following **Komi Conjecture: for board sizes $N \times N$, where N is odd and $N > 9$, fair komi will be 7.0 points under Chinese or AGA area-scoring rules and 6.0 points under Japanese**

territory-scoring rules. While still a conjecture, we provide a mathematical analysis that shows this would highly likely be the case, and of course this conjecture will still require further large-scale data or rigorous quantitative analysis on boards of various sizes to verify.

Methodologically, this research demonstrates a methodological shift in utilizing top Go AI, such as KataGo, to move from a competitive tool to a quantitative rule analysis. The final score is treated as a random variable and then used to fit a parametric komi-winrate curve, thereby yielding both point estimates of komi and a systematic framework for robustness checks, in terms of search depth, temperature settings, and board size. The approach is easily extendable to larger boards, other rulesets, and specific questions such as the interaction of komi and handicap stones or the calibration of komi in human vs AI matches. The same framework, for example, could be used to translate between handicap stones and komi points across board sizes or construct handicapping schemas that are fair and mentally pleasing for human players.

Collectively, our results demonstrate that the era of contemporary AI in Go allows us to advance from ad hoc historical convention to a more mathematically rigorous understanding of komi. By combining top AI self-play, quantitative modeling, and rule-sensitive analysis, we have contributed a foundation for future studies of fairness in Go and other complex games, and support a broader view of Go as a cross-cultural competitive game, cognitive challenge, and enjoyable entertainment.

APPENDIX A Additional Figures

TABLE A.1

STATISTICS OF GO GAMES ON A 7×7 BOARD UNDER KOMI 8.5

Ruleset	White Win Rate	95% CI, White Win Rate	Draw Rate	Total Games	E_{White}	Avg. Margin, Points	Std. Dev. of Margin, Points
Chinese	0.00	[0.000, 0.037]	0.00	100	0.000	-0.52	0.20
Japanese	1.00	[0.963, 1.000]	0.00	100	1.000	0.59	0.38
AGA	0.00	[0.000, 0.037]	0.00	100	0.000	-0.52	0.20

TABLE A.2

STATISTICS OF GO GAMES ON A 7×7 BOARD UNDER KOMI 9.5

Ruleset	White Win Rate	95% CI, White Win Rate	Draw Rate	Total Games	E_{White}	Avg. Margin, Points	Std. Dev. of Margin, Points
CHINESE	1.00	[0.963, 1.000]	0.00	100	1.50	0.56	0.34
JAPANESE	1.00	[0.963, 1.000]	0.00	100	1.00	1.56	0.10
AGA	1.00	[0.963, 1.000]	0.00	100	1.00	0.56	0.34

TABLE A.3

STATISTICS OF GO GAMES ON A 7×7 BOARD UNDER KOMI 10.0

Ruleset	White Win Rate	95% CI, White Win Rate	Draw Rate	Total Games	E_{White}	Avg. Margin, Points	Std. Dev. of Margin, Points
Chinese	1.00	[0.963, 1.000]	1.00	100	1.00	1.00	0.00
Japanese	1.00	[0.963, 1.000]	0.00	100	1.00	1.91	0.38
AGA	1.00	[0.963, 1.000]	0.00	100	1.00	1.00	0.00

TABLE A.4

STATISTICS OF GO GAMES ON A 9×9 BOARD UNDER KOMI 6.5

Ruleset	White Win Rate	95% CI, White Win Rate	Draw Rate	Total Games	E_{White}	Avg. Margin, Points	Std. Dev. of Margin, Points
Chinese	0.01	[0.002, 0.054]	0.00	100	0.010	-1.61	3.35
Japanese	0.98	[0.930, 0.994]	0.00	100	0.980	1.10	1.54
AGA	0.04	[0.016, 0.098]	0.00	100	0.040	-1.66	1.73

TABLE A.5

STATISTICS OF GO GAMES ON A 9×9 BOARD UNDER KOMI 7.5

Ruleset	White Win Rate	95% CI, White Win Rate	Draw Rate	Total Games	E_{White}	Avg. Margin, Points	Std. Dev. of Margin, Points
Chinese	0.99	[0.946, 0.998]	0.00	100	0.990	1.39	2.76
Japanese	1.00	[0.963, 1.000]	0.00	100	1.000	5.63	5.78
AGA	1.00	[0.963, 1.000]	0.00	100	1.000	1.70	1.17

TABLE A.6

STATISTICS OF GO GAMES ON A 9×9 BOARD UNDER KOMI 8.0

Ruleset	White Win Rate	95% CI (White Win Rate)	Draw Rate	Total Games	E_{White}	Avg. Margin (Points)	Std. Dev. of Margin (Points)
Chinese	1.00	[0.963, 1.000]	0.00	100	1.000	1.44	1.57
Japanese	0.94	[0.875, 0.972]	0.06	100	0.970	2.25	1.34
AGA	1.00	[0.963, 1.000]	0.00	100	1.000	1.44	1.16

TABLE A.7

STATISTICS OF GO GAMES ON A 13×13 BOARD UNDER KOMI 6.0

Ruleset	White Win Rate	95% CI, White Win Rate	Draw Rate	Total Games	E_{White}	Avg. Margin, Points	Std. Dev. of Margin, Points
Chinese	0.18	[0.098, 0.308]	0.04	50	0.200	-0.74	2.10
Japanese	0.16	[0.101, 0.244]	0.47	100	0.395	-0.78	2.48
AGA	0.29	[0.210, 0.385]	0.01	100	0.295	-0.63	2.23

TABLE A.8

STATISTICS OF GO GAMES ON A 13×13 BOARD UNDER KOMI 7.5

Ruleset	White Win Rate	95% CI, White Win Rate	Draw Rate	Total Games	E_{White}	Avg. Margin, Points	Std. Dev. of Margin, Points
Chinese	0.84	[0.715, 0.917]	0.02	50	0.850	2.07	3.86
Japanese	0.84	[0.756, 0.899]	0.00	100	0.840	1.58	2.58
AGA	0.96	[0.902, 0.984]	0.00	100	0.960	1.73	3.11

TABLE A.9

STATISTICS OF GO GAMES ON A 13×13 BOARD UNDER KOMI 8.0

Ruleset	White Win Rate	95% CI, White Win Rate	Draw Rate	Total Games	E_{White}	Avg. Margin, Points	Std. Dev. of Margin, Points
Chinese	0.98	[0.895, 0.996]	0.00	50	0.980	1.81	2.25
Japanese	0.82	[0.733, 0.883]	0.10	100	0.870	2.22	3.01
AGA	0.89	[0.814, 0.937]	0.01	100	0.895	1.44	2.24

TABLE A.10

STATISTICS OF GO GAMES ON A 19×19 BOARD UNDER KOMI 6.5

Ruleset	White Win Rate	95% CI, White Win Rate	Draw Rate	Total Games	E_{White}	Avg. Margin, Points	Std. Dev. of Margin, Points
Chinese	0.47	[0.375, 0.567]	0.00	100	0.470	-0.78	9.73
Japanese	0.46	[0.366, 0.557]	0.00	100	0.460	-0.38	8.33
AGA	0.38	[0.291, 0.478]	0.00	100	0.380	-1.95	12.83

TABLE A.11

STATISTICS OF GO GAMES ON A 19×19 BOARD UNDER KOMI 7.5

Ruleset	White Win Rate	95% CI, White Win Rate	Draw Rate	Total Games	E_{White}	Avg. Margin, Points	Std. Dev. of Margin, Points
Chinese	0.49	[0.394, 0.587]	0.00	100	0.49	0.95	6.02
Japanese	0.40	[0.287, 0.525]	0.00	61	0.40	0.22	5.92
AGA	0.61	[0.512, 0.700]	0.00	100	0.61	1.81	6.19

TABLE A.12

STATISTICS OF GO GAMES ON A 19×19 BOARD UNDER KOMI 8.0

Ruleset	White Win Rate	95% CI, White Win Rate	Draw Rate	Total Games	E_{White}	Avg. Margin, Points	Std. Dev. of Margin, Points
Chinese	0.64	[0.542, 0.727]	0.00	100	0.640	1.43	5.90
AGA	0.66	[0.563, 0.745]	0.00	100	0.660	0.37	3.75

TABLE A.13

SENSITIVITY AT KOMI 6.0

Visits	White Win Rate	95% CI, White Win Rate	Draw Rate	Total	E_{White}	Avg. Margin, Points	Std. Dev.
500	0.04	[0.032, 0.060]	0.01	800	0.045	-3.08	4.79
1600	0.08	[0.065, 0.104]	0.00	800	0.080	-1.16	0.59
5000	0.01	[0.005, 0.020]	0.00	800	0.010	-2.56	2.32
8000	0.00	[0.000, 0.007]	0.00	800	0.000	-1.27	1.46

TABLE A.14

SENSITIVITY AT KOMI 6.5

Visits	White Win Rate	95% CI, White Win Rate	Draw Rate	Total	E_{White}	Avg. Margin, Points	Std. Dev.
500	0.02	[0.013, 0.027]	0.00	800	0.020	-0.84	1.68
1600	0.03	[0.023, 0.049]	0.00	800	0.030	-1.63	3.50
5000	0.01	[0.004, 0.017]	0.00	800	0.010	-0.74	1.09
8000	0.00	[0.000, 0.007]	0.00	800	0.000	-1.31	2.35

TABLE A.15

SENSITIVITY AT KOMI 7.5

Visits	White Win Rate	95% CI, White Win Rate	Draw Rate	Total	E_{White}	Avg. Margin, Points	Std. Dev.
500	0.94	[0.924, 0.957]	0.00	800	0.940	1.95	3.17
1600	0.99	[0.980, 0.995]	0.00	800	0.990	1.75	0.66
5000	1.00	[0.989, 0.999]	0.00	800	1.000	1.50	0.00
8000	0.99	[0.979, 0.994]	0.00	800	0.990	2.17	0.94

TABLE A.16

SENSITIVITY AT KOMI 8.0

Visits	White Win Rate	95% CI, White Win Rate	Draw Rate	Total	E_{White}	Avg. Margin, points	Std. Dev.
500	0.99	[0.986, 0.997]	0.01	800	0.995	1.00	0.00
1600	0.99	[0.989, 0.999]	0.00	800	0.990	1.00	0.00
5000	1.00	[0.995, 1.000]	0.00	800	1.000	0.00	0.00
8000	0.99	[0.979, 0.994]	0.00	800	0.990	1.33	0.94

APPENDIX B Mathematical Analysis on Fair komi

Based on the current results, we conjecture that for board sizes $N \times N$, where N is odd and $N \geq 9$, fair komi will be 7.0 points under Chinese or AGA area-scoring rules, and 6.0 points under Japanese territory-scoring. While a formal mathematical proof is currently not available, as the complexity of Go on boards larger than

5×5 or 7×7 remains unsolved in the strict mathematical sense, drawing upon AI heuristics (AlphaZero/KataGo data), combinatorial game theory, and the parity properties of Area Scoring, we can show that it is a highly substantiated conjecture as follows.

A. The Mathematical Constraint: Parity in Area Scoring

To understand why the komi value 7.0 is critical and could be the fair komi value for most board sizes, we must first examine the arithmetic of AGA or Chinese rules (i.e., Area Scoring) on an odd-sized board.

Let N be an odd integer (e.g., 9, 11, 13, 19), the total number of intersection points on the board is

$$T = N^2 \quad (9)$$

Since N is odd, T is also odd.

Under Area Scoring, let's denote points occupied or surrounded by Black as B and points occupied or surrounded by White as W . Then the total points: $B + W = T = N^2$, assuming that all Dame are filled and there are no unresolved Seki that are treated as neutral points, which is standard in modern Area scoring.

The score difference D on the board before komi is:

$$D = B - W \quad (10)$$

Substitute $W = N^2 - B$, we get

$$D = B - (N^2 - B) = 2B - N^2 \quad (11)$$

Since $2B$ is always an even number and N^2 is an odd number, the result of the subtraction is always odd.

Therefore, there is no need to debate whether the fair komi—representing the value of the first move—is an even number or a non-integer (such as 6.5 or 7.3). Under Area Scoring rules, this advantage, and hence the fair komi value, must be an odd integer.

B. The Evidence from AI Self-Play: Convergence on 7

Since we lack a solved game tree, we rely on "Super-Human" AI (such as KataGo, AlphaGo Zero) as a proxy for perfect play.

The 7×7 Board: The 7×7 board is almost exhaustible and the consensus is that the fair komi is 9.0 under AGA or Chinese rules as also confirmed by our study.

The 9×9 Board: The 9×9 board is small enough that top AI engines are extremely convincing, although it is

not "weakly solved" like Checkers. As demonstrated in this study and others, with perfect play, Black wins by 7 points on the board, so the fair komi should be 7.0 under which perfect play would always result in a Draw (Jigo).

The 19×19 Board: Historically, komi has evolved from 0 to 4.5 to 5.5, and then 6.5 or 7.5 [5]. In the modern era of AI, prior studies and ours indicate that under Area Scoring, the fair komi should be 7.5 or 7.0, but then since the above parity analysis shows that it will need to be an odd integer, 7.0 is the only reasonable option[5].

C. The Conjecture for $N > 19$

Now the remaining question is essentially: does the first move advantage scale with board size?

Our conjecture here is that the value of First Move, or the fair komi value, stays at 7.0 as the odd number N goes beyond 9. This is because in Go, the value of the first move is derived from "corner efficiency". A move in the corner secures territory more efficiently than a move on the side or center. For a 5×5 board, this "corner efficiency" is highest—Black playing the first move at the 3-3 point can dominate the whole board, so fair komi would have to be 25. For a 7×7 board, the "corner efficiency" is higher than that of a 9×9 board, and therefore the fair komi is 9.0, as compared to 7.0 for the latter. For 9×9 or larger boards, as N increases, the number of corners (4) and the structure of corners remain unchanged. The efficiency gained by playing the first move in optimal key positions near each corner (e.g., 4-4 point, 3-4 point, etc.) is a local advantage. While the board space increases, the speed advantage of the first move does not multiply, nor is it likely to dilute significantly. Black gets one extra move and it has significant values due to its contribution to building territory around one of the corners. In a nearly infinite board, the density of that single stone approaches zero, but its absolute point value (the ability to dictate a corner structure) could remain unchanged. Therefore, it is highly likely that for all odd integers $N > 9$ (where corner interaction remains distinct from the center), the advantage remains 7 points and hence the fair komi value K^* will remain 7.0.

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Data Availability

All data supporting the findings of this study are available within the paper.

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