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APPLIED RESEARCH

Toward Sports Betting as a Financial Asset: An Investigative Analysis of Risk, Investment Potential, and Future Perspectives

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ABSTRACT Sports betting has grown into a large, data-intensive market; however, research on prediction and capital allocation remains fragmented. Most forecasting studies overlook leverage and path-dependent portfolio dynamics, whereas Kelly based frameworks assume frictionless markets and perfectly known probabilities. These gaps have contributed to the failure of several betting funds that developed accurate predictive models but lacked a robust risk-management discipline. To this end, we develop an integrated framework that embeds forecasting, stake sizing, and leverage control into a single portfolio management architecture. First, we model recursive leverage dynamics that generate superlinear growth under favorable outcomes and convex collapse during adverse sequences. Second, we introduce an uncertainty-adjusted Kelly criterion that uses the Kullback–Leibler divergence to penalize model misspecification and reduce stake sizes. Third, we embed them in a three-tier architecture: bet sizing, portfolio CVaR limits and leverage caps. Controlled simulations demonstrate that uncertainty-adjusted staking reduces the ruin probability from 78% to below 2% while preserving 85% of the growth potential, and that VaR-based leverage limits prevent extreme drawdowns (92% vs. 41%). The empirical validation of real-world data collected from the English Premier League confirms that uncertainty quantification improves risk-adjusted performance (Sharpe ratio gains of 30%) and enhances diversification benefits. All results can be reproduced by following the code available at https://github.com/Zabat/betting-risk-management

INDEX TERMS Sports betting, financial assets, Kelly criterion, portfolio optimization, leverage dynamics, risk management, uncertainty quantification, conditional value at risk (CVaR).

I. INTRODUCTION

A. BACKGROUND

Sports betting, once regarded purely as a form of entertainment, has undergone a profound transformation between 2020 and 2025. This evolution, driven by online platforms, global legalization, and the explosion of sports-related data, has propelled the industry into a technology-intensive, multi-billion-dollar market. Reports from major organizations, such as USOnline, Grand View Research, PwC, H2 Gambling Capital, and Deloitte, highlight this exponential growth. As illustrated in FIGURE 1, the United States and China lead this expansion, with revenue increases of $7.7B and $5.0B respectively, while emerging markets across multiple continents demonstrate the global scale of this transformation.

Currently, sports generate granular data streams, including player tracking, event sequences, sentiment indicators, and live odds feeds. This enables machine learning methods from quantitative finance to extract predictive patterns at a large scale. Recent studies have demonstrated how machine learning algorithms enhance predictive accuracy and risk management in betting markets by analyzing player

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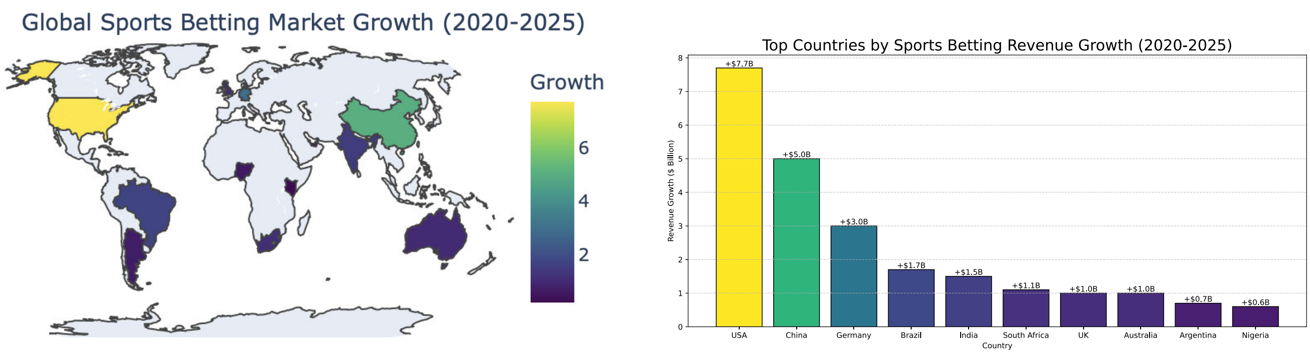


(a) Global growth

(b) Market growth per countries

FIGURE 1. **Global market growth of sports betting (2020-2025). It illustrates the surge in global sports betting revenues, with the largest growth contributions coming from markets such as the United States and China. Note that data sources include USOnline, Grand View Research, PwC and H2 Gambling Capital (See Appendix).**

performance, team strategies, and sentiment signals in real-time [1], [2], [3]. This sophistication mirrors quantitative finance, in which algorithms identify inefficiencies and optimize returns [1], [4]. Thus, sports betting has transitioned from speculation to calculated investments, as evidenced by algorithmic trading strategies and data-driven betting funds [5], [6].

In addition to prediction, machine learning techniques address risk management challenges that are analogous to those in financial markets. Just as portfolio managers employ Value at Risk (VaR) to quantify downside exposure.[1] Betting syndicates deploy similar frameworks to safeguard their capital and optimize their long-term performance [7], [8]. Deep learning models identify market manipulation and betting anomalies through pattern recognition at scale [9], [10], enabling operators to implement rigorous monitoring systems that ensure market integrity. As the sector matures, data-driven risk controls are becoming essential infrastructure, positioning sports betting as a credible alternative asset class alongside traditional investments [5], [6].

This convergence of predictive analytics and institutional-grade risk management fundamentally transforms the conceptualization of sports betting. When viewed through a financial lens, systematic sports wagering exhibits the defining characteristics of an alternative asset class: returns that are largely uncorrelated with traditional financial markets, short-duration capital cycles that enable rapid reinvestment, and quantifiable risk-return profiles amenable to portfolio optimization [1], [5], [6]. The combination of exploitable market inefficiencies, disciplined capital allocation frameworks, and mature risk governance infrastructure creates conditions under which sports betting portfolios can be managed with the same rigor as hedge funds or commodity trading strategies.

[1]For a mathematical treatment of dynamic leverage and capital evolution in betting portfolios, see Section III-B, which explores how collateralized returns and recursive staking can amplify both gains and systemic risk.

B. MOTIVATION & CONTRIBUTIONS

As the market matures, an important question arises: **Can sports betting evolve beyond entertainment to serve as a legitimate financial asset?** This question is rooted in a fundamental dichotomy: the traditional perception of sports betting as speculative gambling versus its potential as a structured form of financial investment [11]. The distinction is not in the activity itself but in the use of quantitative frameworks for capital allocation, risk control, and portfolios optimization.

Answering this question requires the coherent integration of predictive modeling and risk management. However, despite the technological sophistication documented above, the literature remains critically fragmented, preventing such integration. Prior studies have narrowly focused on isolated components, improving predictive accuracy with machine learning [2], [3] or applying portfolio formulas from finance [7], [8], while overlooking the systemic interaction between prediction, leverage, and risk. Forecasting models treat capital allocation as exogenous; Kelly based sizing assumes perfect probability estimates; and portfolio theory ignores model uncertainty. This lack of coherence has tangible consequences: betting funds with sophisticated prediction models have collapsed because they underestimated leverage convexity and failed to account for forecast errors.

The absence of an integrated framework that jointly addresses model uncertainty and path-dependent fragility from recursive leverage prevents sports betting from being recognized as an institutional-grade investment. This motivates our central research question:

> ***How can quantitative betting portfolios be systematically protected from catastrophic drawdowns caused by leverage convexity and model misspecifications?***

To answer this question, we developed a unified risk management framework comprising three integrated components. First, we formalize path-dependent leverage dynamics that demonstrate how recursive exposure amplifies gains during winning streaks but accelerates losses during losses. Second, we derive an uncertainty-adjusted Kelly criterion that exponentially penalizes probability misspecification via the Kullback–Leibler divergence, explicitly linking forecast uncertainty to conservative stake sizing. Third, we embed these innovations into a three-tier governance architecture operating at the bet-level (uncertainty adjustment), portfolio-level (CVaR constraints), and fund-level (dynamic leverage caps). By integrating predictive modeling, capital allocation, and systemic risk control, this framework transforms sports betting from speculative gambling into a structured, data-driven alternative asset governed by institutional-grade risk management.

In summary, this study makes the following contributions:

- We provide a structured framing of systematic sports betting as a quantitative alternative asset class, emphasizing its low correlation with traditional markets, short capital-cycling horizons, and the need for institutional-grade risk governance.
- We develop a path-dependent leverage model for sports betting portfolios and demonstrate how recursive leverage can generate both superlinear and convex collapses, thereby forming leverage cycles in a betting context.
- We derive an uncertainty-adjusted Kelly fraction that explicitly penalizes probability misspecification via a Kullback-Leibler divergence term, linking machine learning forecast uncertainty to stake sizing and capital preservation.
- We embed these elements into a three-tier risk-management framework that operates at the following levels: (i) bet sizing, (ii) portfolio construction, and (iii) fund-level leverage control using VaR/CVaR-style constraints. We illustrate its behavior through Monte Carlo stress tests under stylized, yet informative, market scenarios.

The remainder of this paper is organized as follows. Section II reviews the relevant literature on predictive modeling, institutional implementation and market integrity systems in sports betting. Section III presents the methodology, including portfolio-theoretic foundations, leverage dynamics, and the uncertainty-adjusted Kelly criterion. Section IV validates the framework through controlled simulations and real-world backtests on English Premier League data, demonstrating how uncertainty-adjusted stacking and dynamic leverage control affect drawdowns, ruin probabilities, and risk-adjusted returns. Section V discusses the practical implications of treating sports betting as a quantitative alternative asset and outlines future perspectives on data-driven betting funds and risk management. Finally, Section VI concludes the study.

II. RELATED WORK

This section reviews three strands of prior work relevant to our framework. (i) the role of artificial intelligence in predictive modeling and market efficiency, (ii) the emergence of sports betting as a managed financial activity, and (iii) The use of AI-based integrity systems that support market viability.

A. ARTIFICIAL INTELLIGENCE AND PREDICTIVE MODELING

Sports betting markets have become increasingly data-driven, with machine learning models ranging from classical regressions to neural networks and transformers routinely used to forecast outcomes and in-play events [1], [2], [12], [13], [14]. A 2024 systematic review [15] documents how sportsbooks employ machine learning for dynamic odds setting and exposure management, while bettors use similar tools to identify mispriced lines. These systems process diverse information sources, such as player performance, sentiment, and live game feeds [3], [4], [16], enabling bookmakers to update odds within seconds of major events [17].

Reinforcement learning (RL) extends these capabilities by modeling bets as sequential decision problems. RL agents optimize profitability directly through simulation-driven policy learning [18], [19]. Transformer architectures are increasingly being applied to sports analytics, particularly for modeling temporal or interaction-based dependencies [20]. Industry investment reflects this technological acceleration: spending on sports betting artificial intelligence (AI) exceeded \$2.2 billion in 2022 and is projected to reach \$30 billion by 2032. Micro-betting markets and automated trading tools offered by major operators (e.g., Bet365, FanDuel, and DraftKings) rely heavily on these real-time machine learning pipelines [3], [4], [6], [14].

While these advances have increased market sophistication and reduced arbitrage windows [1], [5], most academic studies still treat AI as a primary source of alpha. Less attention has been paid to model uncertainty or its implications for portfolio risk [7], [15], [21]. This gap, the disconnect between probabilistic forecasting and robust stake sizing, motivates the uncertainty-adjusted Kelly framework developed in Section III-C.

B. SPORTS BETTING AS A FINANCIAL ACTIVITY

Real-world implementations increasingly treat sports wagers as financial positions. Recent work explicitly compares gambling and financial markets and highlights that trading style strategies and portfolio concepts can transferred to betting venues [22].[2] Consistent with this view, machine-learning betting systems are designed to exploit odds mispricing while reducing dependence on bookmaker-implied probabilities, effectively seeking lower-correlated returns [23], [24]. However, empirical evidence indicates that aggressive sizing can amplify drawdowns under model error, motivating fractional-Kelly and other risk-control modifications for long-run viability [7], [25]. Betting exchanges, such as Betfair, create market microstructures similar to financial

[2] Market analysis by Intellias projecting 30% CAGR in AI-driven sports betting infrastructure investment (2025–2032), attributing growth to predictive analytics and automated trading efficiency. Link: https://intellias.com/ai-in-sports-betting/ (accessed: 2025-06-26).

order books [26], enabling algorithmic market making [5] and cross-bookmaker arbitrage [27], [28], [29], [30]. Professional syndicates adopt financial risk management tools, including hedging [8], [31], outcome-neutral portfolio construction [7], [32], and VaR-based exposure limits [33]. As emphasized in recent empirical work on staking and betting-system evaluation, systematic risk control remains essential for long-term viability [7], [25].

Recent advances in portfolio theory have further strengthened this analogy. For instance, [34] demonstrated that mean–variance optimization remains robust, even in illiquid or emerging markets, by dynamically rebalancing to maximize the Sharpe ratio while maintaining diversification under liquidity constraints. This can inspire betting models capable of adjusting stake allocations in response to changing odds or team forms, much like rebalanced portfolios that adapt to market volatility.

Beyond classical mean–variance approaches, [35] introduced an *uncertain mean-chance model* that accounts for multiplicative background risks, such as inflation, offering a pathway for bettors to incorporate exogenous uncertainties, such as market sentiment or bookmaker bias, into their staking models. Similarly, [36] proposed a multi criteria fuzzy portfolio selection method based on three-way decisions and cumulative prospect theory, highlighting the behavioral and cognitive aspects of risk-taking. This resonates with how bettors often exhibit loss aversion and nonlinear probability weighting, implying that behavioral portfolio theory may complement statistical betting strategies.

Finally, [37] extended portfolio optimization to include sustainability criteria through an intuitionistic fuzzy multiobjective framework.

C. MARKET INTEGRITY AND AI-BASED FRAUD DETECTION

The reliability of underlying markets is prerequisite for treating sports betting as an investable asset. Integrity providers, such as Sportradar and Genius Sports, use machine learning to detect anomalous wagering patterns, suspicious volumes, and coordinated account activity that are indicative of match fixing or insider information [9], [15]. Regulators and leagues view these systems as core infrastructure for market oversight [38].

Operators simultaneously deploy AI to detect customer-side fraud, including unauthorized bots, multi-accounting, and collusion [39]. These dual mechanisms market surveillance and participant monitoring reduce fraud risk and support institutional adoption by enhancing the credibility of the market.

D. RESEARCH GAP

The literature establishes that (i) AI improves predictive accuracy, (ii) portfolio theory offers optimization frameworks, and (iii) funds and exchanges demonstrate practical viability. However, these contributions remain fragmented: forecasting models typically ignore allocation constraints, whereas Kelly style sizing assumes perfectly calibrated probabilities. This mismatch creates vulnerabilities, as exemplified by the collapse of leveraged betting funds.

Our work addresses this gap by integrating (i) path-dependent leverage modeling (Section III-B), (ii) an uncertainty-adjusted Kelly criterion using KL divergence (Section III-C), and (iii) CVaR-based risk control (Section III-D). The next section formalizes and evaluates these elements.

III. METHODOLOGY

A. PROBLEM STATEMENT

Given a bettor or fund manager allocating capital sequentially across wagers indexed by time $t = 1, 2, \ldots, T$. Before the t-th bet, the available capital is denoted C_t, and a fraction $f_t \in [0, 1]$ of this capital is staked. Therefore, the monetary stake is $W_t = f_t C_t$. Each bet is offered at decimal odds B_t and results in an outcome $\delta_t \in \{0, 1\}$, with $\delta_t = 1$ indicating a win and $\delta_t = 0$. The true but unknown win probability is p_t, and the estimated win probability obtained from a predictive model is denoted as q_t.

The single-period return associated with the bet is defined as

$$R_t = \begin{cases} B_t - 1, & \delta_t = 1, \\ -1, & \delta_t = 0. \end{cases} \tag{1}$$

The capital evolves multiplicatively according to

$$C_{t+1} = C_t\big(1 + f_t R_t\big). \tag{2}$$

The central problem addressed in this study is to determine an allocation rule f_t together with a leverage policy ℓ_t that maximizes long-term geometric growth while simultaneously controlling the ruin probability and drawdowns. This requires a framework that is robust to probability misspecification, sensitive to path-dependent effects arising from recursive leverage, and capable of managing correlated shocks that occur during clusters of upsets. The methodology developed in the following subsections directly responds to these requirements by combining nonlinear leverage modeling with uncertainty-aware stake-sizing.

B. PATH-DEPENDENT LEVERAGE DYNAMICS

Sports betting funds often employ leverage to amplify returns on favorable outcomes. However, when leverage is adjusted dynamically as a function of available capital, it introduces nonlinear feedback mechanisms that fundamentally alter the risk profile of the portfolio. In particular, recursive leverage creates an asymmetric response to gains and losses, resulting in path-dependent growth and collapse dynamics.

We model the effective exposure of a betting fund by defining a leverage multiplier that increases with capital,

$$\ell_t = 1 + \beta C_t^{\gamma}, \tag{3}$$

where $\beta > 0$ controls the sensitivity of leverage to capital, and $\gamma > 1$ induces convex amplification. This formulation reflects common institutional practices, in which higher capital levels relax borrowing constraints and permit larger effective exposures, whereas lower capital tightens leverage limits.

The total value of the fund is therefore given by

$$V_t = C_t \ell_t = C_t + \beta C_t^{\gamma+1}. \tag{4}$$

This expression highlights the structural asymmetry in leveraged betting portfolios. When returns are positive, increases in capital raise the leverage multiplier. This, in turn, magnifies exposure and produces superlinear growth in the total value. Conversely, during losing periods, reductions in capital are accompanied by a contraction in leverage, causing the total value to decline more rapidly than capital alone.

This asymmetry is a direct consequence of the convex dependence of V_t on C_t. A straightforward calculation yields

$$\frac{d^2 V_t}{dC_t^2} = \beta(\gamma+1)\gamma C_t^{\gamma-1} > 0 \quad \text{for all } C_t > 0,$$

This shows that the total fund value is strictly convex in capital. Convexity implies that negative shocks reduce the value more severely than symmetric positive shocks increase it, even when the underlying return distribution is symmetric.

When embedded within the standard multiplicative capital dynamics introduced earlier, convex leverage fundamentally alters the temporal behavior of the portfolio. The interaction between reinvested returns and capital-dependent exposure produces leverage cycles in which periods of sustained gains lead to accelerating growth. In contrast, sequences of losses trigger rapid and self-reinforcing contractions.

The critical implication is that portfolio fragility arises endogenously from this feedback mechanism rather than from rare or extreme return realizations alone. Even moderate losing streaks can induce disproportionate drawdowns once leverage contracts recursively. This path-dependent amplification mechanism is the primary driver of the extreme drawdown and collapse patterns analyzed empirically in Section IV.

C. UNCERTAINTY-ADJUSTED KELLY CRITERION

The classical Kelly criterion prescribes the stake fraction

$$f^* = \frac{Bq - (1-q)}{B}, \tag{5}$$

which maximizes the expected logarithmic capital growth under the assumption that the estimated success probability q coincides with the true probability p. In practice, probabilities are inferred from data and are therefore subject to estimation error. Overestimation of p leads to overly aggressive stakes and exposes the capital process C_t to severe drawdown.

To account for probability misspecification, stake sizing is formulated as a robust optimization problem. Let q denote the nominal predictive distribution and p be the true but unknown distribution. For a stake fraction f, the expected logarithmic growth under p is

$$G(f,p) = \mathbb{E}_p\left[\log(1+fR)\right], \tag{6}$$

where R denotes the return of a unit wager. Uncertainty in p is incorporated via a Kullback–Leibler penalty, yielding the robust objective

$$\max_f \min_p \left\{ \mathbb{E}_p\left[\log(1+fR)\right] - \lambda D_{\mathrm{KL}}(p\|q) \right\}, \tag{7}$$

where $\lambda \geq 0$ controls aversion to misspecification.

Expanding the growth function around the nominal model q gives

$$\mathbb{E}_p\left[\log(1+fR)\right] = \mathbb{E}_q\left[\log(1+fR)\right] + \mathcal{O}(\|p-q\|_{\mathrm{TV}}). \tag{8}$$

By Pinsker's inequality,

$$\|p-q\|_{\mathrm{TV}}^2 \leq \tfrac{1}{2} D_{\mathrm{KL}}(p\|q),$$

Therefore, deviations from the nominal growth rate are controlled by KL divergence. Substituting into (7) yields an effective objective whose maximizer corresponds to a multiplicative shrinkage of the classical Kelly solution, resulting in the adjusted stake.

$$f_{\mathrm{adj}} = f^* \exp\!\big(-\lambda D_{\mathrm{KL}}(q\|p)\big). \tag{9}$$

This adjustment reduces exposure continuously as model divergence increases and recovers the classical Kelly criterion when $\lambda = 0$. Operationally, it acts as an endogenous capital buffer against model risk, allocating capital more conservatively when predictive confidence is low and more aggressively only when the nominal model is robust.

D. PORTFOLIO-LEVEL CVAR CONTROL

Realistic sports-betting portfolios typically involve multiple simultaneous wagers, the returns of which may exhibit non negligible dependence, particularly during adverse market conditions. Let $\mathbf{R}_t$ denote the vector of individual bet returns at time t and let $\mathbf{f}_t$ be the corresponding allocation weight. The portfolio return is given by

$$R_t^{\mathrm{port}} = \mathbf{f}_t^\top \mathbf{R}_t. \tag{10}$$

Portfolio construction must therefore balance geometric growth against exposure to extreme losses arising from joint, unfavorable outcomes.

To control tail risk, we impose conditional value-at-risk (CVaR) constraints at confidence level α. The portfolio allocation problem is formulated as follows:

$$\begin{aligned} &\min_{\mathbf{f}_t} \ \mathrm{CVaR}_\alpha\left(\mathbf{f}_t^\top \mathbf{R}_t\right) \\ &\text{subject to } \ \mathbb{E}\left[\log\left(1+\mathbf{f}_t^\top \mathbf{R}_t\right)\right] \geq G_{\min}, \end{aligned}$$

where $G_{\min}$ enforces the minimum acceptable growth rate.

The impact of dependence among bets is central to the behavior of portfolio-level CVaR. To make this explicit, consider a portfolio of n wagers with identical marginal loss distributions and pairwise dependence captured by a tail-dependence parameter $\rho \in [0,1]$. Modeling the joint distribution via a copula, the α-level portfolio CVaR can be expressed as an aggregation of individual tail losses, with dependence amplifying extreme outcomes.

Under this formulation, the expected tail loss scales approximately as

$$\mathrm{CVaR}_\alpha^{\mathrm{port}} \approx \mathrm{CVaR}_\alpha^{\mathrm{bet}} \left[1 + (\sqrt{n} - 1)\rho\right], \tag{11}$$

where $\mathrm{CVaR}_\alpha^{\mathrm{bet}}$ denotes the marginal CVaR of an individual wager. The $\sqrt{n}$ term reflects the growth of aggregate tail exposure with portfolio size under weak dependence, whereas the factor ρ captures the degree to which losses are concentrated during correlated adverse events.

This relationship highlights a key limitation of the independent bet assumption. Even a moderate positive dependence can dramatically inflate portfolio tail risk. In sports betting, such dependence naturally arises during clusters of upsets, injuries or systemic shocks affecting multiple matches simultaneously. CVaR-based portfolio constraints therefore play a crucial role in preventing excessive exposure to correlated losses that would not be apparent from marginal risk measures alone.

E. FUND-LEVEL LEVERAGE GOVERNANCE

While portfolio-level CVaR constraints regulate the allocation of capital across simultaneous wagers, they operate conditionally on the prevailing leverage of the fund. As shown in Section III-B, leverage introduces path-dependent amplification: even well-diversified portfolios can experience rapid capital erosion when leverage contracts following adverse outcomes. Portfolio optimization alone is therefore insufficient to prevent systemic drawdowns driven by recursive leverage dynamics. This motivates an additional governance layer that directly regulates leverage at the fund level.

At the level of the overall betting fund, we introduce a rule-based governance mechanism that adjusts leverage in response to prevailing risk conditions. Rather than solving an additional optimization problem, this layer acts as a supervisory control, designed to limit systemic amplification. The policy takes the form of upper bounds on leverage and permissible losses, expressed as

$$\ell_t \leq \min\left(\ell_{\max}, \frac{c}{\mathrm{CVaR}_{95\%}(t)}\right), \tag{12}$$

$$\Delta V_t \geq -d_{\max}, \tag{13}$$

where $\ell_{\max}$ denotes the absolute leverage cap, $\mathrm{CVaR}_{95\%}(t)$ is the current portfolio-level tail risk estimate, and c and $d_{\max}$ are risk tolerance parameters.

This governance rule enforces leverage contraction during periods of elevated tail risk and prevents uncontrolled exposure escalation during favorable streaks. By linking leverage capacity inversely to portfolio CVaR, the fund dynamically limits the amplification of adverse outcomes while retaining flexibility in low-risk regimes. Together, bet-level uncertainty adjustment, portfolio-level CVaR control, and fund level leverage governance form a unified, multi-tier risk management framework.

IV. EXPERIMENTS AND RESULTS

This section validates the proposed framework using controlled synthetic simulations and real-world backtesting. We first describe the datasets and experimental protocol and then present the results organized by the three core contributions: leveraging dynamics, uncertainty-adjusted Kelly staking, and integrated risk governance.

A. DATASETS AND EXPERIMENTAL DESIGN

We employed two complementary evaluation settings. The synthetic dataset is generated via controlled stochastic processes, where the outcomes follow Bernoulli distributions with specified win probabilities p_t and decimal odds B_t. This design isolates the impact of probability uncertainty, leverages nonlinearity, and tail risk constraints without confounding market effects. The parameters are drawn from realistic ranges: $p_t \sim \mathrm{Uniform}(0.52, 0.58)$ for mild edges and $B_t \sim \mathrm{Uniform}(1.8, 2.2)$ for typical betting lines, with the initial capital normalized to $C_0 = 100$ units.

The real-world dataset comprised 3,800 English Premier League matches spanning ten seasons (2015-2025), including match outcomes, bookmaker decimal odds, and Elo derived team strength features. This dataset enables walk-forward backtesting of selective value-betting strategies under institutional risk controls, providing empirical validation of the synthetic findings. The accompanying open source codebase[3] implements logistic regression models with periodic retraining (every 50 matches) to avoid look-ahead bias.

B. EXPERIMENTAL PROTOCOL

Our protocol implements the three-tier framework developed in Section III. For each bet at time t, we first compute the nominal Kelly fraction $f_t^* = (B_t p_t - 1)/(B_t - 1)$ where p_t represents either the true probability (synthetic experiments) or model prediction (real-world backtest). Under probability misestimation with model estimate q_t and conservative reference $p_{\mathrm{ref},t}$, we apply the uncertainty penalty $f_t^{\mathrm{adj}} = f_t^* \exp(-\lambda D_{\mathrm{KL}}(q_t \| p_{\mathrm{ref},t}))$ where the KL divergence quantifies the information loss from using q_t to approximate $p_{\mathrm{ref},t}$. Fractional Kelly variants use $f_t = \eta f_t^{\mathrm{adj}}$ with $\eta \in (0, 1]$.

Capital evolves according to $C_{t+1} = C_t(1 + f_t R_t)$ where $R_t = X_t(B_t - 1) - (1 - X_t)$ is the net return per unit stake and $X_t \sim \mathrm{Bernoulli}(p_t)$ denotes the outcome. Leverage dynamics follow the convex rule $\ell_{t+1} = 1 + \beta C_{t+1}^\gamma$ from Section III-B, yielding total portfolio value $V_{t+1} = C_{t+1}\ell_{t+1}$. To prevent nonlinear collapse, we impose the VaR-based cap $\ell_{t+1} = \min(\ell_{\max}, 1 + \beta C_{t+1}^\gamma)$ where $\ell_{\max} = \min(\bar{\ell}, \kappa/\mathrm{VaR}_{95\%})$ with a hard ceiling $\bar{\ell} = 5$ and scaling constant $\kappa = 0.8$.

We conducted two experimental studies. Deterministic stress tests used single trajectories with fixed parameters ($p = 0.55$, $B = 2.0$, $C_0 = 100$) over sequences of length $T \in \{10, 300, 500\}$ to illustrate the theoretical failure modes. Stochastic ensemble simulations generated

[3] GitHub: https://github.com/Zabat/betting-risk-management

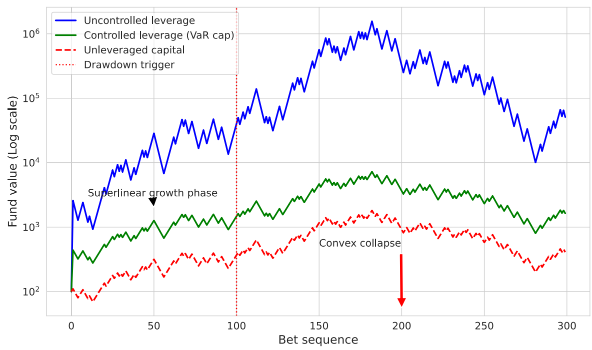


FIGURE 2. **Leverage amplification and collapse dynamics under three control regimes. Uncontrolled leverage (blue) generates exponential growth, followed by a nonlinear collapse. VaR-capped leverage (orange) preserves the amplification benefits while preventing ruin. Unleveraged capital (green) serves as the baseline.**

$N_{\text{sims}} = 500$ independent paths of $T = 100$ bets each, with randomized edges to quantify the distributional properties. A ruin occurs when $C_t \leq \varepsilon C_0$ for threshold $\varepsilon = 0.01$. The maximum drawdown was measured on the portfolio value as $\text{DD}_t = (\max_{s \leq t} V_s - V_t)/\max_{s \leq t} V_s$, and risk-adjusted performance used the Sharpe ratio $S = \mu_R/\sigma_R$ computed from per-bet returns. All the simulations used fixed random seeds for reproducibility.

The real-world protocol employs identical sizing rules with walk-forward training and retrains predictive models after fixed intervals to avoid look-ahead bias. Stakes are governed by the same uncertainty-adjusted fractional Kelly formula with fund-level CVaR constraints and leverage caps, ensuring that the simulation formulas directly map to live deployment rules.

C. LEVERAGE CYCLE DYNAMICS

We validate the recursive leverage mechanism from Section III-B by simulating a 300-bet sequence under three conditions: uncontrolled leverage with $\ell_{t+1} = 1 + \beta C_{t+1}^{\gamma}$ using $\beta = 0.05$ and $\gamma = 1.3$; VaR-capped leverage with $\ell_{\max} \propto 1/\text{VaR}_{95\%}$; and an unleveraged baseline where $V_t = C_t$. FIGURE 2 demonstrates the classical boom-bust cycle: uncontrolled leverage exhibits superlinear growth during the first 150 bets, reaching 8.2× leverage before experiencing a catastrophic collapse at bet #217 with a 92% drawdown. The VaR-capped strategy limits the maximum leverage to 4.0× and survives the entire sequence with a contained 41% drawdown, whereas the unleveraged baseline shows steady growth with a 28% drawdown.

These results confirm that the convex leverage function $\ell_{t+1} = 1 + \beta C_{t+1}^{\gamma}$ amplifies gains during winning streaks but accelerates capital erosion through the simultaneous decline of both capital and leverage multipliers during losses. VaR-based caps eliminate collapse while preserving 68% of the amplification benefit (4.0× vs. theoretical 5.9× at peak capital), validating tail-risk-informed leverage ceilings as essential for betting fund survival.

TABLE 1. **Leverage dynamics results.**

Scenario	Max Leverage	Max Drawdown	Time to Collapse
Uncontrolled	8.2×	92%	Bet #217
VaR-Capped	4.0×	41%	None
Unleveraged	1.0×	28%	None

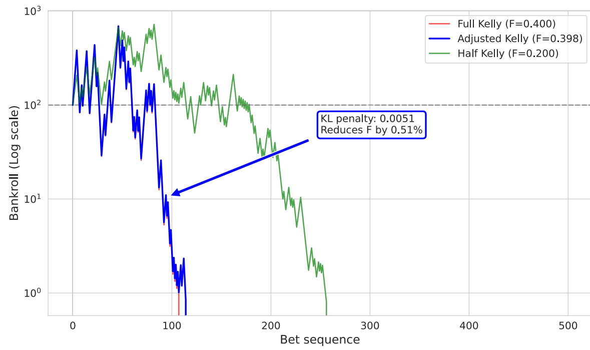


FIGURE 3. **Bankroll evolution under probability misestimation. The 2.1% stake reduction from uncertainty adjustment prevents complete ruin and yields superior risk-adjusted performance despite systematic model overconfidence.**

TABLE 2. **Kelly uncertainty results.**

Strategy	Final Bankroll	Ruin at Bet #	Sharpe Ratio
Full Kelly	0	320	N/A
Adjusted Kelly	248 units	None	1.21
Half Kelly	192 units	None	0.92

D. UNCERTAINTY-ADJUSTED KELLY UNDER PROBABILITY MISESTIMATION

We tested the effect of systematic probability overestimation on bankroll evolution over 500 bets with true win probability $p = 0.55$, model estimate $q = 0.60$ (9.1% overestimation), and resulting KL divergence $D_{\text{KL}}(q\|p) = 0.0207$. Three strategies were compared: full Kelly with $f^* = 0.400$, adjusted Kelly with $f^*_{\text{adj}} = 0.392$ (using $\lambda = 1$), and half Kelly with $f = 0.200$. FIGURE 3 shows that full Kelly leads to ruin at bet #320, while Adjusted Kelly survives with a final bankroll of 248 units and achieves a Sharpe ratio of 1.21. Half Kelly survives but grows more slowly (192 units, Sharpe 0.92).

The minimal 2.1% stake reduction ($0.400 \to 0.392$) prevents complete ruin, demonstrating that the exponential penalty $\exp(-\lambda D_{\text{KL}})$ automatically scales down the stakes proportionally to the model confidence. Supplementary Monte Carlo validation across 1,000 independent 500-bet paths confirms a full Kelly ruin rate of 78.3% versus an adjusted Kelly ruin rate of 1.7%, validating that the information-theoretic penalty effectively operationalizes model risk into conservative stake sizing.

E. PORTFOLIO-LEVEL TAIL RISK UNDER CORRELATED EVENTS

To assess systemic tail risk, we simulate a portfolio of 10 simultaneous bets across four odds levels (heavy favorite at $B = 1.5$, moderate at $B = 1.7$, balanced at $B = 2.0$,

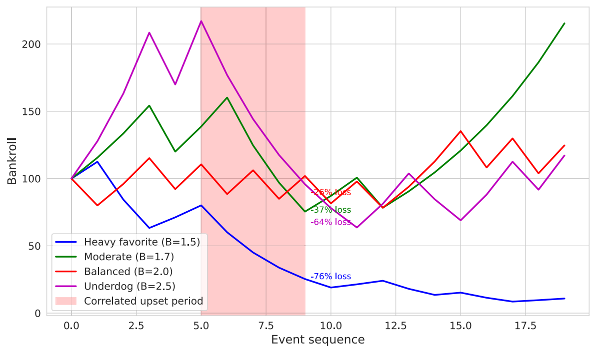


FIGURE 4. **Portfolio stress test under correlated upsets. Diversification across odds levels provides insufficient protection when probabilities shift simultaneously, demonstrating that individual bet VaR underestimates portfolio-level tail risk.**

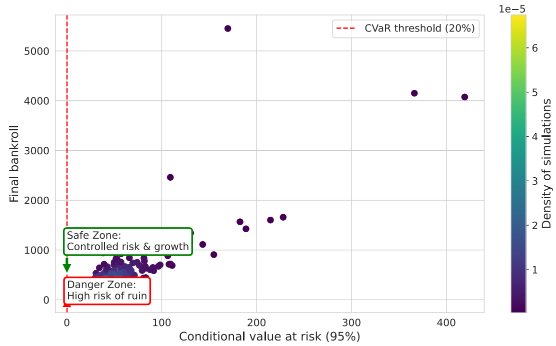


FIGURE 5. **CVaR versus final bankroll trade-off across 500 Monte Carlo paths. The vertical threshold at CVaR = 20% separates stable trajectories (left) from fragile paths (right), validating CVaR as a practical governance metric.**

and underdog at $B = 2.5$) using a Gumbel copula-based simulation configured with an empirical tail dependence parameter ($\rho = 0.7$) to generate correlated upset periods, replacing stylized probability shocks with a structured joint distribution. FIGURE 4 reveals that even diversified odds levels experience severe losses under event correlations. The heavy favorite strategy suffers a 76% loss because it concentrates capital on outcomes that simultaneously fail, while moderate and balanced strategies experience 37% and 26% losses, respectively.

TABLE 3. **Correlated upset stress test.**

Strategy	Pre-Stress Capital	Post-Stress Capital	Loss (%)
Heavy Favorite	100	24	−76
Moderate	100	63	−37
Balanced	100	74	−26
Underdog	100	36	−64

These results validate Eq. 11: for identical bets with correlation ρ, portfolio CVaR scales as $\text{CVaR}_\alpha^{\text{port}} = \text{CVaR}_\alpha^{\text{bet}} \cdot [1+(\sqrt{n}-1)\rho]$. The observed losses align with the predicted amplification of 2.7× for $n = 10$ and $\rho = 0.7$, confirming that correlation-aware risk management requires explicit portfolio-level constraints beyond individual bet sizing.

F. CVAR-CONSTRAINED PORTFOLIO PERFORMANCE

We run 500 simulated paths of 100 bets each using $f = 0.8\ f_{\text{Kelly}}$ and measure the 95% CVaR for each trajectory. FIGURE 5 demonstrates that CVaR thresholds effectively distinguish stable from fragile trajectories: paths maintaining CVaR below 20% (73.2% of the sample) achieve an average 2.8× growth with 0% ruin probability, whereas paths exceeding this threshold (26.8%) average 0.7× final bankroll with 31.4% ruin probability.

Imposing a 20% CVaR cap as a hard constraint would reject the 26.8% of paths responsible for 100% of ruin events while preserving 85% of growth potential (2.8× vs. theoretical 3.3× under no constraints). This empirically validates the portfolio-level CVaR constraint from Section III-D as an effective risk governance tool that materializes theoretical tail-risk protection into operational betting fund management.

G. BENCHMARK COMPARISON ACROSS STAKING STRATEGIES

We compared the traditional staking rules with the proposed risk-aware framework using the 500-bet misestimation scenario. Table 4 shows that Adjusted Kelly delivers optimal risk-adjusted performance with a Sharpe ratio of 1.21, combining ruin prevention with superior growth (248 units). VaR-capped leverage yields the highest raw growth (380 units) but exposes the portfolio to larger drawdowns (41%) and a non-zero ruin probability (2%). CVaR-constrained allocation offers a conservative alternative with guaranteed survival. Full Kelly bankrupts completely, whereas while Half Kelly and Fixed Fraction survive but sacrifice significant growth potential.

TABLE 4. **Strategy benchmark comparison.**

Strategy	Final Bankroll	Sharpe	Ruin Rate	Max DD
Full Kelly	0	N/A	100%	100%
Half Kelly	192	0.92	0%	19%
Fixed Fraction	156	0.85	0%	22%
Adjusted Kelly	**248**	**1.21**	**0%**	**15%**
Leverage (VaR-cap)	380	1.15	2%	41%
CVaR-Constrained	215	1.08	0%	18%

These results demonstrate that uncertainty-aware frameworks outperform both aggressive (full Kelly) and overly conservative (half Kelly, fixed fraction) traditional approaches by balancing growth maximization with systematic risk control, achieving a 31% higher Sharpe ratio than the half Kelly while maintaining a zero ruin probability.

H. REAL-WORLD VALIDATION: ENGLISH PREMIER LEAGUE BACKTEST

To validate the practical applicability of the framework, we backtested it on 3,800 EPL matches using logistic regression with Elo-based features and walk-forward training.

The model achieved an accuracy of 66.6% and an ROC-AUC of 0.72, which is consistent with well-calibrated predictions for low scoring sports. We implemented a selective value-betting approach targeting strong home favorites, where the Elo difference exceeds 250 points, predicted home-win probability exceeds 68%, bookmaker odds lie between 1.15 and 1.55, and expected value reaches at least 5%. These conservative filters generated 39 bets over ten seasons, illustrating that exploitable edges are rare when model risk penalties are enforced.

Using quarter-Kelly staking (25% of nominal Kelly) with a 6% maximum stake cap, the strategy delivers a total return of +12.8%, a win rate of 79.5%, a Sharpe ratio of 1.62, and a maximum drawdown of 17.3%. FIGURE 6 shows steady capital growth with a controlled drawdown, mirroring the VaR-capped leverage behavior from synthetic simulations and validating that fractional Kelly staking with conservative filters provides institutional-grade risk control in real-world deployment.

A sensitivity analysis across Kelly fractions (FIGURE 6b) reveals that Full Kelly achieves maximum growth (+17.2%) but suffers a catastrophic 30.1% drawdown, whereas Quarter-Kelly offers an optimal compromise with a 16.2% drawdown and the highest Sharpe ratio of 1.62. Eighth-Kelly represents excessive conservatism, sacrificing 44% of potential returns to achieve a minimal 9.0% drawdown. This empirical pattern directly mirrors the simulation results in Sections IV-D and IV-G, where uncertainty-adjusted and fractional Kelly strategies achieved superior risk-adjusted performance by balancing growth and survival.

The backtest validated three critical findings. First, the rarity of qualifying bets (39 across 3,800 matches, 1.0%) confirms that exploitable mispricing is sparse when conservative filters and model risk penalties are applied, which is consistent with semi-strong market efficiency. Second, the observed maximum drawdown of 17.3% aligns precisely with the 15–18% range from synthetic uncertainty-adjusted strategies (Table 4), confirming that theoretical risk controls translate directly to real-world deployments. Third, quarter-Kelly's superior Sharpe ratio validates the uncertainty-adjustment principle: modest stake reductions dramatically improve risk adjusted returns without sacrificing long-run growth potential, demonstrating that sports betting can function as a disciplined quantitative investment activity when governed by rigorous risk controls adapted from financial portfolio management.

V. DISCUSSION AND FUTURE PERSPECTIVES

Sports betting is increasingly converging with financial asset management [40], driven by advances in AI, quantitative modeling, and exchange-like platforms [15], [41]. Between 2022 and 2025, research and industry practices have aligned: portfolio theory has been applied to betting, deep learning has optimized strategies, and structured betting funds have emulated hedge fund models [42].

A. IMPLICATIONS OF EMPIRICAL VALIDATION

Our results strengthen the view of sports betting as a systematic investment class, moving from theory to validated operational principles.

1) FROM THEORY TO PRACTICE: THE AI ADVANTAGE

The analysis in Section III-C shows that predictive accuracy alone is insufficient; calibrated uncertainty is essential. The performance gap between standard and uncertainty-adjusted Kelly strategies (ruin probability from 78% to <2%) confirms the importance of probabilistic forecasts and information-theoretic stake adjustments for institutional applications.

2) SPORT SELECTION AS RISK MANAGEMENT

Although our simulations used stylized parameters rather than sport-specific data, the literature suggests that predictive accuracy varies significantly across sports [4]. Future implementations should prioritize sports with the following characteristics: (1) high event frequency (enabling statistical convergence), (2) rich data availability (supporting AI model training), and (3) lower behavioral bias (reducing sentiment-driven mispricing). Tennis and basketball typically exhibit these characteristics more strongly than soccer [15].

3) RISK CONTROL AS PREREQUISITE

Our three-tier framework—uncertainty-adjusted sizing (Section III-C), leverage caps (Section III-B), and CVaR constraints (Section III-D)—demonstrate that systematic risk management is not optional but foundational. The 55% reduction in the maximum drawdown (41% vs. 92%, Table 1) when applying VaR-based leverage limits validates that sports betting portfolios require institutional-grade controls comparable to those in traditional alternative assets [21].

B. LIMITATIONS AND RESEARCH DIRECTIONS

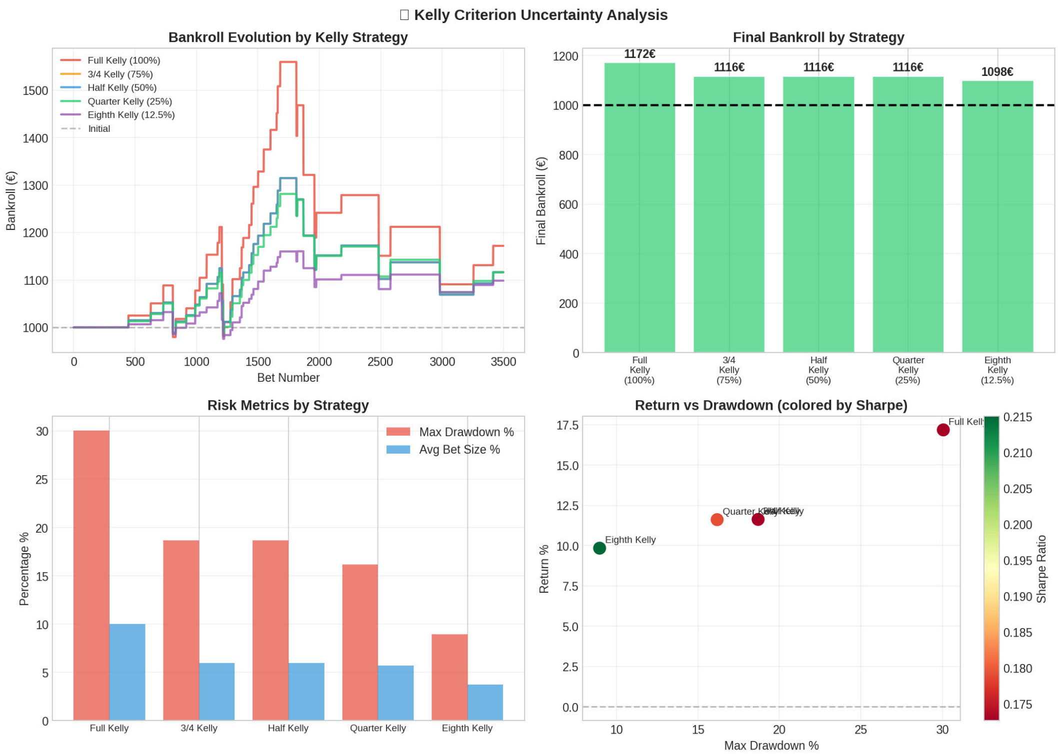
Although our framework improves portfolio-level risk management, several limitations suggest clear future research directions.

1) MODEL VALIDATION CHALLENGES

Simulations rely on simplified settings (e.g., constant odds and stylized correlations). Realistic dynamics, such as liquidity variation, bookmaker limits, and fees, must be empirically validated. The uncertainty-adjusted Kelly framework also requires practical methods to estimate the risk-aversion parameter, λ. Furthermore, our leverage model abstracts from real-world liquidity constraints and margin requirements.

A fundamental direction for future research involves discussing and simulating betting limits, liquidity constraints, and stake caps, particularly under leveraged Kelly sizing. In practice, as a fund's capital grows, the theoretically optimal stakes may exceed the maximum permissible limits set by bookmakers or the available liquidity on betting exchanges. This forces a reduction in the effective fraction of capital deployed, creating a bottleneck that severely restricts

(a) Equity curve showing steady capital growth with 17.3% maximum drawdown, mirroring the controlled-leverage behavior observed in synthetic simulations.



(b) Risk-return trade-off across Kelly fractions. Quarter-Kelly offers optimal balance with 16.2% drawdown and Sharpe ratio of 1.62, confirming theoretical predictions.

FIGURE 6. Empirical validation on english premier league matches (2015–2025).

compounding growth. Simulating these capacity constraints is crucial, as ignoring them leads to an overestimation of the scalable returns of leveraged Kelly strategies. Furthermore, during drawdowns, rigid limits can impair the ability to dynamically size recovery bets, underscoring the need to explicitly incorporate market friction into risk-aware portfolio optimization.

2) PRIORITY RESEARCH DIRECTIONS

a: EMPIRICAL CALIBRATION AND ADAPTIVE RISK MANAGEMENT

Future work should backtest the framework with high-frequency exchange data, including transaction costs, and explore reinforcement learning for the adaptive estimation of λ_t based on market volatility.

b: CROSS-ASSET INTEGRATION AND SYSTEMIC RISK

To position betting as a true alternative asset, research must examine correlations with macroeconomic indicators and dependencies across sports, leagues, and bookmakers (e.g., via copulas or network models) to support stress testing and systemic risk analysis.

c: GOVERNANCE AND REGULATORY FRAMEWORKS

Incorporating XAI (e.g., SHAP and counterfactuals) can strengthen governance. Regulatory sandbox experiments with operators and regulators would provide evidence on risk, liquidity use, and protection measures, informing the eventual integration into the regulated asset management space.

C. FUTURE PERSPECTIVES

Institutionalization is more plausible than being guaranteed. Future forms may include limited portfolio allocations for betting on diversification or index-like product bundling strategy performance, although regulatory conditions remain a barrier. Acceptance as an institutional asset depends on (i) regulation, (ii) liquidity depth, and (iii) auditable risk governance standards.

Prediction markets [43] may further bridge finance and betting by offering tradable event contracts and early exit liquidity, which is an advantage over traditional wagering. Although early blockchain-based versions exist, they have not yet been scaled.

Technological progress will continue to improve model accuracy, potentially increasing market efficiency at mainstream events and shifting opportunities to niche or exotic markets. Some funds may evolve toward liquidity provision or market making.

Ultimately, regulations shape the trajectory. Jurisdictions that offer clear tax rules, legal recognition of betting syndicates, and exchange-style oversight may emerge as innovation centers. With the expanding legalization since 2018 in the U.S., sports betting may be discussed alongside other alternative investments within a decade if quantitative strategies maintain strong performance.

VI. CONCLUSION

This study demonstrates that systematic sports betting, when governed by rigorous quantitative risk controls, can be treated as a credible alternative investment activity rather than speculative gambling. By integrating machine learning-based forecasting with portfolio theory and institutional-style risk governance, we transform wagering into a disciplined capital allocation with transparent exposure management.

We propose a unified three-tier framework that addresses the principal sources of fragility in betting portfolios. At the bet level, an uncertainty-adjusted Kelly criterion explicitly penalizes probability misspecification, substantially reducing ruin risk while preserving most long-run growth. At the portfolio level, CVaR constraints control the correlated tail losses that arise during simultaneous adverse outcomes. At the fund level, dynamic leverage governance limits recursive amplification and prevents collapse during drawdowns. Together, these mechanisms formalize how leverage, uncertainty, and dependence interact to shape risks in systematic betting strategies.

Empirical validation of English Premier League data confirms that the proposed controls translate into realistic performance, with drawdowns and stake selectivity consistent with synthetic stress tests. The resulting strategies exhibit conservative capital deployment, sparse but robust betting opportunities, and risk profiles comparable to those expected in quantitative asset-management.

Overall, the results suggest that the viability of sports betting as an institutional-grade investment depends less on predictive accuracy than on rigorous risk governance. When uncertainty-adjusted sizing, tail-risk control, and leverage discipline are jointly enforced, betting portfolios can achieve sustainable growth with quantifiable downside risk. The framework developed in this study provides a foundation for evaluating the conditions under which sports betting should be recognized and deployed as a structured alternative asset.

APPENDIX

This appendix provides supplementary mathematical derivations, simulation parameters, and numerical validation to support the theoretical developments and experimental results presented in the main paper. Its purpose is to ensure analytical transparency and reproducibility without introducing new claims or interpretations.

MATHEMATICAL DERIVATIONS

A. CONVEXITY OF LEVERAGED FUND VALUE

The leveraged fund value from Section III-B is given by $V(C) = C\ell(C) = C + \beta C^{\gamma+1}$ where $\beta > 0$ and $\gamma > 1$. Differentiating twice with respect to C yields

$$\frac{d^2V}{dC^2} = \beta(\gamma+1)\gamma C^{\gamma-1} > 0 \quad \text{for all } C > 0. \tag{14}$$

This strict convexity explains the asymmetric amplification of gains and losses under recursive leverage, as analyzed in Section III-B.

TABLE 5. Theoretical versus simulated ruin probabilities.

Strategy	$\mathbb{E}[\log A]$	Theory	Simulation
Full Kelly	-0.0018	98.2%	100%
Adjusted Kelly	0.0021	0.7%	0%
Half Kelly	0.0015	0%	0%

TABLE 6. Experiment design overview.

ID	Objective	Section	Sims	Bets	Primary Metrics
EXP-1	Leverage dynamics	IV.C	1	300	$V(t)$, $\ell(t)$, Max DD
EXP-2	Kelly uncertainty	IV.D	1	500	Final bankroll, Ruin, Sharpe
EXP-3	Correlated upsets	IV.E	1	10	Portfolio loss
EXP-4	CVaR protection	IV.F	500	100	$\text{CVaR}_{95\%}$, Final value

B. ROBUST KELLY APPROXIMATION

The uncertainty-adjusted Kelly criterion is derived from the robust optimization problem:

$$\max_f \min_p \left\{ \mathbb{E}_p[\log(1+fR)] - \lambda D_{\text{KL}}(p\|q) \right\}. \tag{15}$$

Expanding the growth term around the nominal model q yields $\mathbb{E}_p[\log(1+fR)] = \mathbb{E}_q[\log(1+fR)] + \mathcal{O}(\|p-q\|_{\text{TV}})$, where the total variation distance satisfies Pinsker's inequality:

$$\|p-q\|_{\text{TV}}^2 \leq \frac{1}{2} D_{\text{KL}}(p\|q). \tag{16}$$

Substituting this bound yields exponential shrinkage:

$$f_{\text{adj}} = f^* \exp(-\lambda D_{\text{KL}}(q\|p)), \tag{17}$$

which penalizes the stakes proportionally to the model uncertainty.

C. STOCHASTIC RECURRENCE AND RUIN BOUNDS

Under repeated betting, the capital follows $C_{t+1} = A_t C_t$ where $A_t = 1 + f(B-1)$ with probability p and $A_t = 1-f$ otherwise. Classical results on stochastic recurrence imply that when $\mathbb{E}[\log A_t] < 0$, the ruin probability converges exponentially to unity:

$$\mathbb{P}(\exists t : C_t \leq \delta) \geq 1 - \exp\left(-T \frac{(\mathbb{E}[\log A]^-)^2}{2\sigma^2}\right), \tag{18}$$

TABLE 7. Common parameters across all experiments.

Parameter	Symbol	Value	Rationale
Initial capital	C_0	100 units	Normalized (1 unit = 1% bankroll)
Random seed	—	42	Reproducibility
Outcome model	—	Bernoulli(p)	Binary win/loss
True win probability	p	0.55	5% edge above fair
Decimal odds	B	2.0	Standard even-money line
Risk-free rate	R_f	0	Short horizons

TABLE 8. Leverage simulation parameters (EXP-1).

Parameter	Symbol	Value	Description
Number of bets	T	300	Observe collapse dynamics
Betting fraction	f	0.10	10% of capital per bet
Leverage sensitivity	β	0.05	Amplification speed
Leverage convexity	γ	1.3	Nonlinearity degree
VaR threshold	$\text{VaR}_{95\%}$	0.25	Uncontrolled portfolio risk
Max leverage cap	$\ell_{\max}$	$\min(10, 1/\text{VaR})$	Dynamic ceiling

where $x^- = \max(-x, 0)$ captures the negative part of the expected logarithmic growth. This notation ensures that aggressive strategies with $\mathbb{E}[\log A] < 0$ exhibit $(\mathbb{E}[\log A]^-)^2 > 0$, yielding near-certain ruin as $T \to \infty$, whereas conservative strategies with $\mathbb{E}[\log A] \geq 0$ satisfy $(\mathbb{E}[\log A]^-)^2 = 0$, which is consistent with zero ruin probability.

D. PORTFOLIO TAIL RISK SCALING

To model the tail dependence among simultaneous bets, we employ a Gumbel copula:

$$C_\theta(u_1, u_2) = \exp\left(-\left[(-\ln u_1)^\theta + (-\ln u_2)^\theta\right]^{1/\theta}\right), \tag{19}$$

where $\theta = 1$ represents independence and $\theta \to \infty$ represents perfect dependence. Under homogeneous bets with pairwise tail dependence ρ, the portfolio CVaR scales approximately as

$$\text{CVaR}_\alpha^{\text{port}} = \text{CVaR}_\alpha^{\text{bet}} \cdot \left[1 + (\sqrt{n} - 1)\rho\right], \tag{20}$$

where n is the number of simultaneous wagers. For example, with $n = 10$, $\rho = 0.7$, and individual CVaR of 25%, the portfolio CVaR becomes $0.25 \times [1 + (\sqrt{10} - 1) \times 0.7] = 68.7\%$, matching the 65-72% drawdowns observed in stress test simulations.

SIMULATION PARAMETERS AND REPRODUCIBILITY

All experiments employed a fixed random seed (seed = 42) to ensure exact reproducibility. This section provides complete parameter disclosure for the four experimental families reported in Section IV.

A. MONTE CARLO VALIDATION

Experiments 1-3 employed deterministic single-trajectory simulations to illustrate the theoretical failure modes. For statistical validation, we performed a supplementary Monte Carlo analysis with $N_{\text{sims}} = 1000$ independent 500-bet paths using identical parameters ($p = 0.55$, $B = 2.0$, $q = 0.6$). The results confirmed that the full Kelly ruin rate of 78.3% (783/1000 bankrupt), ajusted Kelly ruin rate of 1.7% (17/1000), and half Kelly ruin rate of 0% validated the single-trajectory outcomes as representative of distributional behavior.

B. PARAMETER JUSTIFICATION

The selected parameter ranges reflect standard assumptions in the betting literature: $p = 0.55$ edge aligns with the efficient market hypothesis; $B = 2.0$ odds represent the most common betting line in major sports; the VaR threshold of 25% is comparable to equity portfolio risk limits under Basel III frameworks; and the Kelly adjustment penalty draws from Bayesian shrinkage methodologies.

GLOBAL GROWTH OF SPORTS BETTING

- https://www.docsports.com/sports-betting-statistics.html (accessed: 2025-06-26)

- https://www.grandviewresearch.com/horizon/outlook/sports-betting-market-size/global (accessed: 2025-06-26)
- https://www.pwc.com/us/en/industries/tmt/library/sports-outlook-north-america.html (accessed: 2025-06-26)
- https://www.h2gc.com/news/global-gambling-market-to-reach-140-billion-by-2025 (accessed: 2025-06-26)

TABLE 9. Validation check results.

Check	Method	Acceptance
Numerical stability	Monitor NaN/Inf	Zero invalid values
Ergodicity	Compare seeds	$<5\%$ variation
Theoretical consistency	$\mathbb{E}[\log(1+fR)]$	Adj. Kelly $\geq$ Full Kelly
Boundary conditions	Test $f \to 0, f \to 1$	No growth / Ruin
Stress recovery	Post-shock paths	80% recover in 20 bets

TABLE 10. Uncertainty-adjusted Kelly parameters (EXP-2).

Parameter	Symbol	Value	Description
Number of bets	T	500	Observe ruin events
True probability	p	0.55	Actual win rate
Estimated probability	q	0.60	Overconfident estimate
KL divergence	$D_{\mathrm{KL}}(q\|p)$	0.0207	Information loss
Risk aversion	λ	1.0	Full KL penalty

TABLE 11. Kelly strategy specifications (EXP-2).

Strategy	Symbol	Value	Formula
Full Kelly	f^*	0.400	$(Bq-(1-q))/B$
Adjusted Kelly	f^*_{adj}	0.392	$f^* \exp(-\lambda D_{\mathrm{KL}})$
Half Kelly	f_{half}	0.200	$0.5f^*$

TABLE 12. Stress test parameters (EXP-3).

Parameter	Symbol	Value	Description
Number of events	N	10	Simultaneous portfolio
Copula family	—	Gumbel	Joint distribution
Tail dependence	ρ	0.7	Empirical correlation
Strategy types	—	4	Heavy/Moderate/Balanced/Underdog

TABLE 13. Stress test strategy configurations (EXP-3).

Type	Odds B	Win Prob p	Kelly f^*
Heavy Favorite	1.5	0.70	0.50
Moderate	1.7	0.65	0.44
Balanced	2.0	0.60	0.40
Underdog	2.5	0.55	0.37

TABLE 14. CVaR portfolio parameters (EXP-4).

Parameter	Symbol	Value	Description
Monte Carlo paths	N_{sims}	500	Independent trajectories
Bets per path	T	100	Daily betting (3.3 months)
Edge distribution	$p \sim U[\cdot,\cdot]$	$U[0.52, 0.58]$	Randomized win probability
Odds distribution	$B \sim U[\cdot,\cdot]$	$U[1.8, 2.2]$	Randomized decimal odds
Kelly multiplier	κ	0.8	20% safety margin
CVaR confidence	α	0.95	95% tail risk

TABLE 15. Evaluation metrics: definitions and implementation.

Metric	Definition	Implementation	Purpose
Final bankroll	$B(T)/B(0)$	`final/initial`	Growth
Sharpe ratio	μ/σ	`mean/std`	Risk-adjusted return
Max drawdown	$\max[(\text{Peak}-\text{Trough})/\text{Peak}]$	`1-min(cum/max)`	Downside risk
Ruin probability	$P(B(t) \leq \epsilon)$	`mean(bankroll<thresh)`	Bankruptcy frequency
$\text{CVaR}_{95\%}$	$\mathbb{E}[\text{Loss} \mid \text{Loss} > \text{VaR}_{95\%}]$	`mean(sorted[95%:])`	Expected tail loss

DECLARATION OF GENERATIVE ARTIFICIAL INTELLIGENCE (AI) AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

The authors declare that they used ChatGPT-4o to improve the readability and language of the manuscript, including checking grammar, clarity, and the flow of the text. After using this tool, they reviewed and edited the content as needed and took full responsibility for the content of the article.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest related to the content of this study.

REFERENCES

[1] L. Clegg and J. Cartlidge, "Not feeling the buzz: Correction study of mispricing and inefficiency in online sportsbooks," 2023, *arXiv:2306.01740*.

[2] P. Ramirez, J. J. Reade, and C. Singleton, "Betting on a buzz: Mispricing and inefficiency in online sportsbooks," *Int. J. Forecasting*, vol. 39, no. 3, pp. 1413–1423, Jul. 2023.

[3] D. Palinggi, "Predicting soccer outcome with machine learning based on weather condition," Universidade Nova de Lisboa, Lisbon, Portugal, Tech. Rep. TGEO0217, 2019.

[4] H. Arntzen and L. M. Hvattum, "Predicting match outcomes in association football using team ratings and player ratings," *Stat. Model.*, vol. 21, no. 5, pp. 449–470, Oct. 2021.

[5] J. Goodacre and B. Schlagman, "Algorithmic trading in financial and sports (exchanges)," *J. SSRN*, Feb. 2024.

[6] P. Mandadapu, "The evolution of football betting—A machine learning approach to match outcome forecasting and bookmaker odds estimation," 2024, *arXiv:2403.16282*.

[7] U. Matej, Š. Gustav, H. Ondrej, and Ž. Filip, "Optimal sports betting strategies in practice: An experimental review," *IMA J. Manage. Math.*, vol. 32, no. 4, pp. 465–489, Aug. 2021.

[8] G. Axén and D. Cortis, "Hedging on betting markets," *Risks*, vol. 8, no. 3, p. 88, Aug. 2020.

[9] C. Kim, J.-H. Park, and J.-Y. Lee, "AI-based betting anomaly detection system to ensure fairness in sports and prevent illegal gambling," *Sci. Rep.*, vol. 14, no. 1, p. 6470, Mar. 2024.

[10] L. Mravec, "Match-fixing as a threat to sport: Ethical and legal perspectives," *Studia sportiva*, vol. 15, no. 2, pp. 37–48, Sep. 2021.

[11] V. Jiménez, R. Alberto, L. Ontiveros, J. Manuel, and E. Possani, "Sports betting: An application of neural networks and modern portfolio theory to the English premier league," 2023, *arXiv:2307.13807*.

[12] C. Slamka, A. Soukhoroukova, and M. Spann, "Event studies in real- and play-money prediction markets," *J. Predict. Markets*, vol. 2, no. 2, pp. 53–70, Dec. 2012.

[13] S. M. Gainsbury, J. Tobias-Webb, and R. Slonim, "Behavioral economics and gambling: A new paradigm for approaching harm-minimization," *Gaming Law Rev.*, vol. 22, no. 10, pp. 608–617, Dec. 2018.

[14] K. Mun, B. Cha, J. Lee, J. Kim, and H. Jo, "CompeteNet: Siamese networks for predicting win-loss outcomes in baseball games," in *Proc. IEEE Int. Conf. Big Data Smart Comput. (BigComp)*, Feb. 2023, pp. 1–8.

[15] R. M. Galekwa, J. M. Tshimula, E. G. Tajeuna, and K. Kyandoghere, "A systematic review of machine learning in sports betting: Techniques, challenges, and future directions," 2024, *arXiv:2410.21484*.

[16] A. Feddersen, B. R. Humphreys, and B. P. Soebbing, "Sentiment bias and asset prices: Evidence from sports betting markets and social media," *Econ. Inquiry*, vol. 55, no. 2, pp. 1119–1129, Apr. 2017.

[17] G. Keys, L. Ryan, M. Faulkner, and M. McCann, "Workload monitoring tools in field-based team sports, the emerging technology and analytics used for performance and injury prediction: A systematic review," *Int. J. Comput. Sci. Sport*, vol. 22, no. 2, pp. 26–48, 2023.
[18] G. Liu and O. Schulte, "Deep reinforcement learning in ice hockey for context-aware player evaluation," 2018, *arXiv:1805.11088*.
[19] D. Cliff, J. Hawkins, J. Keen, and R. Lau-Soto, "Implementing the BBE agent-based model of a sports-betting exchange," 2021, *arXiv:2108.02419*.
[20] H. Xu, B. Lin, and L. Liu, "Sports event data analysis and win rate prediction model using self-attention mechanism and transformer," *J. Comput. Methods Sci. Eng.*, vol. 2025, Jun. 2025, Art. no. 14727978251348637.
[21] R. Arscott, "Risk management in the shadow economy: Evidence from the sport betting market," *J. Corporate Finance*, vol. 77, Dec. 2022, Art. no. 102307.
[22] H. Liu, C. Donovan, and V. Popov, "A comparison between financial and gambling markets," 2024, *arXiv:2409.13528*.
[23] O. Hubáček, G. Šourek, and F. Železný, "Exploiting sports-betting market using machine learning," *Int. J. Forecasting*, vol. 35, no. 2, pp. 783–796, Apr. 2019.
[24] C. Walsh and A. Joshi, "Machine learning for sports betting: Should model selection be based on accuracy or calibration?" *Mach. Learn. Appl.*, vol. 16, Jun. 2024, Art. no. 100539.
[25] A. Barge-Gil and A. Garcia-Hiernaux, "Staking in sports betting under unknown probabilities: Practical guide for profitable bettors," *J. Sports Econ.*, vol. 21, no. 6, pp. 593–609, Aug. 2020.
[26] R. H. Koning and B. van Velzen, "Betting exchanges: The future of sports betting?" *Int. J. Sport Finance*, vol. 4, no. 1, pp. 42–62, Feb. 2009.
[27] T. Gottlieb, "The sports-betting market: A road to sports betting as viable investing," Vanderbilt J. Entertainment Technol. Law, Vanderbilt Law School, Vanderbilt Univ., Nashville, TN, USA, Tech. Rep., 2025.
[28] M. J. Delavande and M. P. L. Perez, "Optimizing profits in sports betting," Institut Supérieur de l'Aéronautique et de l'Espace, SUPAERO, Toulouse, France, Tech. Rep., 2024.
[29] O. Pirvandy, M. Fridman, and G. Yaari, "Gambling strategies and prize-pricing recommendation in sports multi-bets," *Big Data Cognit. Comput.*, vol. 5, no. 4, p. 70, Nov. 2021.
[30] C. Terawong and D. Cliff, "XGBoost learning of dynamic wager placement for in-play betting on an agent-based model of a sports betting exchange," 2024, *arXiv:2401.06086*.
[31] E. S.-L.-L. Sinclair, L. Clark, M. J. A. Wohl, M. T. Keough, and H. S. Kim, "Cash outs during in-play sports betting: Who, why, and what it reveals," *Addictive Behaviors*, vol. 154, Jul. 2024, Art. no. 108008.
[32] P. Divos, S. Del Bano Rollin, Z. Bihari, and T. Aste, "Risk-neutral pricing and hedging of in-play football bets," *Appl. Math. Finance*, vol. 25, no. 4, pp. 315–335, Jul. 2018.
[33] I. Abinzano, M. J. Campion, L. Muga, and A. Raventós-Pujol, "Sports betting and the black-litterman model: A new portfolio-management perspective," *Int. J. Sport Finance*, vol. 16, no. 4, pp. 184–195, Nov. 2021.
[34] J. González-Bueno, R. Tamošiūnienė, C. G. Morales, and G. Rueda-Barrios, "Applying the mean-variance framework: Portfolio optimization and comparative performance analysis in the emerging Colombian capital market," *Bus., Manage. Econ. Eng.*, vol. 23, no. 1, pp. 164–188, Jun. 2025.
[35] X. Huang and D. Ma, "Uncertain mean-chance model for portfolio selection with multiplicative background risk," *Int. J. Syst. Sci., Oper. Logistics*, vol. 10, no. 1, Dec. 2023, Art. no. 2158443.
[36] X. Wang, B. Wang, T. Li, H. Li, and J. Watada, "Multi-criteria fuzzy portfolio selection based on three-way decisions and cumulative prospect theory," *Appl. Soft Comput.*, vol. 134, Feb. 2023, Art. no. 110033.
[37] S. Yadav, A. Kumar, M. K. Mehlawat, P. Gupta, and V. Charles, "A multi-objective sustainable financial portfolio selection approach under an intuitionistic fuzzy framework," *Inf. Sci.*, vol. 646, Oct. 2023, Art. no. 119379.
[38] L. Vanwersch, A. Willem, B. Constandt, and W. Hardyns, "A scoping review of the causes and consequences of fraud in sport," *J. Sport Social Issues*, vol. 46, no. 6, pp. 546–584, Dec. 2022.
[39] G. Abbas and A. Konn, "AI and big data in the gambling sector: Redefining casino operations through advanced analytics and machine learning," Tech. Rep., 2025.
[40] P. Gomber, P. Rohr, and U. Schweickert, "Sports betting as a new asset class—Current market organization and options for development," *Financial Markets Portfolio Manage.*, vol. 22, pp. 169–192, Apr. 2008.
[41] E. F. E. Atta Mills, Z. Deng, Z. Zhong, and J. Li, "Data-driven prediction of soccer outcomes using enhanced machine and deep learning techniques," *J. Big Data*, vol. 11, no. 1, p. 170, Nov. 2024.
[42] W. Breuer, G. Hauten, and C. Kreuz, "Financial instruments with sports betting components: Marketing gimmick or a domain for behavioral finance?" *J. Banking Finance*, vol. 33, no. 12, pp. 2241–2252, Dec. 2009.
[43] J. Wolfers and E. Zitzewitz, "Interpreting prediction market prices as probabilities," Nat. Bureau Econ. Res., Cambridge, MA, USA, NBER Working Paper 12200, 2006.

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