Analysis of Betting Strategies in the NFL Playoffs Through Bayesian Hierarchical Simulation
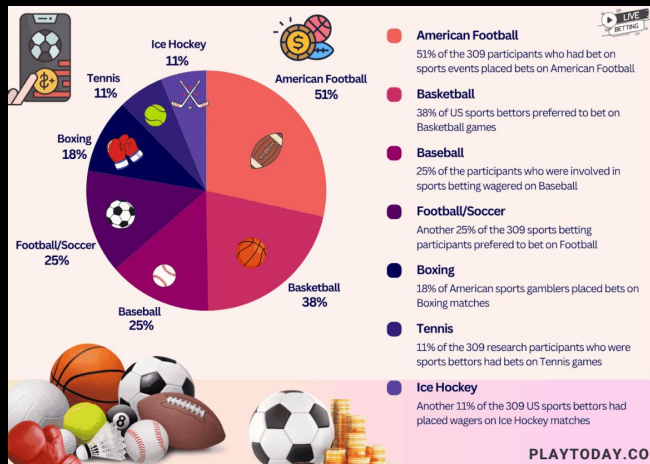
BRANDON OWENS

INTRODUCTION

- Professional and Amateur Sports Protection Act (PASPA)

  - Legalization of online sports betting in 2018

- Journal of Quantitative Analysis in Sports (ASA)

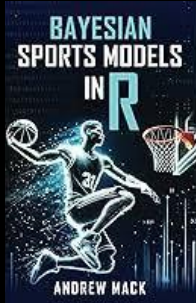- Team-side explosion in Statistics + Analytics

INTRODUCTION

- $70 billion market size in 2024

  - NFL 17.5 million viewers/ game

  - $1.39 Billion wagered on Super Bowl LIX

  - 127.7 million viewers in the super bowl

  - 51% of all sports wagers on the NFL

- 2024–2025 NFL Season

LITERATURE REVIEW

- [BAIO & BLANGIARDO (2010)](#)

- [ATTARD ET AL. (2023)](#)

- [MACK (2024)](#)

- [KELLY (1956)](#)

METHODOLOGY – TOOLS
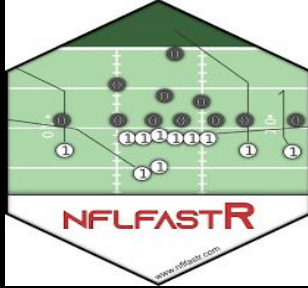
- sportsoddshistory.com
  - BetMGM via Kansas Crossing Casino and Hotel
- R
  - RStan
    - Hamiltonian Monte Carlo (NUTS)
  - nflReadR
    - 2024-2025 Play-by-Play NFL Data
      - – Week 18
    - Data Cleaned and Processed

METHODOLOGY – SCORING

TOUCHDOWNS
(6)
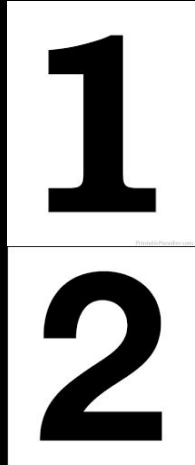
POST-
TOUCHDOWN
(1 OR 2)

FIELD GOAL (3)

SAFETY (2)

METHODOLOGY – MODELING

- $\text{PassingTouchdowns}_{gj} \mid \theta_{gjPassTD} \sim \text{Poisson}(\theta_{gjPassTD})$ (1A)

- $\text{RushingTouchdowns}_{gj} \mid \theta_{gjRushTD} \sim \text{Poisson}(\theta_{gjRushTD})$ (1B)

- $\text{ReturnTouchdowns}_{gj} \mid \theta_{gjRetTD} \sim \text{Poisson}(\theta_{gjRetTD})$ (1C)

- $\text{DefensiveTouchdowns}_{gj} \mid \theta_{gjDefTD} \sim \text{Poisson}(\theta_{gjDefTD})$ (1D)

- $\text{FieldGoals}_{gj} \mid \theta_{gjFG} \sim \text{Poisson}(\theta_{gjFG})$ (1E)

- $\text{Safeties}_{gj} \mid \theta_{gjSafety} \sim \text{Poisson}(\theta_{gjSafety})$ (1F)

- $P(M=m) = (e^{-\theta gjM} * \theta_{gjM}{}^{m}) / (m!)$ (2)

g denotes game #
j denotes home(1) or away(O)
m represents observation of count

METHODOLOGY – MODELING

- θ_{gjM} represent rate of scoring intensity for M scoring type for team j in game g.

- $\log(\theta_{g1M}) = \alpha_{g1,M} + \beta_{g0,M} + int_M + home_M$ (3)

- $\log(\theta_{g0M}) = \alpha_{g0,M} + \beta_{g1,M} + int_M$ (4)

Thus, $\alpha_{g1,M}$ represents the home team's attacking ability, $\beta_{g0,M}$ represents the away team's defensive strength, int_M represents the intercept, and $home_M$ is a home adjustment in the gth game for scoring type M.

METHODOLOGY – MODELING

- Need to account for scoring coming from a strong team attack vs. a

  weak team defense.

  - $\Sigma\alpha_{T, M} = 0$

  - $\Sigma\beta_{T, M} = 0$

  - For team T and scoring type M.

- $N_{gjM} \sim \text{Binomial}(\text{TotalTouchdowns}_{gj}, \delta_{jM})$ (5)

- $x_{gjM} \sim \text{Binomial}(N_{gjM}, \psi_{jM})$ (6)

METHODOLOGY – MODELING

- Hyper Priors

  - $\mu_{\alpha M}, \mu_{\beta M} \sim Normal(0, 0.05)$ (11)

  - $\sigma_{\alpha M}, \sigma_{\beta M} \sim Gamma(0.1, 0.1)$ (12)

  - $\delta_{jEXP}, \delta_{j2P} \sim Dirichlet(9,1)$ (13)

- Priors

  - $\alpha_{TM} \sim Normal(\mu_{\alpha M}, \sigma_{\alpha M}), \beta_{TM} \sim Normal(\mu_{\beta M}, \sigma_{\beta M})$ (9–10)

  - $home_M \sim Normal(0, 0.05),$ $int_M \sim Normal(0, 0.05)$ (7–8)

  - $\psi_{jEXP} \sim Beta(9,1),$ $\psi_{j2P} \sim Beta(1,1)$ (14–15)

METHODOLOGY – DAGs
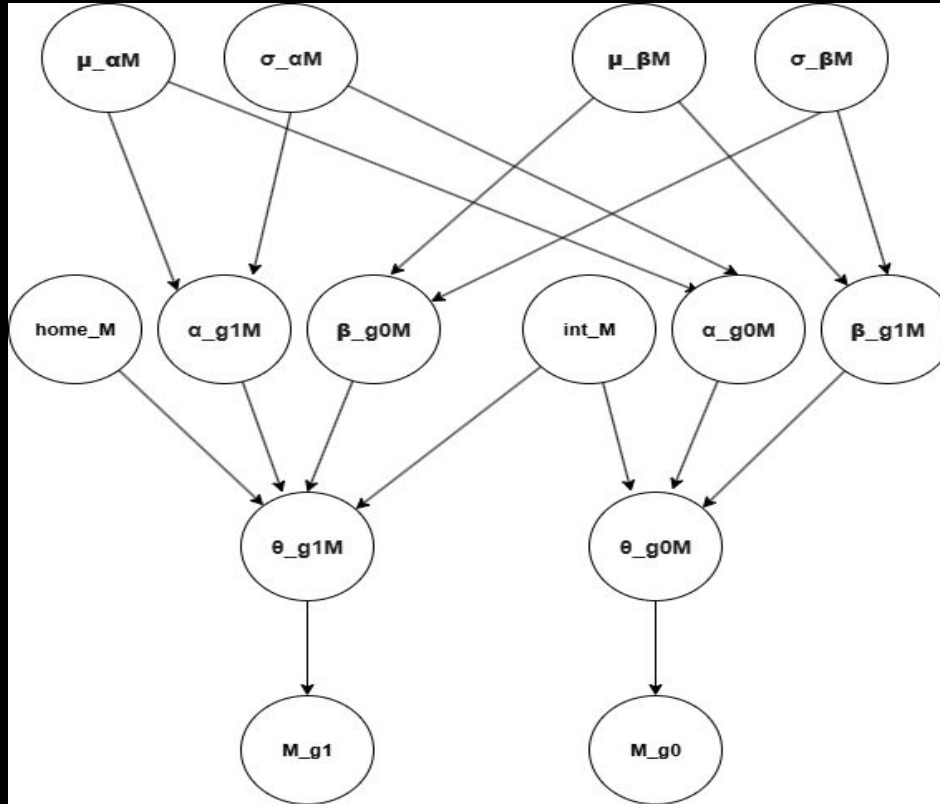
Touchdowns, field goals, and safeties

METHODOLOGY – DAGs
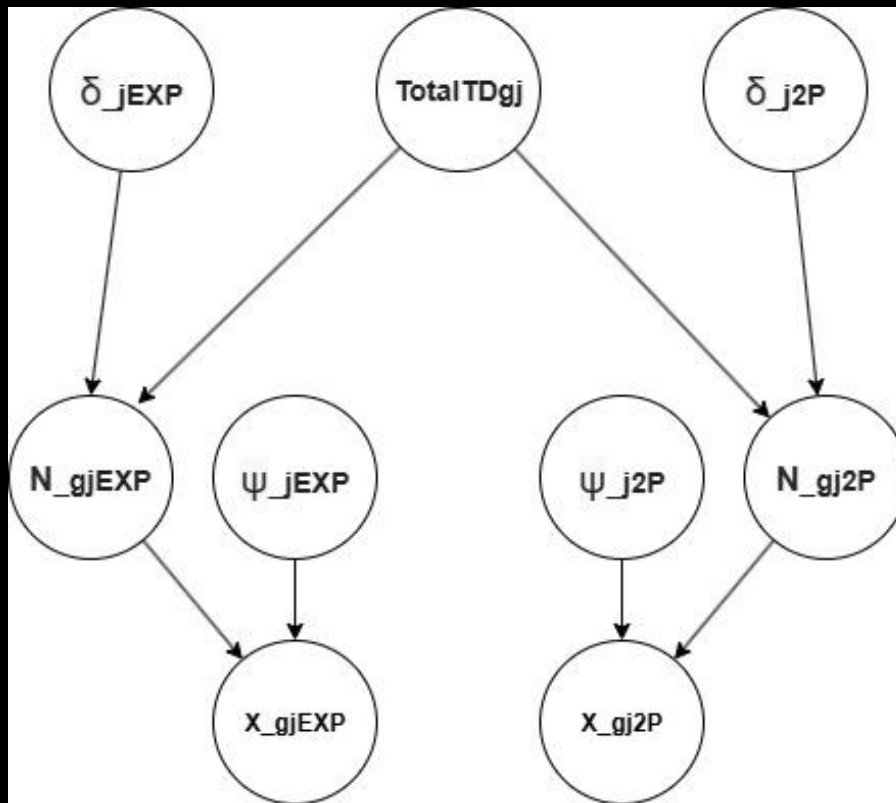
Extra Points and two-point conversions

μ_αM   σ_αM   μ_βM   σ_βM

home_M   α_g1M   β_g0M   int_M   α_g0M   β_g1M

θ_g1M   θ_g0M

M_g1   M_g0

PassTD * 6 +
RushTD * 6 +
RecTD * 6 +
DefTD * 6 +
Safeties * 2 +
FG * 3

FOR td IN TDs:

TEAM j SCORE
IN GAME g

δ_jEXP   Total TDgj   δ_j2P

N_gjEXP   Ψ_jEXP   Ψ_j2P   N_gj2P

X_gjEXP   X_gj2P

EXPs * 1 +
2Ps * 2

13
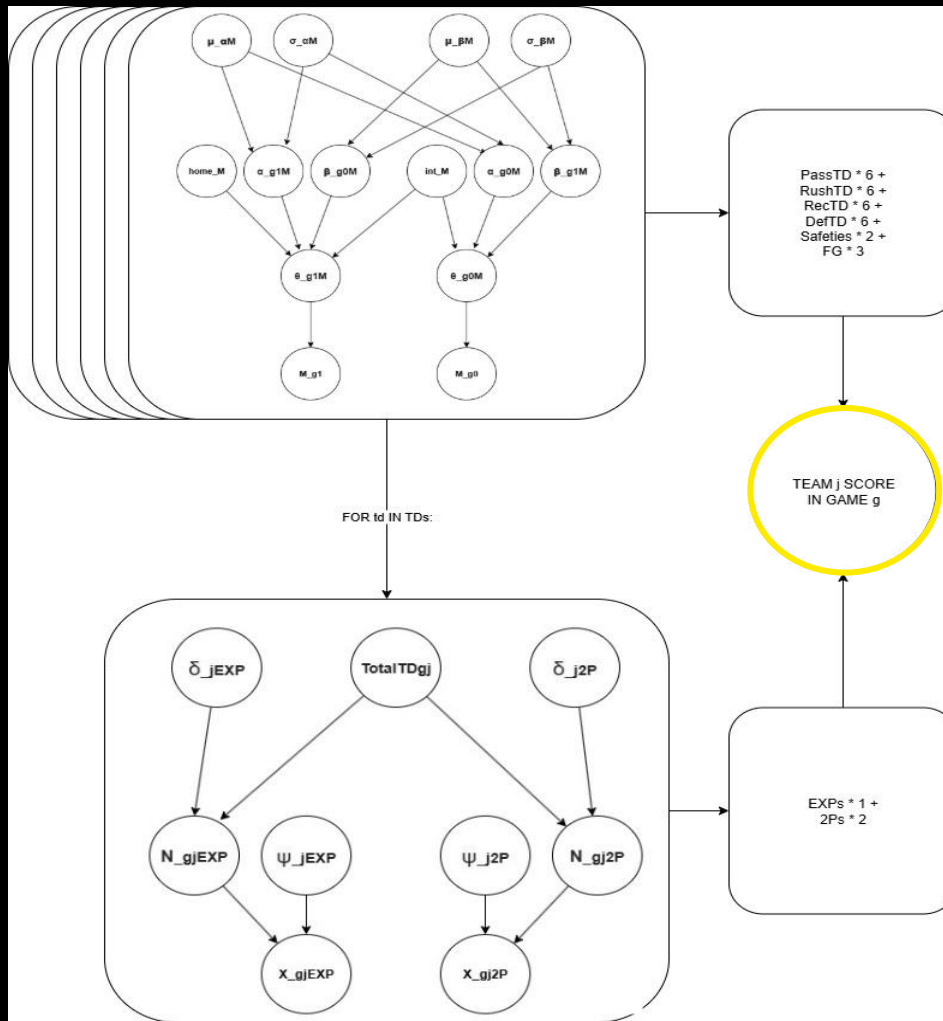
METHODOLOGY – Monte Carlo Simulation

- Hamiltonian Monte Carlo (HMC)

  - Potential Energy landscape defined by negative log-posterior

  - Particle trajectory simulated for acceptance.

- No-U-Turn-Sampler (NUTS)

  - Avoids trajectories that turn back on themselves.

  - Highly efficient.
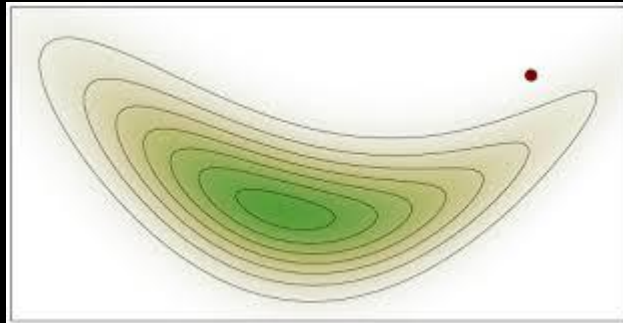
METHODOLOGY – Monte Carlo Simulation

- Sampling:
    - 10,000 iterations / chain
    - 1,000 burn-in
    - 4 parallel chains
    - Thinned

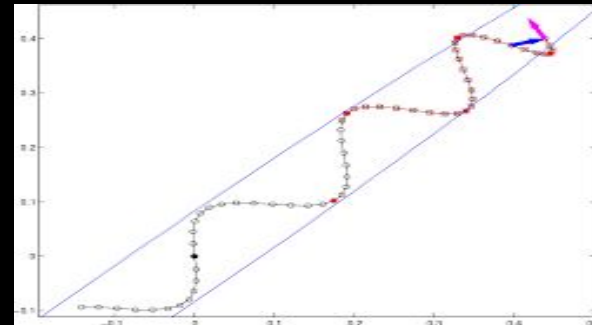- Gelman–Rubin Statistic
    - (R_hat) ~ sqrt(1+ m/ESS)

- Posterior Predictive Updating for every playoff round
    - f(Ỹ| Y, θ) = f(Ỹ|θ) f (θ|Y, prior) dθ   (16)
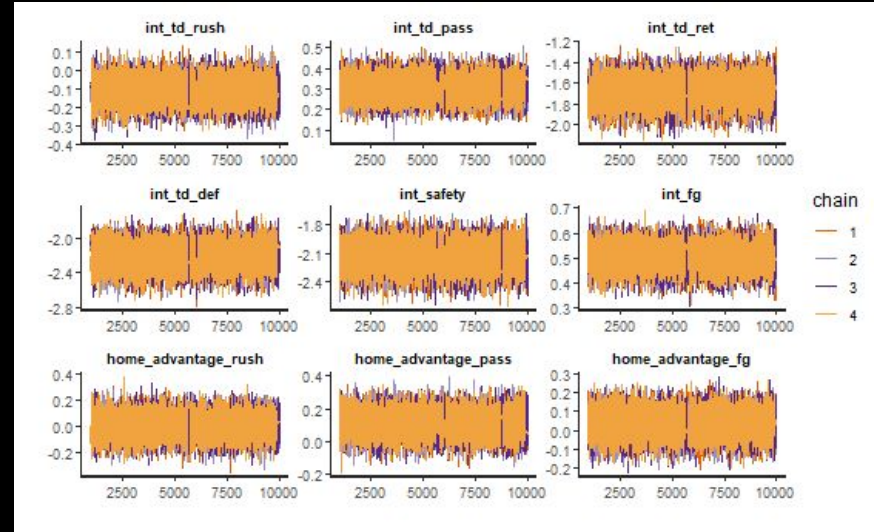
METHODOLOGY – EVALUATION

- Simulate each playoff game 10,000 times.

- Evaluate Spread (+/–)

- Make Decisions ($100 bankroll)

| Decision	Strategy
Straight	Kelly Criterion
Straight	Flat Unit
Value	Kelly Criterion
Value	Flat Unit

- Straight Decision
  - Comparing median simulated outcomes to lines.
- Value Decision
  - $P- = O / (O + 100) * 100$ (18)
  - $P+ = 100 / (O + 100) * 100$ (19)
  - Hold % = $[1 - (P_{favorite} + P_{underdog})] / 2$ (20)
- Kelly Criterion
  - $f = (bp - q) / b$ (17)
- Flat Unit Strategy
  - Fixed wager ($100 / # of games).

RESULTS & ANALYSIS

- 95% credible intervals of team Net Strengths
  - Passing
  - Rushing
- Team MOV
  - "Margin of Victory"
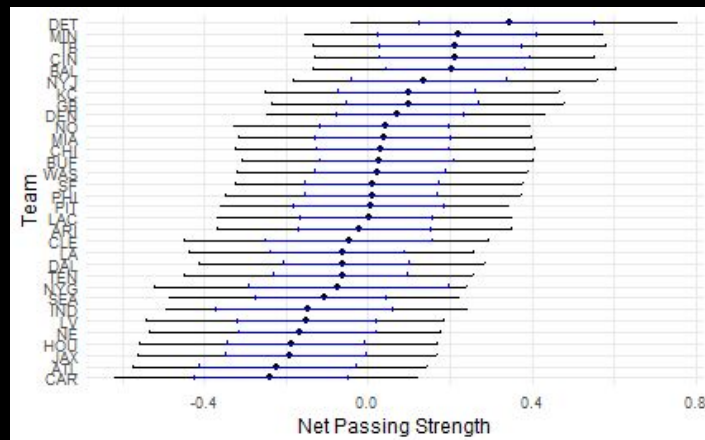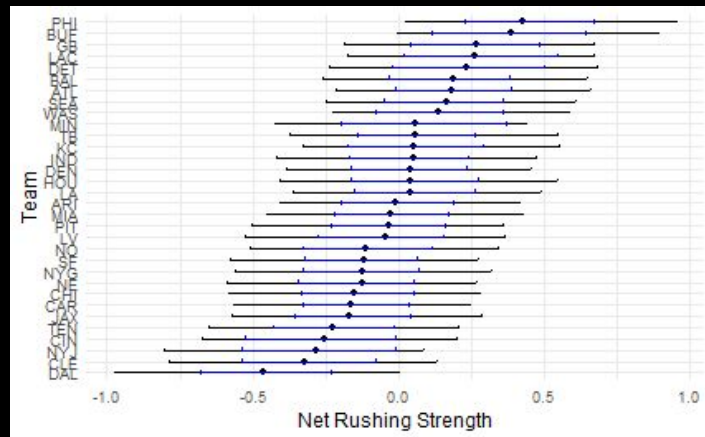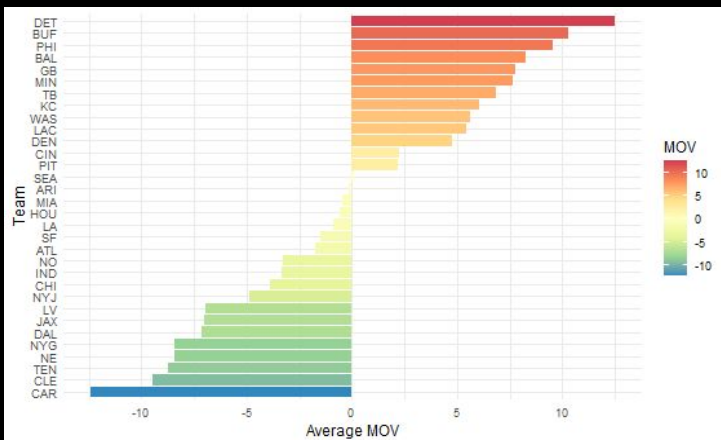
RESULTS & ANALYSIS
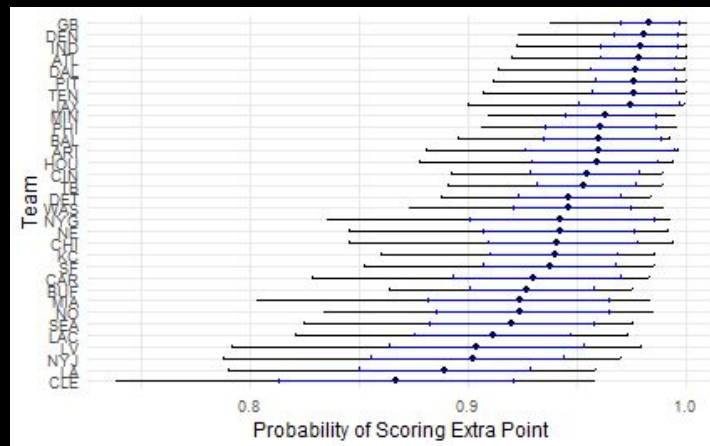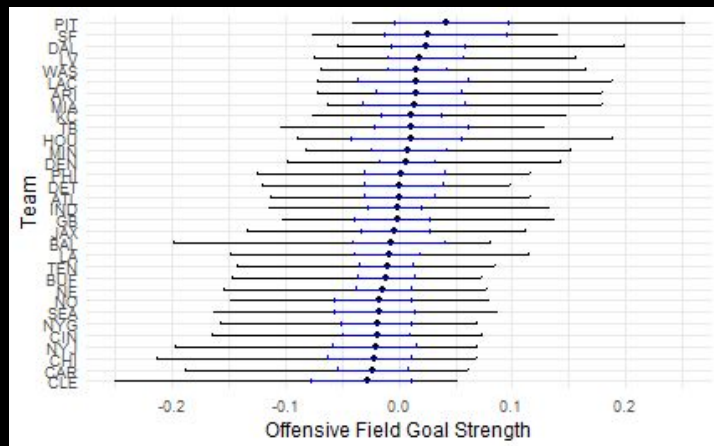
- 95% credible intervals of $\alpha_{T,FG}$ and $\psi_{T,EXP}$
  - Key Point:
    - CLE
      - 66.7% of FG (worst)
      - 27 total FG makes (worst)
      - 85.7% of EXP (worst)

RESULTS & ANALYSIS – PLAYOFFS

- 13 Playoff Games (each simulation 10,000x)
  - (6 Wild Card, 4 Divisional, 2 Conference Championships, Super Bowl)
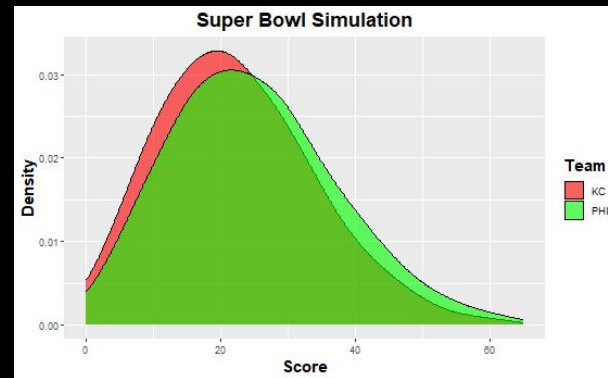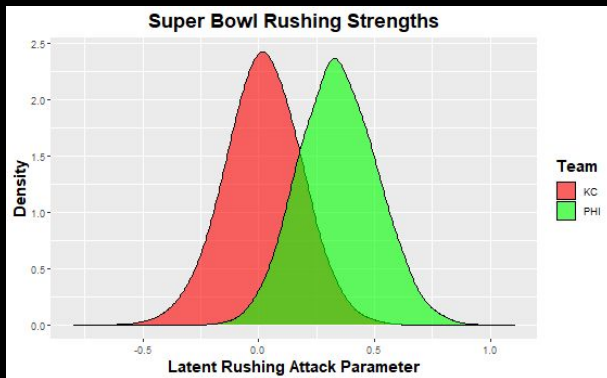- Super Bowl example: Kansas City Chiefs vs. Philadelphia Eagles

RESULTS & ANALYSIS – PLAYOFFS

- Spread Betting

Strategy	Median P/L	95% Prediction Interval P/L	Summarized Singular Choice
Kelly Criterion - Value	0.50%	(-15.45, 12.87)	-2.88%
Kelly Criterion - Straight	11.50%	(3.84, 12.87)	**7.68%**
Flat Unit - Value	2.80%	(-56.00, 47.93)	-10.87%
Flat Unit - Straight	41.70%	(14.70, 63.40)	**28.70%**

CONCLUSION

- **Across All Simulations**

  - Variable profitability

    - Kelly Criterion → Mitigated Risk

    - Flat bets → Nominal Gains

    - Value based → Underperformed

- **Single-Decision**

  - Small sample size, hard to make consistent profitability.

- **More value in less liquid markets**

  - Player Props

  - Smaller market sports

- THIS IS NOT BETTING ADVICE

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APPENDIX

CODE: