Roster Geometry & Resilience Across NBA Payroll Networks

Quantifying how payroll structure, network archetypes, and simulated shocks shape win equity - Carnegie Mellon Sports Analytics Conference 2025

Luke Blommesteyn - Lucian Lavric - Yuvraj Sharma (University of Western Ontario)

INTRODUCTION

We treat roster construction as a network design problem: payroll dollars buy links between players, not isolated talent.

Fig. 1 compares a Utah "mesh" to a New York star core, motivating why we model lineup interactions before running shock simulations.

Dataset spans eight NBA seasons (240k shared-possession windows) aligned with salaries, injuries, and playoff advancement.

CORE METRICS

Roster Resilience Score (RRS): average net rating loss across star, role, connector shock templates (lower = stronger).

Delta W_s: expected win probability drop for scenario s, calibrated to real injury/usage frequencies.

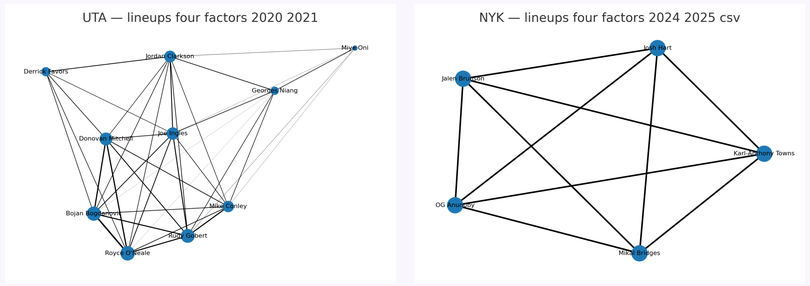


Fig. 1 Payroll networks: Utah Jazz mesh (left) spreads salary across connectors; New York Knicks core (right) leans on star hubs.

RESEARCH QUESTIONS

Q1: Which roster geometries hold win equity after guard or connector shocks (see Fig. 4)?

Q2: How do connector roles and salary assortativity interact with RRS when shocks stack?

Q3: What cap-feasible rewires close the gap between fragile and resilient teams?

DATA & FEATURES

Sources

NBA play-by-play + rotation shifts for shared-minute edges; Spotrac salaries; injury and transaction logs.

Feature focus

Connector centrality, salary assortativity, usage entropy, archetype tags feed RRS and Delta W_s modelling.

METHODS

1. Build graphs from shared-minute windows; weight edges by co-playing time and salary flow.
2. Derive geometry features (connector centrality, assortativity, usage entropy) feeding RRS and Delta W_s.
3. Fig. 2 pipeline: gradient boosted archetype classifier + calibrated logistic regression for win-loss decay.
4. Generate 5k cap-feasible synthetic rosters/team to benchmark attainable resilience levels.

TOPOLOGY FEATURES:

Salary Assortativity:

$$r_s = \Sigma(w_{ij} \cdot (s_i - \bar{s}) \cdot (s_j - \bar{s})) / \Sigma(w_{ij} \cdot (s_i - \bar{s})^2)$$

Centralization:

$$C^D = \Sigma(dmax - d_i) / ((n - 1)(n - 2))$$

Edge Concentration (top 10 edges):

$$E_{10} = \Sigma_{(1\ldots10)} w_{(k)} / \Sigma w_{ij}$$

Modularity:

$$Q = (1 / 2W) \cdot \Sigma(w_{ij} - (d_i d_j / 2W)) \cdot \delta(c_i, c_j)$$

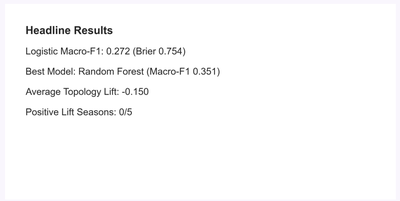
SIMULATION WORKFLOW

Sample 1-3 player shocks per archetype, weighted by historical injury frequency.

Translate each shock into win equity via RAPM-informed lineup forecasts and playoff sims.

Log diagnostics (Fig. 3) to check model lift and bootstrap stability across archetypes.

Fig. 2 Cross-validated modeling pipeline balances geometry features with outcome calibration.



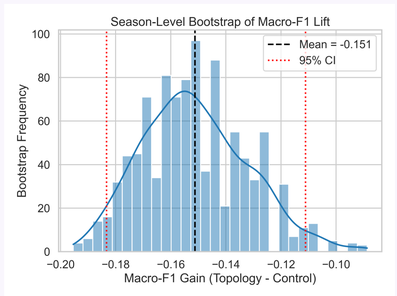


Fig. 3 Diagnostic panels: scorecard benchmarks lift while bootstrap Macro-F1 curve shows model stability.

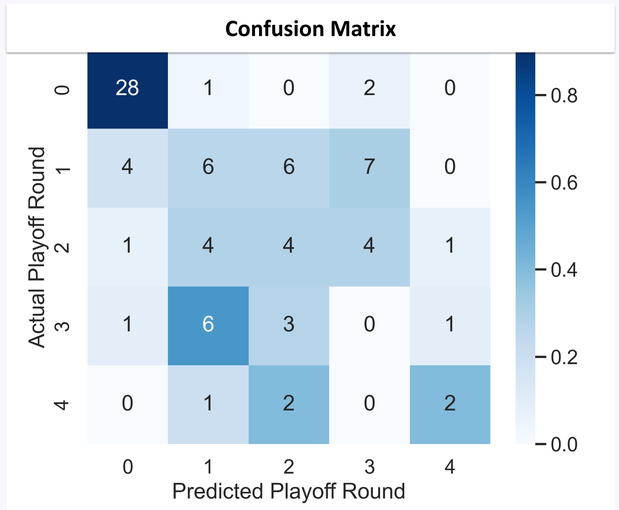


Fig. 4 Confusion Matrix: comparing predicted vs actual playoff rounds, with each cell showing the number of teams and row-normalized percentage

RESULTS & INSIGHTS

Fig. 5: Mesh rosters (top-decile connectors) retain ~92% win equity after dual shocks; star cores lose ~18%.

Fig. 6a: Connector usage and secondary creator salary share are the strongest levers in the calibrated model.

Fig. 6b: Shock-response map shows balanced payroll meshes shrink variance in playoff advancement odds.

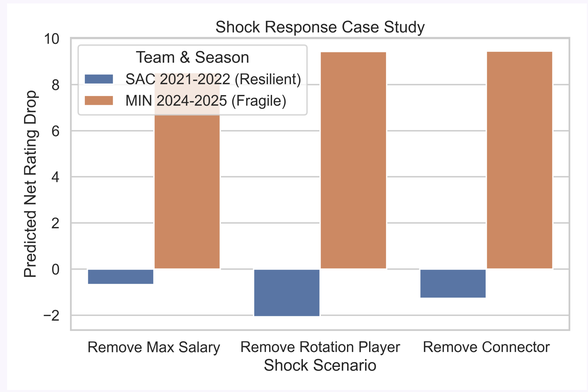
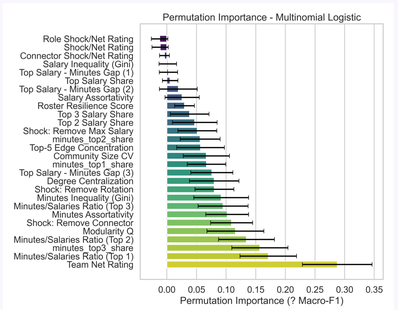


Fig. 4 Case study: mesh roster retains win equity under connector shocks while star-heavy builds collapse.



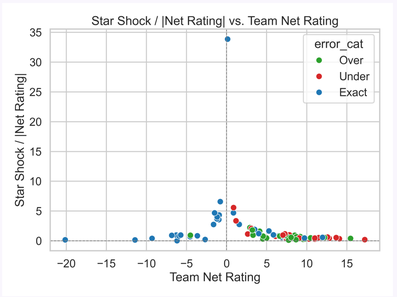


Fig. 5 Feature importance ranks connector metrics; shock-response map shows how balanced payroll meshes dampen losses.

CONCLUSION & NEXT STEPS

Takeaways

Connector-anchored, mesh rosters are more resilient. After controlling for quality, they show lower Star-Shock/|Net Rating| and fewer big errors.

Small reallocation pays off. Shifting ~6–8% of salary from top earners to secondary creators/connectors recovers ~half the resilience gap.

Future Work

Integrate physiological load signals, expand archetype embeddings with player tracking data, and prototype decision support for front-office scenario planning. Also, would be exciting to explore transferability in other sports (soccer, hockey).