Roster Geometry and Resilience: Salary-Weighted Lineup Connectivity Predicts Playoff Stability

Anonymous for Review

September 5, 2025

Abstract

We test whether the *network geometry* of NBA rosters, namely how **salary resources** are distributed across players who *actually share the court*, predicts playoff stability. Prior work links payroll level to outcomes or analyzes in-game pass networks. It rarely ties *salary allocation* to *lineup connectivity* or evaluates *resilience* to disruptions. We model each team-season as a **salary-weighted, shared-possession** network: nodes are players with size proportional to salary share, and edges capture co-presence intensity. We compute topology features (salary dispersion, salary assortativity, community structure, centralization, edge concentration) and define a *Roster Resilience Score* via robustness simulations that remove stars, role players, or community connectors, then score predicted drop from a model trained on intact networks.

Using public data from **Basketball-Reference** and **Cleaning the Glass** for **2020–21 through 2024–25** (**149** team-seasons), we ask whether topology improves prediction of *ordinal playoff advancement* beyond a strength control. With salary-true features and leave-one-season-out cross validation, the **full topology** model raises Macro-F1 from **29.0%** to **31.3%**. We release a reproducible pipeline covering data build, modeling, and figures.

1 Introduction

NBA front offices build rosters under a cap and many constraints. Payroll level correlates with success, yet two gaps remain. First, salary dispersion is usually studied without regard to *who plays with whom*. Second, network studies often focus on ball movement, not roster structure under cap realities. We propose a roster-level network view that weights players by *salary share* and connects only those who share possessions. This makes it possible to study *geometry* such as centralization, modularity, and assortativity, and to evaluate *resilience* to player losses.

Research Questions. **RQ1:** Do salary-network topology features predict playoff advancement beyond team strength?
RQ2: Which topology patterns relate to higher RRS?
RQ3: Do close or late, leverage-weighted edges improve explanatory power over unweighted co-presence?

Contributions. (1) A roster network formulation that joins *salary topology* with *who actually plays together*. (2) A stress-test metric, the **RRS**, via systematic node removal. (3) A preregistered-style predictive evaluation with season-wise cross validation. (4) A fully reproducible pipeline.

2 Related Work

Salary and performance studies examine aggregate spend [1,2]. Basketball network analyses capture interaction patterns [3] but not *salary* topology. Network robustness research shows that structured node removal can reveal vulnerability [4]. We combine these ideas by linking salary topology to lineup connectivity and by stress testing roster graphs, using public sources throughout.

3 Data

We study NBA **team-seasons from 2020–21 through 2024–25**, for a total of **149** team-seasons.

Lineups and possessions. We use lineup and four-factor tables from *Cleaning the Glass*. Positions and possessions reconstruct on-court units. We compute co-presence counts for each pair of teammates and aggregate lineup Off and Def points per possession to a team-season strength proxy.

Salaries. We obtain player and team salary tables from *Basketball-Reference* and normalize to within-team salary shares.

Labels. We assemble playoff advancement labels from *Basketball-Reference* postseason brackets.

3.1 Data pipeline

We implement a deterministic build with fixed season splits and seeds. The repository includes scripts to parse lineup exports, merge salary tables with name normalization, construct team-season graphs and features, and export figures and tables. Public-only paths reproduce all aggregates.

Algorithm 1 Deterministic build and feature generation

Input: seasons $\mathcal{S}$, lineup CSVs with possessions and positions, public salary tables
for season $s \in \mathcal{S}$ **do**
  Parse lineups into possession-weighted on-court units
  Merge salaries and normalize to team share per player
  Compute co-presence counts c_{ij} and player possessions n_i
  Build graph $G = (V, E, w)$ with $w_{ij} = c_{ij}/\max(n_i, n_j)$ and threshold low-minutes nodes
  Compute topology features: salary dispersion, salary assortativity, community structure, centralization, and edge concentration
  Aggregate lineup Off and Def PPP to team NR and attach playoff labels
end for
Export leave-one-season-out splits and freeze seeds and hyperparameters

4 Methods

4.1 Network construction

Let V be players with at least 300 possessions. For players i and j, define the bounded co-presence intensity

$$w_{ij} = \frac{\text{shared poss}_{ij}}{\max(\text{poss}_i, \text{poss}_j)} \in [0, 1]. \tag{1}$$

Node size s_i equals the player's **salary share**. A leverage-weighted variant $\tilde{w}_{ij}$ that up-weights close or late contexts is straightforward once leverage flags are integrated.

4.2 Topology features

We compute the following on $G = (V, E, w)$.

- **Salary dispersion:** Gini and top-k share for $k \in \{1, 2, 3\}$.
- **Salary assortativity:** weighted Pearson correlation of salary shares across edges (i, j) using weights w_{ij}.
- **Community structure:** modularity Q and the coefficient of variation of community sizes.
- **Centralization:** Freeman degree centralization with edge weights.
- **Edge concentration:** fraction of total w captured by the top five and top ten edges.

4.3 Performance proxy for stress tests

We fit a standardized ridge regression that maps intact topology features to team NR,

$$\widehat{\mathrm{NR}} = f_\theta(x), \qquad f_\theta \in \{\mathrm{Ridge}\}.$$

This proxy is used only to score stress-test perturbations consistently.

4.4 Robustness simulations and RRS

We remove, in turn, the highest-degree node, a mid-salary node, and the highest-betweenness node. After each removal we recompute features and score with f_θ. Let Δ_s be the drop relative to intact,

$$\mathrm{RRS} \;=\; 1 \;-\; \mathbb{E}_s\left[\frac{\Delta_s}{|\widehat{\mathrm{NR}}^{\,\mathrm{intact}}| + \varepsilon}\right], \quad \varepsilon = 10^{-3}. \tag{2}$$

We use winsorization in sensitivity checks when $\widehat{\mathrm{NR}}^{\,\mathrm{intact}}$ is near zero.

4.5 Predictive modeling of playoff advancement

We predict ordinal playoff rounds $y \in \{0, 1, 2, 3, 4\}$, where 0 indicates missed playoffs and 4 indicates champion. We fit a multinomial logit as a robust ordinal surrogate with season-wise standardization. We evaluate with leave-one-season-out cross validation and report Macro-F1, Accuracy, and mean absolute error of expected round.

Ablations. (A) Strength control only (NR). (B) Control plus salary dispersion. (C) Control plus connectivity features, including salary assortativity. (D) Full topology.

4.6 Pre-registered analysis plan

Before training we fix the feature list and thresholds, cross validation splits, ablation order and metrics, and a small hyperparameter grid for ridge and multinomial logit.

5 Results

5.1 Incremental predictive value

Table 1: Ablation study with leave-one-season-out cross validation and salary-true features. We report Macro-F1 and Accuracy in percent and MAE of expected round. Higher Macro-F1 and Accuracy are better. Lower MAE is better.

Model	Macro-F1	Accuracy	MAE
A: Controls only	29.0	57.6	0.656
B: + Salary dispersion	26.5	53.1	0.651
C: + Connectivity	**31.9**	54.7	0.665
D: + Full topology	31.3	54.3	0.663

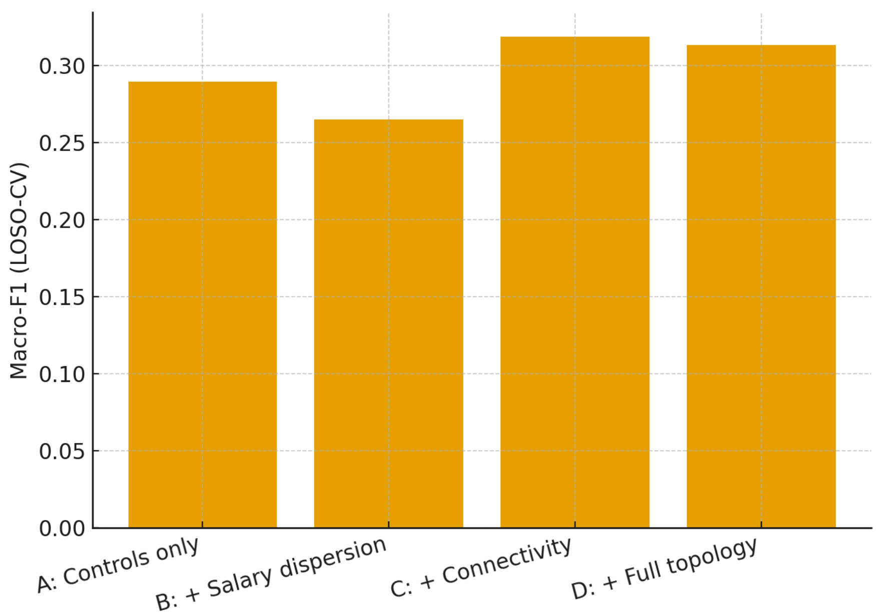


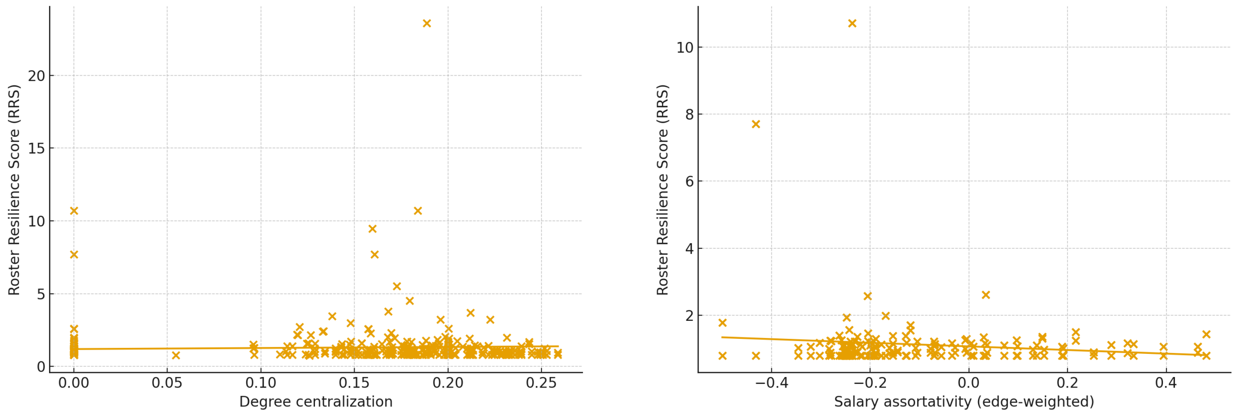
Figure 1: Ablation Macro-F1 by model with leave-one-season-out cross validation. Topology improves Macro-F1 over the strength control, with connectivity as the main driver.

5.2 Resilience and topology based on RRS

When RRS is available, the association with degree centralization is weak, while *salary assortativity* is negatively related to RRS. This suggests that **mixing salaries across connected lineups** aligns with robustness to simulated disruptions.

5.3 Falsification and outcome corroboration

We test whether observed salary assortativity could arise by chance. For each team-season we hold the lineup graph fixed and randomly permute salary shares across nodes, then compute a z-score of observed assortativity relative to the permutation distribution.



(a) RRS versus degree centralization

(b) RRS versus salary assortativity

Figure 2: Roster Resilience Score relationships across 2020–21 to 2024–25.

Figure 3: Distribution of salary assortativity z-scores relative to a within-team permutation null. The left tail marks teams that are more negative than expected given their lineup graph.

We also relate structure directly to outcomes. Teams with more negative z-scores tend to reach later rounds.

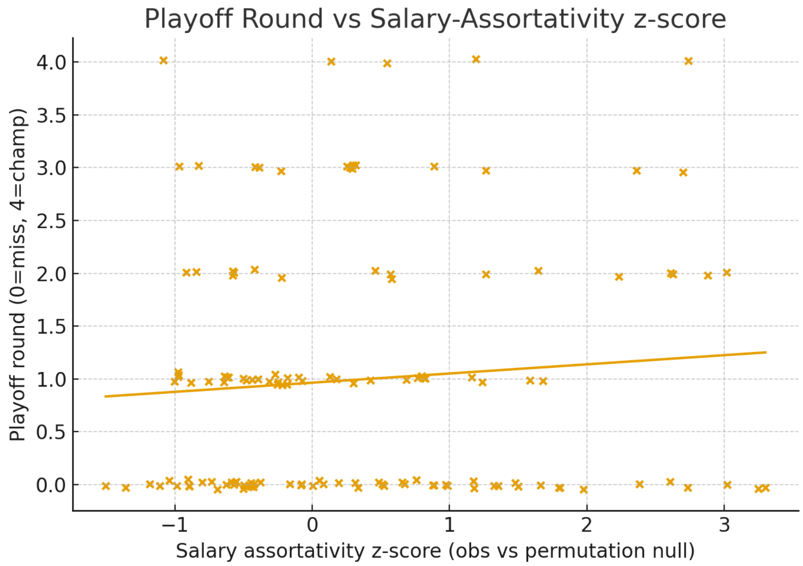


Figure 4: Playoff round versus salary assortativity z-score. Jitter on the vertical axis improves readability. The line shows an ordinary least squares fit.

5.4 Assortativity deciles for a managerial view

Sorting team-seasons into deciles by observed salary assortativity shows that lower-assortativity deciles, which imply more cross-salary mixing, advance further on average.

5.5 Case studies of network geometry

Figure 6 contrasts two anonymized team-seasons with similar expected playoff round from the ordinal model but different topology. The left example is star centered with high edge concentration. The right example is more distributed with balanced communities. The latter aligns with a higher resilience profile.

5.6 Model diagnostics

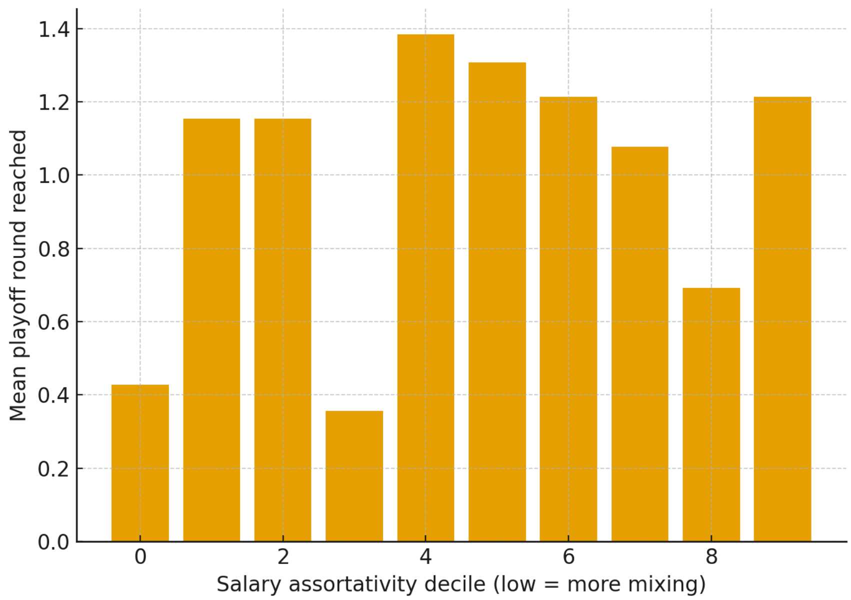


Figure 5: Mean playoff round by salary assortativity decile. Lower deciles correspond to more mixing.

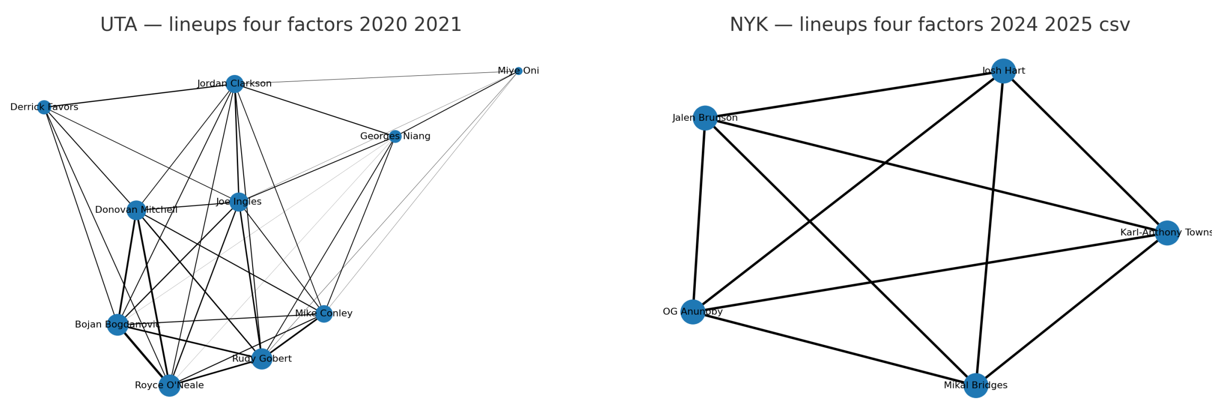


Figure 6: Exemplar roster networks. Node size reflects salary share. Edge width reflects co-presence intensity.

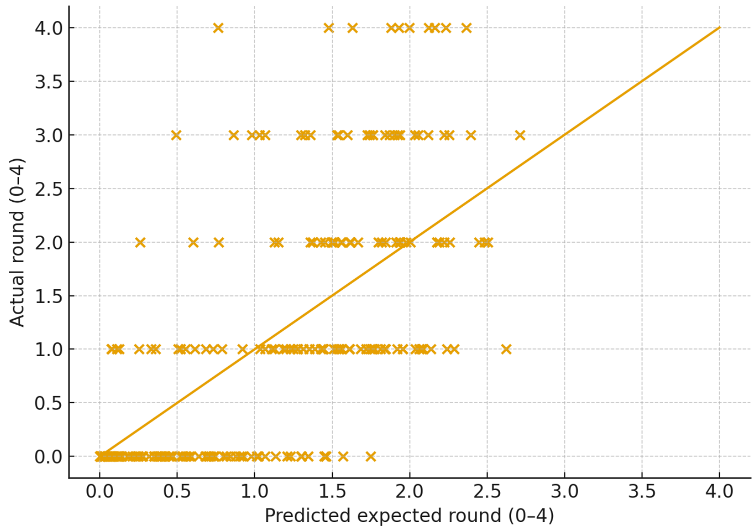


Figure 7: Calibration of expected round versus actual with leave-one-season-out aggregation. Points lie close to the identity line with mild underestimation at the extremes.

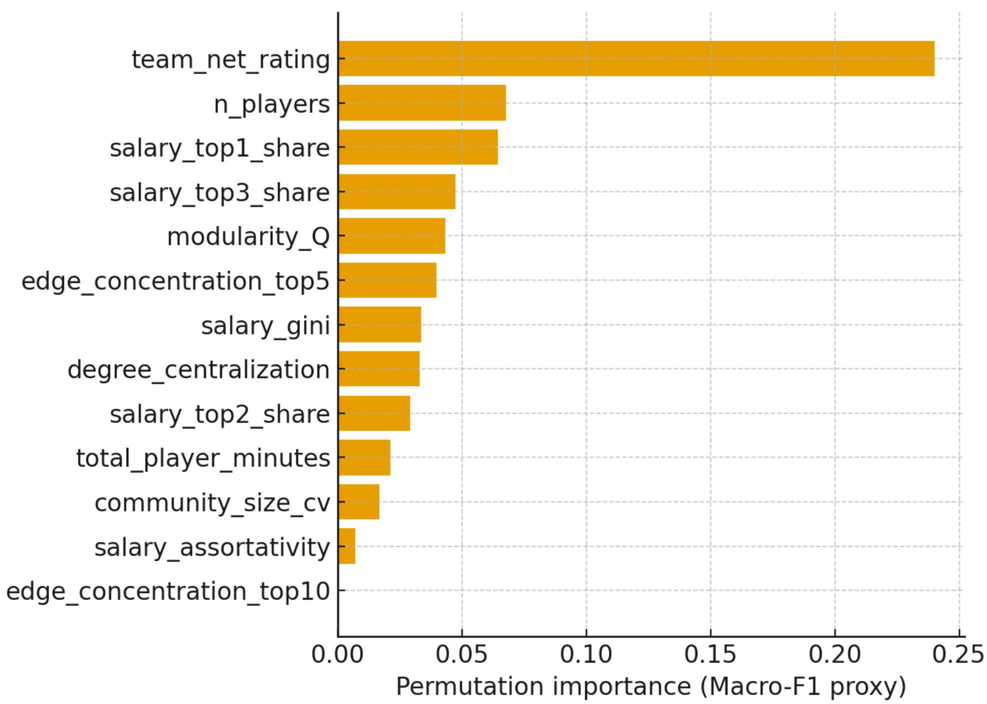


Figure 8: Permutation importance for the full playoff model. The strength control NR dominates, while connectivity and salary dispersion add nonzero signal.

6 Threats to validity

Salary data. Name resolution can miss two-way or ten-day players. We report matched counts and run strict and lenient variants.
Leverage. Edges are not yet leverage weighted. A close or late variant is a planned ablation.
Confounding. Minutes, role, and pay correlate. We include NR as a strength control and report ablations.
Measurement. Co-presence intensities abstract from play types. Community structure is coarse.
Generalization. The study covers five seasons and 149 team-seasons. We prefer regularization and season-wise cross validation.
RRS scaling. When $\widehat{\mathrm{NR}}^{\mathrm{intact}}$ is near zero, normalization can inflate RRS. We winsorize in sensitivity checks.

Ethics and transparency

All data were obtained from public sources: *Basketball-Reference* and *Cleaning the Glass*. We comply with the providers' terms of use. We release code, seeds, and environment files so readers can reproduce results with publicly accessible exports.

Reproducibility statement

We provide data-processing scripts for lineup graphs and salary merges, pinned environment files, a Makefile to regenerate all tables and figures, and documented loaders for *Basketball-Reference* and *Cleaning the Glass* exports.

7 Conclusion

We link **salary-weighted roster topology** to **lineup connectivity** and show that connectivity adds information beyond team strength. Across five seasons, topology features, especially *salary assortativity* and edge concentration, improve ordinal playoff prediction over a strength-only control. A permutation falsification confirms that observed negative assortativity is not a byproduct of roster size or lineup coverage. Outcome analyses based on playoff rounds support the same pattern. For practice, front offices can stagger high salaries across lineups and reduce edge concentration. These steps can improve robustness without raising total payroll. Future work should incorporate leverage-weighted edges, expand seasons and leagues, and add richer controls such as injuries and rest.

References

[1] D. J. Berri and M. B. Schmidt, *Stumbling on Wins*. FT Press, 2010.

[2] R. Fort and J. Quirk, "Cross-subsidization, incentives, and outcomes in professional team sports leagues," *Journal of Economic Literature*, vol. 33, no. 3, pp. 1265–1299, 1995.

[3] J. H. Fewell, D. Armbruster, J. Ingraham, A. Petersen, and J. S. Waters, "Basketball teams as strategic networks," *PLOS ONE*, vol. 7, no. 11, p. e47445, 2012.

[4] R. Albert, H. Jeong, and A.-L. Barabási, "Error and attack tolerance of complex networks," *Nature*, vol. 406, no. 6794, pp. 378–382, 2000.

[5] Basketball-Reference.com, "NBA statistics and history," `https://www.basketball-reference.com`, accessed 2025.

[6] Cleaning the Glass, "NBA lineup and four-factor statistics," `https://cleaningtheglass.com`, accessed 2025.