How do Teams Tank? Evidence from Game-level NBA Playing Time Distribution

Alexander Cardazzi [1] Brad R. Humphreys [2] Kole Reddig [2]

[1]Old Dominion University

[2]West Virginia University

March 02, 2024

- A large literature shows that teams eliminated from playoff contention lose games they would be expected to win: NBA (Taylor & Trogdon, 2002; Price et al., 2010; Lenten, 2016), WNBA (Hill, 2021), NHL (Fornwagner, 2019), MLB (Lenten, 2016), MiLB (Medcalfe, 2009)
- **Research Question**: How do teams tank?

Motivation - How Teams Tank

Broadly, teams can tank in three ways:

1. Players can tank by reducing effort. However, players have career concerns, and it's unlikely that tanking is a good strategy for future employment.
2. Management/ownership can tank by trading away the team's most productive players. Anecdotal evidence supports this idea as a possibility.
3. Coaches can tank by changing the distribution of playing time across players on the team with different levels of production.

Research Question, Context, and Contribution

- We investigate decisions made by coaches about playing time distribution as a mechanism for tanking and explore the distinction between *tanking* and *load management*.
- Develop a theoretical model of coach decisions on playing time allocation with fatigue generated by time spent in the game.
- Develop evidence that the allocation of playing time causes teams to lose games.
- Closest papers to ours:
    - Gong et al. (2022) compared the counts of rested players for teams eliminated from the playoffs before and after elimination, showed that eliminated teams tend to rest more players, and this behavior intensifies as the competition for draft picks increases.
    - Fornwagner (2019) compared time on ice by hockey players on teams eliminated from the playoffs before and after elimination, showed that higher quality players played less after elimination

A Model of Coach Decisions

We develop a dynamic theoretical model of coaches' playing time allocation decisions that assumes coaches care about both the *playoffs* and *draft seeding*, and player quality depreciates both *across* and *within* games. Without these assumptions, the predictions are trivial.

Coaches who expect to make the playoffs will engage in *load management*, substituting some of their stars' playing time with playing time from all other players, reducing player depreciation across games and reducing the concentration of playing time.

Coaches who *do not* expect to make the playoffs also bench their best players. However, coaches do not fill this playing time with many other players, increasing the concentration of playing time (*tanking*)

In other words, both types of teams want to play their good players less. The difference is that good teams distribute playing time across other players where bad teams concentrate playing time among their worst players.

Prediction: coaches pursue load management by distributing playing-time evenly across players, and tanking by concentrating playing-time among the team's worst players.

The literature commonly treats the point of elimination from the playoffs as **exogenous**. However, playoff elimination (or clinching) is often predictable, or even selected, and may be correlated with unobservable factors affecting team success in games. This complicates the standard treatment-control, pre-post strategy.

To get around this, we analyze marginal, exogenous changes in the probabilities of playoff clinching and elimination; identify these changes in incentives through variation in the win-loss records of *other* teams in the same conference.

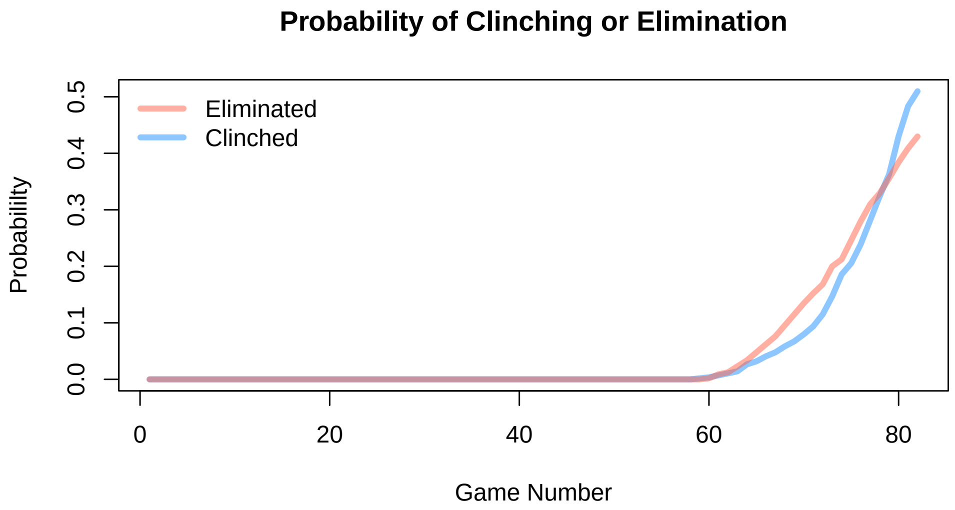
We analyze player-team-game-season level data from the 1999-00 to 2018-19 NBA seasons. Exclude 2011-12 season. For a specific game t in season y, we compute:

$$
\begin{aligned}
q_{iy} &= \text{Season-specific player } i \text{ quality (VORP) in season } y \\
\Psi_{jty} &= \text{Playing-time weighted average player quality of team } j, t, y \\
&= \sum_{i \in \mathcal{R}_{jt}} s_{ijty} \cdot q_{iy} \\
s_{ijty} &= \text{Playing-time share of player } i \text{ on team } j \text{ in game } t \text{ of season } y \\
HHI_{jty} &= \text{Playing-time concentration on team } j, t, y \\
&= \sum_{i \in \mathcal{R}_{jt}} s_{ijty}^2
\end{aligned}
$$

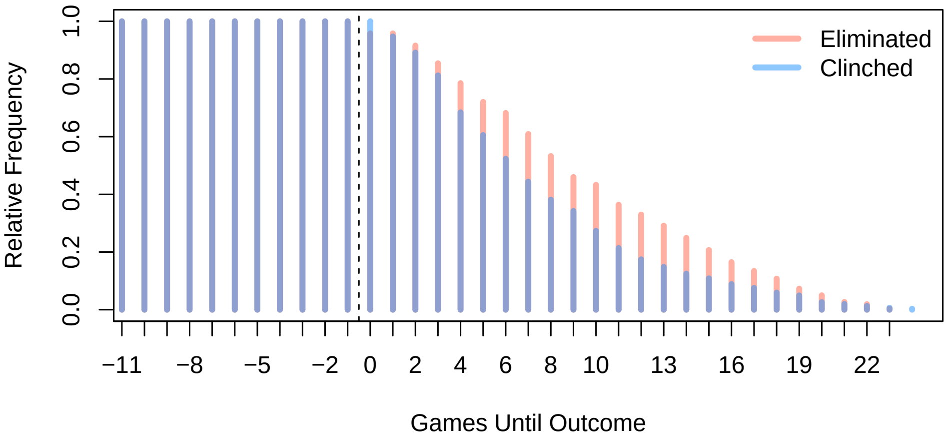
Value Over Replacement Player ($VORP_{iy}$): from Basketball-Reference, based on a player-season fixed effect model on points scored per possession estimated with a regularized regression model.

	Unique Values	Mean	SD	Min	Max
Playing Time HHI	46249	0.12	0.01	0.08	0.19
Playing Time HHI (Normalized)	46249	0	1	-3.06	5.33
Playing Time Weighted VORP*	45149	1.30	0.69	-0.54	3.51
Playing Time Weighted VORP	44983	3.90	0.69	2.06	6.11
Playing Time Weighted VORP (Normalized)	44983	0	1	-2.65	3.20
Games Until Outcome	107	-32.60	24.33	-82	24
Playoffs Clinched	2	0.05	0.21	0	1
Playoffs Eliminated	2	0.05	0.22	0	1
Other Teams Clinched	19	1.27	3.20	-1	17
Other Teams Eliminated	16	1.38	3.11	-1	14

Notes: This table presents summary statistics for the analysis sample (N = 46,328). Note that observations are at the game-by-team-by-season level, which amounts to two observations per NBA game.


Probability of Clinching or Elimination
Eliminated
Clinched
Probability
0.0
0.1
0.2
0.3
0.4
0.5
0
20
40
60
80
Game Number

Distribution of Games Until Outcome

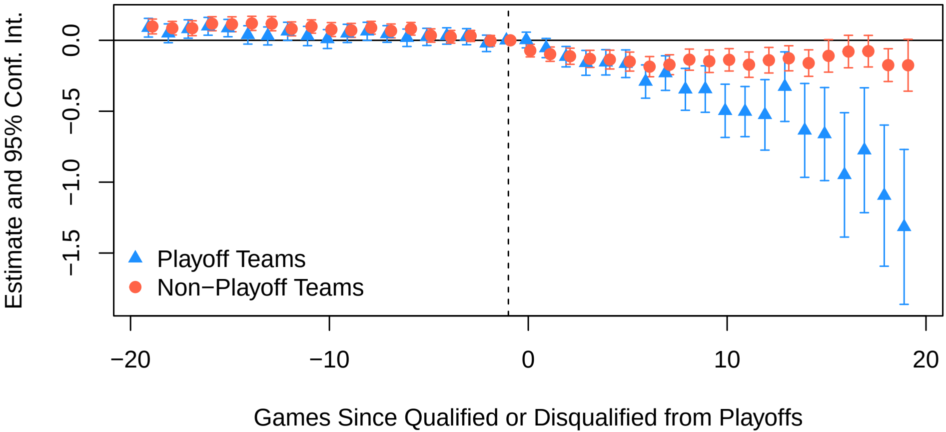


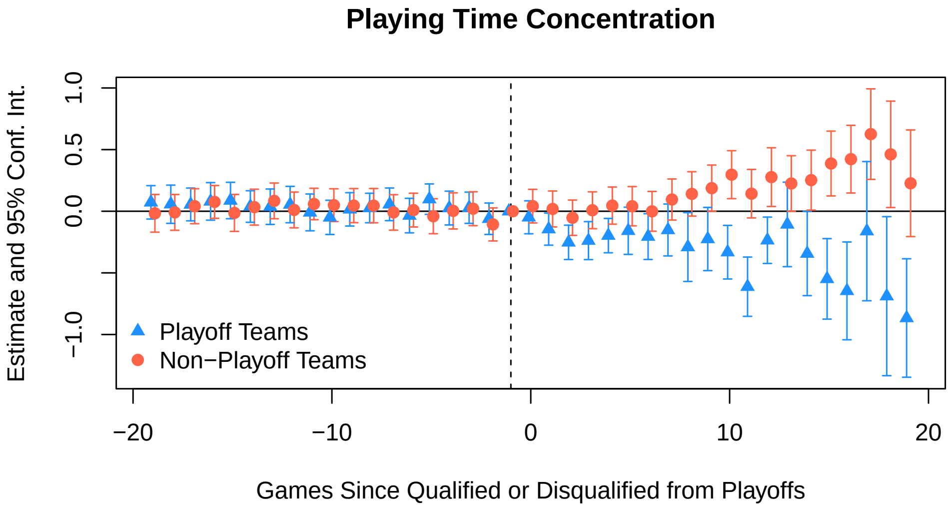
We initially estimate the following regression models

$$\Psi_{jty} = \alpha_t + \alpha_{jy} + \epsilon_{jty} \qquad HHI_{jty} = \alpha_t + \alpha_{jy} + \epsilon_{jty}$$

where $t = 0$ is the first game played where the team knows whether it has clinched, or been eliminated from, the playoffs, and graph the coefficient estimates on the time variables

Playing Time Weighted−Average VORP





Playing Time Concentration
Estimate and 95% Conf. Int.
1.0
0.5
0.0
−1.0
Playoff Teams
Non−Playoff Teams
−20
−10
0
10
20
Games Since Qualified or Disqualified from Playoffs

	Ψ_{jty}	HHI_{jty}	Ψ_{jty}	HHI_{jty}
$Clinch_{jty}$	-0.152***	-0.245***	-0.148***	-0.246***
	(0.029)	(0.036)	(0.029)	(0.037)
$Eliminate_{jty}$	-0.116***	0.148***	-0.114***	0.155***
	(0.026)	(0.045)	(0.025)	(0.047)
Opponent $Clinch_{j't'y}$			-0.019	0.008
			(0.013)	(0.034)
Opponent $Eliminate_{j't'y}$			-0.053***	-0.056**
			(0.012)	(0.022)
N	46328	46328	46328	46328
R^2	0.865	0.300	0.872	0.341

IV Estimation

If we believe that teams can anticipate and/or select into "treatment", we need an IV that exogenously assigns treatment to teams.

- Instrument must be relevant (must *predict* playoff probability)
- Instrument must be excludable (must *only* effect the outcome through the endogenous regressor – playoff probability)

Candidate IVs:

- Changes in *other* teams' records (wins and losses) that effect seeding.
- Number of remaining playoff / lottery slots.

	DiD		IV First Stage		IV Second Stage	
	Ψ_{jty}	HHI_{jty}	$Clinch_{jty}$	$Eliminate_{jty}$	Ψ_{jty}	HHI_{jty}
$Clinch_{jty}$	-0.148***	-0.256***			-0.589***	-0.701***
	(0.029)	(0.037)			(0.070)	(0.126)
$Eliminate_{jty}$	-0.112***	0.157***			-0.040	0.642***
	(0.024)	(0.045)			(0.086)	(0.133)
Opponent $Clinch_{j't'y}$	-0.026**	-0.012	0.007	0.042***	-0.015	-0.005
	(0.012)	(0.030)	(0.010)	(0.012)	(0.014)	(0.032)
Opponent $Eliminate_{j't'y}$	-0.055***	-0.059***	0.040***	0.004	-0.040***	-0.062***
	(0.011)	(0.019)	(0.008)	(0.007)	(0.014)	(0.021)
$\sum_{k \neq j,j'} Clinch_{kty}$			0.126***	-0.115***		
			(0.039)	(0.030)		
$\sum_{k \neq j,j'} Eliminate_{kty}$			-0.258***	0.257***		
			(0.027)	(0.037)		
$t \cdot \sum_{k \neq j,j'} Clinch_{kty}$			-0.002***	0.002***		
			(0.0005)	(0.0004)		
$t \cdot \sum_{k \neq j,j'} Eliminate_{kty}$			0.004***	-0.003***		
			(0.0004)	(0.0005)		
N	46328	46328	46328	46328	46328	46328

Future Research

Consistent with our theoretical model, we find *all* teams reducing the overall talent on the floor following resolved uncertainty. We also find changes in playing time concentration that depends on whether the team clinched, or was eliminated from, a playoff spot.

It's important to note the differences in magnitudes between DiD and IV. These estimates suggest DiD designs may understate the effect(s) due to assumption violations.

Next steps:

- Work through different IV constructions.

Fornwagner, H. (2019). Incentives to lose revisited: The NHL and its tournament incentives. *Journal of Economic Psychology*, *75*, 1-12.

Gong, H., Watanabe, N. M., Soebbing, B. P., Brown, M. T., & Nagel, M. S. (2022). Exploring tanking strategies in the NBA: an empirical analysis of resting healthy players. *Sport Management Review*, *25*(3), 546–566.

Hill, B. (2021). Tournament incentives and performance: Evidence from the WNBA. *Contemporary Economic Policy*, *39*(4), 882–900.

Lenten, L. J. (2016). Mitigation of perverse incentives in professional sports leagues with reverse-order drafts. *Review of Industrial Organization*, *49*(1), 25–41.

Medcalfe, S. (2009). Incentives and league structure in minor league baseball. *Journal of Sport Management*, *23*(2), 119–141.

Price, J., Soebbing, B. P., Berri, D., & Humphreys, B. R. (2010). Tournament incentives, league policy, and nba team performance revisited. *Journal of Sports Economics*, *11*(2), 117–135.

Taylor, B. A., & Trogdon, J. G. (2002). Losing to win: Tournament incentives in the National Basketball Association. *Journal of Labor Economics*, *20*(1), 23–41.