

NBA Player Movement's Impact on EPM

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Research Goal

- Which NBA team has the best system for maintaining and, increasing, productivity in the league for their free agents/acquired players?
- To elaborate, which NBA teams' free agents, on average, have the best EPM increase, relative to their performances on different teams the season prior?



Background

Estimated Plus-Minus (EPM) - A Statistical Measure of Player Impact on Team Performance

- **Comprehensive Metric:** EPM aims to quantify a player's overall impact, including offense, defense, and intangibles that might not be captured by traditional statistics.
- **Team Performance Focus:** It measures how much better a team performs when a player is on the court versus when they are not, in terms of scoring margin.
- **Adjustment for Context:** EPM takes into account the context of the player's minutes, adjusting for factors like the quality of teammates and opponents.
- **Statistical Approach:** It's typically calculated using advanced statistical models, often incorporating play-by-play data and other advanced metrics.
- **Comparison Tool:** EPM provides a basis for comparing players across different positions and roles within a team.
- **Predictive Value:** It can be used to predict future team performance based on player contributions.



Solution

- Obtained EPM Data of players throughout several seasons
- Widen the data sets of each player's path of career
- Only focus on players that changed teams over the offseason
- Combine both paths
- Repeat process over next few years
- Filter offensive players and defensive players
- Rank Teams in overall EPM for offense and defense



Data Set & Data Munging

- Source:
 - ◆ 10 years of EPM data via Dunks & Threes
 - ◆ NBA Seasons 2014 - 2023
- Data Munging Process
 - ◆ Create new datasets looking at pairs of years, filtering to only include players who have switched teams between those two years (FA, Trade etc.) establishing Old & New Teams and changes in EPM, OEPM, DEPM for the player between the two years
 - ◆ Example Dataset (2021 & 2022)

nba_id	name	oldtm	newtm	old.epm	new.epm	old.oepm	new.oepm	old.depm	new.depm	old.yr	new.yr
2546	Carmelo Anthony	POR	LAL	-1.21363000	-0.6344990	-0.0408035	0.0295478	-1.1728300	-0.6640460	2021	2022
2730	Dwight Howard	PHI	LAL	-0.51612300	-1.1446300	-1.6943200	-0.0940018	1.1782000	-1.0506300	2021	2022
2738	Andre Iguodala	MIA	GSW	-3.18129000	0.0947843	-3.6908800	-2.7327200	0.5095850	2.8275000	2021	2022
2772	Trevor Ariza	MIA	LAL	1.19101000	-5.0903300	-0.7730920	-3.3096300	1.9641000	-1.7807100	2021	2022



Data Munging cont.

- Combine all paths to create single data frame of every instance of a player moving teams with EPM summaries from old & new team
- Create Variables Delta EPM, Delta OEPM, Delta DEPM and ensure there are no blank values in this data frame
- Example:

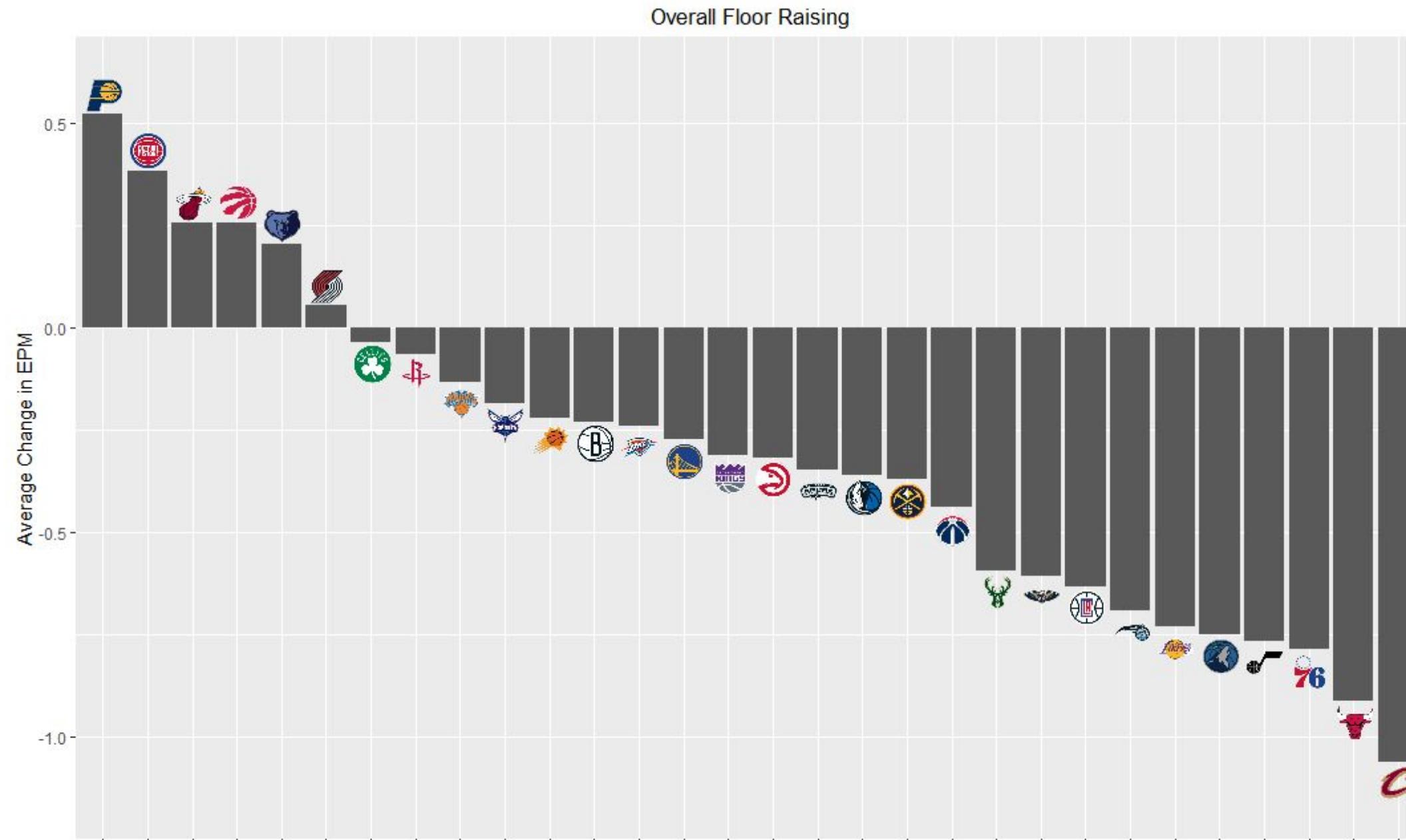
name	oldtm	newtm	old.epm	new.epm	old.oepm	new.oepm	old.depm	new.depm	old.yr	new.yr	delta.epm	delta.oepm
Carmelo Anthony	POR	LAL	-1.2136300	-0.634499	-0.0408035	0.0295478	-1.17283	-0.664046	2021	2022	0.5791310	0.0703513
Carmelo Anthony	CHI	POR	-3.4867800	-1.048460	-1.7372200	-0.4403640	-1.74956	-0.608098	2019	2020	2.4383200	1.2968560
Carmelo Anthony	OKC	CHI	-0.3247050	-3.486780	0.5626760	-1.7372200	-0.88738	-1.749560	2018	2019	-3.1620750	-2.2998960
Carmelo Anthony	NYK	OKC	0.0661633	-0.324705	1.8919700	0.5626760	-1.82581	-0.887380	2017	2018	-0.3908683	-1.3292940



Analysis



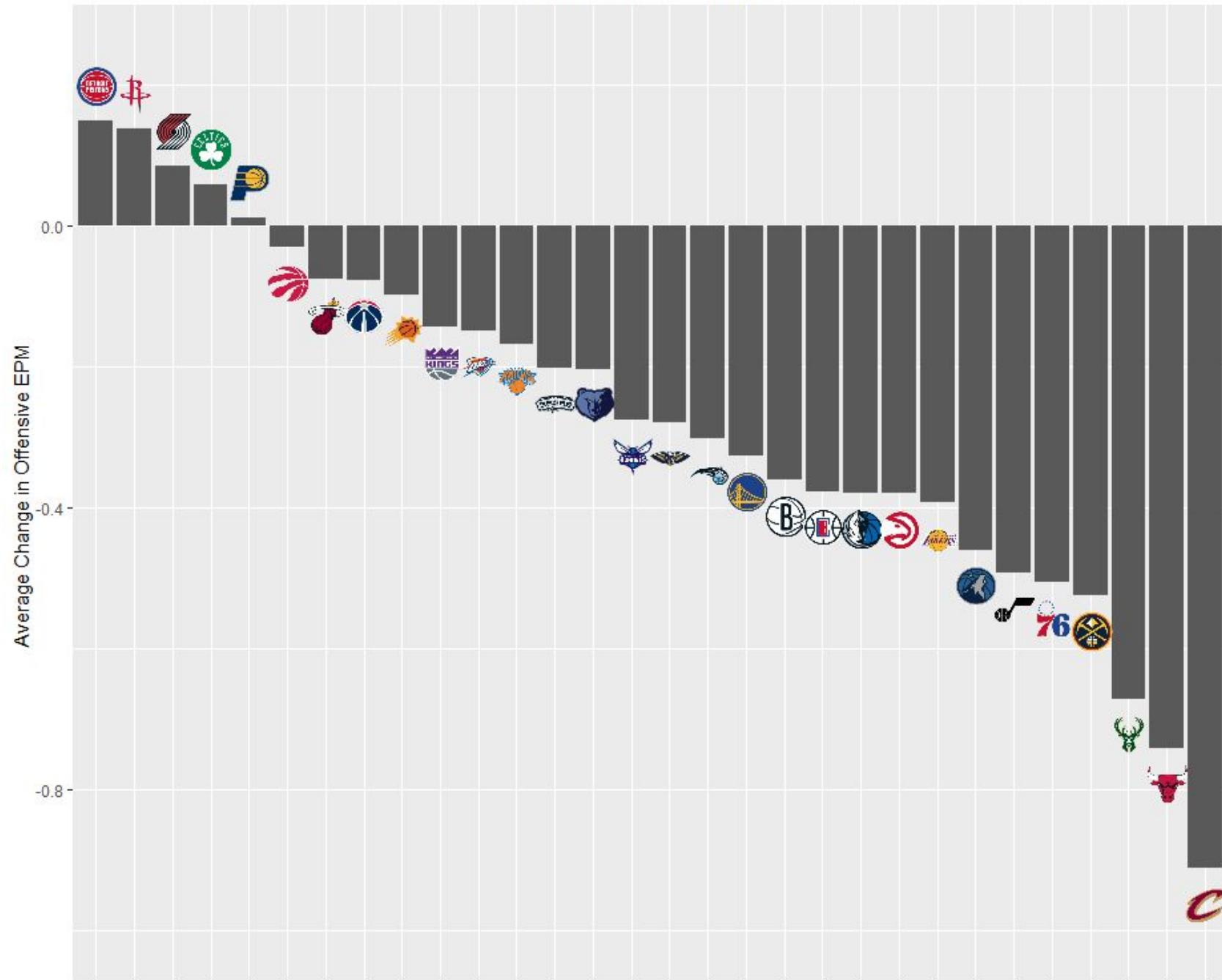
Change in EPM for New Teams



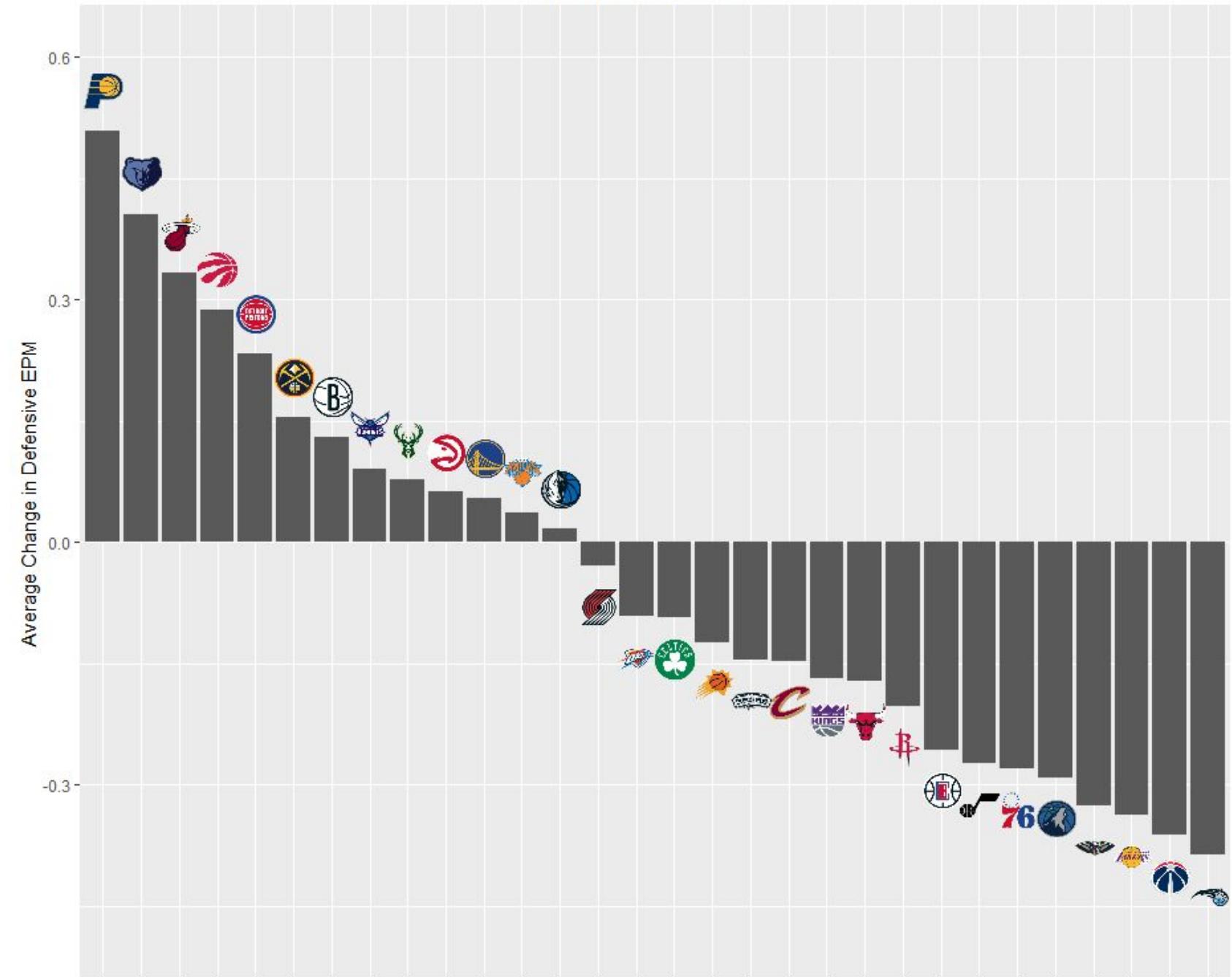
Higher values indicate a team is improving a player's level of play



Offensive Floor Raising

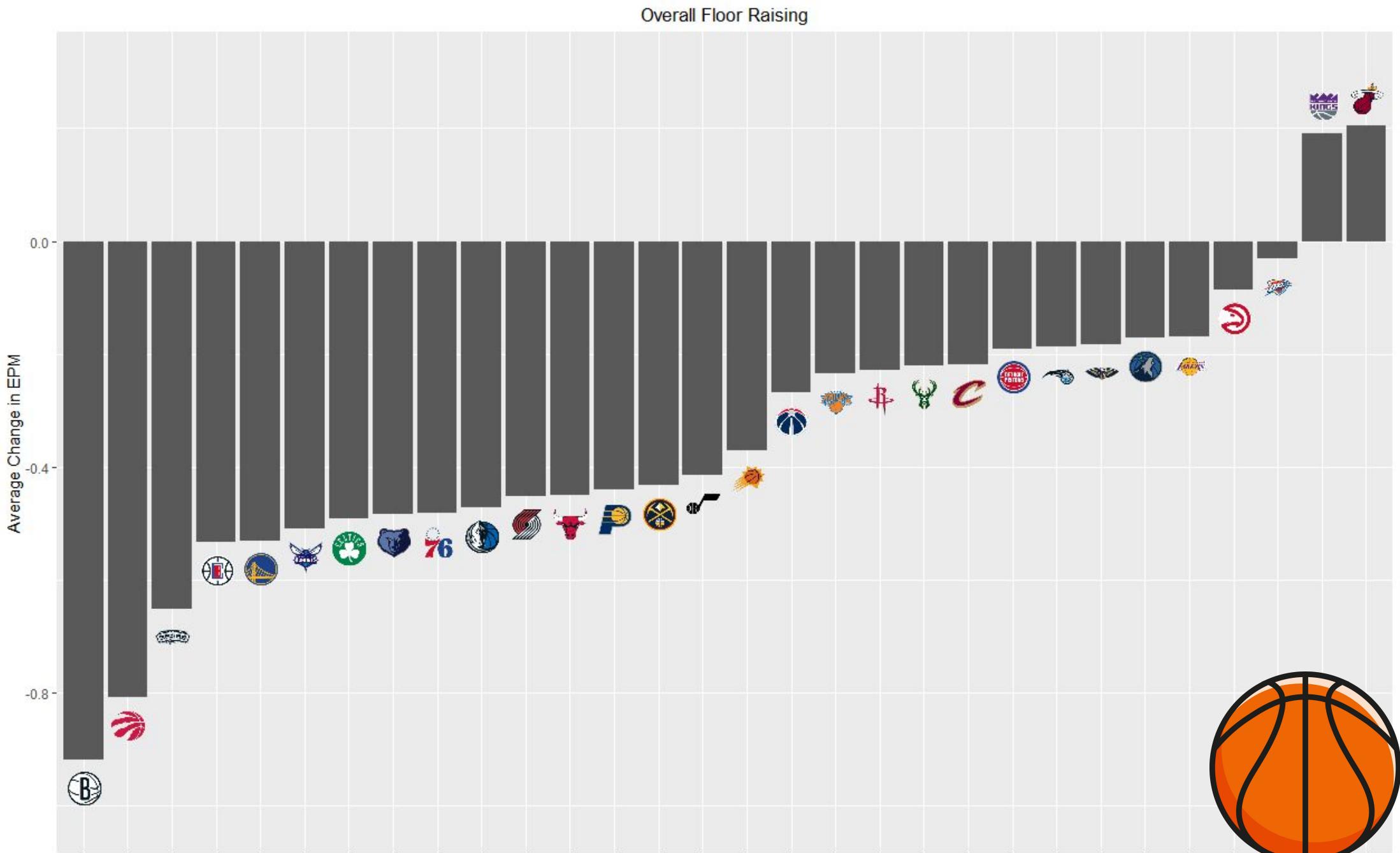


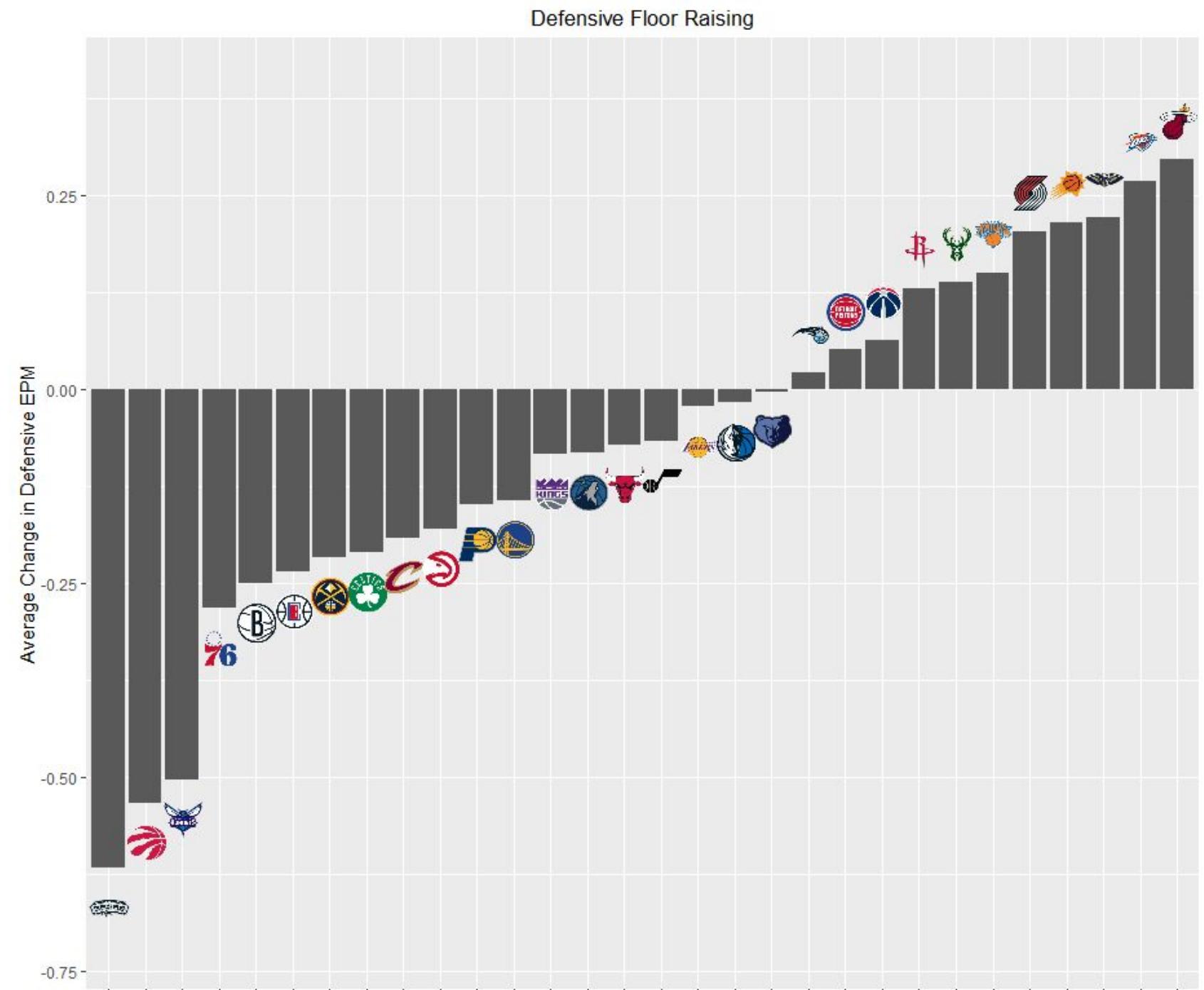
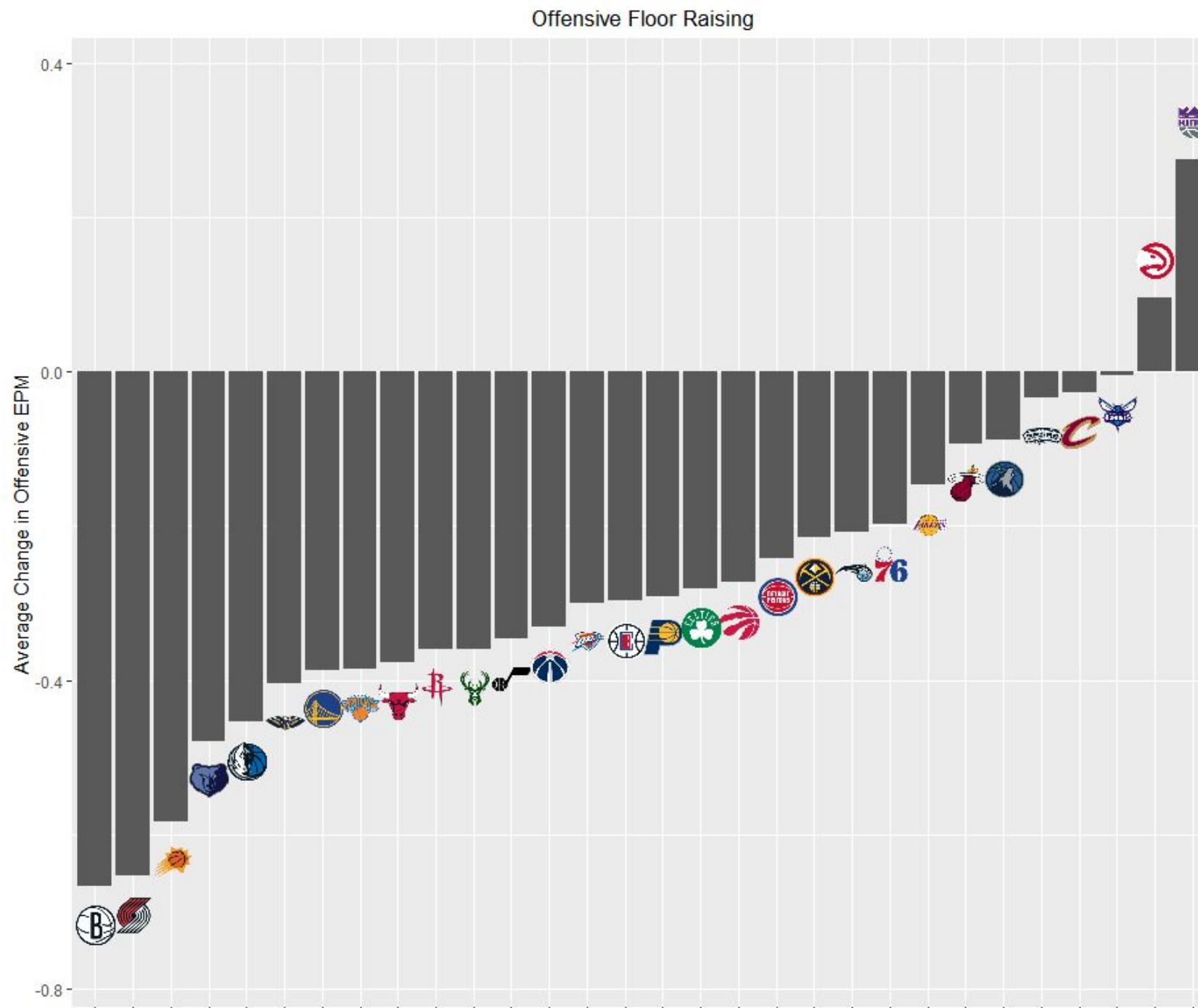
Defensive Floor Raising



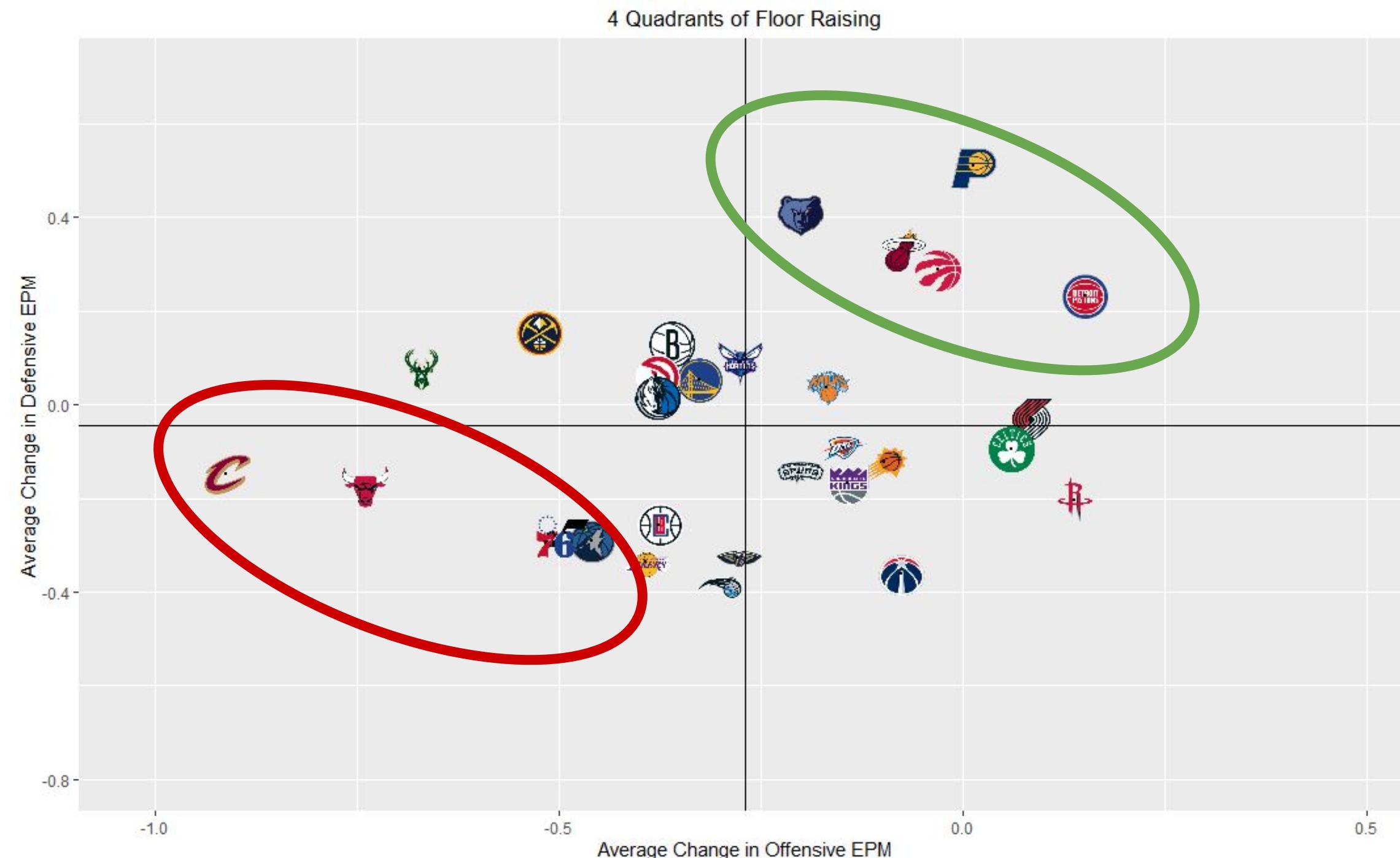
Change in EPM for Old Teams

**Lower values
indicate a
player's level of
play worsened
after they left**





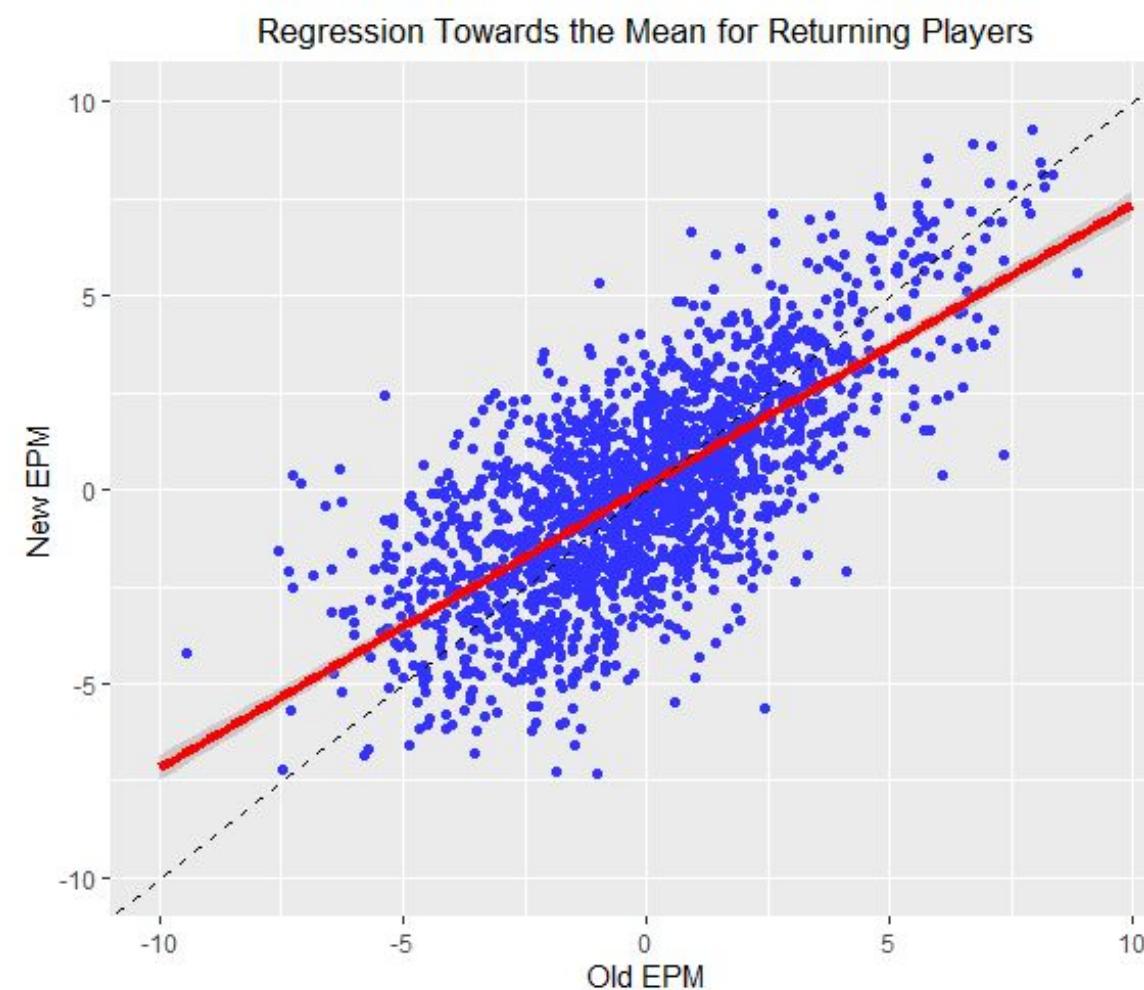
Best Floor Raising Teams



These trends are
not caused by
intuitive
anecdotal
evidence!

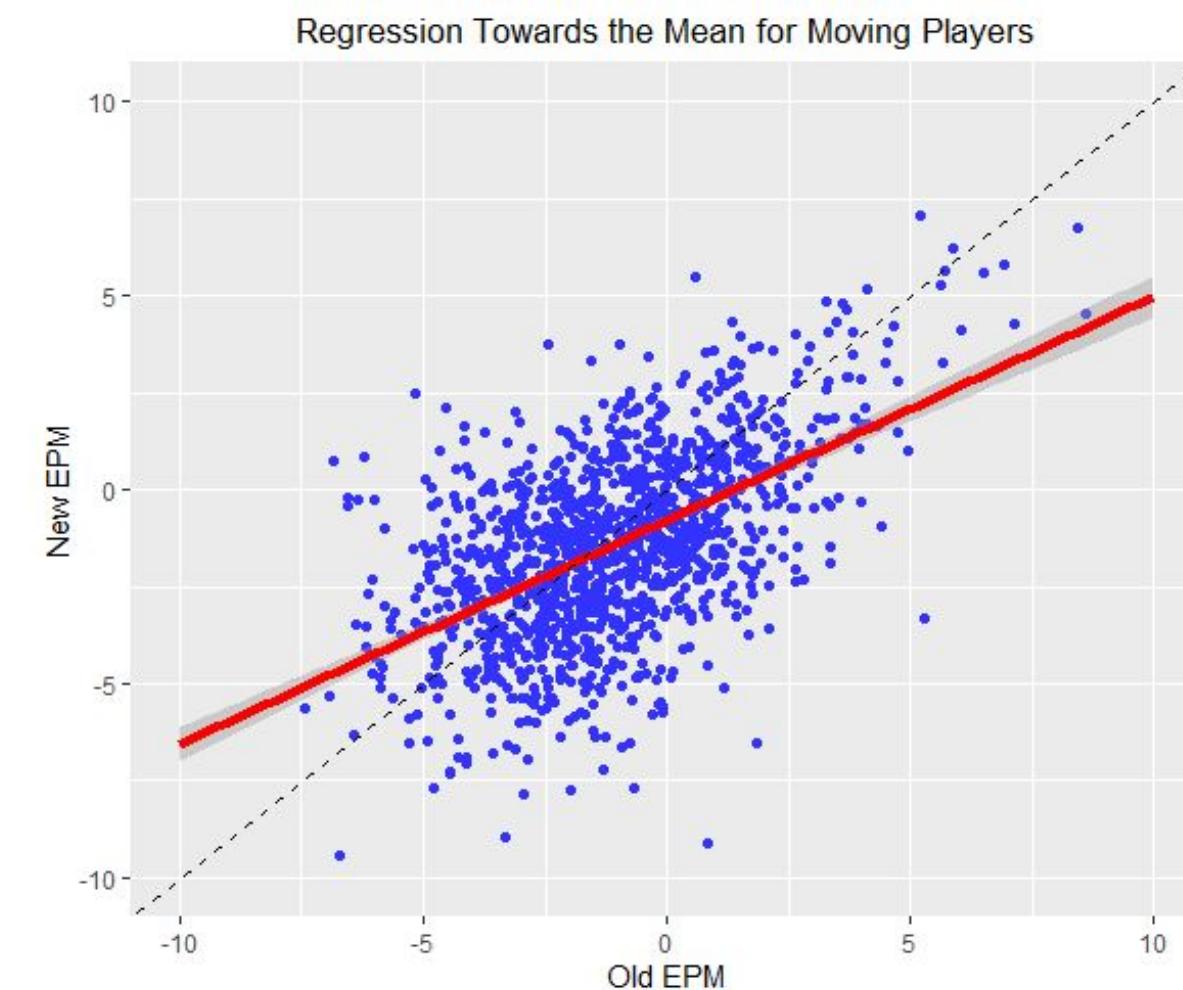


Regression Towards the Mean



Coefficients:

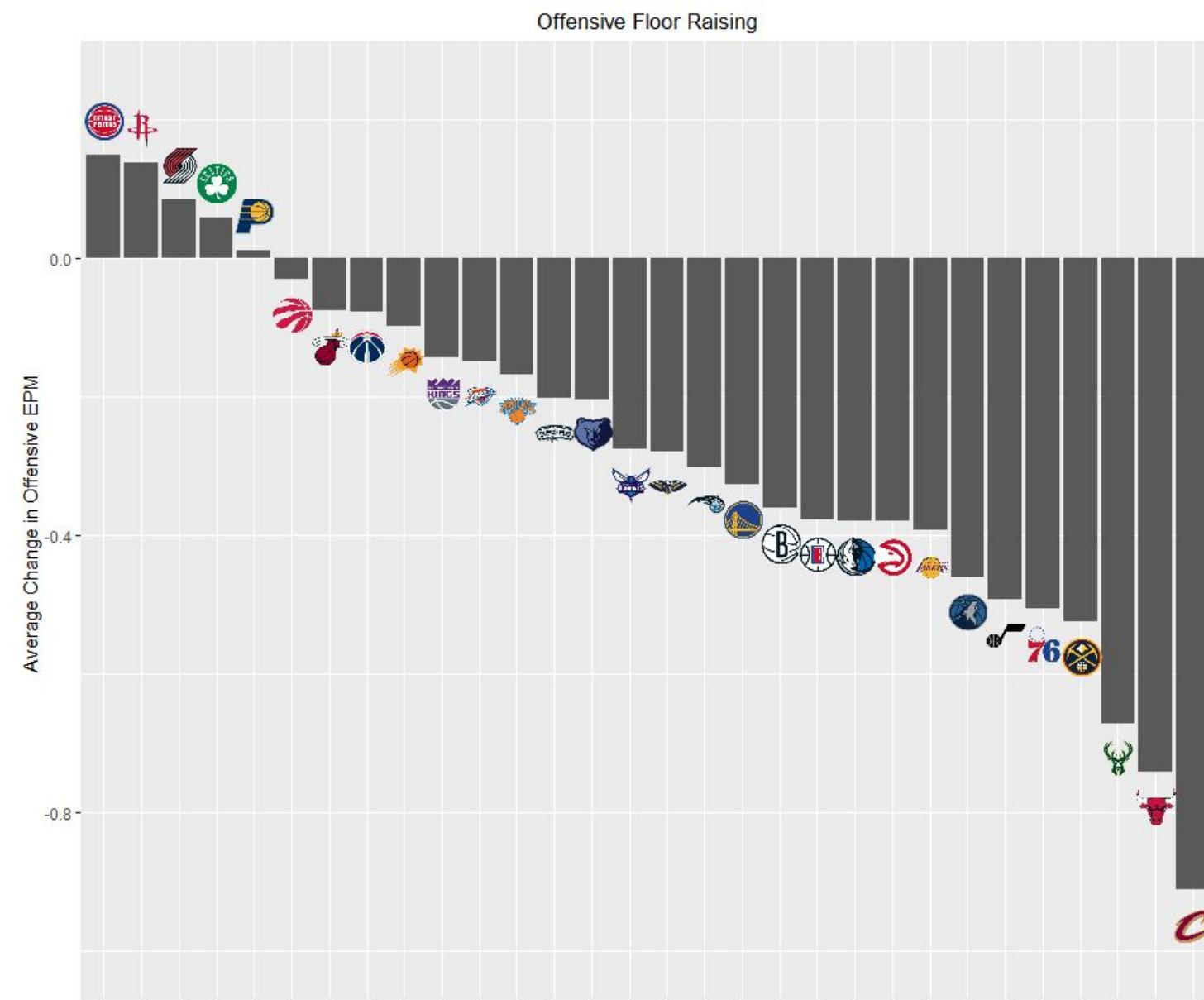
	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.08756	0.04500	1.946	0.0518 .
old.epm	0.73050	0.01629	44.857	<2e-16 ***



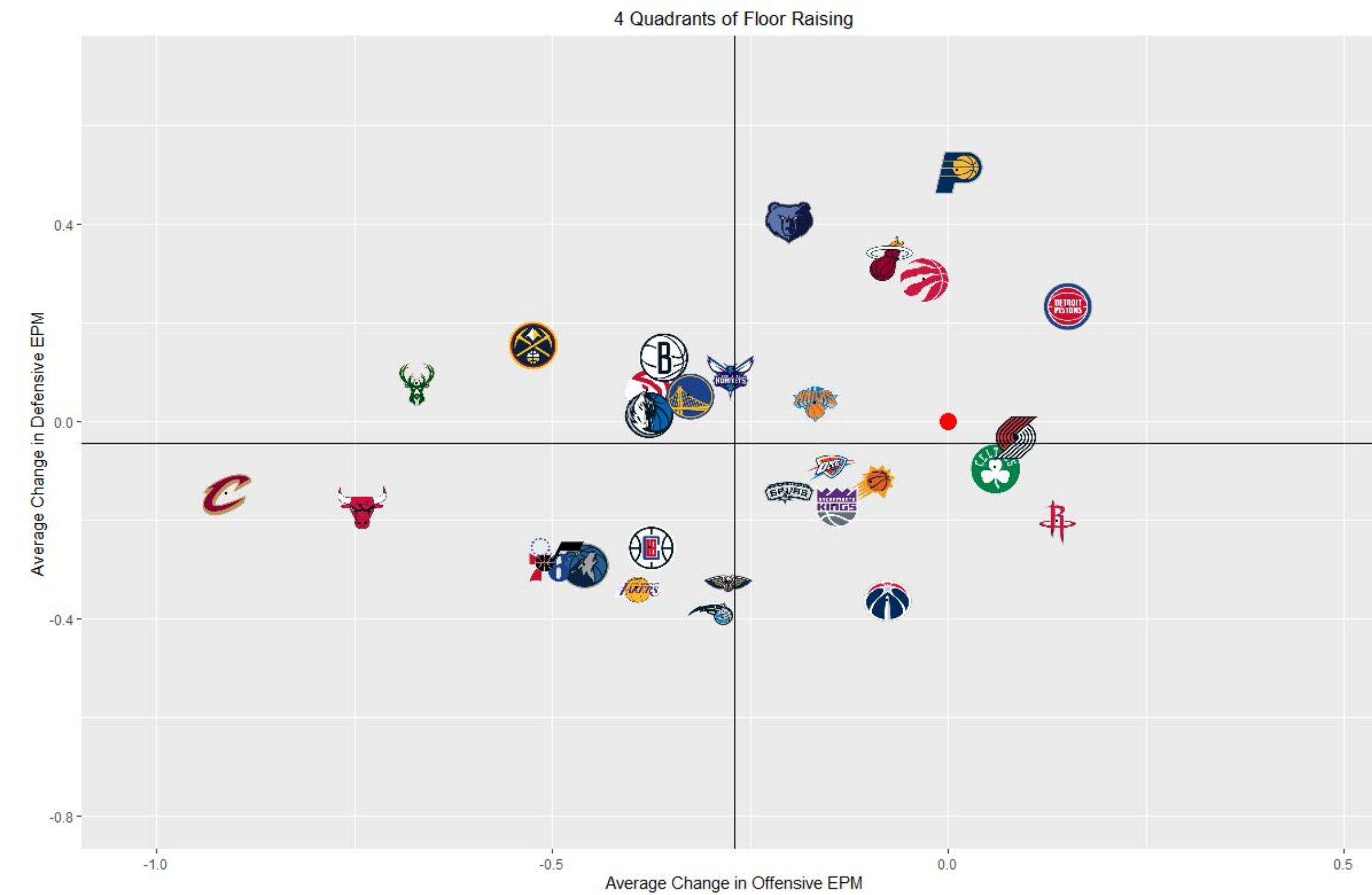
Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.80457	0.06309	-12.75	<2e-16 ***
old.epm	0.57585	0.02467	23.34	<2e-16 ***

Defense is More Sustainable



Players Worsen When Moving Teams



Best Player Increases

Overall



Khyri Thomas
2020 DET → 2021 HOU
+7.64



Jalen Smith
2021 PHX → 2022 IND
+7.59



Wade Baldwin IV
2017 MEM → 2018 POR
+7.05



PJ Tucker
2021 MIL → 2022 MIA
+6.64



Kadeem Allen
2018 BOS → 2019 NYK
+6.32

Offense



Wade Baldwin IV
2017 WAS → 2018 POR
+5.22



Trey Burke
2017 WAS → 2018 NYK
+5.09



Dewayne Dedmon
2020 ATL → 2021 MIA
+4.91



Bruno Fernando
2021 ATL → 2022 HOU
+4.80



Kadeem Allen
2018 BOS → 2019 NYK
+4.72

Defense



Chris Silva
2020 MIA → 2021 SAC
+4.63



JaKarr Sampson
2019 CHI → 2020 IND
+4.59



Gorgui Dieng
2019 MIN → 2020 MEM
+4.00



Skal Labissiere
2019 POR → 2020 ATL
+3.87



MarShon Brooks
2018 MEM → 2019 CHI
+3.77

Worst Player Decreases

Overall



Wade Baldwin IV
2018 POR → 2019 CLE
-9.95



Isaiah Thomas
2017 BOS → 2018 LAL
-8.57



Shaquille Harrison
2020 CHI → 2021 DEN
-8.35



Jeremiah Martin
2020 BKN → 2021 CLE
-6.99



Trevor Ariza
2021 MIA → 2022 LAL
-6.28

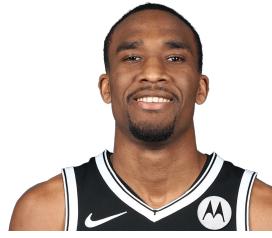
Offense



Isaiah Thomas
2017 BOS → 2018 LAL
-8.18



Ty Lawson
2015 DEN → 2016 IND
-6.23



Jeremiah Martin
2020 BKN → 2021 CLE
-6.20



Tyreke Evans
2018 MEM → 2019 IND
-5.51



Tony Wroten
2015 PHI → 2016 NYK
-5.48

Defense



Chris Kaman
2014 LAL → 2015 POR
-4.89



Boban Marjanovic
2019 PHI → 2020 DAL
-4.83



Tyson Chandler
2019 LAL → 2020 HOU
-4.82



Dewayne Dedmon
2020 ATL → 2021 MIA
-4.53



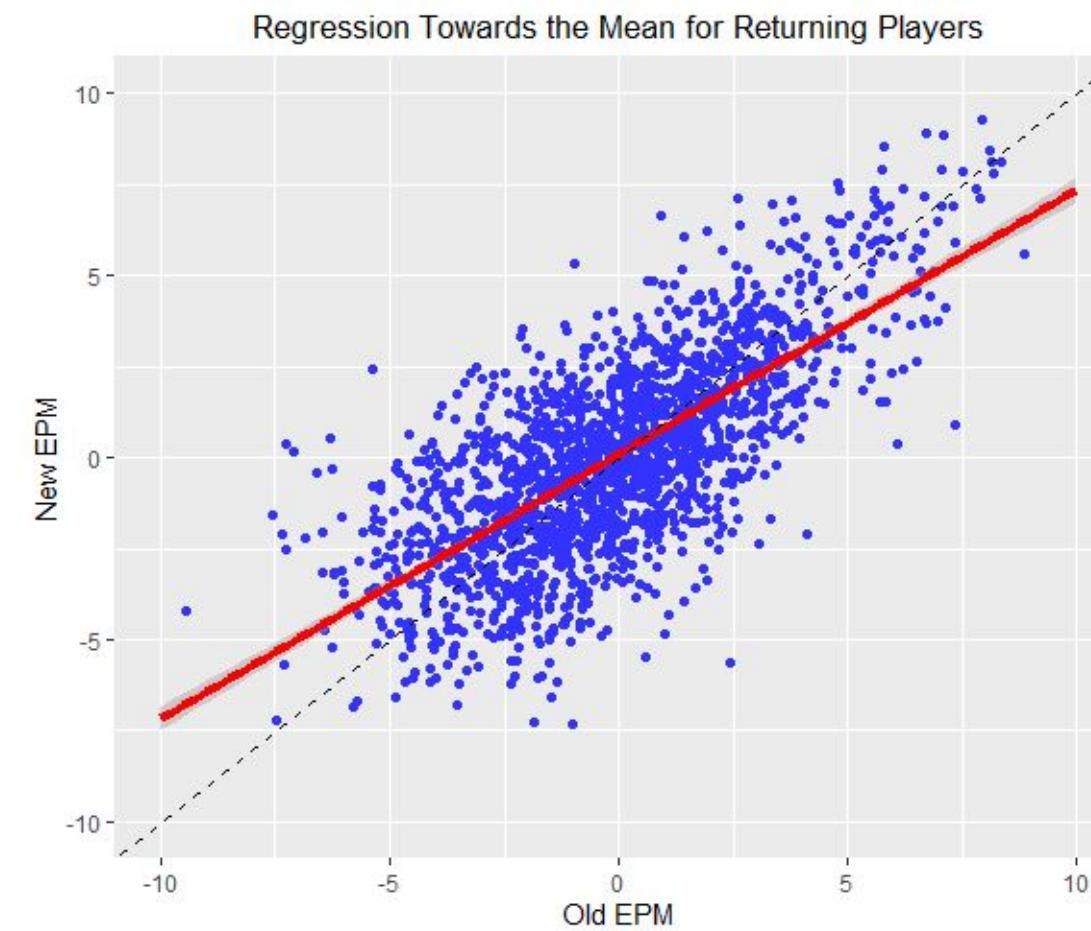
Wade Baldwin IV
2018 POR → 2019 CLE
-4.49

Key Takeaways

- Players tend to regress towards the mean, though players that move teams are more prone to this trend
- Players often get worse when moving teams
 - This is especially true for good players
 - Crazy stat: every single team has an average decrease in EPM when acquiring a new player with a positive EPM
- Maintaining a positive defensive EPM when transferring teams is easier than maintaining a positive offensive EPM
 - 78% of the time, a positive offensive EPM player sees a decrease



Next Steps

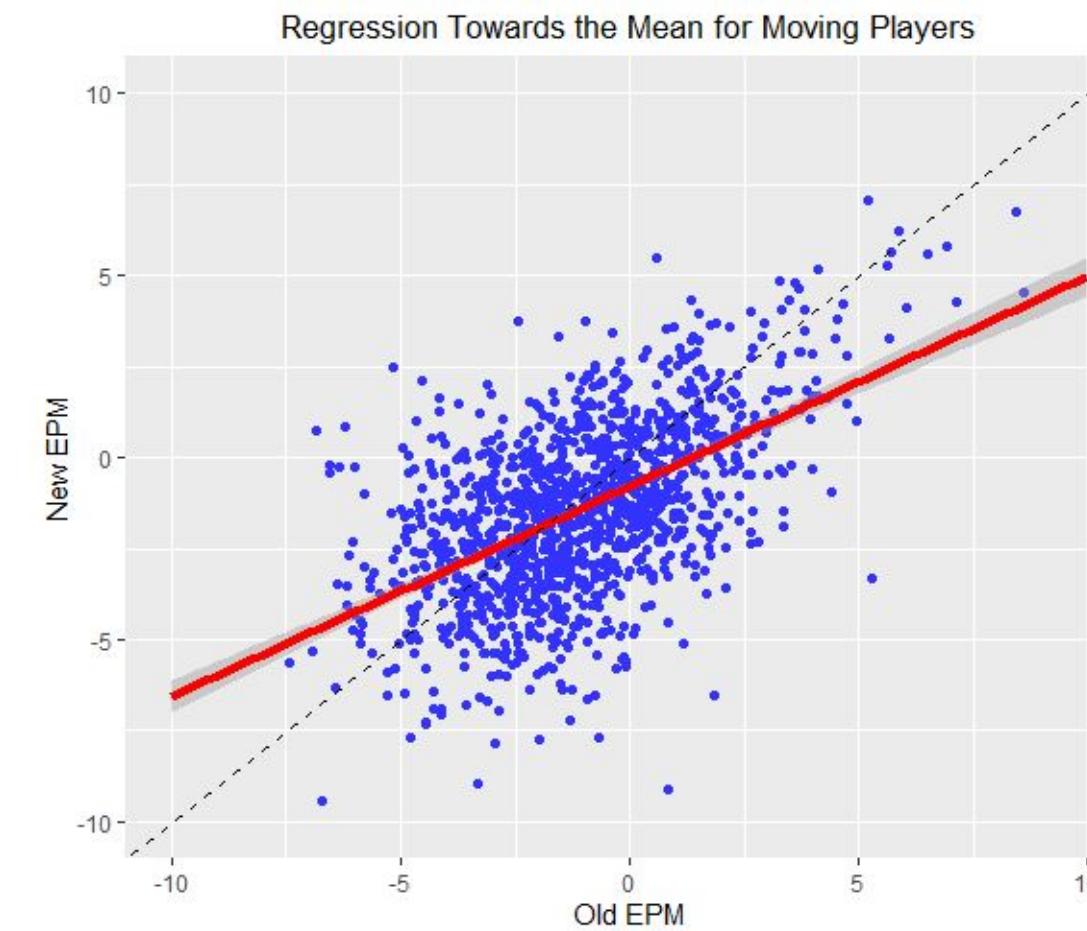


Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.08756	0.04500	1.946	0.0518 .
old.epm	0.73050	0.01629	44.857	<2e-16 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.913 on 1810 degrees of freedom
 Multiple R-squared: 0.5264, Adjusted R-squared: 0.5262
 F-statistic: 2012 on 1 and 1810 DF, p-value: < 2.2e-16



Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.80457	0.06309	-12.75	<2e-16 ***
old.epm	0.57585	0.02467	23.34	<2e-16 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.99 on 1229 degrees of freedom
 Multiple R-squared: 0.3072, Adjusted R-squared: 0.3066
 F-statistic: 544.9 on 1 and 1229 DF, p-value: < 2.2e-16



Next Steps

- Star-centric analysis
 - How do role players around LeBron, Jokic, Steph stack up?
 - Who benefits most from blockbuster trades?
 - Are trades/acquisitions even worth it if they turn out poorly so often?
- Deeper dive into any specific team
 - Break down into any subset of the data, even down to the individual level
 - Hypothesize explanations for these outcomes



Thank You

