CARNEGIE MELLON
SPORTS ANALYTICS CENTER

College Football Volatility:
A Bayesian state-space model of the transfer portal and NIL impact

Ron Yurko (joint work w/ Luke Benz)

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Assistant Teaching Professor
Director of Carnegie Mellon Sports Analytics Center (stat.cmu.edu/cmsac)
Department of Statistics & Data Science, Carnegie Mellon University

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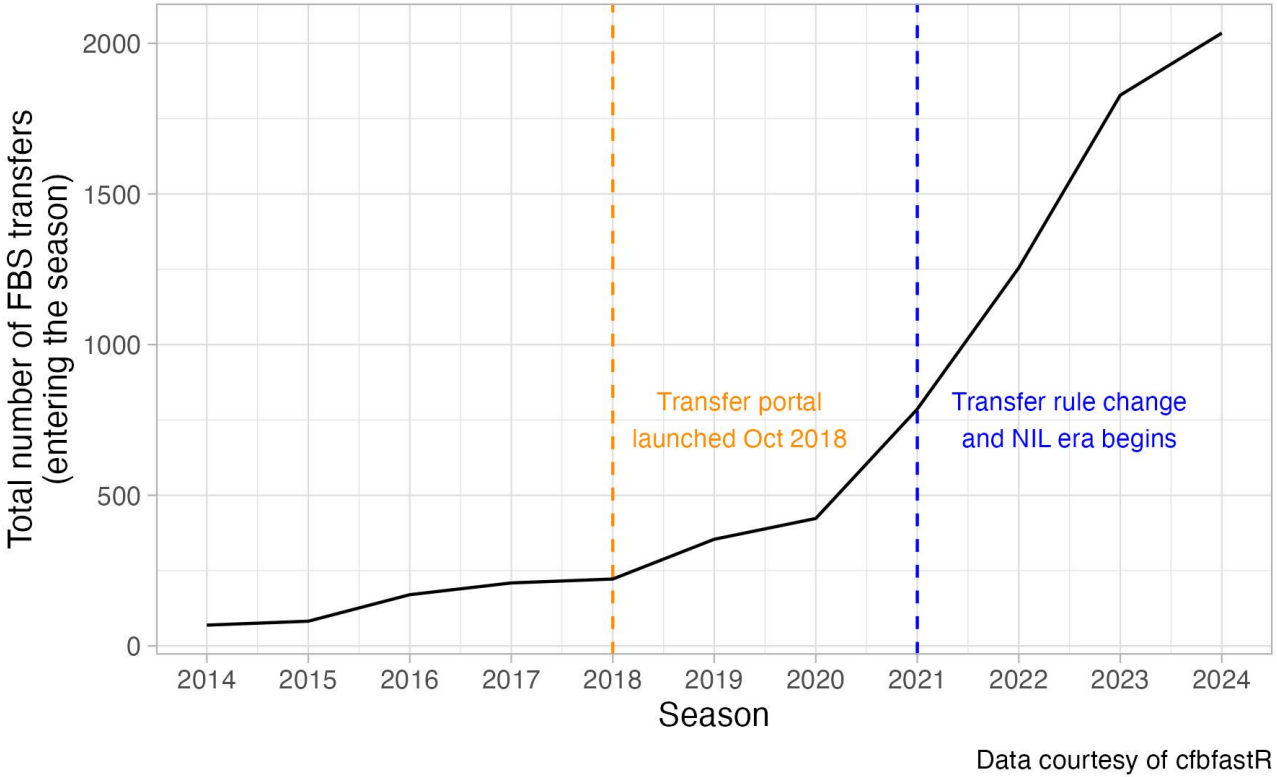
2020 - *Don’t need to remind you*

2021 - **Student athletes allowed to transfer once without sitting out a year**

- Conference realignment madness announcements
- **NIL era begins!** Supreme Court ruling in NCAA vs Alston

2024 - **Immediate eligibility no matter how many times athletes transferred**

Welcome to the era of perpetual free-agency



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“Every player is technically a transfer. We just signed a whole class of guys transferring from high school…”

- Clemson HC Dabo Swinney on **taking 0 transfers in 2024**

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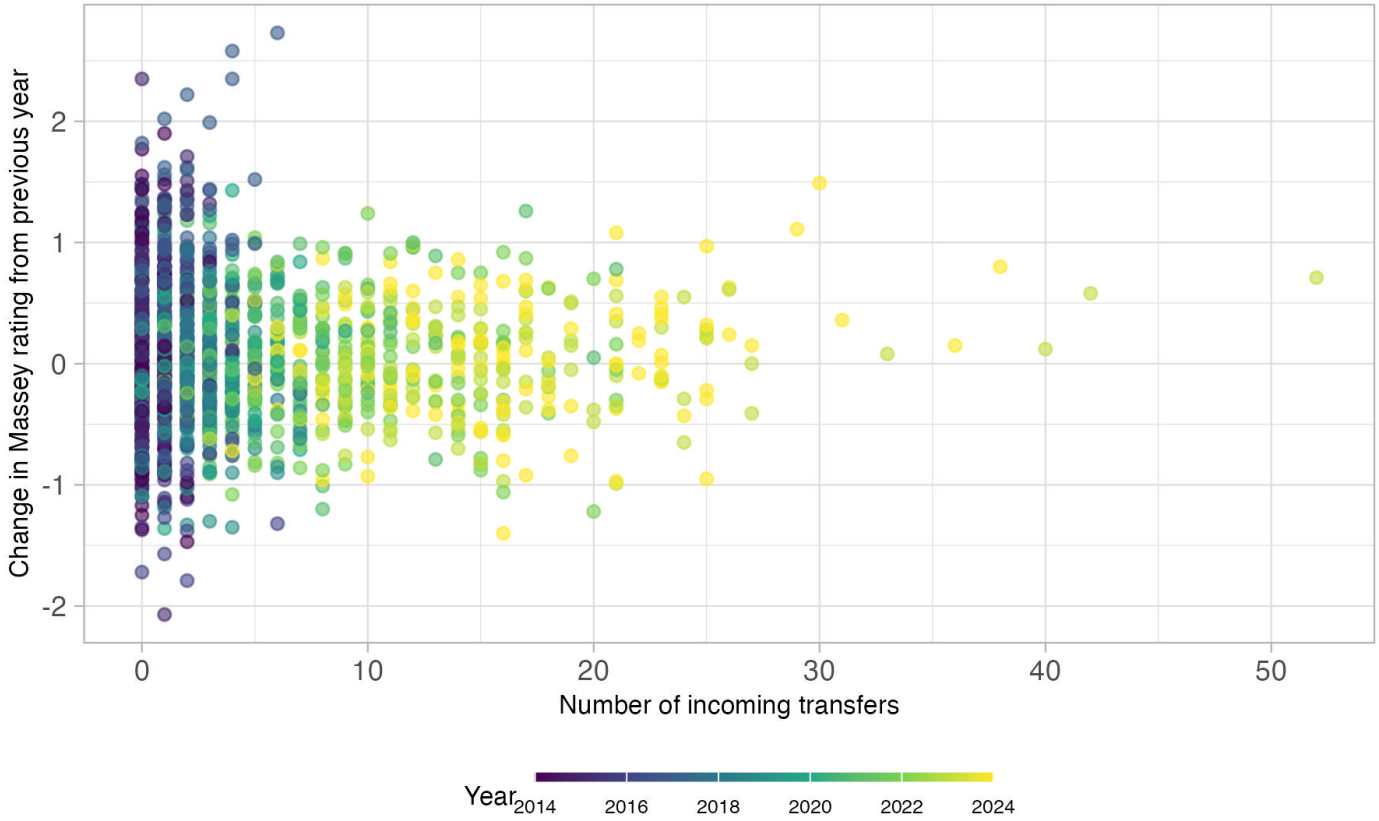
Indiana - Curt Cignetti: 4th most transfers with 30 in 2024, made playoff!

More transfers leads to… different variance?



Modeling team ratings - Glickman & Stern (1998, 2017)

Let Y_{ijt} be the score differential in a game between teams *i* and *j* during year *t*:

$$Y_{ijt} \sim N(\overbrace{\mu_{ijt}}^{\text{game mean}}, \overbrace{\sigma^2}^{\text{game-level variance}})$$

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Autoregressive model for team ratings with constant innovation variance τ^2:

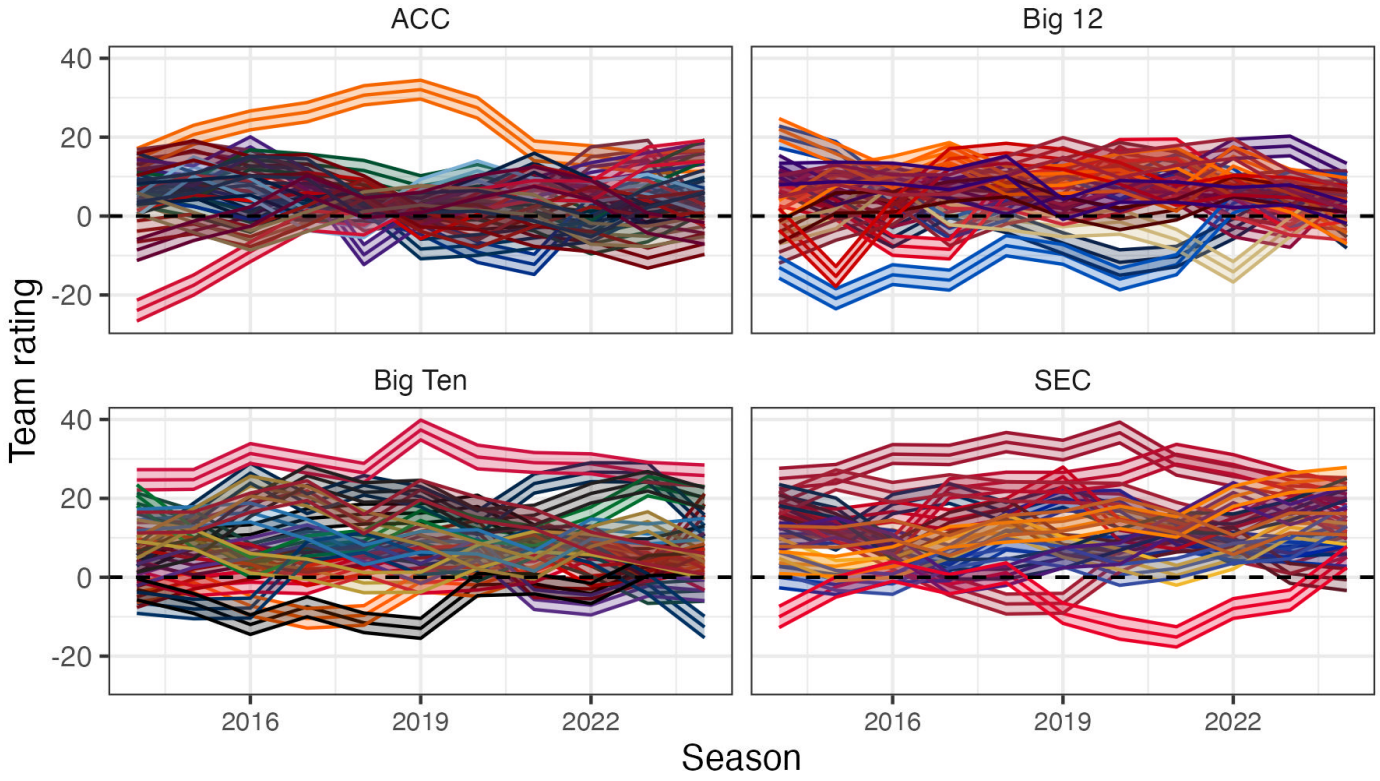
$$\theta_{i(t+1)} \sim N(\gamma \cdot \theta_{i(t)}, \tau^2), \text{ where } 0 < \gamma < 1$$

$$\theta_{it_0} \sim N(0, \sigma^2_{team})$$

Data - FBS games in playoff era (2014-2024)

- Gathered all data using the cfbfastR package (College Football Data API)
- Focus on 9003 regular season NCAA Division I Football Bowl Subdivision (FBS) games in playoff era (2014-2024) - highest level of college football
- Did NOT include bowl games and playoffs due to players sitting out
- Treated all NCAA Division I Football Championship Subdivision (FCS) teams as one ‘FCS team’ - second highest level of college football
- Gathered roster information about each team, counting the number of incoming transfers entering a season (including for different position groups)

Classic model results across major conferences



Posterior median team ratings w/ 50% credible intervals

Stochastic Volatility Extension - Glickman (2001)

Is the constant innovation variance assumption appropriate in this crazy era?

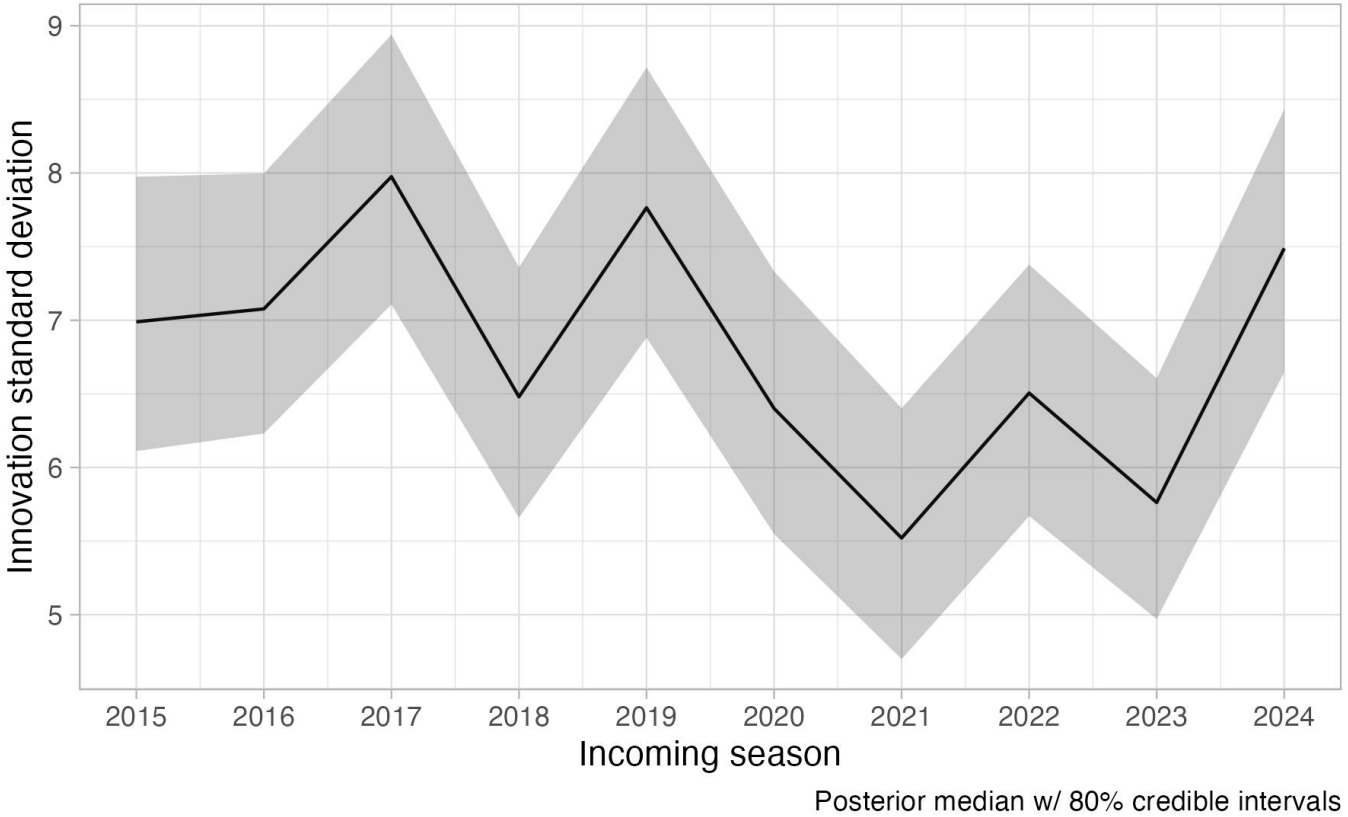
Can consider a dynamic innovation variance instead:

$$\theta_{i(t+1)} \sim N(\gamma \cdot \theta_{i(t)}, \tau^2_{(t+1)})$$

$$\log \tau^2_{(t+1)} \sim N(\log \tau^2_{(t)}, \sigma^2_\tau)$$

$$\log \tau^2_{(t_0)} \sim N(0, \sigma^2_\tau)$$

Innovation variance over time, but constant for each team



Model innovation variance as function of transfers + NIL era

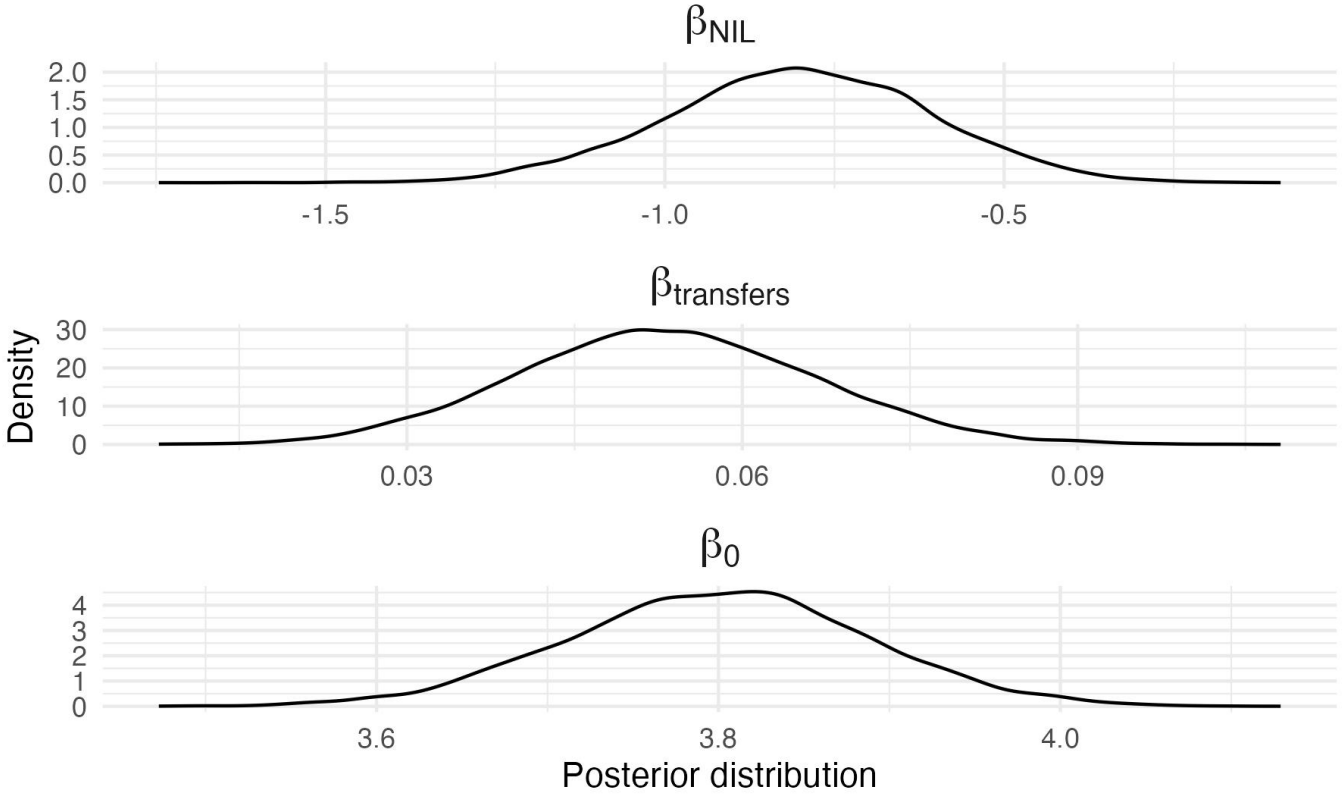
Allow the innovation variance to vary between teams based on transfers and changes to transfer portal + NIL rule (beginning in 2021)

$$\log \tau^2_{i(t)} = \beta_0 + \beta_{\text{NIL}} \cdot 1(t \in \text{NIL era}) + \beta_{\text{transfers}} \cdot \#\ \text{transfers}_{i(t)}$$

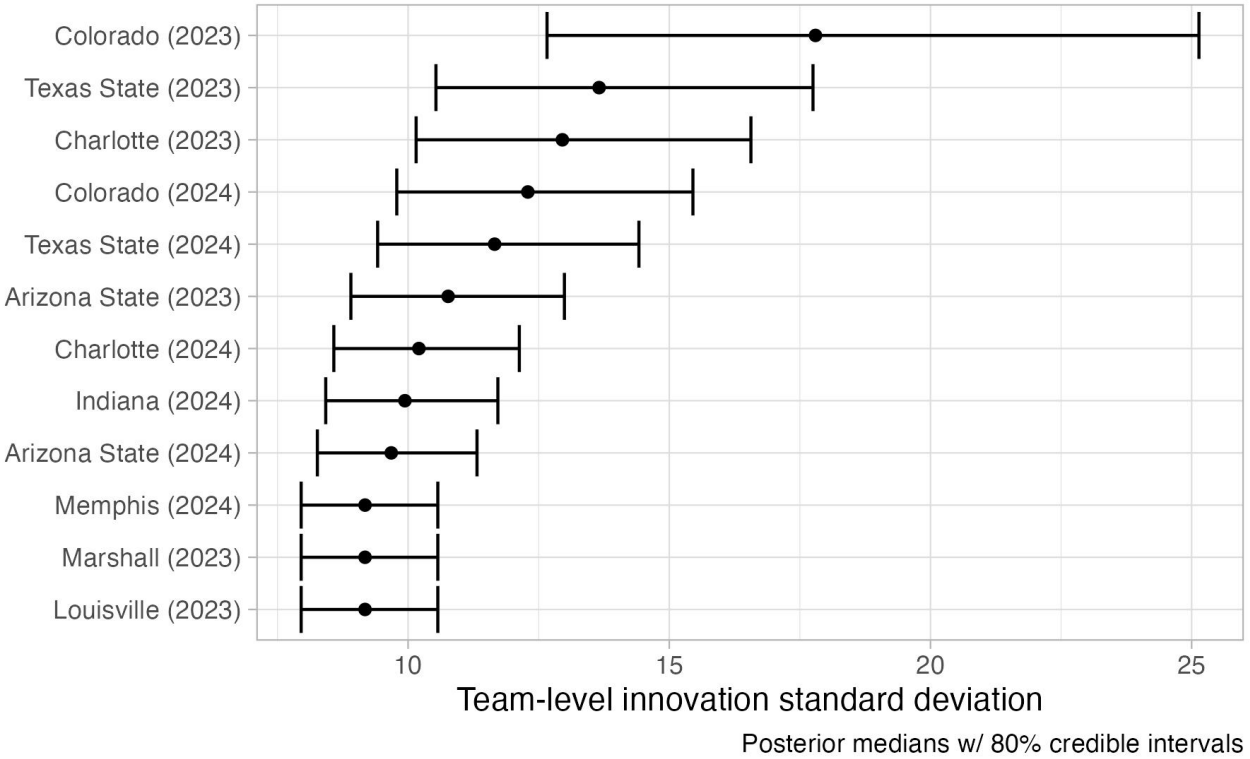
Innovation variance entering season t is a function of:

- Indicator denoting if season t is in the NIL era (ie since 2021)
- Number of incoming transfers for team i entering season t
  - i.e., Counting number of new players transferring to team
- For FCS: use average transfer counts across FCS teams

Lower variance in NIL era, but higher variance with transfers



Innovation variance leaderboard



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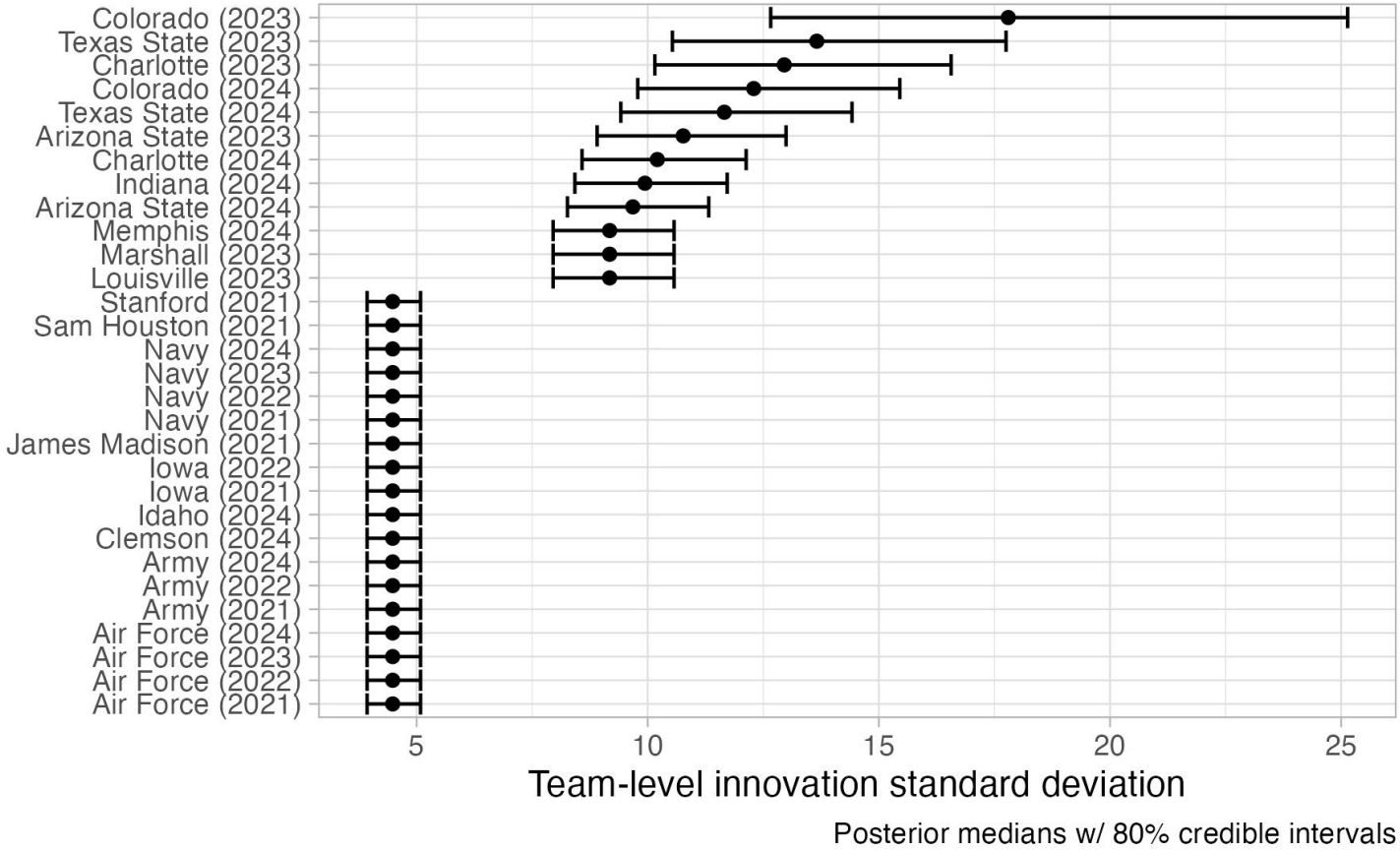
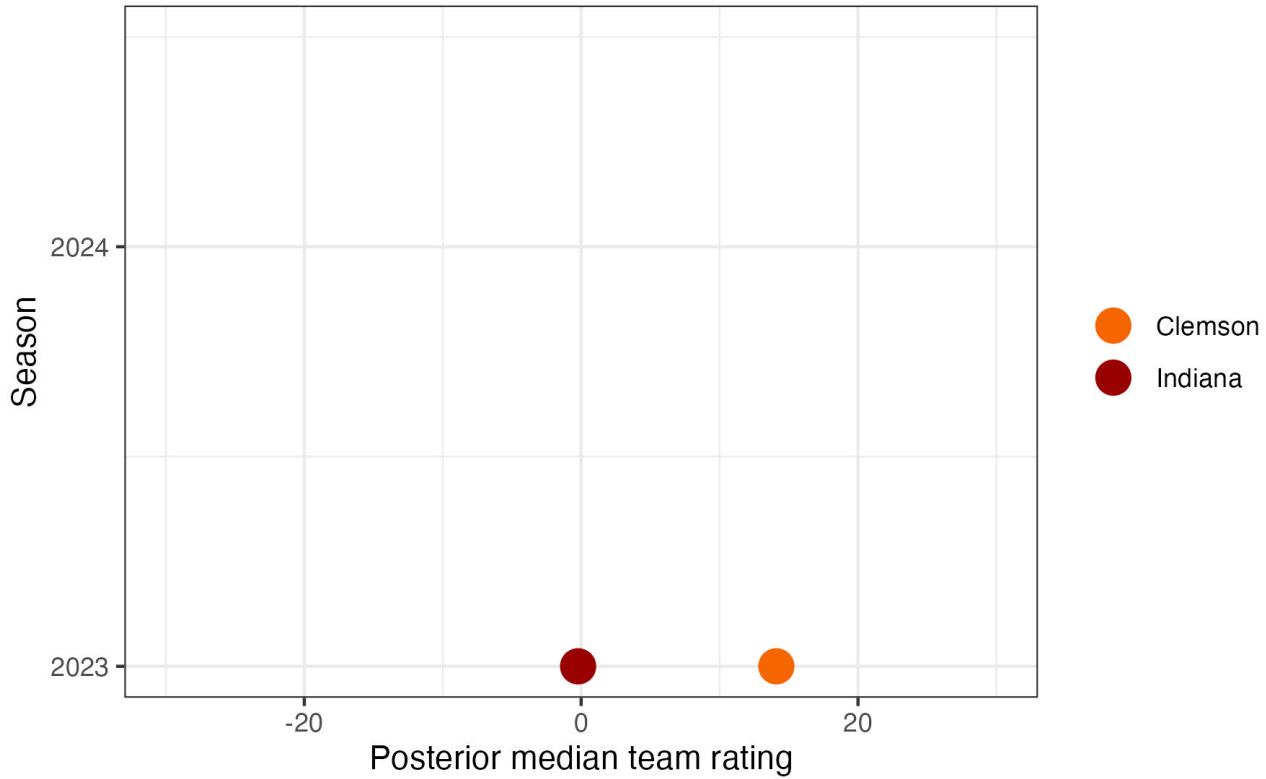


Posterior medians w/ 80% credible intervals

Understanding the impact of innovation variance



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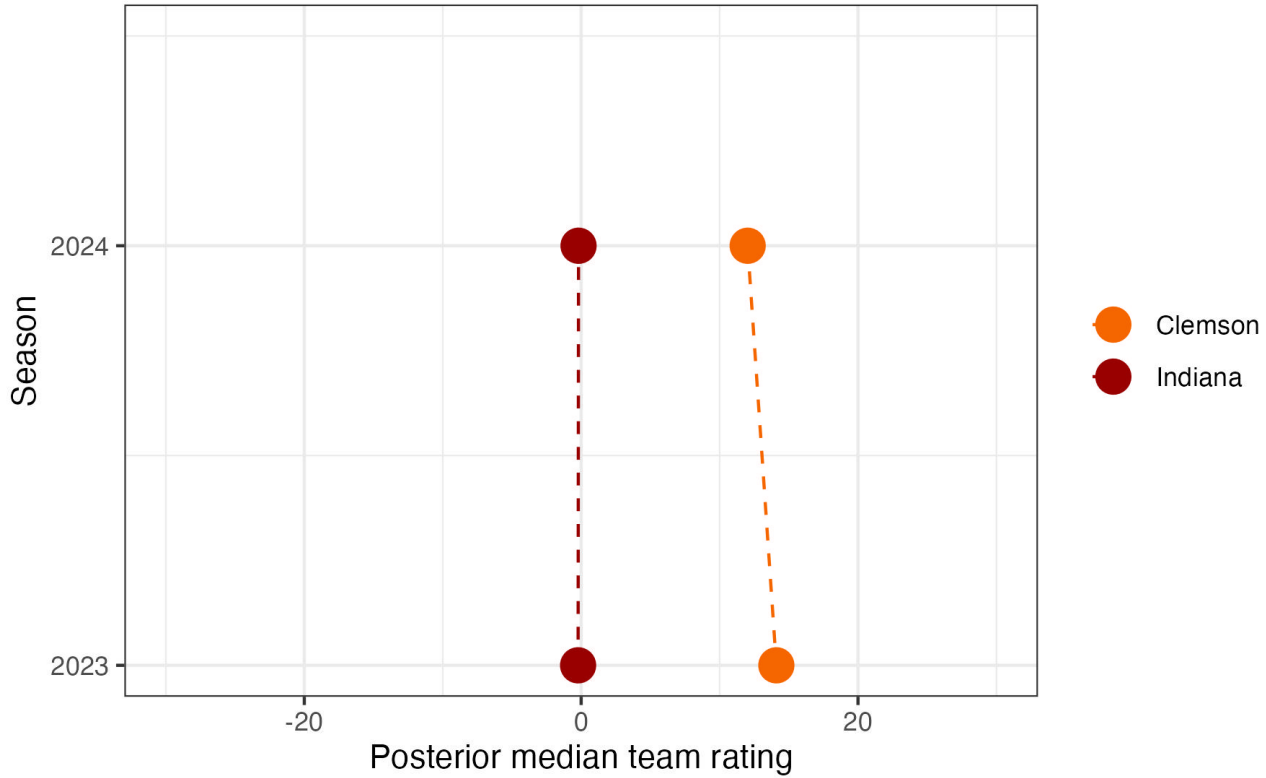

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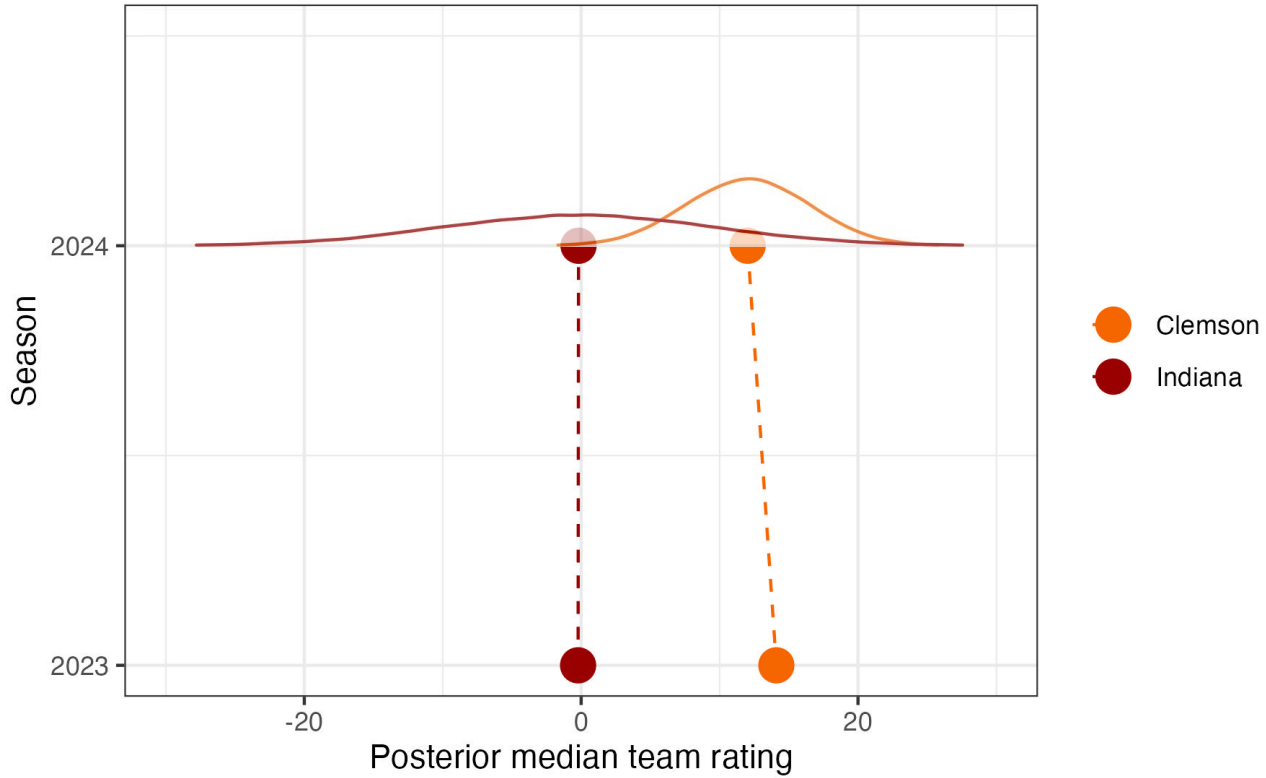
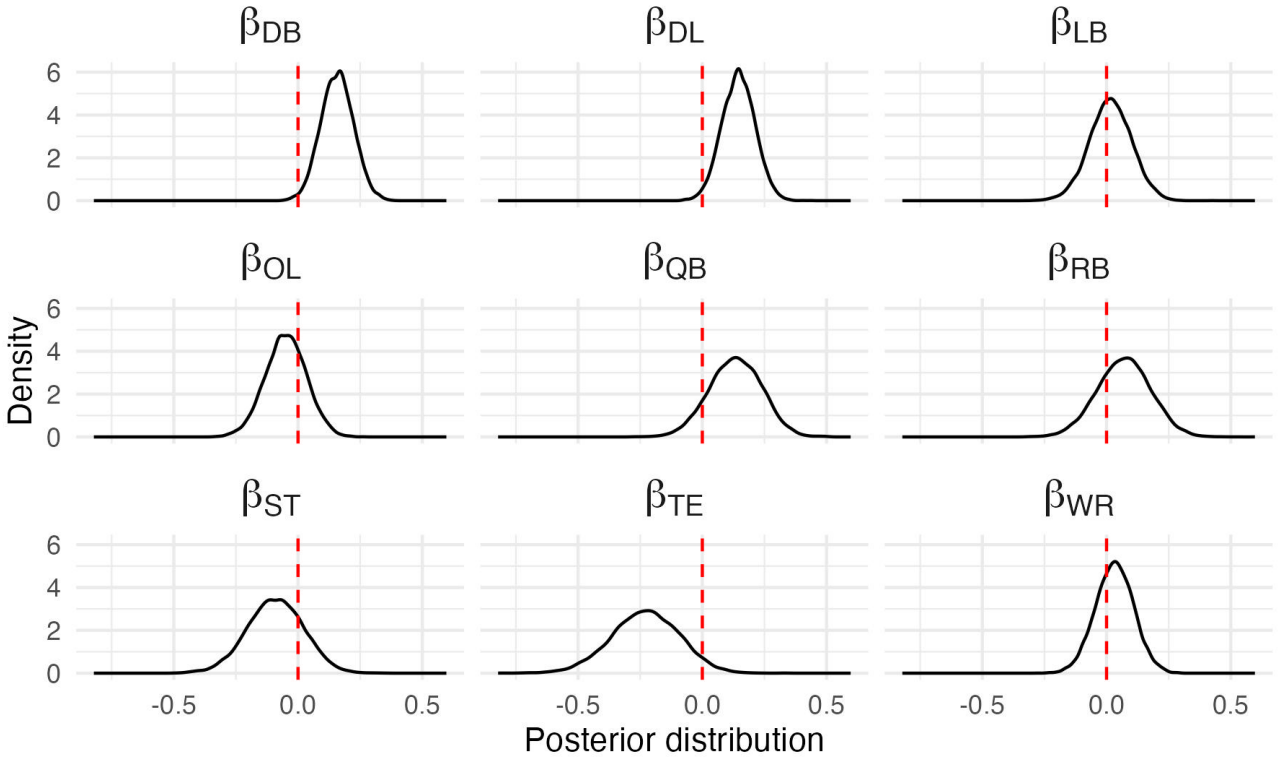


What about positional differences in transfers?

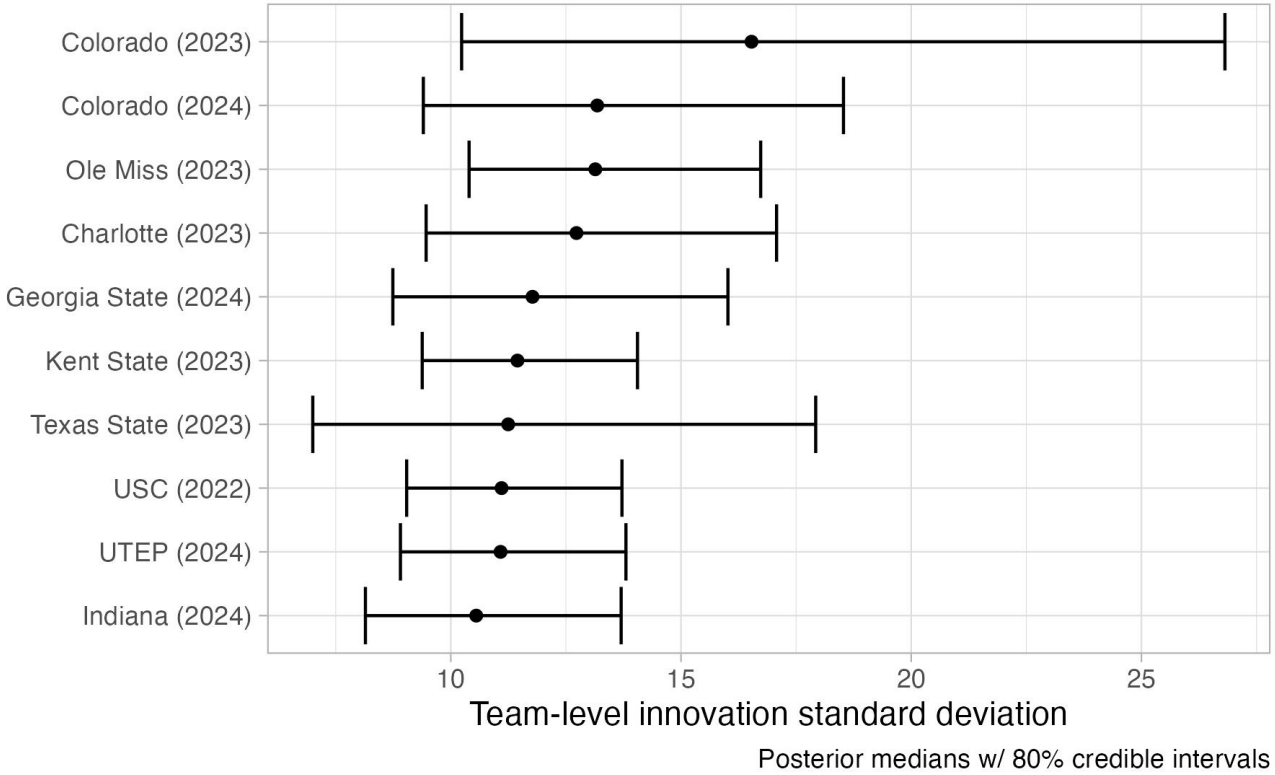
$$\log \tau^2_{i(t)} = \beta_0 + \beta_{\text{NIL}} \cdot 1(t \in \text{NIL era}) + \sum_{p \in \text{positions}} \beta_p \cdot \#\text{transfers}_{p,i(t)}$$

$$\text{positions} = \{\text{QB}, \text{RB}, \text{WR}, \text{TE}, \text{OL}, \text{DL}, \text{DB}, \text{LB}, \text{ST}\}$$

Pass defense transfers are associated with higher variance?



Variance leaderboard based on transfer positions



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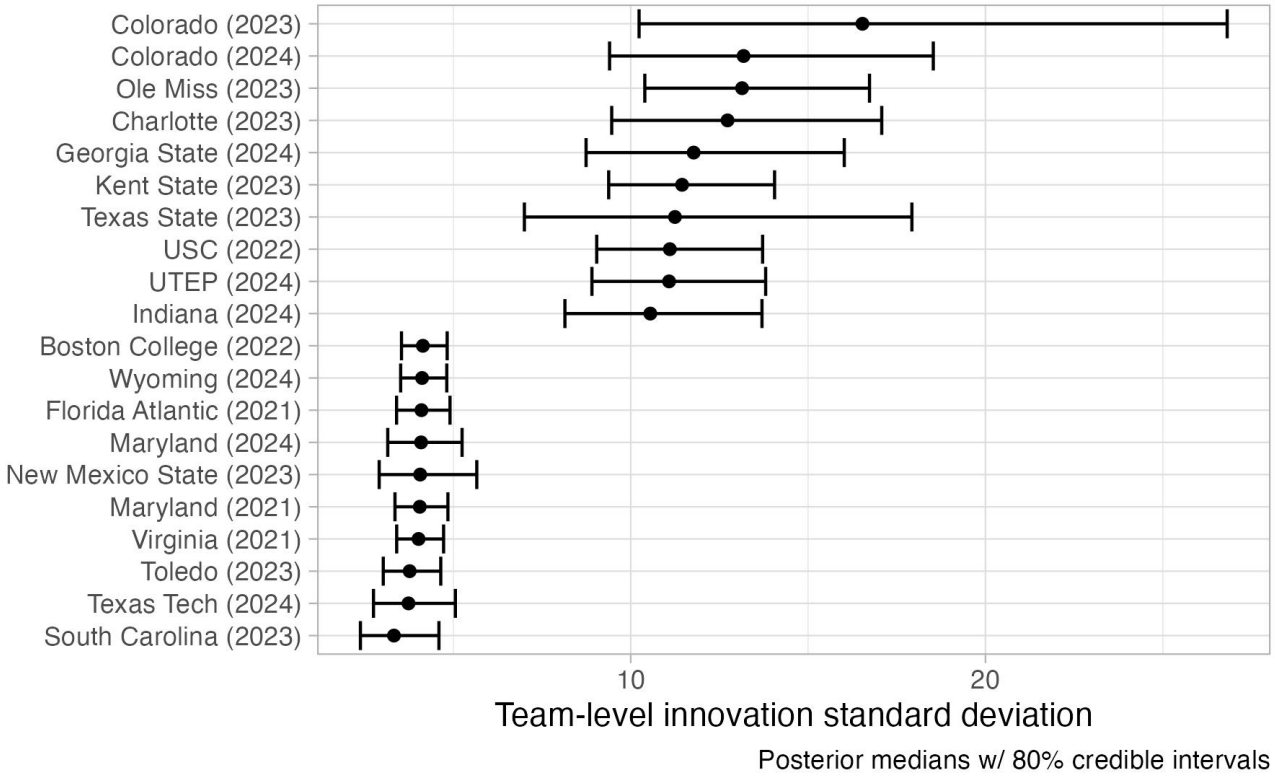

How do these models compare to each other?

Posterior predictive comparison for holdout performance in 2023 and 2024

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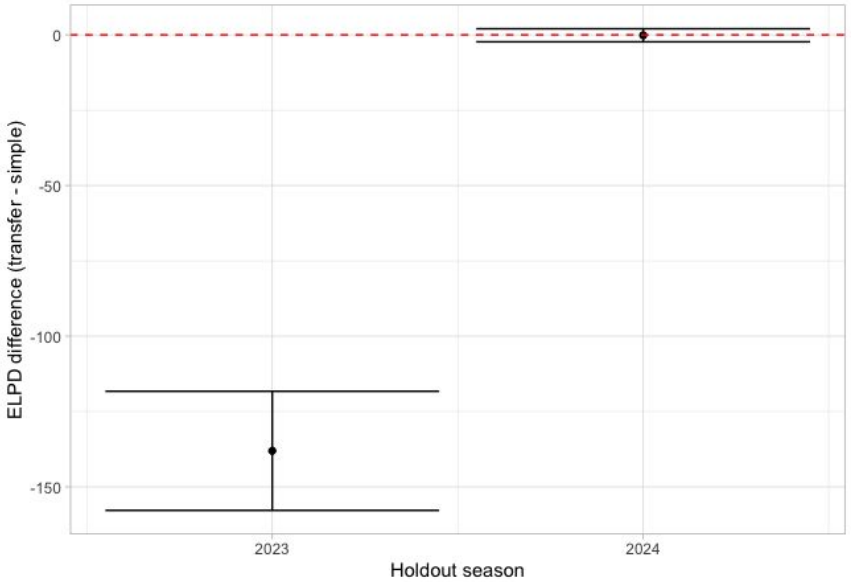

Best game-level predictions (RMSE and ELPD)

- **Glickman & Stern (1998) wins!**
- Transfer model (w/o positions) is next best in performance, w/ comparable results in 2024
- Stochastic volatility extension (2001) is by far the worst of the four

Best in-sample fit during NIL era (WAIC):

- **Transfer model (w/o positions)**

Discussion and Limitations

Evidence indicating that this is a new era of uncertainty in college football

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Several limitations…

- Obvious relationship between new coach and high number of transfers
- What about the selection bias displayed by schools in transfers?
  - e.g., does Ohio State get fewer but better transfers?
- Completely ignored recruiting in this study, **and do not have access to NIL amounts**
- Only considered modeling the variance, but maybe there is a change in the autoregressive parameter instead? **We're completely ignored the quality of the transferring players!**

Key point: we are working with very limited data in the NIL era! Only started in 2021…

What about 2025???

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Purdue	2024: 1-11	->	2025: 2-2
UNLV	11-3	->	4-0
WVU	6-7	->	2-2
UNC	6-7	->	2-2
WKY	8-6	->	3-1
Oklahoma State	3-9	->	1-2

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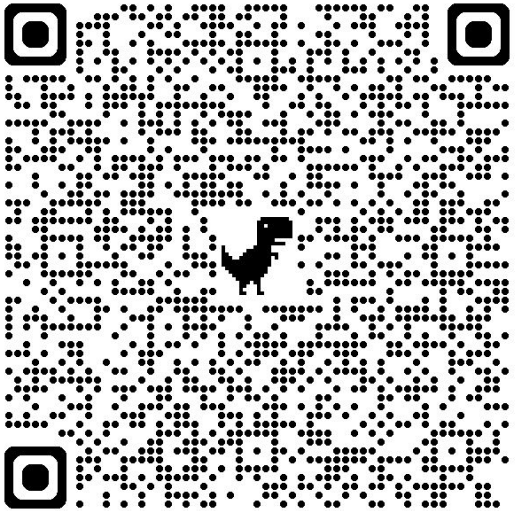
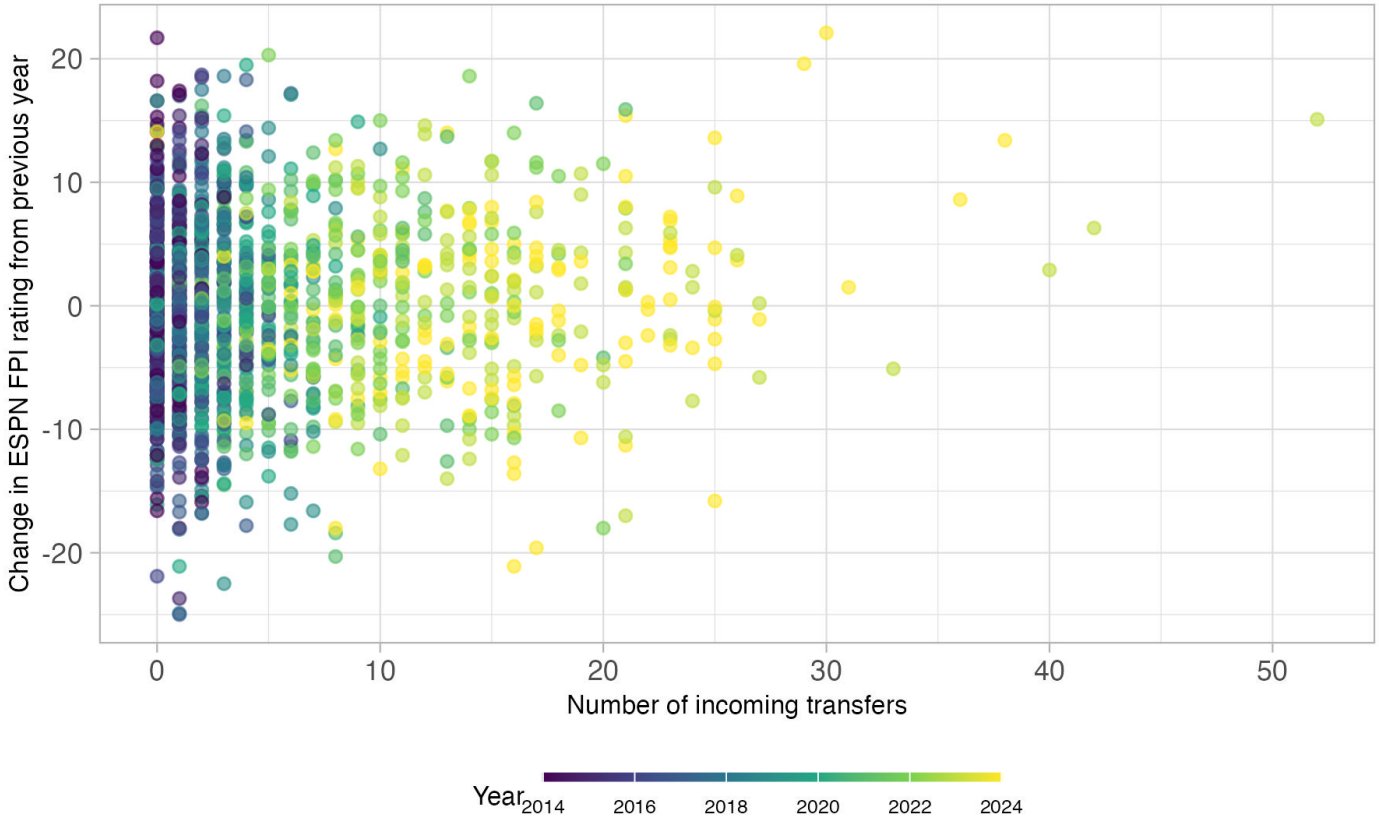
Thanks to co-author Luke Benz, as well as Tom Bliss for expertise!

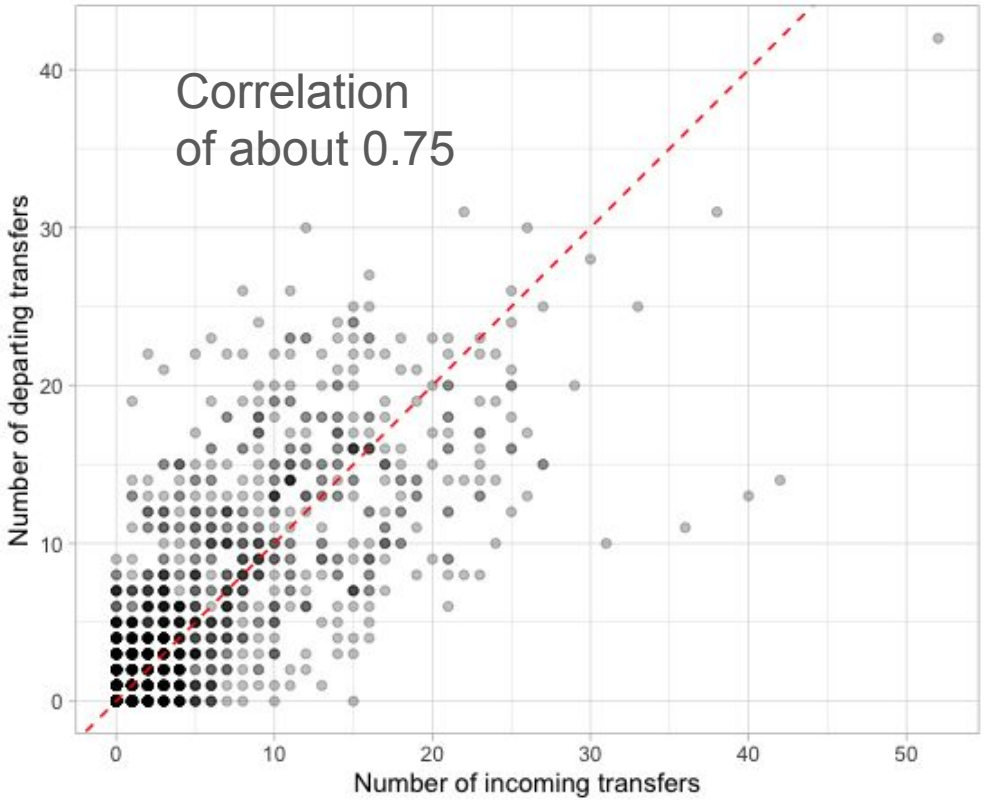


Appendix

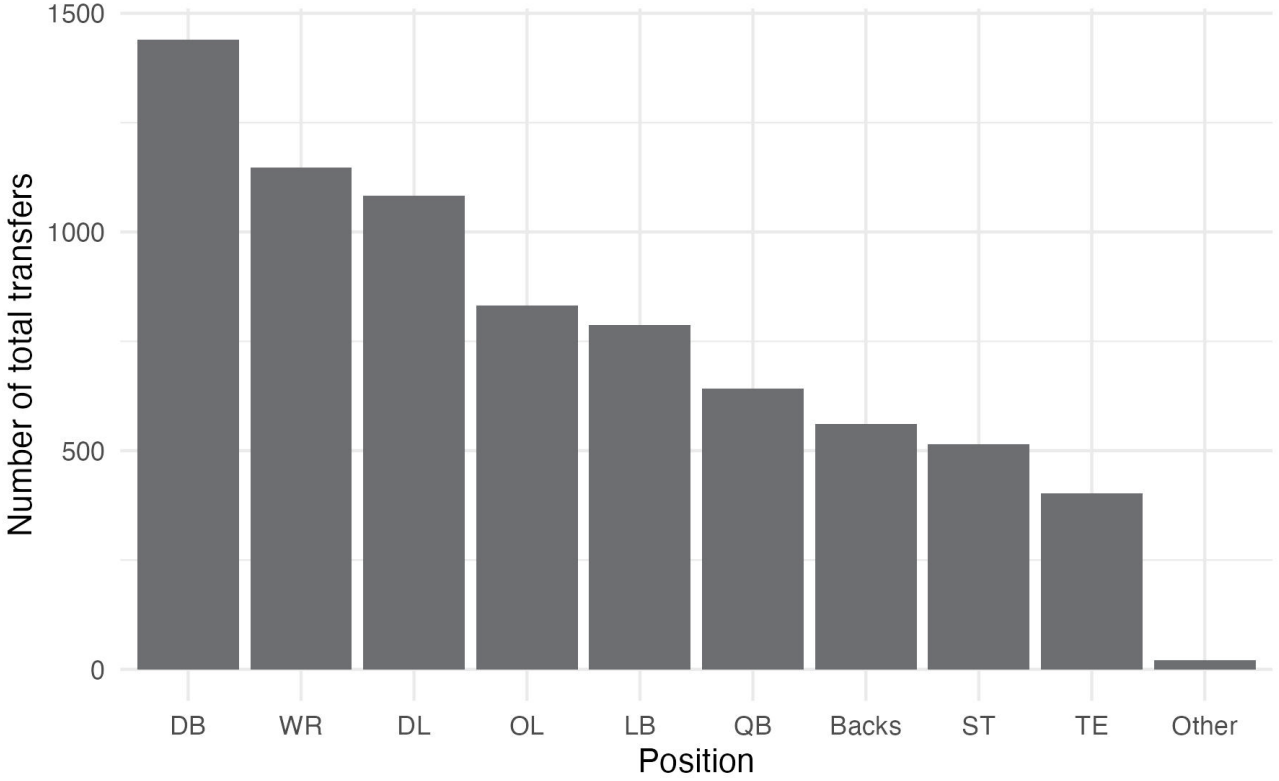
More transfers leads to… different variance?



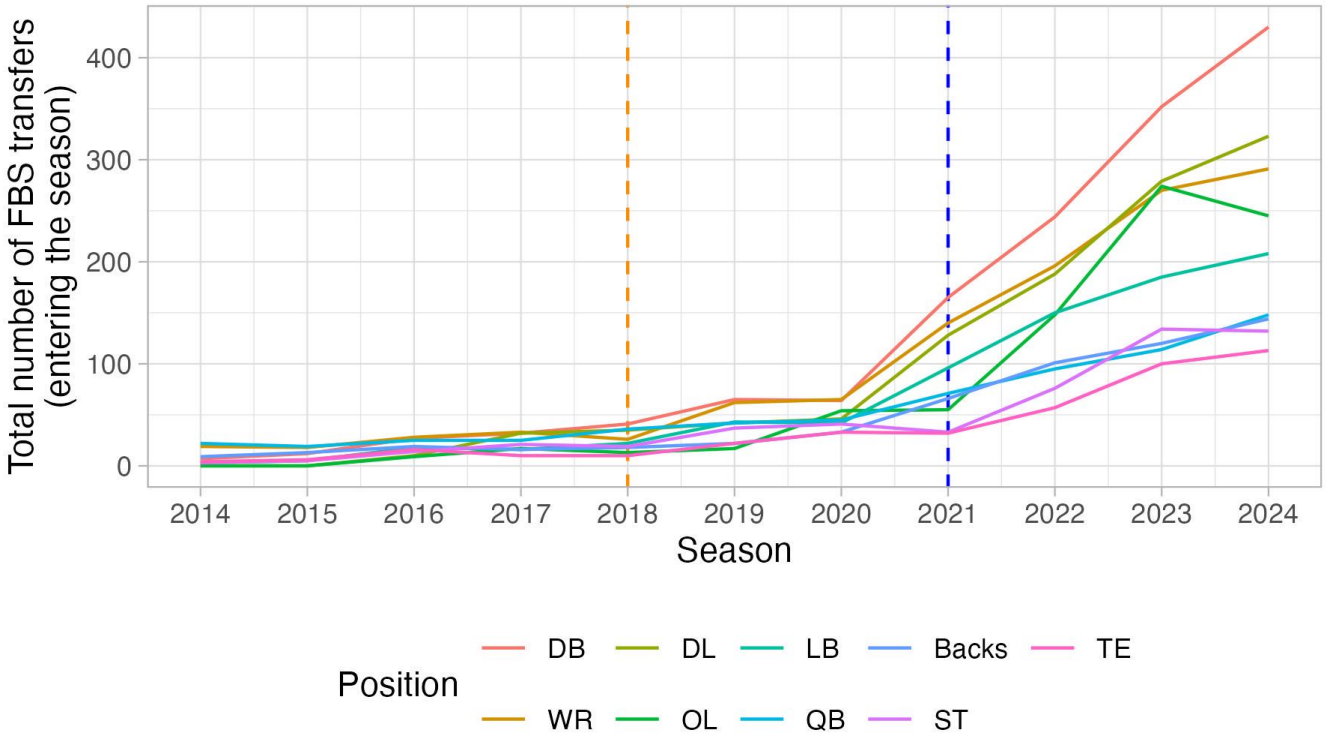
Relationship between incoming and departing transfers



Transfer counts by position



Transfer counts by position over time



Data courtesy of cfbfastR

Change in ESPN FPI ratings by position