



Production Peaks & Declines in NFL Players By Position

Drew Kearny

Introduction & Overview



Forecasting player performance declines is crucial for scouts and executives in the NFL.

Variability By Position:

- Running Backs Often decline in mid-20s due to physical demands.
- Quarterbacks remain effective into their 30s. EX : Tom Brady maintained peak performance into his 40s.

Study Focus:

- Identify on field player production peak and decline trends across Age, Years Played, and Cumulative Snaps
- Focus on Key offensive positions: QB, RB, Wide Receiver (WR), Tight End (TE).
- Utilize different statistical models to predict production by player age, years played, and Cumulative Snaps.
- "Production" is measure by the variable PPR Fantasy Points Per Game

Importance of The Study

Competitive Edges To Teams For:

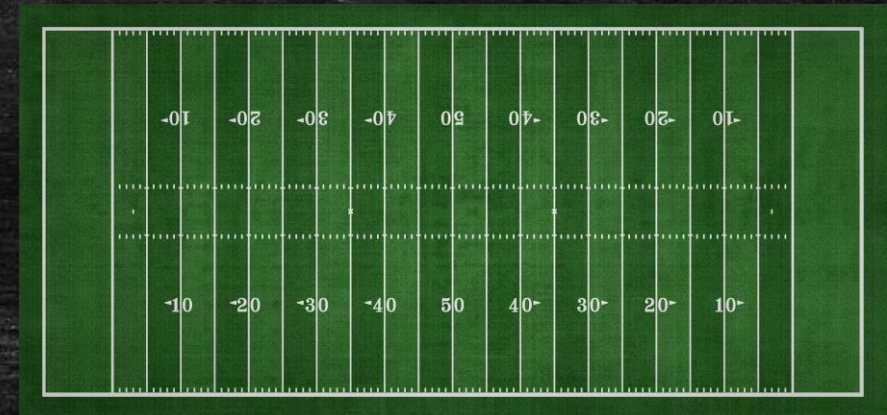
- Contracts, Draft strategies, and Roster management
- Optimizing player usage
- Maximizing output during prime years.

Player Agents Can Use For:

- Contract timing & length

Fantasy Football Industry Can Use For:

- Choosing Players
- Understanding player dynamics



Research Objectives

Objectives:

- Determine the age, years played, and cumulative snap counts when player production begins to decline
- Is there an "age cliff" ? Is the "years played cliff" more informative?

Data

Data Details:

- NFL data from nflverse ranging from 2000 to 2023.
- 3,099 unique NFL players at QB, TE, WR, and RB positions.

Variables Included:

- Player statistics and Snap Counts
- Demographics
- Additional metrics created like Rush yards per carry and PPR fantasy points per game

Exploratory Data Analysis: Data Preparation



2,436 entries removed due to

- Missing birth dates
- Fewer than two games.
- Zero fantasy points per game.

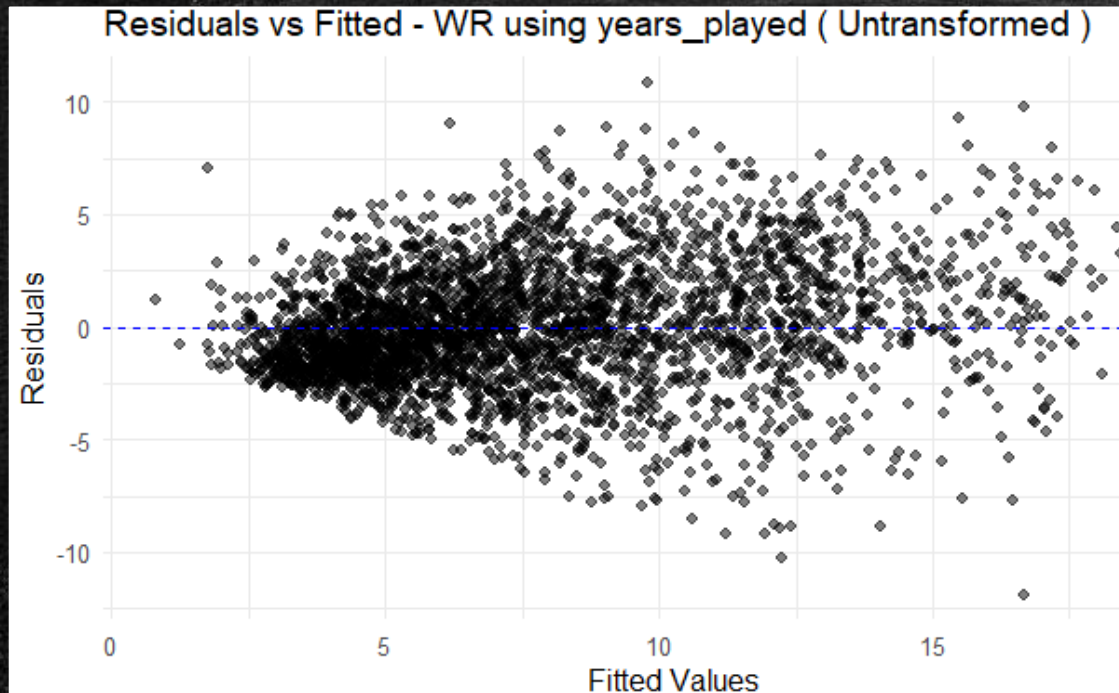
Final Dataset:

- 2,515 unique players.
- 9,156 total rows of player-season data.

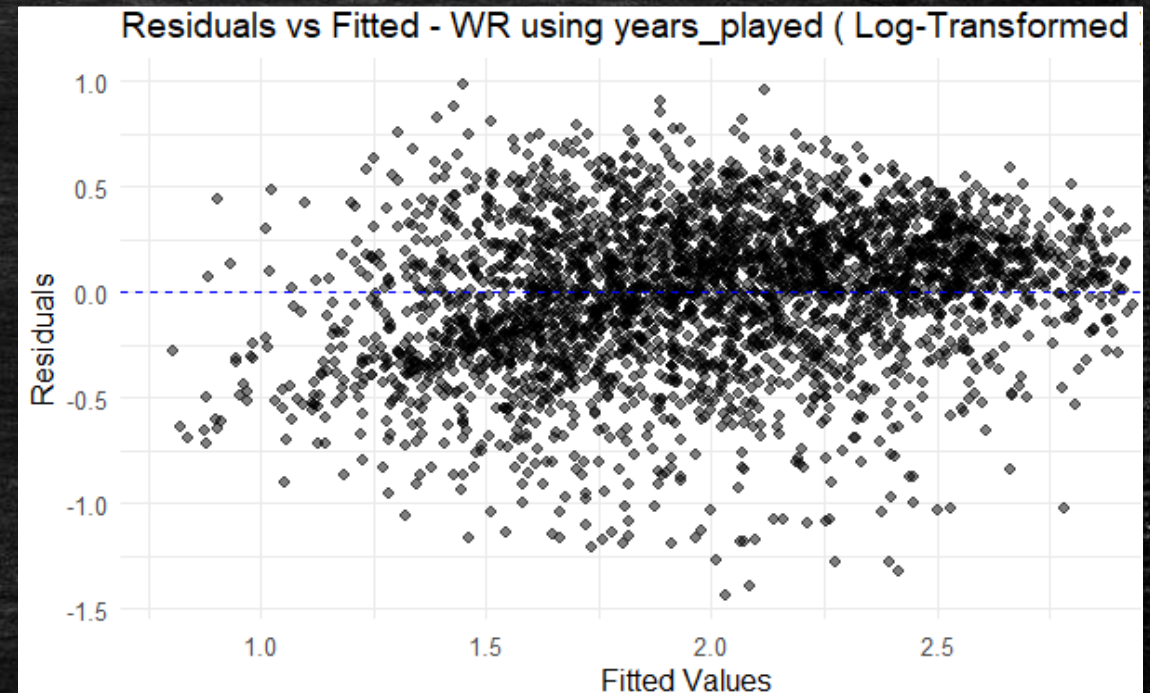
Transformed Response Variable:

- Applied log transformation to 'PPR Fantasy Points' for RBs, WRs, TEs
- Untransformed for QBs

Exploratory Data Analysis

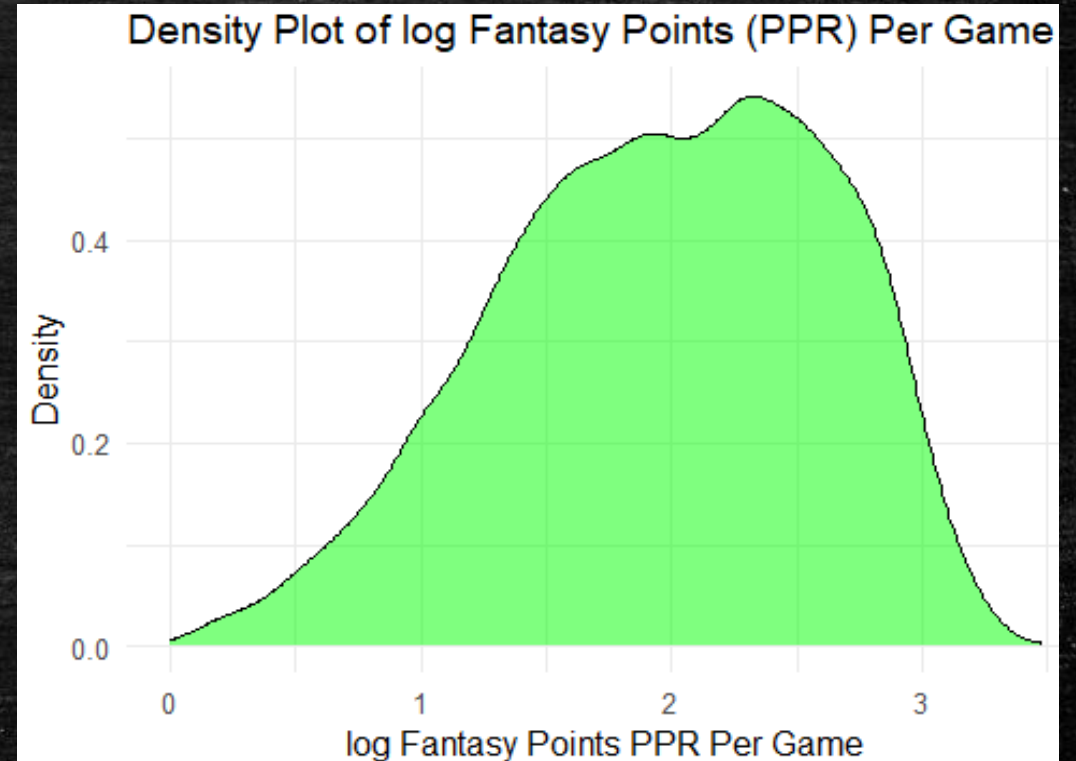
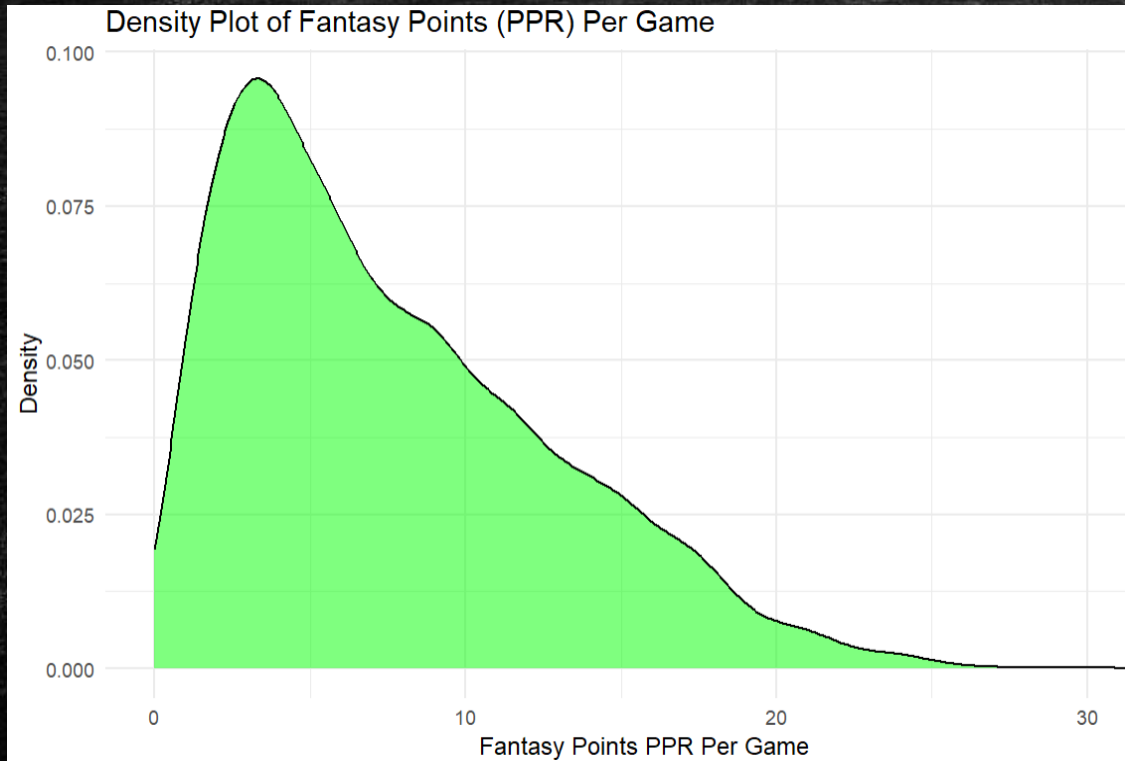


Residuals vs Fitted Plot before log transformation
for the Linear Mixed-Effects years played WR Model

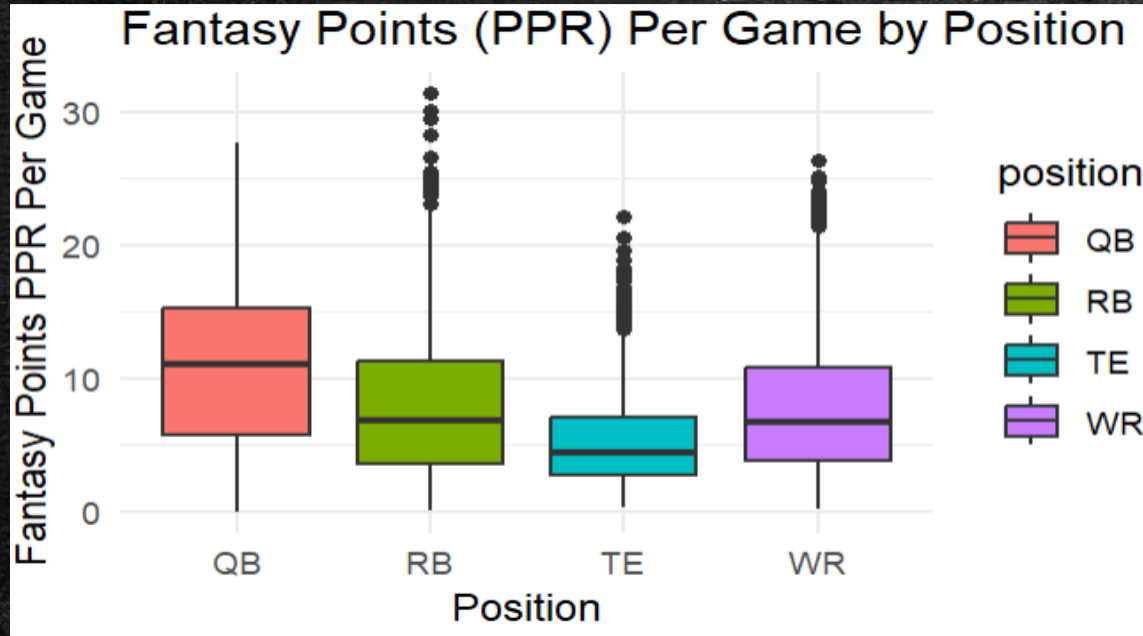


Residuals vs Fitted Plot after log transformation for
the Linear Mixed-Effects years played WR Model

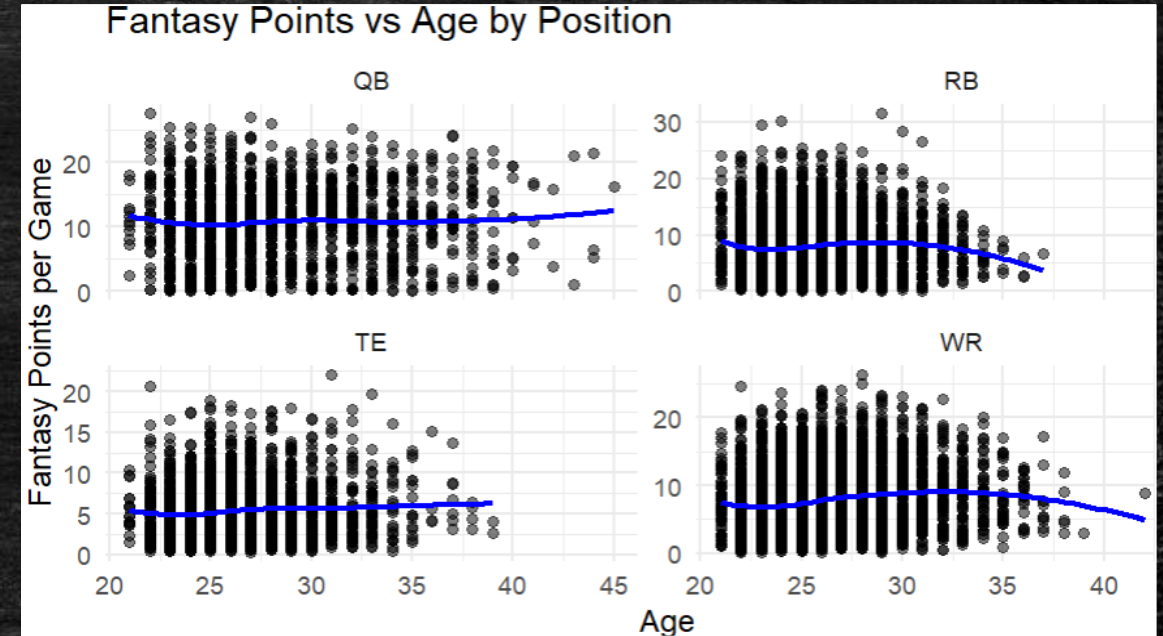
Exploratory Data Analysis



Trend Discoveries



Box Plots of Fantasy Points Per Game By Position

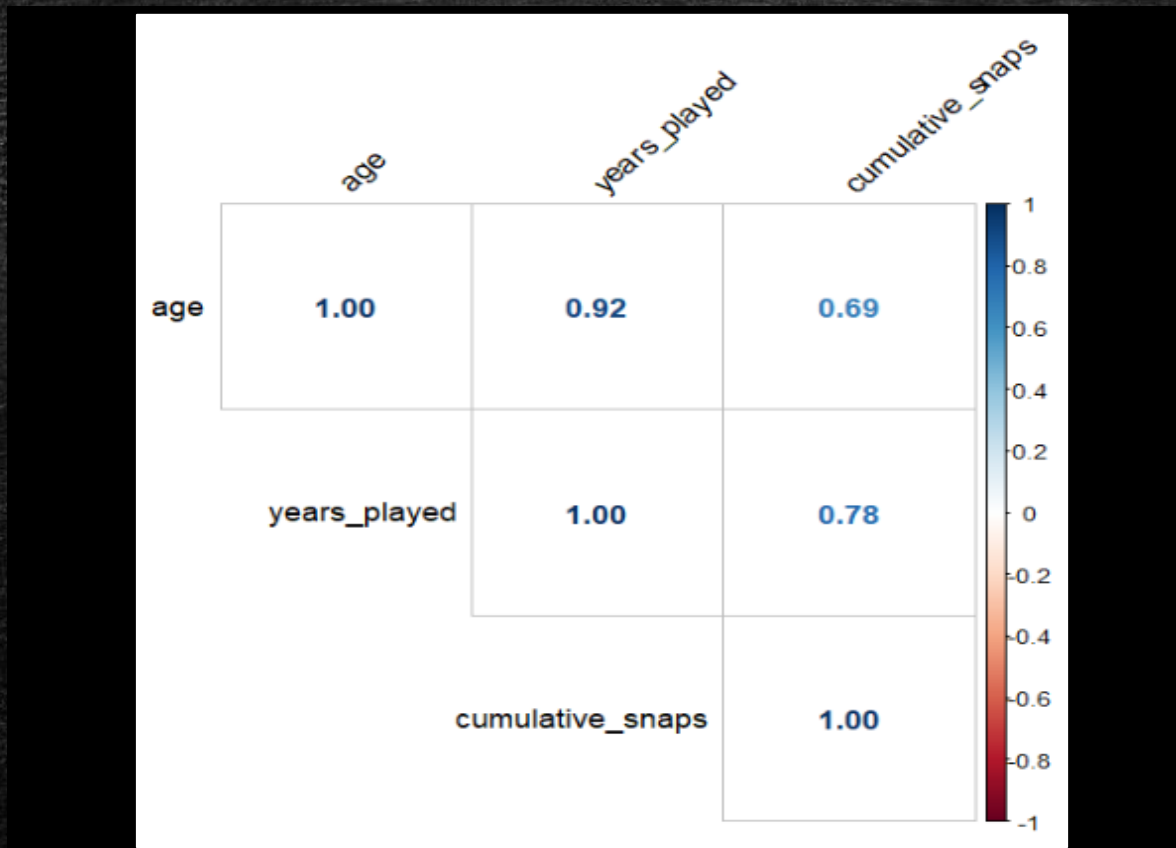


Fantasy Points vs Age Relationship by Position

Separate models for each position group will capture unique characteristics.



Relationships Between Predictors



Predictor Variable Pearson Correlation Matrix

Takeaway:
Separate models for each
predictor rather than all
in one Model

Statistical Methods

Model Types Tested:

- Simple linear models.
- Quadratic models.
- Mixed-effects models.

Selected Quadratic Mixed-Effects Models:

- Created 12 Separate models:
 - 3 predictors (age, years played, cumulative snaps).
 - 4 positions (QB, RB, WR, TE).
- Fixed effects for Age, Years Played, and Snaps
- Random effects for variability among individual players.
- Quadratic terms for non-linear trajectories.

12 Separate Models

Position	Predictor
Wide Receivers	Age
Wide Receivers	Years Played
Wide Receivers	Cumulative Snaps
Running Backs	Age
Running Backs	Years Played
Running Backs	Cumulative Snaps
Tight Ends	Age
Tight Ends	Years Played
Tight Ends	Cumulative Snaps
Quarterbacks	Age
Quarterbacks	Years Played
Quarterbacks	Cumulative Snaps



Model Specification



Models Developed:

- 12 quadratic mixed-effects models:
 - 3 predictors x 4 positions.

Predictors:

- Age
- Years played
- Cumulative snaps (scaled by dividing by 1,000 for interpretability).

For RBs, WRs, TEs (log-transformed response):

$$\log(\text{PPR Fantasy Points}_{ij}) = \beta_0 + \beta_1 X_{ij} + \beta_2 X_{ij}^2 + u_{0i} + \epsilon_{ij}$$

For QBs (untransformed response):

$$\text{PPR Fantasy Points}_{ij} = \beta_0 + \beta_1 X_{ij} + \beta_2 X_{ij}^2 + u_{0i} + \epsilon_{ij}$$

Variables:

- $\beta_0, \beta_1, \beta_2$: Fixed effect coefficients.
- X_{ij} : Predictor for player i in season j .
- $u_{0i} \sim N(0, \sigma_u^2)$: Random intercept for player i .
- $\epsilon_{ij} \sim N(0, \sigma_e^2)$: Residual error term.

Analysis Results

Table displaying the Intercept and Standard Errors for the Predictors in Each Model

Position	Predictor	Term	Estimate	Std. Error	t value
Wide Receivers	Age	(Intercept)	-1.7207	0.4647	-3.703
Wide Receivers	Age	age	0.2731	0.0342	7.996
Wide Receivers	Age	I(age^2)	-0.0052	0.0006	-8.369
Running Backs	Age	(Intercept)	-1.9590	0.7968	-2.459
Running Backs	Age	age	0.3080	0.0599	5.140
Running Backs	Age	I(age^2)	-0.0062	0.0011	-5.556
Quarterbacks	Age	(Intercept)	-1.6297	5.0667	-0.322
Quarterbacks	Age	age	0.7813	0.3398	2.299
Quarterbacks	Age	I(age^2)	-0.0142	0.0056	-2.547
Tight Ends	Age	(Intercept)	-1.9024	0.5955	-3.195
Tight Ends	Age	age	0.2577	0.0432	5.965
Tight Ends	Age	I(age^2)	-0.0047	0.0008	-6.077
Wide Receivers	Years Played	(Intercept)	1.7241	0.0265	65.180
Wide Receivers	Years Played	years_played	0.0695	0.0088	7.908
Wide Receivers	Years Played	I(years_played^2)	-0.0069	0.0007	-9.932
Wide Receivers	Cumulative Snaps	(Intercept)	1.6627	0.0312	53.249
Wide Receivers	Cumulative Snaps	scaled_predictor	0.2711	0.0232	11.688
Wide Receivers	Cumulative Snaps	I(scaled_predictor^2)	-0.0319	0.0033	-9.757

Results:

- Positive Age coefficient means Performance increases with age.
- Negative Age Squared coefficient means production slows and reverses (inverted U-shape).



Interpretation

Table displaying the Intercept and Standard Errors for the Predictors in Each Model

Running Backs	Years Played	(Intercept)	1.7316	0.0370	46.848
Running Backs	Years Played	years_played	0.0781	0.0140	5.589
Running Backs	Years Played	I(years_played^2)	-0.0092	0.0012	-7.504
Running Backs	Cumulative Snaps	(Intercept)	1.6573	0.0392	42.252
Running Backs	Cumulative Snaps	scaled_predictor	0.5987	0.0542	11.048
Running Backs	Cumulative Snaps	I(scaled_predictor^2)	-0.1151	0.0136	-8.439
Tight Ends	Years Played	(Intercept)	1.4728	0.0323	45.591
Tight Ends	Years Played	years_played	0.0551	0.0104	5.321
Tight Ends	Years Played	I(years_played^2)	-0.0048	0.0008	-6.071
Tight Ends	Cumulative Snaps	(Intercept)	1.4712	0.0406	36.263
Tight Ends	Cumulative Snaps	scaled_predictor	0.1653	0.0302	5.470
Tight Ends	Cumulative Snaps	I(scaled_predictor^2)	-0.0149	0.0048	-3.085
Quarterbacks	Years Played	(Intercept)	8.5285	0.4590	18.581
Quarterbacks	Years Played	years_played	0.2380	0.1076	2.211
Quarterbacks	Years Played	I(years_played^2)	-0.0168	0.0061	-2.777
Quarterbacks	Cumulative Snaps	(Intercept)	8.8053	0.5859	15.030
Quarterbacks	Cumulative Snaps	scaled_predictor	2.2618	0.3353	6.746
Quarterbacks	Cumulative Snaps	I(scaled_predictor^2)	-0.1763	0.0352	-5.003

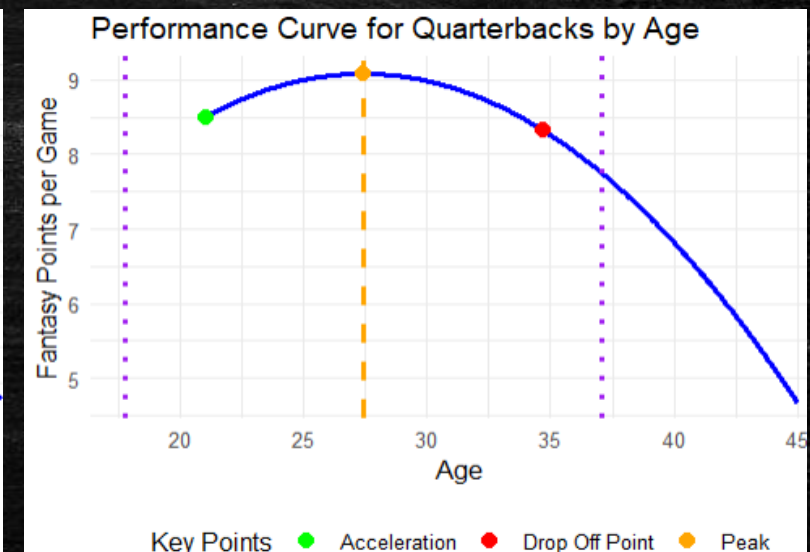
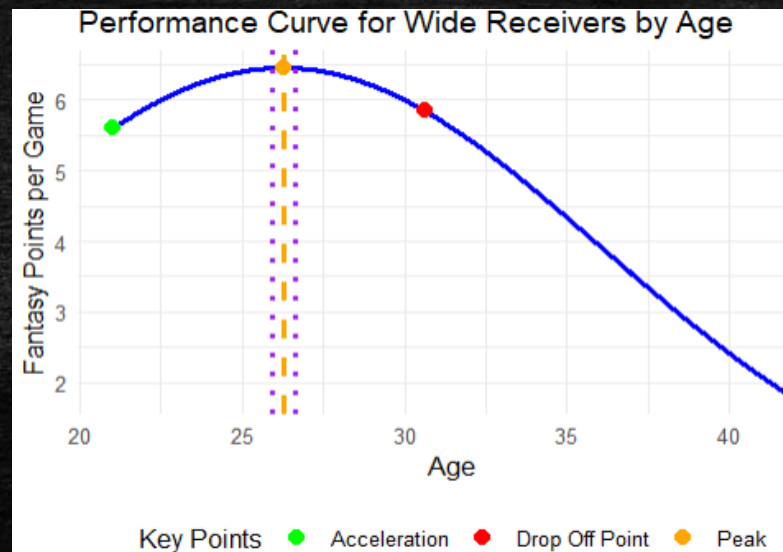
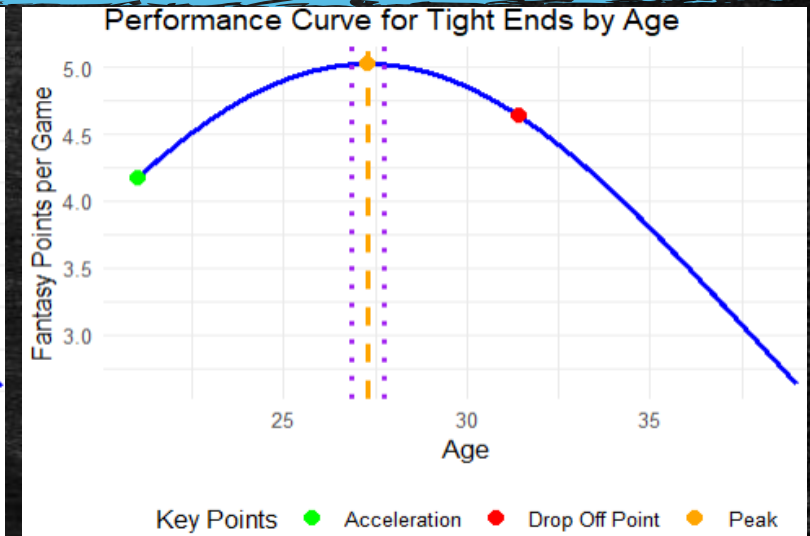
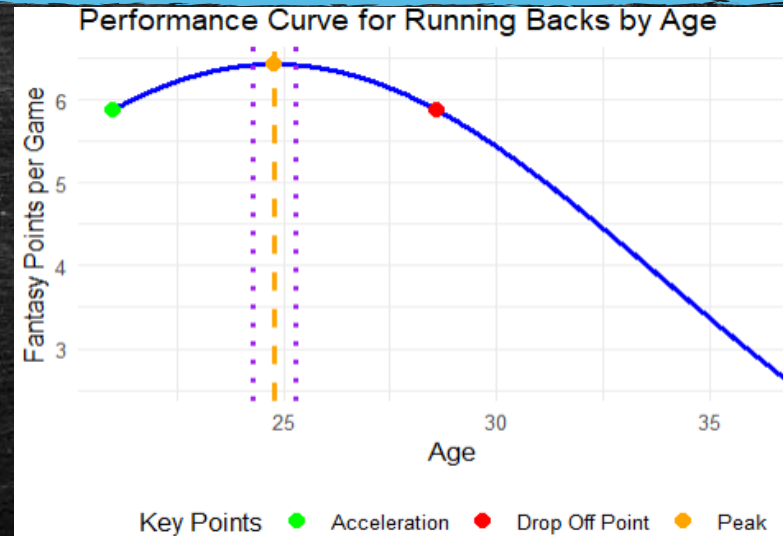
Model Conclusions:

- All coefficients were significant ($p < 0.001$).
- Model captures non-linear productivity trajectory.

Results & Discussion

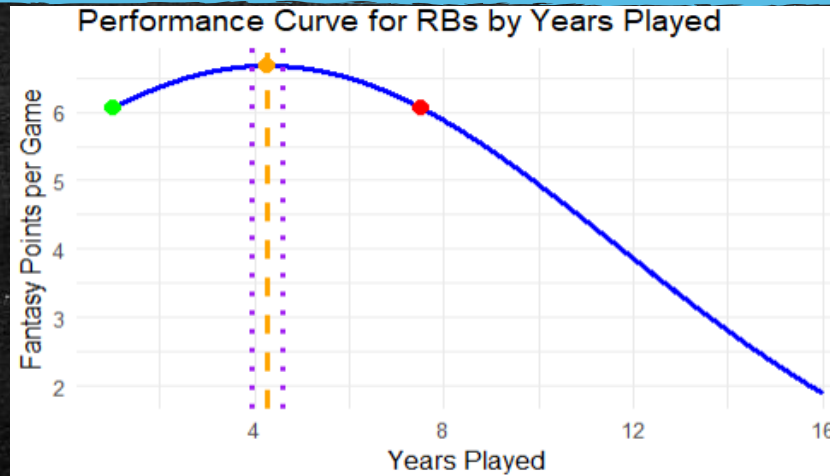
Age Models

- Peak Point is the vertex
- Performed bootstrap resampling to estimate standard errors of peak points.
- Drop-off is where the absolute change in fantasy points exceeds the average.

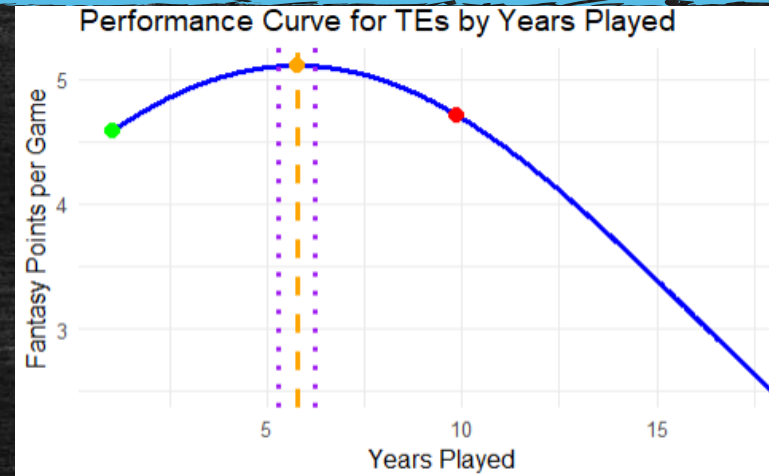


Results & Discussion

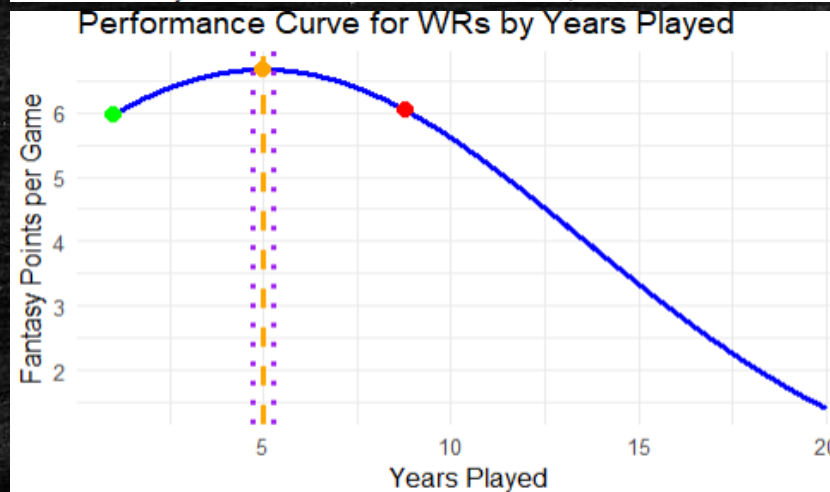
Years Played Models



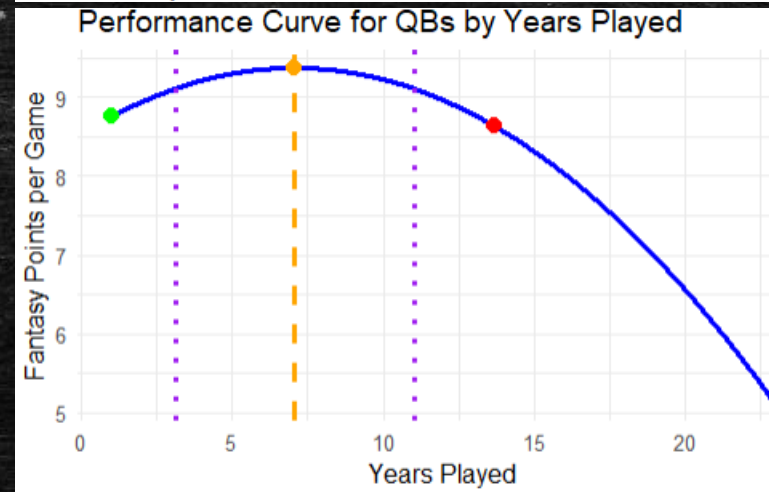
Key Points ● Acceleration ● Drop Off Point ● Peak



Key Points ● Acceleration ● Drop Off Point ● Peak



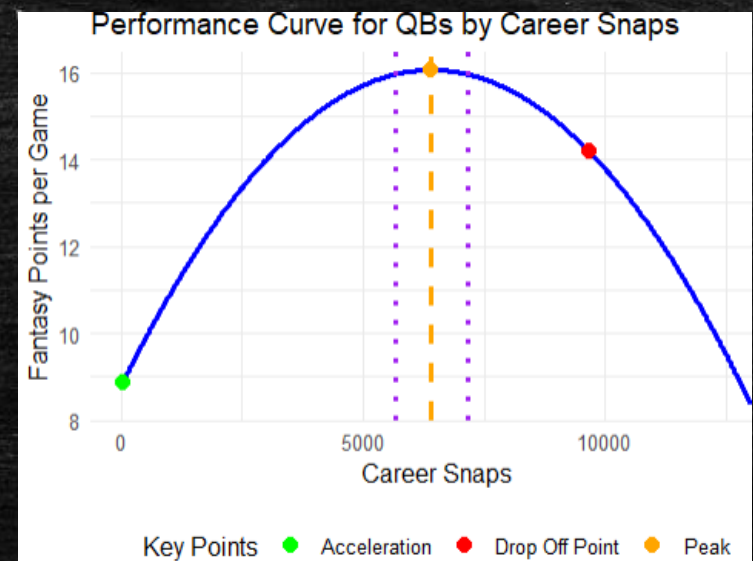
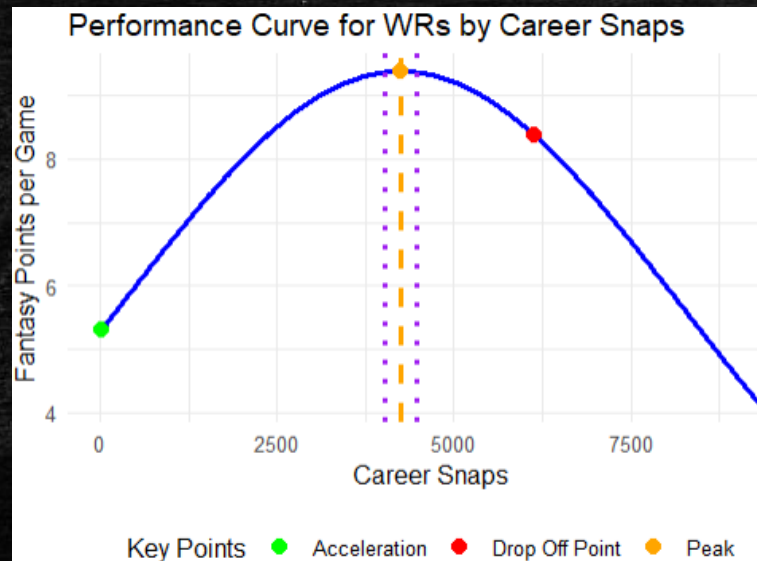
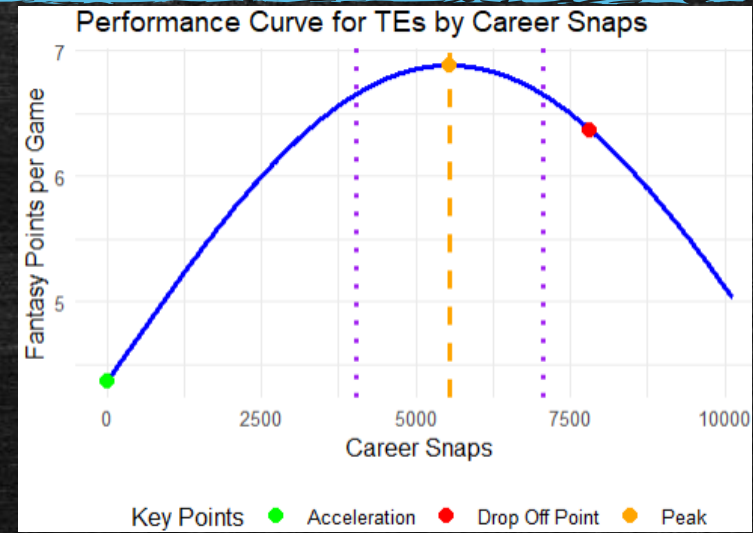
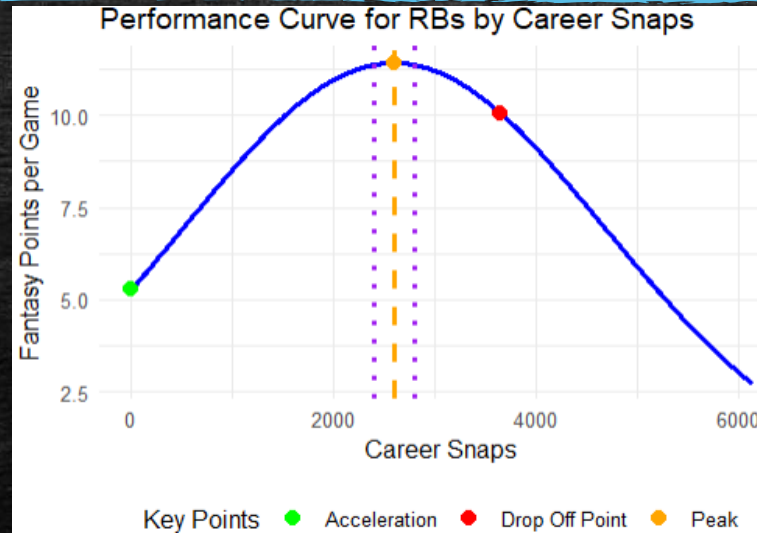
Key Points ● Acceleration ● Drop Off Point ● Peak



Key Points ● Acceleration ● Drop Off Point ● Peak

Results & Discussion

Cumulative Snaps Models





Applications

Predicting the Average Fantasy Points (Production) based on any Input of Predictors

Predicted fantasy points for a Running Backs with:

Age: 24

Years Played: 3

Predicted Fantasy Points from Age Model: 6.4

Predicted Fantasy Points from Years Played Model: 6.58

Average Expected Fantasy Points: 6.49

Predicted fantasy points for a Running Backs with:

Age: 31

Years Played: 10

Predicted Fantasy Points from Age Model: 5.07

Predicted Fantasy Points from Years Played Model: 4.94

Average Expected Fantasy Points: 5



Applications & Conclusions

Key Findings:

- RBs peak earlier and decline sooner
- QBs enjoy longer peak periods.
- Age, years played, and cumulative snaps are all significant predictors of performance decline.
- Years played is the most accurate
- Production typically drops quickly for Non-QBs Aged 30+



Applications & Conclusions

So Now What?

NFL Teams should:

- Limit and monitor workloads for faster declining positions like RB.
- Structure contracts aligning with expected performance.
- Avoid long-term commitments to players likely to decline.
- Give longer term contracts to QBs
- Sign RBs for Shorter Contracts

Players and Agents should:

- Capitalize on high value contracts when players are at their peak
- Ensure financial stability before performance declines.
- Limit over usage to preserve performance.

Fantasy Football Players Should:

- Target players around their peaks.
- Avoid players getting closer to their "age cliff"



References

1. Barrett, S. (2018, March 31). Metrics that matter: The aging curves by position. Pro Football Focus. [Link](#)
2. Hornsby, W. G., & Lewis, M. (2013). Evaluating the effects of aging for professional football players in combine events using performance-aging curves. ResearchGate. [Link](#)
3. Priem, R. L., & Walker, K. (2023). Catching a falling star: Mobility of declining star performers. Journal of Business Research, 161, 113–122. [Link](#)
4. Hilton, R., & Alexiou, C. (2022). No sport for old players: A longitudinal study of aging effects on performance. Sport Management Review, 25(2), 271-285. [Link](#)
5. Baldwin, P., Fisher, B., & Nguyen, L. (2023). nflreadr: Fast, friendly, and free football data (R package version 1.3.2). Retrieved from <https://github.com/nflverse/nflreadr>
6. Wickham, H., François, R., Henry, L., & Müller, K. (2023). dplyr: A Grammar of Data Manipulation (R package version 1.1.1). Retrieved from <https://CRAN.R-project.org/package=dplyr>
7. Wickham, H., Averick, M., Bryan, J., Chang, W., D'Agostino McGowan, L., François, R., Golemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., ... Yutani, H. (2019). Welcome to the tidyverse. Journal of Open Source Software, 4(43), 1686. <https://doi.org/10.21105/joss.01686>



Questions?