Predicting Plays, Revaluing Rushers

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Background

Successfully anticipating whether the offense will run or pass is critical to defensive success.
In the NFL, games are often decided by preparation and play-calling — where strategy on the sideline can be just as important as execution on the field.

Our goals:

- Build a model that predicts the likelihood of a run or pass using pre-snap context.
- Use this model to evaluate pass rushers, with an emphasis on:
  - Their ability to generate pressure in unexpected passing situations, where disruption is harder to achieve.

Data

- **NFL Play-by-Play Data (2016–2023):** Includes down, distance, quarter, yardline, score differential, time remaining, formation info, and team-specific lagged run rate.
- **NFL Player Tracking Data (2022):** Provides (x, y) coordinates for all players and the ball on every frame, plus speed, acceleration, direction, and key event tags (e.g., ball_snap, pass_release, tackle).

Surprisal Metric

Surprisal measures how unexpected a play call is based on model probability:

Surprisal = −log(probability of observed event)

- Higher surprisal = more surprising / harder to anticipate
- Gives context-aware weight to pass rusher performance

Application:

- For pass plays: $-\log(P(\text{Pass}))$
- For run plays: $-\log(1 - P_i(\text{Pass}))$
- Player scores: sum of surprisal values from plays where they record a sack or hit
- Final metric: $\text{Rate} = \dfrac{\text{Weighted Sacks} + \text{Weighted Hits}}{\sum_{j \in \text{All Pass Snaps}} \text{Surprisal}_j}$

Final Model and Features

- **Generalized Additive Model with Feature Selection:** 34 statistically significant features from many candidates (10 linear + 24 smooth terms)
$$\text{logit}(P(\text{Pass})) = \beta_0 + \sum_i \beta_i x_i + \sum_j s_j(z_j)$$
- **Situational Features:** Down/distance interactions, critical game situations, personnel packages (RB/TE/WR counts)
- **Player Tracking Features:** Formation geometry (compactness, symmetry), defensive alignment patterns, receiver positioning
- **Advanced Spatial Analysis:** Voronoi diagrams for field control estimation, graph theory to model defensive connectivity, convex hull calculations for formation footprint analysis

Methods

We built our modeling pipeline in three stages, each adding more football-specific context:

- **Stage 1: Baseline model**
  - Used basic game info like down, distance, score, and time
  - Built with XGBoost, which is good at handling structured data and finding patterns quickly
  - Reached about 70% accuracy, but didn't know anything about formations or tendencies
- **Stage 2: Formation-aware model**
  - Added team and alignment data to account for offensive style
  - Also used XGBoost to take advantage of its flexibility with new features
- **Stage 3: Tracking model**
  - Used player locations, motion, and spacing to model offensive intent
  - Switched to GAMs, which are better at capturing smooth spatial relationships
  - Boosted accuracy by 5–10 points and gave a clearer picture of pre-snap geometry

We then used these models to calculate surprisal, measuring how unexpected a run or pass was for evaluating defensive performance.

Results

We evaluated pass rushers based on both their overall disruption rate and their average surprisal when creating pressure. This surfaces defenders who consistently win in tough, unpredictable situations — not just obvious passing downs.

- Raw: total disruption rate
- Weighted: average surprisal on disruptions

TOP 8 OVERALL (BY WEIGHTED RATE)

RANK	PLAYER	TEAM	WEIGHTED	RAW
1	James Smith-Williams	WAS	0.0758	0.0617
2	Jerry Hughes	HOU	0.0537	0.0689
3	Montez Sweat	WAS	0.0486	0.0837
4	Nick Bosa	SF	0.0484	0.1368
5	Maxx Crosby	LV	0.0466	0.0669
6	Myles Garrett	CLE	0.0460	0.0948
7	Dorance Armstrong	DAL	0.0435	0.0638
8	Aaron Donald	LA	0.0397	0.0441

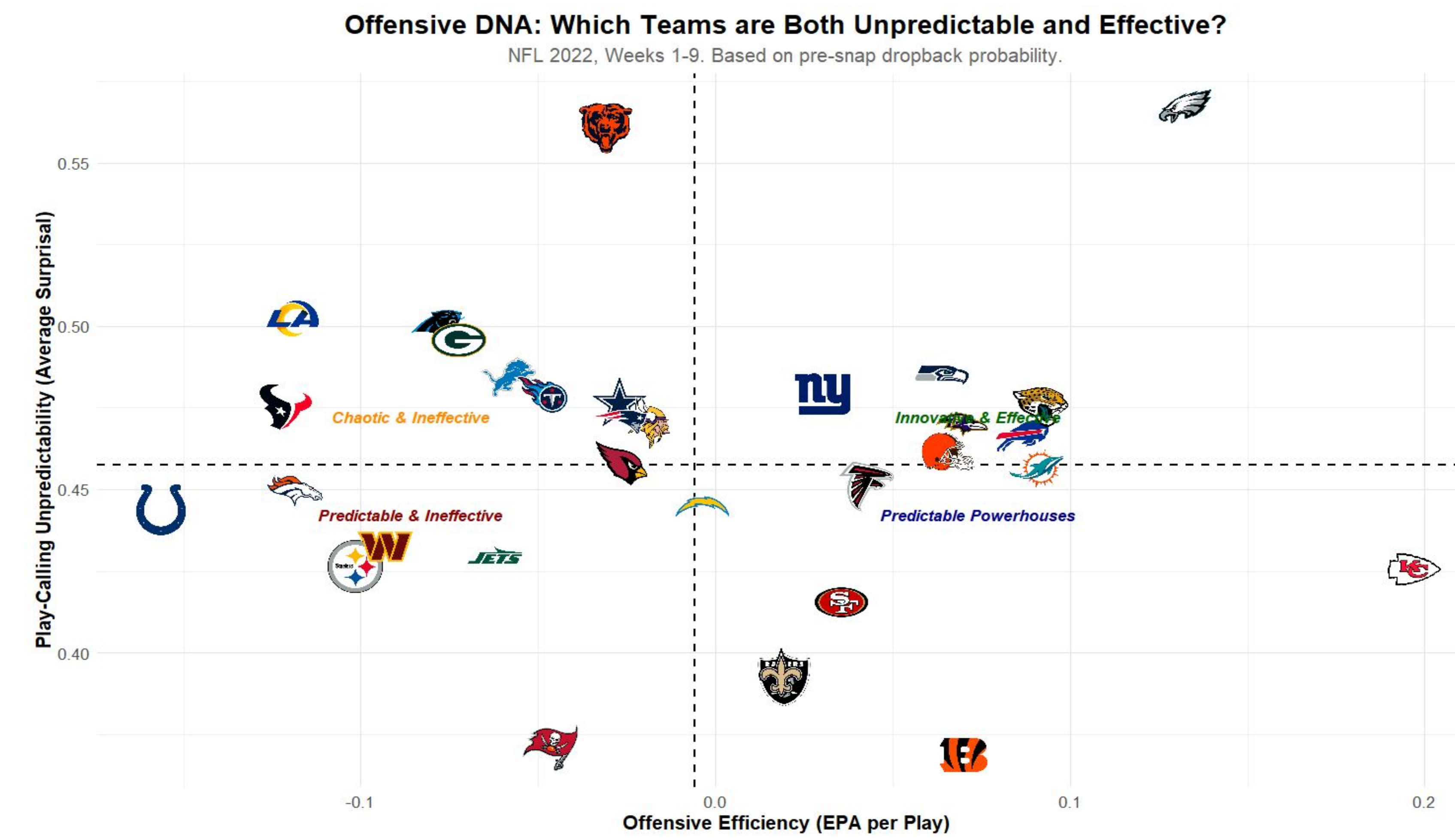
TOP 5 RISERS (BY RANK CHANGE)

PLAYER	NEW	OLD	CHANGE
Logan Hall	9	56	+47
D.J. Jones	22	62	+40
Al-Quadin Muhammad	40	74	+34
Aaron Donald	8	40	+32
Matt Ioannidis	28	59	+31

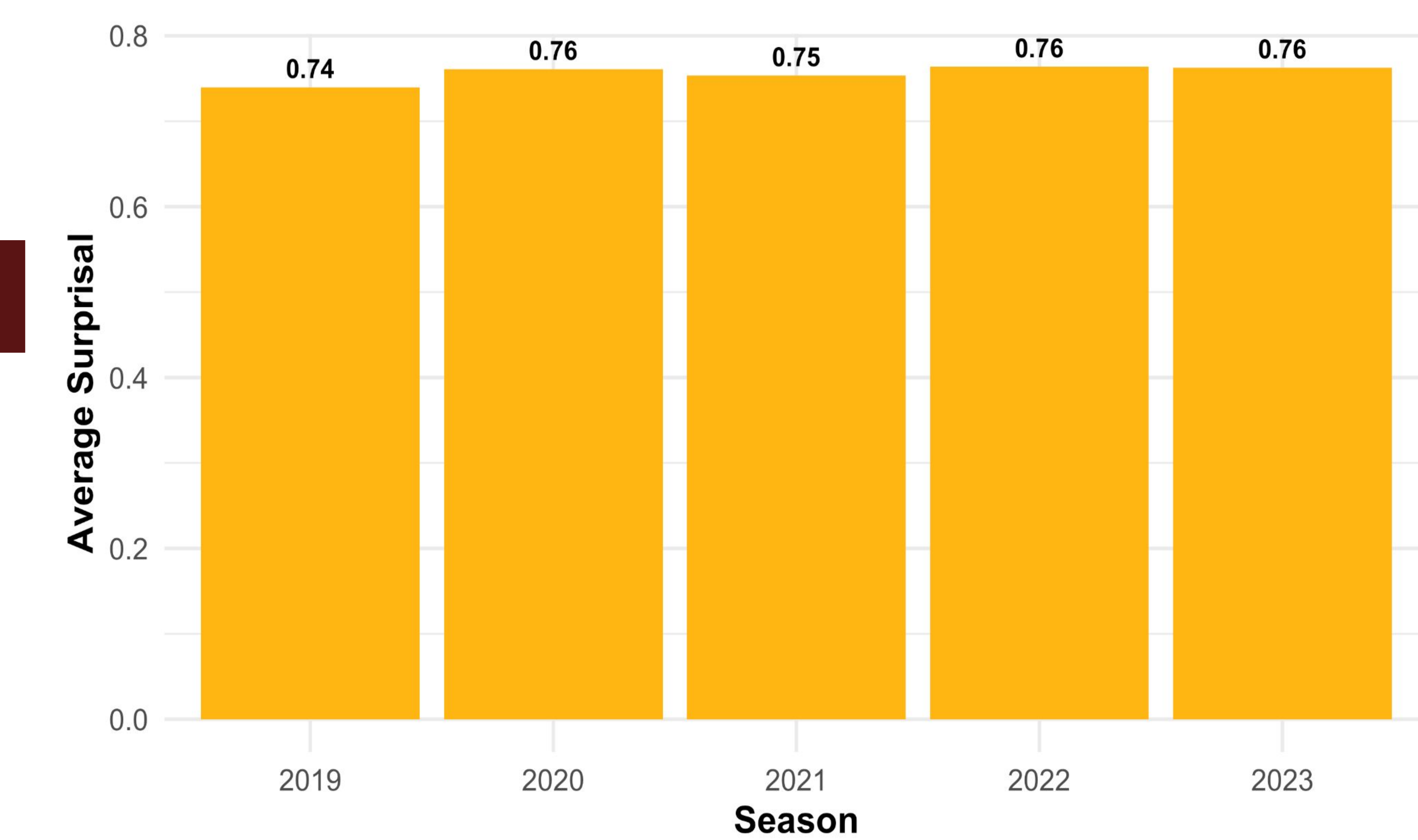
TOP 5 FALLERS (BY RANK CHANGE)

PLAYER	NEW	OLD	CHANGE
Josh Sweat	50	4	-46
Cameron Heyward	56	19	-37
Gregory Rousseau	47	13	-34
Daron Payne	44	11	-33
Jonathan Allen	59	28	-31

Surprisal by Team & Season



Surprisals are a consistent metric from season to season



Discussions

- **Insight:** Surprisal-adjusted pass-rusher scores **lift quiet disruptors** (Dorance Armstrong, Rasheem Green) and **lower some headline names** after context removal.

Limitations

- **Identity-blind:** probabilities ignore team, coach, and individual talent.
- **Short tracking window:** only the first nine weeks of 2022.
- **Single snapshot:** post-snap motion, RPOs, and scrambles not modeled.

Next Steps

1. Inject player grades, coach tendencies, and fatigue to make predictions talent-aware.
2. Add context to pass-rush evaluation—offensive-line strength, slide protections, and double-team rates.