Pressure, Production, and Noise: Offensive Predictors of NBA Clutch Efficiency Preservation

A reproducible quantitative study of the 2025-26 NBA regular season

with validation seasons 2022-23 through 2024-25

Author: Portfolio project

August 7, 2026

Data source: NBA Stats accessed through nba_api 1.11.4

Author: Portfolio research project Date: August 7, 2026 Data: 2025-26 NBA regular season, with 2022-23 through 2024-25 validation seasons Software: Python and `nba_api` 1.11.4

Abstract

Popular discussions of NBA "clutch" performance usually emphasize points scored, memorable makes, or raw late-game percentages. Those quantities confound opportunity, baseline skill, and substantial sampling variation. This study instead asks which normal-condition offensive characteristics predict whether a player preserves or improves true shooting efficiency during standard clutch situations. Programmatic NBA Stats data were collected through `nba_api` for the 2025-26 regular season and three validation seasons. Standard clutch was operationalized as the last five minutes of the fourth quarter or overtime when the score differential was five points or fewer. Non-clutch counting statistics were calculated explicitly by subtracting clutch counts from season totals. The primary outcome was clutch true shooting percentage minus non-clutch true shooting percentage.

The main 2025-26 sample included 99 players with at least 500 minutes, 100 total field-goal attempts, and 25 clutch field-goal attempts. Mean efficiency change was -2.29 percentage points (bootstrap 95% interval -4.06 to -0.54). Robust regression provided limited evidence that shot-profile diversity and assists per 36 minutes were positively associated with preservation, but neither coefficient survived false-discovery-rate adjustment across the full reported family. The primary model explained 0.163 of in-sample variance and had adjusted R-squared 0.089. The best repeated-cross-validation model, Random Forest, produced RMSE 8.78 percentage points and negative out-of-sample R-squared (-0.075). Component empirical-Bayes shrinkage reduced cross-player dispersion by 52.5%, and consecutive-season correlations declined from 0.217 to 0.068. A post-hoc pooled screen identified Derrick White as the strongest multi-season candidate, with positive differentials in all 3 qualifying seasons and pooled Delta TS of 16.01 points, but the selected result did not survive screen-wide FDR correction. The results support a restrained conclusion: offensive traits contain weak descriptive signals, but single-season raw clutch rankings are dominated by uncertainty and are poor evidence of a stable psychological clutch ability.

Keywords: NBA analytics; clutch performance; true shooting percentage; empirical Bayes; Monte Carlo simulation; regression to the mean; sports prediction

1. Introduction

Clutch performance occupies an unusually large place in basketball culture. A small collection of possessions can shape reputations, awards arguments, contract narratives, and retrospective judgments about careers. The attraction is understandable. Late possessions are visible, consequential, and strategically different from ordinary possessions. Defenses switch more readily, star players receive more attention, timeouts allow targeted matchups, and every error feels amplified. Yet the statistical object commonly called "clutch" is frequently unclear. Points per game rewards opportunity. Field-goal percentage ignores three-point value and free throws. Full-season efficiency is an invalid comparison because it contains the clutch possessions being evaluated. Rankings based on a few dozen attempts can elevate noise into a personality judgment.

This study treats the clutch question as a problem of change under pressure rather than a leaderboard of raw production. The outcome is not how efficient a player was in clutch possessions alone. It is how much the player's scoring efficiency changed relative to explicitly non-clutch possessions from the same season. The distinction is central. A player with 63% non-clutch true shooting and 60% clutch true shooting may remain an excellent late-game scorer while experiencing a small decline. Another player may improve from 50% to 56%, a positive differential that does not imply superior absolute offense. Preservation, enhancement, and level are different concepts.

The second departure from conventional analysis is to separate descriptive, predictive, and uncertainty questions. The descriptive question asks who improved or declined. The predictive question asks whether normal-condition offensive role, shot diversity, self-creation, foul pressure, playmaking, or possession control distinguish players who preserve efficiency. The uncertainty question asks how much of the observed variation remains after recognizing that players receive very different numbers of clutch attempts. A serious answer must allow the possibility that little stable ability can be identified from one season.

This framework connects to a long statistical debate about perceived streaks and small samples. Tversky and Kahneman (1971) described the tendency to overexpect local representativeness from limited sequences. Gilovich, Vallone, and Tversky (1985) applied related reasoning to basketball and famously argued that beliefs about the hot hand exceeded evidence in observed shooting sequences. Later work demonstrated that common tests can themselves be biased and that some within-player persistence may have been understated (Miller & Sanjurjo, 2018). The lesson for clutch research is not that all pressure effects are imaginary. It is that the estimand, comparison group, sample size, and selection mechanism must be specified carefully.

Pressure can also affect components of performance differently. Cao, Price, and Stone (2011) found evidence of pressure-related changes in NBA performance, while research on shot selection emphasizes that attempt quality and strategic choice are endogenous to defensive response and offensive role (Skinner, 2012). A late-game possession is not a laboratory repetition of an ordinary possession. The ball is more likely to remain with a primary creator, a defense may deny preferred actions, and intentional fouling can alter free-throw volume. Therefore, this study does not equate a clutch efficiency differential with pure shooting nerve. It is a composite outcome of execution, shot creation, selection, defense, tactics, and variance.

The project makes five contributions. First, it removes clutch possessions from the comparison baseline rather than comparing clutch performance with contaminated full-season rates. Second, it builds interpretable offensive features, including normalized shot entropy and a transparent self-creation proxy. Third, it compares mathematically coupled change-score regression with controlled clutch-TS and residualized outcomes. Fourth, it evaluates prediction with repeated cross-validation instead of training fit alone. Fifth, it adds component shrinkage, bootstrap uncertainty, and a player-specific Monte Carlo null summarized by a project-defined Clutch Beyond Expectation score.

The research question is: Which player-level offensive characteristics best predict the preservation or improvement of scoring efficiency during clutch situations relative to normal game conditions in the NBA? Seven hypotheses were recorded before final model fitting: higher self-creation, foul pressure, shot diversity, and reduced assisted dependence would be associated with preservation; extreme workload would be associated with deterioration; shrinkage would materially reduce raw extremes; and single-season effects would show limited year-to-year persistence. Because the evidence is observational, all conclusions are stated as associations or predictive information, not causal effects.

2. Background and Related Work

2.1 Small samples, streaks, and basketball inference

The hot-hand literature matters because clutch statistics share its central hazard: humans are inclined to infer stable states from short, selected sequences. The original hot-hand study examined whether makes were followed by elevated make probabilities and whether players and observers overperceived streakiness (Gilovich et al., 1985). Subsequent methodological work showed that conditional hit-rate comparisons can be biased in finite sequences, revising the interpretation of some earlier null results (Miller & Sanjurjo, 2018). Other basketball studies have reported momentum or persistence under particular models and data, including free-throw and game-level settings (Arkes, 2010; Arkes & Martinez, 2011).

Clutch analysis adds further selection. Possessions enter the standard clutch sample only when time and score meet a rule. Players do not receive random clutch opportunities. Better teams may avoid close endings; weak teams may generate late possessions against different defensive effort; star players may receive more attempts and harder shots; and intentional fouling changes the composition of scoring opportunities. Consequently, a player's clutch sample is both small and strategically selected. A large observed change can be real as a description of that sample without being a reliable estimate of repeatable ability.

The "law of small numbers" problem is especially visible when rankings ignore denominators. Two players may each improve by ten percentage points, but one may have 15 attempts and the other 90. Their point estimates are identical while their uncertainty differs sharply. Volume thresholds reduce the worst instability but do not eliminate it. This project therefore reports multiple samples, weights regressions by attempt volume, constructs player intervals, and shrinks component shooting rates.

2.2 Pressure, role, and shot selection

Pressure is not a single treatment. Cao et al. (2011) examined NBA performance under pressure and documented heterogeneous responses across performance components. In basketball terms, a player can shoot worse while protecting the ball better, generate more free throws while taking fewer attempts, or preserve efficiency through a different shot profile. The present framework separates efficiency preservation, enhancement, shot creation, ball security, foul pressure, shot-profile adaptation, and playmaking rather than collapsing all late-game value into one number.

Shot selection also complicates interpretation. Skinner (2012) formalized the strategic problem that teams must trade shot quality against the availability of opportunities. Late in a close game, the preferred shot may not be available. A high-usage creator can face aggressive switching or double teams, and teammates who usually finish assisted attempts may be denied actions by scouting and timeout-driven defense. A decline can reflect harder responsibility rather than failure of an invariant skill. Conversely, increased free throws can elevate true shooting even if field-goal efficiency declines.

The study's predictors are designed to describe those pathways. Normal-condition field-goal attempts per 36 minutes and a usage proxy describe workload. Pull-up and catch-and-shoot frequencies approximate creation dependence. Free-throw rate measures foul pressure. Assists per 36 and turnover rate describe playmaking and ball security. Zone shares and entropy describe spatial diversity. These are not direct measures of psychological composure, defender distance, fatigue, or play-call quality. They are measurable offensive characteristics that may supply predictive information.

2.3 Shrinkage and prediction

Empirical-Bayes shrinkage is well suited to sports leaderboards because it combines noisy individual estimates with a population distribution (Efron & Morris, 1975; Morris, 1983). The amount of shrinkage should diminish as information increases. True shooting percentage is not a binomial proportion, so directly applying a beta-binomial model to TS would be incoherent. This project instead shrinks two-point, three-point, and free-throw components separately and reconstructs expected clutch points and TS. The result is a stabilized descriptive estimate, not a claim that the posterior model captures every source of uncertainty.

Prediction is assessed out of sample. Flexible algorithms can fit interactions and nonlinearities, but they can also exploit noise in a sample of fewer than one hundred qualifying players. Random forests (Breiman, 2001) and gradient boosting are compared with linear and regularized models using repeated five-fold cross-validation. The relevant question is not which algorithm produces the highest training R-squared. It is whether normal offensive characteristics predict held-out clutch changes better than a mean-only baseline. This distinction follows the general statistical-learning emphasis on generalization error rather than retrospective fit (Hastie, Tibshirani, & Friedman, 2009).

3. Data

3.1 Source and acquisition

Data came from NBA Stats endpoints accessed programmatically through `nba_api` version 1.11.4 (Patel & contributors, 2026). The acquisition client generated deterministic cache keys from endpoint parameters, saved successful responses as CSV with JSON metadata, logged timestamps and schemas, and used bounded exponential backoff with randomized jitter. A valid cache was always read before any network request. This design makes the analytical pipeline reproducible without repeatedly querying NBA.com.

The core 2025-26 season-total endpoint returned 582 player rows. The standard clutch endpoint returned 492 players with at least one qualifying appearance. Alternative definitions also returned data: last three minutes within five points, last two minutes within three points, and last one minute within three points. Advanced, player-index, estimated-metric, hustle, shot-location, catch-and-shoot, and pull-up endpoints were audited. League-wide total shot-event data hit an exact 102,400-row ceiling and were treated as truncated. They were not used as complete totals. Instead, complete player-zone aggregates were combined with the 7,104 standard-clutch shot events, which reconciled exactly to clutch FGA.

Table 1. Data sources and endpoint roles.

endpoint	role	status	rows
LeagueDashPlayerStats	Season totals and advanced context	success	582
LeagueDashPlayerClutch	Four clutch definitions; base and standard advanced	success	492
LeagueDashPlayerPtShot	Catch-and-shoot and pull-up context	success	582
LeagueDashPlayerShotLocations	Complete zone totals	success	582
LeagueHustleStatsPlayer	Hustle context	success	581
PlayerEstimatedMetrics	Estimated role and turnover context	success	582
PlayerIndex	Position and experience	success	582
ShotChartDetail	Full-season shot events (102,400-row cap; excluded)	success	102400
ShotChartDetail	Standard-clutch shot events	success	7104

NBA's operational clutch parameters were `ClutchTime=Last 5 Minutes`, `PointDiff=5`, and `AheadBehind=Ahead or Behind`. The endpoint is documented in the installed package as a player clutch dashboard and returned separate rows for the requested time-score filters. This study interprets those parameters according to the standard NBA definition: the final five minutes of the fourth quarter or overtime when the score differential is five points or fewer. No alternative definition was silently substituted.

3.2 Seasons and panel structure

The primary analysis used the completed 2025-26 regular season. Equivalent core tables were collected for 2024-25, 2023-24, and 2022-23. Seasons were never pooled as if player observations were independent. Cross-sectional models were fit to 2025-26; year-to-year calculations matched player IDs across adjacent seasons; and a mixed-effects extension included a player grouping term and season indicators. Tracking and shot-location extensions were used only in the primary season because maintaining identical historical coverage could not be guaranteed.

3.3 Cleaning and identity

`PLAYER_ID` was the canonical key. Player names were used only for labels. Season-level NBA endpoint rows were unique by player ID, including aggregate treatment for traded players through the endpoint's team-count convention. Merges were validated one-to-one. The pipeline rejected duplicate IDs, checked negative derived counts, inspected zero denominators, and retained explicit flags rather than silently coercing impossible values.

All arithmetic validation checks passed. Clutch FGA never exceeded total FGA. Total points equaled clutch plus non-clutch points for every player. Derived shooting efficiencies remained in plausible ranges. Ten recognizable players were inspected in a saved validation report; their minutes, attempts, and efficiency values were plausible. These checks do not prove that NBA source data are error-free, but they protect against common pipeline failures such as suffix collisions, team-split duplication, or incorrect result-set selection.

3.4 Eligibility

The main sample required at least 500 regular-season minutes, 100 total FGA, and 25 standard-clutch FGA. The expanded sample required 300 minutes and 15 clutch FGA. The high-confidence sample required 750 minutes, 100 total FGA, and 40 clutch FGA. The thresholds were retained because the realized distribution produced 99, 172, and 45 players respectively. The main threshold was the 75th percentile of clutch FGA among players satisfying the minutes and total-attempt filters, making it a meaningful volume screen rather than an arbitrary way to select stars.

Table 3. Sample eligibility definitions and realized sizes.

sample	minutes_threshold	total_fga_threshold	clutch_fga_threshold	n
Expanded	300	0	15	172
Main	500	100	25	99
High Confidence	750	100	40	45

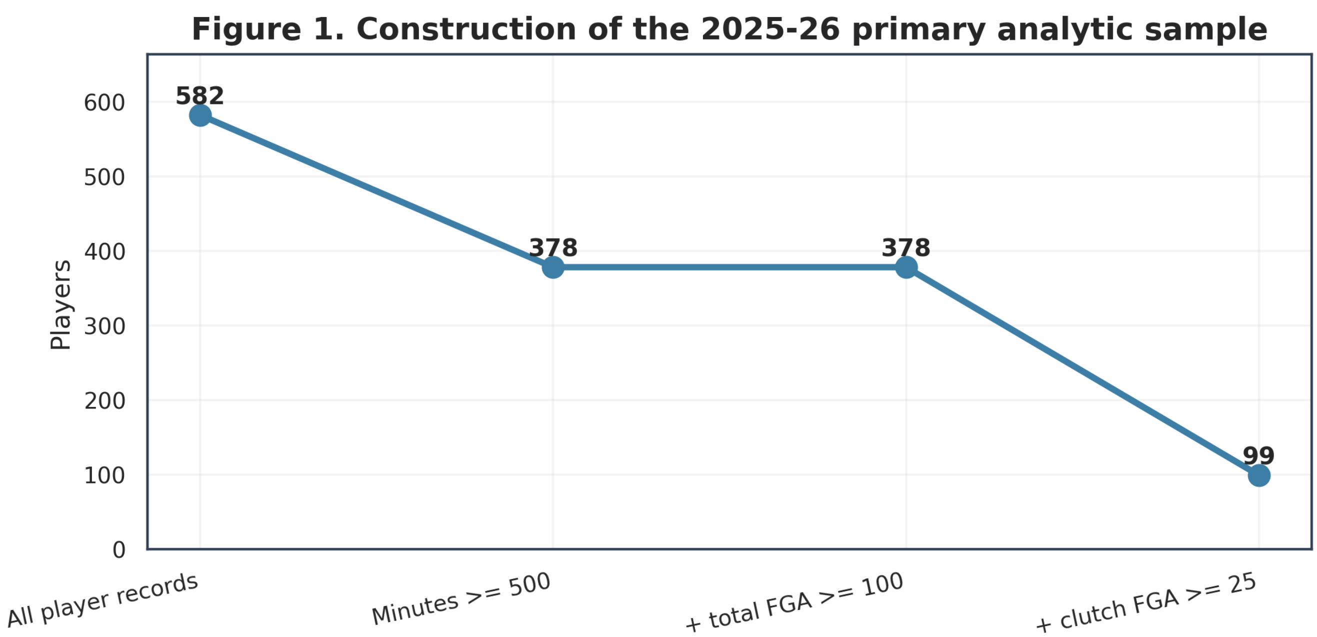


Figure 1. Sample construction from all 2025-26 player records to the main analytic sample.

Figure 1 makes the loss of sample size explicit. The major reduction occurs at the clutch-attempt screen, not at the season workload screen. Figure 2 shows why volume must remain central to interpretation: most rotation players receive few standard-clutch attempts, while a much smaller group accumulates enough observations for comparative modeling.

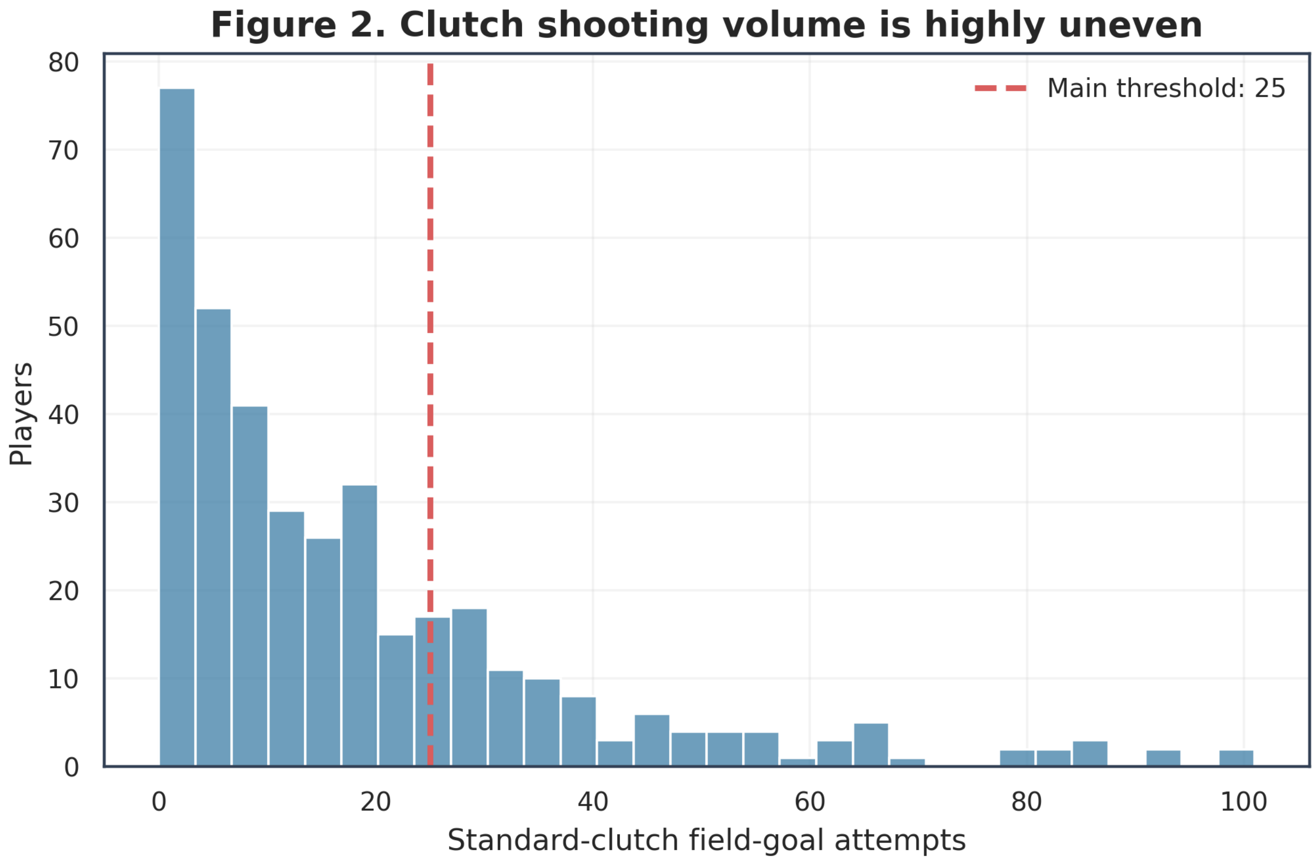


Figure 2. Distribution of standard-clutch FGA among players meeting season workload filters.

4. Variable Construction

4.1 Primary and secondary outcomes

For player i, true shooting percentage was computed from points, field-goal attempts, and free-throw attempts:

$$TS_i = \frac{PTS_i}{2(FGA_i + 0.44FTA_i)}$$

Non-clutch counts were constructed before rates:

$$PTS_{i,n} = PTS_{i,total} - PTS_{i,clutch}$$

with identical subtraction for FGA, FGM, FTA, FTM, three-point attempts and makes, assists, and turnovers. Therefore:

$$TS_{i,n} = \frac{PTS_{i,total} - PTS_{i,clutch}}{2[(FGA_{i,total} - FGA_{i,clutch}) + 0.44(FTA_{i,total} - FTA_{i,clutch})]}$$

The primary outcome was:

$$\Delta TS_i = TS_{i,\,clutch} - TS_{i,\,n}$$

Modeling stored proportions; prose and figures converted changes to percentage points. Secondary outcomes were changes in effective field-goal percentage, ordinary field-goal percentage, three-point percentage, free-throw rate, and an approximate possession-use turnover rate. Effective field-goal percentage was `(FGM + 0.5 x 3PM) / FGA`; free-throw rate was `FTA / FGA`; and turnover rate used `TOV / (FGA + 0.44 x FTA + TOV)`. Zero denominators produced missing values, never zeros.

4.2 Normal offensive predictors

Workload features included minutes, FGA per 36, points per 36, and a transparent usage proxy: 36 times `(FGA + 0.44 x FTA + TOV) / MIN`, calculated from non-clutch counts. This is not the official NBA usage percentage because team possession denominators were unavailable for exact subtraction. Official and estimated season usage fields were retained as season-context variables, explicitly labeled because rates cannot be subtracted like counts.

Shooting features included non-clutch TS, eFG, field-goal percentage, two-point percentage, three-point percentage, free-throw percentage, three-point attempt rate, and free-throw rate. Playmaking features included assists per 36 and assist-to-turnover ratio. Ball security used the non-clutch turnover-rate approximation. Position and experience were retained for secondary interpretation but not allowed to dominate the main model.

Tracking features included pull-up and catch-and-shoot attempt frequencies. These endpoints provided season context rather than perfectly non-clutch tracking splits. Because clutch attempts were a small share of total season attempts, they remain useful descriptive proxies, but the limitation is acknowledged. Drives, touches, possession time, dribbles per touch, potential assists, secondary assists, and percentage unassisted were not available from reliable league-level cached endpoints in a form that could be matched to all qualifying players. They were not invented or imputed.

Table 2. Core variable and data dictionary.

variable	source_endpoint	original_column	transformation	interpretation	unit
PLAYER_ID	LeagueDashPlayerStats	PLAYER_ID	Canonical identity or season label	PLAYER ID	count or index
season	LeagueDashPlayerStats	SEASON	Canonical identity or season label	season	count or index
player_name	LeagueDashPlayerStats	PLAYER_NAME	Canonical identity or season label	player name	count or index
min_total	Engineered from cached NBA counts	MIN_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	min total	count or index
fga_total	Engineered from cached NBA counts	FGA_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	fga total	count or index
fga_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FGA_CLUTCH	Clutch value or total-minus-clutch construction	fga clutch	count or index
ts_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	TS_CLUTCH	Clutch value or total-minus-clutch construction	ts clutch	proportion
ts_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	TS_NONCLUTCH	Clutch value or total-minus-clutch construction	ts nonclutch	proportion
ftr_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FTR_NONCLUTCH	Clutch value or total-minus-clutch construction	ftr nonclutch	proportion
tov_rate_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	TOV_RATE_NONCLUTCH	Clutch value or total-minus-clutch construction	tov rate nonclutch	proportion
delta_ts	LeagueDashPlayerClutch + LeagueDashPlayerStats	DELTA_TS	Clutch value or total-minus-clutch construction	delta ts	proportion (multiply by 100 for percentage points)
delta_efg	LeagueDashPlayerClutch + LeagueDashPlayerStats	DELTA_EFG	Clutch value or total-minus-clutch construction	delta efg	proportion (multiply by 100 for percentage points)

variable	source_endpoint	original_column	transformation	interpretation	unit
delta_fg	LeagueDashPlayerClutch + LeagueDashPlayerStats	DELTA_FG	Clutch value or total-minus-clutch construction	delta fg	proportion (multiply by 100 for percentage points)
delta_fg3	LeagueDashPlayerClutch + LeagueDashPlayerStats	DELTA_FG3	Clutch value or total-minus-clutch construction	delta fg3	proportion (multiply by 100 for percentage points)
delta_ftr	LeagueDashPlayerClutch + LeagueDashPlayerStats	DELTA_FTR	Clutch value or total-minus-clutch construction	delta ftr	proportion (multiply by 100 for percentage points)
delta_tov_rate	LeagueDashPlayerClutch + LeagueDashPlayerStats	DELTA_TOV_RATE	Clutch value or total-minus-clutch construction	delta tov rate	proportion
ast_per36_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	AST_PER36_NONCLUTCH	Clutch value or total-minus-clutch construction	ast per36 nonclutch	count or index
three_rate_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	THREE_RATE_NONCLUTCH	Clutch value or total-minus-clutch construction	three rate nonclutch	proportion
usage_proxy_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	USAGE_PROXY_NONCLUTCH	Clutch value or total-minus-clutch construction	usage proxy nonclutch	count or index
eligible_main	Configured sample thresholds	ELIGIBLE_MAIN	Inclusive eligibility indicator	eligible main	count or index
shot_entropy_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	SHOT_ENTROPY_NONCLUTCH	Clutch value or total-minus-clutch construction	shot entropy nonclutch	count or index
self_creation_index	Engineered composite	SELF_CREATION_INDEX	Standardized equal-weight or PCA score	self creation index	count or index
self_creation_pca	Engineered composite	SELF_CREATION_PCA	Standardized equal-weight or PCA score	self creation pca	count or index
versatility_pc1	Engineered composite	VERSATILITY_PC1	Standardized equal-weight or PCA score	versatility pc1	count or index

4.3 Shot entropy and profile change

Five mutually exclusive zones were used: restricted area, non-restricted paint, midrange, corner three, and above-the-break three. Backcourt attempts were negligible and excluded from the five-zone entropy denominator. For player i and zone z, attempt share was `p_iz`. Normalized Shannon entropy (Shannon, 1948) was:

$$H_i^* = \frac{-\sum_{z=1}^{5} p_{iz} \ln(p_{iz})}{\ln(5)}$$

The index ranges from zero for a single-zone profile to one for equal attempt shares across all five zones. It measures spatial diversity, not shot quality. Non-clutch zone attempts equaled complete season zone totals minus clutch shot events. Shot-profile adaptation was the clutch share minus non-clutch share within each zone.

4.4 Self-creation and versatility

The equal-weight Self-Creation Index averaged standardized non-clutch usage proxy, non-clutch FGA per 36, pull-up frequency, and one minus catch-and-shoot frequency. Each component was oriented so larger values indicated more on-ball creation. PCA supplied a comparison score, with its sign oriented toward the equal-weight index. The index is a project-defined proxy, not an official NBA statistic. It cannot fully replace direct unassisted rate, drives, touches, or time of possession.

The broader versatility representation combined shot entropy, zone shares, foul pressure, playmaking, and self-creation. PCA produced two dimensions rather than forcing all concepts into one scalar. Outcome-free clustering used standardized normal-condition features only. Clutch outcomes were merged after assignments were fixed.

5. Methods

5.1 Descriptive analysis

Descriptive analysis reported N, mean, standard deviation, median, interquartile range, minimum, maximum, and missing percentage. Histograms and density estimates examined clutch TS, non-clutch TS, Delta TS, and clutch FGA. Scatterplots compared clutch with non-clutch TS and showed Delta TS against volume. Player labels were restricted to selected extremes to avoid visual clutter. Raw leaderboards were limited to the main sample.

Table 4. Descriptive statistics for the main sample.

variable	n	mean	sd	median	q1	q3	min	max	missing_n	missing_pct
ts_clutch	99	0.5665	0.0887	0.5698	0.5084	0.6292	0.3568	0.7812	0	0.0000
ts_nonclutch	99	0.5894	0.0349	0.5821	0.5705	0.6120	0.5178	0.6935	0	0.0000
delta_ts	99	-0.0229	0.0901	-0.0137	-0.0932	0.0431	-0.2327	0.1862	0	0.0000
fga_clutch	99	44.6162	19.3737	38.0000	30.0000	53.5000	25.0000	101.0000	0	0.0000
usage_proxy_nonclutch	99	21.0518	4.2310	20.7809	18.0498	23.9703	11.4130	31.5928	0	0.0000
shot_entropy_nonclutch	99	0.8666	0.0941	0.8916	0.8395	0.9217	0.4364	0.9919	0	0.0000
self_creation_index	99	0.8598	0.6878	0.8191	0.4027	1.3362	-0.7309	2.5787	0	0.0000
ftr_nonclutch	99	0.2964	0.1140	0.2848	0.2243	0.3572	0.0567	0.5921	0	0.0000
three_rate_nonclutch	99	0.3934	0.1646	0.3902	0.2818	0.4950	0.0000	0.8951	0	0.0000
ast_per36_nonclutch	99	5.1043	2.1712	4.7013	3.5445	6.5254	1.8731	11.4529	0	0.0000
tov_rate_nonclutch	99	0.1197	0.0265	0.1193	0.1015	0.1379	0.0478	0.1963	0	0.0000

5.2 Correlation and univariate inference

Pearson and Spearman correlations were calculated for a theory-selected predictor set rather than an unreadable matrix of every available variable. Each major predictor was also entered into a univariate robust regression. Benjamini-Hochberg adjustment controlled the false discovery rate within exploratory correlation and coefficient families. Unadjusted p-values are shown because the hypotheses were pre-specified, but conclusions emphasize effect sizes, confidence intervals, model fit, and adjusted evidence.

5.3 Primary regression and mathematical coupling

The primary cross-sectional model regressed Delta TS on non-clutch TS, free-throw rate, three-point rate, shot entropy, self-creation, assists per 36, turnover rate, and clutch FGA. Heteroskedasticity-consistent HC3 standard errors were used because they improve finite-sample robustness (MacKinnon & White, 1985). Standardized coefficients, 95% intervals, p-values, partial R-squared, adjusted R-squared, RMSE, and MAE were saved.

The initial full specification also included the usage proxy. Its VIF with the Self-Creation Index exceeded the pre-specified threshold of 8; the maximum VIF was 8.73. Because usage was already a component of self-creation, the primary specification omitted the separate proxy and retained the theoretically broader index. The full model was reported as a robustness check.

Change-score regression creates mathematical coupling because non-clutch TS appears with a negative sign inside Delta TS. Three outcomes were therefore compared. Model A predicted Delta TS. Model B predicted clutch TS while controlling for non-clutch TS. Model C first fit a square-root-FGA-weighted regression of clutch TS on non-clutch TS and then predicted its residual. Models A and B are algebraically related: predictors other than baseline TS have identical slopes when the design matrix is unchanged. Model C provides a distinct residualized target.

5.4 Weighting, diagnostics, and influence

Unweighted OLS was compared with WLS using square-root clutch FGA and clutch FGA weights. Square-root weighting balances reliability against domination by the highest-volume players. Diagnostics included residual-versus-fitted plots, Q-Q plots, scale-location behavior, leverage, studentized residuals, Cook's distance, Breusch-Pagan tests, and refits excluding observations above `4/N` Cook's distance. Outliers were never deleted automatically.

Nonlinear workload was examined with centered usage and a squared term. Four pre-specified interactions were tested: usage by self-creation, usage by entropy, three-point rate by entropy, and self-creation by free-throw rate. These were treated as exploratory and adjusted as a family.

5.5 Machine learning

Models included a mean-only baseline, OLS, Ridge, Lasso, Elastic Net, Random Forest, Gradient Boosting, and Histogram Gradient Boosting. Median imputation and scaling occurred inside scikit-learn pipelines. Clutch volume, clutch efficiency, Delta TS, CBE, and other outcome-derived fields were prohibited as predictors. Repeated five-fold cross-validation used five repetitions and a fixed seed. Metrics were RMSE, MAE, and R-squared. Permutation importance was calculated for the best-ranked CV model as an exploratory global explanation; impurity-only importance was not used.

5.6 Archetypes

K-means, Gaussian mixture, and hierarchical clustering candidates were compared across feasible cluster counts. Selection required at least five players in each cluster and favored silhouette score. Cluster labels were assigned after inspecting centers. PCA supplied a two-dimensional visualization. Kruskal-Wallis testing compared Delta TS distributions after clustering because small cluster sizes and unequal dispersion weakened ANOVA assumptions.

5.7 Shrinkage, bootstrap uncertainty, and Monte Carlo simulation

Empirical beta priors were estimated separately for clutch two-point, three-point, and free-throw rates. Posterior component means were reconstructed into clutch points and true shooting. This avoids pretending that TS is binomial. Player uncertainty intervals came from 1,000 parametric bootstrap draws of clutch and non-clutch shooting components.

The Monte Carlo null treated each player's non-clutch two-point, three-point, and free-throw rates as approximate baseline abilities. The simulation used the player's actual clutch 2PA, 3PA, and FTA and generated 10,000 binomial component outcomes. Expected clutch TS, a 95% simulation interval, and an empirical tail probability were calculated. The project-defined Clutch Beyond Expectation score was:

$$CBE_i = \frac{TS_{i,\,observed} - E(TS_{i,\,sim})}{SD(TS_{i,\,sim})}$$

CBE is a standardized overperformance measure, not an official NBA statistic and not proof of psychological clutch ability. Its null assumes non-clutch component rates are adequate baselines and ignores defender distance, shot difficulty within zones, fatigue, and dependence among attempts.

5.8 Multi-season stability and mixed effects

Adjacent-season correlations matched players by ID and required main-sample eligibility in both seasons. Pearson and Spearman coefficients were reported. A player-season mixed model used a player grouping term, season indicators, and common normal-condition predictors. The random-effects covariance approached the boundary, so the mixed model is treated as a secondary diagnostic rather than a definitive career-level clutch estimate.

An additional exploratory player screen required main-sample eligibility in at least three seasons. For each eligible player, non-clutch component makes and attempts and clutch attempts were pooled across qualifying seasons. Ten thousand simulations then used pooled non-clutch 2P%, 3P%, and FT% with the player's pooled clutch 2PA, 3PA, and FTA. Players were ranked by pooled CBE; one-sided upper-tail probabilities were adjusted across the full screen using Benjamini-Hochberg. This screen was added to identify a concrete multi-season candidate, not as a pre-specified confirmatory test.

5.9 Sensitivity and reproducibility

Sensitivity analyses varied clutch definition, minimum clutch FGA from 10 through 40, outcome, and model family. Specifications were skipped when the remaining sample could not support the number of predictors. Every random operation used the configured seed. Raw and processed data, endpoint metadata, logs, code, figures, tables, and machine-readable results are retained. The cached pipeline can be regenerated without new network calls.

6. Results

6.1 Descriptive change and volume

Among 99 main-sample players, mean Delta TS was -2.29 percentage points, with a bootstrap 95% interval from -4.06 to -0.54. The median was -1.37 points. Thus, the typical qualifying player declined modestly, while substantial cross-player spread remained. The raw standard deviation was 8.98 points, nearly four times the magnitude of the mean. A mean decline is consistent with late-game defensive pressure and difficult shot creation, but the observational design cannot isolate those mechanisms.

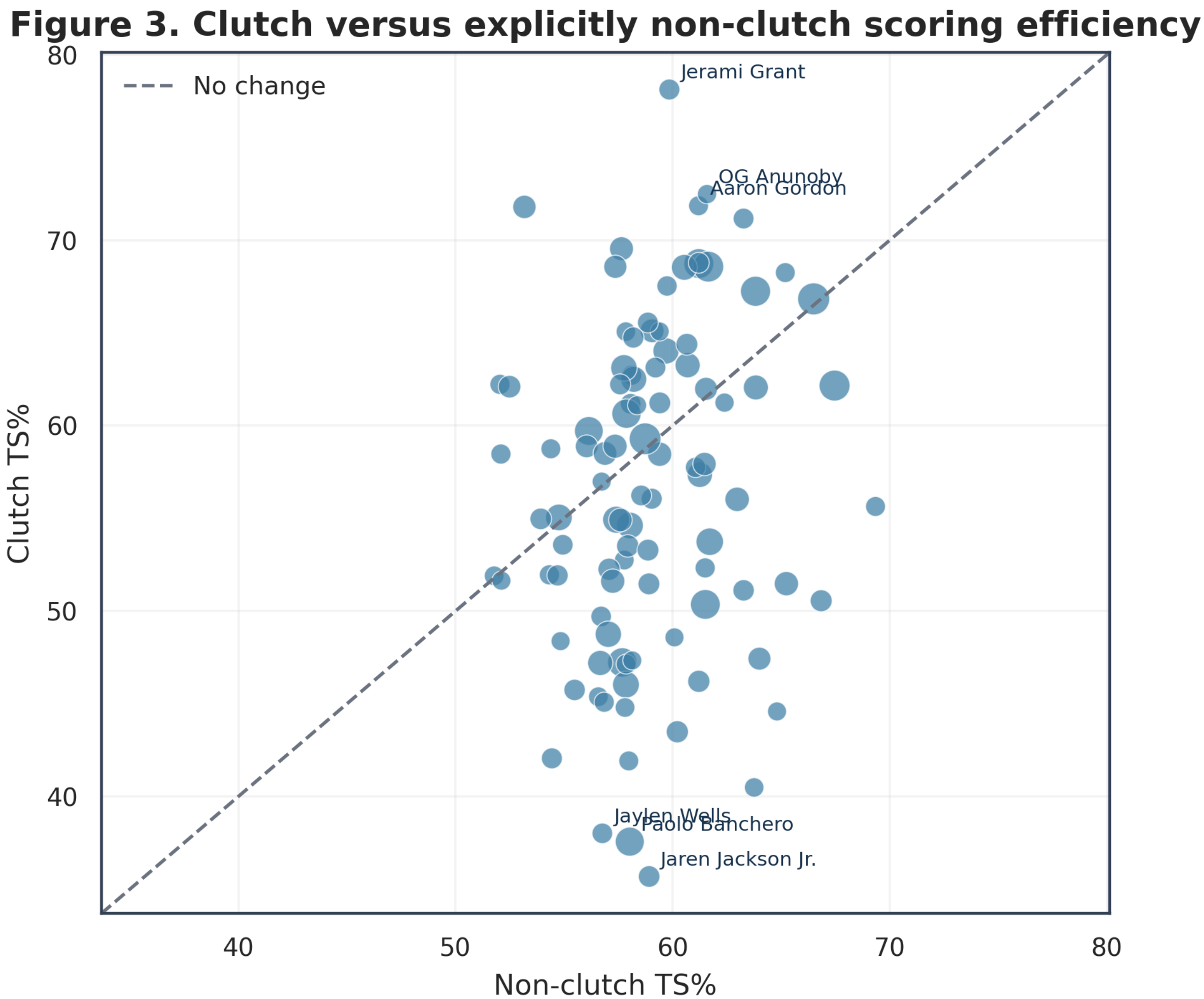


Figure 3. Standard-clutch TS% versus explicitly non-clutch TS%; point size reflects clutch FGA.

Figure 3 shows a broad vertical band around ordinary non-clutch efficiency. Players above the identity line improved; those below declined. Absolute late-game efficiency and change are visibly distinct. Some efficient baseline scorers remained efficient despite negative differentials, while some positive-differential players began from lower baselines.

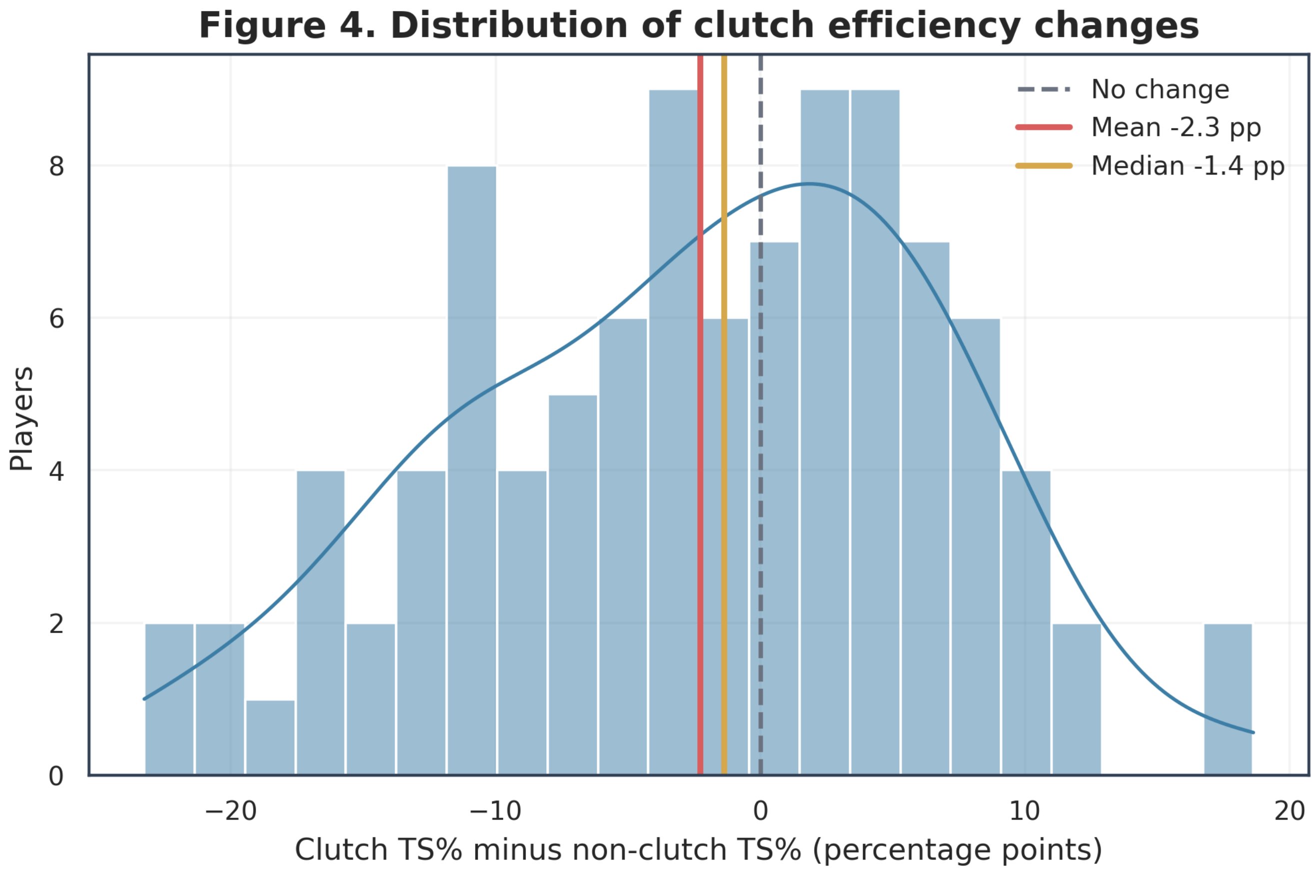


Figure 4. Distribution of Delta TS in the main sample.

The Delta TS distribution in Figure 4 was broad relative to its center. The tails included changes exceeding 15 percentage points in both directions. Such extremes are descriptively real for 2025-26 but require uncertainty analysis before interpretation as stable ability.

Figure 5. Extreme clutch differentials concentrate at lower volume

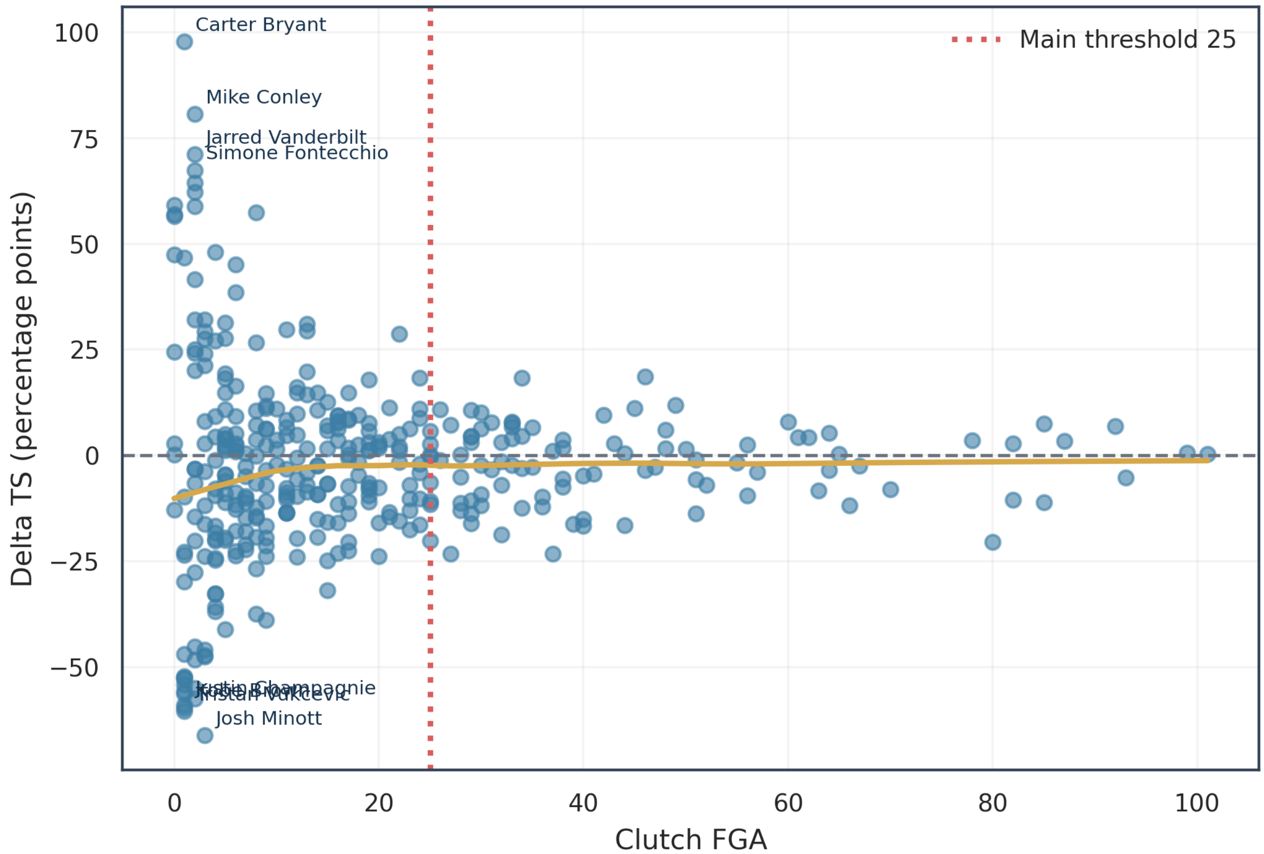


Figure 5. Delta TS versus clutch FGA; the vertical line marks the main threshold.

Figure 5 demonstrates the volume-noise relationship. The most extreme points are more common at lower attempt counts, although large declines can still occur at high volume. Clutch FGA itself had a small standardized coefficient in the adjusted model and is better understood as a reliability variable than an offensive skill.

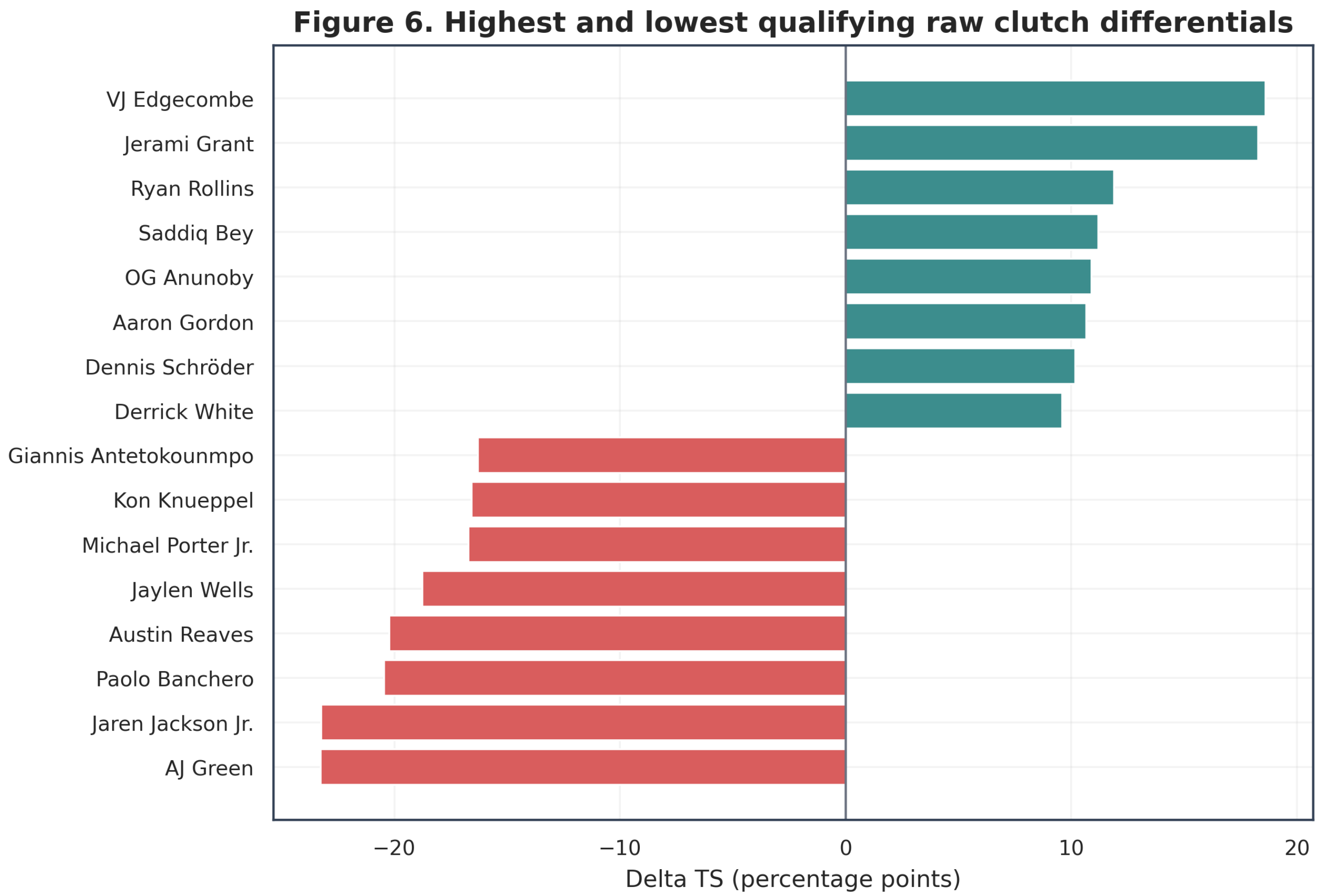


Figure 6. Highest and lowest raw Delta TS players among main-sample qualifiers.

Raw rankings are useful descriptions but not final judgments. VJ Edgecombe and Jerami Grant led the positive tail, while AJ Green, Jaren Jackson Jr., and Paolo Banchero occupied the negative tail. Later shrinkage and simulation results show that rank order and magnitude change substantially after uncertainty is incorporated.

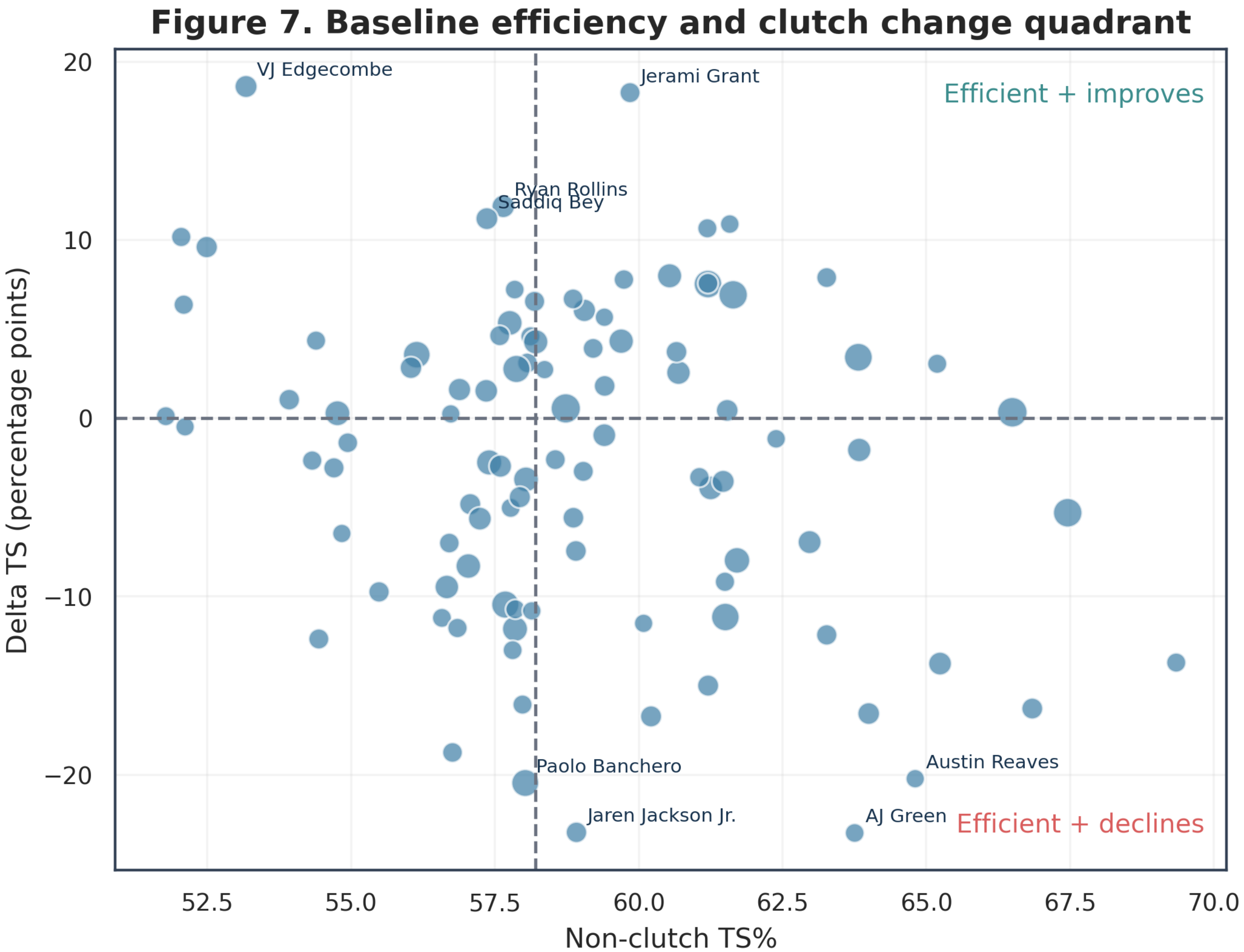


Figure 7. Baseline-efficiency and Delta TS quadrant using the main-sample median non-clutch TS.

The quadrant emphasizes that "efficient" and "improves" are not synonyms. Team decision-making may value absolute expected points more than a change score, while research on pressure adaptation may focus on the change. Both should be reported.

6.2 Correlations

Shot entropy had the strongest Pearson correlation with Delta TS: r = 0.287, unadjusted p = 0.0040, FDR-adjusted p = 0.0362. Non-clutch TS correlated negatively, consistent with mathematical coupling and regression to the mean. The Self-Creation Index had essentially no univariate Pearson association. Pearson and Spearman results differed for entropy, suggesting that part of its relationship was driven by linear magnitude or influential observations rather than a uniformly monotonic ordering.

Table 5. Pearson and Spearman correlations with Delta TS.

predictor	n	pearson_r	pearson_p	spearman_rho	spearman_p	pearson_p_fdr	spearman_p_fdr
ts_nonclutch	99	-0.2348	0.0193	-0.1215	0.2307	0.0869	0.6734
usage_proxy_nonclutch	99	-0.0715	0.4817	-0.1054	0.2993	0.9570	0.6734
ftr_nonclutch	99	-0.0314	0.7576	0.0424	0.6768	0.9570	0.8702
three_rate_nonclutch	99	-0.0229	0.8223	0.0056	0.9565	0.9570	0.9565
shot_entropy_nonclutch	99	0.2867	0.0040	0.1603	0.1130	0.0362	0.6466
self_creation_index	99	0.0055	0.9570	-0.0482	0.6356	0.9570	0.8702
ast_per36_nonclutch	99	0.1421	0.1605	0.1480	0.1437	0.4814	0.6466
tov_rate_nonclutch	99	-0.0163	0.8731	0.0215	0.8329	0.9570	0.9370

predictor	n	pearson_r	pearson_p	spearman_rho	spearman_p	pearson_p_fdr	spearman_p_fdr
fga_clutch	99	0.0544	0.5927	0.0536	0.5984	0.9570	0.8702

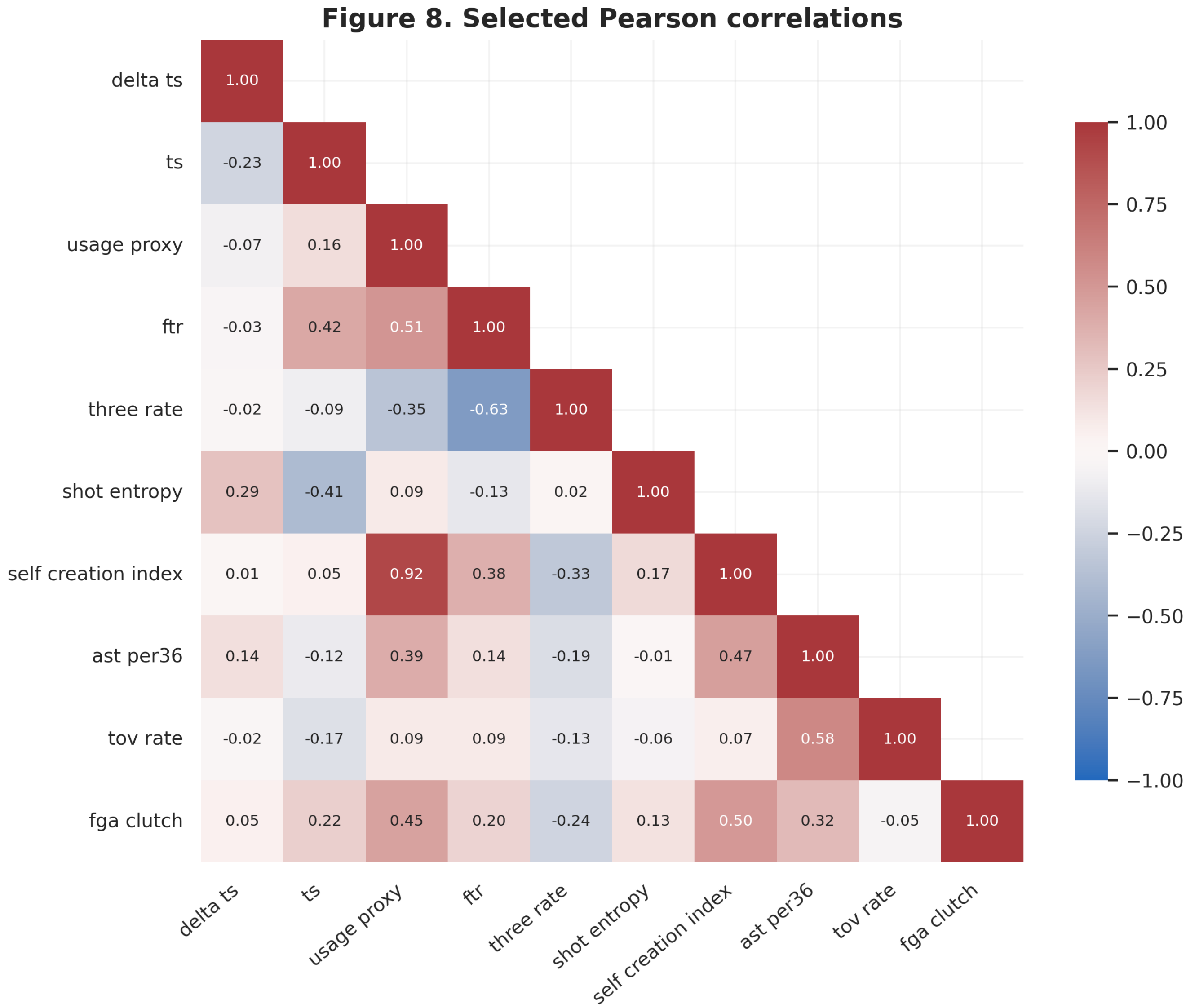


Figure 8. Selected Pearson correlation matrix for the primary outcome and theory-driven predictors.

The matrix also reveals why interpretation must remain multivariate. Foul pressure was related to baseline efficiency and attempt mix; assists and turnovers were related; and the full usage proxy overlapped strongly with self-creation. None of these variables represents an isolated basketball mechanism.

6.3 Primary regression

The primary robust model had R-squared 0.163, adjusted R-squared 0.089, RMSE 8.20 percentage points, and MAE 6.62 points. In-sample explanatory power was therefore modest. The model captured some systematic cross-sectional structure but left most variation unexplained.

Shot entropy had coefficient 0.246, standardized beta 0.257, 95% CI [0.058, 0.434], and p = 0.0109. A full-range one-unit increase in normalized entropy corresponded to approximately 24.6 percentage points of Delta TS, but a one-unit change spans the entire theoretical index and is not a typical player contrast. The standardized effect is the more interpretable magnitude. After adjustment across the regression table, p became 0.0907, so the evidence is suggestive rather than confirmatory.

Assists per 36 had coefficient 0.0138, standardized beta 0.333, 95% CI [0.0008, 0.0269], and p = 0.0383. One additional non-clutch assist per 36 was associated with about 1.38 percentage points more preservation. Its adjusted p-value was 0.1596. The basketball interpretation is plausible: players able to create for teammates may avoid forcing poor attempts when primary options are denied. The statistical evidence, however, does not distinguish that mechanism from role, team system, or other omitted context.

The Self-Creation Index had coefficient -0.0310, standardized beta -0.237, 95% CI [-0.0688, 0.0068], and p = 0.1064. Its direction was negative, contrary to H1, and its interval crossed zero. Turnover rate also had a negative standardized coefficient (-0.221), while baseline TS had standardized coefficient -0.180. Neither supports a simple claim that more on-ball creation automatically protects late-game efficiency.

Table 6. Main regression results for change-score, controlled-clutch, and residualized outcomes.

model	term	coefficient	std_error	ci_low	ci_high	p_value	standardized_beta	partial_r2	n	p_value_fdr_within_table
A-primary-OLS-HC3	const	0.0443	0.2533	-0.4589	0.5475	0.8615	not applicable	0.0003	99	0.9790
A-primary-OLS-HC3	ts_nonclutch	-0.4643	0.3762	-1.2116	0.2830	0.2203	-0.1798	0.0166	99	0.3672
A-primary-OLS-HC3	ftr_nonclutch	0.1056	0.1537	-0.1998	0.4109	0.4940	0.1336	0.0052	99	0.6862
A-primary-OLS-HC3	three_rate_nonclutch	0.0015	0.0707	-0.1389	0.1420	0.9827	0.0028	0.0000	99	0.9827
A-primary-OLS-HC3	shot_entropy_nonclutch	0.2461	0.0946	0.0581	0.4341	0.0109	0.2570	0.0699	99	0.0907
A-primary-OLS-HC3	self_creation_index	-0.0310	0.0190	-0.0688	0.0068	0.1064	-0.2368	0.0287	99	0.2045
A-primary-OLS-HC3	ast_per36_nonclutch	0.0138	0.0066	0.0008	0.0269	0.0383	0.3333	0.0468	99	0.1596
A-primary-OLS-HC3	tov_rate_nonclutch	-0.7498	0.4520	-1.6478	0.1482	0.1006	-0.2209	0.0297	99	0.2045
A-primary-OLS-HC3	fga_clutch	0.0002	0.0007	-0.0012	0.0015	0.8124	0.0344	0.0006	99	0.9790
B-clutchTS-controlled	const	0.0443	0.2533	-0.4589	0.5475	0.8615	not applicable	0.0003	99	0.9790
B-clutchTS-controlled	ts_nonclutch	0.5357	0.3762	-0.2116	1.2830	0.1579	0.2108	0.0220	99	0.2819
B-clutchTS-controlled	ftr_nonclutch	0.1056	0.1537	-0.1998	0.4109	0.4940	0.1357	0.0052	99	0.6862
B-clutchTS-controlled	three_rate_nonclutch	0.0015	0.0707	-0.1389	0.1420	0.9827	0.0029	0.0000	99	0.9827
B-clutchTS-controlled	shot_entropy_nonclutch	0.2461	0.0946	0.0581	0.4341	0.0109	0.2612	0.0699	99	0.0907
B-clutchTS-controlled	self_creation_index	-0.0310	0.0190	-0.0688	0.0068	0.1064	-0.2407	0.0287	99	0.2045
B-clutchTS-controlled	ast_per36_nonclutch	0.0138	0.0066	0.0008	0.0269	0.0383	0.3387	0.0468	99	0.1596
B-clutchTS-controlled	tov_rate_nonclutch	-0.7498	0.4520	-1.6478	0.1482	0.1006	-0.2245	0.0297	99	0.2045
B-clutchTS-controlled	fga_clutch	0.0002	0.0007	-0.0012	0.0015	0.8124	0.0349	0.0006	99	0.9790
C-residualized	const	-0.1943	0.1060	-0.4048	0.0163	0.0702	not applicable	0.0352	99	0.2045
C-residualized	ftr_nonclutch	0.1190	0.1299	-0.1390	0.3770	0.3620	0.1549	0.0090	99	0.5657
C-residualized	three_rate_nonclutch	0.0031	0.0655	-0.1269	0.1332	0.9619	0.0059	0.0000	99	0.9827
C-residualized	shot_entropy_nonclutch	0.2362	0.0874	0.0626	0.4099	0.0082	0.2537	0.0735	99	0.0907
C-residualized	self_creation_index	-0.0294	0.0177	-0.0645	0.0057	0.0991	-0.2308	0.0293	99	0.2045
C-residualized	ast_per36_nonclutch	0.0142	0.0058	0.0026	0.0258	0.0172	0.3510	0.0602	99	0.1074
C-residualized	tov_rate_nonclutch	-0.8010	0.4038	-1.6029	0.0010	0.0503	-0.2426	0.0410	99	0.1796

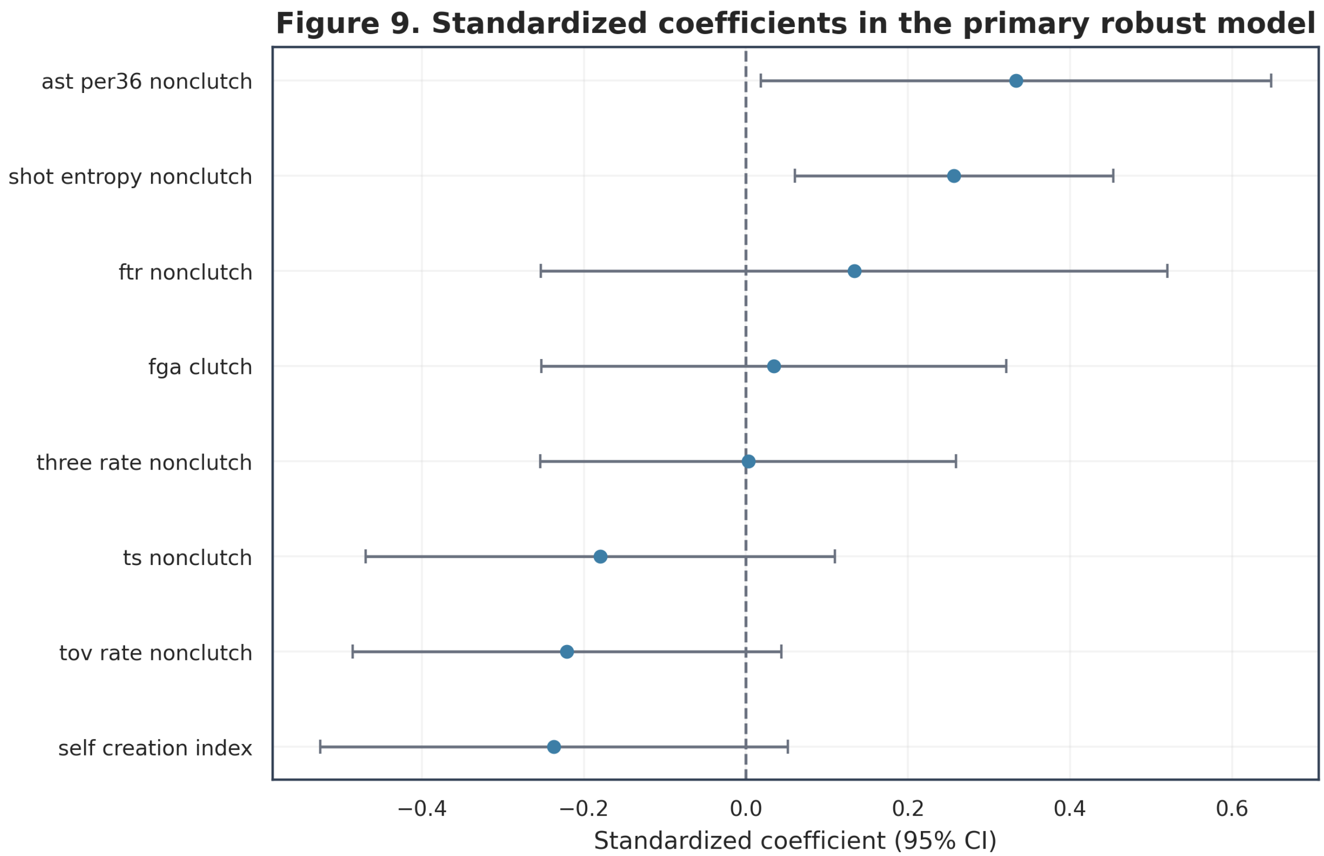


Figure 9. Standardized primary-model coefficients with HC3 95% confidence intervals.

Model B produced the same non-baseline slopes as Model A because `TS_clutch = Delta TS + TS_nonclutch`. The coefficient on baseline TS shifted by exactly one, illustrating why changing the label of the dependent variable does not remove coupling unless the model structure changes. Model C's residualized outcome retained positive entropy and assist directions and negative self-creation and turnover directions. This consistency supports the descriptive pattern, while the intervals and adjusted p-values constrain its strength.

6.4 Weighting, diagnostics, and robustness

Square-root-FGA and FGA weighting did not improve in-sample error materially. The unweighted primary model's RMSE was about 8.20 percentage points; weighted alternatives remained close. Coefficient directions were generally similar, but weighting changed magnitudes because high-volume creators received more influence.

Table 7. Fit statistics for primary and robustness models.

model	n	r_squared	adjusted_r_squared	rmse	mae
A-primary-OLS-HC3	99	0.1632	0.0888	0.0820	0.0662
A-WLS-sqrtFGA	99	0.1476	0.0719	0.0822	0.0663
A-WLS-FGA	99	0.1350	0.0582	0.0827	0.0667
B-clutchTS-controlled	99	0.1356	0.0587	0.0820	0.0662
C-residualized	99	0.1126	0.0547	0.0821	0.0663
A-full-OLS-HC3	99	0.1782	0.0951	0.0813	0.0655

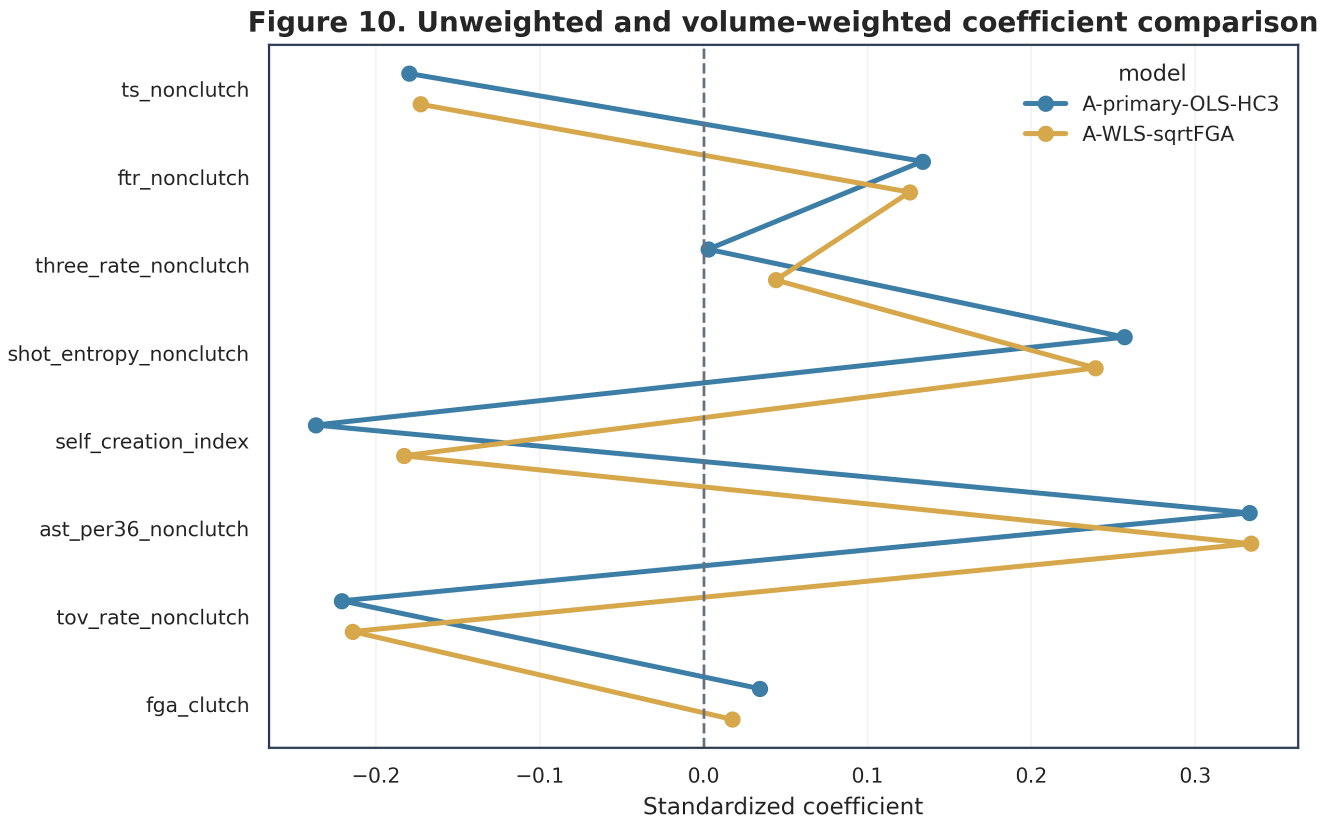


Figure 10. Standardized coefficients from unweighted and square-root-FGA-weighted models.

The Breusch-Pagan LM statistic was 17.68 with p = 0.0237, supporting the use of heteroskedasticity-robust inference. Residual normality was not rejected by Jarque-Bera, but normality is less important than unequal variance for these cross-sectional errors. 5 observations exceeded the Cook's-distance rule. Refit results without them were saved and used as a robustness diagnostic, not as a replacement model.

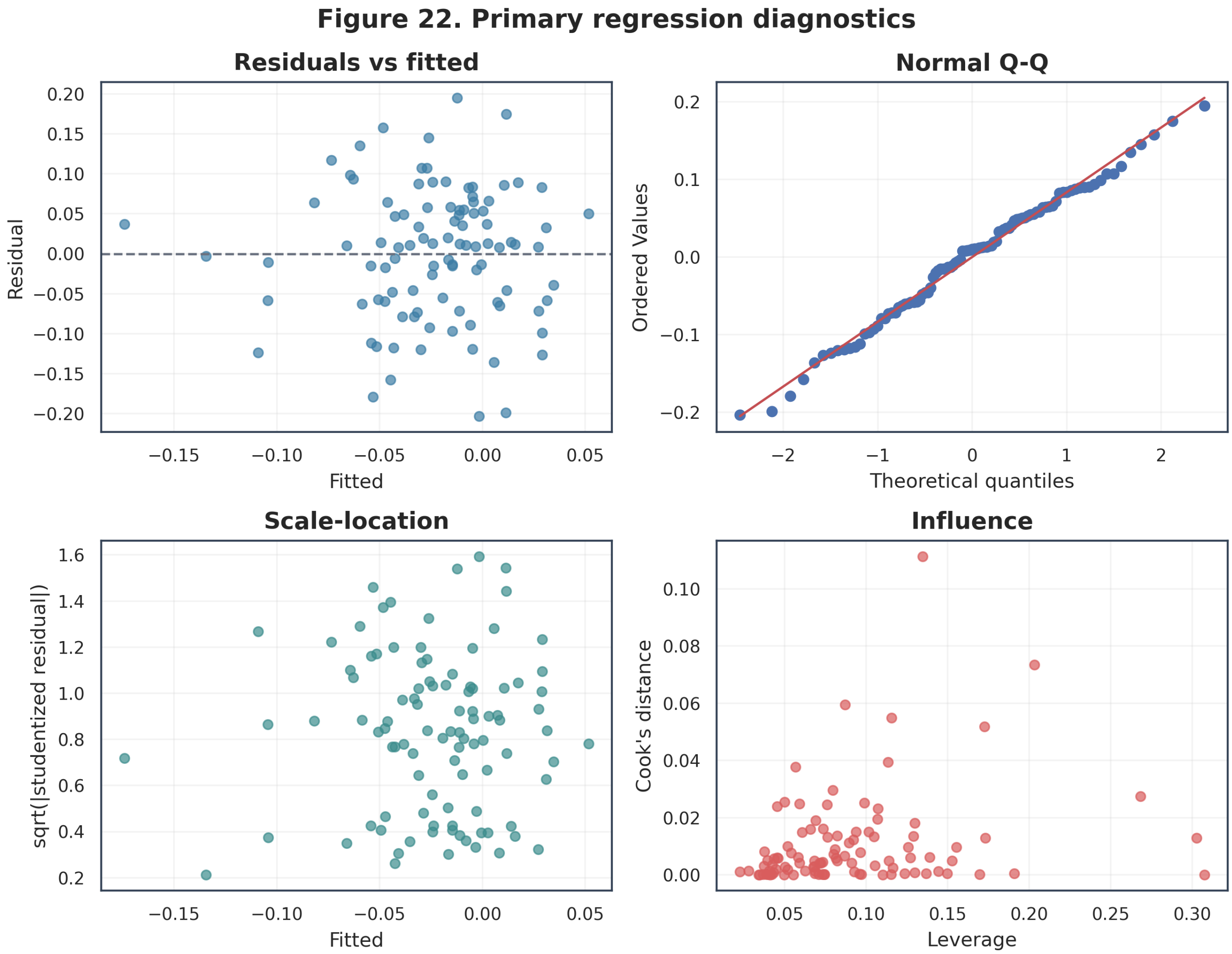


Figure 22. Residual, Q-Q, scale-location, leverage, and Cook's-distance diagnostics.

The quadratic usage term was not supported. None of the four pre-specified interactions survived FDR adjustment. In particular, the data did not show reliable evidence that self-creation became more valuable at high usage or that entropy changed the association of three-point rate with clutch preservation.

6.5 Predictive performance

The best repeated-CV RMSE belonged to Random Forest at 8.78 percentage points, with MAE 7.22 and mean held-out R-squared -0.075. Ridge and OLS were nearly tied. Every model had negative mean held-out R-squared, meaning that fold-specific predictions did not outperform a constant mean in variance-explained terms. Random Forest slightly reduced RMSE relative to the mean baseline but not enough to establish meaningful predictability.

Table 8. Repeated five-fold cross-validation performance.

model	rmse_mean	rmse_sd	mae_mean	mae_sd	r_squared_mean	r_squared_sd
Random Forest	0.0878	0.0093	0.0722	0.0080	-0.0754	0.2254
Ridge	0.0881	0.0117	0.0717	0.0105	-0.0816	0.2580
OLS	0.0882	0.0118	0.0718	0.0106	-0.0868	0.2654
Elastic Net	0.0887	0.0112	0.0732	0.0099	-0.0867	0.1926
Lasso	0.0888	0.0111	0.0734	0.0101	-0.0861	0.1723
Gradient Boosting	0.0901	0.0101	0.0746	0.0077	-0.1397	0.2718
Mean	0.0905	0.0122	0.0749	0.0105	-0.1224	0.1601
Hist Gradient Boosting	0.0957	0.0127	0.0786	0.0116	-0.2958	0.3752

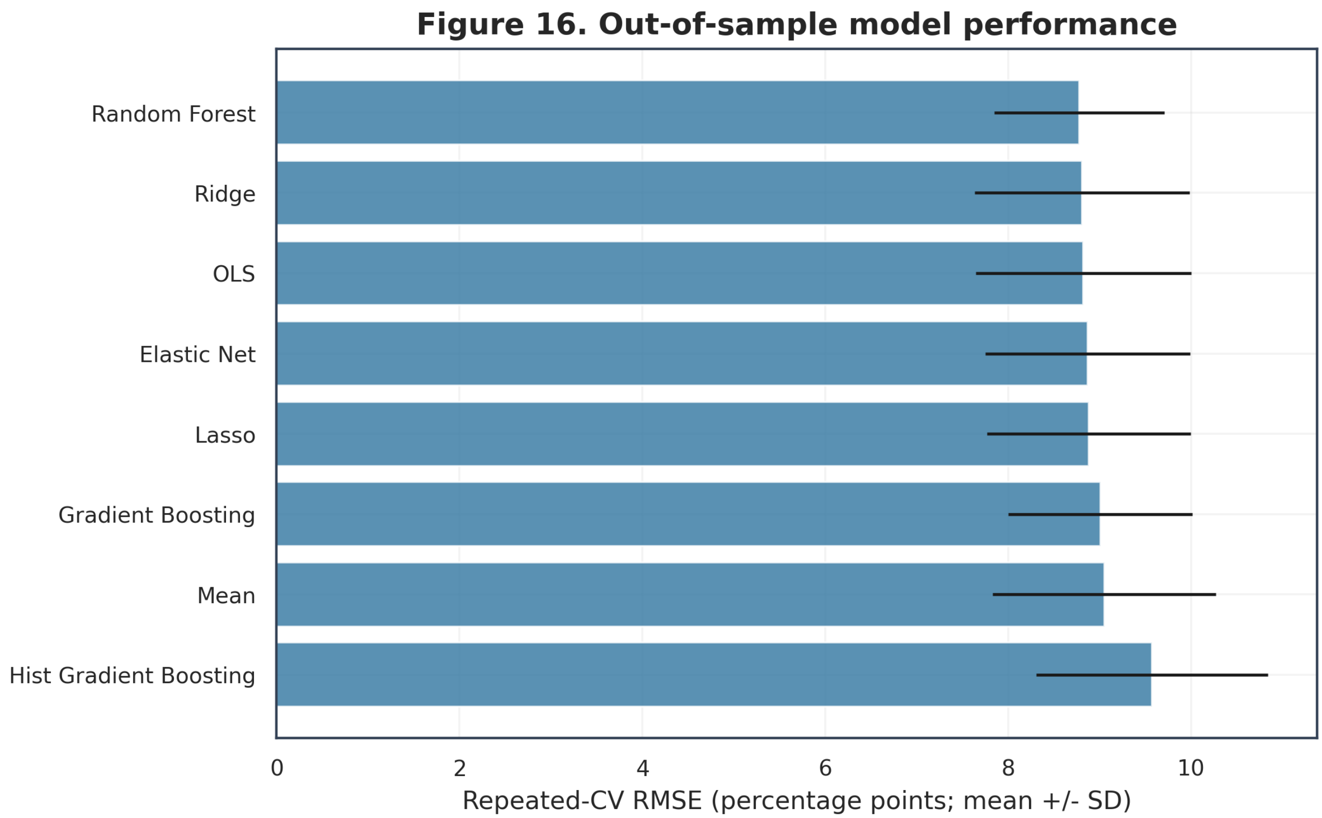


Figure 16. Repeated-cross-validation RMSE comparison.

The most important interpretation of Figure 16 is not that Random Forest "won." Model differences were small relative to split-to-split variability, and the best model's negative R-squared indicates weak generalization. Flexible nonlinear algorithms did not uncover a strong hidden signal missed by regularized linear models.

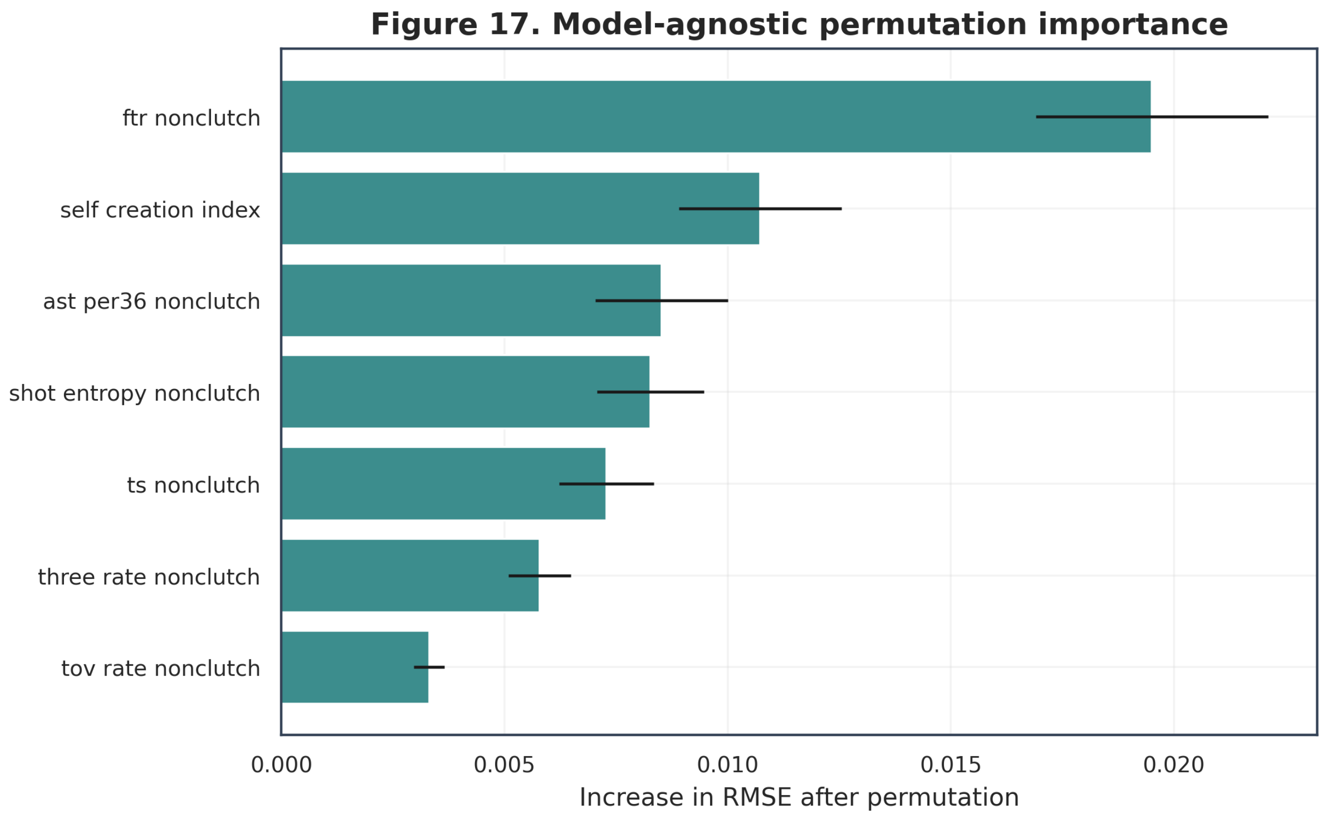


Figure 17. Permutation importance for the best-ranked cross-validation model.

Permutation importance ranked free-throw rate, self-creation, assists, entropy, and baseline TS highest in the fitted Random Forest. Because importance was calculated after full-sample fitting and predictors are correlated, these rankings are exploratory. They do not override the weak out-of-sample performance.

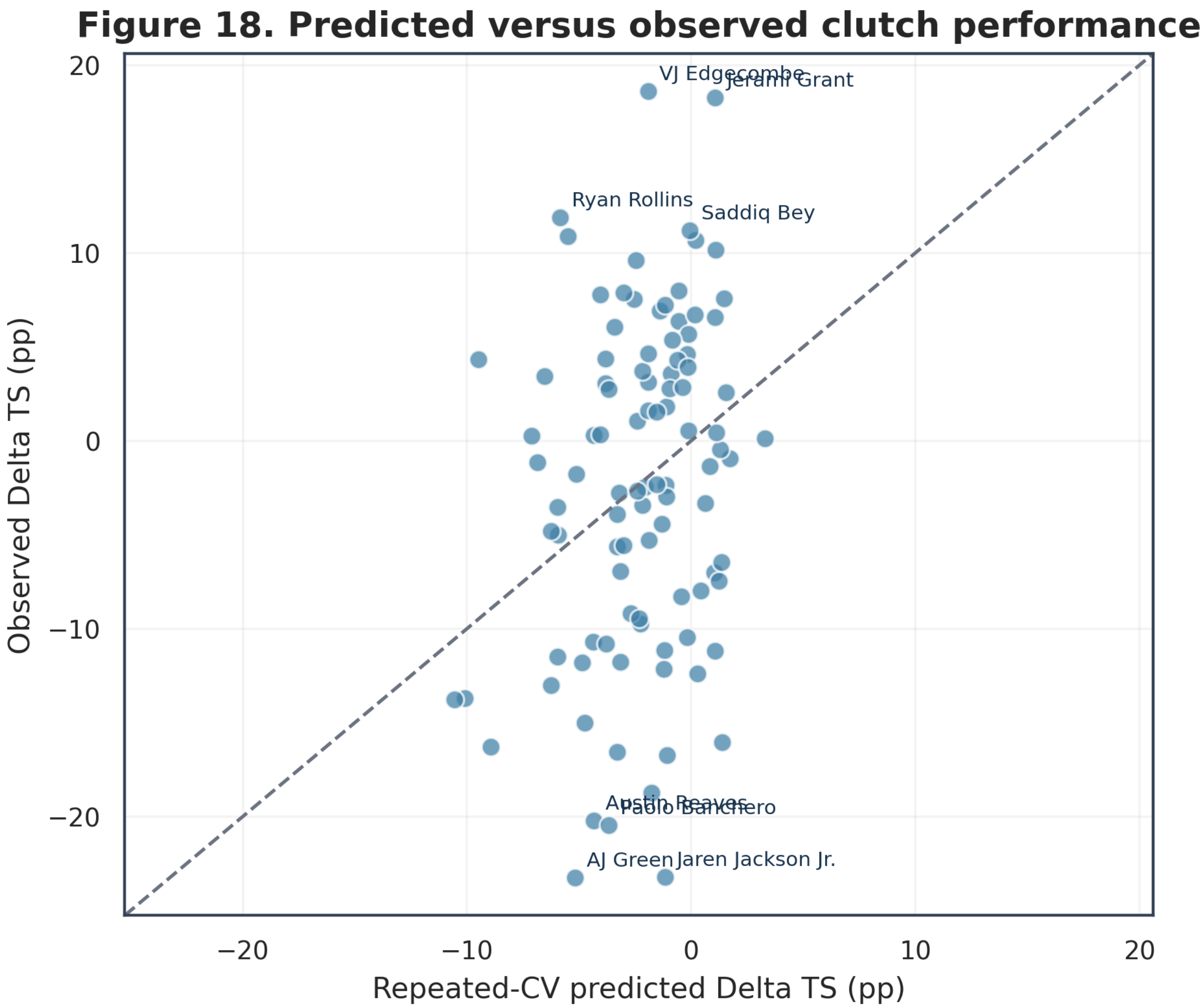


Figure 18. Repeated-CV predicted versus observed Delta TS.

Predictions were compressed toward the mean, while observed outcomes retained wide tails. This is the appropriate behavior for a model facing noisy targets, but it also shows why individual narratives built from a single fitted value are unreliable. Calibration errors were largest at the raw extremes.

6.6 Offensive archetypes

Outcome-free clustering selected three interpretable groups after candidate comparison: perimeter-oriented scorers, primary self-creators, and rim-pressure finishers. These names were assigned from observed centers, not imposed in advance.

Table 9. Offensive archetype characteristics.

cluster	usage_proxy_nonclutch	self_creation_index	shot_entropy_nonclutch	rim_share_nonclutch	midrange_share_nonclutch	three_rate_nonclutch	ftr_nonclutch	ast_per36_nonclutch	catch_shoot_fga_frequency_season	pullup_fga_frequency_season	archetype
0	17.9634	0.3023	0.8730	0.2320	0.0873	0.4964	0.2347	3.6181	0.3800	0.2540	Perimeter-oriented scorers (1)
1	23.7978	1.3903	0.8953	0.2336	0.1710	0.3604	0.3215	6.2647	0.1938	0.4181	Primary self-creators (2)
2	20.8302	0.6714	0.7199	0.5161	0.0705	0.1507	0.4197	5.6858	0.1256	0.1435	Rim-pressure finishers (3)

Figure 14. PCA embedding of normal-condition offensive archetypes

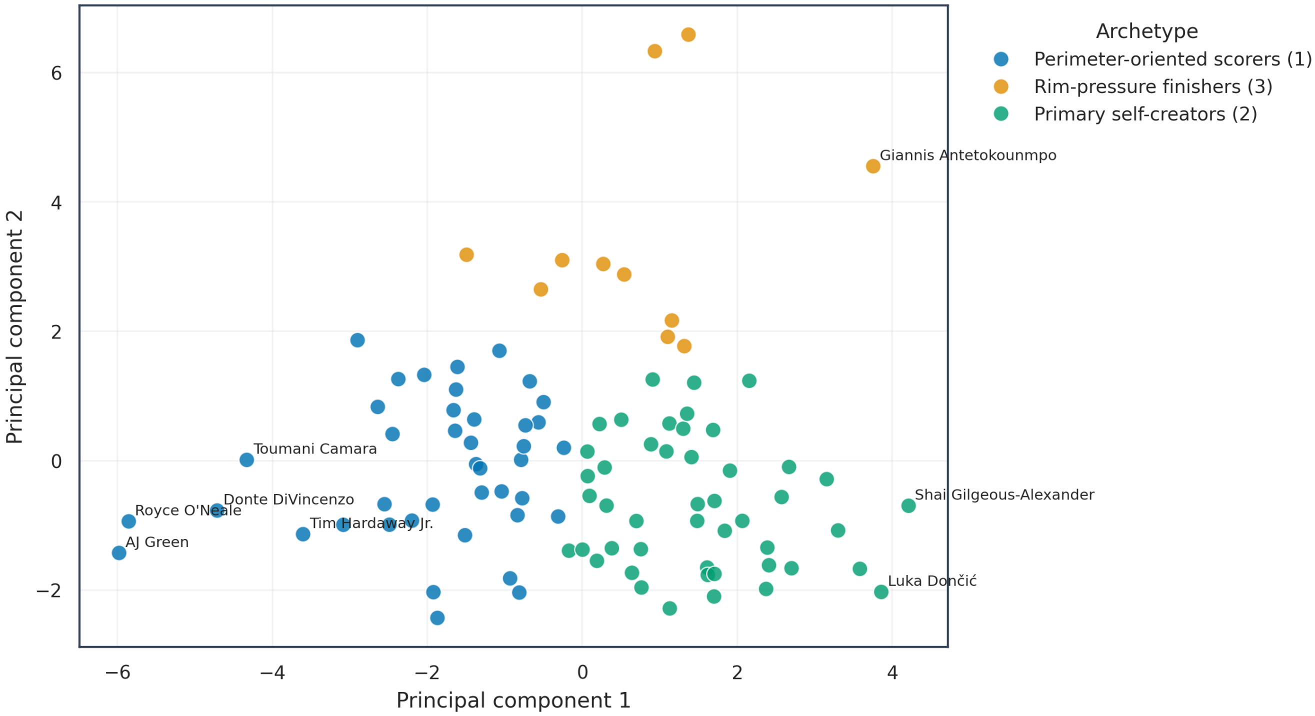


Figure 14. PCA embedding colored by discovered offensive archetype.

The PCA embedding shows overlapping role continua rather than perfectly separated species of player. That overlap is basketball-realistic: modern players mix creation, shooting, and finishing responsibilities.

Table 10. Archetype clutch outcomes.

archetype	n	mean_delta_ts	median_delta_ts	sd_delta_ts	mean_clutch_fga	omnibus_test	omnibus_statistic	omnibus_p_value
Perimeter-oriented scorers (1)	41	-0.0201	-0.0137	0.1037	35.5610	Kruskal-Wallis	1.4482	0.4848
Primary self-creators (2)	47	-0.0182	0.0028	0.0777	53.2766	Kruskal-Wallis	1.4482	0.4848
Rim-pressure finishers (3)	11	-0.0537	-0.0646	0.0875	41.3636	Kruskal-Wallis	1.4482	0.4848

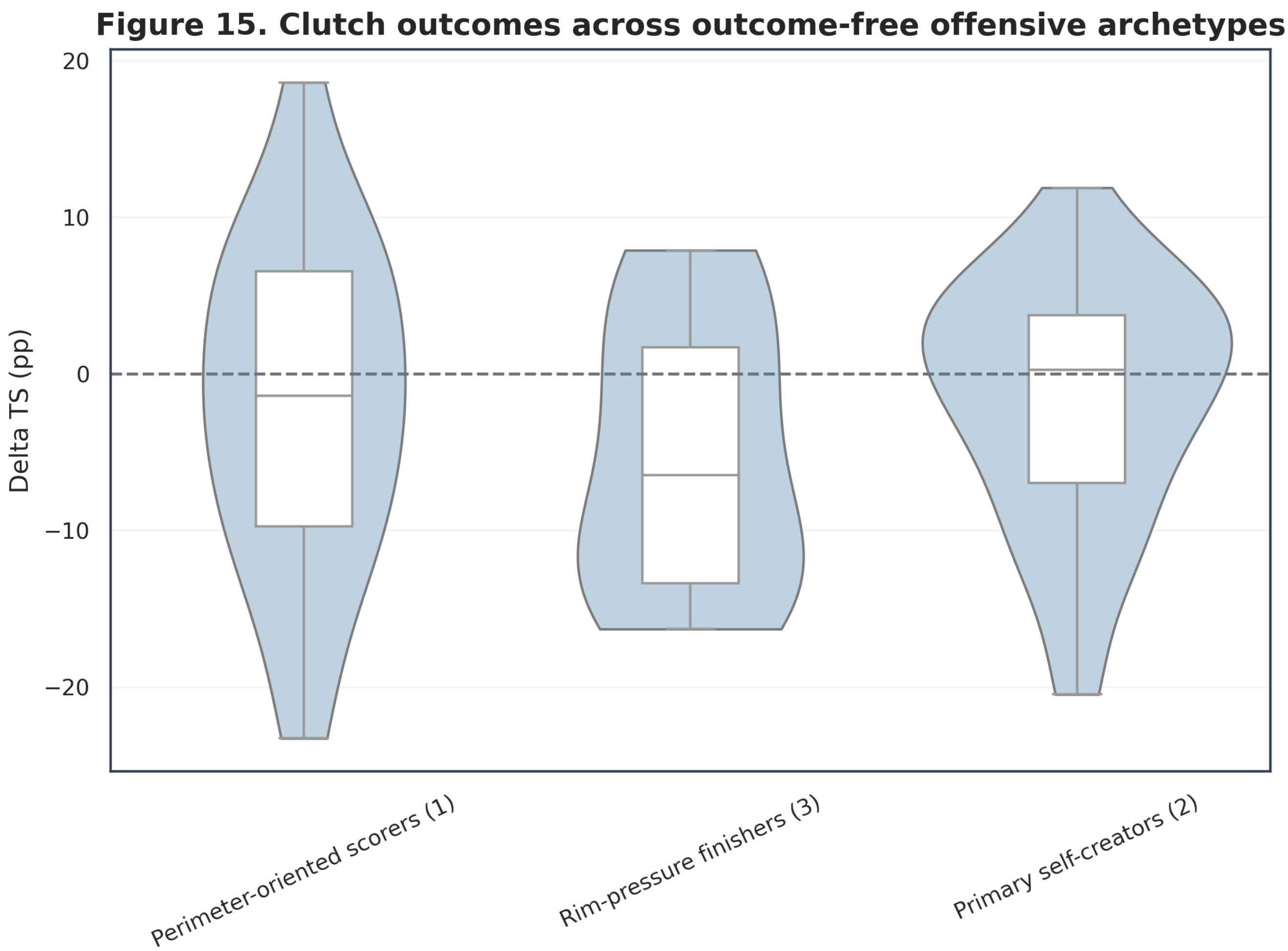


Figure 15. Delta TS distributions by offensive archetype.

The Kruskal-Wallis p-value was 0.4848. The study therefore found no reliable evidence that these broad normal-condition archetypes differed systematically in Delta TS. The rim-pressure group had a more negative mean, but it contained only 11 players and wide variation. This null result is substantively valuable: clustering produced recognizable roles without manufacturing a clutch hierarchy.

6.7 Shot-profile adaptation

Mean clutch-minus-non-clutch attempt-share changes were -0.82 percentage points at the rim, 0.35 in the non-restricted paint, 0.72 in midrange, 0.47 for corner threes, and -0.72 for above-the-break threes. The averages suggest a small shift away from the rim and above-the-break threes toward midrange and corner attempts, but individual patterns varied greatly.

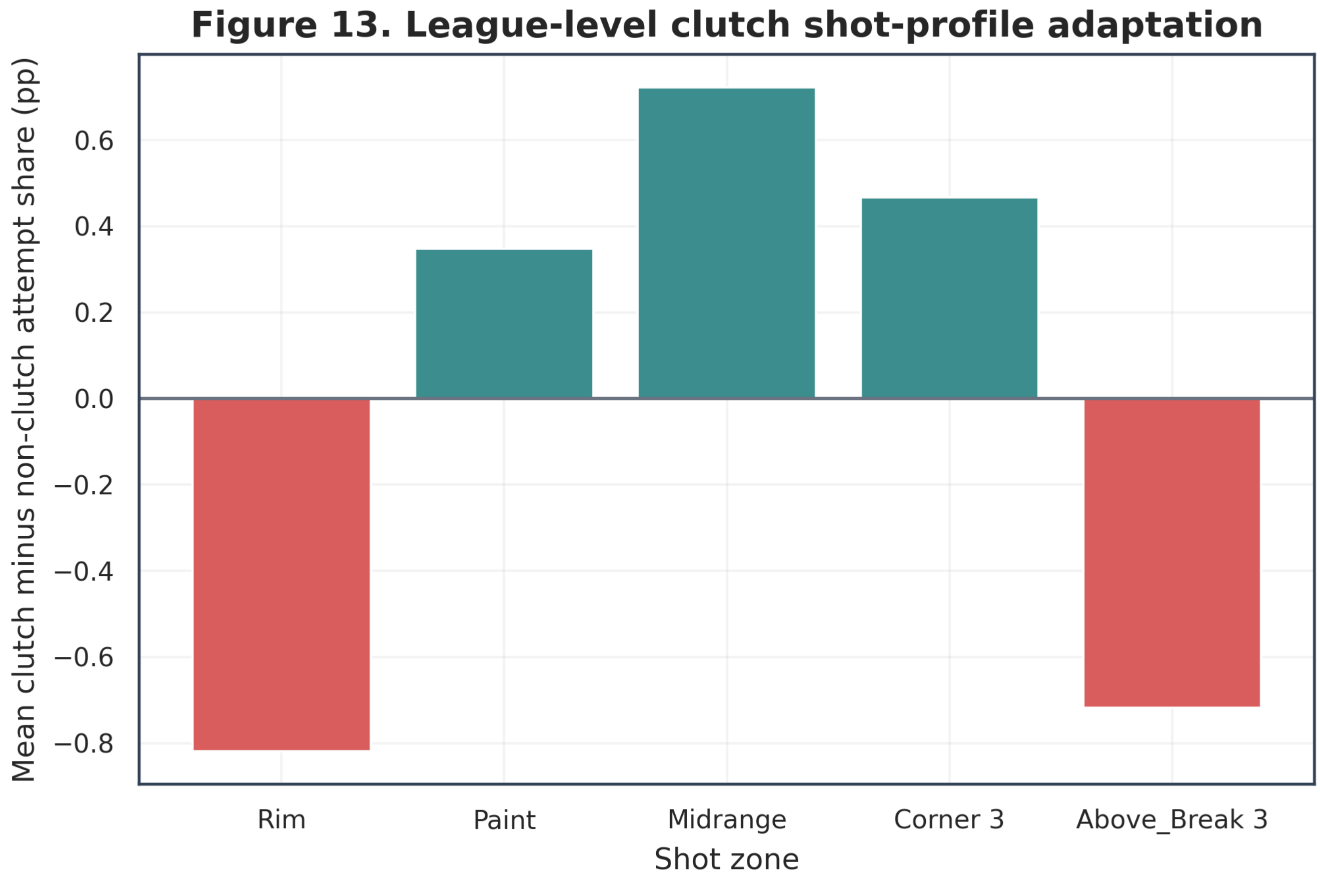


Figure 13. Mean clutch-minus-non-clutch shot-zone share change.

The zone changes should not be interpreted as deliberate preference alone. Defensive coverage, play calls, clock constraints, transition scarcity, and intentional fouling all change the opportunity set. Entropy's positive association may represent adaptability, but it may also proxy for role, skill breadth, or team spacing.

6.8 Shrinkage and player uncertainty

Component shrinkage reduced the standard deviation of Delta TS from 8.98 to 4.27 percentage points, a 52.5% reduction. This directly supports H6. Many apparent stars and failures moved sharply toward the population component rates.

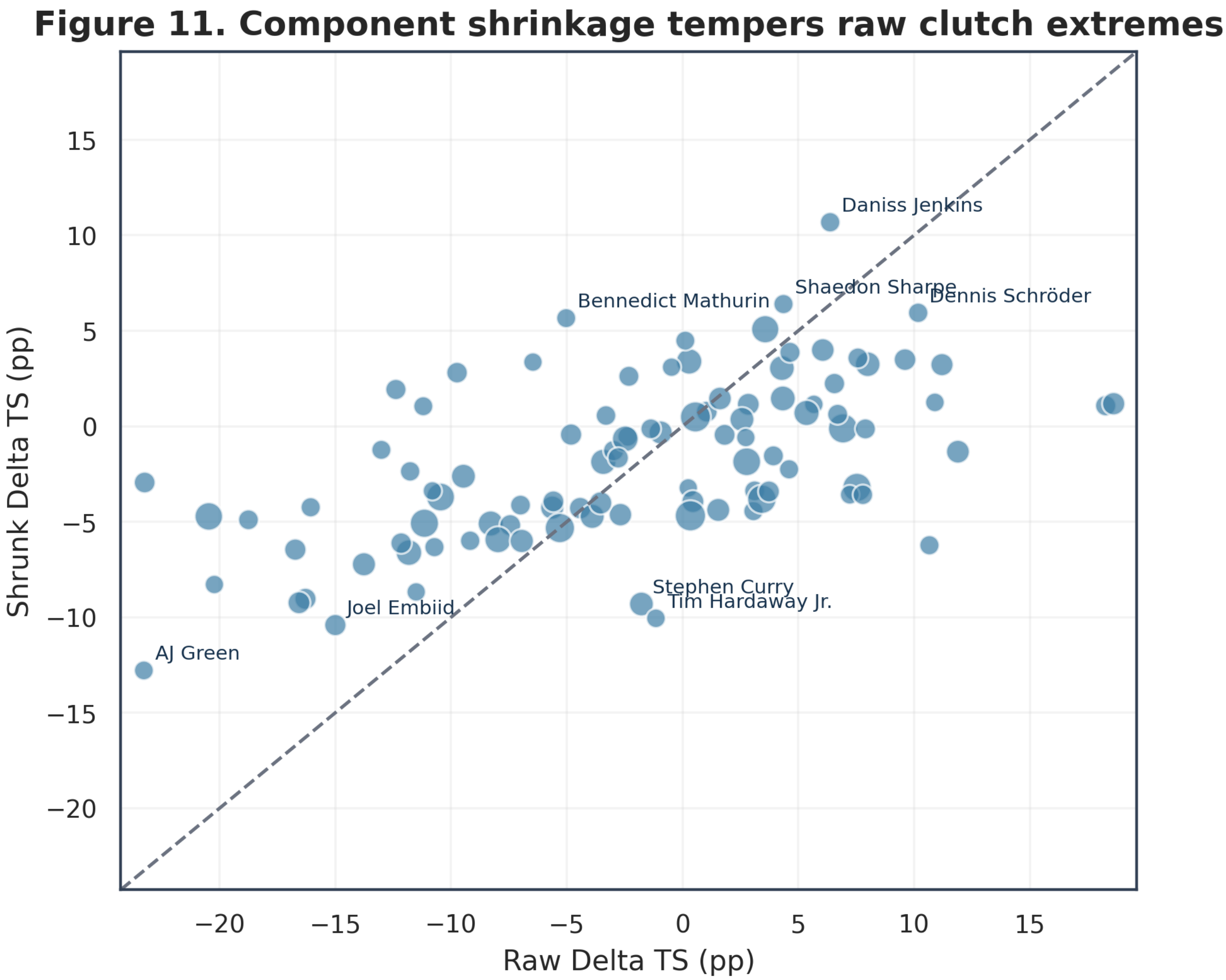


Figure 11. Raw versus component-shrunk Delta TS.

The identity line in Figure 11 makes attenuation visible. VJ Edgecombe's raw differential was 18.62 points, but his shrunk differential was close to zero. Jaren Jackson Jr. moved substantially upward from a large negative raw value. Shrinkage is not evidence that extremes are false; it is a more conservative estimate under a population model.

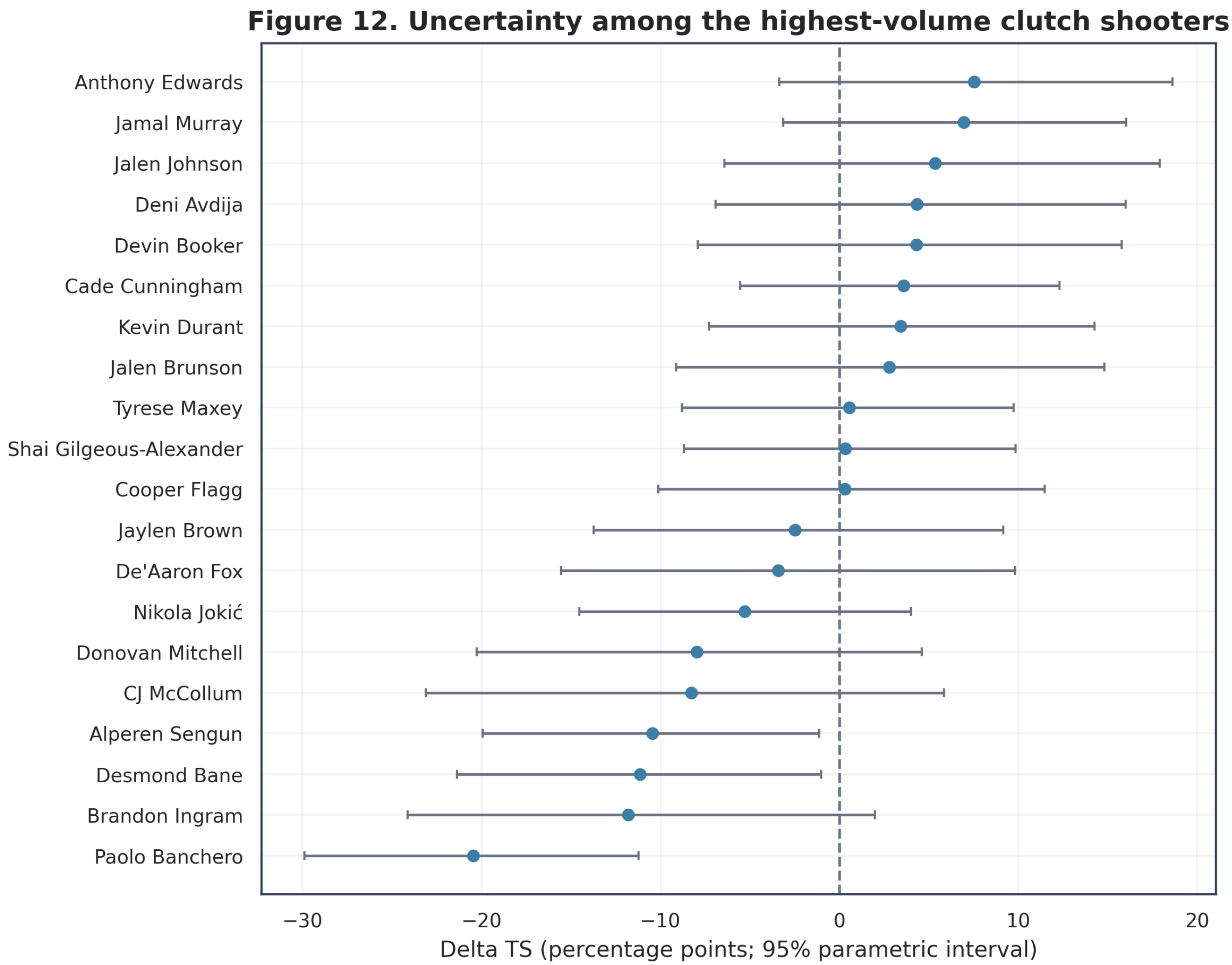


Figure 12. Parametric 95% intervals for selected high-volume clutch shooters.

Even among the highest-volume players, most intervals crossed zero. Paolo Banchero's interval remained entirely negative, while many positive point estimates had intervals spanning modest decline through substantial improvement. The forest plot is the clearest warning against interpreting point estimates alone.

6.9 Monte Carlo expectation and CBE

Observed clutch TS was compared with each player's simulated distribution under non-clutch component rates and actual clutch attempts. VJ Edgecombe had the highest CBE at 2.09 standard deviations, raw Delta TS 18.62 points, and two-sided empirical p = 0.0482. Paolo Banchero had CBE -3.67, raw Delta TS -20.46 points, and empirical p = 0.0004.

Figure 19. Observed clutch efficiency versus shooting-variance expectation

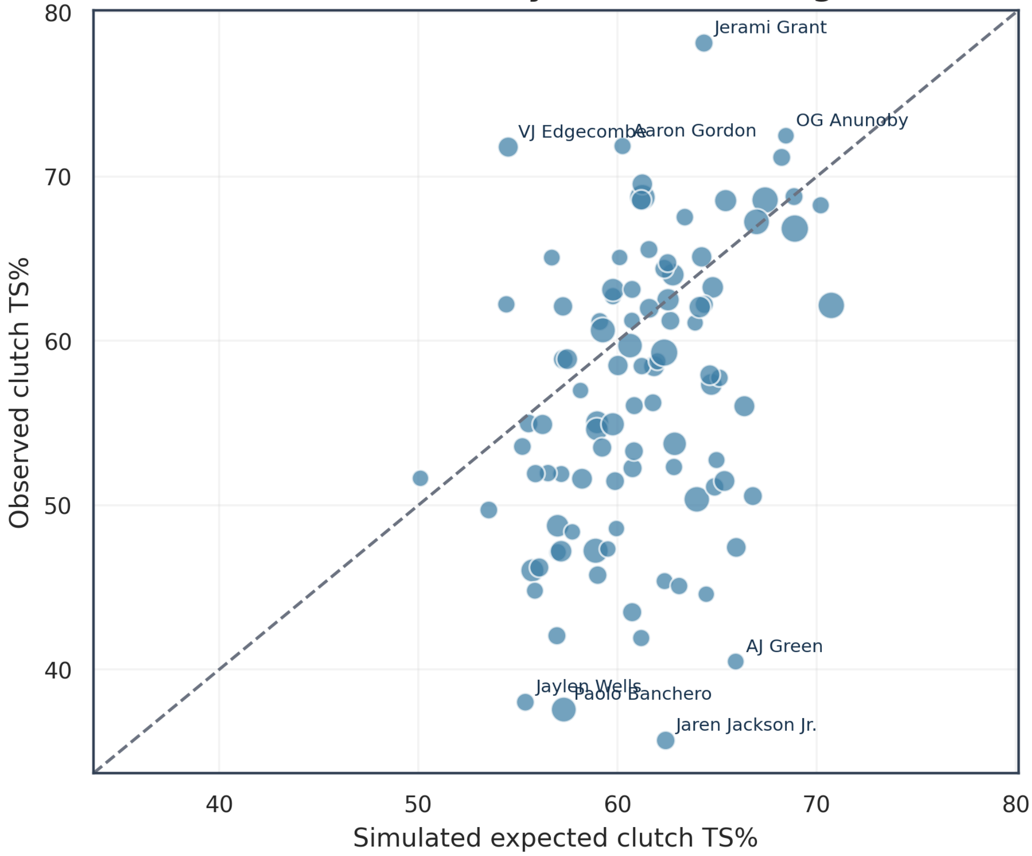


Figure 19. Observed clutch TS versus player-specific Monte Carlo expectation.

Most players lay near the identity line. The Monte Carlo design asks a narrower question than regression: was observed component shooting unusual given the player's own non-clutch component rates and clutch attempt composition? It does not explain why an observation was unusual.

Table 11. CBE leaderboard among main-sample qualifiers.

player_name	fga_clutch	ts_nonclutch	ts_clutch	delta_ts	delta_ts_shrunk	cbe	sim_ci_low	sim_ci_high	empirical_p_two_sided
VJ Edgecombe	46.0000	0.5317	0.7179	0.1862	0.0118	2.0903	0.3836	0.7081	0.0482
Jerami Grant	34.0000	0.5985	0.7812	0.1828	0.0108	1.5825	0.4732	0.8143	0.1328
Anthony Edwards	85.0000	0.6120	0.6874	0.0753	-0.0320	1.2951	0.4990	0.7281	0.2036
Aaron Gordon	29.0000	0.6119	0.7186	0.1066	-0.0623	1.1591	0.4042	0.8084	0.2858
Ryan Rollins	49.0000	0.5765	0.6954	0.1189	-0.0133	1.1068	0.4636	0.7555	0.2916
Saddiq Bey	45.0000	0.5736	0.6857	0.1121	0.0322	1.0324	0.4747	0.7472	0.3280
Dennis Schröder	30.0000	0.5205	0.6222	0.1018	0.0594	0.8580	0.3733	0.7329	0.4230
Kyle Kuzma	27.0000	0.5784	0.6507	0.0722	-0.0358	0.7930	0.3596	0.7705	0.4652
Evan Mobley	25.0000	0.5940	0.6508	0.0567	0.0115	0.5958	0.4338	0.7728	0.6075
Derrick White	42.0000	0.5249	0.6210	0.0961	0.0349	0.5718	0.4107	0.7512	0.5993
Jalen Johnson	64.0000	0.5776	0.6311	0.0535	0.0070	0.5518	0.4830	0.7213	0.6055
James Harden	60.0000	0.6054	0.6853	0.0800	0.0325	0.5213	0.5398	0.7703	0.6359
Naji Marshall	33.0000	0.5886	0.6556	0.0670	0.0062	0.5138	0.4698	0.7758	0.6475
OG Anunoby	26.0000	0.6158	0.7248	0.1090	0.0125	0.4542	0.5197	0.8616	0.6991
Tre Jones	33.0000	0.6327	0.7117	0.0790	-0.0014	0.4066	0.5395	0.8264	0.7461
Max Christie	31.0000	0.5974	0.6753	0.0779	-0.0359	0.4007	0.4272	0.8407	0.7347
Brandin Podziemski	29.0000	0.5812	0.6272	0.0460	-0.0225	0.3002	0.4084	0.7876	0.8195
LeBron James	33.0000	0.5921	0.6313	0.0392	-0.0155	0.2918	0.4545	0.7702	0.8223
Quentin Grimes	35.0000	0.5819	0.6475	0.0656	0.0223	0.2626	0.4609	0.8011	0.8245
Lauri Markkanen	38.0000	0.6066	0.6439	0.0373	-0.0342	0.2568	0.4663	0.7771	0.8431
Jalen Brunson	82.0000	0.5787	0.6064	0.0277	-0.0186	0.2460	0.4810	0.7058	0.8401
Jamal Murray	92.0000	0.6164	0.6857	0.0693	-0.0011	0.2395	0.5783	0.7725	0.8447

player_name	fga_clutch	ts_nonclutch	ts_clutch	delta_ts	delta_ts_shrunk	cbe	sim_ci_low	sim_ci_high	empirical_p_two_sided
Deni Avdija	62.0000	0.5970	0.6403	0.0433	0.0145	0.2277	0.5206	0.7360	0.8665
Darius Garland	32.0000	0.5807	0.6118	0.0311	-0.0338	0.2184	0.4032	0.7786	0.8801
Josh Giddey	43.0000	0.5604	0.5888	0.0284	0.0115	0.2157	0.4247	0.7143	0.8799

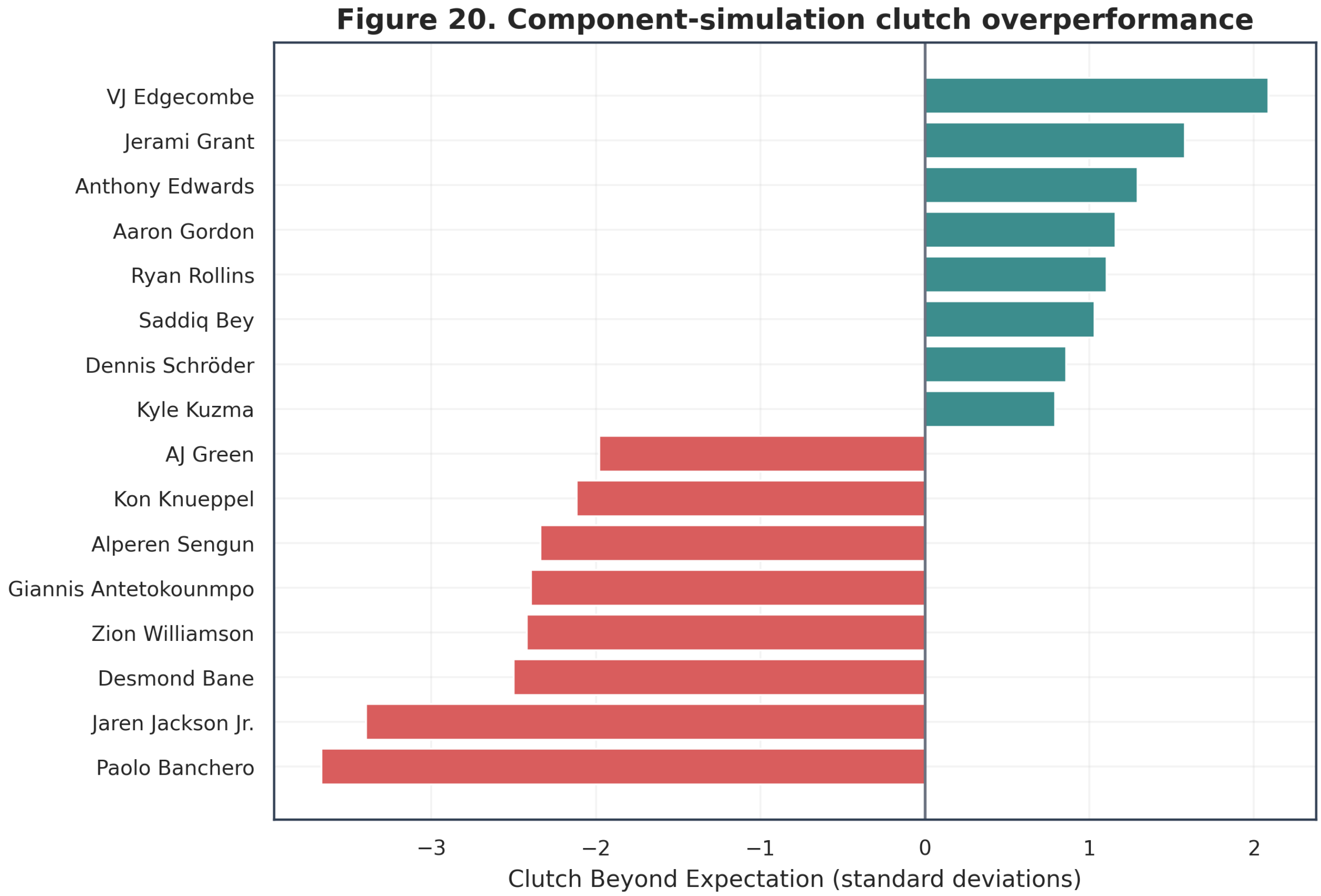


Figure 20. Highest and lowest CBE scores.

Only a small number of players reached conventional two-sided tail thresholds. Multiple comparisons make isolated player p-values even less decisive. CBE is most useful as a screening and uncertainty tool, not as a binary label.

6.10 Sensitivity to definition and threshold

The Self-Creation coefficient was unstable across definitions and minimum volumes. Under the standard definition, its square-root-weighted standardized coefficient ranged around small negative to modest positive values as thresholds changed. Shorter, tighter definitions sometimes produced positive estimates, but their samples became too small for higher thresholds. This pattern is consistent with noise and selection rather than a robust directional effect.

Table 12. Sensitivity-analysis summary.

definition	outcome	model	specifications	median_beta	min_beta	max_beta	median_n
extremely_close	delta_efg	OLS-HC3	2	0.3978	0.0830	0.7127	24.0000
extremely_close	delta_efg	Ridge-in-sample	2	0.3589	0.0877	0.6302	24.0000
extremely_close	delta_efg	WLS-sqrtFGA	2	0.4391	0.1588	0.7193	24.0000
extremely_close	delta_ts	OLS-HC3	2	0.2345	-0.0607	0.5297	24.0000
extremely_close	delta_ts	Ridge-in-sample	2	0.2111	-0.0498	0.4720	24.0000
extremely_close	delta_ts	WLS-sqrtFGA	2	0.2855	0.0231	0.5480	24.0000
extremely_close	ts_clutch	OLS-HC3	2	0.1940	-0.0589	0.4468	24.0000
extremely_close	ts_clutch	Ridge-in-sample	2	0.1767	-0.0463	0.3997	24.0000

definition	outcome	model	specifications	median_beta	min_beta	max_beta	median_n
extremely_close	ts_clutch	WLS-sqrtFGA	2	0.2423	0.0224	0.4622	24.0000
high_pressure	delta_efg	OLS-HC3	4	0.4292	-0.2933	0.7085	32.0000
high_pressure	delta_efg	Ridge-in-sample	4	0.4012	-0.2863	0.6142	32.0000
high_pressure	delta_efg	WLS-sqrtFGA	4	0.4520	-0.2238	0.7234	32.0000
high_pressure	delta_ts	OLS-HC3	4	0.3277	-0.2928	0.4778	32.0000
high_pressure	delta_ts	Ridge-in-sample	4	0.2910	-0.2859	0.4369	32.0000
high_pressure	delta_ts	WLS-sqrtFGA	4	0.3510	-0.2350	0.5072	32.0000
high_pressure	ts_clutch	OLS-HC3	4	0.2893	-0.2877	0.4146	32.0000
high_pressure	ts_clutch	Ridge-in-sample	4	0.2573	-0.2806	0.3786	32.0000
high_pressure	ts_clutch	WLS-sqrtFGA	4	0.3106	-0.2309	0.4400	32.0000
standard	delta_efg	OLS-HC3	6	-0.0722	-0.1697	0.2057	113.0000
standard	delta_efg	Ridge-in-sample	6	-0.0707	-0.1663	0.1961	113.0000
standard	delta_efg	WLS-sqrtFGA	6	-0.0341	-0.0990	0.2345	113.0000
standard	delta_ts	OLS-HC3	6	-0.0785	-0.1546	0.1932	113.0000
standard	delta_ts	Ridge-in-sample	6	-0.0769	-0.1513	0.1834	113.0000
standard	delta_ts	WLS-sqrtFGA	6	-0.0404	-0.0894	0.2197	113.0000
standard	ts_clutch	OLS-HC3	6	-0.0778	-0.1540	0.2043	113.0000
standard	ts_clutch	Ridge-in-sample	6	-0.0763	-0.1508	0.1949	113.0000
standard	ts_clutch	WLS-sqrtFGA	6	-0.0397	-0.0891	0.2323	113.0000
very_late	delta_efg	OLS-HC3	6	0.0583	-0.0907	0.8566	64.0000
very_late	delta_efg	Ridge-in-sample	6	0.0550	-0.0893	0.7685	64.0000
very_late	delta_efg	WLS-sqrtFGA	6	0.1106	-0.0531	0.8601	64.0000
very_late	delta_ts	OLS-HC3	6	0.0271	-0.0699	0.7365	64.0000
very_late	delta_ts	Ridge-in-sample	6	0.0251	-0.0687	0.6591	64.0000
very_late	delta_ts	WLS-sqrtFGA	6	0.0673	-0.0391	0.7373	64.0000
very_late	ts_clutch	OLS-HC3	6	0.0278	-0.0692	0.6166	64.0000
very_late	ts_clutch	Ridge-in-sample	6	0.0263	-0.0682	0.5501	64.0000
very_late	ts_clutch	WLS-sqrtFGA	6	0.0681	-0.0388	0.6173	64.0000

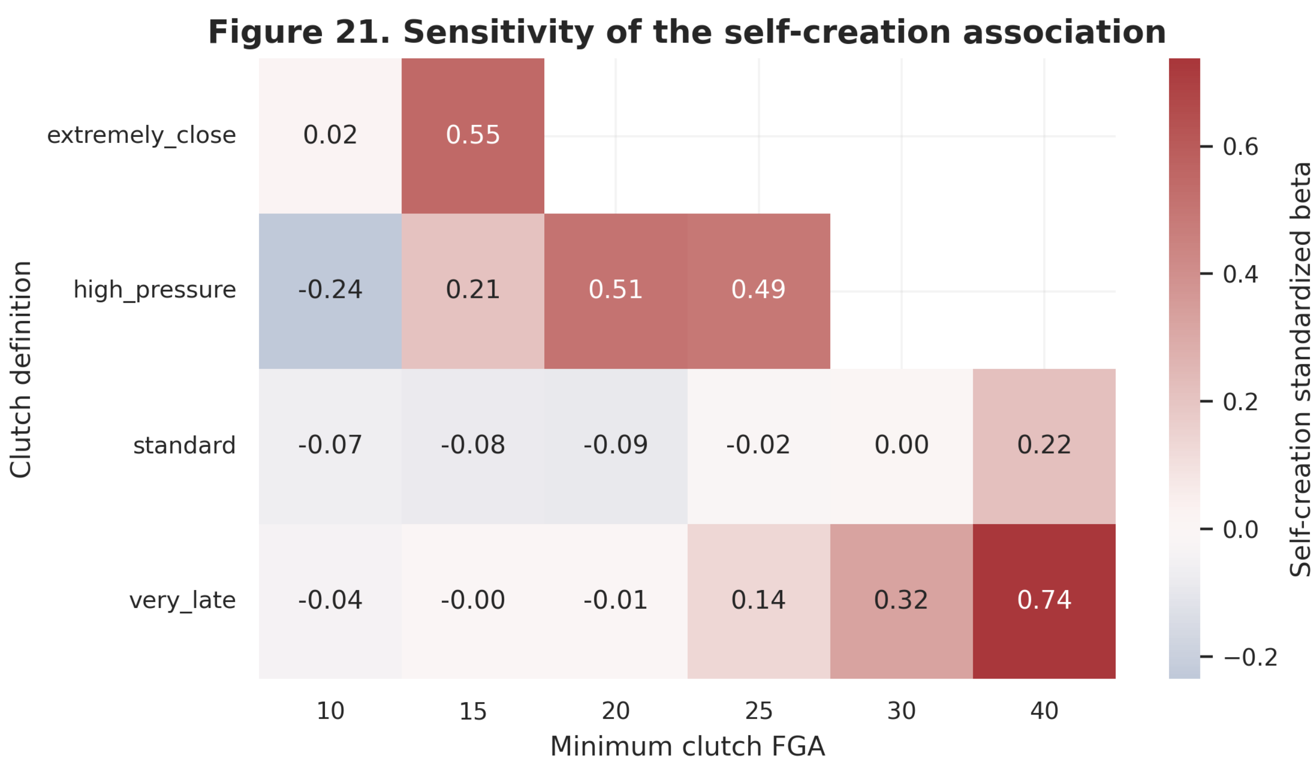


Figure 21. Sensitivity of the Self-Creation association across definitions and volume screens.

The sensitivity grid reinforces a scientific constraint: choosing a clutch definition after seeing results could reverse a narrative. The standard definition remained primary, and alternative definitions were treated as robustness checks rather than opportunities to select favorable coefficients.

6.11 Multi-season stability

Consecutive-season Pearson correlations were 0.217 for 80 matched players, 0.145 for 68, and 0.068 for 57. Spearman coefficients were similarly small. The most recent relationship was nearly zero.

Table 15. Consecutive-season reliability.

previous_season	following_season	n	pearson_r	pearson_p	spearman_rho	spearman_p
2022-23	2023-24	80	0.2173	0.0528	0.2189	0.0511
2023-24	2024-25	68	0.1446	0.2395	0.1325	0.2816
2024-25	2025-26	57	0.0679	0.6159	0.0508	0.7074

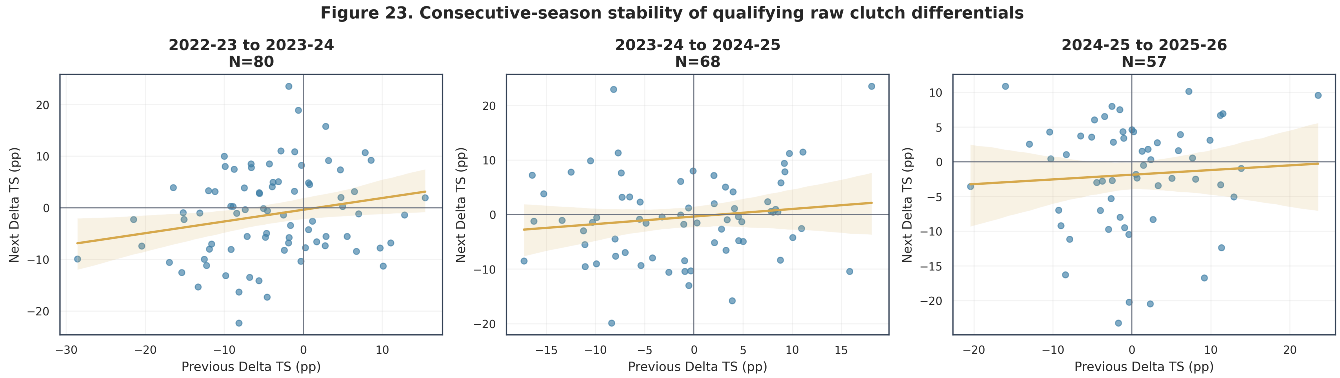


Figure 23. Year-to-year stability of main-sample Delta TS.

Figure 23 shows weak slopes and broad scatter. The earliest transition approached a conventional significance threshold, but the pattern did not strengthen with additional seasons. This supports H7: single-season clutch differentials show limited persistence.

Table 16. Multi-season mixed-effects model.

term	coefficient	std_error	p_value	ci_low	ci_high
Intercept	0.2160	0.0845	0.0106	0.0504	0.3815
C(season)[T.2023-24]	0.0149	0.0111	0.1778	-0.0068	0.0366
C(season)[T.2024-25]	0.0188	0.0112	0.0935	-0.0032	0.0407
C(season)[T.2025-26]	0.0109	0.0114	0.3372	-0.0114	0.0331
ts_nonclutch	-0.3391	0.1299	0.0090	-0.5937	-0.0846
usage_proxy_nonclutch	-0.0021	0.0012	0.0833	-0.0046	0.0003
ftr_nonclutch	-0.0338	0.0584	0.5633	-0.1483	0.0807
three_rate_nonclutch	-0.0539	0.0341	0.1139	-0.1207	0.0129
ast_per36_nonclutch	0.0047	0.0027	0.0868	-0.0007	0.0100
tov_rate_nonclutch	0.0117	0.2055	0.9544	-0.3911	0.4146
Group Var	0.1218	0.0775	0.1162	-0.0302	0.2737

The mixed model estimated a negative baseline-TS coefficient, consistent with coupling and regression to the mean, and weak role effects. Its random-effect covariance was near the boundary, warning that stable between-player clutch heterogeneity was difficult to estimate from four seasons and changing eligibility. The result should not be read as proof that stable individual effects are exactly zero; it indicates that this dataset supplies limited information about them.

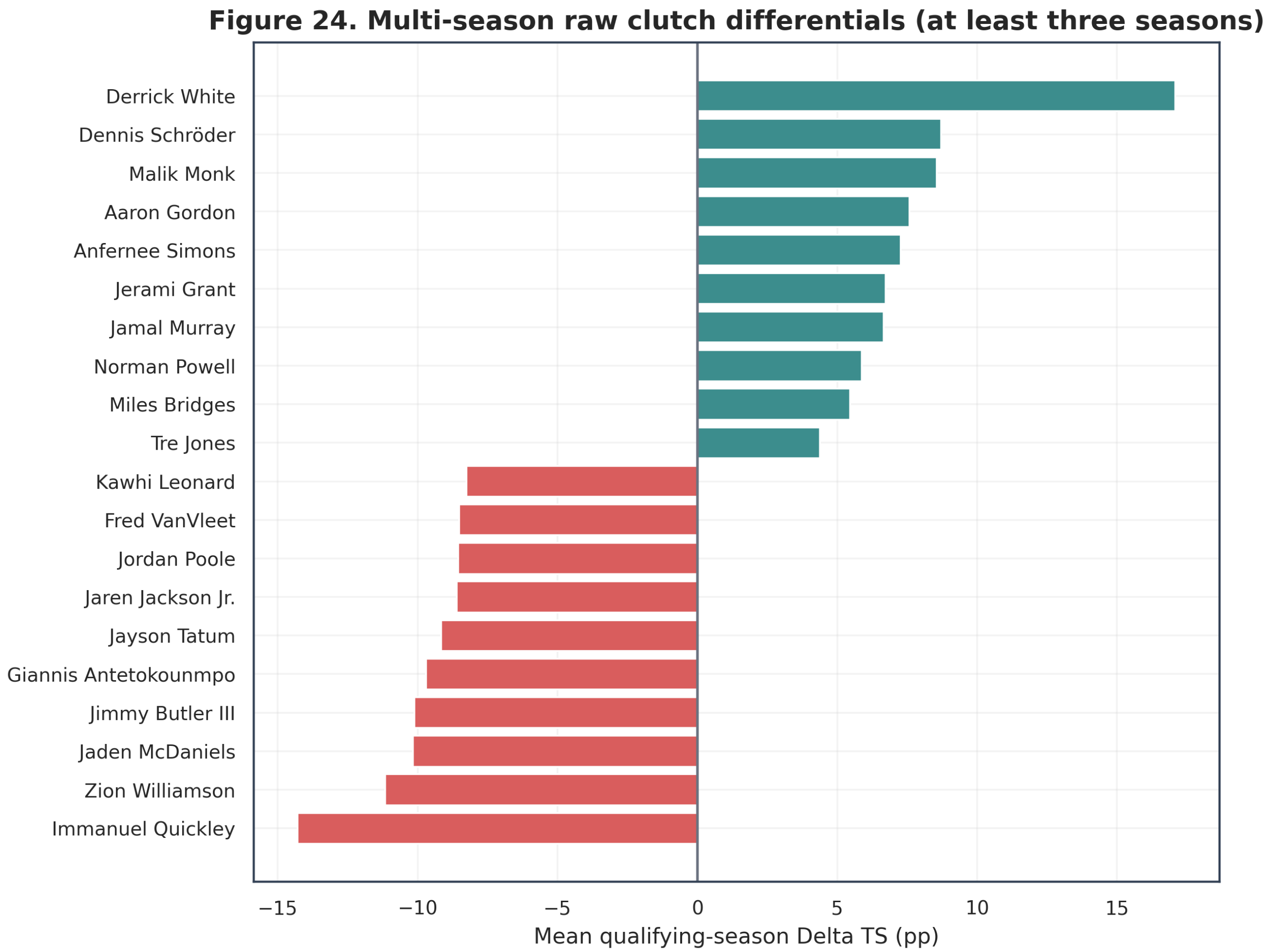


Figure 24. Average raw Delta TS among players qualifying in at least three seasons.

Multi-season averages are less volatile than single-season rankings but remain selected summaries. Players must repeatedly meet volume thresholds, and role, team, health, and age can change across seasons.

The pooled component screen included 83 players with at least three qualifying seasons. Derrick White ranked first: he improved in 3 of 3 qualifying seasons (2023-24:+18.07pp; 2024-25:+23.58pp; 2025-26:+9.61pp), totaling 102 clutch FGA. His pooled non-clutch TS was 57.18%, pooled clutch TS was 73.19%, and pooled Delta TS was 16.01 percentage points. His simulated expectation was 61.36% with a 95% interval of 50.03% to 72.78%, producing pooled CBE 2.05 and one-sided empirical p = 0.0232. Because he was selected as the maximum across the screen, the FDR-adjusted p = 0.9999 is the more appropriate evidentiary reference and does not support a definitive player-level effect.

7. Discussion

7.1 Direct answer to the research question

Which offensive characteristics best predicted clutch efficiency preservation? In 2025-26, shot diversity and assist production provided the clearest adjusted linear signals, while turnover rate and the Self-Creation Index had negative directions. Yet these relationships were modest, did not survive the full regression-family FDR adjustment, and did not translate into positive out-of-sample R-squared. The most defensible conclusion is therefore not that a specific archetype possesses a clutch gene. It is that normal offensive characteristics contain weak descriptive information while most single-season cross-player variation remains difficult to predict.

Shot entropy is the most interesting positive signal. A diverse scorer may have more ways to respond when a defense removes the first option. That interpretation aligns with basketball reasoning, but entropy is not causal versatility. It can reflect team spacing, role, talent, or shot-selection freedom. The difference between its Pearson and Spearman evidence, sensitivity to adjustment, and limited CV contribution all argue for replication.

Assist production may indicate decision flexibility. A player who can punish pressure with passes may avoid a low-quality forced attempt. However, assists per 36 also reflect teammates, scheme, and scorekeeper conventions. The coefficient should motivate possession-level research on playmaking choices, not a causal statement that passing ability creates clutch shooting efficiency.

The negative Self-Creation estimate contradicts the pre-specified H1 direction. One basketball explanation is workload: creators absorb the most difficult late possessions. Another is measurement: the proxy lacks direct unassisted rates, drives, touches, and time of possession. A third is noise. Sensitivity estimates changed with definition, and cross-validation did not support strong prediction. The study therefore rejects a simple "more self-creation equals more clutch resistance" story.

Foul pressure did not emerge as a robust linear coefficient, although it ranked highly in Random Forest permutation importance. This discrepancy illustrates the danger of reading importance as inference. Free-throw rate may matter nonlinearly or interact with role, but the tested interaction with self-creation did not survive multiplicity control.

7.2 What shrinkage changes

The uncertainty analysis changes the player narrative more than any additional predictive feature. Raw dispersion fell by more than half after component shrinkage. High positive and negative rankings often moved close to zero. Monte Carlo intervals remained wide even for high-volume players. These are not technical footnotes; they are central findings.

Basketball audiences often compare the most extreme observed players, which maximizes winner's-curse bias. The player at the top is likely there because of ability plus favorable variance; the player at the bottom combines ability and unfavorable variance. Shrinkage does not erase achievement or failure in the observed games. It estimates how much should be carried forward as a stable expectation.

The CBE framework provides a complementary lens. A player can have positive Delta TS but ordinary CBE if the improvement is plausible under his attempt count. Conversely, a smaller raw change at high volume can be more unusual. Still, CBE inherits the baseline model's limitations. Non-clutch rates may not reflect the difficulty of clutch shots, and independent binomial draws ignore sequences, defense, and game context. CBE should be reported with its construction and uncertainty every time.

7.3 Is there evidence of a stable clutch ability?

The evidence for a stable, player-specific single-season effect is weak. Consecutive-season correlations declined across the panel and were near zero in the latest transition. The mixed-effects covariance was difficult to estimate away from the boundary. Predictive models failed to achieve positive mean held-out R-squared. These findings do not prove that pressure response is identical for every NBA player. They show that the available season-level data and operational definition do not identify a strong, repeatable effect with confidence.

This conclusion is compatible with genuine game-level clutch performances. A player can make high-value shots and materially affect wins. The statistical claim is narrower: raw season-level differentials are unreliable measures of persistent individual disposition. Evaluation should combine baseline level, role difficulty, volume, uncertainty, and multi-season evidence.

The exploratory multi-season screen supplies one concrete exception worth following: Derrick White was the strongest repeated overperformance candidate in these data. His direction was consistent across qualifying seasons and his pooled CBE exceeded two standard deviations. Yet naming the top player after screening 83 candidates introduces winner's-curse and multiplicity concerns. The evidence supports describing him as the study's strongest candidate for repeatable clutch enhancement, not as proof that a stable clutch trait has been established.

7.4 Basketball implications

For analysts, the recommended workflow is to begin with absolute efficiency and opportunity, then add the differential, and finally show uncertainty. Teams should not use raw Delta TS as a scouting grade. A player who declines slightly from an elite baseline may remain a better late-game option than a player who improves from a weak baseline. Shot diversity and playmaking deserve further contextual analysis because they may create alternatives when preferred actions are denied.

For public evaluation, leaderboards should require a meaningful attempt threshold and include intervals or shrunk estimates. The words "clutch" and "not clutch" should be avoided when the data support only noisy overperformance and underperformance. For researchers, possession-level modeling with defender distance, action type, win probability, and shot quality is the natural next step.

8. Player Case Studies

Single-season case studies were selected algorithmically after modeling: top and bottom CBE, largest shrinkage changes, largest positive and negative out-of-fold errors, and the highest-volume player. A separate pooled screen identified the strongest multi-season candidate. This avoids choosing a famous name first and searching for supportive statistics afterward.

Table 14. Data-driven player case studies.

PLAYER_ID	player_name	ts_nonclutch	ts_clutch	delta_ts	fga_clutch	usage_proxy_nonclutch	shot_entropy_nonclutch	self_creation_index	delta_ts_shrunk	cbe	delta_ci_low	delta_ci_high	actual	pred_RandomForest	prediction_error
1631260	AJ Green	0.6375	0.4049	-0.2327	27.0000	11.4130	0.6061	-0.7302	-0.1279	-1.9789	-0.4449	-0.0004	-0.2327	-0.0517	-0.1810
1628991	Jaren Jackson Jr.	0.5892	0.3568	-0.2323	37.0000	22.6408	0.8887	0.7912	-0.0295	-3.3986	-0.3530	-0.1039	-0.2323	-0.0116	-0.2207
1631094	Paolo Banchero	0.5803	0.3756	-0.2046	80.0000	23.4100	0.9036	1.2149	-0.0472	-3.6693	-0.2989	-0.1124	-0.2046	-0.0368	-0.1678
1631157	Ryan Rollins	0.5765	0.6954	0.1189	49.0000	19.6488	0.9492	0.9558	-0.0133	1.1068	-0.0290	0.2655	0.1189	-0.0584	0.1774
1628983	Shai Gilgeous-Alexander	0.6650	0.6683	0.0034	101.0000	27.0656	0.8893	2.1685	-0.0469	-0.4411	-0.0870	0.0985	0.0034	-0.0405	0.0439
1642845	VJ Edgecombe	0.5317	0.7179	0.1862	46.0000	17.3359	0.9249	0.6136	0.0118	2.0903	0.0176	0.3533	0.1862	-0.0192	0.2054

8.1 VJ Edgecombe: raw leader and simulated overperformer

VJ Edgecombe combined the largest positive raw differential with the highest CBE. His observed clutch TS sat near the upper edge of the simulated distribution under his non-clutch component rates. Yet component shrinkage moved most of the raw advantage toward zero, demonstrating that an unusual sample and a stable latent effect are not equivalent. The correct description is that his 2025-26 clutch shooting substantially exceeded the baseline simulation, with uncertainty and multiple-comparison caveats.

8.2 Jerami Grant and Ryan Rollins: large positive raw changes

Jerami Grant and Ryan Rollins appeared near the top of the raw leaderboard. Their CBE values were less extreme than the raw percentage-point changes because their attempt compositions and volumes permitted substantial variance. They illustrate how a ranking can be accurate for observed outcomes while overstating forward-looking separation.

8.3 Paolo Banchero: high-volume negative tail

Paolo Banchero combined substantial volume with the lowest CBE. Unlike many low-volume negative estimates, his simulation result remained far into the lower tail. Even here, the model does not identify psychological cause. Shot difficulty, injury, opponent strategy, late-clock possessions, and tactical burden remain possible explanations.

8.4 Jaren Jackson Jr.: shrinkage collapse

Jaren Jackson Jr. had one of the largest negative raw differentials and one of the largest raw-to-shrunk changes. This is a textbook example of why component priors matter. The observed sample was poor, but the stabilized estimate was far less extreme. A narrative based only on rank would ignore that distinction.

8.5 High-volume stability and prediction errors

Shai Gilgeous-Alexander accumulated the largest clutch FGA total and produced a differential near zero, illustrating efficiency preservation without a dramatic headline. Other high-volume stars displayed intervals crossing zero despite positive or negative point estimates. Out-of-fold overperformers and underperformers identify where the predictive model missed, but negative overall CV R-squared means those residuals are not reliable measures of special hidden ability.

8.6 Derrick White: strongest multi-season candidate

Derrick White provides the clearest player-level result in the study. Across 3 qualifying seasons, his Delta TS values were 2023-24:+18.07pp; 2024-25:+23.58pp; 2025-26:+9.61pp. Pooling 102 clutch FGA produced 73.19% clutch TS against 57.18% outside clutch situations, a 16.01-point improvement. Relative to pooled non-clutch component rates and the observed clutch shot mix, his CBE was 2.05 with one-sided p = 0.0232. This combination of directional consistency and pooled overperformance makes him the most defensible named candidate. However, the screen-wide FDR-adjusted p of 0.9999 prevents the stronger claim that the study has confirmed a persistent individual clutch ability.

9. Limitations

First, this is observational research. Offensive characteristics were not randomly assigned. Team system, teammate quality, coaching, opponent strength, and defensive attention influence both predictors and outcomes. Coefficients describe conditional associations, not causal effects.

Second, standard clutch is a rule based on time and score, not a direct measure of psychological pressure. A possession at 4:59 with a five-point margin and a possession with five seconds in a tie game both qualify, while a critical possession at 5:05 does not. Sensitivity definitions help but cannot convert clock-score filters into a continuous pressure measure.

Third, sample size remains limited. Twenty-five clutch FGA is enough to exclude the smallest samples but not enough to estimate a shooting rate precisely. The high-confidence sample contained only 45 players. Tighter definitions reduced samples further, forcing some high-threshold specifications to be skipped.

Fourth, true shooting is an aggregate efficiency measure. The 0.44 free-throw coefficient is a conventional approximation, not exact possession accounting. Intentional fouls, and-one attempts, technical free throws, and three-shot fouls complicate the denominator. The component simulation treats makes as independent binomial draws and does not model free-throw trip structure.

Fifth, the shot-profile data identify zones but not full shot quality. A contested step-back and an open catch-and-shoot attempt can occupy the same zone. Defender distance, release time, screen action, mismatch type, and clock pressure were not consistently available at league scale. The total league-wide shot-event endpoint was truncated at 102,400 rows and therefore excluded as a complete source; the study instead used complete zone aggregates plus complete clutch events.

Sixth, the Self-Creation Index is a proxy. Direct unassisted rate, drives, touches, possession time, and dribbles per touch were unavailable in a reliable league-level structure for all players. The index uses pull-up and inverse catch-and-shoot frequency along with non-clutch workload. Its negative coefficient may reflect role burden or measurement limitations.

Seventh, tracking and advanced season-context rates include a small amount of clutch exposure because rates cannot be validly subtracted without their denominators. The main outcome is explicitly non-clutch, and the core count-derived predictors are non-clutch, but some extension variables are contextual rather than pure pre-clutch measures.

Eighth, eligibility creates selection. Players must receive late-game opportunities, which depend on team closeness, coaching trust, health, and role. A team that dominates may produce fewer clutch possessions for excellent players. Results generalize to qualifying player-seasons, not automatically to every NBA player.

Ninth, multiple comparisons remain a concern. The study pre-specified hypotheses and applied FDR adjustment, but it also reports exploratory interactions, clusters, case studies, and sensitivity grids. Unadjusted signals should be treated as hypotheses for replication.

Tenth, multi-season models cover four seasons. Player roles, teams, aging, and health change within that window. Boundary behavior in the random-effects model shows that the panel cannot cleanly separate persistent player ability from seasonal noise. Longer historical analysis with consistent tracking definitions would improve reliability estimates.

Finally, the API is not an official supported research interface. Endpoint behavior and availability can change, NBA.com can rate-limit requests, and the live CDN scoreboard was blocked from this environment. Caching, schema inspection, and endpoint audit logs reduce operational risk but do not eliminate source instability.

10. Future Research

The highest-priority extension is a possession- or shot-level model that includes defender distance, action type, shot-clock state, fatigue, lineup context, and continuous win-probability leverage. Such a design could separate selection from execution and distinguish whether players preserve efficiency by changing shots, drawing fouls, or creating for teammates.

Playoff clutch performance should be analyzed separately because opponent quality, scouting intensity, and rotation patterns differ from the regular season. A Bayesian career model with season-varying player effects could estimate persistent ability while allowing role changes. Exact free-throw-trip reconstruction would improve TS simulation. Team and lineup spacing metrics could test whether individual preservation depends on environment. Finally, pre-registered out-of-time validation on 2026-27 would provide a stronger test than repeated cross-validation within one season.

11. Conclusion

The project set out to identify offensive characteristics associated with preserving or improving scoring efficiency under standard NBA clutch conditions. The data did not support a strong, simple predictive story. Shot diversity and assists per 36 showed the clearest positive adjusted associations, but evidence weakened after multiple-testing control, and the Self-Creation Index did not support the hypothesized positive direction. Flexible machine learning did not produce positive held-out R-squared. Offensive archetypes did not differ reliably.

The strongest findings concern uncertainty. Raw clutch differentials were highly dispersed, component shrinkage reduced that dispersion by 52.5%, most high-volume player intervals crossed zero, and year-to-year persistence was weak. Some 2025-26 performances were statistically unusual relative to player-specific shooting baselines, but those observations are better described as overperformance or underperformance than as proof of a stable clutch trait.

At the individual level, Derrick White was the strongest multi-season candidate. He posted positive Delta TS in all 3 qualifying seasons and a pooled 16.01-point improvement across 102 clutch FGA. That result is noteworthy and merits future out-of-time testing, but its screen-wide FDR-adjusted p of 0.9999 means it should not overturn the broader uncertainty conclusion.

The direct answer is therefore cautious: certain traits, especially shot-profile diversity and playmaking, may provide limited information about efficiency preservation, but apparent NBA clutch performance is substantially shaped by sampling variation, role, and context. Evaluating players responsibly requires absolute efficiency, volume, explicit non-clutch baselines, uncertainty, and multi-season evidence. The data do not justify treating a one-season raw clutch leaderboard as a measurement of character.

References

Arkes, J. (2010). Revisiting the hot hand theory with free throw data in a multivariate framework. Journal of Quantitative Analysis in Sports, 6(1). https://doi.org/10.2202/1559-0410.1198

Arkes, J., & Martinez, J. (2011). Finally, evidence for a momentum effect in the NBA. Journal of Quantitative Analysis in Sports, 7(3). https://doi.org/10.2202/1559-0410.1304

Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5-32. https://doi.org/10.1023/A:1010933404324

Cao, Z., Price, J., & Stone, D. F. (2011). Performance under pressure in the NBA. Journal of Sports Economics, 12(3), 231-252. https://doi.org/10.1177/1527002511404785

Efron, B., & Morris, C. (1975). Data analysis using Stein's estimator and its generalizations. Journal of the American Statistical Association, 70(350), 311-319. https://doi.org/10.1080/01621459.1975.10479864

Gilovich, T., Vallone, R., & Tversky, A. (1985). The hot hand in basketball: On the misperception of random sequences. Cognitive Psychology, 17(3), 295-314. https://doi.org/10.1016/0010-0285(85)90010-6

Hastie, T., Tibshirani, R., & Friedman, J. (2009). The elements of statistical learning (2nd ed.). Springer. https://doi.org/10.1007/978-0-387-84858-7

MacKinnon, J. G., & White, H. (1985). Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties. Journal of Econometrics, 29(3), 305-325. https://doi.org/10.1016/0304-4076(85)90158-7

Miller, J. B., & Sanjurjo, A. (2018). Surprised by the hot hand fallacy? A truth in the law of small numbers. Econometrica, 86(6), 2019-2047. https://doi.org/10.3982/ECTA14943

Morris, C. N. (1983). Parametric empirical Bayes inference: Theory and applications. Journal of the American Statistical Association, 78(381), 47-55. https://doi.org/10.1080/01621459.1983.10477920

Patel, S., & contributors. (2026). nba_api: An API client package to access NBA.com APIs (Version 1.11.4) [Computer software]. https://github.com/swar/nba_api

Shannon, C. E. (1948). A mathematical theory of communication. Bell System Technical Journal, 27(3), 379-423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Skinner, B. (2012). The problem of shot selection in basketball. PLOS ONE, 7(1), e30776. https://doi.org/10.1371/journal.pone.0030776

Tversky, A., & Kahneman, D. (1971). Belief in the law of small numbers. Psychological Bulletin, 76(2), 105-110. https://doi.org/10.1037/h0031322

Appendix A. Full Data Dictionary

The following table is generated from the processed 2025-26 schema. The machine-readable version is stored at `data/metadata/data_dictionary.csv`.

variable	source_endpoint	original_column	transformation	interpretation	unit
PLAYER_ID	LeagueDashPlayerStats	PLAYER_ID	Canonical identity or season label	PLAYER ID	count or index
season	LeagueDashPlayerStats	SEASON	Canonical identity or season label	season	count or index
player_name	LeagueDashPlayerStats	PLAYER_NAME	Canonical identity or season label	player name	count or index
team_id	LeagueDashPlayerStats	TEAM_ID	Canonical identity or season label	team id	count or index
team_abbreviation	LeagueDashPlayerStats	TEAM_ABBREVIATION	Canonical identity or season label	team abbreviation	count or index
age	LeagueDashPlayerStats	AGE	Canonical identity or season label	age	count or index
gp_total	Engineered from cached NBA counts	GP_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	gp total	count or index
min_total	Engineered from cached NBA counts	MIN_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	min total	count or index
pts_total	Engineered from cached NBA counts	PTS_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	pts total	count or index
fga_total	Engineered from cached NBA counts	FGA_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	fga total	count or index
fgm_total	Engineered from cached NBA counts	FGM_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	fgm total	count or index
fg3m_total	Engineered from cached NBA counts	FG3M_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	fg3m total	count or index
fg3a_total	Engineered from cached NBA counts	FG3A_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	fg3a total	count or index
fta_total	Engineered from cached NBA counts	FTA_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	fta total	count or index
ftm_total	Engineered from cached NBA counts	FTM_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	ftm total	count or index
ast_total	Engineered from cached NBA counts	AST_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	ast total	count or index
tov_total	Engineered from cached NBA counts	TOV_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	tov total	count or index
oreb_total	Engineered from cached NBA counts	OREB_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	oreb total	count or index
dreb_total	Engineered from cached NBA counts	DREB_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	dreb total	count or index
reb_total	Engineered from cached NBA counts	REB_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	reb total	count or index
stl_total	Engineered from cached NBA counts	STL_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	stl total	count or index
blk_total	Engineered from cached NBA counts	BLK_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	blk total	count or index
pf_total	Engineered from cached NBA counts	PF_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	pf total	count or index
pfd_total	Engineered from cached NBA counts	PFD_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	pfd total	count or index
gp_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	GP_CLUTCH	Clutch value or total-minus-clutch construction	gp clutch	count or index
min_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	MIN_CLUTCH	Clutch value or total-minus-clutch construction	min clutch	count or index
pts_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	PTS_CLUTCH	Clutch value or total-minus-clutch construction	pts clutch	count or index
fga_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FGA_CLUTCH	Clutch value or total-minus-clutch construction	fga clutch	count or index

variable	source_endpoint	original_column	transformation	interpretation	unit
fgm_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FGM_CLUTCH	Clutch value or total-minus-clutch construction	fgm clutch	count or index
fg3m_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FG3M_CLUTCH	Clutch value or total-minus-clutch construction	fg3m clutch	count or index
fg3a_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FG3A_CLUTCH	Clutch value or total-minus-clutch construction	fg3a clutch	count or index
fta_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FTA_CLUTCH	Clutch value or total-minus-clutch construction	fta clutch	count or index
ftm_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FTM_CLUTCH	Clutch value or total-minus-clutch construction	ftm clutch	count or index
ast_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	AST_CLUTCH	Clutch value or total-minus-clutch construction	ast clutch	count or index
tov_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	TOV_CLUTCH	Clutch value or total-minus-clutch construction	tov clutch	count or index
oreb_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	OREB_CLUTCH	Clutch value or total-minus-clutch construction	oreb clutch	count or index
dreb_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	DREB_CLUTCH	Clutch value or total-minus-clutch construction	dreb clutch	count or index
reb_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	REB_CLUTCH	Clutch value or total-minus-clutch construction	reb clutch	count or index
stl_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	STL_CLUTCH	Clutch value or total-minus-clutch construction	stl clutch	count or index
blk_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	BLK_CLUTCH	Clutch value or total-minus-clutch construction	blk clutch	count or index
pf_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	PF_CLUTCH	Clutch value or total-minus-clutch construction	pf clutch	count or index
pfd_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	PFD_CLUTCH	Clutch value or total-minus-clutch construction	pfd clutch	count or index
pts_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	PTS_NONCLUTCH	Clutch value or total-minus-clutch construction	pts nonclutch	count or index
fga_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FGA_NONCLUTCH	Clutch value or total-minus-clutch construction	fga nonclutch	count or index
fgm_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FGM_NONCLUTCH	Clutch value or total-minus-clutch construction	fgm nonclutch	count or index
fg3m_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FG3M_NONCLUTCH	Clutch value or total-minus-clutch construction	fg3m nonclutch	count or index
fg3a_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FG3A_NONCLUTCH	Clutch value or total-minus-clutch construction	fg3a nonclutch	count or index
fta_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FTA_NONCLUTCH	Clutch value or total-minus-clutch construction	fta nonclutch	count or index
ftm_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FTM_NONCLUTCH	Clutch value or total-minus-clutch construction	ftm nonclutch	count or index
ast_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	AST_NONCLUTCH	Clutch value or total-minus-clutch construction	ast nonclutch	count or index
tov_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	TOV_NONCLUTCH	Clutch value or total-minus-clutch construction	tov nonclutch	count or index
oreb_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	OREB_NONCLUTCH	Clutch value or total-minus-clutch construction	oreb nonclutch	count or index
dreb_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	DREB_NONCLUTCH	Clutch value or total-minus-clutch construction	dreb nonclutch	count or index
reb_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	REB_NONCLUTCH	Clutch value or total-minus-clutch construction	reb nonclutch	count or index
stl_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	STL_NONCLUTCH	Clutch value or total-minus-clutch construction	stl nonclutch	count or index
blk_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	BLK_NONCLUTCH	Clutch value or total-minus-clutch construction	blk nonclutch	count or index
pf_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	PF_NONCLUTCH	Clutch value or total-minus-clutch construction	pf nonclutch	count or index

variable	source_endpoint	original_column	transformation	interpretation	unit
pfd_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	PFD_NONCLUTCH	Clutch value or total-minus-clutch construction	pfd nonclutch	count or index
min_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	MIN_NONCLUTCH	Clutch value or total-minus-clutch construction	min nonclutch	count or index
ts_total	Engineered from cached NBA counts	TS_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	ts total	proportion
efg_total	Engineered from cached NBA counts	EFG_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	efg total	proportion
fg_pct_total	Engineered from cached NBA counts	FG_PCT_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	fg pct total	proportion
fg3_pct_total	Engineered from cached NBA counts	FG3_PCT_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	fg3 pct total	proportion
ftr_total	Engineered from cached NBA counts	FTR_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	ftr total	proportion
tov_rate_total	Engineered from cached NBA counts	TOV_RATE_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	tov rate total	proportion
fg2m_total	Engineered from cached NBA counts	FG2M_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	fg2m total	count or index
fg2a_total	Engineered from cached NBA counts	FG2A_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	fg2a total	count or index
fg2_pct_total	Engineered from cached NBA counts	FG2_PCT_TOTAL	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	fg2 pct total	proportion
ts_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	TS_CLUTCH	Clutch value or total-minus-clutch construction	ts clutch	proportion
efg_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	EFG_CLUTCH	Clutch value or total-minus-clutch construction	efg clutch	proportion
fg_pct_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FG_PCT_CLUTCH	Clutch value or total-minus-clutch construction	fg pct clutch	proportion
fg3_pct_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FG3_PCT_CLUTCH	Clutch value or total-minus-clutch construction	fg3 pct clutch	proportion
ftr_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FTR_CLUTCH	Clutch value or total-minus-clutch construction	ftr clutch	proportion
tov_rate_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	TOV_RATE_CLUTCH	Clutch value or total-minus-clutch construction	tov rate clutch	proportion
fg2m_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FG2M_CLUTCH	Clutch value or total-minus-clutch construction	fg2m clutch	count or index
fg2a_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FG2A_CLUTCH	Clutch value or total-minus-clutch construction	fg2a clutch	count or index
fg2_pct_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FG2_PCT_CLUTCH	Clutch value or total-minus-clutch construction	fg2 pct clutch	proportion
ts_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	TS_NONCLUTCH	Clutch value or total-minus-clutch construction	ts nonclutch	proportion
efg_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	EFG_NONCLUTCH	Clutch value or total-minus-clutch construction	efg nonclutch	proportion
fg_pct_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FG_PCT_NONCLUTCH	Clutch value or total-minus-clutch construction	fg pct nonclutch	proportion
fg3_pct_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FG3_PCT_NONCLUTCH	Clutch value or total-minus-clutch construction	fg3 pct nonclutch	proportion
ftr_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FTR_NONCLUTCH	Clutch value or total-minus-clutch construction	ftr nonclutch	proportion
tov_rate_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	TOV_RATE_NONCLUTCH	Clutch value or total-minus-clutch construction	tov rate nonclutch	proportion
fg2m_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FG2M_NONCLUTCH	Clutch value or total-minus-clutch construction	fg2m nonclutch	count or index
fg2a_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FG2A_NONCLUTCH	Clutch value or total-minus-clutch construction	fg2a nonclutch	count or index
fg2_pct_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FG2_PCT_NONCLUTCH	Clutch value or total-minus-clutch construction	fg2 pct nonclutch	proportion

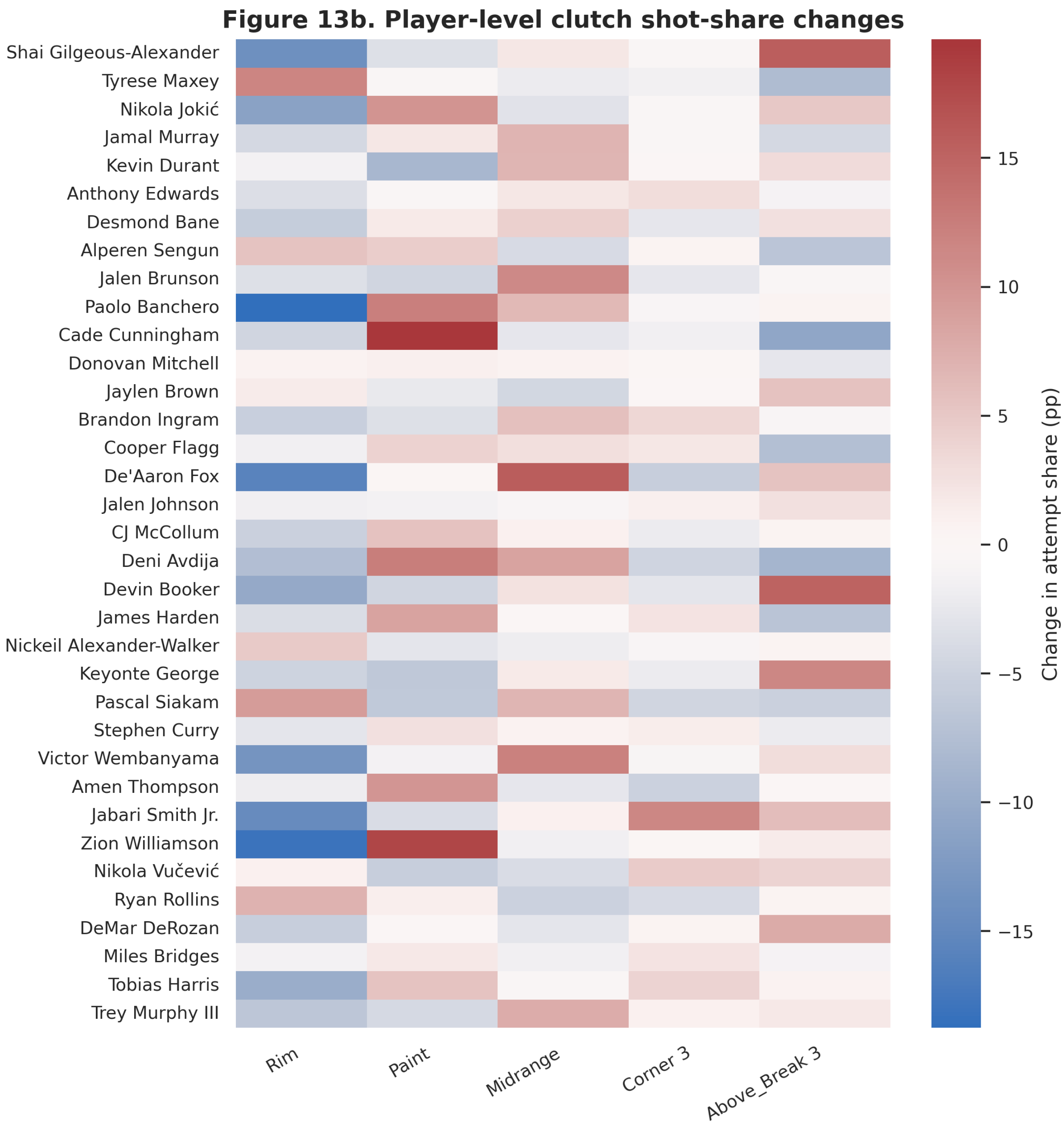
variable	source_endpoint	original_column	transformation	interpretation	unit
delta_ts	LeagueDashPlayerClutch + LeagueDashPlayerStats	DELTA_TS	Clutch value or total-minus-clutch construction	delta ts	proportion (multiply by 100 for percentage points)
delta_efg	LeagueDashPlayerClutch + LeagueDashPlayerStats	DELTA_EFG	Clutch value or total-minus-clutch construction	delta efg	proportion (multiply by 100 for percentage points)
delta_fg	LeagueDashPlayerClutch + LeagueDashPlayerStats	DELTA_FG	Clutch value or total-minus-clutch construction	delta fg	proportion (multiply by 100 for percentage points)
delta_fg3	LeagueDashPlayerClutch + LeagueDashPlayerStats	DELTA_FG3	Clutch value or total-minus-clutch construction	delta fg3	proportion (multiply by 100 for percentage points)
delta_ftr	LeagueDashPlayerClutch + LeagueDashPlayerStats	DELTA_FTR	Clutch value or total-minus-clutch construction	delta ftr	proportion (multiply by 100 for percentage points)
delta_tov_rate	LeagueDashPlayerClutch + LeagueDashPlayerStats	DELTA_TOV_RATE	Clutch value or total-minus-clutch construction	delta tov rate	proportion
invalid_count_subtraction	Engineered from cached NBA counts	INVALID_COUNT_SUBTRACTIO N	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	invalid count subtraction	count or index
pts_per36_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	PTS_PER36_NONCLUTCH	Clutch value or total-minus-clutch construction	pts per36 nonclutch	count or index
fga_per36_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FGA_PER36_NONCLUTCH	Clutch value or total-minus-clutch construction	fga per36 nonclutch	count or index
fg3a_per36_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FG3A_PER36_NONCLUTCH	Clutch value or total-minus-clutch construction	fg3a per36 nonclutch	count or index
fta_per36_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FTA_PER36_NONCLUTCH	Clutch value or total-minus-clutch construction	fta per36 nonclutch	count or index
ast_per36_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	AST_PER36_NONCLUTCH	Clutch value or total-minus-clutch construction	ast per36 nonclutch	count or index
tov_per36_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	TOV_PER36_NONCLUTCH	Clutch value or total-minus-clutch construction	tov per36 nonclutch	count or index
three_rate_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	THREE_RATE_NONCLUTCH	Clutch value or total-minus-clutch construction	three rate nonclutch	proportion
usage_proxy_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	USAGE_PROXY_NONCLUTCH	Clutch value or total-minus-clutch construction	usage proxy nonclutch	count or index
ast_tov_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	AST_TOV_NONCLUTCH	Clutch value or total-minus-clutch construction	ast tov nonclutch	count or index
ft_pct_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	FT_PCT_NONCLUTCH	Clutch value or total-minus-clutch construction	ft pct nonclutch	proportion
eligible_expanded	Configured sample thresholds	ELIGIBLE_EXPANDED	Inclusive eligibility indicator	eligible expanded	count or index
eligible_main	Configured sample thresholds	ELIGIBLE_MAIN	Inclusive eligibility indicator	eligible main	count or index
eligible_high_confidence	Configured sample thresholds	ELIGIBLE_HIGH_CONFIDENCE	Inclusive eligibility indicator	eligible high confidence	count or index
usg_pct_season	Advanced/tracking/bio extension endpoint	USG_PCT_SEASON	Season-context field; includes a small amount of clutch exposure	usg pct season	proportion
ast_pct_season	Advanced/tracking/bio extension endpoint	AST_PCT_SEASON	Season-context field; includes a small amount of clutch exposure	ast pct season	proportion
tm_tov_pct_season	Advanced/tracking/bio extension endpoint	TM_TOV_PCT_SEASON	Season-context field; includes a small amount of clutch exposure	tm tov pct season	proportion
ast_ratio_season	Advanced/tracking/bio extension endpoint	AST_RATIO_SEASON	Season-context field; includes a small amount of clutch exposure	ast ratio season	count or index
poss_season	Advanced/tracking/bio extension endpoint	POSS_SEASON	Season-context field; includes a small amount of clutch exposure	poss season	count or index
off_rating_season	Advanced/tracking/bio extension endpoint	OFF_RATING_SEASON	Season-context field; includes a small amount of clutch exposure	off rating season	count or index
e_usg_pct_season	Advanced/tracking/bio extension endpoint	E_USG_PCT_SEASON	Season-context field; includes a small amount of clutch exposure	e usg pct season	proportion
e_tov_pct_season	Advanced/tracking/bio extension endpoint	E_TOV_PCT_SEASON	Season-context field; includes a small amount of clutch exposure	e tov pct season	proportion
e_ast_ratio_season	Advanced/tracking/bio extension endpoint	E_AST_RATIO_SEASON	Season-context field; includes a small amount of clutch exposure	e ast ratio season	count or index
position	Engineered from cached NBA counts	POSITION	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	position	count or index

variable	source_endpoint	original_column	transformation	interpretation	unit
height	Engineered from cached NBA counts	HEIGHT	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	height	count or index
weight	Engineered from cached NBA counts	WEIGHT	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	weight	count or index
from_year	Engineered from cached NBA counts	FROM_YEAR	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	from year	count or index
to_year	Engineered from cached NBA counts	TO_YEAR	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	to year	count or index
nba_experience_seasons	Engineered from cached NBA counts	NBA_EXPERIENCE_SEASONS	Documented calculation in src/feature_engineering.py or src/clutch_metrics.py	nba experience seasons	count or index
catch_shoot_fga_frequency_season	Advanced/tracking/bio extension endpoint	CATCH_SHOOT_FGA_FREQUENCY_SEASON	Season-context field; includes a small amount of clutch exposure	catch shoot fga frequency season	count or index
catch_shoot_fga_season	Advanced/tracking/bio extension endpoint	CATCH_SHOOT_FGA_SEASON	Season-context field; includes a small amount of clutch exposure	catch shoot fga season	count or index
catch_shoot_fg_pct_season	Advanced/tracking/bio extension endpoint	CATCH_SHOOT_FG_PCT_SEASON	Season-context field; includes a small amount of clutch exposure	catch shoot fg pct season	proportion
catch_shoot_efg_pct_season	Advanced/tracking/bio extension endpoint	CATCH_SHOOT_EFG_PCT_SEASON	Season-context field; includes a small amount of clutch exposure	catch shoot efg pct season	proportion
pullup_fga_frequency_season	Advanced/tracking/bio extension endpoint	PULLUP_FGA_FREQUENCY_SEASON	Season-context field; includes a small amount of clutch exposure	pullup fga frequency season	count or index
pullup_fga_season	Advanced/tracking/bio extension endpoint	PULLUP_FGA_SEASON	Season-context field; includes a small amount of clutch exposure	pullup fga season	count or index
pullup_fg_pct_season	Advanced/tracking/bio extension endpoint	PULLUP_FG_PCT_SEASON	Season-context field; includes a small amount of clutch exposure	pullup fg pct season	proportion
pullup_efg_pct_season	Advanced/tracking/bio extension endpoint	PULLUP_EFG_PCT_SEASON	Season-context field; includes a small amount of clutch exposure	pullup efg pct season	proportion
rim_fga_total	LeagueDashPlayerShotLocations + ShotChartDetail	RIM_FGA_TOTAL	Zone aggregation; non-clutch equals total minus standard-clutch events	rim fga total	count or index
paint_fga_total	LeagueDashPlayerShotLocations + ShotChartDetail	PAINT_FGA_TOTAL	Zone aggregation; non-clutch equals total minus standard-clutch events	paint fga total	count or index
midrange_fga_total	LeagueDashPlayerShotLocations + ShotChartDetail	MIDRANGE_FGA_TOTAL	Zone aggregation; non-clutch equals total minus standard-clutch events	midrange fga total	count or index
corner3_fga_total	LeagueDashPlayerShotLocations + ShotChartDetail	CORNER3_FGA_TOTAL	Zone aggregation; non-clutch equals total minus standard-clutch events	corner3 fga total	count or index
above_break3_fga_total	LeagueDashPlayerShotLocations + ShotChartDetail	ABOVE_BREAK3_FGA_TOTAL	Zone aggregation; non-clutch equals total minus standard-clutch events	above break3 fga total	count or index
rim_fga_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	RIM_FGA_CLUTCH	Clutch value or total-minus-clutch construction	rim fga clutch	count or index
paint_fga_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	PAINT_FGA_CLUTCH	Clutch value or total-minus-clutch construction	paint fga clutch	count or index
midrange_fga_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	MIDRANGE_FGA_CLUTCH	Clutch value or total-minus-clutch construction	midrange fga clutch	count or index
corner3_fga_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	CORNER3_FGA_CLUTCH	Clutch value or total-minus-clutch construction	corner3 fga clutch	count or index
above_break3_fga_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	ABOVE_BREAK3_FGA_CLUTCH	Clutch value or total-minus-clutch construction	above break3 fga clutch	count or index
rim_fga_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	RIM_FGA_NONCLUTCH	Clutch value or total-minus-clutch construction	rim fga nonclutch	count or index
paint_fga_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	PAINT_FGA_NONCLUTCH	Clutch value or total-minus-clutch construction	paint fga nonclutch	count or index
midrange_fga_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	MIDRANGE_FGA_NONCLUTCH	Clutch value or total-minus-clutch construction	midrange fga nonclutch	count or index
corner3_fga_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	CORNER3_FGA_NONCLUTCH	Clutch value or total-minus-clutch construction	corner3 fga nonclutch	count or index
above_break3_fga_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	ABOVE_BREAK3_FGA_NONCLUTCH	Clutch value or total-minus-clutch construction	above break3 fga nonclutch	count or index
rim_share_total	LeagueDashPlayerShotLocations + ShotChartDetail	RIM_SHARE_TOTAL	Zone aggregation; non-clutch equals total minus standard-clutch events	rim share total	proportion

variable	source_endpoint	original_column	transformation	interpretation	unit
paint_share_total	LeagueDashPlayerShotLocations + ShotChartDetail	PAINT_SHARE_TOTAL	Zone aggregation; non-clutch equals total minus standard-clutch events	paint share total	proportion
midrange_share_total	LeagueDashPlayerShotLocations + ShotChartDetail	MIDRANGE_SHARE_TOTAL	Zone aggregation; non-clutch equals total minus standard-clutch events	midrange share total	proportion
corner3_share_total	LeagueDashPlayerShotLocations + ShotChartDetail	CORNER3_SHARE_TOTAL	Zone aggregation; non-clutch equals total minus standard-clutch events	corner3 share total	proportion
above_break3_share_total	LeagueDashPlayerShotLocations + ShotChartDetail	ABOVE_BREAK3_SHARE_TOTAL	Zone aggregation; non-clutch equals total minus standard-clutch events	above break3 share total	proportion
shot_entropy_total	LeagueDashPlayerShotLocations + ShotChartDetail	SHOT_ENTROPY_TOTAL	Zone aggregation; non-clutch equals total minus standard-clutch events	shot entropy total	count or index
rim_share_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	RIM_SHARE_CLUTCH	Clutch value or total-minus-clutch construction	rim share clutch	proportion
paint_share_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	PAINT_SHARE_CLUTCH	Clutch value or total-minus-clutch construction	paint share clutch	proportion
midrange_share_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	MIDRANGE_SHARE_CLUTCH	Clutch value or total-minus-clutch construction	midrange share clutch	proportion
corner3_share_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	CORNER3_SHARE_CLUTCH	Clutch value or total-minus-clutch construction	corner3 share clutch	proportion
above_break3_share_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	ABOVE_BREAK3_SHARE_CLUTCH	Clutch value or total-minus-clutch construction	above break3 share clutch	proportion
shot_entropy_clutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	SHOT_ENTROPY_CLUTCH	Clutch value or total-minus-clutch construction	shot entropy clutch	count or index
rim_share_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	RIM_SHARE_NONCLUTCH	Clutch value or total-minus-clutch construction	rim share nonclutch	proportion
paint_share_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	PAINT_SHARE_NONCLUTCH	Clutch value or total-minus-clutch construction	paint share nonclutch	proportion
midrange_share_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	MIDRANGE_SHARE_NONCLUTCH	Clutch value or total-minus-clutch construction	midrange share nonclutch	proportion
corner3_share_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	CORNER3_SHARE_NONCLUTCH	Clutch value or total-minus-clutch construction	corner3 share nonclutch	proportion
above_break3_share_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	ABOVE_BREAK3_SHARE_NONCLUTCH	Clutch value or total-minus-clutch construction	above break3 share nonclutch	proportion
shot_entropy_nonclutch	LeagueDashPlayerClutch + LeagueDashPlayerStats	SHOT_ENTROPY_NONCLUTCH	Clutch value or total-minus-clutch construction	shot entropy nonclutch	count or index
delta_rim_share	LeagueDashPlayerClutch + LeagueDashPlayerStats	DELTA_RIM_SHARE	Clutch value or total-minus-clutch construction	delta rim share	proportion (multiply by 100 for percentage points)
delta_paint_share	LeagueDashPlayerClutch + LeagueDashPlayerStats	DELTA_PAINT_SHARE	Clutch value or total-minus-clutch construction	delta paint share	proportion (multiply by 100 for percentage points)
delta_midrange_share	LeagueDashPlayerClutch + LeagueDashPlayerStats	DELTA_MIDRANGE_SHARE	Clutch value or total-minus-clutch construction	delta midrange share	proportion (multiply by 100 for percentage points)
delta_corner3_share	LeagueDashPlayerClutch + LeagueDashPlayerStats	DELTA_CORNER3_SHARE	Clutch value or total-minus-clutch construction	delta corner3 share	proportion (multiply by 100 for percentage points)
delta_above_break3_share	LeagueDashPlayerClutch + LeagueDashPlayerStats	DELTA_ABOVE_BREAK3_SHARE	Clutch value or total-minus-clutch construction	delta above break3 share	proportion (multiply by 100 for percentage points)
delta_shot_entropy	LeagueDashPlayerClutch + LeagueDashPlayerStats	DELTA_SHOT_ENTROPY	Clutch value or total-minus-clutch construction	delta shot entropy	count or index
non_catch_shoot_frequency_season	Advanced/tracking/bio extension endpoint	NON_CATCH_SHOOT_FREQUENCY_SEASON	Season-context field; includes a small amount of clutch exposure	non catch shoot frequency season	count or index
self_creation_index	Engineered composite	SELF_CREATION_INDEX	Standardized equal-weight or PCA score	self creation index	count or index
self_creation_pca	Engineered composite	SELF_CREATION_PCA	Standardized equal-weight or PCA score	self creation pca	count or index
versatility_pc1	Engineered composite	VERSATILITY_PC1	Standardized equal-weight or PCA score	versatility pc1	count or index
versatility_pc2	Engineered composite	VERSATILITY_PC2	Standardized equal-weight or PCA score	versatility pc2	count or index

Appendix B. Additional Diagnostics and Visualizations

B.1 Player-level shot-profile heatmap



Appendix Figure A1. Clutch-minus-non-clutch attempt-share changes for the 35 highest-volume clutch shooters.

The heatmap shows that aggregate zone shifts conceal heterogeneous player adaptations. Rows are restricted to high-volume players for readability. Positive and negative cells represent changes in share, not changes in efficiency within the zone.

B.2 Missingness

Table 13. Missingness in modeled features.

variable	missing_n	missing_pct	likely_reason
ts_nonclutch	0	0.0000	Complete in analytic sample
usage_proxy_nonclutch	0	0.0000	Complete in analytic sample
ftr_nonclutch	0	0.0000	Complete in analytic sample
three_rate_nonclutch	0	0.0000	Complete in analytic sample
shot_entropy_nonclutch	0	0.0000	Complete in analytic sample
self_creation_index	0	0.0000	Complete in analytic sample
ast_per36_nonclutch	0	0.0000	Complete in analytic sample
tov_rate_nonclutch	0	0.0000	Complete in analytic sample
fga_clutch	0	0.0000	Complete in analytic sample

Outcome variables were never imputed. Predictor imputation was confined to machine-learning and clustering pipelines and occurred within their preprocessing steps. The primary regression used complete cases, which equaled the full main sample for the chosen predictors.

B.3 Reproducibility notes

All core raw endpoint responses are cached under `data/raw/<season>/` with JSON metadata sidecars. Processed player-season data are under `data/processed/`. Model outputs are under `results/`; figures are saved as PNG and PDF; and tables are saved as CSV and Markdown. `python run_pipeline.py` regenerates processing, analysis, reporting, and quality-control artifacts from the raw cache. The configured random seed is 20260807.

The endpoint audit records successful extension calls and documents the truncated total ShotChartDetail response. The validation report records arithmetic checks and recognizable-player inspection. The quality-control report checks file existence, image links, placeholder absence, sample-size consistency, numeric agreement, and PDF readability.