Are the Markets Just Bandwagon Fans?

Recency Bias in NBA Betting Markets

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Abstract

This paper examines whether NBA betting markets process information efficiently by testing for systematic overweighting of recent team performance. Using a dataset from 2007 to 2023 with over 35,000 regular-season games, I compare market-implied win probabilities, derived from de-vigged moneyline odds, to a benchmark model that predicts true win probabilities using only pre-game information such as season performance, opponent strength, and home-court advantage. The difference between these predictions provides a game-level measure of market bias. Across all specifications, I find that bookmakers consistently place more weight on recent performance than its predictive value warrants. Recent win rate raises market-implied probabilities by about two percentage points, even though the benchmark model shows that short-term momentum has only a modest effect on true win likelihood. The bias is stronger for underdog teams and appears during short winning or losing streaks. Although not large, the pattern is statistically significant and persistent over time. These findings indicate that NBA betting markets exhibit a stable form of recency bias, suggesting that even highly liquid and information-rich environments may deviate from full informational efficiency.

1 Research Question

Sports betting markets provide a setting to test how efficiently prices reflect available information. This thesis investigates how a team's recent performance affects market-implied win probabilities in NBA betting markets.

2 Motivation

Financial markets rely on the principle that information has economic value, and market efficiency depends on the speed and accuracy with which prices adjust to new information. Sports betting markets are well suited for studying these dynamics because outcomes are clearly defined, information updates are frequent, and win probabilities are continuously repriced.

Determining whether bettors overweight recent wins is important for assessing how markets process information. If recent performance is largely noise or is overstated, but markets respond strongly to it, this would indicate a deviation from informational efficiency. The NBA is an appropriate context for this analysis because teams play often, performance varies from week to week, and bettors may interpret short streaks as evidence of underlying team quality.

3 Literature Review

Sports betting markets are frequently studied as prediction markets that aggregate information into prices. Under standard assumptions, betting odds can be interpreted as probabilistic beliefs about future outcomes, allowing researchers to assess market efficiency directly (Wolfers and Zitzewitz 2004). Early work shows that such markets can generate accurate forecasts, though their performance depends on market structure and informational conditions (Luckner, Schröder, and Slamka 2008).

Many studies document systematic pricing biases in sports betting markets. In the NBA context, Arkes (2011) finds that while recent performance contains genuine predictive information, bettors tend to overstate the importance of momentum when pricing teams. Related evidence indicates that behavioral biases can persist even in liquid markets with frequent outcomes (Krieger, Davis, and Strode 2021). Using data from a sports gambling contest, Metz and Jog (2023) further show that recency bias affects both skilled and unskilled participants.

Other studies emphasize that market responses to information vary with context and prior expectations. Davis and Krieger (2017) document systematic mispricing in preseason NFL and NBA point spread markets, a setting characterized by heightened uncertainty. More broadly, evidence on favorite–underdog biases suggests asymmetric belief updating, with different pricing behavior observed for favorites and underdogs (Newall and Cortis 2021).

Several papers address how betting odds should be interpreted and evaluated. Kain and Logan (2014) question whether sports betting markets fully satisfy the criteria of prediction markets and propose tests that jointly use multiple betting lines to assess predictive content. Koning and Zijm (2023) examine the construction of implied probabilities and show how normalization procedures affect inference in binary-outcome markets. Review evidence further indicates that inefficiencies can persist without guaranteeing exploitable profits, underscoring the distinction between mispricing and arbitrage opportunities (Vandenbruaene, De Ceuster, and Annaert 2022).

4 Empirical Strategy

This thesis tests for recency bias in NBA betting markets by comparing the extent to which betting markets price recent team performance to the actual predictive value of that information for game outcomes. A systematic difference between these responses indicates market mispricing. The empirical strategy includes a market pricing model, a benchmark model of true win probabilities, and a bias measure that captures the difference between market and benchmark probabilities.

4.1 Market Model: Response of Implied Probabilities

The market model estimates how sportsbooks use observable pre-game information to set implied win probabilities. In this model, market-implied probabilities are regressed on recent team performance, season win rate, opponent strength, and home-court advantage.

The coefficient on recent performance measures how strongly betting markets respond to short-term momentum, controlling for long-run fundamentals. If markets overweight recent outcomes, this coefficient will be larger than the true predictive value of recent performance.

$$
\begin{aligned}
\text{ImpliedWinProb}_{it} = \alpha &+ \beta_1 \,\text{RecentWinRate}_{it} + \beta_2 \,\text{SeasonWinRate}_{it} \\
&+ \beta_3 \,\text{OppRecentWinRate}_{it} + \beta_4 \,\text{OppSeasonWinRate}_{it} \\
&+ \beta_5 \,\text{Home}_{it} + \varepsilon_{it}.
\end{aligned} \tag{1}
$$

4.2 Benchmark Model: Predicting True Win Probability

To establish a rational benchmark, I estimate a logistic regression of realized game outcomes on the same set of pre-game covariates. This model predicts the probability that a team wins using only information available before tip-off.

The fitted values from this model represent the win probabilities implied by a rational observer who uses recent performance only as far as it predicts actual outcomes. Comparing this response to the market's response isolates whether recent performance is overweighted in prices.

$$
\begin{aligned}
\Pr(\text{Win}_{it} = 1) = \Lambda\Big(&\theta_0 + \theta_1\,\text{SeasonWinRate}_{it} + \theta_2\,\text{RecentWinRate}_{it} \\
&+ \theta_3\,\text{OppRecentWinRate}_{it} + \theta_4\,\text{OppSeasonWinRate}_{it} \\
&+ \theta_5\,\text{Home}_{it}\Big).
\end{aligned} \tag{2}
$$

$$
\Lambda(x) = \frac{1}{1 + e^{-x}}.
$$

4.3 Bias Measure: Market Probability Minus Benchmark Probability

The bias model quantifies mispricing by calculating the difference between the market-implied win probability and the benchmark probability for each game. This difference serves as a game-level measure of market bias.

Regressing this bias measure on recent performance tests whether teams that have performed well in the short run are systematically overpriced relative to fundamentals. A positive relationship provides direct evidence of recency bias in betting markets.

$$
\text{Bias}_{it} = \hat{p}_{it}^{market} - \hat{p}_{it}^{bench}. \tag{3}
$$

$$
\begin{aligned}
\text{Bias}_{it} = \delta_0 &+ \delta_1\,\text{RecentWinRate}_{it} + \delta_2\,\text{SeasonWinRate}_{it} \\
&+ \delta_3\,\text{OppRecentWinRate}_{it} + \delta_4\,\text{OppSeasonWinRate}_{it} \\
&+ \delta_5\,\text{Home}_{it} + u_{it}.
\end{aligned} \tag{4}
$$

Together, these models evaluate recent performance from three perspectives: how markets price it, how actual outcomes justify it, and whether the difference is systematic.

5 Data Sources

5.1 Data source

This study uses NBA regular-season game data from the 2007–08 through 2022–23 seasons, combining game outcomes with pre-game moneyline odds from publicly available sportsbook archives.[1] The data include game dates, teams, locations, final scores, and betting odds.

After constructing lagged performance measures and excluding observations with missing covariates, the final analytic sample consists of 34,570 team-game observations.

5.2 Market-Implied Win Probabilities

Moneyline odds reflect both the market's assessment of win probabilities and a built-in sportsbook margin ("vig"). Following standard practice, I convert moneyline odds into implied probabilities and remove this margin by renormalizing the probabilities for each team so they sum to one (Koning and Zijm 2023).

The resulting de-vigged implied win probability represents the market's stated belief about a team's likelihood of winning and serves as the dependent variable in the market and bias regressions.

5.3 Performance Measures and Controls

Recent performance is measured as a rolling five-game win rate, calculated using only games played before each matchup. Season-long performance is defined as cumulative win percentage up to the game date. The regressions also control for the opponent's recent and season-long performance and for home-court advantage.

[1] The original odds were scraped from Sportsbook Review's historical archives and combined with game scores using the `nbastatR` package.

6 Test and Justification of Assumptions

This section outlines the key assumptions underlying the empirical design and explains why they are appropriate in the context of NBA betting markets.

6.1 Information Availability and Timing

A key assumption is that all explanatory variables reflect information available to bettors and sportsbooks at the time odds are set. Measures of recent performance use only lagged game outcomes, and season win rates, opponent strength, and home-court status are all determined before tip-off.

This timing structure ensures that the regressions capture market responses to past performance rather than mechanical correlations with realized outcomes. This preserves the interpretation of the estimates as market reactions to observable history.

6.2 Omitted Variables and Team Fixed Effects

Unobserved team characteristics, such as talent, coaching quality, or organizational stability, may correlate with both recent performance and betting odds. To address this, the empirical strategy includes team fixed effects that absorb all time-invariant team-specific factors.

By comparing each team to itself over time, the fixed effects specification isolates within-team variation in recent performance and limits confounding from persistent differences across franchises.

6.3 Benchmark Model and Interpretation of Bias

The benchmark logit model provides a counterfactual mapping from pre-game fundamentals to actual win probabilities. This allows deviations between market-implied and benchmark probabilities to be interpreted as mispricing rather than as the result of omitted fundamentals.

6.4 Remaining Threats to Identification

Despite the empirical design, some threats to identification remain. Injuries, rest days, travel schedules, late roster changes, public sentiment, and differences in bookmaker pricing strategies may affect betting odds in ways not fully captured by the available controls.

7 Results

This section presents the empirical findings in a sequence that begins with the simplest specification and adds structure to isolate whether betting markets overweight recent performance. Unless otherwise noted, regression estimates in this section are drawn from Table 1.

7.1 Baseline Estimate of Recency Effects

The baseline regression shows a strong positive relationship between implied win probability and recent team performance. A one percentage point increase in recent win rate is associated with an increase in implied win probability of about 0.34 percentage points, which is a large and precisely estimated effect. This indicates that betting markets respond meaningfully to short winning streaks.

Because this specification does not control for season-long strength or opponent form, the baseline estimate reflects both genuine predictive content and potential mispricing. The purpose of this model is to establish the raw empirical relationship, which is refined in later models.

7.2 Market Model: Controlling for Season Fundamentals

When season win rate and opponent form are included as controls, the estimated effect of recent performance declines sharply, from 0.34 to about 0.05. This reduction indicates that much of the baseline association reflected underlying team quality rather than market overreaction.

However, the coefficient on recent performance remains economically and statistically significant. Recent outcomes continue to influence prices beyond what long-run fundamentals would justify, providing initial evidence that markets may overweight short-term fluctuations.

7.3 Team Fixed Effects Model

Adding team fixed effects sharpens the test by ensuring that comparisons are made within teams rather than across franchises. The estimated effect of recent win rate remains stable at about 0.05, even after absorbing all time-invariant team characteristics.

This stability implies that the recency effect persists relative to a team's own historical baseline. Since fixed effects remove persistent differences in team quality, the remaining sensitivity to recent performance is most consistent with market behavior rather than unobserved team strength.

7.4 Benchmark Model: Predicting True Win Probabilities

The benchmark logit model shows that recent performance has limited predictive power for actual game outcomes. The marginal effect of recent win rate on realized win probability is about 0.14, which is substantially smaller than the market's response. This difference indicates that betting markets overweight recent performance. Calibration evidence in Figure 1 supports this conclusion, showing that for teams with strong recent performance, implied win probabilities systematically exceed observed win frequencies.

7.5 Bias Model: Direct Evidence of Mispricing

The bias model directly examines the gap between implied win probability and realized win frequency. The coefficient on recent win rate is small but statistically significant, approximately 0.02. Although modest in magnitude, this effect indicates that recency contributes directly to systematic pricing errors.

Comparing estimates across models reveals a consistent gap: the market's response to recent performance is about two to three times larger than the response justified by actual outcomes. This comparison provides direct evidence that recency bias leads to predictable mispricing.

7.6 Secondary Analyses

The extended analyses test whether recency bias varies by context, team type, or over time. Results from these extensions are summarized in Tables 3 to 5 and Figures 2 and 3.

7.6.1 Win and Loss Streaks

Decomposing recent performance into streak indicators shows a pronounced asymmetry, as reported in Table 3. A three-game losing streak reduces implied win probability by about 0.023, while a three-game winning streak increases it by only 0.014.

Markets penalize losing streaks more than they reward winning streaks. This pattern is consistent with loss-related behavioral biases documented in other asset markets.

7.6.2 Favorites versus Underdogs

To test whether recency effects depend on baseline expectations, I interact recent performance with a favorite indicator. Recency effects are concentrated among underdogs (Table 4): for underdogs, the coefficient on recent performance is positive and economically meaningful, at approximately 0.010, while the incremental effect for favorites is negative and close to zero. This asymmetry indicates stronger belief updating when recent outcomes conflict with prior expectations, consistent with broader evidence of asymmetric market responses for favorites and underdogs (Newall and Cortis 2021).

7.6.3 Time Trend in Recency Bias

Despite substantial growth in analytics and information availability over the sample period, there is no meaningful time trend in recency bias. The interaction between recent win rate and calendar year is small in magnitude and statistically insignificant.

Recency bias appears to be a stable and persistent feature of NBA betting markets, rather than a temporary result of limited information.

8 Conclusion

This paper provides evidence that NBA betting markets systematically overweight recent team performance when setting moneyline probabilities. While recent outcomes contain some predictive information, market responses are disproportionately strong, especially for underdogs, where short-term success conflicts with prior expectations. These findings suggest that recency bias operates through asymmetric belief updating rather than uniform mispricing. Future research should examine how prior beliefs interact with new information in shaping prices in betting and financial markets.

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Tables

Table 1: Main Regression Results

	(1) Baseline	(2) Market Model	(3) FE (Team)	(4) Benchmark Model	(5) Bias Model
Intercept	0.331***	0.413***		−0.391***	−0.002
	(0.009)	(0.010)		(0.051)	(0.010)
Recent Win Rate	0.337***	0.052***	0.051***	0.143*	0.020***
	(0.015)	(0.004)	(0.004)	(0.060)	(0.004)
Season Win Rate		0.670***	0.646***	3.244***	−0.027
		(0.017)	(0.020)	(0.097)	(0.017)
Opponent Recent Win Rate		−0.051***	−0.051***	−0.137*	−0.020***
		(0.003)	(0.003)	(0.060)	(0.003)
Opponent Season Win Rate		−0.674***	−0.674***	−3.262***	0.027***
		(0.007)	(0.007)	(0.097)	(0.006)
Home		0.175***	0.175***	0.788***	0.004+
		(0.002)	(0.002)	(0.023)	(0.002)
Observations	34570	34570	34570	34570	34570
R^2	0.156	0.745	0.750		0.003
Adjusted R^2	0.156	0.745	0.750		0.003
R^2 Within			0.730		
Clustered SEs	Team	Team	Team	Team	Team
Fixed Effects	None	None	Team	None	None
Model Type	OLS	OLS	OLS (FE)	Logit	OLS

$*p < 0.10, \quad **\ p < 0.05, \quad ***p < 0.01$

Table 2: Alternative Forms of Recent Performance

	(1) 3-Game Form	(2) 5-Game Form	(3) 10-Game Form	(4) Weighted Form
Recent Win Rate (Last 3 Games)	0.036***			
	(0.003)			
Recent Win Rate (Last 5 Games)		0.051***		
		(0.004)		
Recent Win Rate (Last 10 Games)			0.127***	
			(0.007)	
Recent Win Rate (Weighted Decay)				0.056***
				(0.004)
Season Win Rate	0.665***	0.646***	0.582***	0.647***
	(0.019)	(0.020)	(0.019)	(0.020)
Opponent Recent Win Rate	−0.051***	−0.051***	−0.050***	−0.050***
	(0.003)	(0.003)	(0.003)	(0.003)
Opponent Season Win Rate	−0.676***	−0.674***	−0.678***	−0.677***
	(0.007)	(0.007)	(0.007)	(0.007)
Home	0.175***	0.175***	0.175***	0.175***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	34474	34570	34250	34410
R^2	0.751	0.750	0.756	0.752
Adjusted R^2	0.751	0.750	0.756	0.752
R^2 Within	0.731	0.730	0.736	0.732
Clustered SEs	Team	Team	Team	Team
Fixed Effects	Team	Team	Team	Team
Model Type	OLS (FE)	OLS (FE)	OLS (FE)	OLS (FE)

$*p < 0.10$, $**\ p < 0.05$, $***p < 0.01$

Table 3: Streak Effects Model (Team Fixed Effects)

	(1) Streak Effects Model
Win Streak (3+ Games)	0.014***
	(0.002)
Losing Streak (3+ Games)	−0.023***
	(0.003)
Season Win Rate	0.670***
	(0.019)
Opponent Recent Win Rate	−0.051***
	(0.003)
Opponent Season Win Rate	−0.674***
	(0.007)
Home	0.175***
	(0.002)
Observations	34570
R^2	0.750
Adjusted R^2	0.749
R^2 Within	0.729
Clustered SEs	Team
Fixed Effects	Team
Model Type	OLS (FE)

$*p < 0.10$, $**\ p < 0.05$, $***p < 0.01$

Table 4: Asymmetry Model

	(1) Asymmetry Model
Intercept	−0.070***
	(0.006)
Recent Win Rate	0.010+
	(0.005)
Favorite Team	0.202***
	(0.005)
Recent Win Rate × Favorite Team	−0.014
	(0.008)
Season Win Rate	−0.271***
	(0.011)
Opponent Recent Win Rate	−0.003
	(0.002)
Opponent Season Win Rate	0.272***
	(0.006)
Home	−0.059***
	(0.002)
Observations	34570
R^2	0.404
Adjusted R^2	0.404
Clustered SEs	Team
Fixed Effects	None
Model Type	OLS

$*p < 0.10, \quad ** \; p < 0.05, \quad ***p < 0.01$

Table 5: Time Trend Model (Team Fixed Effects)

	(1) Time Trend Model
Recent Win Rate	-2.507
	(2.494)
Calendar Year	-0.001
	(0.001)
Recent Win Rate × Year	0.001
	(0.001)
Season Win Rate	0.647***
	(0.020)
Opponent Recent Win Rate	-0.051***
	(0.003)
Opponent Season Win Rate	-0.674***
	(0.007)
Home	0.175***
	(0.002)
Observations	34570
R^2	0.750
Adjusted R^2	0.750
R^2 Within	0.730
Clustered SEs	Team
Fixed Effects	Team
Model Type	OLS (FE)

$*p < 0.10, \quad ** \, p < 0.05, \quad ***p < 0.01$

Figures

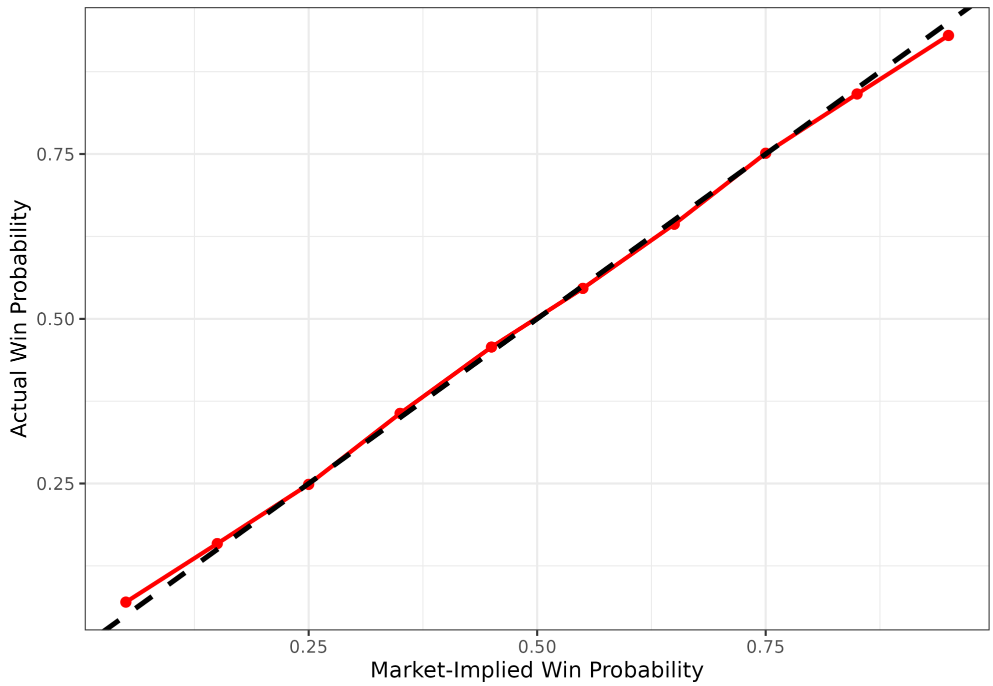

Figure 1: Calibration Curve - Market-Implied vs Actual Win Probabilities

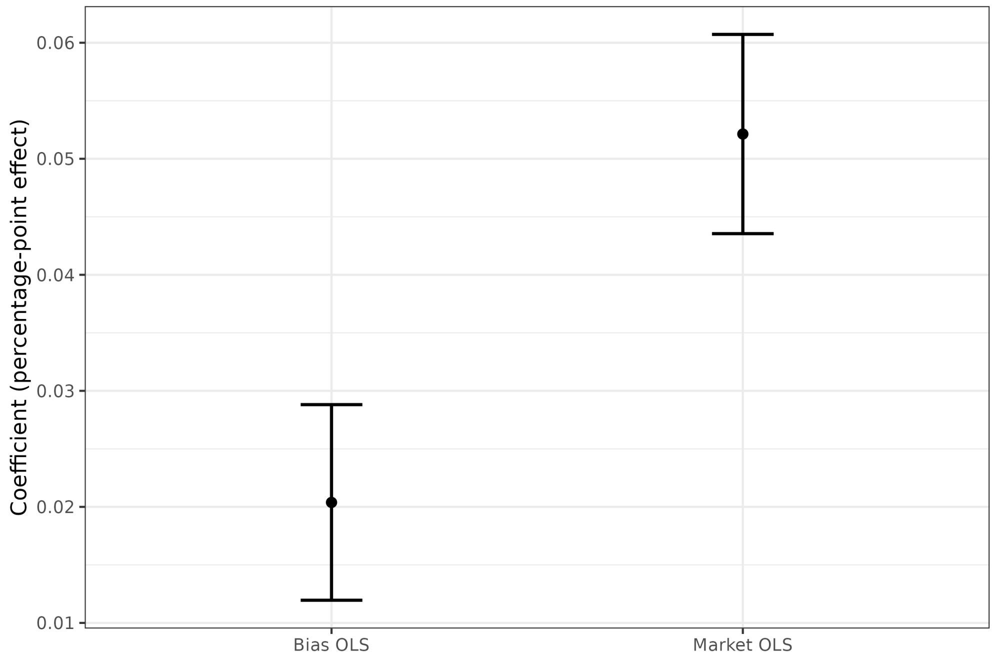

Figure 2: Estimated Recency Effect in Market Pricing and Bias Models

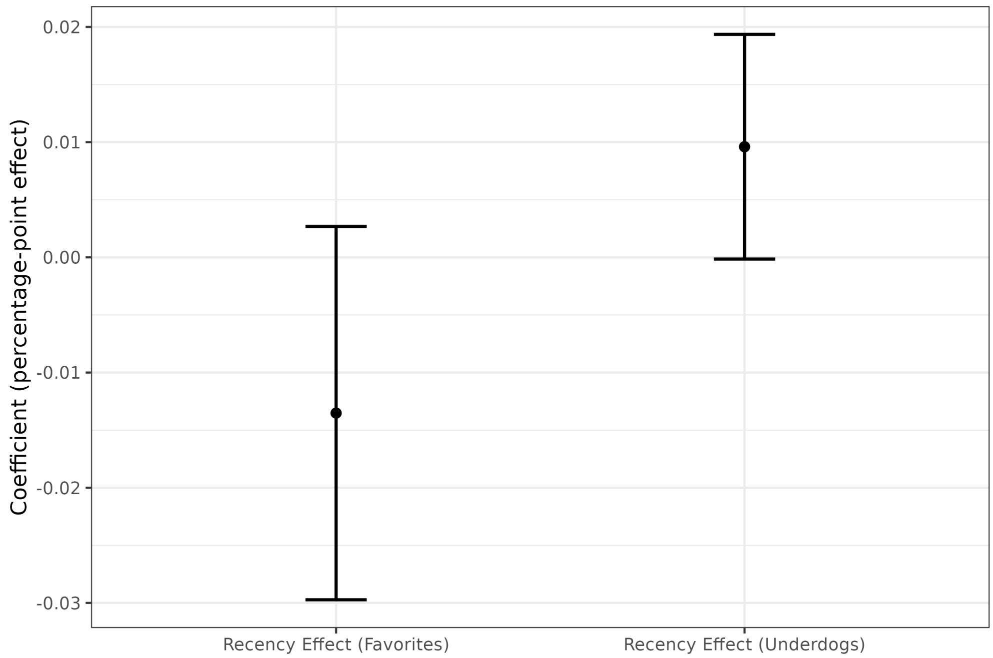

Figure 3: Estimated Recency Effect for Favorites and Underdogs