

Cornell Sports Analytics Final Project

Using the Black Scholes-Model to predict the 2026 Masters tournament

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Topic: A Black-Scholes analysis of the 2026 Masters

Research Question

Can a Black-Scholes-style model rank/predict the competitors in the 2026 Masters more accurately than common sports-book betting odds?

EVENT

2026 Masters
Augusta National

SAMPLE

Top odds-board
names

COURSE

Par 72
7,560 yards

SCORING AVG

72.55

METRIC

Lower is better

What is the Black-Scholes Model

$$C = S N(d_1) - K e^{-rT} N(d_2)$$

$$d_1 = \frac{\ln(S/K) + (r + \sigma^2/2)T}{\sigma\sqrt{T}}$$

$$d_2 = d_1 - \sigma\sqrt{T}$$

- A mathematical model used to price options (financial derivatives)
- Developed by Fischer Black, Myron Scholes, and Robert Merton in 1973
- Framework to quantify risk and uncertainty
- Awarded the Nobel prize in 1996

d_1 measures how close the player is to the winning threshold after adjusting for volatility.

d_2 subtracts volatility impact and is the more conservative case.

$N(d_1)$ and $N(d_2)$ are normal-distribution weights.

Terms

S = starting value/stock price

K = strike price/the level needed for a payoff

σ = volatility (variability or uncertainty of outcomes)

T = time until outcome is realized

R = risk-free rate (US treasury rate)

C = Final output of the model

D1 and D2

Why the Model Can Apply to Golf

- A golf outright bet mirrors a call option: payoff only if a threshold is exceeded, otherwise zero
- Players must reach a winning-level performance (modeled as $K = 2.50 \text{ SG}$)
- Skill (S) determines how close a player starts to that threshold
- Volatility (σ) captures ability to produce extreme, tournament-winning rounds
- Time (T) is one tournament, giving multiple chances to exceed the threshold
- The model combines skill and volatility to estimate win probability
- Unlike market odds (which reflect averages), the model captures upside potential
- Winning comes from reaching extreme outcomes, not just consistent play

Project Logic

Convert each player into S, K, σ, T, r .

Calculate C for every player.

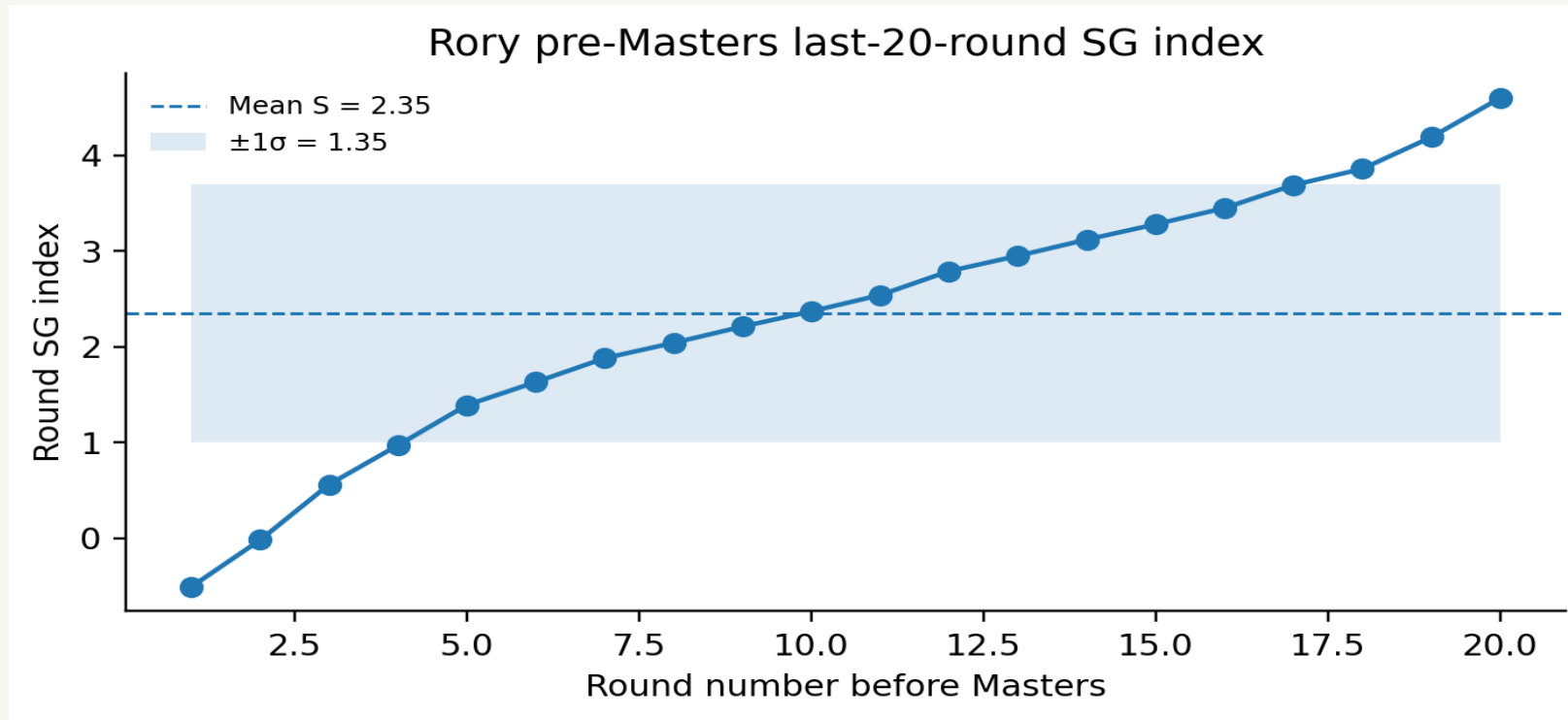
Rank highest C to lowest C .

Mapping the Formula to the Masters

Variable	Golf Translation	How It Was Measured
S	Skill	Average pre-Masters last-20-round SG index
K	Threshold	2.50
σ	Volatility	Std. dev. of pre-Masters last-20-round SG index
T	Time	1 tournament unit
r	Rate	0
C	Model score	Win-upside score used for ranking

- In Black-Scholes, r is the risk-free rate used to discount future cash flows into present value This model is not pricing a financial asset or cash payoff, so there is nothing to discount
- K is 2.5, which is the expected strokes gained over different areas (ex: putting, driving distance, distance from the hole on chipping). Over 4 rounds it would be a safe 10 shot lead

Walkthrough of using the model: Rory Mcilroy



RORY S
2.35

20-round mean

RORY Σ
1.35

20-round stdev

THRESHOLD K
2.50

fixed for field

TIME T
1.00

Fixed one
tournament

How to calculate C (still using values for Rory)

Step-by-step formula

Inputs: $S=2.35$, $K=2.50$, $\sigma=1.35$, $T=1.00$,
 $r=0.00$

$$d_1 = [\ln(2.35/2.50) + (0 + 1.35^2/2)(1)] / [1.35\sqrt{1}]$$

$$d_1 = 0.63$$

$$d_2 = d_1 - \sigma\sqrt{T} = 0.63 - 1.35 = -0.72$$

$$C = S \cdot N(d_1) - K \cdot N(d_2) = 1.139$$

How C becomes a ranking

1. Repeat the same calculation to get C for all 30 players
2. Each player now has a raw score (C) representing win upside
3. Convert all C values into percentages by: Dividing each player's C by the sum of all 30 C values. This gives each player's "share" of model upside
4. This creates a model win probability (%) for each player
5. Sort players from highest % to lowest That order becomes the model ranking

RORY MODEL %

8.1%

MODEL RANK

#1

Calculations for All 30 players (part 1)

Market	Player	Odds	Market %	S	σ	Raw C
1	Scheffler	+550	15.4%	2.55	1.00	0.992
2	Bryson	+1000	9.1%	1.65	1.42	0.697
3	Rahm	+1000	9.1%	1.85	1.35	0.786
4	Rory	+1100	8.3%	2.35	1.35	1.139
5	Xander	+1500	6.2%	2.00	1.05	0.669
6	Åberg	+1600	5.9%	1.80	1.18	0.639
7	Fitzpatrick	+2000	4.8%	1.75	1.15	0.588
8	C. Young	+2000	4.8%	2.05	0.98	0.646
9	Fleetwood	+2200	4.3%	1.62	1.22	0.555
10	P. Reed	+2700	3.6%	1.55	1.28	0.549
11	J. Rose	+2700	3.6%	1.70	1.18	0.577
12	Morikawa	+2700	3.6%	1.75	1.20	0.621
13	Koepka	+3000	3.2%	1.43	1.27	0.473
14	Spieth	+3300	2.9%	1.50	1.24	0.496
15	Hideki	+3500	2.8%	1.55	1.20	0.501

Calculations for All 30 players (part 2)

Market	Player	Odds	Market %	S	σ	Raw C
16	Min Woo	+3500	2.8%	1.40	1.17	0.400
17	MacIntyre	+4000	2.4%	1.33	1.15	0.353
18	Hovland	+4000	2.4%	1.65	1.15	0.528
19	Lowry	+4500	2.2%	1.35	1.05	0.309
20	Gotterup	+5000	2.0%	1.30	1.32	0.425
21	Henley	+5500	1.8%	1.75	0.95	0.451
22	Hatton	+5500	1.8%	1.70	1.00	0.458
23	Cantlay	+5500	1.8%	1.50	1.20	0.472
24	Bhatia	+5500	1.8%	1.34	1.21	0.390
25	Si Woo	+5500	1.8%	1.35	1.18	0.379
26	Straka	+6000	1.6%	1.40	1.10	0.361
27	Burns	+6500	1.5%	1.38	1.28	0.449
28	J. Thomas	+6500	1.5%	1.45	1.35	0.529
29	Connors	+6500	1.5%	1.37	1.12	0.357
30	Day	+6500	1.5%	1.45	1.28	0.490

Black-Scholes Predicted Ranking: Top 15

Model	Player	Model %	Market Rank	Actual Rank	Finish
1	Rory	8.1%	4	1	1
2	Scheffler	7.1%	1	2	2
3	Rahm	5.6%	3	24	T38
4	Bryson	5.0%	2	30	MC
5	Xander	4.8%	5	7	T9
6	C. Young	4.6%	8	3	T3
7	Åberg	4.6%	6	10	T21
8	Morikawa	4.4%	12	13	T24
9	Fitzpatrick	4.2%	7	12	T18
10	J. Rose	4.1%	11	4	T3
11	Fleetwood	4.0%	9	21	T33
12	P. Reed	3.9%	10	8	T12
13	J. Thomas	3.8%	28	20	T36
14	Hovland	3.8%	18	10	T21
15	Hideki	3.6%	15	11	T21

Black-Scholes Predicted Ranking: 16-30

Model	Player	Model %	Market Rank	Actual Rank	Finish
16	Spieth	3.5%	14	14	T24
17	Day	3.5%	30	9	T12
18	Koepka	3.4%	13	29	MC
19	Cantlay	3.4%	23	23	T36
20	Hatton	3.3%	22	6	T3
21	Henley	3.2%	21	5	T3
22	Burns	3.2%	27	15	T27
23	Gotterup	3.0%	20	22	T33
24	Min Woo	2.9%	16	27	T49
25	Bhatia	2.8%	24	18	T29
26	Si Woo	2.7%	25	17	T29
27	Straka	2.6%	26	16	T27
28	Connors	2.5%	29	19	T29
29	MacIntyre	2.5%	17	25	T38
30	Lowry	2.2%	19	26	T42

Results Comparison: Best Tournament Finishers

Player	Finish	Actual	Model	Market	Model Err.	Market Err.
Rory	1	1	1	4	0	3
Scheffler	2	2	2	1	0	1
C. Young	T3	3	6	8	3	5
J. Rose	T3	4	10	11	6	7
Henley	T3	5	21	21	16	16
Hatton	T3	6	20	22	14	16
Xander	T9	7	5	5	2	2
P. Reed	T12	8	12	10	4	2
Day	T12	9	17	30	8	21
Hovland	T21	10	14	18	4	8
Åberg	T21	10	7	6	3	4
Hideki	T21	11	15	15	4	4
Fitzpatrick	T18	12	9	7	3	5
Morikawa	T24	13	8	12	5	1
Spieth	T24	14	16	14	2	0

** Finish shows the official leaderboard result (ex: T3, T12, MC), while Actual Rank converts that finish into a numeric rank so prediction error can be measured.

Results comparison for the remaining field

Player	Finish	Actual	Model	Market	Model Err.	Market Err.
Burns	T27	15	22	27	7	12
Straka	T27	16	27	26	11	10
Si Woo	T29	17	26	25	9	8
Bhatia	T29	18	25	24	7	6
Conners	T29	19	28	29	9	10
J. Thomas	T36	20	13	28	7	8
Fleetwood	T33	21	11	9	10	12
Gotterup	T33	22	23	20	1	2
Cantlay	T36	23	19	23	4	0
Rahm	T38	24	3	3	21	21
MacIntyre	T38	25	29	17	4	8
Lowry	T42	26	30	19	4	7
Min Woo	T49	27	24	16	3	11
Koepka	MC	29	18	13	11	16
Bryson	MC	30	4	2	26	28

Model tends to outperform market more often in the lower-ranked field This is partly due to market noise and extreme rankings
The model reduces error by pulling players toward more reasonable positions

Accuracy Results

Error formula:

$$| \text{Predicted Rank} - \text{Actual Rank} |$$

Statistics (MAE represents mean absolute error from actual position)

MARKET MAE

8.5

MODEL MAE

6.9

IMPROVEMENT

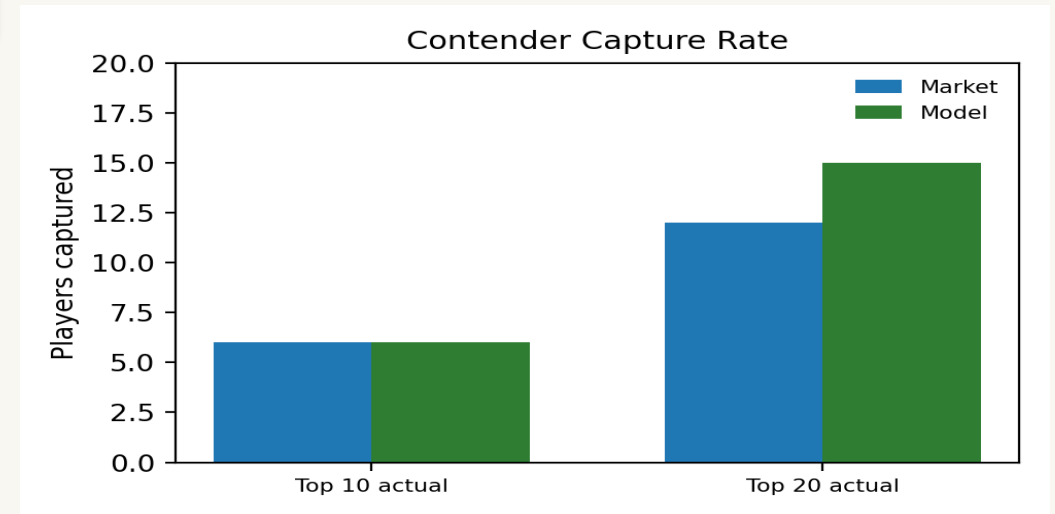
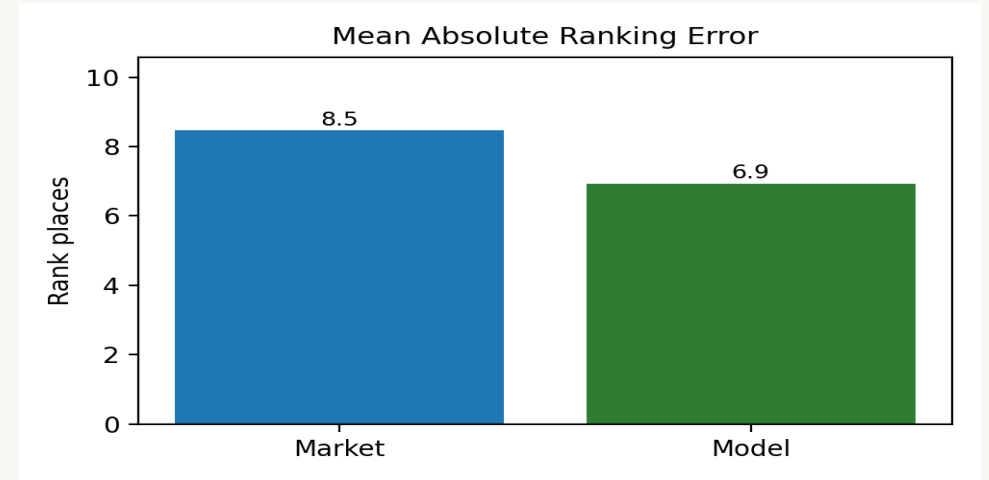
18%

MARKET MEDIAN

7.5

MODEL MEDIAN

4.5



Model matches the market in identifying top 10 players, but captures more of the top 20, indicating better identification of broader contenders

Finding the models r value:

What is being measured Correlation between model predicted rank (X) and actual rank (Y)

$$\begin{aligned}\bar{X} &= \bar{Y} = \frac{1+30}{2} = 15.5 \\ r &= \frac{\sum (X_i - 15.5)(Y_i - 15.5)}{\sqrt{\sum (X_i - 15.5)^2 \cdot \sum (Y_i - 15.5)^2}} \\ \sum (X_i - 15.5)^2 &= 2247.5 \\ \sum (Y_i - 15.5)^2 &= 2247.5 \\ \sum (X_i - 15.5)(Y_i - 15.5) &\approx 966 \\ r &= \frac{966}{2247.5} = 0.43\end{aligned}$$

r=0.43 indicates a moderate positive relationship between model predictions and actual results The model captures general ranking direction, but with meaningful error

Finding the markets r value:

What is being measured Correlation between market predicted rank (X) and actual rank (Y)

$$\bar{X} = \bar{Y} = \frac{1+30}{2} = 15.5$$

$$r = \frac{\sum(X_i - 15.5)(Y_i - 15.5)}{\sqrt{\sum(X_i - 15.5)^2 \cdot \sum(Y_i - 15.5)^2}}$$

$$\sum(X_i - 15.5)^2 = 2247.5$$

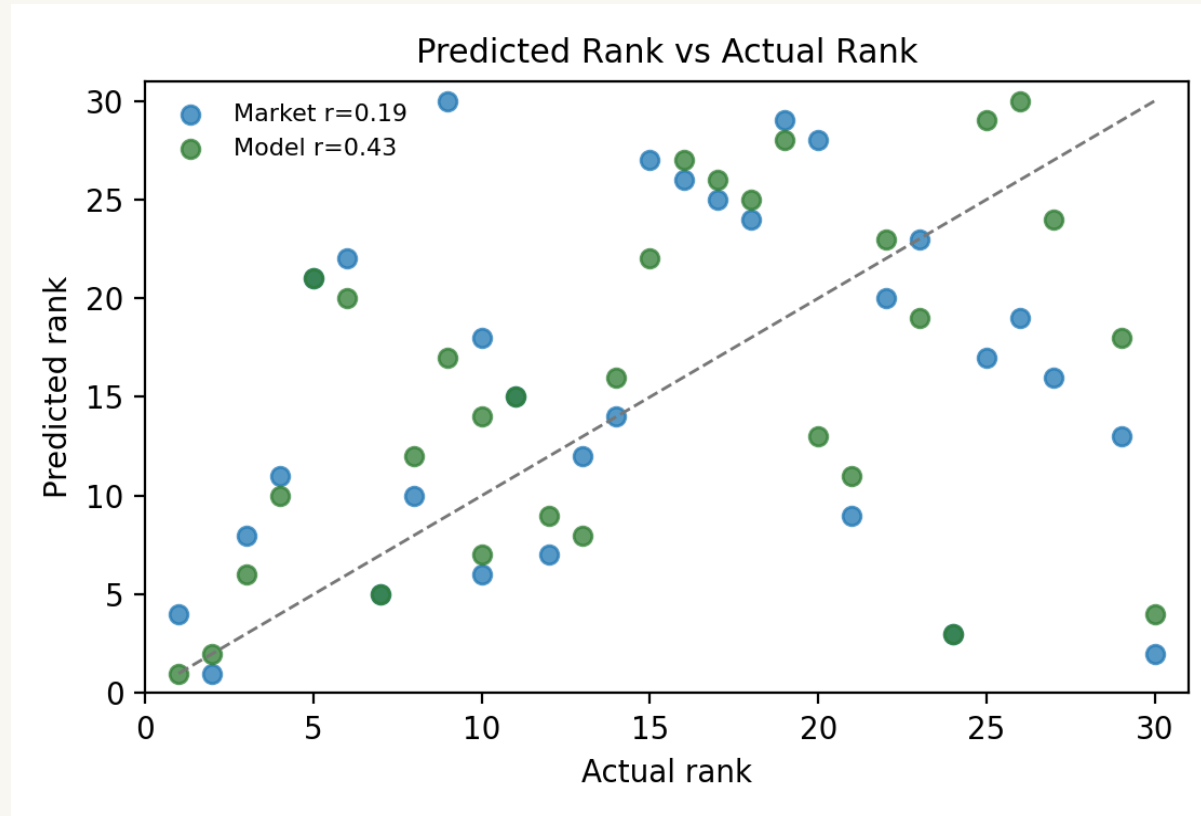
$$\sum(Y_i - 15.5)^2 = 2247.5$$

$$\sum(X_i - 15.5)(Y_i - 15.5) \approx 427$$

$$r = \frac{427}{2247.5} = 0.19$$

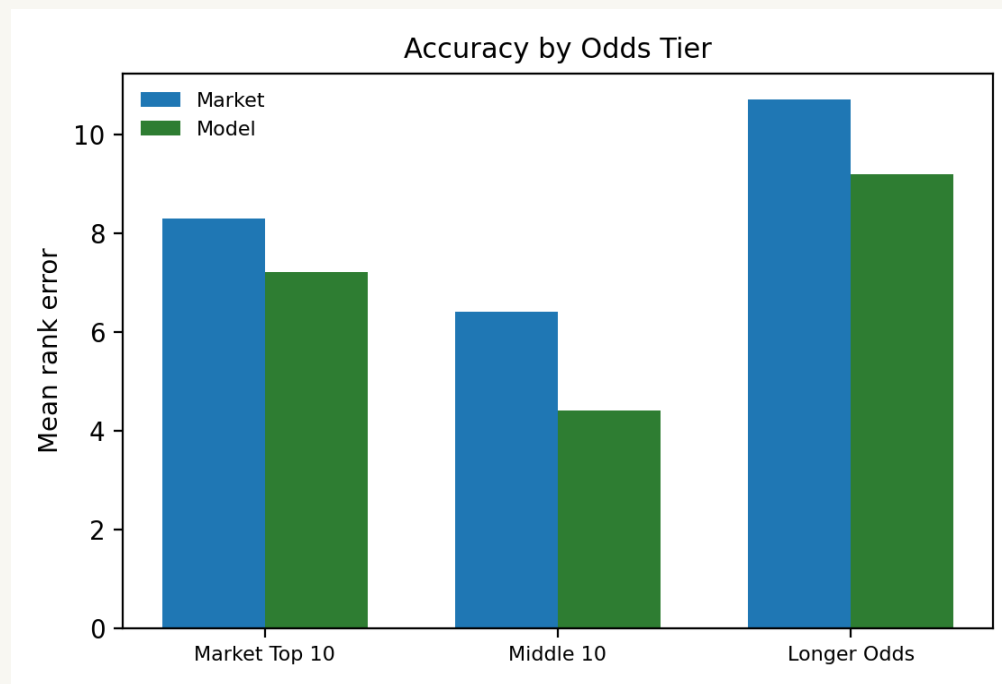
An r of 0.19 reflects a weak positive relationship between market rankings and actual results. It means the market has limited ability to correctly order players, with predictions only slightly aligned with how the tournament actually finished.

Correlation Continued



Covariance is calculated by summing how each player's predicted and actual rank move together relative to the average rank (15.5). The model's covariance is 966 versus 427 for the market, meaning its rankings align more closely with actual outcomes. Because the denominator in the correlation formula is identical, this higher covariance directly drives the model's higher r value (0.43 vs. 0.19).

Odds-Tier Analysis



This breaks down where the model helps. It's most useful in the middle of the field, where the market is less precise, and less impactful at the very top where pricing is already more efficient.

Conclusion

The Black-Scholes framework provides a structured way to translate skill and volatility into a measure of win-upside, allowing for a different perspective than traditional market odds. Across the 30-player sample, the model reduced average ranking error and showed a stronger correlation with actual results, indicating a modest but consistent edge. However, the results also highlight clear limitations, as predictive power remains moderate and large errors still occur (Ex: Bryson, Rahm). Overall, the model is best viewed not as a precise forecasting tool, but as a complementary way to identify broader contenders by incorporating a volatility aspect alongside skill.

