Varying reference-point salience

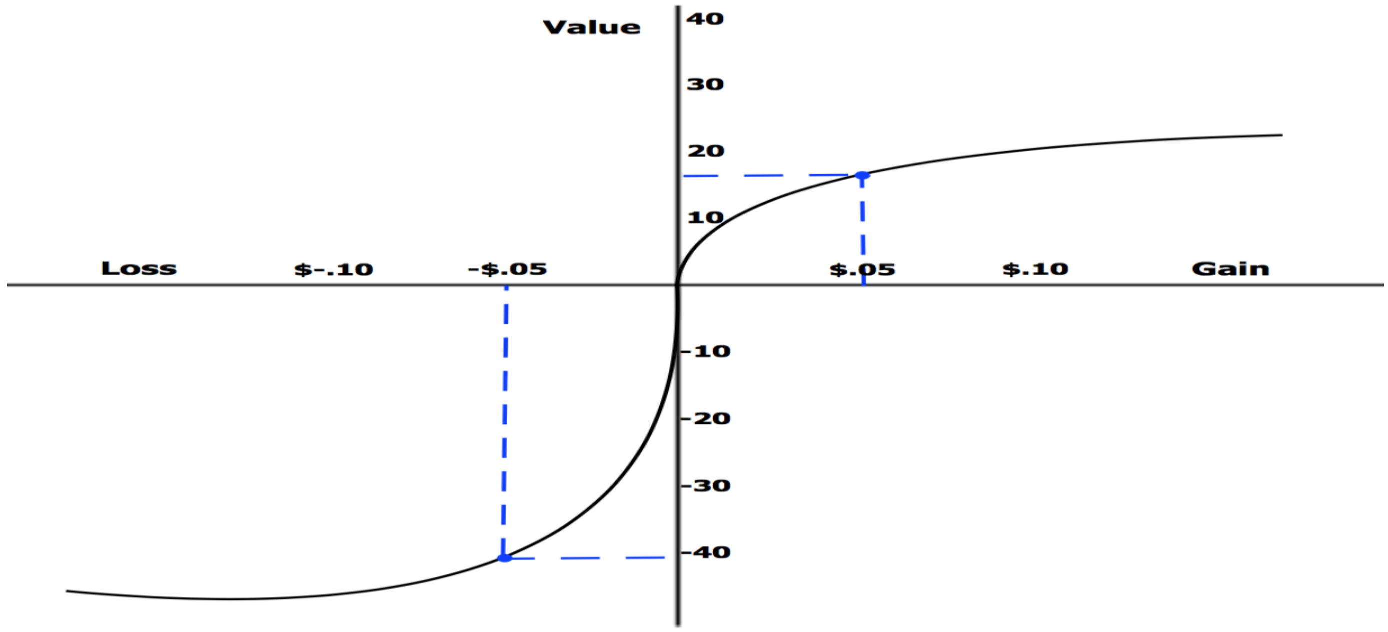
Alex Krumer - Molde University College

Felix Otto - University of Tübingen

Tim Pawlowski - University of Tübingen

Motivation

- Loss aversion is a fundamental feature in economic behavior (Kahneman & Tversky, 1979, *Econometrica*; Tversky & Kahneman, 1992, *JRiskUncert*).
    - Losses are more painful than gains are enjoyable.



Motivation

- For decades, economists have sought to identify the key factors that shape the formation of reference points.

- One of them relates to attention to salient stimuli (Bordalo et al., 2022, *AnnRevEc*).

- Put simply, a reference point should be salient enough to activate the loss aversion mechanism in effort provision.
  - This is especially important in the presence of several reference points (Allen et al., 2017, *ManSci*; Pope and Schweitzer, 2011, *AER*).

Motivation

- Another important factor in the formation of reference points is expectations.
- Kőszegi and Rabin (2006, *QJE*) put forward the idea that reference points may rather evolve endogenously from individual rational expectations.
- Thus, disregarding expectations may lead to incorrect predictions regarding effort provision (Abeler et al., 2011, *AER*)

Motivation

- While salience and expectations are important factors in their own right in reference-point formation, the complex interplay between them and loss aversion has not yet been studied.

- Ideally, one needs to find a natural setting with an exogenous variation of reference-point salience that would create different expectations and then compare individuals' effort provision when reference points are more and less salient.

- However, nature rarely creates settings where one can observe exogenous variation of salience and a clean identification of the loss aversion effect on effort or performance.

- This could be the reason why this interaction has never been studied.

Our aim

- In this paper, we use a unique opportunity to exploit an ideal natural experiment where highly professional individuals perform in a real competitive environment with transparent and known rules, large monetary prizes, and, most importantly, exogenous variation of reference-point salience.

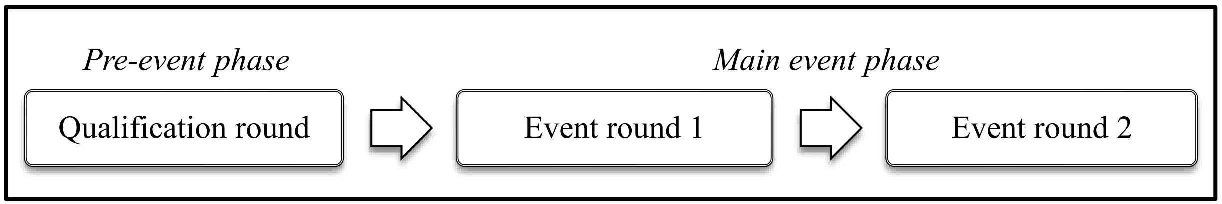
- While a relevant reference point is salient in some cases, influencing individuals' expectations, it is obscured in others.

- This enables us to examine the interplay between reference-point salience and expectation-based loss aversion in shaping effort provision.

Real-life experiment

- We employ a change in rules that occurred in professional ski jumping where 50 jumpers who qualified for the main event compete in the first round.

- Then, the top 30 jumpers in the first round advance to the second and final round of the main event.



Real-life experiment

- Most importantly, up to the 2017/18 season, the top 10 athletes did not have to compete in the qualification round to be among the 50 jumpers in the main event.

- However, after the rule change, all athletes must compete in the qualification.

- This means that before the change, those who were effectively ranked 30 were nominally ranked 20 in the qualification.

- After the change, those who were effectively ranked 30 were also nominally ranked 30 in the qualification.

Real-life experiment

Before rule change				After rule change			
Pre-event phase		*Main event phase*		*Pre-event phase*		*Main event phase*	
Quali rank	Pre-event rank	Event round 1 rank	Event round 2 final rank	Quali rank	Pre-event rank	Event round 1 rank	Event round 2 final rank
Top 10 in World Cup standings	1	1	1	1	1	1	1
	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	10	10	10	10	10	10	10
1	11	11	11	11	11	11	11
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
20	30	30	30	30	30	30	30
21	31	31	*keep ranks from round 1*	31	31	31	*keep ranks from round 1*
⋮	⋮	⋮		⋮	⋮	⋮	
40	50	50		50	50	50	
41 and worse	>=51	*eliminated from main event*		>=51	>=51	*eliminated from main event*	

Real-life experiment

- According to Shafir et al. (1997, *AER*), nominal values are the simpler and more natural representation of information.

- This is why people give them more weight and thus tend to think in nominal terms, giving rise to nominal value illusion.
  - Salient nominal anchors that are used as a reference points for evaluations are, for example, the original purchasing price for property owners in case of reselling (Genesove & Mayer, 2001, *QJE*), nominal performance measures of CEOs (Jenter & Kanaan, 2015, *JF*), or nominal prices of stocks (Birru & Wang, 2016, *JFE*).

- In other words, before the change, the reference point of being around 30th position is less salient than after the change.

- Which in turn may affect the loss aversion mechanism in effort provision.

Sports as laboratory

- Using data from professional sports for economic research has many advantages.
  - participants compete under fixed and known rules with strong incentives to win.
  - The outcomes and the identities of the participants are fully observable.

- According to Kahn (2000, *JEPers*), sports data are unique in that no other setting provides researchers with such detailed information.

- A growing number of articles have used sports data to investigate economic behavior, with many of these being published in top economic journals, including all traditional top five journals (Bar-Eli, Krumer, and Morgulev, 2020, *JBEE;* Palacios-Huerta, 2025, *JEL*).

Krumer, A., Otto, F., & Pawlowski, T. (2022): " Nationalistic bias among International experts: Evidence from professional ski jumping", *Scandinavian Journal of Economics*, 124 (1), 278-300

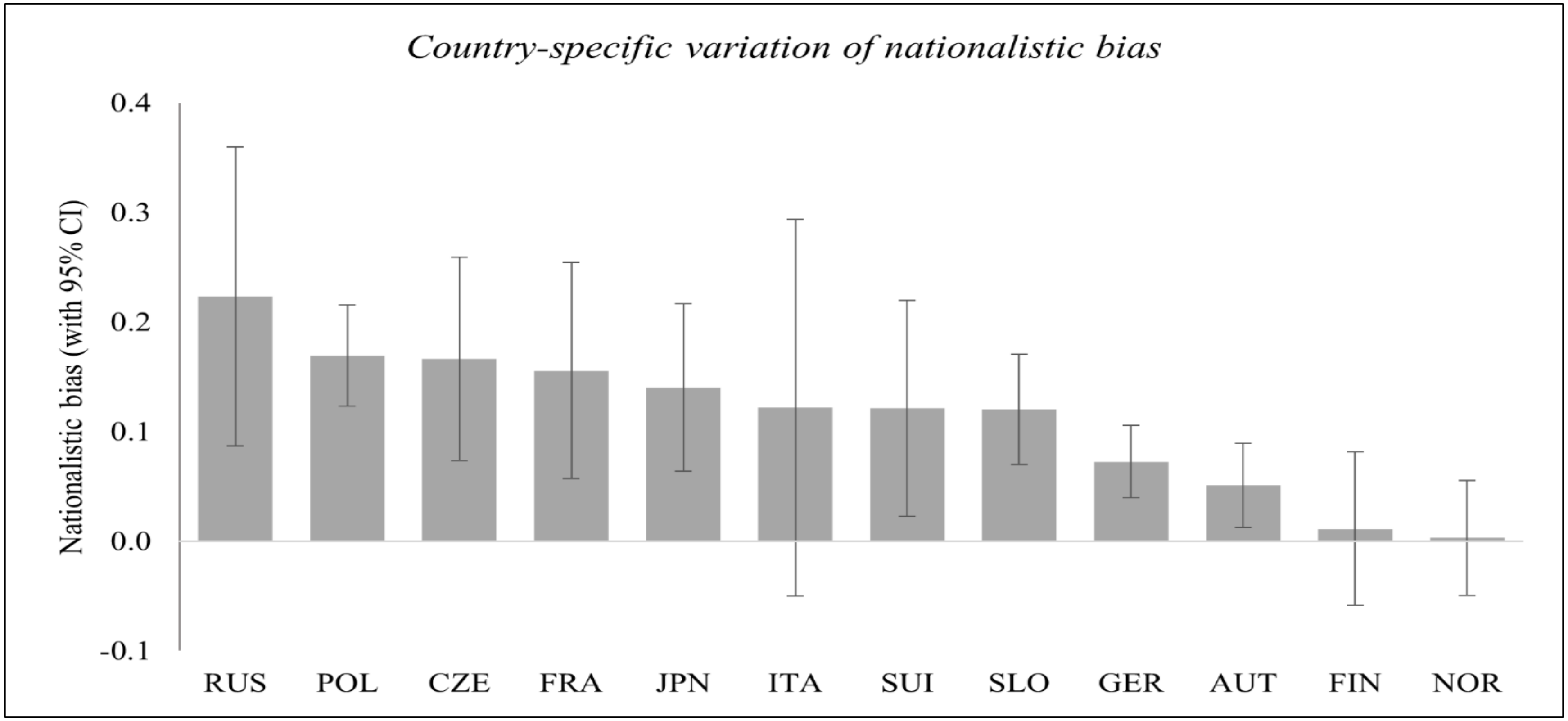


Figure 3: The figure shows the average nationalistic bias with 95% confidence intervals of judges when they evaluate performances of their compatriot jumpers. The estimates are based on subsample estimations of model (1) without judge-per-season fixed effects for the performances of all ski jumpers from the respective countries. The 12 countries are those with the most performance observations. The order of countries is based on the size of nationalistic bias.

Data

- We collected data from the World Cup seasons 2015 to 2020.
  - including three seasons before and after the rule change to generate a balanced dataset.

- The last 2019/20 season ended a bit earlier due to the COVID-19 pandemic.

- The data were retrieved from the official result protocols, provided on the FIS website.

- We only use data from ordinary WC competitions on normal and large hills because their contest design allows for performance comparisons.

Data

- We further restrict the data by only including events where a qualification round and both rounds in the main event were held.

- We also exclude athletes who were disqualified, did not start, or did not finish in a given event.

Table 2. Sample size.

	Before rule change (2015-2017 seasons)	After rule change (2018-2020 seasons)
Number of World Cups	53	44
Number of athletes	164	140
Number of jumps	2,629	2,161
Total no of obs. (jumps)	4,790	

Comparison of performances in round 1 as a function of ski jumpers' pre-event ranks.

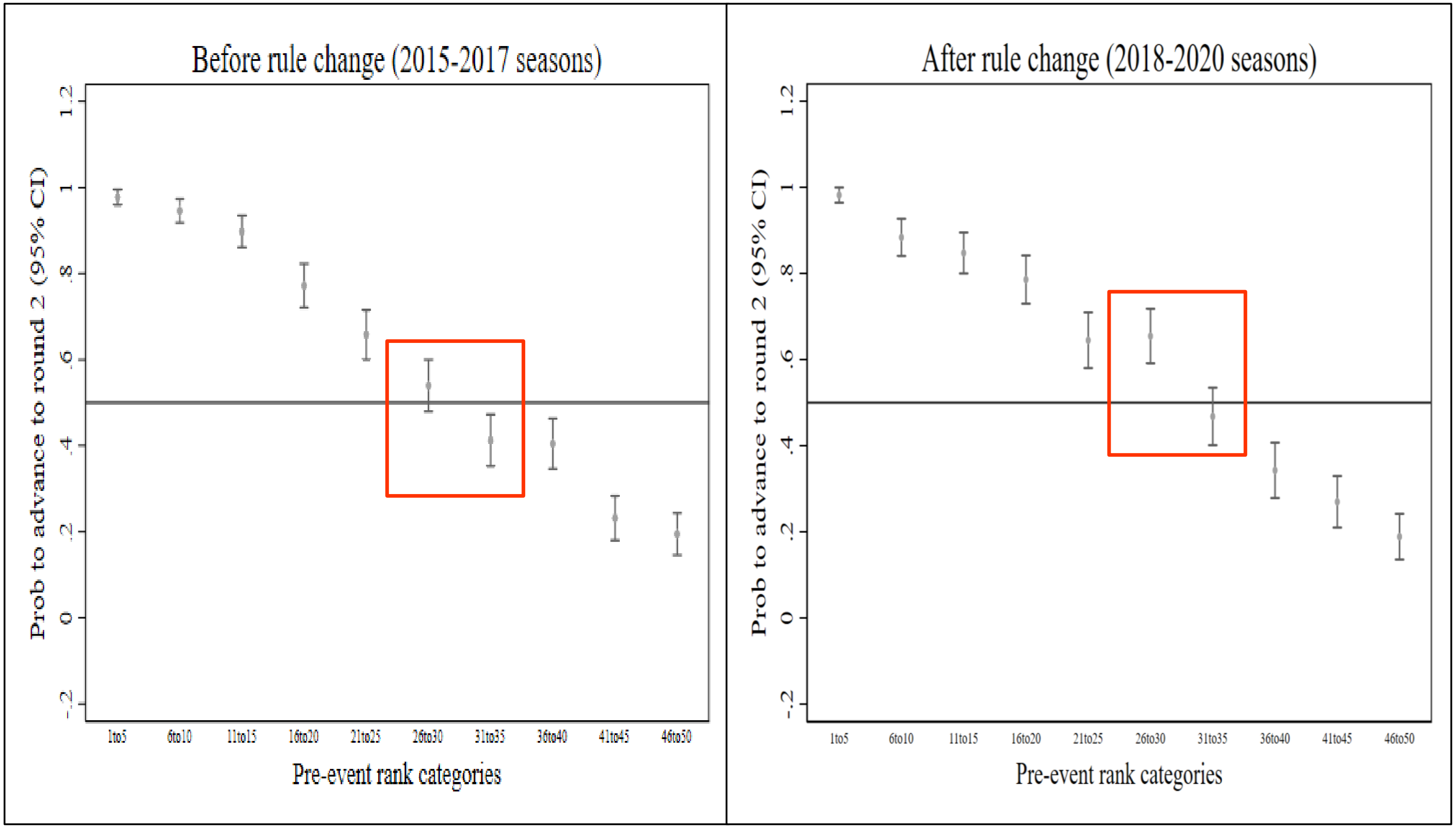


Table A1. Comparison of probabilities to advance to round 2 for pre-event rank groups.

	Before rule change (2015-2017 seasons)	After rule change (2018-2020 seasons)		
	Mean (SD)	Mean (SD)	Difference in means	*p*-value
Pre-event rank 1-5	0.977 (0.149)	0.982 (0.134)	-0.005	0.726
Pre-event rank 6-10	0.946 (0.227)	0.884 (0.321)	0.062	0.014
Pre-event rank 11-15	0.898 (0.304)	0.848 (0.360)	0.050	0.096
Pre-event rank 16-20	0.772 (0.420)	0.786 (0.411)	-0.014	0.719
Pre-event rank 21-25	0.658 (0.475)	0.645 (0.480)	0.013	0.769
Pre-event rank 26-30	0.540 (0.499)	0.655 (0.477)	-0.115	0.010
Pre-event rank 31-35	0.412 (0.493)	0.468 (0.500)	-0.057	0.222
Pre-event rank 36-40	0.404 (0.492)	0.343 (0.476)	0.062	0.165
Pre-event rank 41-45	0.232 (0.423)	0.270 (0.445)	-0.038	0.341
Pre-event rank 46-50	0.195 (0.400)	0.189 (0.392)	0.006	0.873
No of obs.	4,790			

Notes. Dependent variable is a dummy denoting if a ski jumper advances to round 2 in the main event. Standard deviations (SD) are reported in parentheses. Reported are two-sided p-values of *t*-tests.

Table A3. Comparison of WC standing points for pre-event rank groups.

	Before rule change (2015–2017 seasons)	After rule change (2018–2020 seasons)		
	Mean (SD)	Mean (SD)	*z*-statistic	P-value
Pre-event rank 1–5	731.559 (451.733)	462.597 (405.154)	6.955	0.000
Pre-event rank 6–10	417.707 (254.890)	309.991 (294.289)	5.195	0.000
Pre-event rank 11–15	166.599 (148.355)	231.897 (252.598)	-1.766	0.077
Pre-event rank 16–20	121.498 (128.311)	188.324 (253.588)	-1.503	0.133
Pre-event rank 21–25	97.608 (112.605)	137.435 (200.296)	-0.082	0.935
Pre-event rank 26–30	86.117 (115.820)	110.832 (176.245)	-1.392	0.164
Pre-event rank 31–35	67.752 (100.954)	95.573 (173.395)	-1.119	0.263
Pre-event rank 36–40	58.901 (90.961)	61.310 (136.083)	2.010	0.044
Pre-event rank 41–45	34.544 (74.479)	41.274 (99.553)	-0.082	0.935
Pre-event rank 46–50	34.650 (73.940)	33.689 (125.563)	1.671	0.095
No of obs.	4,790			

Notes. The dependent variable is the ski jumpers' points in the WC standings prior to each event. Standard deviations (SD) are reported in parentheses. Since only the best 30 ski jumpers from each competition get WC points and the distribution of points is inconsistent across the finals ranks, including linear and exponential components, the variable is not normally distributed. Therefore, we use a rank-sum test to analyze differences in the distribution. Reported are *z*- and two-sided *p*-values of Mann-Whitney *U* tests.

Estimation strategy

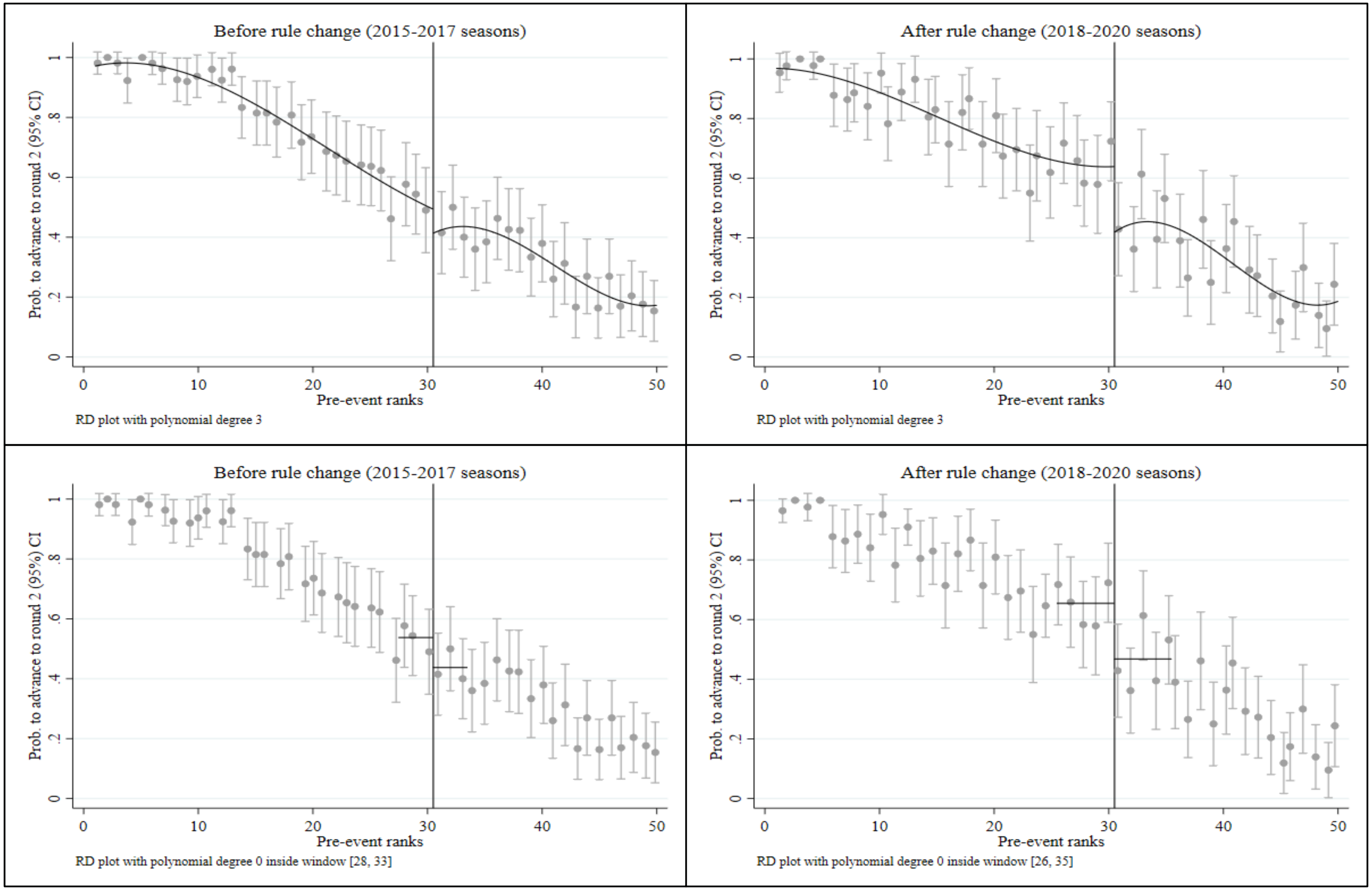
- Selection predominantly exists in the top rank groups.

- The rank groups of interest, i.e., pre-event ranks 26-30 and 31-35, are not statistically different.

- Nonetheless, we cannot clearly rule out that this issue biases our results because we cannot disentangle potential reference point-effects from selection.

- Our identification approach to overcome this issue is therefore based on the idea to not just compare pre-event ranking effects <u>between</u> the two sample periods but to compare athletes ranked just below the reference point to those ranked just above <u>within</u> the same period.

- This <u>within-comparison</u> is plausible because it is reasonable to assume that athletes with pre-event ranks around the cutoff are very similar in ability and thus comparable <u>within</u> each of the two periods.



Notes. The dots mark the sample means within bins, i.e., pre-event ranks, with 95% confidence intervals. In the upper plots, the lines display the polynomial fit of degree 3 on each side of the cutoff. In the lower plots, the lines display the polynomial fit of degree 0, i.e., as a constant, within the relevant windows on each side of the cutoff.

Table 4. Local randomization RD estimates on advancing to Round 2.

	Before rule change (2015–2017 seasons)			After rule change (2018–2020 seasons)		
	(1)	(2)	(3)	(4)	(5)	(6)
Point estimate	0.075	0.061	0.100	0.295	0.266	0.187
P-value	0.516	0.476	0.102	0.008	0.000	0.000
Window	[30, 31]	[29, 32]	[28, 33]	[30, 31]	[29, 32]	[26, 35]
Effective no of obs. (treated / controls)	51 / 53	108 / 105	160 / 160	47 / 42	85 / 89	220 / 218
No of obs.		2,629			2,161	

Notes. The dependent variable is a dummy denoting if a ski jumper advances to Round 2 in the main event. The running variable is the pre-event rank and the cutoff is between rank 30 and 31. The windows for RD analyses in Columns 3 and 6 derive from optimal window selection based on the predetermined covariates WC standing points, previous event rank, and home event. Point estimates report the difference in means and *p*-values derived from Fisherian simulation-based methods.

Table A4. RD estimates on predetermined covariates.

	Before rule change (2015–2017 seasons)			
Variable	Window W/ bandwidth h	Point estimate	P-value	Effective no. of obs.
WC standing points	W [30, 31]	10.485	0.694	51 / 53
	W [28, 33]	16.919	0.198	160 / 160
	h [25, 36]	6.258	0.788	320 / 316
Previous event rank	W [30, 31]	2.412	0.360	39 / 47
	W [28, 33]	-0.144	0.944	133 / 143
	h [25, 36]	1.724	0.455	276 / 273
Home event	W [30, 31]	0.063	0.508	51 / 53
	W [28, 33]	0.013	0.882	160 / 160
	h [25, 36]	0.031	0.544	320 / 316

	After rule change (2018–2020 seasons)			
Variable	Window W/ bandwidth h	Point estimate	P-value	Effective no. of obs.
WC standing points	W [30, 31]	-14.893	0.882	47 / 42
	W [26, 35]	15.258	0.356	220 / 218
	h [24, 37]	-39.921	0.165	302 / 308
Previous event rank	W [30, 31]	1.026	0.716	40 / 38
	W [26, 35]	-0.324	0.768	188 / 184
	h [22, 39]	3.091	0.200	333 / 328
Home event	W [30, 31]	-0.079	0.350	47 / 42
	W [26, 35]	0.026	0.350	220 / 218
	h [27, 34]	-0.078	0.224	174 / 171

Notes. Dependent variables are the predetermined covariates. The running variable is the pre-event rank and the cutoff is between rank 30 and 31. Point estimates report the difference in means (with Fisherian p-values) of the local randomization RD analyses (with Fisherian p-values) or the MSE-optimal point estimates (with robust p-values) of local linear RD analyses. Before the rule change, the small and large window is between pre-event ranks [30, 31] and [28, 33], respectively. After the rule change, the small and large window is between pre-event ranks [30, 31] and [26, 35], respectively. The continuity-based RD analyses estimate local linear regressions with MSE-optimal bandwidth selection and with triangular kernel.

Table A5. Frequency distribution of mass points of the running variable around the cutoff.

		Before rule change (2015–2017 seasons)	After rule change (2018–2020 seasons)
	Treatment status	No. of obs.	No. of obs.
Pre-event rank 26	treated	53	46
Pre-event rank 27	treated	52	41
Pre-event rank 28	treated	52	48
Pre-event rank 29	treated	57	38
Pre-event rank 30	treated	51	47
Pre-event rank 31	controls	53	42
Pre-event rank 32	controls	52	47
Pre-event rank 33	controls	55	44
Pre-event rank 34	controls	50	38
Pre-event rank 35	controls	52	47

Notes. Presented are the absolute numbers of observations at closest mass points around the cutoff, which is between pre-event rank 30 and 31.

Table 5. Continuity-based RD estimates on advancing to Round 2.

	Before rule change (2015–2017 seasons)			After rule change (2018–2020 seasons)		
	(1)	(2)	(3)	(4)	(5)	(6)
Point estimate	0.046	0.047	0.043	0.274	0.302	0.288
	(0.089)	(0.077)	(0.080)	(0.090)	(0.089)	(0.010)
P-value	0.669	0.556	0.650	0.003	0.001	0.005
Bandwidth	[25, 36]	[24, 37]	[22, 39]	[25, 36]	[25, 36]	[26, 35]
Effective no of obs. (treated / controls)	320 / 316	373 / 370	422 / 404	262 / 259	262 / 259	188 / 184
No of obs.		2,629			2,161	

Notes. The dependent variable is a dummy denoting if a ski jumper advances to Round 2 in the main event. The running variable is the pre-event rank and the cutoff is between ranks 30 and 31. The continuity-based RD analyses estimate local (first-order) polynomial regressions with a triangular kernel function to assign weights to the observations and common mean squared error (MSE)-optimal bandwidth selection, reporting the MSE-optimal point estimates. Standard errors are clustered at the athlete level and presented in parentheses. P-values are obtained with the robust bias-correction method. The RD analyses in Columns 2 and 5 use covariate adjustment based on the predetermined covariates WC standing points and home event; the RD analyses in Columns 3 and 6 additionally include previous event rank as covariate.

Table A6. RD estimates on advancing to Round 2 at placebo cutoffs.

	Before rule change (2015–2017 seasons)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Point estimate	0.050	0.047	0.082	0.020 (0.073)	0.119	0.071	0.135	0.070 (0.117)
P-value	0.776	0.544	0.134	0.701	0.310	0.290	0.016	0.532
Window / bandwidth	[20, 21]	[19, 22]	[18, 23]	[14, 27]	[40, 41]	[39, 42]	[38, 43]*	[38, 43]
Placebo cutoff	20.5	20.5	20.5	20.5	40.5	40.5	40.5	40.5
Effective no of obs. (treated / controls)	53/51	106/103	158/155	371/368	58/50	112/98	164/152	164/152

Notes. The dependent variable is a dummy denoting if a ski jumper advances to Round 2 in the main event. The running variable is the pre-event rank. Columns 1–3 and 5–7 report local randomization RD analyses and the difference in means as point estimates with Fisherian *p*-values. Columns 4 and 8 present local linear regressions with MSE-optimal bandwidth selection and with triangular kernel. Reported are the MSE-optimal point estimates with standard errors clustered at the athlete level presented in parentheses and robust *p*-values. *This window does not pass covariate balance tests.

Table 6. Difference-in-discontinuities at the elimination cutoff before and after the rule change.

	(1)	(2)	(3)
Point estimate	0.179	0.208	0.219
	(0.102)	(0.102)	(0.125)
P-value	0.081	0.044	0.080
Bandwidth	[24, 37]	[24, 37]	[25, 36]
Effective no of obs. (treated / controls)	675 / 678	675 / 678	500 / 493
No of obs.	4,790	4,790	4,167

Notes. The dependent variable is a dummy denoting if a ski jumper advances to Round 2 in the main event. The running variable is the pre-event rank and the cutoff is between ranks 30 and 31. The Diff-in-Disc analyses is based on local (first-order) polynomial regressions with a triangular kernel function to assign weights to the observations and common mean squared error (MSE)-optimal bandwidth selection. Point estimates report the Diff-in-Disc estimate. Standard errors are clustered at the athlete level and presented in parentheses. Conventional *p*-values are reported. The analysis in Column 2 controls for the predetermined covariates WC standing points and home event; the analysis in Column 3 additionally controls for previous event rank. All coefficients from the full regression models can be found in the supplementary replication material.

Concluding Remarks

- The “more to lose” approach incentivizes more than the “more to gain” approach.

- This means that contestants with positive expectations are expected to exert more effort to avoid losses.

- No such effect is observed when the reference point lacks salience, suggesting that sufficient salience is necessary to activate the loss aversion mechanism in effort provision.

Concluding Remarks

- Our paper emphasizes the significance of the correct framing of the expectation-based reference points in contests.

- This is because by disregarding the competitive structure of zero-sum games, one can predict that a lagging player who has more to gain should do better than the leading player who has more to lose.

- We offer theoretical and empirical evidence of why this prediction is not correct if players rely on performance expectations to decide on their effort provision.

Concluding Remarks

- Given the uniqueness of our setting, it is natural to discuss external validity of our findings.

- According to List (2020), the uniqueness of our setting is more of an advantage since it allows us to make the relevant test as no other settings can have that level of relevance.
  - "all results are externally valid to some settings, and no results will be externally valid to all settings" (List, 2020. p. 45).

- Nevertheless, we need to be cautious about generalizing our findings for several reasons:
  - our results come from competitions among men.
  - ski jumping is a sport where performances are executed in a few seconds, and which requires a strong focus and specific abilities.
  - there are certainly not many other settings where the margin for mistakes is comparably small eventually causing severe injuries.

Concluding Remarks

- Still, identifying such a significant effect among high-profile professionals suggests that expectation-based loss aversion (Kőszegi & Rabin, 2006, *QJE*) and the salience of a reference point (Bordalo et al., 2022, *AnnRevEc*) may play a significant role in human behavior in general and in highly competitive settings in particular.

Make sport, not war!