

From Winning to Giving: The Effect of Gold Medals in Crowdsourcing Contests

Online Appendix

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Appendix A: Empirical Identification

Leaderboard

One of the most important aspects of Kaggle Competitions is the Leaderboard. The Competition leaderboard has two parts.

The public leaderboard provides publicly visible submission scores based on a representative sample of the test data. This leaderboard is visible throughout the competition.

The private leaderboard, by contrast, tracks model performance using the remainder of the test data. The private leaderboard thus has final say on whose models are best, and hence, who the winners and losers of the Competition will be. Which subset of data is calculated on the private leaderboard or a submission's performance on the private leaderboard is not released to users until the competition has been closed.

Many users watch the public leaderboard closely, as breakthroughs in the competition are announced by score gains in the leaderboard. These jumps in turn motivate other teams working on the competition in search of those advancements. But it's important to keep the public leaderboard in perspective. It's very easy to overfit a model, creating something that performs very well on the public leaderboard, but very badly on the private one. This is called overfitting.

In the event of an exact score tie, the tiebreaker is the team which submitted earlier. Kaggle always uses full precision when determining rankings, not just the truncated precision shown on the Leaderboard.

Figure A1. Kaggle Description about Leaderboard (Screenshot)

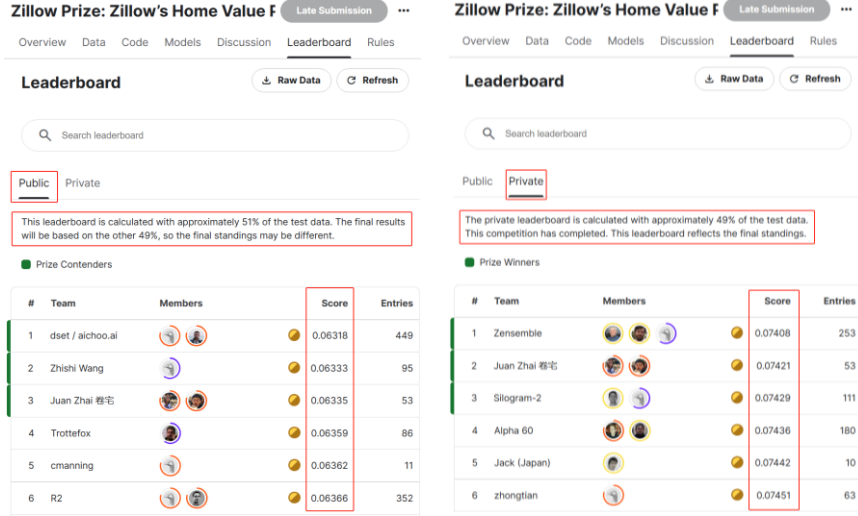


Figure A2. Public vs. Private Leaderboards (Screenshot)

Table A1. Correlations Between Public and Final Rankings

Sample	Correlation	Sample	Correlation
Top 500 on public leaderboard	0.159***	Top 500 on private leaderboard	0.215***
Top 250 on public leaderboard	0.081***	Top 250 on private leaderboard	0.113***
Top 100 on public leaderboard	0.038***	Top 100 on private leaderboard	0.037***
Top 50 on public leaderboard	0.015	Top 50 on private leaderboard	0.019*
Top 25 on public leaderboard	0.014	Top 25 on private leaderboard	0.001
Top 10 on public leaderboard	0.004	Top 10 on private leaderboard	0.015

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2. Definitions of Predetermined Covariates in Table 2

Variable	Description
<i>Post</i>	Number of posts a user had made before receiving or not receiving a medal
<i>Contest</i>	Number of contests a user entered before receiving or not receiving a medal
<i>Voting</i>	Number of upvotes a user gave to others' posts before receiving or not receiving a medal
<i>Bronze</i>	Number of bronze medals a user had won before receiving or not receiving a medal
<i>Silver</i>	Number of silver medals a user had won before receiving or not receiving a medal
<i>Gold</i>	Number of gold medals a user had won before receiving or not receiving a medal
<i>RecVote</i>	Number of upvotes a user's posts received before receiving or not receiving a medal
<i>AveSub</i>	Average number of solutions submitted per contestant per day during they participation
<i>MultiTask</i>	Whether a contestant participated in other contests while participating in this contest
<i>Tenure</i>	Number of days since a user registered on the platform

Appendix B: Robustness Checks

A. Alternative Bandwidths

Table A3. Local Linear Estimates with Different Bandwidths

Bandwidth	(1) 0.50	(2) 0.75	(3) 1.00	(4) 1.25	(5) 1.50	(6) 1.75	(7) 2.00
<i>DV = Participation</i>							
$I(r_{ij} \geq 0)$	-0.072** (0.030)	-0.053** (0.025)	-0.049** (0.022)	-0.047** (0.020)	-0.043** (0.018)	-0.043** (0.017)	-0.043*** (0.017)
<i>DV = PostProb</i>							
$I(r_{ij} \geq 0)$	0.069* (0.041)	0.092*** (0.034)	0.114*** (0.030)	0.127*** (0.027)	0.140*** (0.025)	0.154*** (0.024)	0.165*** (0.023)
<i>DV = log(Volume)</i>							
$I(r_{ij} \geq 0)$	0.139 (0.088)	0.186** (0.073)	0.229*** (0.064)	0.257*** (0.059)	0.283*** (0.055)	0.314*** (0.052)	0.340*** (0.050)
<i>DV = log(Length)</i>							
$I(r_{ij} \geq 0)$	0.454* (0.247)	0.579*** (0.204)	0.693*** (0.180)	0.783*** (0.163)	0.881*** (0.152)	0.979*** (0.144)	1.056*** (0.137)
<i>DV = log(Votes)</i>							
$I(r_{ij} \geq 0)$	0.158* (0.090)	0.211*** (0.074)	0.253*** (0.065)	0.272*** (0.060)	0.283*** (0.056)	0.302*** (0.053)	0.319*** (0.051)
Observations	2,737	3,828	4,761	5,632	6,471	7,327	8,132
Contest FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tier FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses. The local linear regressions are estimated using triangular kernel weights based on the “rdrobust” method of Calonico et al. (2015).

A notable pattern in Table A3 is the systematic variation in estimate magnitudes with changing bandwidth sizes. This variation may arise from the inherent smoothing bias and the bias-variance trade-off in RDD (Cattaneo et al. 2019). Similar patterns have been documented in other RDD studies (e.g., Forderer and Burtch 2025, Ludwig and Miller 2007, Flammer 2015).

The local linear regression (LLR) assumes that the conditional expectation function, $E(Y|RV)$, is approximately linear within a sufficiently narrow bandwidth around the cutoff. In principle, if the true functional form of $E(Y|RV)$ were known and correctly specified, estimated local effects would remain stable across different bandwidths. However, when the unknown conditional expectation function is nonlinear, applying LLR over wider bandwidths may introduce smoothing bias (Cattaneo et al. 2019). This occurs because the inclusion of observations farther from the cutoff increases the influence of regions where the linearity assumption no longer holds. Consequently, wider bandwidths tend to yield estimates that are increasingly distorted by the smoothing bias, potentially resulting in upward or downward bias in the

estimated treatment effect.

Figure A3 illustrates this mechanism. Within a narrow bandwidth h_0 , the estimated effect $\hat{\beta}_{LLR} = b - a$ closely approximates the true treatment effect at the cutoff. In contrast, with a wider bandwidth h_1 , the fitted linear model incorporates observations from nonlinear regions, leading to a larger estimate $\hat{\beta}_{LLR} = c - d$. Therefore, the estimated RDD effects could be contingent upon the size of the bandwidth. This sensitivity may reflect the bias-variance trade-off in RDD: narrower bandwidths reduce smoothing bias but increase variance due to smaller sample sizes, while wider bandwidths reduce variance but introduce bias.

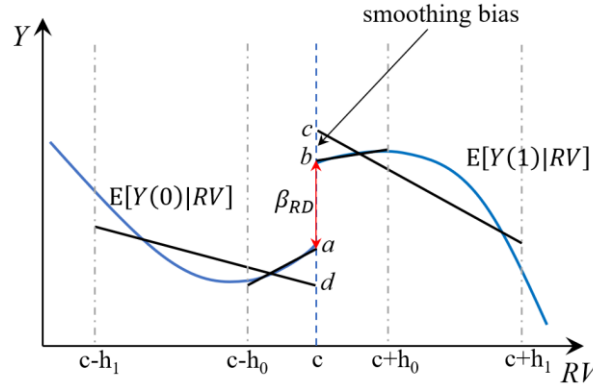


Figure A3. Relationship Between the RD Effect and Bandwidth

Table A4. RDD Estimates with CER-optimal Bandwidths

	<i>Participation</i>	<i>PostProb</i>	<i>log(Volume)</i>	<i>log(Length)</i>	<i>log(Votes)</i>
	(1)	(2)	(3)	(4)	(5)
$I(r_{ij} \geq 0)$	-0.043** (0.018)	0.096*** (0.033)	0.197*** (0.070)	0.575*** (0.206)	0.267*** (0.061)
Contest FE	Yes	Yes	Yes	Yes	Yes
Tier FE	Yes	Yes	Yes	Yes	Yes
CER-Optimal Bandwidth	1.597	0.801	0.816	0.737	1.179
Observations	6,788	4,021	4,068	3,779	5,396

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses. The local linear regressions are estimated using triangular kernel weights based on the “rdrobust” method of Calonico et al. (2015).

B. Alternative Model Implementations

Table A5. RDD Estimates with Different Kernels

	<i>Participation</i> (1)	<i>PostProb</i> (2)	<i>log(Volume)</i> (3)	<i>log(Length)</i> (4)	<i>log(Votes)</i> (5)
Rectangular Kernel					
$I(r_{ij} \geq 0)$	-0.045*** (0.016)	0.131*** (0.026)	0.268*** (0.058)	0.796*** (0.169)	0.297*** (0.053)
MSE-Optimal Bandwidth	1.785	1.011	0.981	0.902	1.350
Observations	7,428	4,800	4,699	4,407	5,975
Epanechnikov Kernel					
$I(r_{ij} \geq 0)$	-0.043*** (0.015)	0.139*** (0.025)	0.282*** (0.055)	0.818*** (0.159)	0.321*** (0.051)
MSE-Optimal Bandwidth	2.482	1.315	1.321	1.219	1.821
Observations	9,773	5,871	5,889	5,539	7,537
Contest FE	Yes	Yes	Yes	Yes	Yes
Tier FE	Yes	Yes	Yes	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses. The local linear regressions are estimated using the “rdrobust” method of Calonico et al. (2015).

Table A6. RDD Estimates with Additional Controls

	(1) <i>Participation</i>	(2) <i>PostProb</i>	(3) <i>log(Volume)</i>	(4) <i>log(Length)</i>	(5) <i>log(Votes)</i>
$I(r_{ij} \geq 0)$	-0.035*** (0.013)	0.120*** (0.022)	0.217*** (0.043)	0.710*** (0.131)	0.260*** (0.043)
r_{ij}	-0.004 (0.005)	0.117*** (0.018)	0.227*** (0.033)	0.868*** (0.114)	0.114*** (0.019)
$r_{ij} \times I(r_{ij} \geq 0)$	-0.001 (0.020)	0.221*** (0.038)	0.609*** (0.079)	1.902*** (0.247)	0.334*** (0.071)
Controls					
<i>Post</i>	0.014** (0.006)	0.086*** (0.011)	0.314*** (0.022)	0.520*** (0.067)	0.267*** (0.021)
<i>Contest</i>	0.037*** (0.006)	-0.057*** (0.010)	-0.186*** (0.020)	-0.401*** (0.059)	-0.160*** (0.018)
<i>Voting</i>	-0.001 (0.004)	0.015** (0.006)	0.030** (0.012)	0.114*** (0.037)	0.026** (0.011)
<i>Bronze</i>	0.051*** (0.008)	-0.012 (0.013)	-0.016 (0.026)	-0.078 (0.077)	-0.013 (0.024)
<i>Silver</i>	-0.003 (0.008)	-0.013 (0.013)	-0.044 (0.027)	-0.068 (0.080)	-0.010 (0.026)
<i>Gold</i>	0.002 (0.012)	-0.083*** (0.019)	-0.084** (0.039)	-0.481*** (0.112)	-0.071* (0.039)
<i>AveSub</i>	0.018* (0.010)	0.047** (0.018)	0.227*** (0.035)	0.402*** (0.107)	0.146*** (0.032)
<i>RecVote</i>	-0.006 (0.005)	0.024** (0.010)	0.012 (0.018)	0.185*** (0.057)	-0.012 (0.017)
<i>MultiTask</i>	0.304*** (0.014)	0.051*** (0.018)	0.256*** (0.040)	0.280** (0.109)	0.178*** (0.038)
<i>Tenure</i>	-0.011*** (0.002)	0.006 (0.004)	0.010 (0.008)	0.059** (0.025)	0.011* (0.007)
Contest FE	Yes	Yes	Yes	Yes	Yes
Tier FE	Yes	Yes	Yes	Yes	Yes
Bandwidth	3.042	1.526	1.555	1.405	2.245
Observations	11,655	6,563	6,665	6,156	8,955

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses. The bandwidths are the same as the MSE-optimal bandwidths used in the main analyses.

Table A7. RDD Estimates Using Logit and Poisson Estimators

	(1) <i>Participation</i>	(2) <i>PostProb</i>	(3) <i>Volume</i>	(4) <i>Length</i>	(5) <i>Votes</i>
$I(r_{ij} \geq 0)$	-0.319** (0.132)	0.524*** (0.119)	0.290* (0.149)	0.296** (0.126)	0.630*** (0.179)
r_{ij}	-0.098** (0.043)	0.568*** (0.097)	0.678*** (0.171)	0.974*** (0.162)	0.243* (0.146)
$r_{ij} \times I(r_{ij} \geq 0)$	-0.135 (0.207)	1.557*** (0.257)	0.068 (0.235)	0.124 (0.208)	0.372 (0.228)
Estimator	Logit	Logit	Poisson	Poisson	Poisson
Contest FE	Yes	Yes	Yes	Yes	Yes
Tier FE	Yes	Yes	Yes	Yes	Yes
Bandwidth	3.042	1.526	1.555	1.405	2.245
Observations	11,655	6,563	6,665	6,156	8,955

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses. The bandwidths are the same as the MSE-optimal bandwidths used in the main analyses.

Table A8. Parameterized Local Quadratic Regression

	(1) <i>Participation</i>	(2) <i>PostProb</i>	(3) <i>log(Volume)</i>	(4) <i>log(Length)</i>	(5) <i>log(Votes)</i>
$I(r_{ij} \geq 0)$	-0.049*** (0.019)	0.070** (0.033)	0.145** (0.073)	0.383* (0.207)	0.194*** (0.065)
r_{ij}	-0.011 (0.019)	0.341*** (0.074)	0.697*** (0.145)	2.478*** (0.474)	0.313*** (0.079)
r_{ij}^2	-0.000 (0.007)	0.183*** (0.051)	0.379*** (0.097)	1.413*** (0.353)	0.112*** (0.037)
$r_{ij} \times I(r_{ij} \geq 0)$	0.045 (0.051)	0.127 (0.130)	0.236 (0.288)	1.136 (0.867)	0.333 (0.216)
$r_{ij}^2 \times I(r_{ij} \geq 0)$	-0.040 (0.028)	-0.330*** (0.106)	-0.502** (0.233)	-2.400*** (0.748)	-0.295** (0.149)
Contest FE	Yes	Yes	Yes	Yes	Yes
Tier FE	Yes	Yes	Yes	Yes	Yes
Bandwidth	3.042	1.526	1.555	1.405	2.245
Observations	11,655	6,563	6,665	6,156	8,955

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses. The bandwidths are the same as the MSE-optimal bandwidths used in the main analyses.

Table A9. Non-parameterized Local Quadratic Regression

	(1) <i>Participation</i>	(2) <i>PostProb</i>	(3) <i>log(Volume)</i>	(4) <i>log(Length)</i>	(5) <i>log(Votes)</i>
$I(r_{ij} \geq 0)$	-0.046** (0.019)	0.113*** (0.029)	0.209*** (0.065)	0.631*** (0.181)	0.265*** (0.063)
Contest FE	Yes	Yes	Yes	Yes	Yes
Tier FE	Yes	Yes	Yes	Yes	Yes
MSE-Optimal Bandwidth	3.460	2.694	2.444	2.454	2.933
Observations	13,079	10,471	9,634	9,661	11,277

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses. The local quadratic regressions are estimated using triangular kernel weights based on the “rdrobust” method of Calonico et al. (2015).

Table A10. Effects of Winning Gold on Contest Participation (Global Polynomial)

	<i>Dependent variable: Participation</i>			
	2 nd polynomial (1)	3 rd polynomial (2)	4 th polynomial (3)	5 th polynomial (4)
$I(r_{ij} \geq 0)$	-0.037*** (0.013)	-0.040** (0.016)	-0.046** (0.019)	-0.051** (0.021)
r_{ij}	-0.008** (0.004)	-0.016** (0.008)	-0.014 (0.014)	-0.014 (0.021)
r_{ij}^2	0.001 (0.000)	-0.002 (0.002)	-0.001 (0.005)	-0.000 (0.012)
r_{ij}^3		-0.000 (0.000)	0.000 (0.001)	0.000 (0.003)
r_{ij}^4			0.000 (0.000)	0.000 (0.000)
r_{ij}^5				0.000 (0.000)
$I(r_{ij} \geq 0) \times r_{ij}$	-0.007 (0.022)	0.040 (0.037)	0.066 (0.062)	0.100 (0.090)
$I(r_{ij} \geq 0) \times r_{ij}^2$	-0.001 (0.004)	-0.026 (0.019)	-0.060 (0.055)	-0.114 (0.109)
$I(r_{ij} \geq 0) \times r_{ij}^3$		0.003* (0.002)	0.013 (0.014)	0.040 (0.046)
$I(r_{ij} \geq 0) \times r_{ij}^4$			-0.001 (0.001)	-0.006 (0.008)
$I(r_{ij} \geq 0) \times r_{ij}^5$				0.000 (0.000)
Contest FE	Yes	Yes	Yes	Yes
Tier FE	Yes	Yes	Yes	Yes
Observations	16,906	16,906	16,906	16,906

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses.

Table A11. Effects of Winning Gold on Posting Probability (Global Polynomial)

	<i>Dependent variable: PostProb</i>			
	2 nd polynomial (1)	3 rd polynomial (2)	4 th polynomial (3)	5 th polynomial (4)
$I(r_{ij} \geq 0)$	0.225*** (0.019)	0.164*** (0.022)	0.125*** (0.026)	0.095*** (0.030)
r_{ij}	0.046*** (0.005)	0.082*** (0.010)	0.097*** (0.017)	0.119*** (0.026)
r_{ij}^2	0.003*** (0.001)	0.013*** (0.003)	0.020*** (0.006)	0.034** (0.014)
r_{ij}^3		0.001*** (0.000)	0.002* (0.001)	0.005 (0.003)
r_{ij}^4			0.000 (0.000)	0.000 (0.000)
r_{ij}^5				0.000 (0.000)
$I(r_{ij} \geq 0) \times r_{ij}$	0.149*** (0.033)	0.264*** (0.051)	0.431*** (0.084)	0.575*** (0.124)
$I(r_{ij} \geq 0) \times r_{ij}^2$	-0.040*** (0.007)	-0.143*** (0.027)	-0.357*** (0.078)	-0.633*** (0.155)
$I(r_{ij} \geq 0) \times r_{ij}^3$		0.011***	0.071***	0.199***

		(0.003)	(0.021)	(0.066)
$I(r_{ij} \geq 0) \times r_{ij}^4$			-0.005***	-0.030***
			(0.002)	(0.011)
$I(r_{ij} \geq 0) \times r_{ij}^5$				0.002**
				(0.001)
Contest FE	Yes	Yes	Yes	Yes
Tier FE	Yes	Yes	Yes	Yes
Observations	16,906	16,906	16,906	16,906

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses.

Table A12. Effects of Winning Gold on Post Volume (Global Polynomial)

	<i>Dependent variable: $\log(\text{Volume})$</i>			
	2 nd polynomial (1)	3 rd polynomial (2)	4 th polynomial (3)	5 th polynomial (4)
$I(r_{ij} \geq 0)$	0.468*** (0.042)	0.339*** (0.050)	0.234*** (0.058)	0.211*** (0.067)
r_{ij}	0.085*** (0.009)	0.143*** (0.020)	0.181*** (0.033)	0.190*** (0.051)
r_{ij}^2	0.006*** (0.001)	0.023*** (0.005)	0.039*** (0.013)	0.045 (0.027)
r_{ij}^3		0.001*** (0.000)	0.003** (0.002)	0.005 (0.006)
r_{ij}^4			0.000 (0.000)	0.000 (0.001)
r_{ij}^5				0.000 (0.000)
$I(r_{ij} \geq 0) \times r_{ij}$	0.328*** (0.074)	0.632*** (0.118)	1.100*** (0.191)	1.242*** (0.288)
$I(r_{ij} \geq 0) \times r_{ij}^2$	-0.081*** (0.015)	-0.326*** (0.058)	-0.917*** (0.171)	-1.159*** (0.356)
$I(r_{ij} \geq 0) \times r_{ij}^3$		0.027*** (0.007)	0.195*** (0.045)	0.313** (0.149)
$I(r_{ij} \geq 0) \times r_{ij}^4$			-0.014*** (0.003)	-0.037 (0.025)
$I(r_{ij} \geq 0) \times r_{ij}^5$				0.001 (0.001)
Contest FE	Yes	Yes	Yes	Yes
Tier FE	Yes	Yes	Yes	Yes
Observations	16,906	16,906	16,906	16,906

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses.

Table A13. Effects of Winning Gold on Post Length (Global Polynomial)

	<i>Dependent variable: $\log(\text{Length})$</i>			
	2 nd polynomial (1)	3 rd polynomial (2)	4 th polynomial (3)	5 th polynomial (4)
$I(r_{ij} \geq 0)$	1.498*** (0.115)	1.043*** (0.136)	0.684*** (0.159)	0.598*** (0.184)
r_{ij}	0.311*** (0.024)	0.560*** (0.055)	0.720*** (0.093)	0.776*** (0.142)
r_{ij}^2	0.023*** (0.003)	0.092*** (0.014)	0.161*** (0.034)	0.198*** (0.075)

r_{ij}^3		0.004*** (0.001)	0.014*** (0.004)	0.023 (0.016)
r_{ij}^4			0.000** (0.000)	0.001 (0.001)
r_{ij}^5				0.000 (0.000)
$I(r_{ij} \geq 0) \times r_{ij}$	1.387*** (0.203)	2.285*** (0.330)	3.780*** (0.523)	4.214*** (0.787)
$I(r_{ij} \geq 0) \times r_{ij}^2$	-0.320*** (0.044)	-1.106*** (0.171)	-3.045*** (0.471)	-3.860*** (0.984)
$I(r_{ij} \geq 0) \times r_{ij}^3$		0.082** (0.020)	0.629*** (0.126)	1.011** (0.419)
$I(r_{ij} \geq 0) \times r_{ij}^4$			-0.046*** (0.010)	-0.120* (0.070)
$I(r_{ij} \geq 0) \times r_{ij}^5$				0.005 (0.004)
Contest FE	Yes	Yes	Yes	Yes
Tier FE	Yes	Yes	Yes	Yes
Observations	16,906	16,906	16,906	16,906

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses.

Table A14. Effects of Winning Gold on Upvotes (Global Polynomial)

	<i>Dependent variable: log (Votes)</i>			
	2 nd polynomial (1)	3 rd polynomial (2)	4 th polynomial (3)	5 th polynomial (4)
$I(r_{ij} \geq 0)$	0.364*** (0.045)	0.296*** (0.053)	0.226*** (0.061)	0.261*** (0.070)
r_{ij}	0.065*** (0.009)	0.103*** (0.020)	0.137*** (0.033)	0.134*** (0.051)
r_{ij}^2	0.005*** (0.001)	0.016*** (0.005)	0.031** (0.013)	0.028 (0.028)
r_{ij}^3		0.001** (0.000)	0.003 (0.002)	0.002 (0.006)
r_{ij}^4			0.000 (0.000)	0.000 (0.001)
r_{ij}^5				-0.000 (0.000)
$I(r_{ij} \geq 0) \times r_{ij}$	0.250*** (0.081)	0.376*** (0.130)	0.660*** (0.215)	0.404 (0.324)
$I(r_{ij} \geq 0) \times r_{ij}^2$	-0.060*** (0.017)	-0.173*** (0.066)	-0.547*** (0.206)	-0.135 (0.423)
$I(r_{ij} \geq 0) \times r_{ij}^3$		0.012 (0.008)	0.117** (0.056)	-0.089 (0.185)
$I(r_{ij} \geq 0) \times r_{ij}^4$			-0.009** (0.004)	0.030 (0.032)
$I(r_{ij} \geq 0) \times r_{ij}^5$				-0.002 (0.002)
Contest FE	Yes	Yes	Yes	Yes
Tier FE	Yes	Yes	Yes	Yes
Observations	16,906	16,906	16,906	16,906

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses.

C. Alternative Measures

Table A15. Effects of Gold Medals Using Alternative Measures

	Panel A: Contest Participation		
	Contest Participation	Log Number of Contests	Log Number of Solutions
	(1)	(2)	(3)
$I(r_{ij} \geq 0)$	-0.041*** (0.014)	-0.031*** (0.011)	-0.093** (0.045)
MSE-Optimal Bandwidth	2.794	2.650	2.780
Observations	10,805	10,330	10,753
	Panel B: Code Sharing		
	Log Number of Scripts	Log Number of Versions	Log Number of Lines
	(1)	(2)	(3)
$I(r_{ij} \geq 0)$	0.028** (0.013)	0.020 (0.030)	0.122 (0.086)
MSE-Optimal Bandwidth	2.312	1.882	1.814
Observations	9,185	7,734	7,510
Contest FE	Yes	Yes	Yes
Tier FE	Yes	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses. The local linear regressions are estimated using triangular kernel weights based on the “rdrobust” method of Calonico et al. (2015).

D. Alternative Samples

Table A16. Effect of Gold Medal on Contest Participation and Post Contributions, Excluding Contests without Monetary Awards

	Participation	PostProb	$\log(\text{Volume})$	$\log(\text{Length})$	$\log(\text{Votes})$
	(1)	(2)	(3)	(4)	(5)
$I(r_{ij} \geq 0)$	-0.039** (0.016)	0.149*** (0.025)	0.302*** (0.054)	0.908*** (0.155)	0.327*** (0.051)
Contest FE	Yes	Yes	Yes	Yes	Yes
Tier FE	Yes	Yes	Yes	Yes	Yes
MSE-Optimal Bandwidth	2.171	1.576	1.578	1.479	2.136
Observations	8,513	6,575	6,579	6,258	8,390

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses. The local linear regressions are estimated using triangular kernel weights based on the “rdrobust” method of Calonico et al. (2015).

Table A17. Effect of Gold Medal on Contest Participation and Post Contributions, Featured Contests Only

	Participation	PostProb	$\log(\text{Volume})$	$\log(\text{Length})$	$\log(\text{Votes})$
	(1)	(2)	(3)	(4)	(5)
$I(r_{ij} \geq 0)$	-0.039** (0.018)	0.177*** (0.025)	0.364*** (0.053)	1.127*** (0.152)	0.323*** (0.055)
Contest FE	Yes	Yes	Yes	Yes	Yes
Tier FE	Yes	Yes	Yes	Yes	Yes
MSE-Optimal Bandwidth	3.264	2.581	2.677	2.427	2.918
Observations	9,217	7,478	7,711	7,091	8,311

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses. The local linear regressions are estimated using triangular kernel weights based on the “rdrobust” method of Calonico et al. (2015).

Table A18. The Effect of Gold Medal on Contest Participation and Post Contributions, Excluding Winners Who Also Received Monetary Awards

	<i>Participation</i> (1)	<i>PostProb</i> (2)	<i>log(Volume)</i> (3)	<i>log (Length)</i> (4)	<i>log (Votes)</i> (5)
$I(r_{ij} \geq 0)$	-0.042** (0.017)	0.170*** (0.027)	0.369*** (0.059)	1.094*** (0.171)	0.349*** (0.058)
Contest FE	Yes	Yes	Yes	Yes	Yes
Tier FE	Yes	Yes	Yes	Yes	Yes
MSE-Optimal Bandwidth	3.096	1.535	1.556	1.425	1.840
Observations	11,165	5,964	6,035	5,621	6,947

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses. The local linear regressions are estimated using triangular kernel weights based on the “rdrobust” method of Calonico et al. (2015).

E. Alternative Identification Strategies

E.1. Local Randomization RDD

Table A19. Local Randomization RDD with Five Teams Just Above and Below the Cutoff

Dependent Variables	Mean of Controls	Mean of Treated	Diff-in-Means Statistic	Fisherian p -value
<i>Participation</i>	0.192	0.146	-0.045	0.019
<i>PostProb</i>	0.448	0.617	0.169	0.000
<i>log(Volume)</i>	0.723	1.068	0.345	0.000
<i>log (Length)</i>	2.378	3.626	1.248	0.000
<i>log (Votes)</i>	0.492	0.798	0.306	0.000

E.2. Difference-in-Differences (DID)

To enhance the robustness of our findings, we conduct a complementary DID analysis. This approach allows us to (1) estimate average treatment effects (ATE) across a broader population, and (2) examine the temporal evolution of treatment effects (Forderer and Burtch 2025). On Kaggle, medal outcomes are revealed only after the contest concludes, and participants cannot predict their final rankings during the contest due to the lack of information about the competitive landscape. Following Foerderer et al. (2021), we argue that gold and silver medalists constitute comparable groups in terms of ability and performance, making silver medalists a suitable counterfactual group for estimating gold medal effects. As illustrated in Figure A4, our DID design designates first-time gold medalists as the treatment group and silver medalists who have never previously won a gold medal as the control group. By focusing exclusively on participants with no prior gold medals, we mitigate the risk of confounding effects stemming from accumulated experience or prior success.

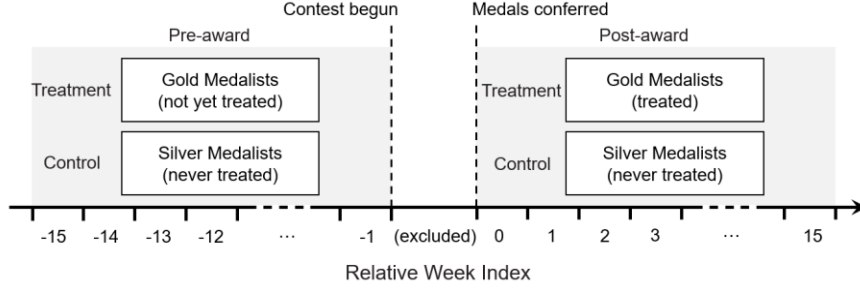


Figure A4. Difference-in-Differences Research Design

We construct a contestant-week panel covering contests from July 2016 to December 2025. Our observation window spans 15 weeks before through 16 weeks after each contest, excluding the active competition period to avoid confounding behavioral effects during the contest itself. The panel is aligned with week 0 corresponding to the award announcement week for each contest. Our dependent variables are: (1) *Contest Participation*: the weekly number of contest submissions (log-transformed); (2) *Prosocial Behavior*: weekly metrics including a binary indicator for posting, post volume, post length, and post upvotes (the latter three log-transformed).

To estimate the treatment effect of winning a gold medal, we use the following two-way fixed effects DID model:

$$Y_{ijt} = \beta_0 + \beta_1 After_{jt} \times Winner_{ij} + \alpha_i + \rho_t + \gamma_j + \varepsilon_{ijt}$$

where Y_{ijt} is any dependent variable for contestant i in week t within contest j , $After_{jt}$ is a post-treatment indicator equal to 1 if week t falls after the conclusion of contest j and 0 otherwise, and $Winner_{ij}$ identifies whether contestant i won a gold medal in contest j . The model includes contestant fixed effects (α_i), week fixed effects (ρ_t), and contest fixed effects (γ_j). The coefficient of interest, β_1 , captures the relative change in outcomes for gold medalists compared to their silver medalist counterparts.

Table A20 presents the estimation results. Gold medal winners significantly reduce their contest participation following the award. Conversely, they exhibit increased prosocial behavior, evidenced by more frequent posting, longer contributions, and a higher number of upvotes. These findings align with our RDD results, further supporting the robustness of the main effects.

Table A20. Difference-in-Differences Estimates of Gold Medals Effects

	(1) <i>Participation</i>	(2) <i>PostProb</i>	(3) <i>log(Volume)</i>	(4) <i>log(Length)</i>	(5) <i>log(Votes)</i>
$After_t \times Winner_i$	-0.091*** (0.005)	0.055*** (0.003)	0.098*** (0.005)	0.333*** (0.015)	0.069*** (0.004)
User fixed effects	Yes	Yes	Yes	Yes	Yes
Contest fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	325,717	325,717	325,717	325,717	325,717

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses.

To further explore the dynamics of the treatment effect, we estimate following relative time model:

$$Y_{ijt} = \beta_0 + \vec{\beta_1} \times \overrightarrow{Week_{jt}} \times Winner_{ij} + \alpha_i + \rho_t + \gamma_j + \varepsilon_{ijt}$$

where $\overrightarrow{Week_{jt}}$ is a vector of week-specific dummy variables centered around the award week of contest j (excluding the reference week immediately prior), and $\vec{\beta_1}$ captures week-by-week differences in outcomes between gold medalists and controls relative to baseline.

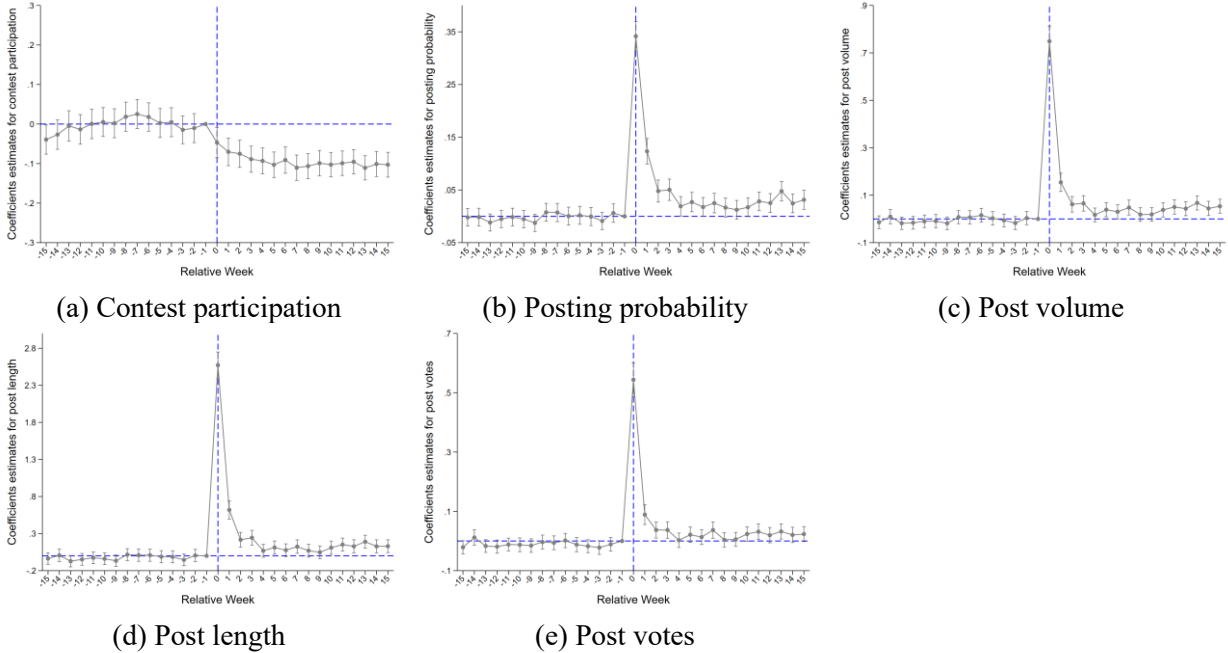
**Figure A5. The Effects of Winning Gold Medals Over Time**

Figure A5 presents the dynamic treatment effects, with three key findings. First, pre-treatment trends are flat and statistically indistinguishable between groups, supporting the parallel trends assumption. Second, contest participation shows persistent treatment effects: gold medalists experience an immediate reduction that remains stable throughout the post-treatment window. Third, prosocial engagement peaks immediately

following the award announcement and stabilizes at a higher level above the pre-treatment baseline, indicating a net increase in prosocial behavior rather than a mere temporal shift. Overall, the DID results corroborate our RDD estimates and provide additional insights into the timing and persistence of the treatment effects.

Appendix C: Underlying Mechanisms

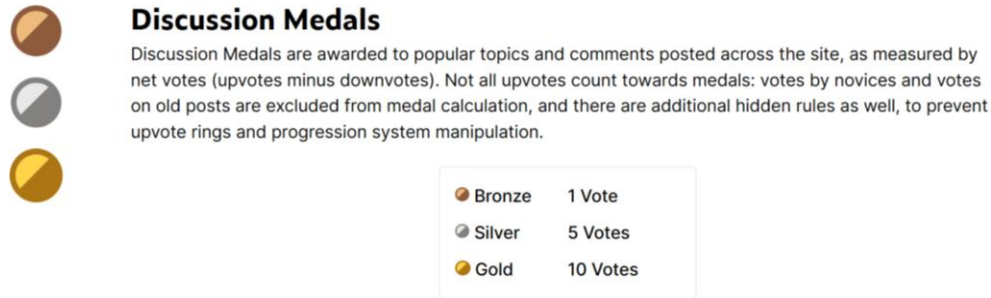


Figure A6. Rules for Awarding Discussion Medals (Snapshot)

Table A21. Interview Evidence

ID	Tenure	Achievements	Tier	Representative Quotes
1	8 years	3 Gold 10 Silver 1 Bronze	M	1. <i>My initial goal on Kaggle was to win a gold medal.</i> 2. <i>To me, that medal was validation of my work and abilities—an official acknowledgment.</i> 3. <i>What mattered even more was that it came from trusting my own judgment; winning gold with my own strategy was exciting.</i> 4. <i>Winning my first gold medal inspired me to set up a WeChat group, where I invited like-minded friends to exchange ideas and experiences. I've also become more active in Kaggle forums, feeling more confident and motivated to answer questions, especially on problems I've already solved in competitions.</i>
2	7 years	2 Gold 5 Silver 1 Bronze	M	1. <i>Seeing others win a gold medal always made me want one too. But it's really hard. It took me several years to earn my first one.</i> 2. <i>That gold medal, in the field of computer vision, was meaningful as proof of my technical skills.</i> 3. <i>I keep pets and care about stray cats, so the competition topic really matched my interests. Winning the medal in that context was deeply fulfilling.</i> 4. <i>After winning the gold medal, I shared my experience through posts and write-ups.</i> 5. <i>The Kaggle community is always full of fresh ideas. After winning, I started paying more attention to posts about unconventional methods, trying to understand them and share my own reproductions and validations. This helped spark discussion and further development.</i> 6. <i>Since winning my second gold medal, I've basically stopped participating in competitions myself.</i>
3	4 years	1 Gold 2 Silver 1 Bronze	M	1. <i>Winning this gold medal proved that my previous research was effective and confirmed the value of my work. It showed me that I am capable of doing this kind of work.</i> 2. <i>During the competition, I didn't get too obsessed; I stuck to my own ideas and decisions.</i> 3. <i>In some later competitions, I signed up but didn't submit much. I only tried the ones that interested me, taking a more casual approach than before.</i> 4. <i>My experience allows me to provide practical insights that help others improve their models' performance.</i> 5. <i>I also joined groups of other gold medalists to discuss various technical problems together.</i>
4	9 years	1 Gold 7 Silver	M	1. <i>I really wanted to win a gold medal, and when I finally did, I felt as happy as I had aced a major exam.</i> 2. <i>The whole process was really exhausting, especially because I was desperate to win the gold. The relief after finally getting it was huge.</i>

		1 Bronze		- At first, I was aiming for a gold medal, but after I got it, I wasn't as motivated. I didn't participate in many competitions afterward, as the effort often required hundreds of hours and the payoff didn't feel as meaningful. - After achieving the gold, I feel free to pursue what I was interested in on Kaggle without being so utilitarian as before. - Kaggle is an amazing community with many top experts sharing their work. Posting is my main way of staying connected with them. I've open-sourced many general-purpose tools and modules because, as a systems engineer, I enjoy creating things that others can reuse. Many public notebooks on Kaggle are messy and hard to follow, so I try to keep my work well-structured. This makes it easier for others to use, makes the process more enjoyable for me, and knowing that others might rely on it motivates me to take my work seriously. - In addition, I've created tutorials on topics like cross-validation and how to quickly check a model's performance. Although these are basic steps, even minor errors can cause major problems. I aim to help newcomers avoid these common pitfalls.
5	9 years	1 Gold 2 Silver	M	- For me, winning the gold medal was proof of my skills. - I joined purely out of personal interest, with no outside pressure or other considerations. Winning that medal was deeply satisfying. - After winning gold, I signed up for a few contests, but honestly, I wasn't very motivated. I only made one or two submissions, just to get a sense of how to approach the problems. I treated it more as a learning experience than a serious competition.
6	5 years	6 Gold 3 Silver	GM	- When you compete on your own, the psychological pressure and sense of loneliness can be pretty intense. - Winning my first gold medal gave me a thrilling moment of "Wow, I can actually do it!" However, as my skills improved and gold medals became more predictable, that excitement faded. - Before my first win, I joined almost every new competition. After that, I became more selective, entering only those that genuinely interested me. - Winning gold also gave me a sense of freedom. I used to chase medals and titles, but now I focus more on learning new things or exploring interesting problems. Sometimes I just review the community baseline and study the workflow, and that's enough. - Recently, I haven't joined many competitions. Instead, I've been more active in the forums, answering algorithm questions. I enjoy helping others avoid the mistakes I made. I also noticed how beginners often struggle with messy datasets and complex algorithms, which I can totally relate to. That's why I post and share resources more actively now.
7	4 years	9 Gold 13 Silver 7 Bronze	GM	- Before winning my first gold medal, I had already earned six silver medals. The more I failed, the stronger my craving for gold became. - When I finally won, it was a big confidence boost. I felt that, compared to my classmates, I wasn't behind and even had something unique. It also made me realize that everyone's path is different, but we can reach similar places in the end. - Competitions are exhausting; you have to stay focused on your performance every day. Once you win the gold, you're free. You no longer have to think about the competition constantly. - For solo participation, the key issue is the lack of someone to discuss ideas with. The whole process is just you working alone, with no one to consult or talk to. It feels very lonely, especially when you hit a bottleneck—you feel isolated and really struggling. During my solo participation, I worked alone and was entirely focused on the competition. After I finally won, I really wanted to talk to others about these topics. - When I first started, I made a lot of mistakes, so now I focus on sharing what I've learned from different competitions to help others avoid the same pitfalls. I believe that writing tutorials, answering forum questions, and publishing well-annotated notebooks are the best ways to lower technical barriers and help others get started. This engagement is also how I build connections and strengthen my ties to the community.
8	8 years	7 Gold 13 Silver 10 Bronze	GM	- Back when I started, I had earned a silver and a bronze medal, but I really wanted a gold. Over the next two years, I earned eight more silvers. Failing so many times without getting a gold was really frustrating. By the time I won my first gold medal, I had been on Kaggle for almost three years and had accumulated nine silvers and two bronzes. That first gold felt like true proof of all the effort and skill I had developed over such a long period. - I've been competing since around 2017, so it's been eight years now. Many of my former teammates have stopped competing, and

				<i>very few individuals stick with it consistently. Some quit immediately after their first gold. From my experience, only genuine interest sustains long-term participation. Those who treat gold medals as stepping stones for utilitarian purposes, like job hunting or studying abroad, tend to quit quickly once they achieve their goal. In my observation, about 70–80% of participants fall into this category.</i> 3. <i>After winning many gold medals, the medals themselves don't hold as much meaning for me anymore. What keeps me engaged is contributing to the community. I'm quite active on forums, and I also run a blog with over 4,000 followers that provides guidance for beginners. I know how confusing competitions can be at first, so I enjoy helping newcomers navigate them. What really motivates me are comments like, 'Thanks to your answer, I finally understood this.' That feeling is far more rewarding than any medal.</i> 4. <i>Competition golds are valued far above code and discussion golds. Discussion golds are often seen as the easiest to obtain, as they rely mostly on upvotes. Code golds require more skill and effort but still lack the intensity of competitions. Competition golds, by contrast, demand sustained effort, strong technical ability, and even some luck, which is why they carry the highest prestige within the community.</i>
9	4 years	1 Gold 2 Silver 4 Bronze	M	1. <i>Before winning this gold medal, I had already earned two silvers and a bronze, so I really wanted to get a gold.</i> 2. <i>Winning it gave me a real sense of affirmation about my abilities and a strong feeling of self-validation. It also helped me better demonstrate my competence during my job hunt.</i> 3. <i>When submitting my files, I relied on my own reverse-engineering approach, and the medal confirmed that my thinking was correct.</i> 4. <i>Competing solo can be tough. You can only validate experiments yourself, and if you get stuck on an idea, there's no one to discuss it with. Without someone to communicate with, it's easy to overlook key points, and doing all the work alone is exhausting.</i> 5. <i>After winning the gold, my enthusiasm for competitions remained high. For example, I originally planned to participate in future competitions with friends, but we eventually gave up as higher priorities like jobs, papers, and graduation took over.</i> 6. <i>I also shared some effective strategies with the community, such as not trusting the public leaderboard too much and doing thorough local validation, as well as methods for handling text-type data, so others could avoid common pitfalls.</i>

Notes: “M” denotes the Master tier, and “GM” denotes the Grandmaster tier in the Kaggle competitions. A total of nine gold medalists were interviewed, and each anonymized with a unique identifier (ID 1–9). All interviews were conducted via video call in August 2025 and were minimally edited for clarity and readability, without altering the substantive content of the responses. To conserve space, only representative quotes from each interviewee are presented.

Appendix D: Anecdotal Evidence of Gold Medals as Meaningful Milestones

Anecdotal evidence from Kaggle forums indicates that gold medals are perceived as significant achievements rather than mere consolations. Users consistently frame gold medals as major milestones and symbols of accomplishment. For example, one user stated, *“Winning my first gold medal on Kaggle marks a significant milestone in my journey as a data scientist,”* while another shared, *“I am thrilled to share a significant milestone in my data science journey: I recently received my very first Kaggle Gold Medal!”* Others highlight their symbolic value, describing them as a testament to *“technical prowess...resilience and willingness to embrace challenges”* or *“a culmination of hard work, dedication, and passion.”* Additionally, on LinkedIn, Kaggle gold medals are often listed in the “Honors & Awards” sections of user profiles, indicating their career value as competence markers. This perception of high professional regard is echoed in professional forums; as one Reddit user noted, *“Winning a Kaggle competition is quite a feather in your cap... you will have to fend off recruiters with bear spray.”*

Appendix E: Effects of Surprise Gold Medals

In June 2016, Kaggle launched its medal system and retrospectively awarded medals to participants of prior competitions. These medals came as a surprise to recipients, as they had no expectation of receiving awards when they participated in the contests. A total of 156 contests held between April 2010 and June 2016 were included in this retrospective awarding, involving 46,710 unique contestants who formed 88,567 teams. Among these participants, 1,518 received gold medals and 4,505 received silver medals, with some earning multiple medals across different contests. To isolate the effect of medal type, our analysis focuses on 767 pure gold medalists, who received only gold medals, and 3,631 pure silver medalists, who received only silver medals.

We construct a user-week panel dataset for these medalists, covering 12 weeks before and after the award system launch. Following Foerderer et al. (2021), we implement a quasi-experimental design that treats pure gold medalists as the treatment group and pure silver medalists as the control group. The dependent variables are: (1) *Contest Participation*: the weekly number of contest submissions (log-transformed); (2) *Prosocial Behavior*: weekly metrics including a binary indicator for posting, post volume, post length, and post upvotes (the latter three log-transformed). We estimate the effects of receiving surprise gold medals using the following two-way fixed effects DID model:

$$Y_{it} = \beta_0 + \beta_1 \text{After}_t \times \text{Winner}_i + \alpha_i + \rho_t + \varepsilon_{it}$$

where Y_{it} is any dependent variable for contestant i in week t , After_{jt} is a post-treatment indicator equal to 1 if week t falls after the launch of the award system and 0 otherwise, and Winner_i indicates whether user i received any surprise gold medal. The model includes contestant fixed effects (α_i) and week fixed effects (ρ_t). Because some users received multiple medals across different contests, we do not include contest fixed effects. The coefficient of interest, β_1 , captures the relative change in outcomes for gold medalists compared to their silver medalist counterparts following the introduction of the award system.

The model-free evidence in Figures A7 and A8 tracks the weekly number of contest submissions and

posts for both gold and silver medalists before and after the award system’s launch. The figures demonstrate that both treatment and control groups followed parallel trends prior to the award conferral, satisfying the parallel trends assumption of the DID model. Following the intervention, we observe no significant divergence between groups in either contest participation or prosocial behavior.

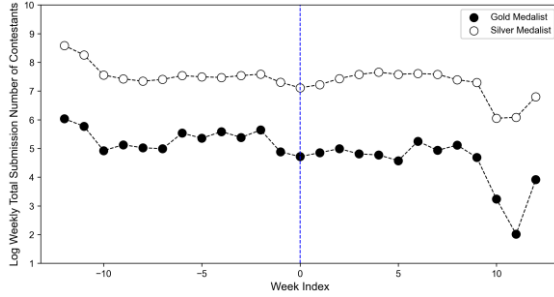


Figure A7. Number of Contest Submissions

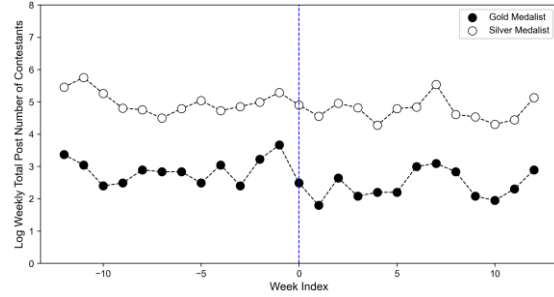


Figure A8. Number of Post Sharing

The DID estimates reported in Table A22 corroborate these visual patterns. All the estimates are statistically indistinguishable from zero, with point estimates and standard errors both approaching zero. This high precision of these estimates provides strong support for the absence of treatment effects (Abdulkadiroğlu et al. 2014). This null result for surprise awards presents a sharp contrast to the robust effects we observe for anticipated gold medals, suggesting that the timing and predictability of awards could elicit fundamentally distinct post-award behavioral responses.

Table A22. DID Effects of Surprise Gold Medals

	(1) <i>Participation</i>	(2) <i>PostProb</i>	(3) <i>log(Volume)</i>	(4) <i>log(Length)</i>	(5) <i>log(Votes)</i>
$After_t \times Winner_i$	0.012 (0.009)	0.000 (0.002)	0.000 (0.003)	-0.001 (0.011)	-0.001 (0.002)
User fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	109,950	109,950	109,950	109,950	109,950

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses.

The null effects in Table A22 warrant cautious interpretation, as contextual factors specific to Kaggle’s rollout may have obscured potential effects. Specifically, surprise medals could be awarded long after the respective contests had ended, when many recipients were likely no longer active. Moreover, the unexpected nature of these medals means some users may have been unaware of the recognition (Gallus 2017). Therefore, these results should be taken as suggestive rather than conclusive evidence that surprise awards have no impact.

Reference

- Abdulkadiroğlu A, Angrist J, Pathak P (2014) The elite illusion: Achievement effects at Boston and New York exam schools. *Econometrica* 82(1):137–196.
- Calonico S, Cattaneo MD, Titiunik R (2015) rdrobust: An R package for robust nonparametric inference in regression-discontinuity designs. *R Journal* 7(1):38.
- Cattaneo MD, Idrobo N, Titiunik R (2019) *A practical introduction to regression discontinuity designs: Foundations* (Cambridge University Press).
- Flammer C (2015). Does corporate social responsibility lead to superior financial performance? A regression discontinuity approach. *Management Science* 61(11):2549–2568.
- Foerderer J, Lueker N, Heinzl A (2021) And the winner is ...? The desirable and undesirable effects of platform awards. *Information Systems Research* 32(4):1155–1172.
- Foerderer J, Burtch G (2025) Estimating career benefits from online community leadership: Evidence from Stack Exchange moderators. *Management Science* 71(3):2443–2466.
- Gallus J (2017) Fostering public good contributions with symbolic awards: A large-scale natural field experiment at Wikipedia. *Management Science* 63(12):3999–4015.
- Ludwig J, Miller DL (2007). Does Head Start improve children’s life chances? Evidence from a regression discontinuity design. *The Quarterly Journal of Economics* 122(1):159–208.