Supplementary Material for The Role of Linguistic Agency in Mobilizing Election Candidate Support

Additional Figures

Tweet counts breakout

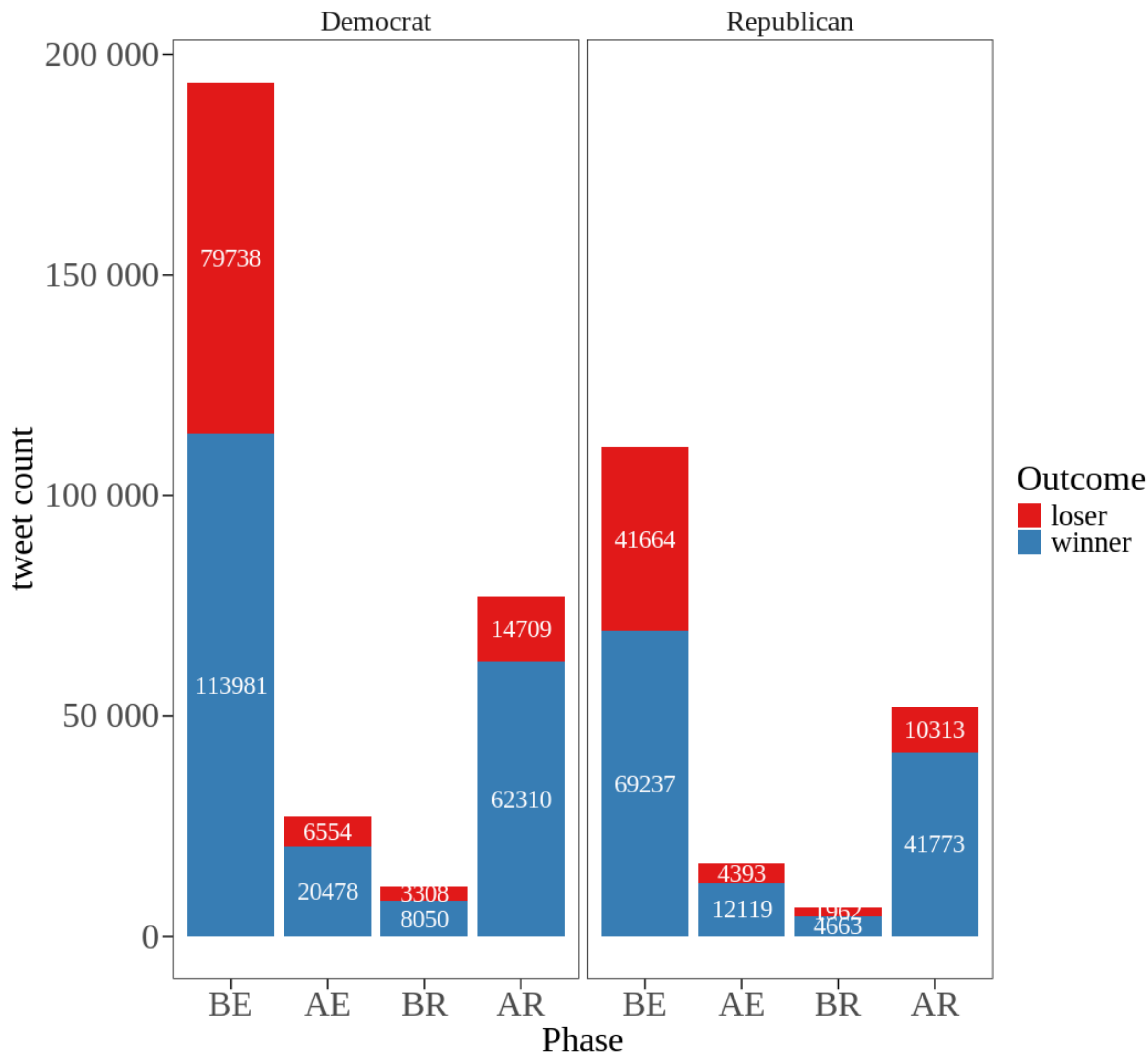

Figure S1. Tweet counts breakout. Number of tweets by party, outcome and election cycle phase (BE = Before Election, AE = After Election, BR = Before Riot, and AR = After Riot).

Daily tweet count time course

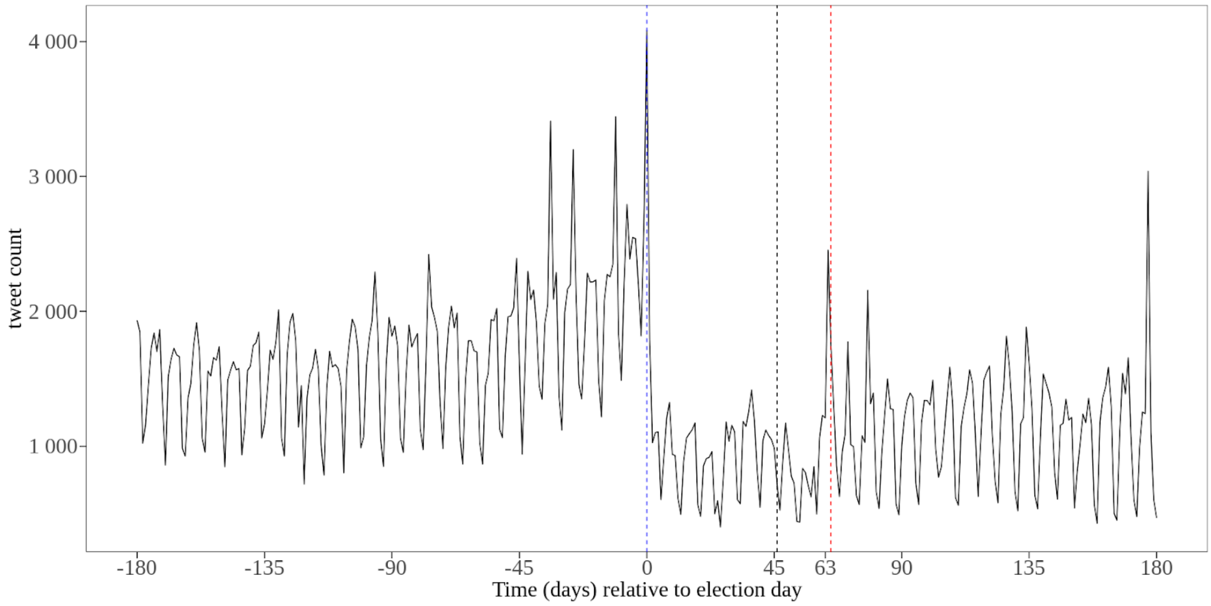

Figure S2. Daily tweet count time course (with evident 7-day regular pattern).

Additional model summaries

Model 3

As presented in the main manuscript, Model 3 tested the relationship between linguistic agency slope over time split between election cycle phases. Below in Tables S1 and S2 we provide additional data for slope estimates and slope differences respectively.

Phase	Slope	95% CI	p
BE	0.04	0.04, 0.05	< .001
AE	-0.31	-0.36, -0.26	< .001
BR	1.65	1.47, 1.84	< .001
AR	-0.06	-0.07, -0.04	< .001

Table S1: Model3: Average linear trend for linguistic agency slope over time by election cycle phase. BE = Before Election, AE = After Election, BR = Before Riot, and AR = After Riot.

Phase	Contrast	95% CI	p
BE-AE	0.36	0.31, 0.41	< .001
BE-BR	-1.61	-1.80, -1.42	< .001
BE-AR	0.10	0.09, 0.11	< .001
AE-BR	-1.97	-2.16, -1.77	< .001
AE-AR	-0.26	-0.31, -0.21	< .001
BR-AR	1.71	1.52, 1.90	< .001

Table S2: Model3: Differences between election cycle phases with respect to the average linear trend for linguistic agency slope over time. BE = Before Election, AE = After Election, BR = Before Riot, and AR = After Riot.

Model 4

As presented in the main manuscript, Model 4 tested the relationship between linguistic agency slope over time split between election cycle phases separately for election losers and winners. Below in Tables S3 and S4 we provide additional data for slope estimates and slope differences respectively. Additionally, for clarity in Table S5 we provide a selection of contrasts from Table 4, that can be

Outcome	Phase	Slope	95% CI	p
Slopes are presented as counts.				
loser	BE	0.48	-12.31, 13.27	0.942
loser	AE	207.68	176.73, 238.62	< .001
loser	BR	107.68	91.38, 123.98	< .001
loser	AR	49.63	35.00, 64.27	< .001
winner	BE	-74.14	-101.88, -46.41	< .001
winner	AE	160.29	79.72, 240.86	< .001
winner	BR	733.86	642.82, 824.90	< .001
winner	AR	-1172.36	-1311.92, -1032.79	< .001

Table S3: Model4: Average linear trend for linguistic agency slope over time by election cycle phase and election outcome. BE = Before Election, AE = After Election, BR = Before Riot, and AR = After Riot.

Outcome	Phase	Contrast	95% CI	p
Contrasts are presented as counts.				
loser-loser	BE-AE	-207.20	-240.63, -173.77	< .001
loser-loser	BE-BR	-107.20	-127.87, -86.53	< .001
loser-loser	BE-AR	-49.15	-68.57, -29.74	< .001
loser-winner	BE-BE	74.62	44.10, 105.14	< .001
loser-winner	BE-AE	-159.81	-241.41, -78.22	< .001
loser-winner	BE-BR	-733.38	-825.37, -641.39	< .001
loser-winner	BE-AR	1172.83	1032.76, 1312.91	< .001
loser-loser	AE-BR	100.00	82.52, 117.48	< .001

loser-loser	AE-AR	158.04	130.68, 185.41	< .001
loser-winner	AE-BE	281.82	247.11, 316.52	< .001
loser-winner	AE-AE	47.39	-45.23, 140.00	0.316
loser-winner	AE-BR	-526.18	-646.25, -406.12	< .001
loser-winner	AE-AR	1380.03	1269.70, 1490.37	< .001
loser-loser	BR-AR	58.05	41.91, 74.18	< .001
loser-winner	BR-BE	181.82	154.18, 209.46	< .001
loser-winner	BR-AE	-52.61	-138.30, 33.07	0.237
loser-winner	BR-BR	-626.18	-732.17, -520.19	< .001
loser-winner	BR-AR	1280.04	1155.70, 1404.37	< .001
loser-winner	AR-BE	123.77	94.47, 153.07	< .001
loser-winner	AR-AE	-110.66	-194.18, -27.14	0.010
loser-winner	AR-BR	-684.23	-782.91, -585.55	< .001
loser-winner	AR-AR	1221.99	1088.87, 1355.11	< .001
winner-winner	BE-AE	-234.43	-321.57, -147.29	< .001
winner-winner	BE-BR	-808.00	-910.88, -705.13	< .001
winner-winner	BE-AR	1098.22	964.74, 1231.69	< .001
winner-winner	AE-BR	-573.57	-680.73, -466.41	< .001
winner-winner	AE-AR	1332.65	1155.91, 1509.38	< .001
winner-winner	BR-AR	1906.22	1678.39, 2134.04	< .001

Table S4: Model4: Differences between election cycle phases and election outcome with respect to the average linear trend for linguistic agency slope over time. BE = Before Election, AE = After Election, BR = Before Riot, and AR = After Riot.

Time	Outcome	Phase	Contrast	conf.low	conf.high	p.value
slope	loser-winner	AE	-0.147	-0.262	-0.0321	0.0127
slope	loser-winner	AR	0.0652	0.0321	0.0982	0.000134

slope	loser-winner	BE	0.0204	0.00628	0.0345	0.00518
slope	loser-winner	BR	-0.605	-1.04	-0.172	0.00662
slope	loser	AE-AR	-0.432	-0.535	-0.33	2.45e-16
slope	loser	AE-BR	-1.64	-2.03	-1.26	1.47e-16
slope	loser	BE-AE	0.491	0.392	0.59	7.06e-22
slope	loser	BE-AR	0.0582	0.0284	0.0881	0.000153
slope	loser	BE-BR	-1.15	-1.52	-0.779	1.82e-09
slope	loser	BR-AR	1.21	0.836	1.58	3.23e-10
slope	winner	AE-AR	-0.22	-0.281	-0.16	1.55e-12
slope	winner	AE-BR	-2.1	-2.33	-1.87	5.37e-72
slope	winner	BE-AE	0.323	0.264	0.382	2.74e-26
slope	winner	BE-AR	0.103	0.0869	0.119	2.74e-35
slope	winner	BE-BR	-1.78	-2.0	-1.56	9.36e-56
slope	winner	BR-AR	1.88	1.66	2.1	7.56e-62

Table S5: Model4: Selected differences between election cycle phases and election outcome with respect to the average linear trend for linguistic agency slope over time. BE = Before Election, AE = After Election, BR = Before Riot, and AR = After Riot.

Models Comparison Controlling for Concreteness

Bhatia and Walasek (2016; Study 2) investigated the temporal dynamics of concreteness in the language used in *New York Times* articles discussing US elections. They used a piecewise model with two periods (before and after elections). Although their analysis did not focus on the language of candidates directly, and therefore they did not consider the differences between the language used by winners and losers, they demonstrated that the concreteness of words in New York Times articles discussing US elections increased with temporal proximity to Election Day. Below we provide comparison of estimates from all models reported in the main manuscript together with additional model (Model 4_{concr}) in which we included Concreteness as an additional control variable (formula: Agency ~ (Time | Name) + Concreteness + Time * Phase * Outcome). As we can see from Figure S3, inclusion of Concreteness did not alter estimates of the remaining variables in any meaningful way.

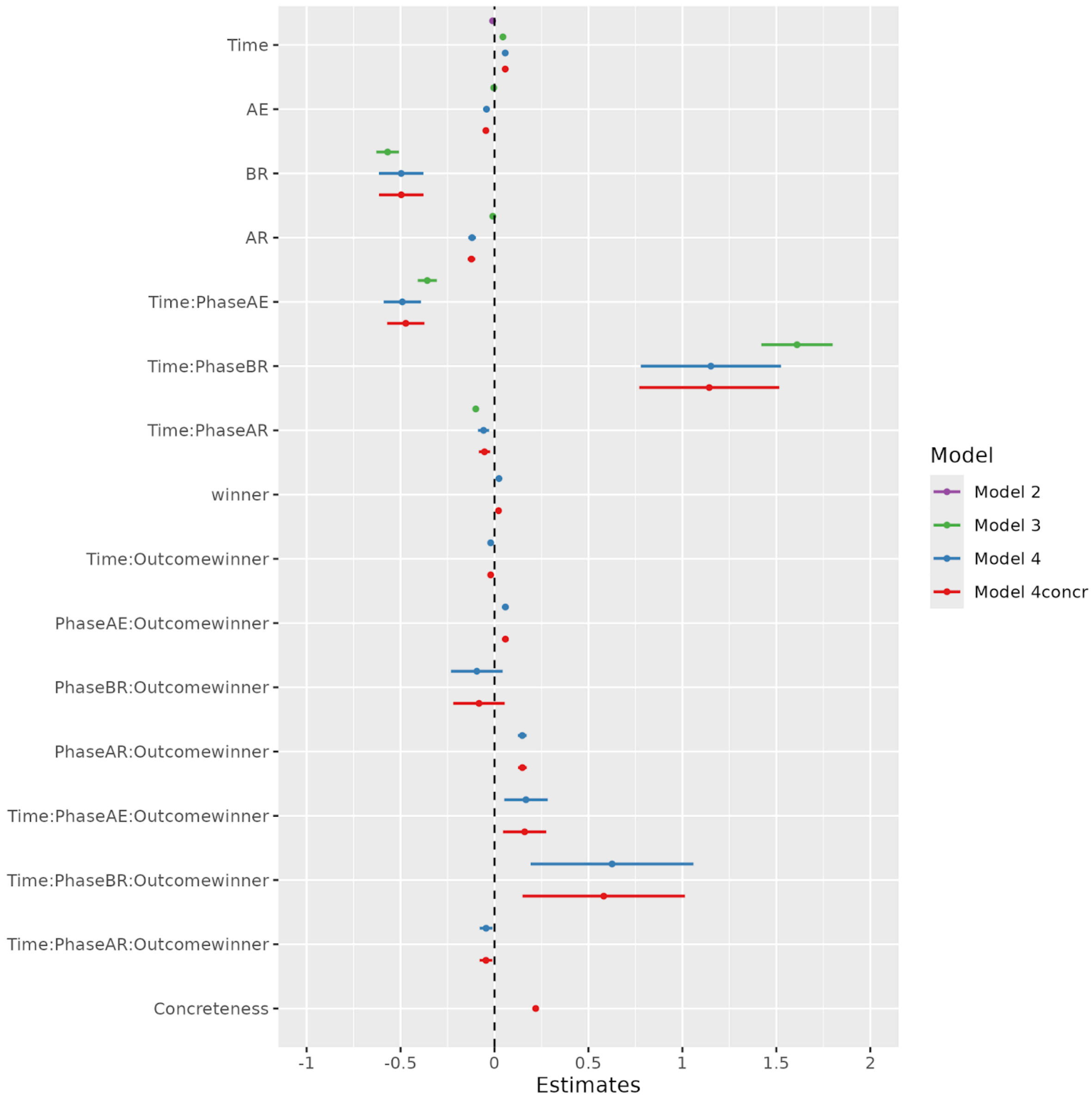

Figure S3: Comparison of model estimates for Models 1-4 with additional Model 4_{concr} that included Concreteness as a control predictor (formula: Agency ~ (Time | Name) + Concreteness + Time * Phase * Outcome).