Supplementary Information for: Cognitive distortions are associated with increasing political polarization

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Introduction

Table S1. Cognitive distortion types, definitions, and sample tweets from our data. CDS n-grams in the sample tweets are denoted with bold font. We also include the frequency of each n-gram type as a number of tweets and as a percentage of all tweets in our dataset for the given year. Note that some tweets may be associated with more than one type of cognitive distortion.

Type	2016 n (%)	2020 n (%)	Definition	Sample Tweet
Catastrophizing	7954 (0.06)	12443 (0.1)	Exaggerating the importance of negative events	"all supporting communists. makes total sense. they hate us but they **will fail**. hundreds of george w. bush administration officials to back biden #tcot #maga #kag"
Dichotomous reasoning	1486776 (11.11)	2066595 (17.44)	Thinking that an inherently continuous situation can fall into only two categories	"the trump economy was **the best** in our history and democrats knew without a doubt they'd have no chance in november. democrats are more than happy to destroy the economy and put you out of work for their political goals after all they get paid **no matter** what the economy does"
Disqualifying the positive	8136 (0.06)	10756 (0.09)	Unreasonably discounting positive experiences	"listen up gov. cuomo... you own up to all the nursing home deaths and shut up about trump. you haven't accepted the fact you screwed up. dr. fauci **isn't that good** either gov cuomo. why don't you tell the truth?"
Emotional reasoning	472 (0.004)	987 (0.01)	Thinking that something is true on the basis of how one feels, ignoring the evidence to the contrary	"@hollymaxwell77 @realdonaldtrump not sure about others, but **i feel** even more confident about voting for trump in 2020 than i did in 2016. he's exceeded my expectations and kept his word more than i ever imagined! #maga #kag2020"
Fortune-telling	49724 (0.37)	61884 (0.52)	Making predictions, usually negative ones, about the future	"trump is done. he **will not** survive this. that's why they're trotting out pence. deutsche bank and taxes just icing on the cake. wish carl reiner could be here"
Labeling and mislabeling	210160 (1.57)	246603 (2.08)	Labeling yourself or others while discounting evidence that could lead to less disastrous conclusions	"@realdonaldtrump @foxnews the women he assaulted don't miss him, you heinous hemorrhoid. also, what happened to @foxnews (barely, but occasionally) was the truth that **you're just a loser** the morally bankrupt ailes banked his entire network on. just like you and the casino. one big bust. sad!"

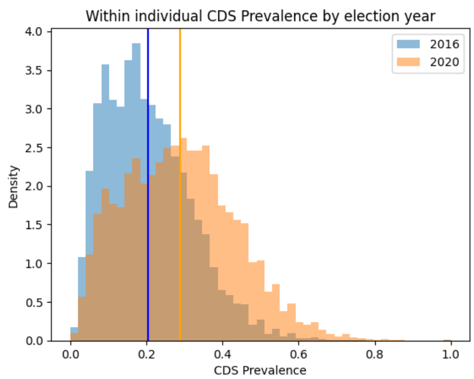
Table S2. Table 1 (cont.)

Type	**2016 n (%)**	**2020 n (%)**	**Definition**	**Sample Tweet**
Magnification and minimization	146609 (1.1)	190099 (1.6)	Magnifying negative aspects or minimizing positive aspects	"trump is **the most** traitorous, cowardly, punkass sonovabitch to **ever** occupy the oval office. fact."
Mental filtering	1639 (0.01)	2068 (0.02)	Paying too much attention to negative details instead of the whole picture	"@boringburner @isaacgallegos02 @cmoney7189 @mpenny55 @thepearl64 @brinkstar3k @thejtlewis @realdonaldtrump prove it. **all i see** is the left calling white people this and that, none of it positive. we on the other hand, treat people as individuals. it's thuggery that we're against, no matter the color of their skin."
Mindreading	158970 (1.19)	240695 (2.03)	Believing you know what others are thinking	"@realdonaldtrump your own press secretary had to assure reporters that you read. **nobody believes** her. that's embarrassing, spanky. even for you."
Overgeneralizing	34812 (0.26)	61132 (0.52)	Making sweeping negative conclusions on the basis of a few examples	"it seems a lifetime ago, but didn't someone warn us that trump was #putinspuppet? #hillaryclinton was right about **everything**. fuck **every single one of you** who didn't vote for her. #trumpkillsus #trumpisatraitor #trumpknew"
Personalizing	13774 (0.1)	20297 (0.17)	Believing others are behaving negatively because of oneself, without considering more plausible or external explanations for behaviour	"sang the national anthem together you felt it in your heart. i walked away **because i** listened, i learned, i developed my own opinion. i am looked over **because my** opinion is not like other teenagers. i have registered to vote in 2020 (r) for trump. i was very liberal minded, (9/x)"
Should statements	498935 (3.73)	652223 (5.5)	Having a fixed idea on how you and/or others should behave	"it's not just donald trump who **must** lose in november. every senate republican **must** lose as well. they all enabled him."

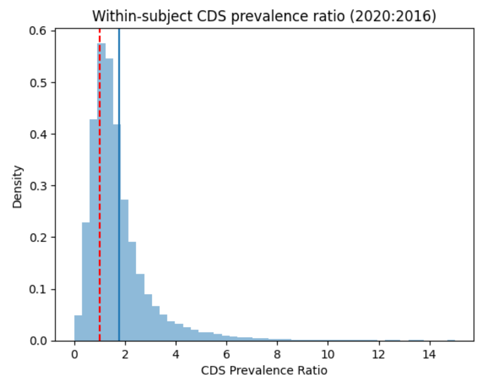
Population CDS prevalence

Figure S1a shows the individual CDS prevalence from 2016 to 2020 for all users in our data set who produced at least 10 tweets in 2016 and 10 tweets in 2020, regardless of whether their latent ideology could be defined. We observe a clear trend of increasing CDS prevalence from 2016 (in blue) to 2020. The mean CDS prevalence rose from 0.205 in 2016 to 0.288 in 2020 ($p << 0.01$), representing an increase of over 40%.

Figure S1b shows the distribution of within-individual prevalence ratios (see Methods) for each user. We find a mean prevalence ratio of 1.76 (solid blue line). In other words, for the average user in our dataset, there is a 76% increase in the prevalence of tweets that contain at least one instance of a cognitive distortion.



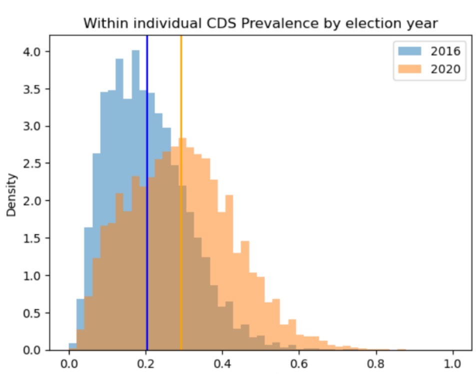
(a) User CDS prevalence in 2016 and 2020.



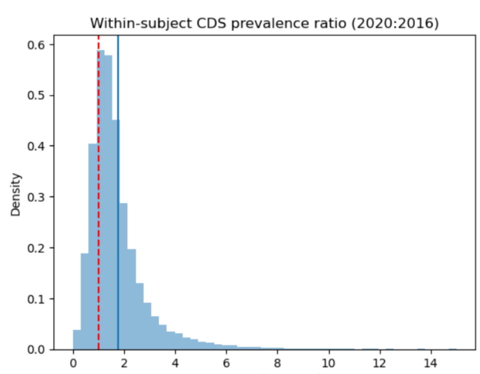
(b) User CDS prevalence ratios from 2016 to 2020.

Figure S1. **(a)** CDS prevalence of all the users between 2016 (in blue) and 2020 (in orange) for whom we could define CDS prevalence. Solid vertical lines represent corresponding population means. **(b)** Within-subject ratios of CDS prevalence. Solid vertical lines represent corresponding population means. The red dashed line is plotted at a ratio of 1, or equal prevalence, to highlight the signal of the measured prevalence ratio.

Figure S2 shows the results of repeating the above analyses restricted to those users who meet the above inclusion criteria and for whom we were able to define latent ideology scores. This subgroup of the user population exhibits the same trend of increasing CDS prevalence from 2016 (in blue) to 2020. The mean CDS prevalence rose from 0.204 in 2016 to 0.291 in 2020 ($p << 0.01$), an increase of over 43%. The distribution of prevalence ratios also closely matches that of the broader user population with a mean PR of 1.75 (solid blue line). These repeated analyses demonstrate that further restricting our user population to those users for whom we can define latent ideology imposes no change in the broader CDS trends in question.



(a) User CDS prevalence in 2016 and 2020.



(b) User CDS prevalence ratios from 2016 to 2020.

Figure S2. **(a)** CDS prevalence of the users between 2016 (in blue) and 2020 (in orange) for whom we could define both CDS prevalence and latent ideology. Solid vertical lines represent corresponding population means. **(b)** Within-subject ratios of CDS prevalence. Solid vertical lines represent corresponding population means. The red dashed line is plotted at a ratio of 1, or equal prevalence, to highlight the signal of the measured prevalence ratio.

CDS prevalence & latent ideology

Controlling for Activity Level

To verify that our findings were not driven by differences in user activity levels, we re-estimated our linear mixed-effects models including total activity (i.e., number of tweets) as a covariate. This approach controls for the possibility that variation in CDS prevalence is merely a byproduct of general user engagement rather than ideological positioning. Results are presented in Table S3.

Table S3. Linear Mixed-Effects Model Results and Effect Sizes for CDS Prevalence by Ideological Group (including *total*)

Group	Variable	β	SE	p	Effect size	95% CI
Left	Intercept	0.150^{***}	0.005	$< .0001$	–	[0.140, 0.160]
	year[T.2020]	0.082^{***}	0.001	$< .0001$	$d = 0.69$	[0.080, 0.083]
	polarization_distance	0.069^{***}	0.006	$< .0001$	$\beta^* = 0.05$	[0.058, 0.081]
	total	-0.000^{***}	0.000	$< .0001$	$\beta^* = -0.06$	[-0.000, -0.000]
	Group variance	0.005	0.001	–	–	–
Left-leaning users: $n = 58{,}096$, $k = 29{,}048$ groups, df $\approx$ 29,044						
Right	Intercept	0.188^{***}	0.006	$< .0001$	–	[0.176, 0.200]
	year[T.2020]	0.090^{***}	0.001	$< .0001$	$d = 0.73$	[0.088, 0.092]
	polarization_distance	0.013^{*}	0.007	0.041	$\beta^* = 0.01$	[0.001, 0.026]
	total	-0.000^{***}	0.000	$< .0001$	$\beta^* = -0.05$	[-0.000, -0.000]
	Group variance	0.006	0.002	–	–	–
Right-leaning users: $n = 37{,}262$, $k = 18{,}631$ groups, df $\approx$ 18,627						

Note. β = unstandardised coefficient; SE = standard error. Effect size is Cohen's d for binary contrasts and standardised β^* for continuous predictors. *df* indicates approximate degrees of freedom (number of groups minus fixed effects). ***$p < .001$, **$p < .01$, *$p < .05$.

Among left-leaning users, including activity in the model did not qualitatively alter the results. CDS prevalence continued to increase significantly from 2016 to 2020 ($\beta = 0.082$, SE = 0.001, $p < .0001$), and polarization remained positively associated with CDS prevalence ($\beta = 0.069$, SE = 0.006, $p < .0001$). That is, more ideologically extreme left-leaning users were more likely to engage in disorder-related discourse within a given year. Total activity showed a statistically significant but negligible negative effect ($\beta = -0.000$, SE = 0.000, $p < .0001$), indicating that highly active users were marginally less likely to post CDS-related content. Among right-leaning users, the same pattern held. CDS prevalence significantly increased over time ($\beta = 0.090, SE = 0.001, p < .0001$), and polarization was weakly but significantly associated with higher CDS prevalence ($\beta = 0.013, SE = 0.007, p = .041$). As with left-leaning users, total activity had a significant but trivially small negative association with CDS prevalence.

Taken together, these results confirm the robustness of our main findings: the positive relationship between ideological extremity and CDS engagement remains even when controlling for general user activity. Although highly active users tend to engage slightly less with CDS discourse, this effect is minimal in size and does not account for the observed polarization effects.

Interaction Between Year and Ideological Group

To further investigate ideological asymmetries in the temporal dynamics of CDS prevalence, we estimated a linear mixed-effects model that included an interaction between year (2016 vs. 2020) and ideological group (left-leaning vs. right-leaning), while also controlling for users' ideological extremity using a polarization. The model was specified as: CDS prevalence $\sim$ year+group+(year*group)+polarization As shown in Table S4, CDS prevalence increased significantly from 2016 to 2020 across the full sample ($\beta = 0.084, SE = 0.001, p < .0001$). Right-leaning users exhibited significantly lower baseline levels of CDS prevalence compared to left-leaning users in 2016 ($\beta = -0.013, SE = 0.001, p < .0001$). However, the interaction term between year and group was positive and significant ($\beta = 0.007, SE = 0.001, p < .0001$), indicating that CDS prevalence increased more rapidly among right-leaning users over time. Additionally, polarization was positively associated with CDS prevalence ($\beta = 0.039, SE = 0.004, p < .0001$). This suggests that users with more polarized positions, regardless of direction, were more likely to engage in CDS-related discourse within a given year.

Overall, these findings show that although CDS engagement has increased for all ideological groups, the rise was slightly steeper for right-leaning users. This model shows a modest positive relationship between polarization and CDS prevalence, potentially reflecting shifting patterns in how polarized users participate in disorder-related conversations.

Table S4. Linear Mixed-Effects Model Results and Effect Sizes for CDS Prevalence with Year × Group Interaction

Variable	β	SE	p	Effect size	95% CI
Intercept	0.174***	0.004	$< .0001$	–	[0.167, 0.182]
year[T.2020]	0.084***	0.001	$< .0001$	$d = 0.69$	[0.082, 0.085]
group[T.right]	−0.013***	0.001	$< .0001$	–	[−0.015, −0.011]
year[T.2020]:group[T.right]	0.007***	0.001	$< .0001$	$d = 0.05$	[0.004, 0.009]
polarization_distance	0.039***	0.004	$< .0001$	$\beta^* = 0.03$	[0.031, 0.048]
Group variance	0.006	0.001	–	–	–
All users: $n = 95{,}358$, $k = 47{,}679$ groups, df $\approx 47{,}674$					

Note. β = unstandardised coefficient; SE = standard error. Effect size is Cohen's d for binary contrasts and standardised β^* for continuous predictors. *df* indicates approximate degrees of freedom (number of groups minus fixed effects). ***$p < .001$, **$p < .01$, *$p < .05$.

Repeated Downsampling by Ideological Group

To assess the robustness of the relationship between polarization and CDS prevalence across ideologically balanced samples, we conducted a bootstrapped downsampling analysis. Left-leaning users were defined as those with latent ideology scores below -0.5 in both 2016 and 2020 ($n = 29{,}048$), while right-leaning users had scores above 0.5 in both years ($n = 18{,}631$). To correct for the imbalance in group sizes, we repeatedly subsampled both groups to the smaller class size ($n = 18{,}631$) and re-estimated the following mixed-effects model 100 times: CDS prevalence $\sim$ year + polarization + (1|user id). Table S5 presents the mean coefficient estimates, standard deviations, and the proportion of iterations in which each predictor was statistically significant ($p < .05$). The 95% Confidence Interval is calculated as: Mean $\pm$ 1.96 $\times$ SE.

Table S5. Bootstrapped Mixed-Effects Model Results: CDS Prevalence by Ideological Group

Variable	Left-leaning users			Right-leaning users			95% CI (Left / Right)
	Mean β	SE	% Sig.	Mean β	SD	% Sig.	
Intercept	0.150	0.0051	100%	0.188	0.0062	100%	[0.1400, 0.1600] / [0.1764, 0.1996]
year[T.2020]	0.082	0.0010	100%	0.090	0.0011	100%	[0.0800, 0.0840] / [0.0878, 0.0922]
Polarization Distance	0.069	0.0059	100%	0.013	0.0064	41%	[0.0574, 0.0806] / [0.0005, 0.0255]
Total	-0.000	0.0000	100%	-0.000	0.0000	100%	[0.0000, 0.0000] / [0.0000, 0.0000]

Note: Results reflect averages across 50 bootstrapped samples ($n = 18{,}631$ per group). % Sig. indicates the percentage of models in which the predictor was statistically significant at $p < .05$. Standard deviations (SE) are based on bootstrapped coefficients. 95% Confidence Intervals are based on normal approximation.

Table S5 reports the average coefficients, standard deviations, and the proportion of models in which each term was statistically significant at $p < .05$. Results show a consistently strong and significant positive association between polarization and CDS prevalence among left-leaning users ($M = 0.101$, $SE = 0.0084$; 100% significant), indicating that users farther from the ideological center tended to post more CDS-related content within a given year. In contrast, among right-leaning users, the average effect of polarization distance was small ($M = 0.012$) and only significant in 20% of models, suggesting a more inconsistent and weaker relationship.

Together, these results underscore the asymmetry in how polarization relates to CDS engagement. While ideological extremity robustly predicts increased CDS prevalence among left-leaning users, the pattern is notably weaker and less stable among right-leaning users.

CDS prevalence vs. latent ideology

Change-on-Change Model

To verify that the effect of polarization change holds under an alternative modeling approach, we estimated a simplified "change-on-change" linear mixed-effects model. In this specification, the dependent variable is the change in CDS prevalence between 2016 and 2020 for each user, and the key predictor is the change in polarization over the same period (ΔP). We also included ideological group and year as covariates and included a random intercept for each user to account for repeated observations. $\Delta CDS \sim$ year+group $+ \Delta P + (1|\text{user}_i)$. As shown in Table S6, the results confirm the robustness of our main finding. Users who became more ideologically polarized between 2016 and 2020 exhibited significantly larger increases in CDS prevalence ($\beta = 0.031, SE = 0.008, p < .0001$). Additionally, right-leaning users showed a significantly greater increase in CDS prevalence overall ($\beta = 0.017, SE = 0.002, p < .0001$). As expected, the year term was not significant, given that the dependent variable already reflects the temporal change. These findings reinforce the association between rising polarization and increased CDS engagement using a more direct measure of user-level change, thus supporting the stability of our core results across modeling specifications.

Table S6. Change-on-Change Linear Mixed-Effects Model: Predicting Change in CDS Prevalence

Variable	β	**SE**	p	**Effect size**	95% CI
Intercept	0.063***	0.002	$< .0001$	–	[0.058, 0.067]
year[T.2020]	0.000	0.000	1.000	$d = 0.00$	[−0.000, 0.000]
group[T.right]	0.017***	0.002	$< .0001$	$d = 0.13$	[0.012, 0.021]
ΔP (delta_P)	0.031***	0.008	$< .0001$	$\beta^* = 0.03$	[0.015, 0.047]
Group variance	0.008	87.211	–	–	–
Moderate users: $n = 14{,}636$, $k = 7{,}318$ groups, df $\approx 7{,}314$					

Note. β = unstandardised coefficient; SE = standard error. Effect size is Cohen's d for binary contrasts and standardised β^* for continuous predictors. df indicates approximate degrees of freedom, estimated as number of groups minus number of fixed effects. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

Controlling for User Activity

To ensure that the observed relationship between polarization change (ΔP) and CDS prevalence is not confounded by differences in user engagement, we included total tweet activity as a covariate in our linear mixed-effects model. This controls for the possibility that users who tweet more are also more likely to mention CDS-related content. The model includes year, ideological group, ΔP, total tweet count, and a random intercept for each user: CDS prevalence $\sim$ **year+group** $+ \Delta P + (1|\text{user}_i)$. As shown in Table S7, polarization change remained a strong and statistically significant predictor of CDS prevalence ($\beta = 0.063, SE = 0.009, p < .0001$). The coefficient for total tweet activity was negative and significant ($\beta = -0.000 SE = 0.000, p < .0001$), but extremely small in magnitude, indicating that users who posted more tweets were only marginally less likely to engage in CDS-related content. These results confirm that the relationship between polarization change and CDS prevalence is not driven by differential tweeting behavior.

Table S7. Linear Mixed-Effects Model: CDS Prevalence with Polarization Change and Tweet Activity

Variable	β	**SE**	p	**Effect size**	95% CI
Intercept	0.170***	0.003	$< .0001$	–	[0.164, 0.175]
year[T.2020]	0.076***	0.001	$< .0001$	$d = 0.65$	[0.074, 0.079]
group[T.right]	0.015***	0.002	$< .0001$	$d = 0.12$	[0.011, 0.020]
ΔP (delta_P)	0.063***	0.009	$< .0001$	$\beta^* = 0.07$	[0.045, 0.080]
Total activity	−0.000***	0.000	$< .0001$	$\beta^* = -0.06$	[−0.000, −0.000]
Group variance	0.005	0.002	–	–	–
All users: $n = 14{,}636$, $k = 7{,}318$ groups, df $\approx 7{,}313$					

Note. β = unstandardised coefficient; SE = standard error. Effect size is Cohen's d for binary contrasts and standardised β^* for continuous predictors. df indicates approximate degrees of freedom, estimated as number of groups minus number of fixed effects. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

Reduced Model without Group or Activity Controls

As a final robustness test, we estimated a reduced mixed-effects model including only year and polarization change (ΔP) as fixed effects, with a random intercept for each user. This model removes ideological group and tweet activity to assess whether the observed association between ΔP and CDS prevalence persists in a more parsimonious specification. CDS prevalence $\sim$ year $+ \Delta P + (1|\text{user}_i)$

As shown in Table S8, polarization change remained a statistically significant predictor of CDS prevalence ($\beta = 0.059, SE = 0.009, p < .0001$). The effect of year also remained strongly positive, confirming a general increase in CDS discourse over time. These results demonstrate that the link between ideological radicalization and disorder-related discourse is robust even in the absence of ideological group and user activity controls.

Table S8. Reduced Mixed-Effects Model: CDS Prevalence by Year and Polarization Change

Variable	β	**SE**	p	**Effect size**	95% CI
Intercept	0.174***	0.003	$< .0001$	–	[0.169, 0.179]
year[T.2020]	0.076***	0.001	$< .0001$	$d = 0.65$	[0.073, 0.079]
ΔP (delta_P)	0.059***	0.009	$< .0001$	$\beta^* = 0.06$	[0.041, 0.076]
Group variance	0.006	0.003	–	–	–
Moderate users: $n = 14{,}636$, $k = 7{,}318$ groups, df $\approx 7{,}315$					

Note. β = unstandardised coefficient; SE = standard error. Effect size is Cohen's d for binary contrasts and standardised β^* for continuous predictors. df indicates approximate degrees of freedom, estimated as number of groups minus number of fixed effects. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

Bootstrap Analysis Controlling for Group Size Imbalance

To assess whether unequal group sizes influenced our findings, we conducted a bootstrapped mixed effects modeling procedure with 100 iterations, each using equal-sized samples of left- and right-leaning users. See Table S9. Across these resampled models, polarization change (ΔP) remained a strong predictor of CDS prevalence for left-leaning users (mean $\beta = 0.101, SE = 0.021, p = .0013$), while the interaction with group (right-leaning users) was not significant (mean $\beta = -0.067, SE = 0.023, p \approx .079$). This pattern replicates our main model, suggesting that the observed ideological asymmetry is robust to differences in sample size. Notably, right-leaning users continued to exhibit slightly higher baseline CDS prevalence (mean $\beta = 0.032, SE = 0.0068, p = .0027$), while CDS prevalence increased in 2020 across both groups (mean $\beta = 0.079, SE = 0.003, p < .001$). The 95% Confidence Interval is calculated as: Mean $\pm$ 1.96 $\times$ SE.

Table S9. Bootstrapped Mixed Effects Model of CDS Prevalence on Polarization and Group Interaction (100 Iterations, Equal-Sized Samples)

Variable	Mean β"	**SE**	p**-value (Mean)**	**95% CI**
Intercept	0.1563	0.0060	$< .001$	[0.1445, 0.1681]
Year [2020]	0.0790	0.0034	$< .001$	[0.0724, 0.0856]
Group [Right]	0.0319	0.0068	.0027	[0.0186, 0.0452]
Polarization Change (ΔP)	0.1006	0.0208	.0013	[0.0598, 0.1414]
Group $\times$ ΔP	-0.0666	0.0232	.079	[-0.1121, -0.0211]
Note: Each iteration draws equal-sized user samples from left and right groups.				

Temporal Link Between Polarization and CDS

Two-Way Fixed Effects Regression

To investigate potential directional effects between CDS engagement and ideological polarization, we conducted two Difference-in-Differences (DiD) analyses using user-level panel data from 2019 to 2020. For each model, users were assigned to a treatment or control group based on whether they exhibited an increase in the independent variable of interest—either CDS prevalence ($\Delta\text{CDS} > 0$) or polarization ($\Delta P > 0$). The models were estimated using linear mixed-effects regression with random intercepts for users, allowing us to account for within-subject variability across time. The key parameter of interest in each model was the interaction between year and treatment, which captures the DiD estimate: the differential change in the outcome variable over time between treated and control groups.

In the first model, we tested whether users who became more polarized exhibited greater increases in CDS prevalence. This model yielded a non-significant interaction term, suggesting that increases in polarization did not lead to subsequent increases in CDS use. In contrast, the second model tested whether users who increased their CDS engagement became more polarized. This model produced a statistically significant interaction term, indicating that CDS increases were associated with greater subsequent polarization. While these findings are consistent with a directional influence of CDS on polarization, the observational nature of the data and the potential for unobserved confounding mean the results should not be interpreted as causal. Nonetheless, the analysis supports a temporal asymmetry in which CDS engagement may be more predictive of ideological change than the reverse.

Table S10. Difference-in-Differences Mixed-Effects Model: CDS Prevalence by Year and Polarization Increase

Variable	β	**SE**	p	**Effect size**	95% CI
Intercept	0.180^{***}	0.007	$< .0001$	–	[0.166, 0.194]
year[T.2020]	0.072^{***}	0.008	$< .0001$	$d \approx 0.58$	[0.057, 0.087]
Treatment (ΔP>0)	0.009	0.007	0.227	$\beta^* = 0.01$	[−0.006, 0.023]
year[T.2020]×Treatment	0.004	0.008	0.577	–	[−0.011, 0.020]
Group variance	0.006	0.003	–	–	–
All users: $n = 14{,}636$, $k = 7{,}318$ groups, df $\approx 7{,}314$					

Note. β = unstandardised coefficient; SE = standard error. Effect size is Cohen's d for binary contrasts (year) and standardised β^* for continuous/binary predictors treated as continuous (treatment). df indicates approximate degrees of freedom (groups minus fixed effects). $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

Table S11. Difference-in-Differences Mixed-Effects Model: Polarization by Year and CDS Increase

Variable	β	**SE**	p	**Effect size**	95% CI
Intercept	0.685^{***}	0.002	$< .0001$	–	[0.681, 0.690]
year[T.2020]	0.242^{***}	0.003	$< .0001$	$d \approx 1.95$	[0.236, 0.248]
Treatment (ΔCDS>0)	−0.002	0.003	0.335	$\beta^* = -0.01$	[−0.008, 0.003]
year[T.2020]×Treatment	0.009^{**}	0.003	0.008	$d \approx 0.07$	[0.002, 0.016]
Group variance	0.001	0.001	–	–	–
All users: $n = 14{,}636$, $k = 7{,}318$ groups, df $\approx 7{,}314$					

Note. β = unstandardised coefficient; SE = standard error. Effect size is Cohen's d for binary contrasts (*year*, interaction) and standardised β^* for continuous/binary predictors treated as continuous (treatment). df indicates approximate degrees of freedom (number of groups minus fixed effects). $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.