Supplementary Information for

Reducing opinion polarization: Effects of exposure to similar people with differing political views

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This PDF file includes:

Supplementary text
Figs. S1 to S21 (not allowed for Brief Reports)
Tables S1 to S25 (not allowed for Brief Reports)
SI References

Supporting Information Text

1. Additional Information

A. Stance Questions. Participants' stance measurement consisted of nine questions, which we report below in the same order in which they were asked, together with the alias used to reference them in Fig.3 and Tab. S2.

A.1. General Views about Government Redistribution. First, we asked a general question about attitudes towards redistribution (Question 1); its formulation was adapted from the General Social Survey (http://www.gss.norc.org/; GSS).

> **Q1. govred.** Some people think that the government in Washington *ought to reduce* the income differences between the rich and the poor, perhaps by raising the taxes of wealthy families or by giving income assistance to the poor.
>
> Others think that the government *should not concern* itself with reducing this income difference between the rich and the poor.
>
> **What score between 1 and 7 comes closer to the way you feel about government redistribution?**
>
> A score of **1** means that the government should not concern itself with reducing income differences.
>
> A score of **7** means that the government ought to reduce the income differences between rich and poor.

A.2. Views About Specific Policies. Then, on a separate page, we asked eight questions about increasing or decreasing different programs (Questions 2-9); the formulation of Questions 2-7 was adapted from **(author?)** (1), and we added Questions 8-9 using the same format. Questions 2-9 required an answer on a categorical scale, however, the exact wording of the categories depended on the question and may be one of the following (see squared brackets after the text of question).

A. 'Significantly decreased', 'Moderately decreased', 'Slightly decreased', 'Left as is', 'Slightly increased', 'Moderately increased', 'Significantly increased'.

B. 'Significantly decreased', 'Moderately decreased', 'Slightly decreased', 'Stay the same', 'Slightly increased', 'Moderately increased', 'Significantly increased'.

C. 'Significantly decrease', 'Moderately decrease', 'Slightly decrease', 'Keep at current level', 'Slightly increase', 'Moderately increase', 'Significantly increase'.

Q2. estatetax. The federal estate tax is a tax imposed on the transfer of wealth from a deceased person to his or her heirs. Do you think the federal estate tax should be decreased, left as is or increased? *[A]*

Q3. millionaires. As you may know, there have been proposals recently to decrease the federal deficit by raising income taxes on millionaires. Do you think income taxes on millionaires should be increased, stay the same or decreased? *[B]*

Q4. aidpoor. Should the federal government increase or decrease spending on aid to the poor? *[C]*

Q5. minimalwage. The federal minimum wage is currently $7.25 per hour. Do you think it should be decreased, stay the same or increased? *[B]*

Q6. publichousing. Should the federal government increase or decrease its spending on public housing for low income families? *[C]*

Q7. foodstamps. Food stamps provide financial assistance for food purchasing to families and individuals with low or no income. Should the federal government increase or decrease its spending on food stamps? *[C]*

Q8. publicedu. Should the federal government increase or decrease spending on public education? *[C]*

Q9. healthcare. Should the federal government increase or decrease spending on public health care coverage (e.g., Medicaid, Medicare)? *[C]*

A.3. Analysis of Individual Stance Questions. Our aggregated stance measure is the sum of all answers to the individual stance questions ($S[-27;+27]$; Fig. S1). In order to be meaningful, people's answers need to be consistent across all questions. Fig. S2 shows that this is indeed the case. To begin with, answers to all the individual questions are highly correlated with each other (panel A). Second, principal component analysis shows that the first component captures most of the variance: the elbow of the curve in the scree plot is found right after the first component (panel B). Furthermore, the biplot in the inset of panel B shows that all observations are close to each other, and that all question vectors are of similar length and point in the same direction (slightly less so for the estate tax). Third, exploratory factor analysis reveals that a single latent variable is a good model for the observable variables (panel C).

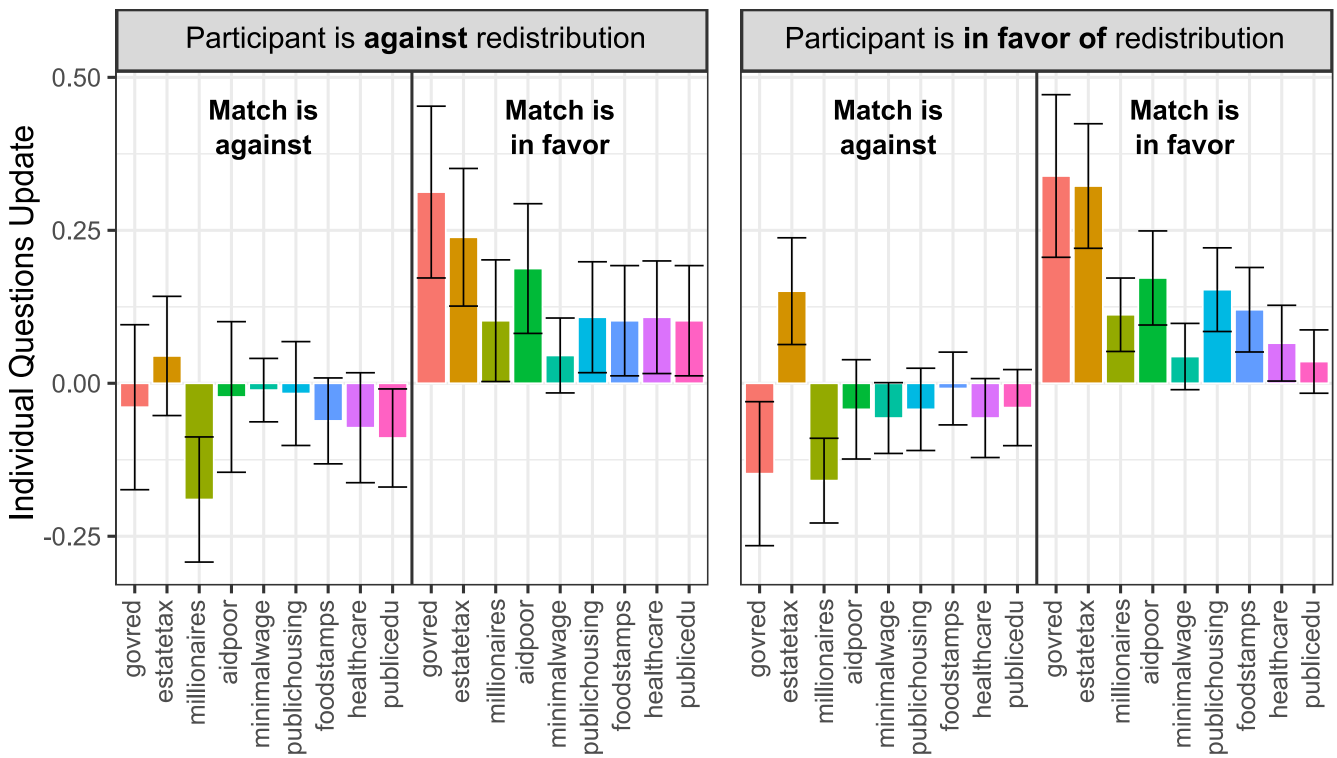

Fig. S1. Average update for all individual stance questions. The update is asymmetric in favor of redistribution. Error bars are 95% confidence intervals.

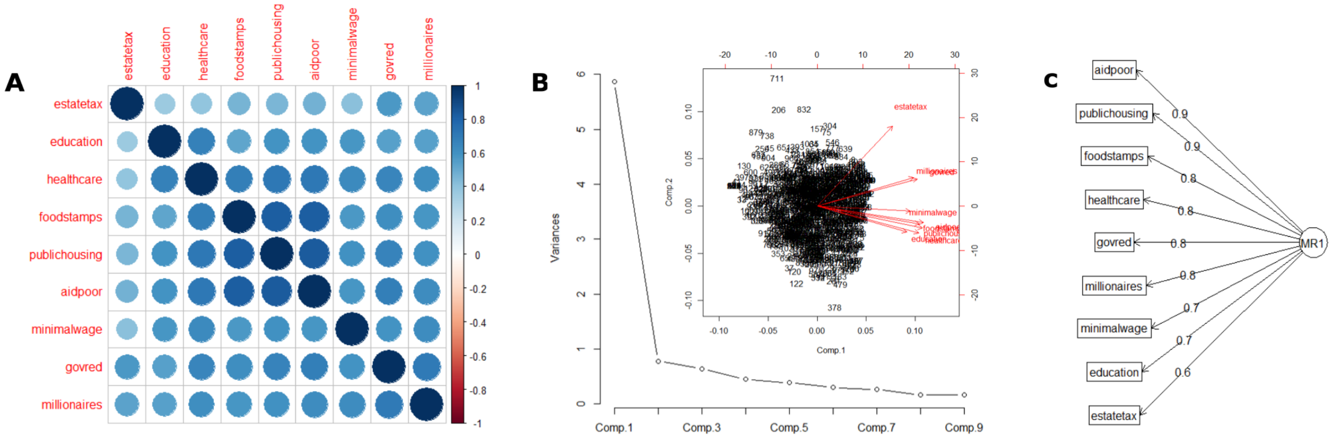

Fig. S2. Analysis of individual stance questions. A. Correlation matrix. **B.** Principal component analysis: scree plot and biplot in inset. **C.** Factor analysis: visual representation of loadings for one latent variable.

A.4. Attitude Extremity and Strength. Attitude's strength describes "the extent to which an attitude is consequential in shaping thinking and action across situations" (2). Our stance measure is technically a measure of attitude's extremity, which is a central dimension of attitude's strength, but by all means not the only one. Features like attitude's importance, accessibility, and certainty are related to extremity, but conceptually distinct (3). For instance, someone who sleeps only one night in a hotel and is disturbed by the noise of the ventilator might have an extremely negative opinion with little certainty ("maybe in another room it would have been different..."); likewise, she might deem judging the comfort of that particular hotel of little importance. Unlike hotel ratings, the topic of inequality and redistribution is central in the political discussion in the US and very present in the media nowadays, which heightens its accessibility. Therefore, given the contentious nature of the topic, we take our stance extremity measure as a good approximation of attitude strength in general. Indeed, several works found that holding an extreme opinion with little certainty or importance is uncommon (4–6), however sometimes correlations of extremity with other strength-related variables can be small (7).

B. Focal Survey. Here, we report about the answers to the focal survey questions on political leaning (Fig. S3) and perception about inequality in the US (Fig. S4).

Fig. S3A shows that, in our sample, Democrats and Republicans follow US politics similarly, while independents report a significant lower level of attention. Fig. S3B shows the distribution of self-identified party affiliations, which is consistent with the distribution of self-identification along the liberal vs conservative values scale in Fig. S3C. The majority of Republicans in our sample supported Donald Trump in the 2016 elections, while the majority of Democrats supported Hillary Clinton (Fig. S3D); however, support for several other candidates was expressed, i.e., Sanders for Democrats and Johnson for independents (Fig. S3E).

Fig. S4A shows the distribution of perception of socio-economic inequality as a problem in the US. For a narrow majority of Republicans (54%), inequality is a small problem or not a problem at all, whereas only a tiny fraction of Democrats holds the same views (4%); on the contrary, the vast majority of Democrats think that inequality is a serious or very serious problem (76%). Independents' views are more heterogeneous, with the majority of them seeing inequality as a serious or a very serious problem (46%). When it comes to the roots of socio-economic inequality in the US, Democrats and Republicans disagree starkly (Fig. S4B and aggregates in C). Democrats believe that political factors—such as policies against labor unions and discrimination against minorities—played a major role, whereas Republicans stress the importance of personal factors—such as talent and work attitude. Interestingly, luck, in the form of the family one is born into, is generally acknowledged as a key factor, but more so for Democrats. Independents tend to hold a middle-ground position between the Democratic and Republican views across all factors.

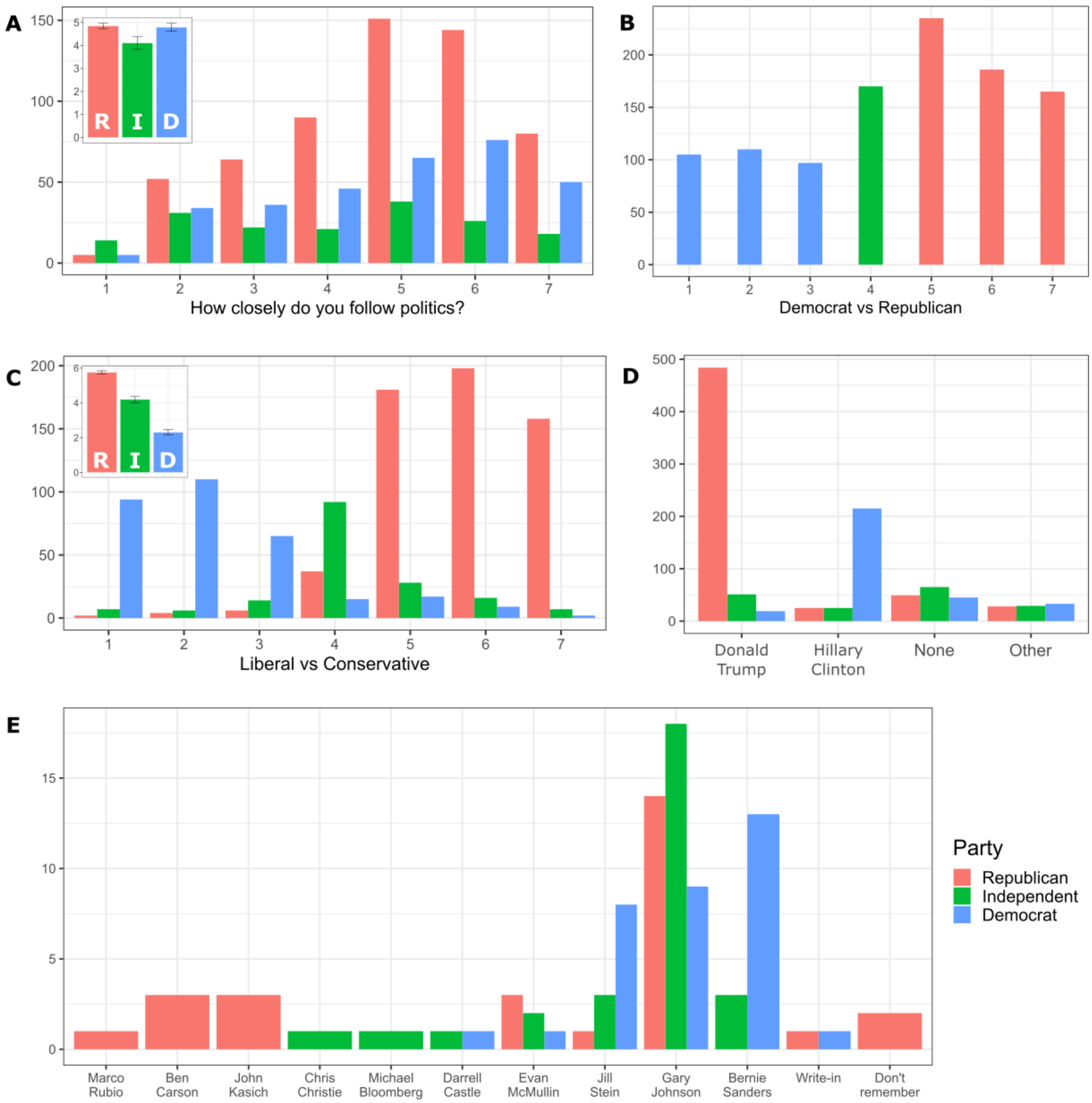

Fig. S3. Focal survey answers to questions about participants' political leaning. Sub-panels show counts over available options. **A.** How closely participants follow US politics (1-7; higher values more closely). **B.** Self-identification with Republican and Democrat parties (1-7; 1=strong Democrat, 7=strong Republican). **C.** Self-identification with liberal and conservative values (1-7, 1=strongly liberal, 7=strongly conservative). **D.** Candidate supported in 2016 elections. **E.** Open-ended answers for "Other" candidate supported in 2016 elections. Insets show averages by party, R=Republican, I=Independent, D=Democrat based on answers in sub-panel B; error bars = 95% CI.

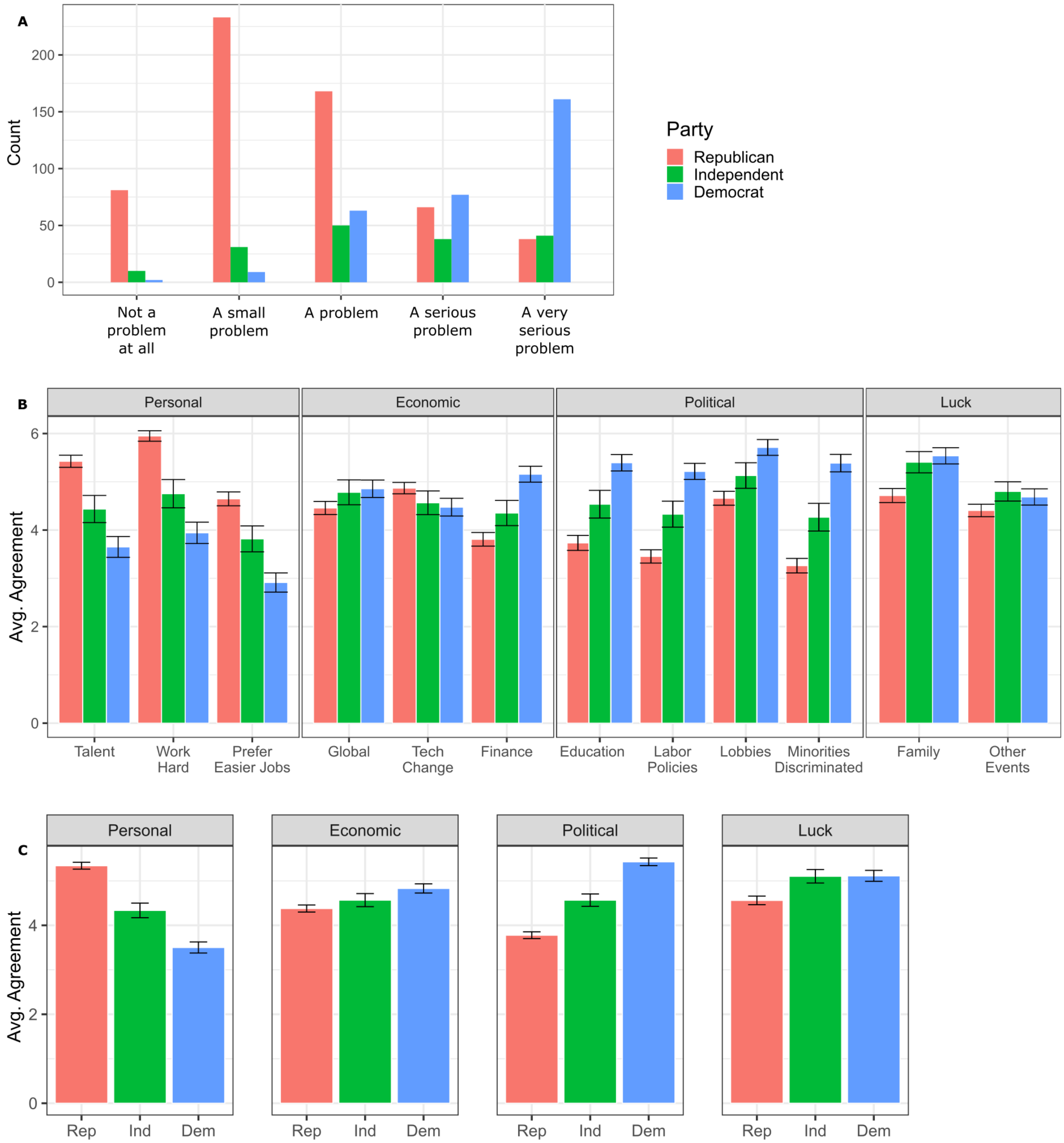

Fig. S4. Focal survey answers to questions about inequality perception in the US. A. How big of a problem is socio-economic inequality in the US. **B.** Agreement with a series of statements describing the roots of socio-economic inequalities in the US (1-7; higher values indicate higher agreement); full text of statements in Sec. B. **C.** Aggregated averages to the questions in sub-panel B by self-identified party; Rep=Republican, Ind=Independent, Dem=Democrat. Error bars = 95% CI.

C. Experimental Protocol.

C.1. Informed Consent Procedures. Upon accepting the task on Amazon Mechanical Turk, participants would be shown the consent page and had the opportunity to withdraw from the study immediately or at any later point with no penalty. The full consent form is available online: https://osf.io/pbvh5/?view_only=4f59af9f5bfb4e29aff2262dfa8aa66d.

C.2. Attention Confirmation. Right after the survey page about redistributive policies and *before* the interaction part of our survey, we implemented a attention confirmation question, as in **(author?)** (8). The question aims to raise the attention of the respondent for what comes next in the survey (i.e., the interaction part). Below is the full text, adapted from **(author?)** (8).

> Before proceeding to the next set of questions, we want to ask for your feedback about the responses you provided so far.
>
> It is vital to our study that we only include responses from people who devoted their **full attention** to this study. *This will not affect in any way the payment you will receive for taking this survey.*
>
> In your honest opinion, should we use your responses, or should we discard your responses since you did not devote your full attention to the questions so far? *(Please answer)*
>
> [Yes, I have devoted full attention to the questions so far and I think you should use my responses for your study, No, I have not devoted full attention to the questions so far and I think you should not use my responses for your study]

C.3. Essay Collection. Our Phase 1 database contained 158 profiles, which originated from past respondents who performed a similar survey and were asked to write a short essay about redistribution by the government. The instructions for this essay were tested in a smaller pilot (N=35) and then finalized in the main survey (N=123); both versions are reported in Tab. S1 and were loosely inspired by the instructions in Ref. (9).

PILOT VERSION (N=35)
Now, we'd like you to describe your views in your own words in the form below. *Imagine that you are explaining to a friend how wealth redistribution by the government works. How does it work? Strive to take into consideration the effects of wealth redistribution on the whole society. What are the pros and cons? Do you have a personal note to add? Feel free to personalize your essay describing how policies for wealth redistribution might impact your life or the life of somebody you know.* **Please take your time, as we expect you to carefully explain your views.**
FINAL VERSION (N=123)
Now, we'd like you to justify your views in your own words in the form below. *Imagine that you are talking to a friend about wealth redistribution by the government. Why is your view correct? Why should your friend believe you? Try to explain the costs and benefits of wealth redistribution on the whole of society and also how it might impact your life or the life of somebody you know.* **Please take your time, as we expect you to carefully justify your views.**

Table S1. Text of the writing task. Line breaks, italic and bold font as in survey.

The essays needed to be at least 250 words long and respondents had no time limit when creating them. The median number of words per essay is 273, the mean 302, and the max 812; the median time to complete it is 11.5 minutes, the mean 14.7 minutes, the max 2 hours and 13 minutes, and the min 14 seconds (if a person disconnected, composed the essay offline, and then reconnected to upload it, the time spent offline was not counted). The distributions of time and words are shown in Fig. S5.

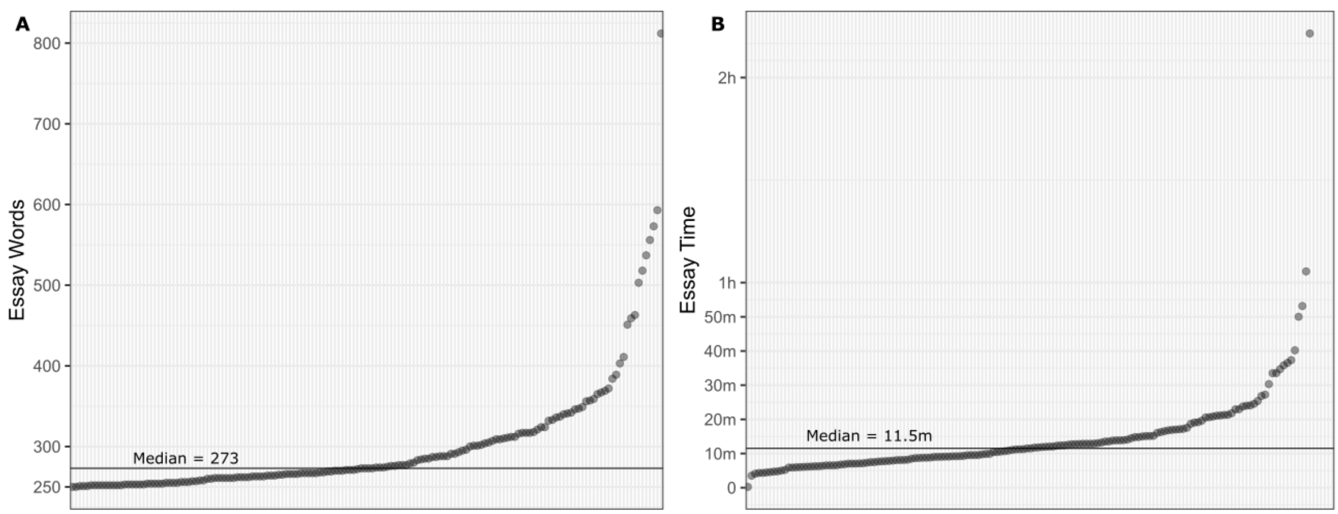

Fig. S5. Essay statistics. A. Number of words per essay; 250 was required minimum. **B.** Time to complete essay; note: (i) reconnections reset the time to zero, and (ii) we cannot distinguish between active and idle time.

C.4. Sampling Protocol. We recruited a total of 1252 respondents from the labor market Amazon Mechanical Turk (AMT). We required all respondents to be from the United States. Furthermore, given that the population of workers on AMT is known to be more liberal (10), we oversampled conservative respondents via the AMT API. For every session, we aimed to collect at least 60% of respondents who previously declared themselves to be politically conservative. This allowed us to obtain enough variation on the views about government redistribution across both sides of the stance spectrum.

C.5. Matching Protocol. After obtaining the first measurement of the stance $S[-27; +27]$ towards redistribution, every respondent is categorized into one of the four cells in Tab. S2:

Strongly Against	Mildly Against	Mildly in Favor	Strongly in Favor
$S \geq -12$	$-12 < S \leq 0$	$0 < S \leq 12$	$S > 12$

Table S2. Stance *S* categories. Neutral stance respondents (stance=0) are assigned to the mildly against category for balancing purposes.

Since we cannot control the stance of a person, the total number of respondents in each cell might differ (see Fig. 2 of main text). However, within each cell, we balance the assignment of the matched partners according to a 2x2 design crossing stance agreement and non-political similarity. Namely, within each cell of Tab. S2 we operationalize four nested cells, as described in Tab. S3:

	Non-Political Similarity	
Stance Agreement	Agreement, Low	Agreement, High
	Disagreement, Low	Disagreement, High

Table S3. Match categories. 2x2 balanced design for partner assignment within each cell in Tab. S2

Non-focal similarity. We measure the non-focal (i.e., non-political) similarity between two respondents as a weighted sum of all common answers to the *non-focal* survey. A list with all the questions categories is available in the anonymous timestamped repository used in the preregistration: https://osf.io/pbvh5/?view_only=4f59af9f5bfb4e29aff2262dfa8aa66d, and the full list of question is available is Sec. A. In line with the evidence that people's rare common interests have special bonding power (11), answers are weighted based on how common a match to any given question is plausibly expected to be. For instance, eye color is rated lower than favorite actor, and hazel eye color is weighted higher than brown eye color.* To take into account typos and different spellings, we used fuzzy logic to matched answers to open-ended questions. For instance, "Portland Trail Blazers" would match words such as "Trailblazers" and "Portland Blazers" and so forth. Location and Zip/Postal code—when provided—are not used to compute the similarity score for privacy reasons. Full details about the weights are available in the anonymous timestamped repository used in the preregistration: https://osf.io/7ghnj/?view_only=4f59af9f5bfb4e29aff2262dfa8aa66d

The non-political similarity score is 0 for two individuals who do not have a single answer in common and it grows proportionally to the number of common answers. In our sample, the minimum similarity score was 62, the mean 432.3, and the max 795. We defined two individuals to have low non-political similarity if their compound score is below 300 points, vice versa a similarity score above 600 points is considered of high-similarity. We strove to match individuals only within these two categories, however it was not always possible, and in this case we returned the next available best match (see Fig. S6).

*The resulting weights are arbitrary, but we composed them *before* looking at any data.

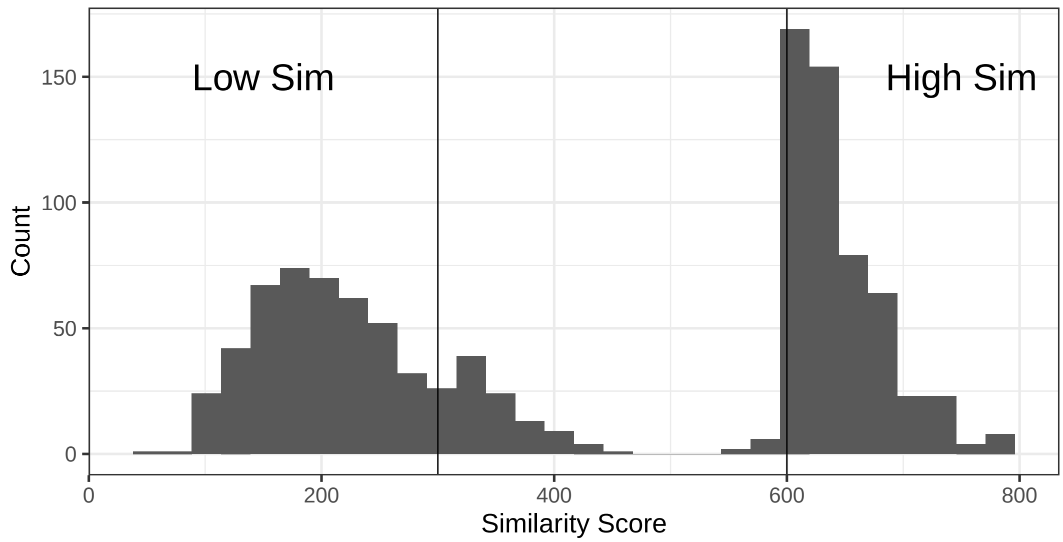

Fig. S6. Distribution of non-focal similarity scores.

Limit to Number of Matches. Every profile could be matched with at most 35 survey respondents.[†] After cleaning the data, no profile was matched with more than 28 respondents, and the final distribution of matches is shown in Fig. S7.

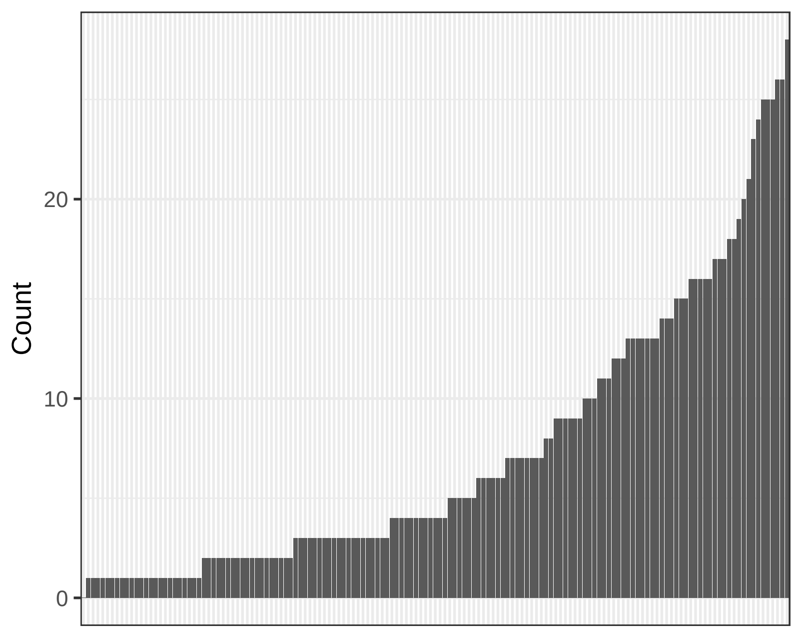

Fig. S7. Distribution of matches per profile.

C.6. Profile Page. The profile page displays information about a match based on the common answers to the non-focal survey. It consists of a large header displaying the initial of the first name and the US state of residence, followed by a 0-100 number corresponding to the rank similarity of the match with the respondent.

Immediately under the header, a first-person computer generated description of the match lists all the shared features between match and respondent. Lastly, the profile may include a quirky fact about the match (if any was provided). Below, we report an example of a full profile with high similarity to a fictitious respondent:

[†] We deviated from the preregistered protocol and raised this limit from 15 to 35 to ensure that most of respondents would fall either in the category High (> 600) or in the category Low similarity(< 300).

Demographics
I am Asian.
I have brown eyes, and I am right handed.
I am an atheist.

Family
I am single, I have no children, and I have two siblings.
My parents divorced.
I went to college.
I have friends in the LGBT community.

Finance
I managed to elevate my socio-economic status compared to my childhood.

Personality
I enjoy taking part in competitions and prove my skills, and I am very careful to details, I consider myself a perfectionist.
Taking care of the body is important for me.
I am not a confrontational person.
I am fascinated by technological progress, and, I know that some people will think that it is silly, but sometimes I like to believe that fantastic creatures like fairies, gnomes and the like are real.

Behavior
I have read that more and more people have problems giving away things they do not really need or use any more, but not me!
I am not that type of person that sends back food at the restaurant if I don't like it.
I never read horoscopes or similar silly things.

Favorite Color, Food, and Vacation
My favorite color is blue.
My dream country for a vacation is Japan.
My favorite food is Japanese, I like my food spicy, but not too much.

Things I Do
If I use social media? I am a somewhat active user.
I don't smoke.
I go dancing, but only sometimes.

Things I like
I like to play video games.

A Quirk or Interesting Fact About Me
I was the first of my family to attend and graduate from a university.

D. Sample Statistics. We collected 1252 observations and, following our preregistered criteria, we excluded:[‡]

- 179 respondents for spending too little time to read the profile or the essay of their match;
- 52 respondents for writing nonsensical text in the feedback form;
- 13 respondents who declared that they did not pay attention to the survey questions;
- 2 respondents for straightlining in at least two of the following survey blocks: causes of inequality, hobbies ("No" answers only), and policies for inequality (both before and after the treatment).[§]

After cleaning the dataset, there were 1068 remaining valid responses for which we report the following descriptive statistics.

Gender. Our sample is slightly more female (51%) and includes two respondents who self-identifies as "genderfluid" and "non binary" (Fig S8A).

Education. The majority (67%) of our sample is at least college educated—in line with US rates—while only 3 respondents did not finish high-school (Fig S8B).

Race. Respondents in our sample are predominantly White (85%), African Americans being the largest minority (7%), followed by Latino (5%), Asian (4%), American Indian (2%), Pacific Islander (0.2%), and Native Hawaiian (0.1%). The sum overflows 100% because respondents were allowed to select all races they self-identified with: 4% selected 2 races, 0.5% selected 3 races (Fig S8C).

[‡] Some respondents were flagged for multiple criteria
[§] Unambiguously detecting straightlining in other survey blocks is not possible given the different format of the questions in those blocks.

Age. The median age in our sample is 40, which is slightly higher than the US median age (however, we require all respondents to be at least 18 years old to participate). The first quartile-split is at 32 years, the third quartile split is 51 years, and the max age is 81 years (Fig S8D).

Residence State. Our sample spreads across 48 states and the District of Columbia (Fig S8E). The distribution of respondents roughly follows US states' population. In fact, most of our respondents are from the populous states of California, Texas, and Florida, while we could not collect any valid response from North Dakota and Wyoming (we eliminated one response from North Dakota after cleaning).

Income. The median income in our sample is $40,000 USD, which is below the US median income, but it is to be expected in an online labor market such as MTurk. However, high-earners are not missing, as 10% of our sample reports an income of 100 thousand US dollars or more (Fig S8F).

Urbanicity. Finally, 27% of our sample lives in rural areas, which is a bit higher than US average (Fig S8G).

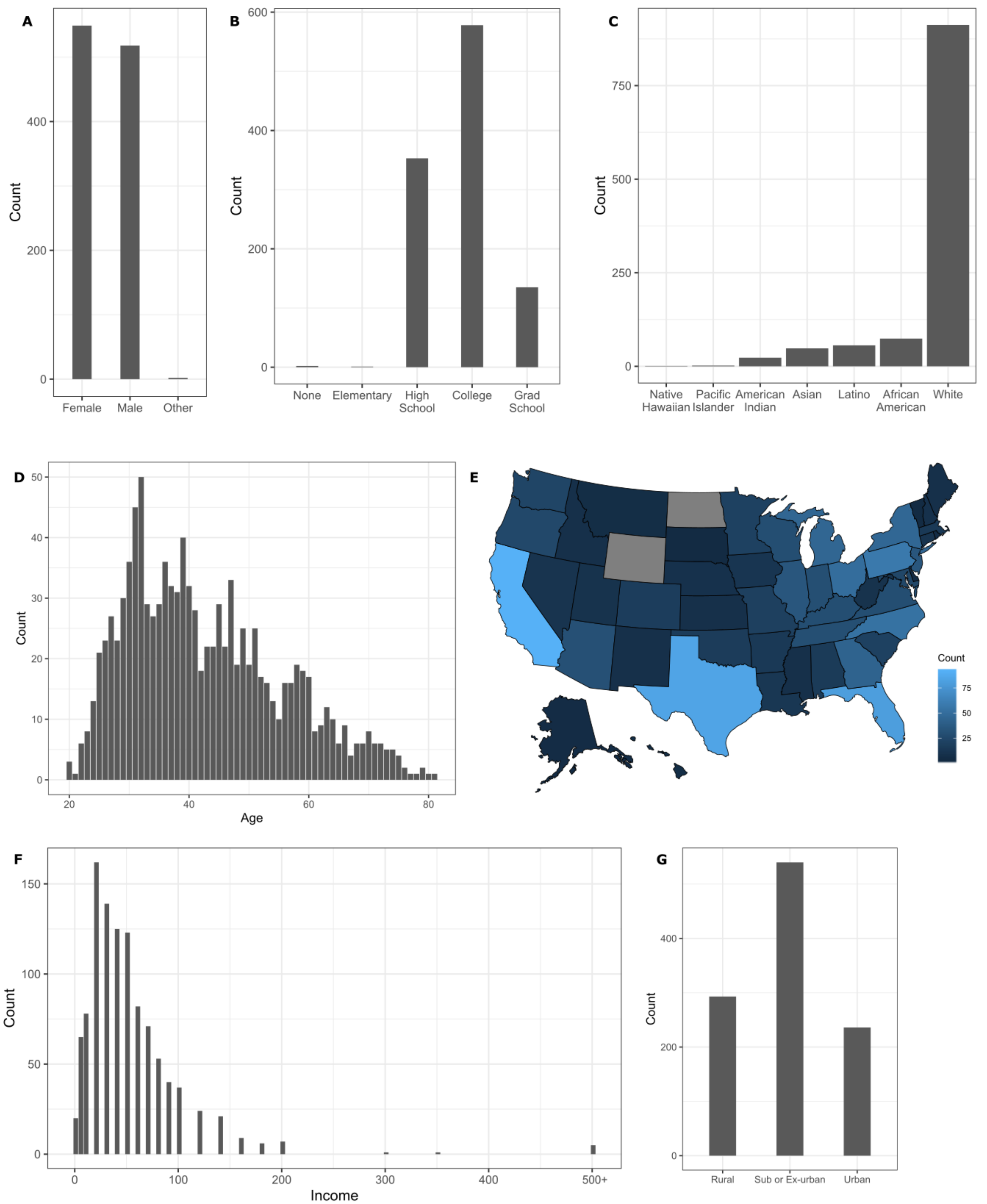

Fig. S8. Sample statistics. A. Gender. **B.** Maximum education level attained. **C.** Self-identified race (multiple responses allowed). **D.** Age. **E**. Current state. **F.** Income. **G.** Urbanicity.

E. Statistical Analysis for Stance Update and Closeness. We ran a number of linear mixed models (LMM) to predict the stance update after the interaction. We used the match id as random effect to control for the fact that the same profile could be matched with more survey respondents (see Sec. C.5). We ran all multilevel regressions using the lme4 package version 4.1.1-21 (12) in R version 3.6.0 (13).

We have already reported the key results of these regressions in the main text, but here we highlight some additional findings:

- None of the preregistered controls is significant without including the initial stance and/or the match type (Tab. S4). If so, the party affiliation becomes significant ($p < 0.05$) and income becomes marginally significant ($p < 0.1$).

- When we take into account the directional stance—i.e., *more* in favor and *more* against instead of in favor and against—the coefficients of the interactions of both closeness measures grow larger in size (Tab. S19; $p < 0.001$). This might indicate a substantial effect of closeness for same-stance interactions.

- Tab. S5 shows that neither experienced and nor expected closeness alone is significant in predicting the stance update. This is because of cross-over interactions with the two opposite stances. However, the stance distance is significant ($p < 0.05$) and positive, reflecting the overall positive shift in favor of redistribution after the interaction. When controls are added (Tab. S6), experienced closeness becomes significant ($p < 0.05$), while expected closeness is not. This might indicate that, after controlling for the match type, respondents evaluate the past interaction more positively in case they become more in favor of redistribution.

- Tab. S15 tests the interactions with discrete stance categories: Strongly Against, Mildly Against, Mildly in Favor, and Strongly in Favor (see Sec. C.5). All signs are in the expected direction, and we find some significant effects, mainly when a person is interacting with a match with opposite views, as also confirmed by the results in Tab. S17. However, the effects become stronger when we include the directional stance—i.e., more in favor instead of just in favor (Tab. S19).

	Model 1	Model 2	Model 3
(Intercept)	0.22	0.17	-0.98^{+}
	(0.49)	(0.49)	(0.53)
Gender Male	-0.18	-0.18	-0.18
	(0.20)	(0.20)	(0.19)
Gender Other	0.78	0.68	0.23
	(2.20)	(2.20)	(2.17)
Income	-0.00	-0.00^{+}	-0.00^{+}
	(0.00)	(0.00)	(0.00)
Social Media Use: Rare	0.59	0.63	0.67
	(0.45)	(0.45)	(0.45)
Social Media Use: Somewhat Active	0.25	0.30	0.32
	(0.43)	(0.43)	(0.42)
Social Media Use: Very Active	0.30	0.38	0.34
	(0.45)	(0.46)	(0.45)
Match Believed Real	0.22	0.24	0.23
	(0.25)	(0.25)	(0.24)
Party Independent	0.27	0.36	0.32
	(0.27)	(0.28)	(0.28)
Party Democrat	0.33	0.56^{*}	0.52^{*}
	(0.22)	(0.27)	(0.27)
Initial Stance		-0.01	-0.02
		(0.01)	(0.01)
Match Type: Against $\rightarrow$ in Favor			1.83^{***}
			(0.35)
Match Type: in Favor $\rightarrow$ in Favor			1.90^{***}
			(0.40)
Match Type: in Favor $\rightarrow$ Against			0.13
			(0.38)
AIC	5492.08	5499.33	5458.13
BIC	5551.77	5563.99	5537.71
Log Likelihood	-2734.04	-2736.67	-2713.07
Num. obs.	1068	1068	1068
Num. groups: matchId	146	146	146
Var: matchId (Intercept)	1.18	1.21	0.31
Var: Residual	8.99	8.97	9.05

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table S4. Multilevel regression predicting stance update with match-id as random effect. *Controls only.*

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.65^{***}	0.15	0.39	0.65^{***}
	(0.15)	(0.29)	(0.36)	(0.13)
Scaled Similarity Score	-0.06			
	(0.14)			
Experienced Closeness		0.10		
		(0.05)		
Expected Closeness			0.05	
			(0.07)	
Match Stance Distance				0.02^{***}
				(0.01)
AIC	5473.69	5467.77	5474.73	5466.43
BIC	5493.58	5487.66	5494.63	5486.32
Log Likelihood	-2732.84	-2729.89	-2733.37	-2729.21
Num. obs.	1068	1067	1068	1068
Num. groups: matchId	146	146	146	146
Var: matchId (Intercept)	1.19	1.18	1.20	0.73
Var: Residual	9.00	8.98	8.99	9.10

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table S5. Multilevel regression predicting stance update with match-id as random effect. ***Similarity score, expected closeness, experienced closeness, and match stance distance.***

	Model 1	Model 2	Model 3	Model 4
(Intercept)	-0.98^{+}	-1.52^{*}	-1.20^{*}	-0.74
	(0.54)	(0.60)	(0.61)	(0.55)
Scaled Similarity Score	-0.03			
	(0.11)			
Experienced Closeness		0.12^{*}		
		(0.06)		
Expected Closeness			0.05	
			(0.07)	
Match Stance Distance				0.03^{*}
				(0.02)
Gender: Male	-0.17	-0.15	-0.17	-0.18
	(0.19)	(0.19)	(0.19)	(0.19)
Gender: Other	0.24	0.37	0.22	0.22
	(2.17)	(2.17)	(2.17)	(2.17)
Income	-0.00^{+}	-0.00^{+}	-0.00^{+}	-0.00^{+}
	(0.00)	(0.00)	(0.00)	(0.00)
Social Media Use: Rare	0.67	0.69	0.67	0.70
	(0.45)	(0.45)	(0.45)	(0.45)
Social Media Use: Somewhat Active	0.32	0.30	0.31	0.35
	(0.42)	(0.42)	(0.42)	(0.42)
Social Media Use: Very Active	0.34	0.32	0.32	0.38
	(0.45)	(0.45)	(0.45)	(0.45)
Match Believed Real	0.23	0.16	0.21	0.23
	(0.24)	(0.25)	(0.25)	(0.24)
Party: Independent	0.32	0.35	0.34	0.31
	(0.28)	(0.28)	(0.28)	(0.28)
Party: Democrat	0.52^{*}	0.55^{*}	0.53^{*}	0.54^{*}
	(0.27)	(0.27)	(0.27)	(0.27)
Initial Stance	-0.02	-0.02	-0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.02)
Match Type: Against $\rightarrow$ in Favor	1.82^{***}	2.03^{***}	1.83^{***}	1.12^{*}
	(0.35)	(0.36)	(0.35)	(0.49)
Match Type: in Favor $\rightarrow$ in Favor	1.90^{***}	1.87^{***}	1.89^{***}	1.21^{*}
	(0.40)	(0.40)	(0.40)	(0.52)
Match Type: in Favor $\rightarrow$ Against	0.13	0.23	0.12	0.15
	(0.38)	(0.38)	(0.38)	(0.38)
AIC	5462.67	5455.41	5463.18	5462.45
BIC	5547.22	5539.94	5547.73	5547.00
Log Likelihood	-2714.33	-2710.70	-2714.59	-2714.23
Num. obs.	1068	1067	1068	1068
Num. groups: matchId	146	146	146	146
Var: matchId (Intercept)	0.32	0.33	0.32	0.29
Var: Residual	9.05	9.02	9.05	9.04

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table S6. Multilevel regression predicting stance update with match-id as random effect. ***Similarity score, expected closeness, experienced closeness, and match stance distance. Controls added.***

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.65^{***}	0.64^{**}	0.75^{**}	1.96^{***}
	(0.15)	(0.22)	(0.28)	(0.09)
Scaled Similarity Score	-0.06			
	(0.14)			
Experienced Closeness		0.28^{***}		
		(0.04)		
Expected Closeness			0.24^{***}	
			(0.05)	
Match Stance Distance				0.00
				(0.00)
AIC	5473.69	5013.03	5037.11	5061.52
BIC	5493.58	5032.92	5057.01	5081.41
Log Likelihood	-2732.84	-2502.51	-2514.56	-2526.76
Num. obs.	1068	1067	1068	1068
Num. groups: matchId	146	146	146	146
Var: matchId (Intercept)	1.19	0.10	0.11	0.09
Var: Residual	9.00	6.25	6.36	6.50

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table S7. Multilevel regression predicting the absolute value of the stance update with match-id as random effect. ***Similarity score, expected closeness, experienced closeness, and match stance distance.***

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.57	-0.84	-0.33	0.60
	(0.44)	(0.49)	(0.50)	(0.45)
Scaled Similarity Score	0.06			
	(0.08)			
Experienced Closeness		0.30^{***}		
		(0.05)		
Expected Closeness			0.20^{***}	
			(0.05)	
Match Stance Distance				0.00
				(0.01)
Gender: Male	-0.12	-0.06	-0.08	-0.12
	(0.16)	(0.16)	(0.16)	(0.16)
Gender: Other	-0.19	0.17	-0.27	-0.19
	(1.81)	(1.78)	(1.79)	(1.81)
Income	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Social Media Use: Rare	0.21	0.27	0.20	0.21
	(0.37)	(0.37)	(0.37)	(0.37)
Social Media Use: Somewhat Active	0.26	0.21	0.23	0.27
	(0.35)	(0.35)	(0.35)	(0.35)
Social Media Use: Very Active	0.30	0.24	0.21	0.31
	(0.38)	(0.37)	(0.37)	(0.38)
Match Believed Real	0.51^{*}	0.31	0.41^{*}	0.50^{*}
	(0.20)	(0.20)	(0.20)	(0.20)
Party: Independent	-0.23	-0.15	-0.16	-0.23
	(0.23)	(0.23)	(0.23)	(0.23)
Party: Democrat	-0.41	-0.32	-0.36	-0.41
	(0.22)	(0.22)	(0.22)	(0.22)
Initial Stance	-0.03^{*}	-0.03^{*}	-0.03^{**}	-0.03
	(0.01)	(0.01)	(0.01)	(0.02)
Match Type: Against $\rightarrow$ in Favor	0.48	0.99^{***}	0.50	0.42
	(0.28)	(0.29)	(0.28)	(0.38)
Match Type: in Favor $\rightarrow$ in Favor	1.63^{***}	1.56^{***}	1.59^{***}	1.57^{***}
	(0.32)	(0.32)	(0.32)	(0.41)
Match Type: in Favor $\rightarrow$ Against	1.37^{***}	1.62^{***}	1.31^{***}	1.37^{***}
	(0.32)	(0.31)	(0.31)	(0.32)
AIC	5070.59	5030.39	5057.98	5074.86
BIC	5155.14	5114.92	5142.53	5159.41
Log Likelihood	-2518.29	-2498.19	-2511.99	-2520.43
Num. obs.	1068	1067	1068	1068
Num. groups: matchId	146	146	146	146
Var: matchId (Intercept)	0.06	0.08	0.07	0.06
Var: Residual	6.36	6.13	6.28	6.36

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table S8. Multilevel regression predicting the absolute value of the stance update with match-id as random effect. ***Similarity score, expected closeness, experienced closeness, and match stance distance. Controls added.***

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.32^{**}	0.13	0.39	0.24
	(0.12)	(0.27)	(0.35)	(0.14)
Scaled Similarity Score	-0.16			
	(0.12)			
Match Stance	0.07^{***}	-0.04	-0.03	0.07^{***}
	(0.01)	(0.02)	(0.03)	(0.01)
Scaled Similarity Score x Match Stance	0.00			
	(0.01)			
Experienced Closeness		0.03		
		(0.05)		
Experienced Closeness x Match Stance		0.02^{***}		
		(0.00)		
Expected Closeness			-0.02	
			(0.07)	
Expected Closeness x Match Stance			0.02^{***}	
			(0.01)	
Match Stance Distance				-0.00
				(0.01)
Match Stance Distance x Match Stance				0.00
				(0.00)
AIC	5446.16	5413.65	5436.12	5458.92
BIC	5476.01	5443.48	5465.96	5488.76
Log Likelihood	-2717.08	-2700.82	-2712.06	-2723.46
Num. obs.	1068	1067	1068	1068
Num. groups: matchId	146	146	146	146
Var: matchId (Intercept)	0.34	0.37	0.43	0.33
Var: Residual	9.07	8.78	8.90	9.08

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table S9. Multilevel regression predicting stance update with match-id as random effect and interactions with match stance value. ***Similarity score, expected closeness, experienced closeness, and match stance distance.***

	Model 1	Model 2	Model 3	Model 4
(Intercept)	-0.70	-1.06	-0.82	-0.74
	(0.55)	(0.61)	(0.62)	(0.54)
Scaled Similarity Score	-0.09			
	(0.12)			
Scaled Similarity Score x Match Stance	0.00			
	(0.01)			
Experienced Closeness		0.06		
		(0.06)		
Experienced Closeness x Match Stance		0.03^{***}		
		(0.00)		
Expected Closeness			-0.01	
			(0.07)	
Expected Closeness x Match Stance			0.02^{***}	
			(0.01)	
Match Stance Distance				0.02
				(0.01)
Match Stance Distance x Match Stance				0.00
				(0.00)
Match Stance	0.04^{*}	-0.10^{***}	-0.07^{*}	0.02
	(0.02)	(0.03)	(0.03)	(0.02)
Gender: Male	-0.18	-0.21	-0.18	-0.18
	(0.19)	(0.19)	(0.19)	(0.19)
Gender: Other	0.21	0.52	0.26	0.21
	(2.17)	(2.13)	(2.16)	(2.17)
Income	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Social Media Use: Rare	0.70	0.77	0.70	0.69
	(0.45)	(0.44)	(0.45)	(0.45)
Social Media Use: Somewhat Active	0.35	0.38	0.41	0.35
	(0.42)	(0.42)	(0.42)	(0.42)
Social Media Use: Very Active	0.38	0.40	0.39	0.37
	(0.45)	(0.44)	(0.45)	(0.45)
Match Believed Real	0.23	0.18	0.21	0.25
	(0.24)	(0.24)	(0.24)	(0.24)
Party: Independent	0.32	0.28	0.34	0.32
	(0.28)	(0.27)	(0.27)	(0.28)
Party: Democrat	0.54^{*}	0.41	0.51	0.54^{*}
	(0.27)	(0.26)	(0.26)	(0.27)
Initial Stance	-0.02	-0.03^{*}	-0.02	
	(0.01)	(0.01)	(0.01)	
Match Type: Against $\rightarrow$ in Favor	1.05^{*}	1.56^{**}	1.28^{**}	0.95
	(0.50)	(0.51)	(0.50)	(0.52)
Match Type: in Favor $\rightarrow$ in Favor	1.13^{*}	1.31^{*}	1.34^{*}	1.15^{*}
	(0.53)	(0.52)	(0.53)	(0.52)
Match Type: in Favor $\rightarrow$ Against	0.15	0.28	0.24	0.04
	(0.38)	(0.37)	(0.38)	(0.39)
AIC	5475.99	5434.15	5464.67	5476.94
BIC	5570.48	5528.63	5559.17	5566.46
Log Likelihood	-2718.99	-2698.08	-2713.34	-2720.47
Num. obs.	1068	1067	1068	1068
Num. groups: matchId	146	146	146	146
Var: matchId (Intercept)	0.30	0.35	0.34	0.26
Var: Residual	9.05	8.67	8.90	9.06

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table S10. Multilevel regression predicting stance update with match-id as random effect and interactions with match stance value. ***Similarity score, expected closeness, experienced closeness, and match stance distance. Controls added***

	Model 1	Model 2	Model 3
(Intercept)	0.66^{***}	-0.16	0.09
	(0.13)	(0.28)	(0.36)
Scaled Similarity Score	-0.10		
	(0.12)		
Match Stance Distance	0.02^{***}	-0.04^{***}	-0.05^{*}
	(0.01)	(0.01)	(0.02)
Scaled Similarity Score x Match Stance Distance	0.00		
	(0.01)		
Experienced Closeness		0.18^{***}	
		(0.05)	
Experienced Closeness x Match Stance Distance		0.02^{***}	
		(0.00)	
Expected Closeness			0.12
			(0.07)
Expected Closeness x Match Stance Distance			0.01^{***}
			(0.00)
AIC	5480.33	5435.92	5465.10
BIC	5510.17	5465.76	5494.94
Log Likelihood	-2734.16	-2711.96	-2726.55
Num. obs.	1068	1067	1068
Num. groups: matchId	146	146	146
Var: matchId (Intercept)	0.71	0.89	0.77
Var: Residual	9.12	8.66	8.94

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table S11. Multilevel regression predicting stance update with match-id as random effect and interactions with match stance distance. ***Similarity score, expected closeness, and experienced closeness***

	Model 1	Model 2	Model 3
(Intercept)	-0.70	-1.90^{**}	-1.18
	(0.55)	(0.62)	(0.63)
Scaled Similarity Score	-0.08		
	(0.11)		
Scaled Similarity Score x Match Stance Distance	0.00		
	(0.01)		
Experienced Closeness		0.21^{***}	
		(0.06)	
Experienced Closeness x Match Stance Distance		0.02^{***}	
		(0.00)	
Expected Closeness			0.09
			(0.07)
Expected Closeness x Match Stance Distance			0.01^{***}
			(0.00)
Match Stance Distance	0.04^{*}	-0.05^{*}	-0.03
	(0.02)	(0.02)	(0.02)
Gender: Male	-0.18	-0.17	-0.17
	(0.19)	(0.19)	(0.19)
Gender: Other	0.22	0.39	0.28
	(2.17)	(2.13)	(2.16)
Income	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)
Social Media Use: Rare	0.70	0.66	0.66
	(0.45)	(0.44)	(0.45)
Social Media Use: Somewhat Active	0.35	0.24	0.34
	(0.42)	(0.42)	(0.42)
Social Media Use: Very Active	0.38	0.27	0.34
	(0.45)	(0.44)	(0.45)
Match Believed Real	0.22	0.15	0.20
	(0.24)	(0.24)	(0.24)
Party: Independent	0.31	0.41	0.38
	(0.28)	(0.27)	(0.28)
Party: Democrat	0.54^{*}	0.50	0.53^{*}
	(0.27)	(0.26)	(0.26)
Initial Stance	0.02	-0.01	0.01
	(0.02)	(0.02)	(0.02)
Match Type: Against $\rightarrow$ in Favor	1.05^{*}	1.96^{***}	1.24^{*}
	(0.50)	(0.53)	(0.50)
Match Type: in Favor $\rightarrow$ in Favor	1.13^{*}	1.71^{**}	1.32^{*}
	(0.53)	(0.54)	(0.53)
Match Type: in Favor $\rightarrow$ Against	0.15	0.48	0.22
	(0.38)	(0.38)	(0.38)
AIC	5476.92	5435.34	5467.09
BIC	5571.41	5529.82	5561.58
Log Likelihood	-2719.46	-2698.67	-2714.54
Num. obs.	1068	1067	1068
Num. groups: matchId	146	146	146
Var: matchId (Intercept)	0.29	0.43	0.34
Var: Residual	9.05	8.62	8.92

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table S12. Multilevel regression predicting stance update with match-id as random effect and interactions with match stance distance. ***Similarity score, expected closeness, and experienced closeness. Controls added.***

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.66^{***}	-0.03	0.20	0.42^{**}
	(0.15)	(0.31)	(0.39)	(0.14)
Own Stance	-0.00	0.03	0.03	0.07^{***}
	(0.01)	(0.02)	(0.02)	(0.01)
Scaled Similarity Score	-0.07			
	(0.14)			
Scaled Similarity Score x Own Stance	0.00			
	(0.01)			
Experienced Closeness		0.15^{**}		
		(0.06)		
Experienced Closeness x Own Stance		-0.01		
		(0.00)		
Expected Closeness			0.09	
			(0.07)	
Expected Closeness x Own Stance			-0.01	
			(0.00)	
Match Stance Distance				0.06^{***}
				(0.01)
Match Stance Distance x Own Stance				0.00^{*}
				(0.00)
AIC	5493.39	5485.78	5493.37	5455.61
BIC	5523.23	5515.62	5523.21	5485.45
Log Likelihood	-2740.70	-2736.89	-2740.69	-2721.80
Num. obs.	1068	1067	1068	1068
Num. groups: matchId	146	146	146	146
Var: matchId (Intercept)	1.19	1.37	1.20	0.36
Var: Residual	9.02	8.89	8.99	9.03

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table S13. Multilevel regression predicting stance update with match-id as random effect and interactions with own stance. ***Similarity score, expected closeness, experienced closeness, and match stance distance. Own Stance is Initial Stance in other regression tables.***

	Model 1	Model 2	Model 3	Model 4
(Intercept)	-0.97	-2.15^{***}	-1.38^{*}	-0.66
	(0.54)	(0.63)	(0.62)	(0.54)
Own Stance	-0.02	0.04	0.01	0.02
	(0.01)	(0.02)	(0.03)	(0.02)
Scaled Similarity Score	-0.04			
	(0.12)			
Scaled Similarity Score x Own Stance	0.00			
	(0.01)			
Experienced Closeness		0.22^{***}		
		(0.07)		
Experienced Closeness x Own Stance		-0.01^{***}		
		(0.00)		
Expected Closeness			0.09	
			(0.07)	
Expected Closeness x Own Stance			-0.01	
			(0.00)	
Match Stance Distance				0.02
				(0.02)
Match Stance Distance x Own Stance				0.00^{**}
				(0.00)
Gender: Male	-0.18	-0.14	-0.16	-0.16
	(0.19)	(0.19)	(0.19)	(0.19)
Gender: Other	0.24	0.32	0.24	0.08
	(2.18)	(2.16)	(2.17)	(2.16)
Income	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Social Media Use: Rare	0.67	0.62	0.64	0.71
	(0.45)	(0.45)	(0.45)	(0.45)
Social Media Use: Somewhat Active	0.32	0.20	0.29	0.33
	(0.42)	(0.42)	(0.42)	(0.42)
Social Media Use: Very Active	0.34	0.24	0.30	0.36
	(0.45)	(0.45)	(0.45)	(0.45)
Match Believed Real	0.23	0.14	0.21	0.20
	(0.24)	(0.25)	(0.25)	(0.24)
Party: Independent	0.32	0.43	0.36	0.35
	(0.28)	(0.27)	(0.28)	(0.27)
Party: Democrat	0.52^{*}	0.57^{*}	0.54^{*}	0.71^{**}
	(0.27)	(0.26)	(0.27)	(0.27)
Match Type: Against $\rightarrow$ in Favor	1.82^{***}	2.45^{***}	1.83^{***}	1.52^{**}
	(0.35)	(0.38)	(0.35)	(0.51)
Match Type: in Favor $\rightarrow$ in Favor	1.89^{***}	2.24^{***}	1.90^{***}	1.14^{*}
	(0.40)	(0.42)	(0.40)	(0.52)
Match Type: in Favor $\rightarrow$ Against	0.13	0.40	0.13	0.20
	(0.38)	(0.38)	(0.38)	(0.38)
AIC	5476.33	5460.27	5476.53	5470.49
BIC	5570.83	5554.75	5571.03	5560.01
Log Likelihood	-2719.17	-2711.14	-2719.27	-2717.24
Num. obs.	1068	1067	1068	1068
Num. groups: matchId	146	146	146	146
Var: matchId (Intercept)	0.29	0.38	0.30	0.30
Var: Residual	9.05	8.87	9.03	8.98

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table S14. Multilevel regression predicting stance update with match-id as random effect and interactions with own stance. ***Similarity score, expected closeness, experienced closeness, and match stance distance. Controls added. Own Stance is Initial Stance in other regression tables.***

	Model 1	Model 2	Model 3	Model 4
(Intercept)	-0.46^{+}	-0.84	-0.21	-0.47^{+}
	(0.25)	(0.86)	(0.79)	(0.24)
Scaled Similarity Score	-0.02			
	(0.26)			
Match Type: Against → in Favor	1.80^{***}	0.02	-0.47	2.52^{***}
	(0.35)	(1.00)	(1.09)	(0.66)
Match Type: in Favor → in Favor	1.81^{***}	-0.00	0.40	1.83^{***}
	(0.31)	(1.04)	(0.97)	(0.30)
Match Type: in Favor → Against	0.05	1.83^{+}	1.47	0.08
	(0.28)	(0.95)	(0.99)	(0.44)
Scaled Similarity Score x Match Type: Against → in Favor	-0.02			
	(0.34)			
Scaled Similarity Score x Match Type: in Favor → in Favor	0.02			
	(0.31)			
Scaled Similarity Score x Match Type: in Favor → Against	-0.08			
	(0.31)			
Experienced Closeness		0.07		
		(0.15)		
Experienced Closeness x Match Type: Against → in Favor		0.53^{**}		
		(0.20)		
Experienced Closeness x Match Type: in Favor → in Favor		0.34^{+}		
		(0.19)		
Experienced Closeness x Match Type: in Favor → Against		-0.41^{*}		
		(0.18)		
Expected Closeness			-0.05	
			(0.16)	
Expected Closeness x Match Type: Against → in Favor			0.48^{*}	
			(0.22)	
Expected Closeness x Match Type: in Favor → in Favor			0.28	
			(0.19)	
Expected Closeness x Match Type: in Favor → Against			-0.28	
			(0.19)	
Match Stance Distance				-0.02
				(0.02)
Match Stance Distance x Match Type: Against → in Favor				-0.01
				(0.04)
Match Stance Distance x Match Type: in Favor → in Favor				0.08^{**}
				(0.03)
Match Stance Distance x Match Type: in Favor → Against				0.02
				(0.03)
AIC	5441.95	5392.53	5426.10	5445.94
BIC	5491.69	5442.25	5475.83	5495.68
Log Likelihood	-2710.98	-2686.26	-2703.05	-2712.97
Num. obs.	1068	1067	1068	1068
Num. groups: matchId	146	146	146	146
Var: matchId (Intercept)	0.31	0.47	0.38	0.25
Var: Residual	9.10	8.57	8.88	9.02

$^{***}p < 0.001, ^{**}p < 0.01, ^{*}p < 0.05, ^{+}p < 0.1$

Table S15. Multilevel regression predicting stance update with match-id as random effect and interactions with match type (4 categories). ***Similarity score, expected closeness, experienced closeness, and match stance distance.***

	Model 1	Model 2	Model 3	Model 4
(Intercept)	-0.97 (0.54)	-1.69 (0.97)	-0.93 (0.92)	-0.76 (0.54)
Scaled Similarity Score	-0.02 (0.27)			
Scaled Similarity Score x Match Type: Against $\rightarrow$ in Favor	-0.00 (0.35)			
Scaled Similarity Score x Match Type: in Favor $\rightarrow$ in Favor	0.01 (0.31)			
Scaled Similarity Score x Match Type: in Favor $\rightarrow$ Against	-0.07 (0.31)			
Experienced Closeness		0.11 (0.16)		
Experienced Closeness x Match Type: Against $\rightarrow$ in Favor		$0.54\ (0.20)^{**}$		
Experienced Closeness x Match Type: in Favor $\rightarrow$ in Favor		0.33 (0.19)		
Experienced Closeness x Match Type: in Favor $\rightarrow$ Against		$-0.50\ (0.18)^{**}$		
Expected Closeness			-0.01 (0.16)	
Expected Closeness x Match Type: Against $\rightarrow$ in Favor			$0.44\ (0.22)^{*}$	
Expected Closeness x Match Type: in Favor $\rightarrow$ in Favor			0.23 (0.19)	
Expected Closeness x Match Type: in Favor $\rightarrow$ Against			-0.31 (0.20)	
Match Stance Distance				-0.01 (0.03)
Match Stance Distance x Match Type: Against $\rightarrow$ in Favor				-0.01 (0.04)
Match Stance Distance x Match Type: in Favor $\rightarrow$ in Favor				$0.08\ (0.03)^{**}$
Match Stance Distance x Match Type: in Favor $\rightarrow$ Against				0.03 (0.03)
Match Type: Against $\rightarrow$ in Favor	$1.82\ (0.35)^{***}$	0.08 (1.01)	-0.26 (1.10)	$2.26\ (0.72)^{**}$
Match Type: in Favor $\rightarrow$ in Favor	$1.89\ (0.40)^{***}$	0.72 (1.07)	0.79 (1.03)	$1.23\ (0.52)^{*}$
Match Type: in Favor $\rightarrow$ Against	0.14 (0.38)	$2.95\ (1.04)^{**}$	1.81 (1.06)	-0.08 (0.46)
Gender: Male	-0.17 (0.19)	-0.19 (0.19)	-0.16 (0.19)	-0.17 (0.19)
Gender: Other	0.24 (2.18)	0.97 (2.12)	0.22 (2.16)	0.19 (2.16)
Income	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Social Media Use: Rare	0.66 (0.45)	0.66 (0.44)	0.62 (0.45)	0.67 (0.45)
Social Media Use: Somewhat Active	0.32 (0.42)	0.32 (0.41)	0.32 (0.42)	0.34 (0.42)
Social Media Use: Very Active	0.34 (0.45)	0.33 (0.44)	0.30 (0.45)	0.33 (0.45)
Match Believed Real	0.23 (0.24)	0.12 (0.24)	0.20 (0.24)	0.23 (0.24)
Party: Independent	0.32 (0.28)	0.39 (0.27)	0.37 (0.28)	0.34 (0.27)
Party: Democrat	$0.53\ (0.27)^{*}$	0.42 (0.26)	0.52 (0.27)	$0.68\ (0.27)^{*}$
Initial Stance	-0.02 (0.01)	$-0.04\ (0.01)^{**}$	-0.02 (0.01)	0.01 (0.02)
AIC	5471.08	5416.29	5455.67	5469.96
BIC	5570.55	5515.74	5555.14	5569.43
Log Likelihood	-2715.54	-2688.14	-2707.83	-2714.98
Num. obs.	1068	1067	1068	1068
Num. groups: matchId	146	146	146	146
Var: matchId (Intercept)	0.33	0.52	0.41	0.26
Var: Residual	9.07	8.48	8.85	8.96

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table S16. Multilevel regression predicting stance update with match-id as random effect and interactions with match type (4 categories). ***Similarity score, expected closeness, experienced closeness, and match stance distance. Controls added.***

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.51^{**}	0.72^{*}	0.88^{+}	0.51^{**}
	(0.18)	(0.34)	(0.50)	(0.17)
Scaled Similarity Score	-0.13			
	(0.17)			
Consistent Stance	0.26	-1.59^{**}	-0.97	0.23
	(0.20)	(0.59)	(0.67)	(0.20)
Scaled Similarity Score x Consistent Stance	0.13			
	(0.19)			
Experienced Closeness		-0.06		
		(0.07)		
Experienced Closeness x Consistent Stance		0.36^{**}		
		(0.12)		
Expected Closeness			-0.08	
			(0.09)	
Expected Closeness x Consistent Stance			0.25^{+}	
			(0.13)	
Match Stance Distance				0.02^{***}
				(0.01)
Match Stance Distance x Consistent Stance				0.01
				(0.01)
AIC	5478.44	5465.52	5477.00	5476.86
BIC	5508.28	5495.35	5506.84	5506.70
Log Likelihood	-2733.22	-2726.76	-2732.50	-2732.43
Num. obs.	1068	1067	1068	1068
Num. groups: matchId	146	146	146	146
Var: matchId (Intercept)	1.10	1.14	1.08	0.69
Var: Residual	9.04	8.93	9.01	9.13

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table S17. Multilevel regression predicting stance update with match-id as random effect and interactions with match type (2 categories). ***Similarity score, expected closeness, experienced closeness, and match stance distance.***

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.05	0.26	0.41	-0.26
	(0.50)	(0.57)	(0.67)	(0.49)
Scaled Similarity Score	-0.11			
	(0.17)			
Consistent Stance	0.24	-1.55^{**}	-1.00	0.06
	(0.20)	(0.60)	(0.67)	(0.20)
Scaled Similarity Score x Consistent Stance	0.12			
	(0.20)			
Experienced Closeness		-0.04		
		(0.08)		
Experienced Closeness x Consistent Stance		0.35^{**}		
		(0.12)		
Expected Closeness			-0.07	
			(0.09)	
Expected Closeness x Consistent Stance			0.25^{+}	
			(0.13)	
Match Stance Distance				0.07^{***}
				(0.01)
Match Stance Distance x Consistent Stance				0.01
				(0.01)
Gender: Male	-0.18	-0.15	-0.18	-0.20
	(0.20)	(0.20)	(0.20)	(0.19)
Gender: Other	0.59	1.01	0.51	0.30
	(2.21)	(2.20)	(2.20)	(2.17)
Income	-0.00	-0.00^{+}	-0.00^{+}	-0.00^{+}
	(0.00)	(0.00)	(0.00)	(0.00)
Social Media Use: Rare	0.64	0.69	0.64	0.73
	(0.45)	(0.45)	(0.45)	(0.45)
Social Media Use: Somewhat Active	0.29	0.33	0.30	0.38
	(0.43)	(0.43)	(0.43)	(0.42)
Social Media Use: Very Active	0.37	0.38	0.34	0.43
	(0.46)	(0.45)	(0.46)	(0.45)
Match Believed Real	0.22	0.11	0.18	0.24
	(0.25)	(0.25)	(0.25)	(0.24)
Party: Independent	0.34	0.38	0.40	0.32
	(0.28)	(0.28)	(0.28)	(0.28)
Party: Democrat	0.56^{*}	0.52^{+}	0.58^{*}	0.56^{*}
	(0.27)	(0.27)	(0.27)	(0.27)
Initial Stance	-0.01	-0.01	-0.01	0.06^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
AIC	5508.39	5495.34	5506.66	5474.38
BIC	5587.97	5574.90	5586.24	5553.95
Log Likelihood	-2738.20	-2731.67	-2737.33	-2721.19
Num. obs.	1068	1067	1068	1068
Num. groups: matchId	146	146	146	146
Var: matchId (Intercept)	1.13	1.17	1.12	0.38
Var: Residual	9.01	8.90	8.98	9.02

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table S18. Multilevel regression predicting stance update with match-id as random effect and interactions with match type (2 categories). ***Similarity score, expected closeness, experienced closeness, and match stance distance. Controls added.***

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.17	0.78^{*}	1.09^{*}	0.44^{+}
	(0.16)	(0.38)	(0.47)	(0.24)
Scaled Similarity Score	-0.13			
	(0.16)			
Match Is More in Favor	0.93^{***}	-1.68^{**}	-1.93^{**}	0.72^{*}
	(0.21)	(0.55)	(0.67)	(0.33)
Scaled Similarity Score x Match Is More in Favor	0.09			
	(0.20)			
Experienced Closeness		-0.12^{+}		
		(0.07)		
Experienced Closeness x Match Is More in Favor		0.55^{***}		
		(0.11)		
Expected Closeness			-0.19^{*}	
			(0.09)	
Expected Closeness x Match Is More in Favor			0.59^{***}	
			(0.13)	
Match Stance Distance				0.02
				(0.01)
Match Stance Distance x Match Is More in Favor				-0.02
				(0.02)
AIC	5462.98	5433.25	5444.56	5471.04
BIC	5492.82	5463.08	5474.40	5500.88
Log Likelihood	-2725.49	-2710.62	-2716.28	-2729.52
Num. obs.	1068	1067	1068	1068
Num. groups: matchId	146	146	146	146
Var: matchId (Intercept)	0.70	0.99	0.75	0.68
Var: Residual	9.10	8.71	8.89	9.10

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table S19. Multilevel regression predicting stance update with match-id as random effect and interactions with directional stance. ***Similarity score, expected closeness, experienced closeness, and match stance distance.***

	Model 1	Model 2	Model 3	Model 4
(Intercept)	-1.28^{*}	-0.47	-0.38	-1.03^{+}
	(0.54)	(0.67)	(0.68)	(0.57)
Scaled Similarity Score	-0.05			
	(0.14)			
Match Is More In Favor	0.81^{**}	-2.78^{***}	-1.75^{*}	0.73^{*}
	(0.30)	(0.73)	(0.71)	(0.33)
Scaled Similarity Score x Match Is More in Favor	0.01			
	(0.20)			
Experienced Closeness		-0.14^{+}		
		(0.08)		
Experienced Closeness x Match Is More in Favor		0.66^{***}		
		(0.12)		
Expected Closeness			-0.17^{*}	
			(0.09)	
Expected Closeness x Match Is More in Favor			0.51^{***}	
			(0.13)	
Match Stance Distance				0.03
				(0.02)
Match Stance Distance x Match Is More in Favor				-0.03
				(0.03)
Gender: Male	-0.18	-0.15	-0.17	-0.18
	(0.19)	(0.19)	(0.19)	(0.19)
Gender: Other	0.23	-0.10	0.40	0.17
	(2.17)	(2.14)	(2.15)	(2.17)
Income	-0.00^{+}	-0.00^{+}	-0.00^{+}	-0.00^{+}
	(0.00)	(0.00)	(0.00)	(0.00)
Social Media Use: Rare	0.69	0.66	0.62	0.71
	(0.45)	(0.44)	(0.44)	(0.45)
Social Media Use: Somewhat Active	0.34	0.26	0.33	0.35
	(0.42)	(0.42)	(0.42)	(0.42)
Social Media Use: Very Active	0.38	0.28	0.35	0.39
	(0.45)	(0.44)	(0.45)	(0.45)
Match Believed Real	0.23	0.13	0.21	0.22
	(0.24)	(0.24)	(0.24)	(0.24)
Party: Independent	0.36	0.43	0.43	0.37
	(0.28)	(0.27)	(0.27)	(0.28)
Party: Democrat	0.54^{*}	0.50^{+}	0.54^{*}	0.60^{*}
	(0.27)	(0.26)	(0.26)	(0.27)
Initial Stance	-0.00	-0.02	-0.00	0.01
	(0.01)	(0.02)	(0.01)	(0.02)
Match Type: Against → in Favor	1.42^{***}	2.36^{***}	1.48^{***}	1.41^{**}
	(0.37)	(0.41)	(0.37)	(0.55)
Match Type: in Favor → in Favor	1.53^{***}	1.93^{***}	1.55^{***}	1.24^{*}
	(0.42)	(0.43)	(0.42)	(0.52)
Match Type: in Favor → Against	0.21	0.34	0.26	0.35
	(0.38)	(0.38)	(0.38)	(0.40)
AIC	5461.34	5424.66	5447.14	5466.50
BIC	5555.84	5519.14	5541.64	5561.00
Log Likelihood	-2711.67	-2693.33	-2704.57	-2714.25
Num. obs.	1068	1067	1068	1068
Num. groups: matchId	146	146	146	146
Var: matchId (Intercept)	0.26	0.42	0.31	0.29
Var: Residual	9.05	8.65	8.88	9.00

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table S20. Multilevel regression predicting stance update with match-id as random effect and interactions with directional stance. ***Similarity score, expected closeness, experienced closeness, and match stance distance. Controls added.***

F. Social Influence and Stance Update. Here we provide additional analyses to support and to extend the results reported in the main text, about polarization reduction and increase in support for redistribution.

F.1. Positive Social Influence. Fig. S9B shows the scatter plot of stance update vs stance distance from the match. The sign of the stance distance indicates whether the match is more in favor (> 0) or more against (< 0) than the reference respondent. Quadrants *II* and *IV* contain data points from respondents who updated their stance to become more similar to their match's stance. As the regression line passes close to the origin (0,0) and largely through those quadrants, this is evidence of positive social influence.

We find a similar pattern if we disaggregate this analysis for respondents who are initially in favor, and initially against, redistribution (Fig. S9C). For the latter, the regression lines goes almost precisely through the origin, but for the former it is shifted back and it crosses the x-axis after passing through quadrant *I*. This might indicate the presence negative social influence or a backfire effect (14). However, this effect is limited, as that portion of the space is mainly occupied by respondents who are strongly in favor of redistribution and are matched with respondents who are less in favor—but still in favor—so it is mostly a reinforcement effect, as we show in the next subsections.

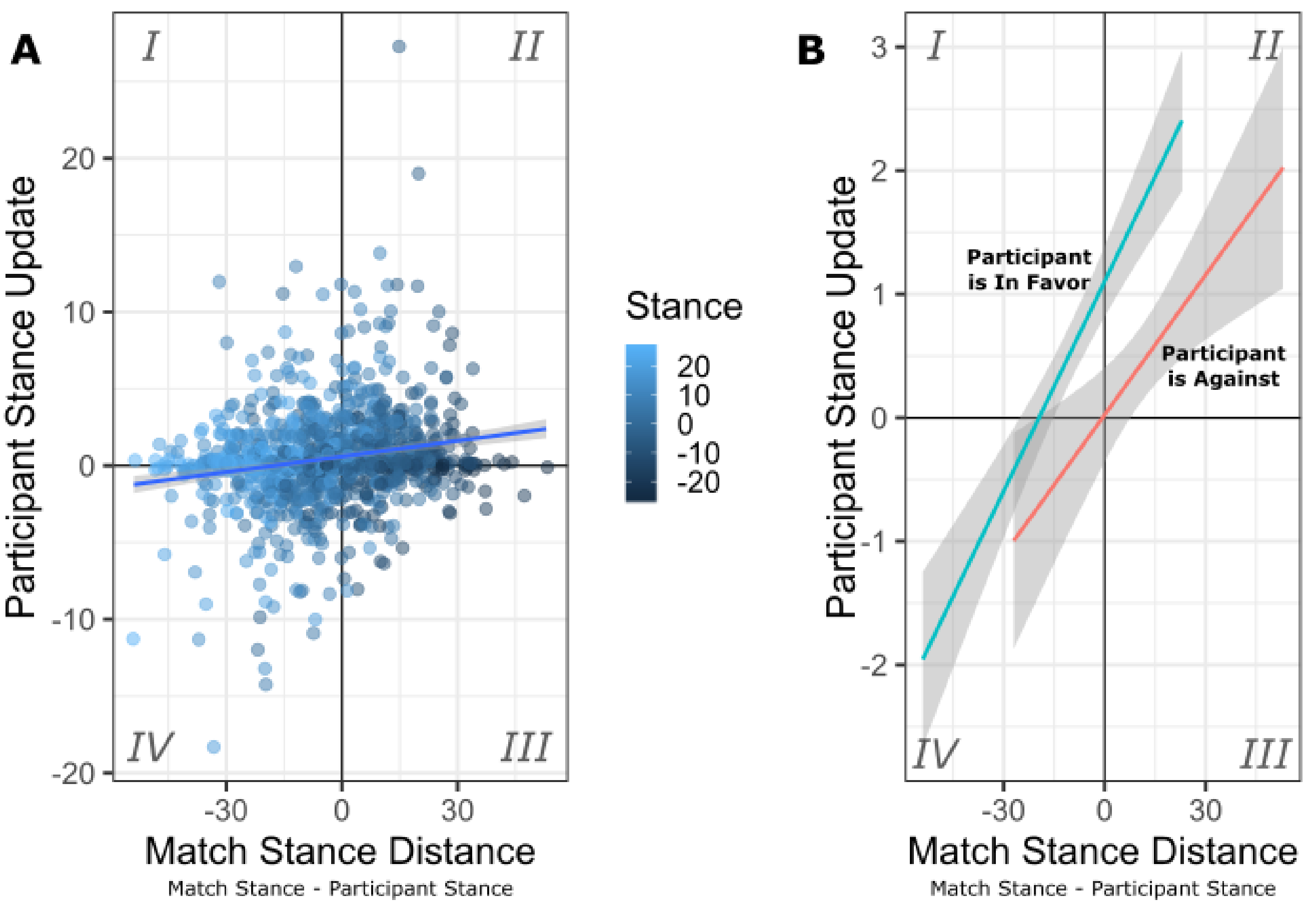

Fig. S9. Informal political communication leads to positive social influence. A positive stance update indicates that a participant has become more in favor of redistribution after the interaction, whereas a negative stance update indicates that a participant has become more against it; the match stance distance is computed as the difference between the stance of the match and the stance of the participant: positive values indicate that the match is more in favor of redistribution than the participant is. **A:** Scatter plot of stance update and distance from the stance of the match (stance ranges from -27 to +27, so the maximum stance distance for two persons at the antipodes for their views on redistribution is equal to 54). **B:** Regression lines predicting stance update with the distance from the match stance for respondents in favor and against redistribution. Shaded areas are 95% CI.

F.2. Polarization reduction: Diff-in-diff extended analysis. In Fig. 4C in the main text we showed the average diff-in-diff measure binned by stance distance from the match. We argued that there exists a distance for which polarization reduction is largest and that the the main reason for that lies in the composition of the type of interactions within that distance: i.e., mainly cross-stance interactions with fewer participants with strong views (see Tab. S21).

Bin	Obs.	Strong Views	Same Stance	Both
[0,5]	234	0.34	0.94	0.34
(5,10]	224	0.27	0.70	0.27
(10,15]	184	0.29	0.53	0.26
(15,20]	**138**	**0.38**	**0.34**	**0.20**
(20,25]	109	0.57	0.17	0.09
(25,30]	79	0.70	0.06	0.05
(30,55]	99	0.86	0.00	0.00

Table S21. Descriptive statistics for diff-in-diff bins. Shares of same-stance interactions and interactions with participants with strong views in each stance distance bin. In bold the distance bin (15,20] for which polarization reduction is largest.

As shown in Fig. S10A, cross-stance interactions are generally more effective than same-stance interactions to reduce polarization at different bins. Hence, the peak at bin (15,20] in Fig.4C is mainly generated by cross-stance interactions, however for same-stance interactions this bin holds the second-largest reduction in polarization (albeit not significant). In Fig. S10B, we can observe at a more fine grained level what types of interactions lead to large reductions in polarization. As also reported in the main text, participants with mild views have the largest reductions: this is the case when the match is more in favor of the participant, that is mildly or strongly in favor for mildly against participants, and strongly in favor for mildly in favor participants (confirming the pro-redistribution bias reported in the main text). These types of interactions are expected to be found in the interval (15,20], but not exclusively.

In Fig. 4C, the bin [0,5] is the only one in which the participants move further apart from the match, whereas in the all others the distance is either reduced or remains statistically unchanged. Our analysis reveals that in the distance bin [0,5] just 6% of the interactions are cross stance, meaning that this distancing is likely to be a reinforcement effect. As a robustness check, we removed all the observations (9%) for which the diff-in-diff cannot be negative—initial stance distance equal to zero (same stance only obviously)—and repeated the analysis. We find that in the bin [0,5] the diff-in-diff remains positive but only marginally significant ($p < 0.1$), confirming qualitatively the reinforcement effect in the bin [0,5].

Finally, the diff-in-diff measure does not capture "overshooting interactions," that is those cases in which the stance update in the direction of the match is larger than the distance from the stance of the match itself. For instance, a participant with an initial stance of $+5$, matched with participant with stance $+4$, ending up with an updated stance of $+2$, will result in a positive diff-in-diff, even if the entire initial stance gap has been filled. In the entire dataset, only 2% of the interactions overshot (25 cases), of which: 80% in the [0-5] bin, 16% in (5-10] bin, 4% in the (10-15] bin (just 1 obs); and of which: 92% are same-stance interactions, and the remaining 8% (2 obs) are one each in the 5-10 and 10-15 bins. To correct for this possible bias, we set the diff-in-diff for all overshot interactions to zero, and the results did not change qualitatively.

In conclusion, same-stance interactions are less effective at reducing polarization, and at small distances they are even more likely lead to a reinforcement effect. Cross-stance interactions in general, and those at intermediate distances in particular, are the most effective at polarization reduction.

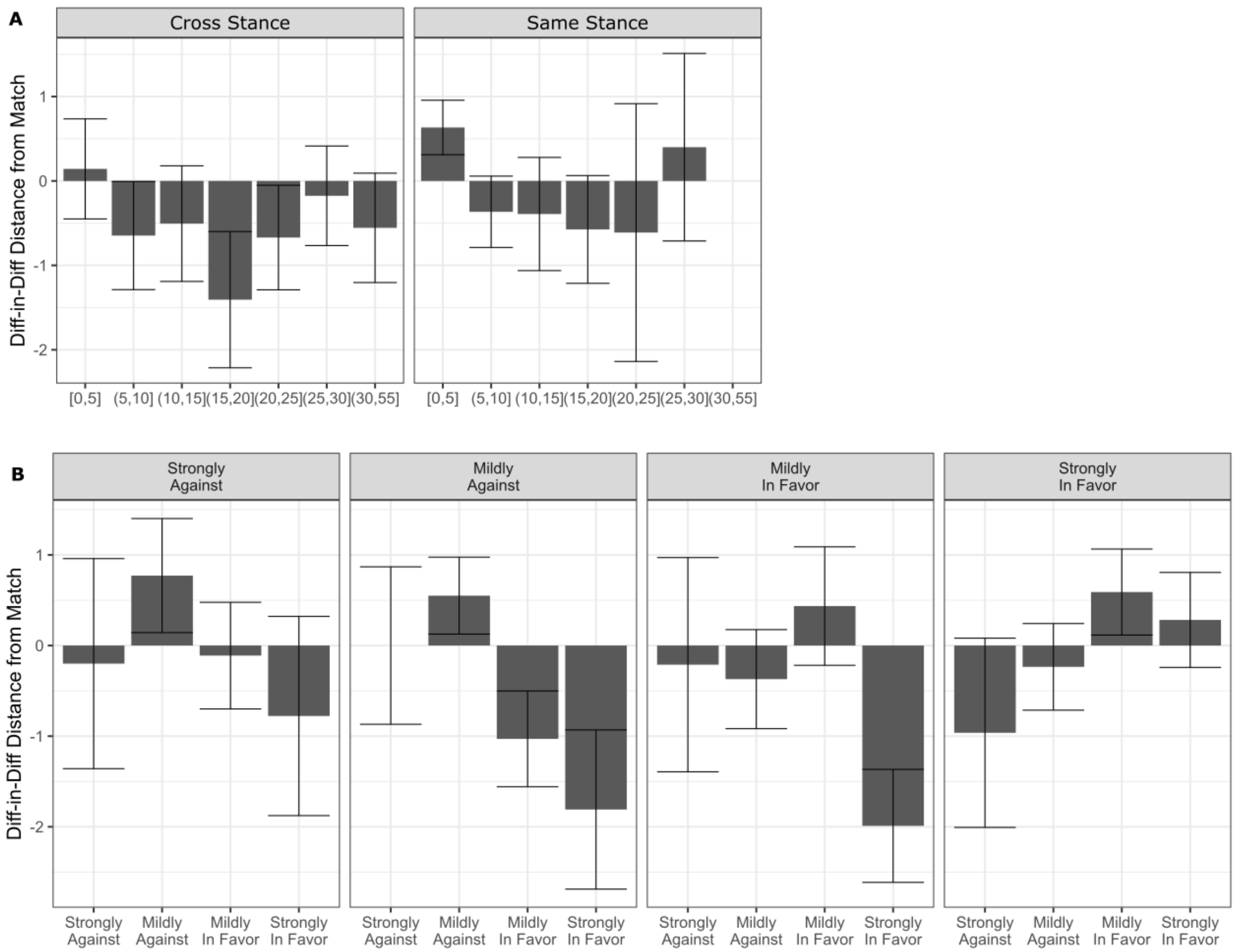

Fig. S10. Diff-in-diff extended analysis. Negative values indicate the distance from the match's stance is reduced, positive values that it increased. **A.** Match type vs match stance distance. **B.** Participant stance type vs match stance type. Outer boxes indicate the participant stance type, and inner columns the stance type of the match. Error bars 95% CI.

F.3. Backfire Effect. An interaction is said to "backfire" if a respondent's views towards redistribution become more extreme after it. However, not all interactions are eligible to generate a backfire effect. In fact, it is required that the match views are "sufficiently different" from the respondents' views. How do we define different? We can set an *absolute* threshold and count all interactions with someone holding the opposite stance, i.e., a respondent who is in favor of redistribution interacting with someone who is against it and vice versa. In our sample, 49% of the interactions are between opposite stances, and about 25% of these lead to a backfire effect. However, backfires are unevenly distributed: for respondents who are initially against the rate is close to 18%, while for respondents who are initially in favor the rate is almost 30%.

Computing the backfire effect with an absolute threshold does not take into account that two participants with opposite stances may in fact hold very similar views around the indifference point (i.e., close to zero, but one in the positive realm and the other one in the negative realm). Likewise, two participants holding the same stance but very far apart, may perceive each other as different (e.g., a participant strongly in favor and one with a stance just above zero). So, we also computed a *relative* backfire effect, measured as a function of the distance between two stance positions, for different distance thresholds.

In Fig. S11A we report the share of all interactions with someone *holding a more moderate or opposite stance* that backfired (therefore leading to more extreme views in either direction), at every 5-units of stance distance. That is: the first column in the plot includes all eligible interactions, the second column all interactions with someone more than 5 stance-units away, the third column more than 10 stance-units away, and so on. The results are consistent with the absolute backfire levels (horizontal red lines), with some deviations for larger stance distances (however, the last columns contain few observations and might not be reliable).

Finally, if we disaggregate by same-stance vs cross-stance interactions (Fig. S11B), we observe a stronger backfire effect within same-stance interactions. This indicates the presence of a *reinforcement* effect for someone holding stronger views interacting with someone with similar but more moderate views.

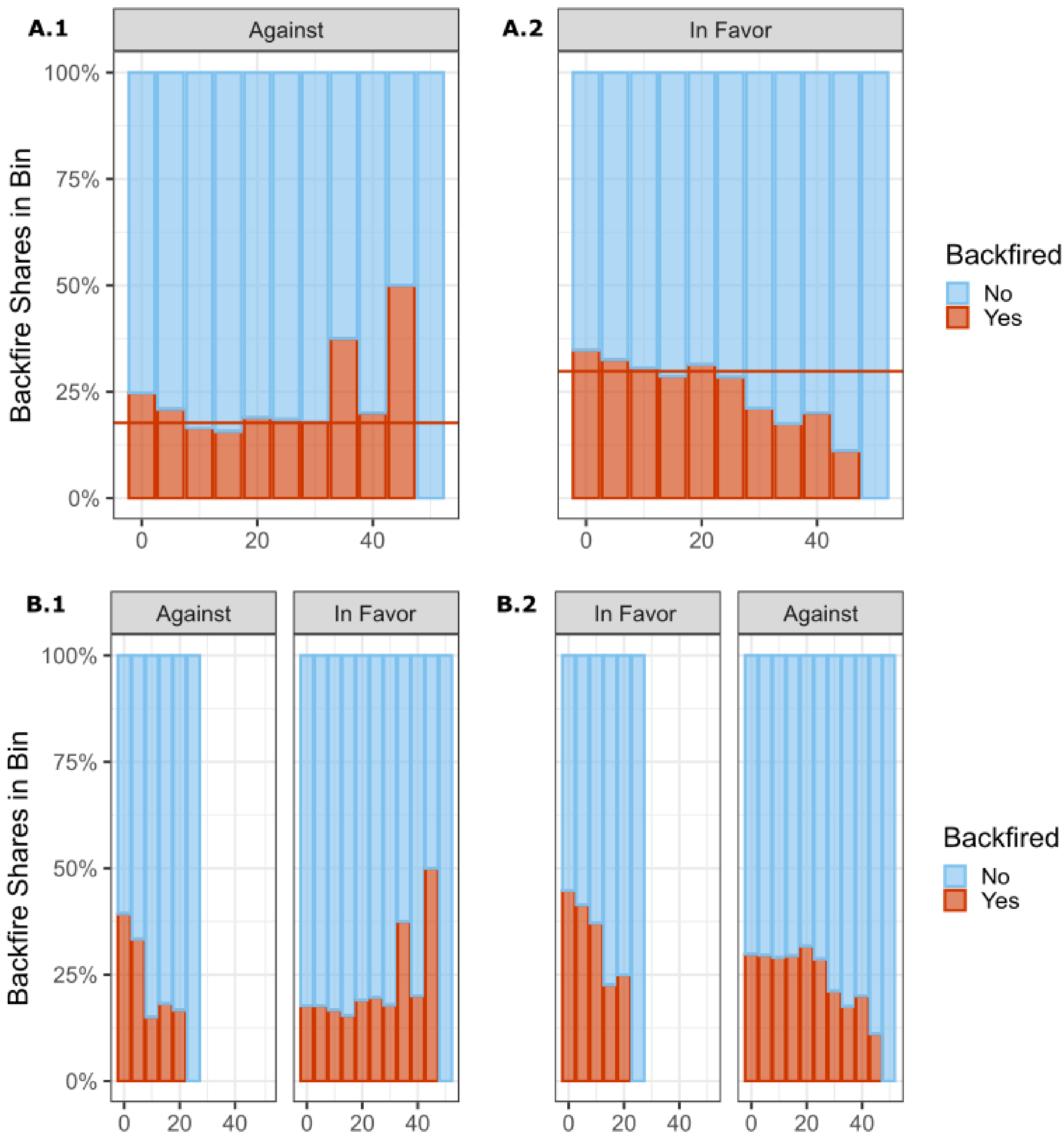

Fig. S11. Relative backfire effect for different distance thresholds. A. By initial stance. **B.** By initial stance (left and right) and match type (inner panels). X-axis indicates the relative distance thresholds (i.e., stance distance must be strictly greater than threshold). Red horizontal lines display the absolute backfire effect levels.

F.4. Consensus Gap. We ran multilevel logistic regressions to quantify how the feeling of closeness changes the probability of reducing the consensus gap (Tab. S22). To do so, we created a dummy variable equal to 1 if the stance distance between a respondent and his or her match became smaller after the interaction, or equal to 0 if the gap remained the same or increased.

We did not preregister this analysis, however the coefficients for both closeness measures are strongly significant after controlling for the match type, which gives us confidence in the robustness of the regression results. We used the same controls that we preregistered for the rest of the analysis; however the logistic models did not converge when both stance and party affiliation were used as regressors, so we included only stance (results did not change including only party affiliation).

Taking Model 4 from Tab. S22 as reference, one unit-increase in closeness increases the odds of reducing the consensus gap by about 16.3%. In terms of probabilities, we can insert the values in the following model:[¶]

$$P_d = -2.23613 + 0.15089 * C + 1.60719 * AF + 0.99379 * FF + 1.06132 * FA$$

and compute the probability ratio of two extreme values of closeness (1 and 7). Respectively, for the match types Against–Against, Against–In Favor, In Favor–Against, In Favor–In Favor, we get the following probability ratios: 1.13, 0.58, 0.80, 0.80. This means that on average, respondents who develop a strong feeling of closeness (value=7) are 82% more likely to converge towards the political views of their match, than those who do not develop closeness at all (value=1). Expressed in percentage points, this is an average increase of 19%.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
(Intercept)	-0.89^{***}	-1.30^{***}	-2.24^{***}	-2.17^{***}	-2.92^{***}	-2.96^{***}	-2.58^{***}	-2.60^{***}
	(0.19)	(0.25)	(0.30)	(0.31)	(0.47)	(0.48)	(0.32)	(0.32)
Experienced Closeness	0.07^{*}		0.15^{***}		0.13^{**}		0.14^{***}	
	(0.04)		(0.04)		(0.04)		(0.04)	
Expected Closeness		0.15^{**}		0.15^{**}		0.15^{**}		0.16^{***}
		(0.05)		(0.05)		(0.05)		(0.05)
Match Type: Against → in Favor			1.61^{***}	1.35^{***}	1.60^{***}	1.38^{***}	1.61^{***}	1.37^{***}
			(0.27)	(0.26)	(0.27)	(0.26)	(0.27)	(0.26)
Match Type: in Favor → in Favor			0.99^{***}	0.94^{***}	2.02^{***}	2.01^{***}	1.99^{***}	1.96^{***}
			(0.23)	(0.23)	(0.30)	(0.30)	(0.30)	(0.30)
Match Type: in Favor → Against			1.06^{***}	0.85^{***}	2.04^{***}	1.89^{***}	2.02^{***}	1.85^{***}
			(0.23)	(0.22)	(0.30)	(0.29)	(0.30)	(0.29)
Initial Stance					-0.05^{***}	-0.05^{***}	-0.05^{***}	-0.05^{***}
					(0.01)	(0.01)	(0.01)	(0.01)
Gender: Male					-0.24^{+}	-0.24^{+}		
					(0.14)	(0.14)		
Gender: Other					0.56	0.36		
					(1.46)	(1.45)		
Scaled Income					0.01	0.04		
					(0.07)	(0.07)		
Social Media Use: Rare					0.40	0.37		
					(0.35)	(0.35)		
Social Media Use: Somewhat Active					0.64^{+}	0.65^{+}		
					(0.33)	(0.33)		
Social Media Use: Very Active					0.45	0.42		
					(0.35)	(0.35)		
Match Believed Real					-0.03	-0.01		
					(0.18)	(0.18)		
AIC	1402.15	1397.23	1367.15	1371.91	1345.04	1346.46	1340.70	1343.10
BIC	1417.07	1412.15	1396.98	1401.75	1414.65	1416.09	1375.50	1377.92
Log Likelihood	-698.07	-695.62	-677.57	-679.95	-658.52	-659.23	-663.35	-664.55
Num. obs.	1067	1068	1067	1068	1067	1068	1067	1068
Num. groups: matchId	146	146	146	146	146	146	146	146
Var: matchId (Intercept)	0.10	0.11	0.09	0.09	0.08	0.08	0.08	0.08

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table S22. Multilevel logistic regression predicting a decrease in the consensus gap after the interaction with match-id as random effect. Dummy 1=(consensus gap reduced) and 0=(not changed or increased).

F.5. Asymmetric Update Pro Redistribution. Result 1 in the main text argued that participants asymmetrically updated their views in favor of redistribution. Fig. S12 shows that the effect is larger for participant holding mild views (in favor or against redistribution); the effect is still there for participants strongly in favor of redistribution, while it disappears for those strongly against it. However, the sample size for strongly against participants is of 45 participants in each column, so the analysis for this stance category might be underpowered.

[¶] In this model, C is the level of closeness and AF, FF, FA are dummies for the type of match (omitted base level AA Against–Against)

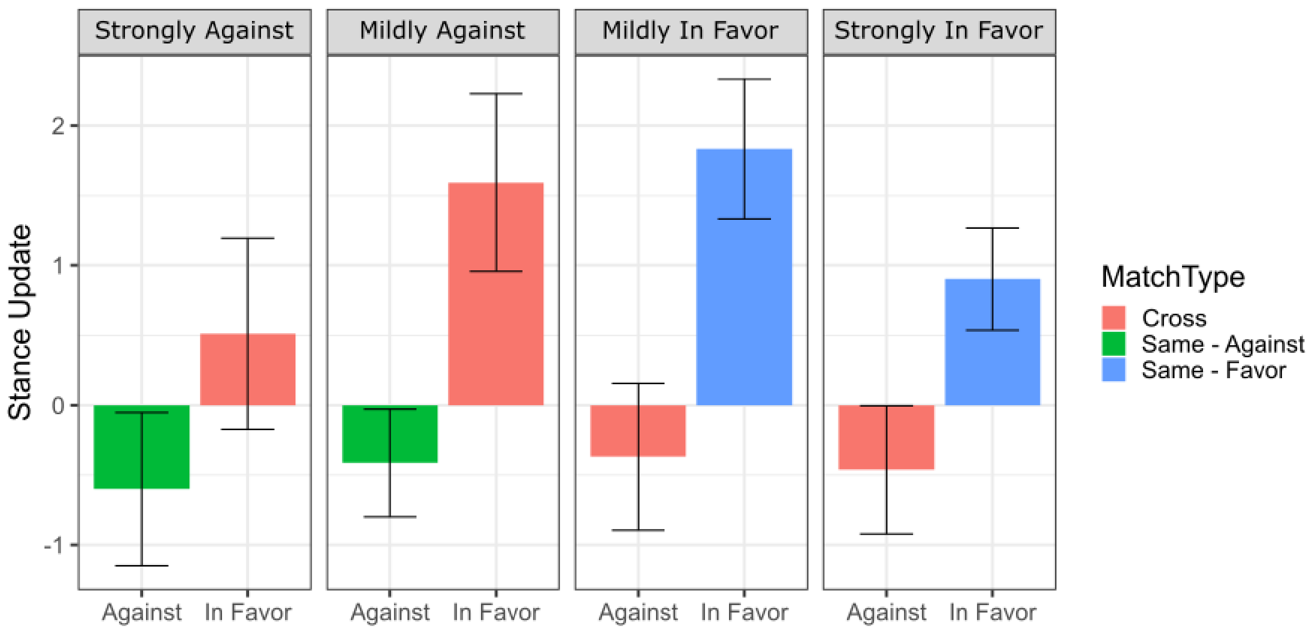

Fig. S12. Average stance update by stance category and the stance of the match (columns within boxes) Negative values indicate the support is reduced, while positive values indicate the support is increased. Error bars 95% CI.

F.6. Closeness Moderates Stance Update for Participants with Strong and Mild Views. The feeling of closeness moderates assimilation of political views for participants with both strong and mild views, however the effect is larger for participants with mild views (see Fig. S13).

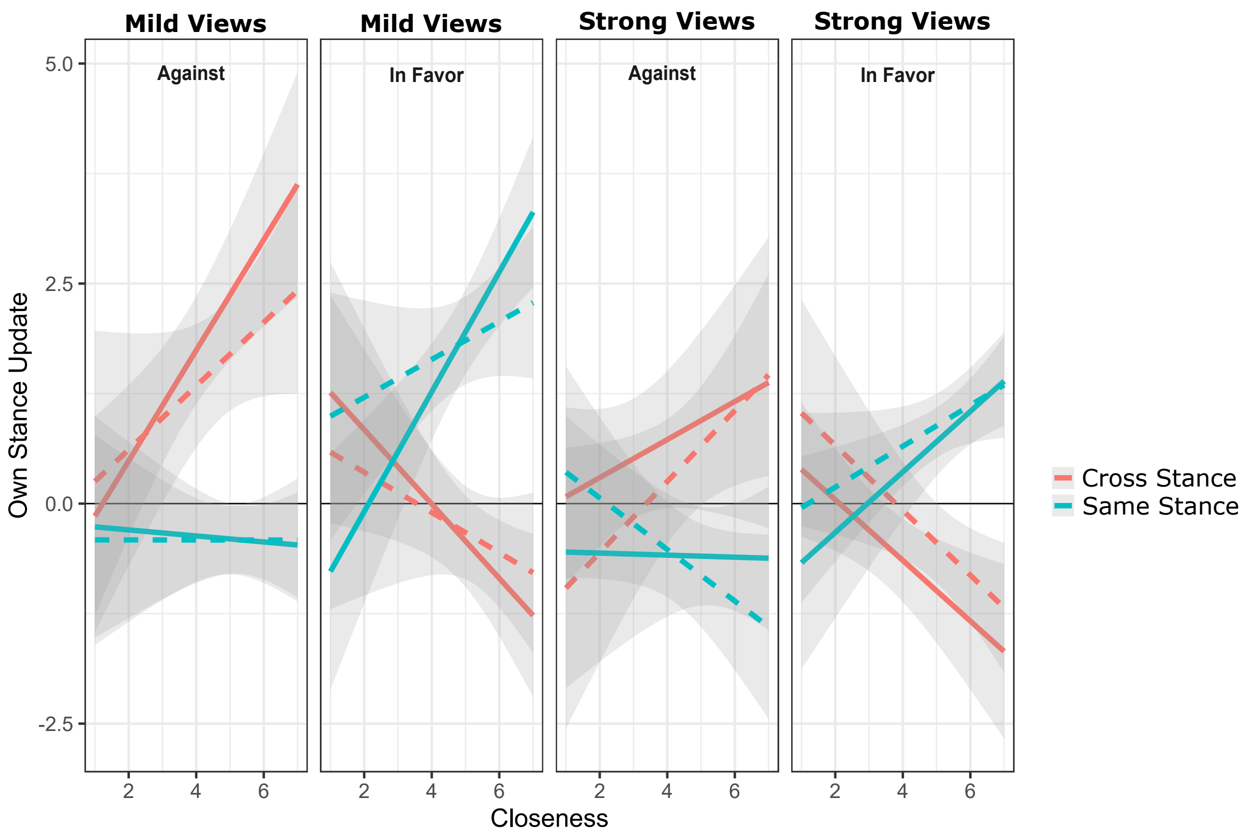

Fig. S13. The feeling of closeness moderates assimilation of political views for participants with both strong and mild views. Regression slopes predicting stance update after the political interaction using expected (dashed lines) and experienced (solid lines) closeness. Positive values indicate that the person has become more in favor of redistribution. Shaded areas are 95% confidence intervals.

G. Feelings of Closeness and Similarity. In our regression analysis in Sec. E, the similarity index alone is not significant for predicting the stance update, while closeness is. This may appear surprising given its correlation with both measures of closeness (Fig. S14B). Therefore, here we perform additional exploratory analysis on the relationship between the similarity index and expected closeness for different levels of the similarity index.

First, we looked at higher order polynomial regressions (Tab. S23). Albeit not significant, the square term for the scaled similarity index is negative, while its cube is positive, but smaller in size than the linear term (Model 2, and Model 3). This suggests a positive effect of similarity on expected closeness overall, but a larger effect when similarity increases from low to moderate, rather than from moderate to high.

To further investigate this issue we performed regression discontinuity analysis with different cutoff thresholds. The goal is to detect jumps expected closeness, as similarity varies (Fig. S15). Visual inspection confirms the same intuition from the polynomial regressions, however, the coefficients in the regression tables S23 and S24 are not significant. Only Model 6 in Tab. S23 indicates a marginally significant ($p < 0.1$) negative effect for a level of scaled closeness larger than -1 (panel C in Fig. S15).

Overall, visual inspections and regression results seem to indicate a stronger effect moving from low to moderate similarity. However, this result should be taken very carefully because of its limited statistical significance and because of the discrete nature of our treatment conditions (low vs high similarity; see Fig. S6), which may invalidate the assumptions for the regression discontinuity analysis—the density of points around a given threshold should not be highly dissimilar.

Another potential issue is that high similarity scores may be perceived ad less credible. In fact, we found that high values of the similarity index are more likely to induce the respondents to believe that the match is fabricated by the experimenter, a belief which in turns reduces closeness (Tab. S25). However, this reduction is small, and perhaps a simpler explanation is that similarity alone is not enough to capture closeness, and that we feel close to people for different reasons.

336 Finally, our analysis does not exclude that a different version of the similarity index (e.g., with different feature weights) might turn out to be significant in predicting stance update, and we leave this avenue for future research.

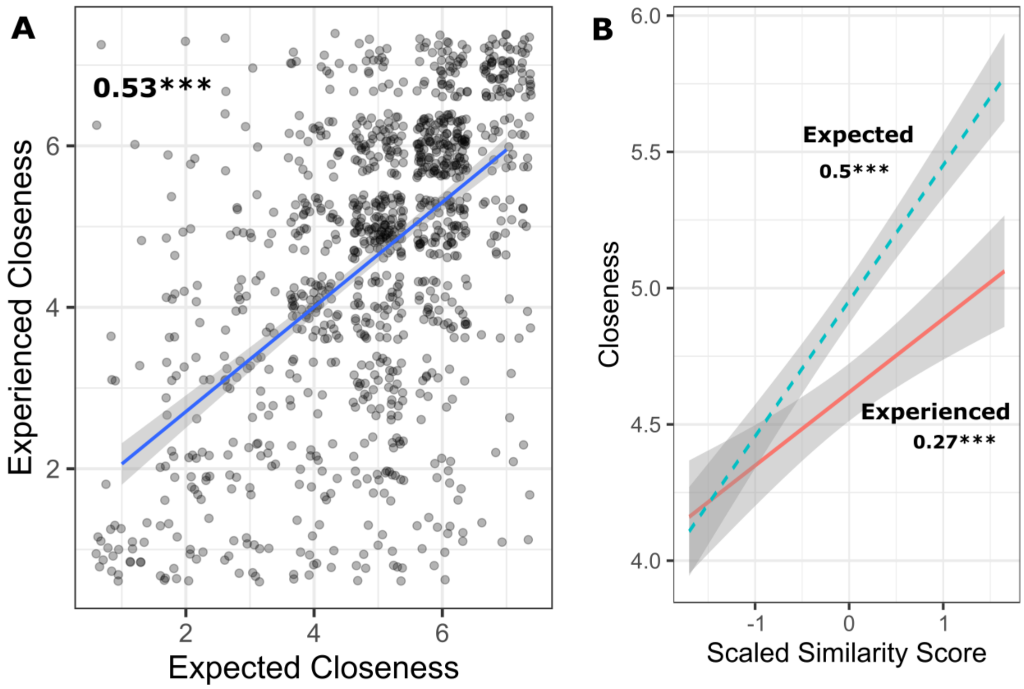

Fig. S14. Feelings of closeness and Similarity. A. Scatter plot expected vs experienced closeness. Number above the regression slope is the Pearson correlation. **B.** Regression slope predicting expected and experienced closeness using the degree of similarity between match and respondent. Number above the regression lines is the coefficient of the regression. Shaded areas and error bars are 95% CI.

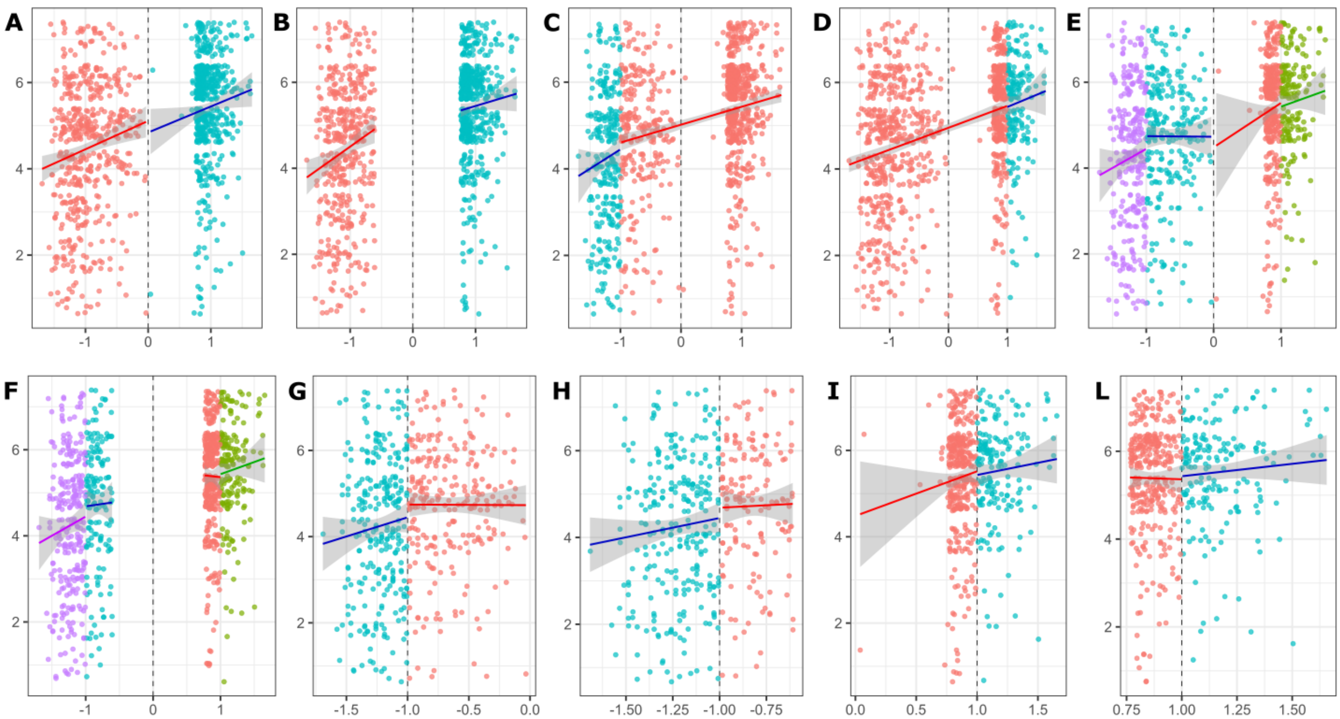

Fig. S15. Discontinuity Analysis: Similarity and Expected Closeness. In all scatter plots in this panel, scaled similarity in on the x-axis and expected closeness in on the y-axis, and the discontinuity threshold is varied. **A,B.** Threshold 0; dropped observations outside of preregistered similarity intervals (*B*). **C** Threshold -1. **D.** Threshold +1. **E,F.** Thresholds -1, 0, and +1 all in the same plot, dropped observations outside of preregistered similarity intervals (*F*). **G,H** Only *low similarity* observations, dropped observations outside preregistered low similarity interval (*G*). **I,L.** Only *high similarity* observations, dropped observations outside preregistered high similarity interval (*L*). Notes: dots are jittered and may slightly vary their position from plot to plot; observations around the thresholds are dropped in some of the plots to make their density less unequal; preregistered low and high similarity thresholds can be found in Sec. C.5 and in Fig. S6; colors have no special meaning and simply highlight observations before and after a threshold cutoff; shaded areas and error bars are 95% CI.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
(Intercept)	4.95^{***}	5.03^{***}	5.02^{***}	5.10^{***}	5.11^{***}	5.02^{***}	5.02^{***}	4.95^{***}	4.95^{***}
	(0.04)	(0.09)	(0.09)	(0.16)	(0.17)	(0.06)	(0.06)	(0.05)	(0.05)
Scaled Sim.	0.50^{***}	0.49^{***}	0.34^{**}	0.64^{***}	0.66^{***}	0.42^{***}	0.41^{***}	0.51^{***}	0.50^{***}
	(0.04)	(0.04)	(0.11)	(0.15)	(0.17)	(0.06)	(0.06)	(0.05)	(0.05)
Scaled Sim.^{2}		-0.08	-0.06						
		(0.08)	(0.08)						
Scaled Sim.^{3}			0.12						
			(0.08)						
High Sim.				-0.30	-0.27				
				(0.30)	(0.35)				
Scaled Sim.:High Sim.					-0.05				
					(0.36)				
Lowest Sim.						-0.26^{+}	0.32		
						(0.14)	(0.70)		
Scaled Sim.:Lowest Sim.							0.47		
							(0.57)		
Highest Sim.								-0.02	-0.09
								(0.13)	(0.81)
Scaled Sim.:Highest Sim.									0.06
									(0.68)
AIC	3734.89	3738.99	3742.05	3736.48	3738.68	3735.65	3736.24	3739.08	3739.99
BIC	3754.79	3763.86	3771.89	3761.35	3768.52	3760.52	3766.08	3763.95	3769.83
Log Likelihood	-1863.45	-1864.49	-1865.03	-1863.24	-1863.34	-1862.82	-1862.12	-1864.54	-1864.00
Num. obs.	1068	1068	1068	1068	1068	1068	1068	1068	1068
Num. groups: matchId	146	146	146	146	146	146	146	146	146
Var: matchId (Intercept)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Var: Residual	1.91	1.91	1.90	1.91	1.91	1.90	1.90	1.91	1.91

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table S23. Multilevel regression predicting expected closeness with match-id as random effect. Models 1-3 test polynomial terms of scaled similarity; Models 4-9 test discontinuity effects with same and varying slope for various thresholds over all data. Lowest Sim. = Scaled Sim. $<$ 1; Highest Sim. = Scaled Sim. $>$ 1.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	5.11^{***}	4.89^{***}	4.73^{***}	4.84^{***}	4.72^{***}	4.48^{***}
	(0.19)	(0.23)	(0.27)	(0.28)	(0.41)	(0.63)
Scaled Sim.	0.66^{***}	0.23	-0.01	0.60^{*}	0.76	1.03
	(0.19)	(0.32)	(0.38)	(0.28)	(0.47)	(0.73)
Lowest Sim.		-0.36	0.61			
		(0.23)	(0.81)			
Scaled Sim. :Lowest Sim.			0.90			
			(0.72)			
Highest Sim.					-0.08	0.38
					(0.19)	(0.96)
Scaled Sim. :Highest Sim.						-0.47
						(0.96)
AIC	1970.52	1971.08	1970.33	1753.04	1756.35	1756.37
BIC	1987.65	1992.50	1996.04	1770.14	1777.74	1782.03
Log Likelihood	-981.26	-980.54	-979.17	-872.52	-873.18	-872.18
Num. obs.	536	536	536	532	532	532
Num. groups: matchId	58	58	58	117	117	117
Var: matchId (Intercept)	0.00	0.00	0.00	0.00	0.00	0.00
Var: Residual	2.27	2.26	2.26	1.55	1.55	1.55

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table S24. Multilevel regression predicting expected closeness with match-id as random effect. Models 1-3 test discontinuity effects with same and varying slope for low-similarity observations only, while Models 4-6 use high-similarity observations only. Lowest Sim. = Scaled Sim. $<$ 1; Highest Sim. = Scaled Sim. $>$ 1.

	Believe Real (1)	Believe Real (2)	Expec. Cl. (3)	Exper. Cl. (4)
(Intercept)	0.80^{***}	1.43^{***}	4.56^{***}	4.01^{***}
	(0.01)	(0.09)	(0.11)	(0.13)
Scaled Similarity Score	-0.02^{*}	-0.17^{*}		
	(0.01)	(0.08)		
Initial Stance	0.00^{*}	0.01^{*}	0.01^{**}	0.00
	(0.00)	(0.01)	(0.00)	(0.00)
Match Believed Real			0.52^{***}	0.77^{***}
			(0.11)	(0.14)
R^2	0.01			
Adj. R^2	0.01			
Num. obs.	1068	1068	1068	1067
RMSE	0.39			
AIC		1012.29	3822.80	4243.66
BIC		1027.21	3847.67	4268.52
Log Likelihood		-503.15	-1906.40	-2116.83
Deviance		1006.29		
Num. groups: matchId			146	146
Var: matchId (Intercept)			0.19	0.06
Var: Residual			1.93	3.01

$^{***}p < 0.001, ^{**}p < 0.01, ^{*}p < 0.05, ^{+}p < 0.1$

Table S25. Match perceived as real, similarity, and experienced closeness. Model 1 and 2: linear (1) and logistic (2) regressions predicting a binary variable equal to 1 if the respondent believed that the match was real and not fabricated by the experimenter (random effect model failed to converge). Model 3 and 4: linear mixed models with match id as random effect predicting expected (3) and experienced (4) closeness based on respondent perception of the match as real.

2. Essays' Text Analysis

In this section we report exploratory analysis about the essays' texts. First, we evaluate their English quality and sentiment and check whether essays against and in favor of redistribution differ significantly on any of these dimensions. Second, we report about NLP (natural language processing) analysis highlighting the most important words used by essays in favor and against redistribution, as well as their topic extracted through Latent Dirichlet Allocation (LDA). Finally, we measure the effect of essay characteristics on stance update, polarization reduction, and experienced closeness of participants.

A. English Quality. We implemented this analysis in Node.JS using packages from the Words repository (https://github.com/words/).

Readability Scores. We computed eight different scores (Flesh Kincaid Read Ease and Grade Level, Flesh, Auto Readability, Coleman Liau, SMOG Formula, SPACHE Formula, and Dale Chall) and we obtained a consistent picture across all of them. The median English level is "conversational" (Fig. S16A and B), and, although there is some variation in quality, this is evenly spread out for essays with different stances. Importantly, readers with different stances have been exposed to the same variation in quality of essay (Fig. S16C). Finally, the correlation across all readability indexes is very high, with only the Coleman-Liau index slightly behind (Fig. S16D).

Word Counts. For each essay we counted the number of instances for each of the following categories: buzzwords (e.g., "blockchain," "brick-and-mortar," "frictionless"), fillers (words that fill a space, such as eh, ah, okay, etc.), hedge words (words that pull us back from the edge, such as almost, nearly, somewhat, etc.), profanities (no examples), and weasels (words or expressions that confer authority, e.g., "there is evidence that"). As shown in Fig. S16E, and F the number of profanities and buzzwords is very limited, which indicates the civil yet spontaneous nature of the essays. The distribution of these word categories is similar across essays with different stance (Fig. S16F). Finally, correlation with essay quality for any such category is very low (Fig. S16D).

B. Sentiment. We conducted sentiment analysis with multiple dictionaries from several packages of different programming languages to get a better picture. Precisely, we used: Vader in Python (15), SentimentAnalysis (https://www.rdocumentation.org/packages/SentimentAnalysis/) and TidyText in R (16).

Results are mostly consistent, however some packages hightlighted a larger negative sentiment of essays against redistribution, while others did not. At the two extremes we find: SentimentAnalysis in R and TidyText R with the AFINN Dictionary (Fig. S17). Using bigrams and reversing the polarity of the sentiment of words preceded by a negation word (i.e., no, not, never, without) lead to similar results. Finally, there is an indication that essays strongly against redistribution have the most negative sentiment.

C. NLP. We conducted all NLP analysis with TidyText in R (16).

Word Frequencies. We conducted NLP analysis with TidyText in R. The word frequencies for essays against and in favor of redistribution are highly correlated (ranging from 0.81 to 0.94, $p < 0.001$), even when disaggregated by stance type (Fig. S18).

TF-IDF. We computed term frequency–inverse document frequency (TF-IDF) scores to find out which words are the most important conditionally to the stance of an essay (Fig. S19). Results are consistent with the outcome of the focal survey (Sec. B): essays against redistribution use words such as "communist," "theft," "punish," and "liberty" to highlight a focus on the individual; essays in favor of redistribution instead use words such as "healthcare," "families," "program," and "rate" indicating a focus on collectives. A similar picture is painted by the network visualization in Fig. S20.

Latent Dirichlet Allocation (LDA). LDA is an unsupervised learning method that let us probabilistically assign words to topics and topics to essays. LDA requires specifying the number of topics in advance, so we tested two (Against/In Favor), three (Against/Neutral/In Favor), and four (Strongly Against/Mildly Against/Mildly In Favor/Strongly In Favor) topics. Overall, there is a large overlap in the top words in each topic. For instance, "people,", "wealth," "money," are always found in the top three or four most important words in all topics; "govermnent" is often completing the top four (Fig. S21). Overall, LDA largely fails to assign distinct topics to essays with different stance, suggesting that, in fact, all essays approach the topic of inequality and redistribution with a similar angle. After assigning to each essay the topic with the highest probability γ, we performed a series of Chi Square tests of independence for the proportions of topics in essays pro and against redistribution (2 classes) and for essays with given stance type (4 classes), both in the dataset of essays and in their actual assignment to participants in the experiment. The Chi Square tests were never significant, suggesting no strong association for any topic. However, we do find some deviations: in a classification with three topics, Strongly Against essays are more often associated with Topic 3, and in a classification with four topics, Topic 4 is associated with fewer essays, mostly Strongly in Favor.

D. Impact on stance update, polarization reduction, and experienced closeness. We ran a number of linear mixed models with the essay as random effect predicting stance update, the absolute value of stance update, consensus gap update, and experienced closeness. Generally, we found null effects for all readability scores, word categories, and sentiment scores, and topics allocated via LDA with and without preregistered controls.

For completeness, we report about three exceptions.

- Using bigrams, the sentiment computed by the TidyText in R with the BING dictionary was found to reduce the stance update and the absolute value of the stance update ($p < 0.05$) only after controlling for match stance type (against/in favor).
- The number of buzzwords was found to reduce the consensus gap ($p < 0.05$), but this result does not hold with controls.
- In a LDA with four topics, Topic 4 was found to increase stance update ($p < 0.05$), but this result does not hold when controlling for the match type; when adding all preregistered controls Topic 3 becomes significant ($p < 0.05$).

Given that the above-reported cases are the only inconsistent results of an otherwise coherent large battery of exploratory tests, and also given their small significance level, we discard them as random variations.

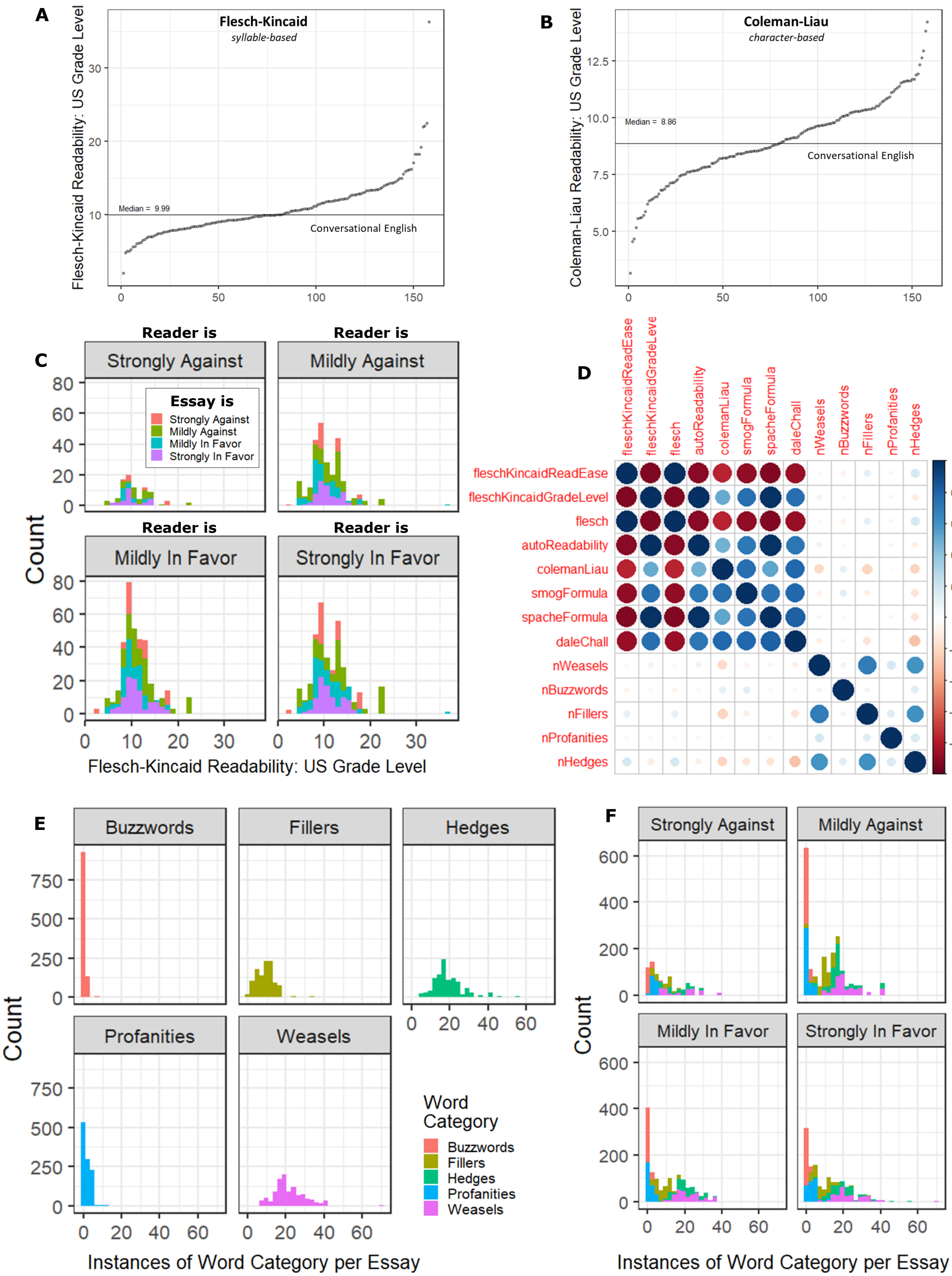

Fig. S16. Readability and other word-based statistics about essays.

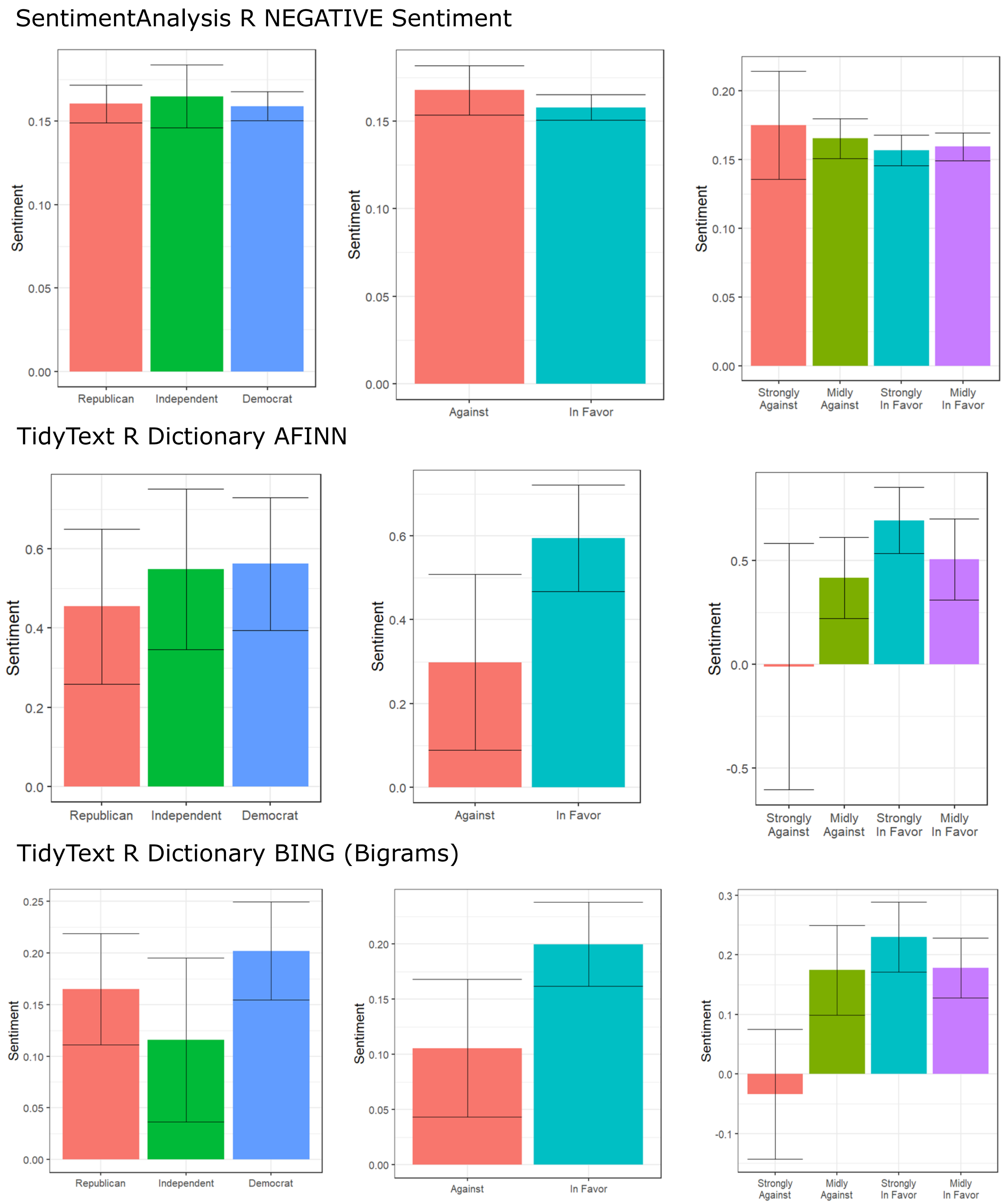

Fig. S17. Sentiment analysis essays.

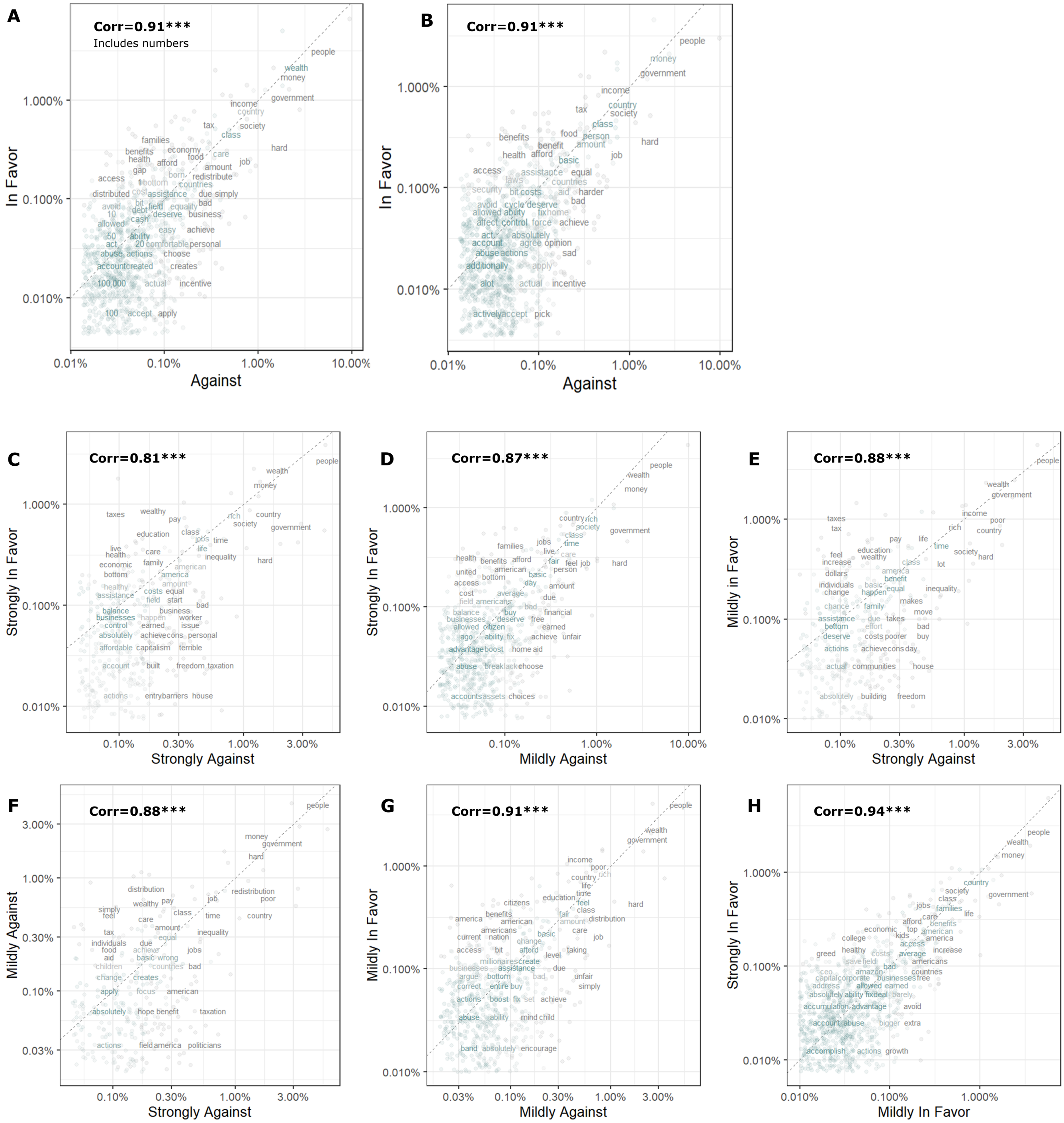

Fig. S18. Word frequencies in essays. A, B Against and In favor essays, with and without numbers. **C, D, E, F, G, H**. Disaggregated by stance type (without numbers).

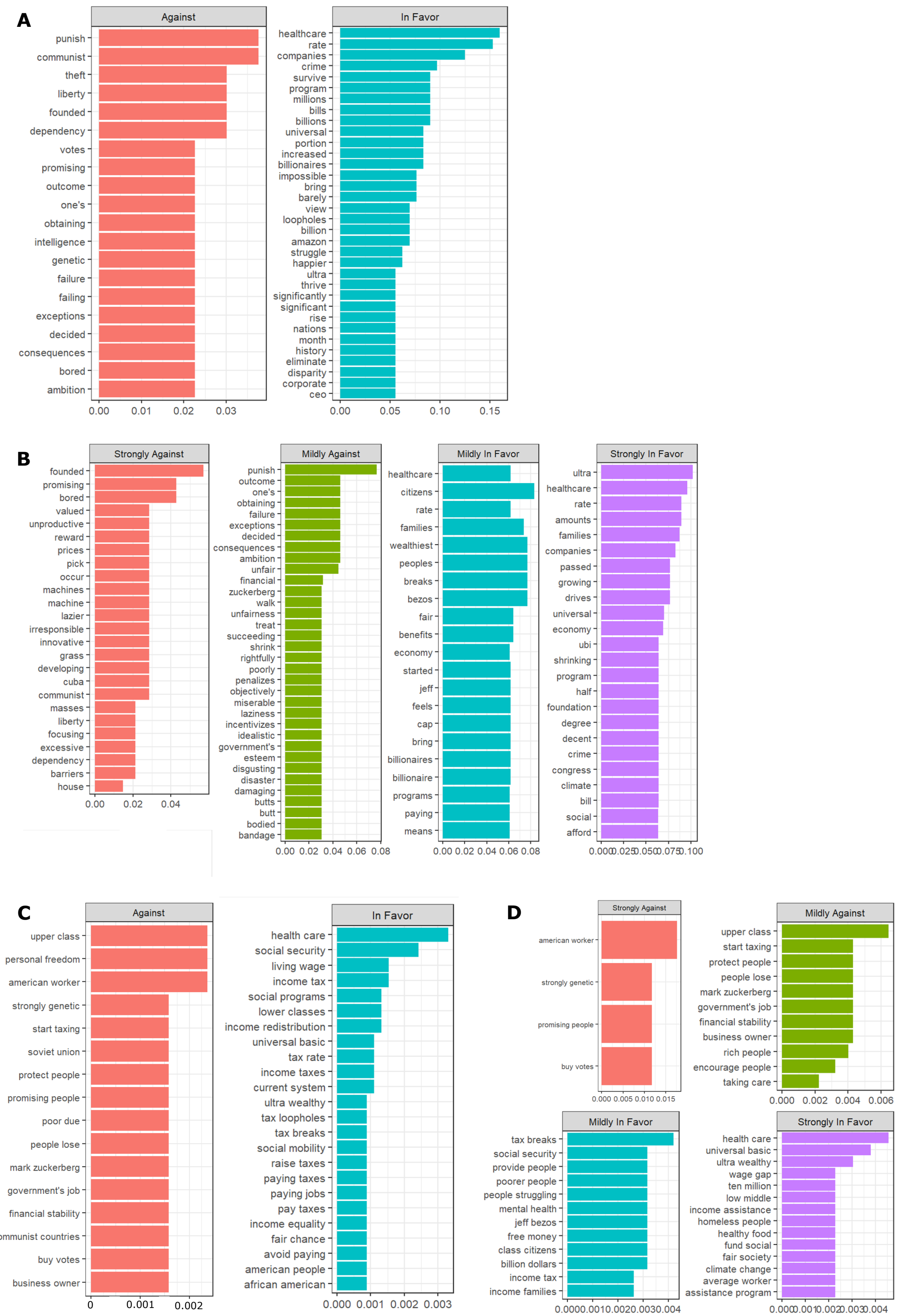

Fig. S19. TF-IDF analysis for essays. A, B Monograms. **C, D**. Bigrams.

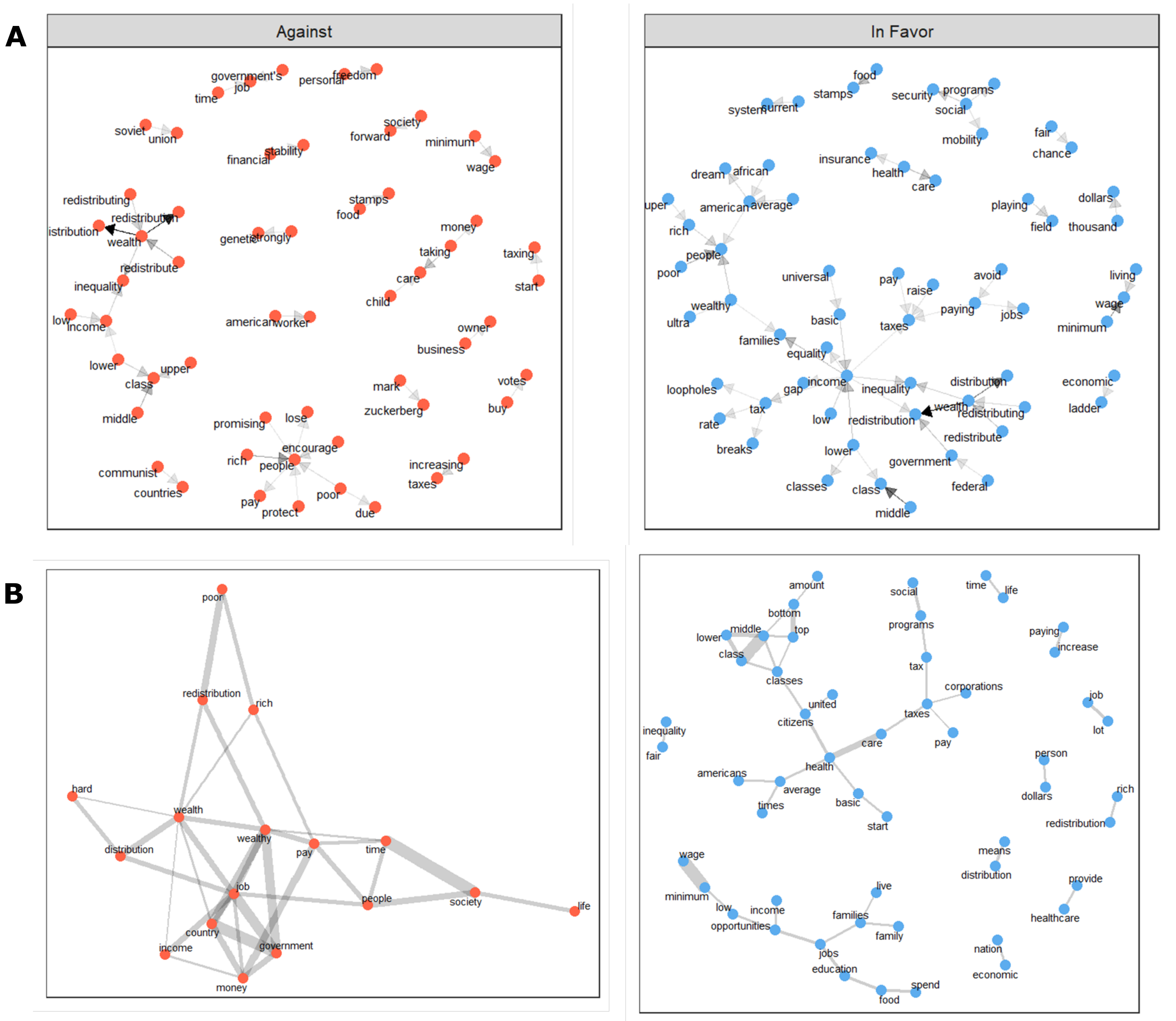

Fig. S20. Words co-occurrence network visualization. A. Bigrams in essays. **B**. Pairwise correlation in corpus. Left hand-side essays Against, right hand-side essays in Favor of redistribution.

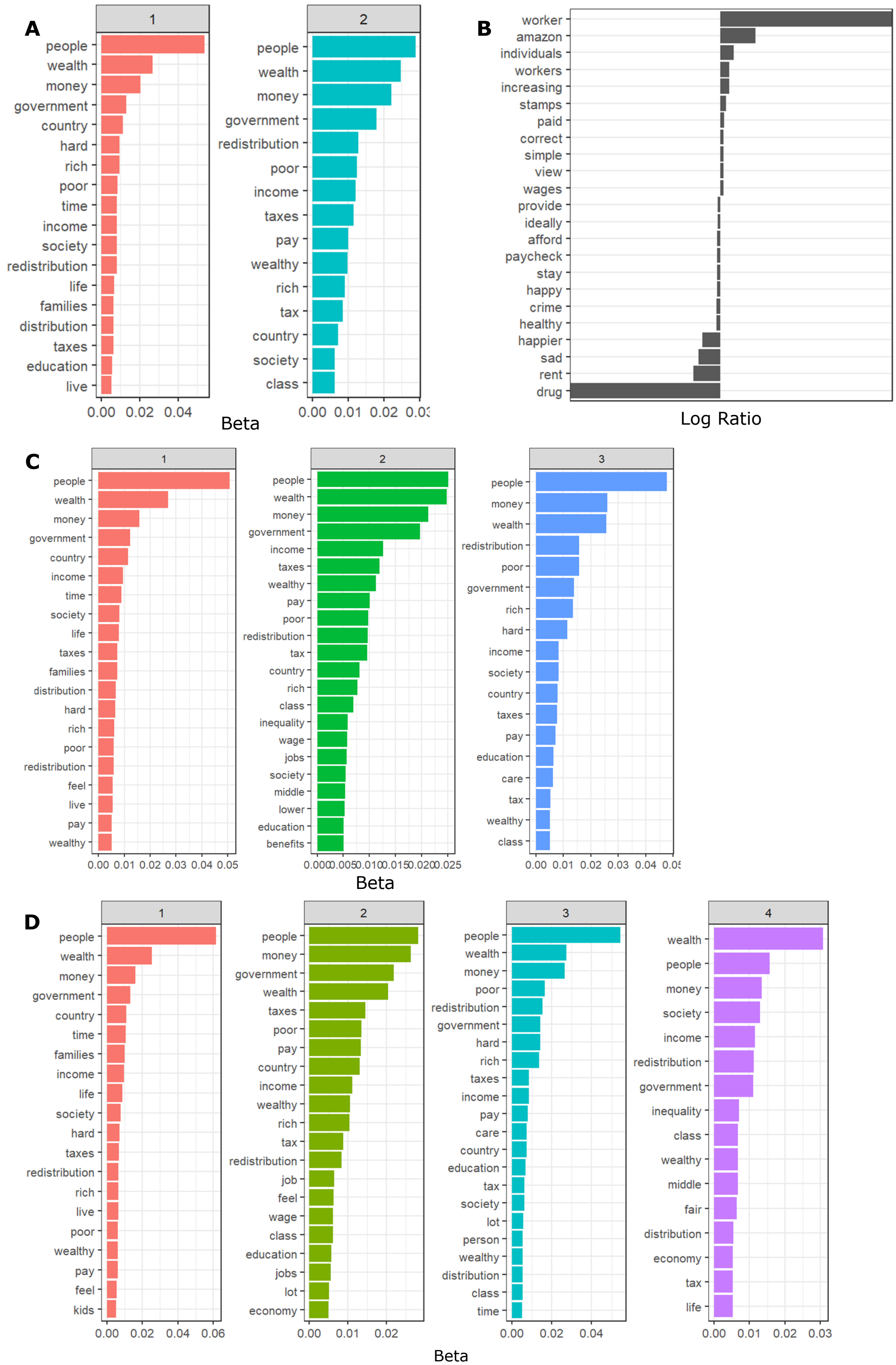

Fig. S21. LDA topic modeling for essays. Two topics: most important words (**A**) and words that most clearly belong to either topic (**B**). Three topics: most important words (**C**). Four topics: most important words. (**D**)

3. Survey Questions

Here we report the text of all remaining survey questions not already presented before. Questions are reported in the order in which they have been asked to participants; each subsection below was displayed in a separate survey page. Text in square brackets report answers to multiple choice questions'; text in curly brackets provides additional information to the reader for specific questions.

A. Non-Focal Survey.

A.1. Your demographics..

Q1. What is the initial of your first name? *(If you do not have a first name, pick the initial of person you admire)*

Q2. What is your gender? [Male, Female, Other]

Q3. Please name your gender? {If Q2=Other}

Q4. Do you identify with any of the following races/ethnic groups? [White, African American, Latino, Asian, American Indian, Alaska Native, Native Hawaiian, Pacific Islander]

Q5. What is the color of your eyes? [Brown, Blue, Green, Other]

Q6. Please say the color of your eyes. *(If more than one color, order alphabetically and unite with a dash)* {If Q5=Other}

Q7. Are you right or left handed? [Right, Left, Ambidextrous]

Q8. What is your first language?

Q9. Do you speak other languages? If Yes,list them here, otherwise leave empty. *(if English is not your first language, list it first; if you speak more than one language, separate them with comma)*

Q10. When is your birthday? {Optional}

Q11. You chose not provide your birthday. Please answers the following questions: What is your age group? [18-19, 20-29, 30-39, 40-49, 50-59, 60-69, 70-79, 80+] {If Q10 is not answered}

Q12. What is your zodiac sign? [Aries, Taurus, Gemini, Cancer, Leo, Virgo, Libra, Scorpio, Sagittarius, Capricorn, Aquarius, Pisces] {If Q10 is not answered}

A.2. Your spirituality..

Q1. Do you believe in God? [Yes, No]

A.3. Where you live and have lived..

Q1. In which US state do you currently live?

Q2. In which US city/town do you currently live? {Optional}

Q3. What is your zip code? {Optional}

Q4. Would you describe the area where you currently live as mostly rural or urban? [Rural, Sub or Ex-urban, Urban]

Q5. Did you grow up in the US? [Yes, No]

Q6. In which US state did you grow up? {If Q5=Yes; Checkbox available: Same as current state}

Q7. In which US city/town did you grow up? {If Q5=Yes; Checkbox available: Same as current city}

Q8. What is the zip code of the location where you grew up? {If Q5=Yes; Checkbox available: Same as current zip code}

Q9. Would you describe the area where you grew up as mostly rural or urban? [Rural, Sub or Ex-urban, Urban] {If Q5=Yes; Checkbox available: Same as current area}

Q10. Have your parents or grandparents immigrated to the US from a foreign country? [Parents, Grandparents, No] {If Q5=Yes}

Q11. Please say the country or countries from which your parents or grandparents came from. {If Q10=Parents or Q10=Grandparents}

Q12. In which foreign country did you grow up? *(Type the full name of the foreign country in **English**)* {If Q5=No}

Q13. In which foreign city/town did you grow up? {If Q5=No}

Q14. What is the post code of the foreign location where you grew up? {If Q5=No}

Q15. Would you describe the area where you grew up as mostly rural or urban? [Rural, Sub or Ex-urban, Urban] {If Q5=No}

A.4. Family, friends, pets, and education..

Q1. What is your civil status? [Married, Single, Separated, Divorced, Widowed, Cohabiting Not Married]

Q2. Are your parents divorced? [Yes, No, They never married, I dont́ know them]

Q3. How many children do you have? [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10+]

Q4. How many brothers and sisters do you have? [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10+]

Q5. Do you have a pet or companion animal? [Cat, Dog, Fish, Reptile, Bird, Rodent, Other, None]

Q6. Please say what other pet animal/s you have. {If Q5=Other}

Q7. Have you served in the military? [Yes, No]

Q8. In which military branch were/are you? [Army, Air Force, Navy, Marine Corps, Coast Guard] {If Q7=Yes}

Q9. What is your highest education level? [None, Elementary, High-School, College, Grad School]

Q10. Where did you go to college? *(type the **full name** of the college, not the abbreviation)* {If Q9=College or Q9=Grad School}

Q11. Do you have any gay, bisexual or transgender friends? [Yes, No]

Q12. In your day-to-day life, do you look after an elderly, sick, or disabled person? [Yes, No]

Q13. Have you experienced the loss of a significant person in your life? [Yes, No]

A.5. Job and finances..

Q1. What is your employment status? [Unemployed, Self-employed, Employed, Retired]

Q2. Do you own a house or an apartment? [Yes, No]

Q3. Do you own a car? [Yes, No]

Q4. What number come closest to your yearly income? *(in thousands of dollars)* [0, 5, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100 , 120, 140, 160, 180, 200, 250, 300, 350, 400, 450, 500, 500+]

Q5. Do you have a student debt? ["Yes, and it is large", "Yes, but it is manageable", "No, I have paid it off", "No, I never had it"]

Q6. To which social class do you feel you belong?
(If unsure, make your best guess)

Q6.1. Now [Bottom, Lower, Lower-Middle, Middle, Upper-Middle, Upper, Elite]
Q6.2. As a child [Bottom, Lower, Lower-Middle, Middle, Upper-Middle, Upper, Elite]
Q6.3. In the Future [Bottom, Lower, Lower-Middle, Middle, Upper-Middle, Upper, Elite]

A.6. Your personality..

Q1. What is more important to you? [Work, Play]

Q2. How energetic are you? [Hyperactive, Active, Occasionally active, Sedentary]

Q3. Do you enjoy taking part in competitive activities? [Yes, No]

Q4. Do you consider yourself a perfectionist? [Yes, No]

Q5. Are you patient? [Yes, No]

Q6. Would your friends or family members describe you as messy? ["Yes, really messy", "Yes, a bit", "No"]

Q7. Is taking care of your body important for you? [Yes, No]

Q8. What describes you better? [Confrontational, Non-confrontational]

A.7. Two extra questions about your personality..

Q1. Of the following, what fascinates you more? [Stars and galaxies, Technological progress, Ancient civilizations, Nature and wildlife]

Q2. Do you sometimes wish that fantastic creatures were real? *(fairies, gnomes, trolls, ghosts, etc.)* [Yes, No]

A.8. Your typical behavior in situated contexts..

Q1. How many times do you typically hit the snooze button before getting up? ["Zero, I get up immediately", "One or two", "Three or more", "I do not use an alarm clock"]

Q2. Have you ever taken free furniture that somebody left at the side of the street? [Yes, No]

Q3. Is it easy for you to throw or give away things that you do not really use anymore? [Yes, No]

Q4. Have you ever stolen a glass from a bar? [Yes, No, Not appropriate to ask]

Q5. If you dislike food in a restaurant do you usually send it back? [Yes, No]

Q6. Have you ever "regifted" a gift that you did not like? [Yes, No]

Q7. Do you use profane language? [Never, Occasionally, Often, Regularly]

Q8. How often do you read the horoscope? [Daily, Weekly, Occasionally, Never]

A.9. Things you like: color, food and travels..

Q1. What is your favorite color? [Red, Green, Blue, Yellow, Brown, Gray, Purple, Orange, White, Black, Pink, Other]

Q2. Please say which other color is your favorite. {If Q1=Other}

Q3. What is your favorite food? [Mexican, Italian, Indian, Cajun, Thai, Greek, Chinese, Mediterranean, Japanese, French, American, Spanish, German, Korean, Vietnamese, Turkish, Other, None]

Q4. Please say what other type of food is your favorite. {If Q3=Other}

Q5. How spicy do you like your spicy food? ["I dont́ like spicy food", "Spicy, but not too much", "Hot", "Extremely Hot"]

Q6. Are you vegetarian or vegan? [Yes, No]

Q7. How many foreign countries have you visited? [Zero, Between 1 and 2, Between 3 and 5, Between 6 and 10, More than 10]

Q8. Imagine you just won a free vacation in a foreign country of your choice. Which one would you pick? *(Type the full name of the foreign country in **English**)*

A.10. Things you do..

Q1. Do you spend time on social media? [I am a very active user, I am a somewhat active user, I rarely use them, I never use them]

Q2. How much effort do you devote for your appearance? *(follow the latest fashion trends, spend time searching for clothes and accessories, use personal care products, etc.)* [A lot, Moderate, Not much]

Q3. Do you smoke? ["Yes", "Yes, socially", "No", "No, I quit it"]

Q4. Do you play sports? [Football, Baseball, Basketball, Volleyball, Tennis, Hockey, Cricket, Soccer, Field Hockey, Cycling, Track and Field, Table Tennis, Running, Martial Arts, Climbing, Skiing, Yoga, Swimming, Fishing, Other, None] {Up to three items may be selected}

Q5. Please say what other sport you play. {If Q4=Other}

Q6. Do you like to go to museums? ["Yes, I love it", "Yes, sometimes", "No"]

Q7. Do you like to go to dance? ["Yes, I love it", "Yes, sometimes", "No"]

A.11. Your hobbies and free time..

Q1. Do you like to listen to music? [Yes, No]

Q2. What musical genre/s do you like the most? [Blues, Classical, Country, Rock, Hip-Hop, Latin, Pop, Religious, Funk, R&B, Rap, Electronic, Folk, Jazz, New Age, Reggae, Other, None] {If Q1=Yes; up to three items may be selected}

Q3. Please say what other musical genre you like. {If Q2=Other}

Q4. Who is your favorite music artist? *(composer, singer, DJ, band, etc.)* {If Q1=Yes}

Q5. Do you enjoy watching movies? [Yes, No]

Q6. What movie genre/s do you like the most? [Action, Adventure, Comedy, Crime, Drama,Fantasy, Historical, Horror, Mystery, Political, Romance, SciFi, Thriller, War, Western, Surreal, Other, None] {If Q5=Yes; up to three items may be selected}

Q7. Please say what other movie genre you like. {If Q6=Other}

Q8. What is the title of your favorite movie? {If Q5=Other}

Q9. Who is your favorite actor/actress? *(Please type the full name)* {If Q5=Other}

Q10. Are you a sport fan? [Yes, No]

Q11. What sport do you really love to follow? [Golf, Football, Baseball, Basketball, Volleyball, Tennis, Hockey, Cricket, Soccer, Field Hockey, Nascar, F1, Cycling, Darts, Snooker, Boxing, Other, None] {If Q10=Other}

Q12. Please say what other sport do you really love to follow. {If Q11=Other}

Q13. What is your favorite team? *(Or sportsman/woman for individual sports. Type the **full name** to avoid ambiguity.)* {If Q10=Other}

Q14. Do you watch TV shows? [Yes, No]

Q15. Which TV shows do you like to watch? {If Q14=Other}

Q16. Do you enjoy reading books? [Yes, No]

Q17. What books or authors are your favorites? {If Q16=Other}

Q18. Do you follow any Web channel? *(Examples are: YouTube channels or podcasts.)* [Yes, No]

Q19. Which web channels do you follow? {If Q18=Other}

Q20. Do you play video games? [Yes, No]

Q21. What are the names of your favorite video games? {If Q20=Other}

Q22. Do you perform creative activities? *(Examples: play an instrument, paint, sing, etc.)* [Yes, No]

Q23. What creative activities do you do? {If Q22=Other}

Q24. Is there anything that you really like that we have missed? Please let us know.

A.12. Something Special About You That You Would Like to Share.

Q1. If you feel like, you could tell us a quirk or interesting fact about you.

Examples are: something funny or unusual that has happened to you, something you have accomplished that made you proud, something that changed your life, or how you changed the life of somebody else.

Do *not* report about criminal or illegal activities, but pick an experience or a fact that you would be comfortable to share with others. {Optional}

B. Focal Survey. You just completed Part 1.
Part 2 about your political orientation and perception of inequality begins now.

B.1. Your political orientation.

Q1. On a scale from 1 to 7, where 1 means "not at all" and 7 means "very closely," how closely do you follow US politics? [0, 1, 2, 3, 4, 5, 6, 7]

Q2. On a scale from 1 to 7, where 1 means "strong Democrat" and 7 means "strong Republican," where do you position yourself? [0, 1, 2, 3, 4, 5, 6, 7]

Q3. On a scale from 1 to 7, where 1 means "very liberal" and 7 means "very conservative," where do you position yourself? [0, 1, 2, 3, 4, 5, 6, 7]

Q4. Which candidate did you support in the 2016 election? [Hillary Clinton, Donald Trump, Other, None]

Q5. Please say the name of the other candidate that supported in the 2016 election. {If Q4=Other}

B.2. Your perception of socio-economic inequality in the US.

Q1. Do you think inequality is a serious problem in America? [Not a problem at all, A small problem, A problem, A serious problem, A very serious problem]

Q2. Express your agreement on a scale from 1 to 7, where 1 means complete disagreement and 7 complete agreement, with the following statements.
Socio-economic inequality in the US is mainly caused by:

- Personal Factors:

Q2.1 Some people are more talented. [0, 1, 2, 3, 4, 5, 6, 7]
Q2.2 Some people work harder. [0, 1, 2, 3, 4, 5, 6, 7]
Q2.3 Some people prefer easier, low-paying jobs. [0, 1, 2, 3, 4, 5, 6, 7]

- Economic Factors:

Q2.4 Globalization has squeezed the salary of lower-income families. [0, 1, 2, 3, 4, 5, 6, 7]
Q2.5 Technological change has raised the salary of highly-educated workers. [0, 1, 2, 3, 4, 5, 6, 7]
Q2.6 Salaries of people working in financial sector are driving inequality. [0, 1, 2, 3, 4, 5, 6, 7]

- Political Factors:

Q2.7 Interests lobbies in Washington. [0, 1, 2, 3, 4, 5, 6, 7]
Q2.8 Discrimination against some minorities. [0, 1, 2, 3, 4, 5, 6, 7]
Q2.9 Restricted access to high-quality education. [0, 1, 2, 3, 4, 5, 6, 7]
Q2.10 'Social policies in favor of workers and unions have been removed by politicians. [0, 1, 2, 3, 4, 5, 6, 7]

Luck:

Q2.11 Family one is born into. [0, 1, 2, 3, 4, 5, 6, 7]
Q2.12 Other external events. [0, 1, 2, 3, 4, 5, 6, 7]

C. Post-interaction Survey.

C.1. You and Your Match.

Q1. On a scale from 1 to 7, where 1 means "not connected at all" and 7 means "very connected," how much of a connection did you feel with your match? [0, 1, 2, 3, 4, 5, 6, 7]

C.2. About Your Match.

Q1. On a scale from 1 to 7, where 1 means "very liberal" and 7 means "very conservative," where do you imagine *your match* to be? [0, 1, 2, 3, 4, 5, 6, 7]

Q2. On a scale from 1 to 7, where 1 means "strongly against" and 7 means "strongly in favor" of redistribution by the government, where do you imagine *your match* to be? [0, 1, 2, 3, 4, 5, 6, 7]

C.3. About Your Match.

Q1. Your match was a real participant from a previous session. We do not use deception in our experiments. When we said that you will be reading a text from a real participant in one of our past studies, we meant it literally. Please let us know if you did not believe that your match was a real person. *(We need your honest answer, in no way this choice will affect your payoff)* ["Yes, I believed it", "No, I thought it was made up"]

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