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ABSTRACT

We study how two groups, those inside vs those outside echo chambers, react to a political event when we vary social media status (Twitter). Our treatments mimic two strategies often suggested as a way to limit polarization on social media: they expose people to counter-attitudinal data, and they get people to switch off social media. Our main result is that subjects that started inside echo chambers became more polarized when these two strategies were implemented. The only scenario where they did not become more polarized is when they did not even experience the political event. Interestingly, subjects that were outside echo chambers before our study began experienced no change (or a reduction) in polarization. We also study a group of non-Twitter users in order to have a simple, offline benchmark of the debate's impact on polarization.

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1. Introduction

Polarization appears to have risen in the US and other Western democracies and it is standard to blame this, at least in part, on the rise of social media.[1] An early influential view has identified the creation of echo chambers as an important factor in this increase (Sunstein, 2001). The contention is that echo chambers limit the benefits of the easy access to new information offered by platforms such as Twitter or Facebook by exposing users to like-minded people and by offering information tailored to their interests and prejudices. Of course, people join echo chambers for a reason, even if sometimes their decisions are affected by behavioral biases. For example, people might prefer to experience a political event in contact with other like-minded people, perhaps because this makes it easier to form ideological reactions and interpretations. Two strategies have been proposed to reduce social media's apparent impact on polarization: to limit people's access to echo chambers and to ensure that people in them receive information that they would not otherwise receive (i.e., ensuring that they access "counter-attitudinal" data).[2]

In this paper, we study data from a pre-registered field experiment designed to study the role of social media in fostering polarization in the presence of a politically salient event: the 2019 Argentine presidential debate.[3] We focus on the way in which a person who has formed a political echo chamber on Twitter in the period prior to the elections reacts to its absence at the precise time when it is presumably most valuable. We consider two ways in which an echo chamber can be "absent" corresponding, broadly, to the two strategies mentioned above. Specifically, on the day of presidential debate, a group of subjects was invited to come to a neutral venue and participate in an academic study in exchange for economic compensation. After filling a short questionnaire and providing a saliva sample, they were randomly assigned to different groups. Subjects were randomly allocated to four groups. The first two involved switching off their cell phones, with one group assigned to a

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[1] See, for example, Lelkes et al. (2017) who find that access to broadband Internet increases partisan hostility. There is not, however, a consensus on this (see for example, Boxell, Gentzkow, and Shapiro (2017) who observe that polarization has increased the most among the demographic groups least likely to use the Internet). On the rise of affective polarization in international context, see Boxell, Gentzkow, and Shapiro (2020). For recent work using geolocation data for the US, see Brown and Enos (2021).

[2] Two recent experimental tests of these strategies implemented on Facebook (the most common source of news about politics amongst young people, Pew Research Center, 2014a) are Allcott et al. (2020) and Levy (2021). Field experiments estimating media effects are relatively rare even if, as emphasized by Levy (2021), they "combine the strong identification of lab experiments with high external validity".

[3] Hernández, et al., (2021) find a positive relationship between the salience of elections and political polarization. A large literature in political science has emphasized the role of TV debates as critical events in the formation of voter choice. See, for example, Jamieson and Birdsell (1988), and Shaw (1999). See McKinney and Carlin (2004) for a review. For a contrarian view, see the comprehensive study by Le Pennec and Pons (2019) who finds very little role for debates in changing vote intentions. They also find that 65% of their large, multi-country, multi-election sample watched the debates. For experimental evidence see Mullainathan, Washington, and Azari (2010) and Fridkin et al. (2007).

Documentary group that watched a short film on Argentine political institutions and the other assigned to watch a live broadcast of the presidential debate (the Debate-Only group). The remaining two treatments involved actively using their cell phones, with one group assigned to a group allowed to watch the debate in normal conditions (the Twitter-Allowed group), while the remaining subjects were assigned to a group that was requested to interact with a Twitter account of our own — which mainly shared polarized content (the Twitter-Interact group). Participants that did not have prior Twitter accounts were randomly allocated to just the first two groups (Documentary and Debate-Only groups). After the treatments, subjects had to answer a set of standard questions regarding polarization and interest in politics, as well as provide a second saliva sample. These data allow us to construct a set of standard survey-based outcomes, as well as a measure of cortisol levels.[4] For Twitter users, we also have information regarding their Twitter activity (e.g., retweets, likes), so we can also study their Twitter interactions both during the debate as well as before and after coming to our experiment.

Importantly, the data we collected on their interactions during the weeks prior to the experiment also allow us to separate the group of subjects that were ideologically moderate before coming to our experiment from those that were already "segregated" (i.e., that were already in an "echo chamber").[5] Non-segregated users are those who either do not follow politicized accounts that were popular on Twitter (which we call the "Twitter elite"), or that follow politicized Twitter accounts but covering a wide ideological spectrum. Thus, the focus of our study is the set of heterogeneous treatment effects produced by our four treatments across segregated and non-segregated Twitter users. For reference, we also repeat our estimates for non-Twitter users.[6]

Our main finding is that subjects that were not segregated according to their Twitter activity prior to the event, react similarly in terms of our survey-based measures of polarization in all treatment arms. In contrast, the group that came to the event already segregated differ in their ensuing polarization depending on their treatment. Interestingly, the lowest level of subsequent polarization in this group was observed when they watched the debate with normal access to Twitter (Twitter-Allowed). While the difference with the Documentary group is not significant, the difference with the "switch off" and counter-attitudinal treatments is large and significant. Our results using measures of changes in Twitter activity the day after the debate are consistent with those obtained using survey data: while there is a negative or insignificant change in the nature of Twitter activity for the non-

[4] Cortisol is a steroid hormone often employed to capture response to stress (see Kirschbaum and Hellhammer, 1989).

[5] Cinelli et al. (2021) define social media echo chambers as environments in which social media users' opinions, political leaning, or beliefs get reinforced due to repeated interactions with peers having similar tendencies and attitudes, and show that they are prevalent in online dynamics. Bakshy et al. (2015) find a large role of individual choice (relative to Facebook's algorithm) in creating echo chambers. For an experiment where subjects seek selective exposure to media based on partisan affinity see Iyengar and Hahn (2009).

[6] Although in this case we use predicted segregation (as they do not have Twitter activity; see Section 2.c.). Gentzkow and Shapiro (2011) show that ideological segregation in news consumption is somewhat higher online than offline.

segregated, there is a significant increase in polarization for the segregated group in the Twitter-Interact treatment (i.e., their activity tends to lie to a greater degree in echo chambers).[7]

Since the Twitter-Allowed group is a treatment designed to be as close as possible to what users would have done in normal (non-experimental) circumstances, the low level of subsequent polarization appears to be the result of a "service" provided by the echo chambers, perhaps because the most popular, like-minded Twitter users help out with robust, nuanced interpretations of a political event. Indeed, when segregated Twitter users are not stimulated by the political event (Documentary), their subsequent polarization is similar to the "normal" condition (Twitter-Allowed). But when the political event is active, depriving them from access to the messages and reactions of their preferred accounts from the Twitter elite (Debate-Only), or exposing them to partisan messages they would otherwise not see (Twitter-Interact), only helps to increase their subsequent polarization. Segregated Twitter users' Cortisol levels are lowest in the Twitter-Allowed group (significantly lower than in the Twitter-Interact group), and their Twitter interactions during the debate were mainly within their echo chamber. Since the only difference with the Twitter-Interact group is that these have to interact with messages from outside their own echo chamber, we see their higher polarization as a result of the process of rejecting alternative interpretations of the political event. Higher cortisol levels in this condition suggest that this process is stressful.

Our paper follows a growing literature documenting an increase in political polarization in the US and elsewhere, and the tendency of users to associate and learn from like-minded people, forming echo chambers.[8] Our treatment "shutting off" social media is perhaps closest to the treatments in Allcott et al. (2020) and Mosquera et al. (2020). Allcott et al. (2020) study the effect of Facebook deactivation in the four weeks prior to the 2018 US mid-term elections and find that the intervention increased subjective well-being and reduced both factual news knowledge and political polarization.[9]

[7] The difference is statistically significant at the 1% level. Note that we did not randomize segregation status.

[8] See, for example, Baldassarri and Gelman (2008), Iyengar and Westwood (2015), Fiorina and Abrams (2008), Algan et al. (2017), Rieljan (2020), *inter alia.* On echo chambers see, for example, Sunstein (2018), McPherson et al. (2001) and Gorodnichenko, Pham, and Talavera (2021); for a recent review, see Levy and Razin (2019). In particular, Halberstam and Knight (2016) show that Twitter users during the 2012 election were disproportionately exposed to like-minded information, in part because it reached them faster. The evidence on the role of online search technologies is mixed; see, for example, Flaxman et al. (2016). Baum and Groeling (2008) document a change in what new online blogs consider news worthy (relative to traditional news sources like Reuters). For a review of social networks, see Jackson (2011).

[9] Their paper can also be seen as studying the effect of social media on how a political event (the campaign prior to the 2018 election) is experienced, although theirs is more protracted than the one we analyze. For a study of the effects of social media access when censorship is the default, see Chen and Yang (2019). Bursztyn et al. (2019) present evidence of the causal role of social media in persuading some groups (young and low-education) to hold more xenophobic attitudes. Aruguete et al. (2021) document a negative effect of social media on trust, while Fergusson and Molina (2019), Enikolopov, Makarin, and Petrova (2020) and Boxell and Steinert-Threlkeld (2021) study the effect on protests. DellaVigna and Kaplan (2007) is a classic demonstration of the causal effect of media exposure on voting.

Mosquera et al. (2020) find similar effects of deactivating Facebook for one week. For recent reviews, see Levy and Razin (2019), Iyengar et al. (2019), and Zhuravskaya et al. (2020).

Our Twitter-Interact treatment exposes subjects to counter-attitudinal content, connecting it to prior work on interpersonal contact between opposing groups. Part of this work suggests that these contacts can help challenge stereotypes and intergroup prejudice (see Pettigrew and Tropp, 2006). A recent paper by Levy (2021) is also consistent with the idea that social media platforms affect news consumption and political polarization. He offers subjects subscriptions to liberal or conservative news outlets on Facebook and demonstrates that exposure to counter-attitudinal news decreases negative attitudes toward the opposing political party, with no effect on political opinions. The hypothesis is that subjects in a counter-attitudinal condition are able to better understand the other side's arguments. In contrast, Bail et al. (2018) find that exposing Twitter users to bots retweeting content deemed as counter-attitudinal increases political polarization. A follow up study suggests that this occurs due to the fact that when users step outside their echo chamber the contrast between "us" and "them" is sharpened, which induces them to defend their identities (see Bail, 2021).[10]

The rest of the paper is organized as follows: Section 2 describes the context of our experiment, as well as our data and methods. Section 3 presents our results while Section 4 offers a brief summary and discussion. Section 5 concludes.

2. Materials and Methods

2.a. Experimental design

Figure 1 summarizes our experimental design and time line. Participants were invited to attend a university campus located in the City of Buenos Aires on Sunday, October 13, 2019. Although this introduced some costs, it has purposely the benefit of allowing us to collect more information (such as cortisol in saliva), besides limiting attrition and non-compliance. The experiment was timed so as to take place at the same time as the presidential debate, which was going to be broadcasted live on public TV. This was the first presidential debate mandated by law in Argentina's history. The main protagonists were incumbent President Mauricio Macri from *Juntos por el Cambio* (*JxC*) — a coalition often described as center-right — and Alberto Fernandez from *Frente de Todos* (*FdT*) — a coalition often described as populist anchored in the Peronist party that featured former President Cristina Kirchner in the role of vice-president. There was enormous interest in this event: the broadcast on

[10] Similarly, Yang et al. (2020) report that exposing users to bots posting only pro-immigration content consistently showed a "backfire effect" relative to a control group. Jo (2020) implements an online field experiment giving subjects curated articles and finds they are less likely to adopt extreme policy views if they are allowed to choose partisan media outlets from which to receive the articles.

TV had a rating nearly as high as the country's most popular sports event (a soccer match between Boca Juniors vs River Plate — the *superclásico*, which was played the following week).[11]

Argentine society is characterized by a high degree of political polarization and, at the time, the country was in the midst of an economic crisis that included an IMF economic program. In line with Hernández et al. (2021), our expectation is that such a politically charged event provides a reasonable setting to study the way in which social media affects the reaction to a political event.

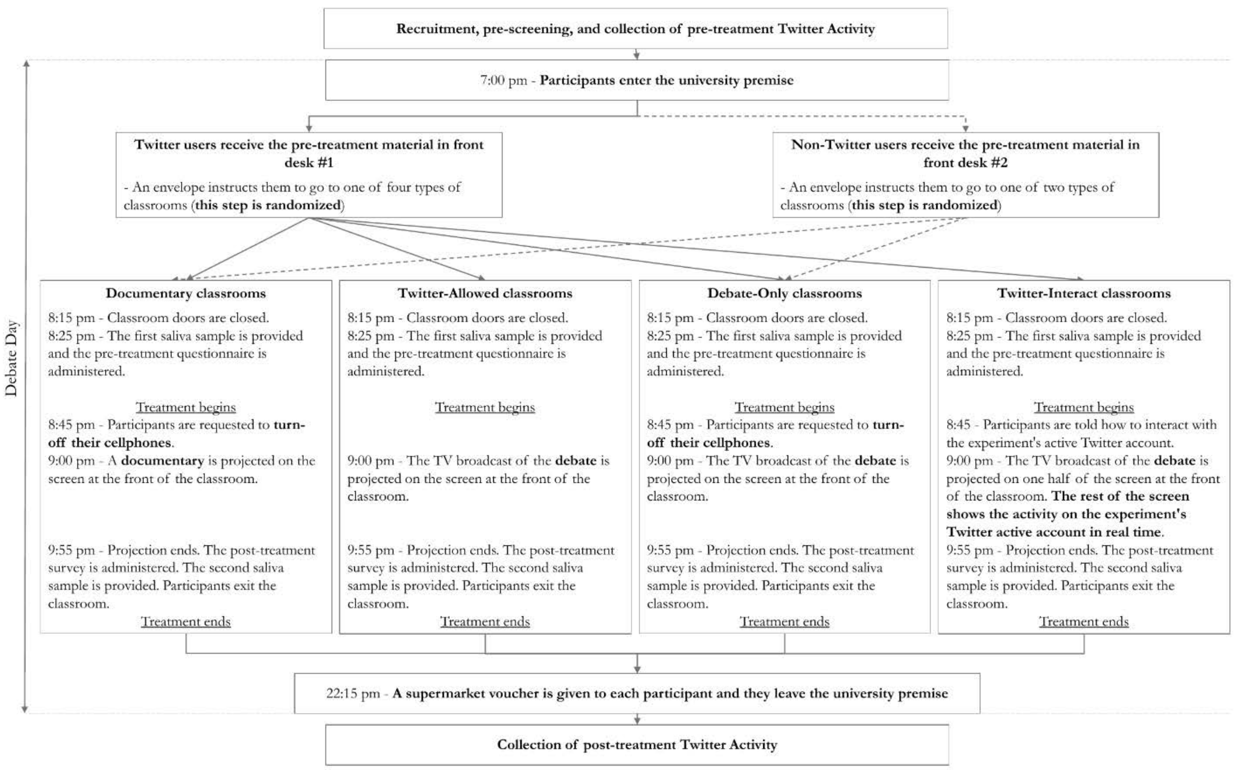

Figure 1. Experiment overview

2.a.1. *Recruitment*

Recruitment began on October 4 and ended the day before the debate (October 12). Participants were required to be between 18 and 70 years old, and eligible to vote in the 2019 presidential election. Twitter users were required to have some Twitter experience (they had to have a personal Twitter account created before June 20, 2019, and had to have tweeted or retweeted at least three messages between June 20, 2019, and September 20, 2019).

[11] The debate measured nearly 30 TV rating points (see Ámbito, 2019), while the following week's *superclásico* measured nearly 34 TV rating points (see Clarín 2019).

The recruitment strategy followed two complementary approaches. First, we created a Twitter account devoted exclusively to recruitment and pinned to its profile a tweet inviting Twitter users to participate in an academic study on electoral preferences — without mentioning the presidential debate (see Figure A1 in Appendix C). It mentioned that participants would receive a supermarket voucher as a reward for taking part. It also included a link to a Google form so that participants could register (see Appendix D). This Tweet was then retweeted by several local influential academics on Twitter. Participants recruited using this strategy are the *Twitter recruited* sample (n = 126). Second, we hired a recruitment agency which used two strategies. First, it recruited participants through an online recruitment panel of their own (n=220, 106 Twitter users and 114 non-Twitter users). We refer to this sample as the *recruitment agency online* sample. Second, it recruited participants not belonging to any recruitment panel through recruitment agents (n = 342, with 215 Twitter users and 127 non-Twitter users). This can be called the *recruitment agency offline* sample. Table A1, Table A2 and Table A3 provide pre-treatment characteristics (Twitter vs non-Twitter users and across recruitment strategies). Given these data, we control for recruitment strategies in all our regressions. During recruitment, prospective participants were pre-screened for eligibility, Twitter users were requested to follow the experiment's recruitment Twitter account, and Twitter data was collected for Twitter users (including which accounts they followed). Eligible participants were asked to come to the experiment location at 7:30 pm (this was 1.5 hours before the start of the debate), although the doors opened earlier (at 7:00).[12]

2.a.2. *Randomization strategy*

When people arrived on campus, Twitter users and non-Twitter users were asked to report at different front desks, where they presented their document so we could check their identity and confirm that they had in fact pre-registered and we had all their relevant information. They were then given a sealed envelope with instructions written on the outside indicating a classroom where they had to go. Instructions also explained that they were not supposed to open the envelope until explicitly instructed to do so. Our assistants provided guidance in the hallways in case participants got lost.

Classrooms were divided into four types, each corresponding to a treatment arm. Envelopes provided at the front desk randomly assigned participants to classrooms (and in consequence to treatment arms). In total, there were twenty-four classrooms devoted to the experiment (mean classroom capacity 52.3 participants, std. dev. = 10.8). Twitter users were assigned to one of twenty-four classrooms divided into four types (Documentary, Twitter-Allowed, Debate-Only and Twitter-Interact classrooms). Non-Twitter users were assigned to one of sixteen classrooms divided into two

[12] Participants had to provide their Twitter account information and follow the experiment's own Twitter account during recruitment in order to receive further instructions. See Appendix D. Eligible participants received a confirmation email (and non-eligible participants received an explanatory email). We had to sync our study with the debate, so our experiment took place relatively late in the day (although note, for context, that it is standard in Argentina to have supper at 9 pm).

types (Documentary and Debate-Only classrooms).[13] Participants did not know the existence of multiple types of classrooms and only found out the type of their assigned classroom after entering it and opening the envelope. The way in which envelopes were provided ensured that: 1) any group of sixteen consecutive non-Twitter users arriving at the front desk were randomly assigned to different classrooms, and 2) any group of twenty-four consecutive Twitter users arriving at the front desk were randomly assigned to different classroom. The assignment strategy has two important properties: it allowed filling up classrooms evenly, and it assigned to different classrooms participants who entered the experiment together.[14] Table A4 and Table A5 provide details on participants' pre-treatment characteristics across treatment arms. Pre-treatment characteristics are balanced across treatment arms suggesting a successful randomization.

All classrooms had large screen projectors and audio speakers installed. Additionally, an experiment assistant was assigned to each classroom and was in charge of coordinating all of the activities. Before closing the doors, the assistants had to check that all participant entering the classroom had been, in fact, assigned to that classroom and reminded them not to open the envelopes until instructed. By 8:15 pm all participants had arrived to their respective classrooms and the doors were closed. Participants received, read and signed the informed consent form (no subject refused to sign) and handed it back to the assistants. Subjects were told to open a first set of instructions, provide a first saliva sample, and fill out a pre-treatment questionnaire (see Appendix D).

2.a.3. Treatments

All four treatment arms lasted the same amount of time. The details are as follows:

Documentary

Participants who entered a classroom in the Documentary condition were requested to turn-off their cellphones. They were then requested to watch, on the classroom front screen, *Historia Argentina, DVD 3 (1838 – 1880)*, a documentary on Argentine history (related to the period when the country's first constitution was promulgated). This took place from 9 pm up to 9:55 pm (the debate was not screened). The rationale behind the Documentary group is to avoid having participants update their opinions and beliefs due to watching the debate or interacting in social media.

[13] Both Twitter and non-Twitter users were assigned to Documentary and Debate-Only classrooms, while only Twitter users were assigned the Twitter-Allowed and Twitter-Interact classrooms. In total, there were eight Documentary classrooms, four Twitter-Allowed classrooms, eight Debate-Only classrooms, and four Twitter-Interact classrooms.

[14] This was a desirable feature if some participants arrived in groups (e.g., of friends, family members, etc.).

Twitter-Allowed (benchmark)

Participants who entered a Twitter-Allowed classroom watched a live broadcast of the presidential debate and could interact naturally with their cellphones (as well as with their Twitter accounts). From 9 pm up to 9:55 pm participants watched the first half of the presidential debate. Topics covered in the first half of the debate included international affairs followed by economics. Once the candidates' exposition on these two topics ended, the debate went to a break and classrooms screens were turned-off. The rationale behind the Twitter-Allowed treatment is to have participants experience the debate in conditions that are as close as possible to those they would otherwise have experienced (for example, when watching it in their houses). This is our benchmark group.

Debate-Only

Participants who entered a Debate-Only classroom watched a live broadcast of the presidential debate but were asked to turn-off their cellphones. From 9 pm up to 9:55 pm participants watched the first half of the presidential debate and, once the debate went to a break, classrooms screens were turned-off. The logic behind the Debate-Only treatment is that participants under this condition experienced the debate without the influence of social media.

Twitter-Interact

Participants who entered a Twitter-Interact classroom watched a live broadcast of the presidential debate. They were asked to follow a Twitter account created for the occasion (which we call the experiment's "active account") and interact with it. Specifically, participants were requested to perform an action (a "like", retweet or reply) to at least three of its tweets or retweets every ten minutes.[15] The active account produced four kinds of tweets. First, it retweeted tweets from politicized Twitter accounts that commented the debate. Specifically, it retweeted around ten tweets of this kind every ten minutes (approximately half produced by *JxC*-leaning accounts and half by *FdT*-leaning accounts).[16] Second, it tweeted one neutral tweet every ten minutes. Third, it retweeted a tweet from a fact checker NGO every ten minutes.[17] Finally, every ten minutes it tweeted a series of tweets reminding participants to interact with the active account's tweets and retweets. To boost the salience of the active account activity, the screen at the front of the classroom was split in two: on the left side, the debate was broadcasted (as in the Twitter-Allowed and Debate-Only treatments), while the right

[15] To increase the probability of a participant seeing the active account tweets in their feeds, they were also requested to switch their Twitter feed to a chronological timeline.

[16] During the experiment, the active account retweeted twenty-one *FdT* leaning tweets and twenty-three *JxC* leaning tweets. Of these, 97.8% were authored by accounts included in the political landscape network and 47.8% were authored by seed accounts (see Section 2.b.1).

[17] An example of a neutral tweet is "*Great idea for politicians to debate in front of the public.*" Messages tweeted by the account *Chequeado* (the most important fact-checking Argentine NGO), referred to previous *Chequeado* studies (i.e., they did not check in real time the candidates' statements).

half projected an embedded timeline showing all the tweets and retweets produced by the active account in real time (see Figure A3 in Appendix C). From 9 pm up to 9:55 pm participants watched the first half of the presidential debate and interacted with the active account content as requested. The rationale behind the Twitter-Interact group was to ensure that participants inside echo chambers received at least some counter-attitudinal information.

2.a.4. *Post-treatment procedures*

Once the projection of the TV debate broadcast (or the institutional video in the Documentary group) was turned off, participants in all arms were handed a post-treatment questionnaire (see Appendix D). When they finished taking the survey, participants were requested to provide a second saliva sample. Finally, each participant was asked to hand back the completed questionnaires and both saliva samples to the classroom experiment assistant. Having done so, participants could leave the university premise or go to the university cafeteria to watch the rest of the presidential debate. When participants left the university premise, they were identified and received the supermarket gift voucher. One advantage of this protocol is that it resulted in no attrition and full compliance.[18] We also tracked their Twitter activity for the following day.

2.b. Measuring participants' political positions from pre-treatment data

Social media activity provides valuable information regarding the ideological positions of their users (see, for example, Kosinski et al. 2013 and Barberá, 2015, *inter alia*). Considering this, we estimate the political position of the participants by following a three-step procedure. First, using Twitter data, we propose a simple strategy for building a network that captures the Argentine political landscape. Second, for Twitter participants, we estimate their party preference by analyzing their interactions with this network. Third, we combine the information gathered in the second step with pre-treatment questionnaire answers and train a machine learning model which allows to predict political positions for non-Twitter participants. Below we provide details on each step.

2.b.1. *The Argentine political landscape network*

As in Barberá (2015) and Bail et al. (2018), we start by creating a curated list of partisan Twitter accounts and assign to each account i an ideological score (θ), where θ_i equal to 0 indicates that an account i is an *FdT* leaning account and θ_i equal to 1 indicates that an account i is an *JxC* leaning account. We refer to these accounts as "seed accounts." They are what could be called the "Twitter

[18] We know there was no attrition because nobody left the premise before the experiment ended and all the envelopes handed out at the moment of registration were completed and returned as expected. All the corresponding vouchers were collected by the participants. We also know there was compliance because there were no instances where an envelope that was assigned to one classroom eventually ended in at another one.

elite", and include the main electoral candidates' Twitter accounts (for each of the main districts' legislative and executive branches), the main political parties' Twitter accounts, accounts of journalists and media outlets often described as partisan, as well as accounts of youth activists, artists, academics, and scientists described as partisan. Additionally, the list includes some popular Twitter accounts described as partisan. Overall, we listed 95 seed accounts (48 *JxC* leaning and 47 *FdT* leaning).

Then, for each seed account, we identify all of their friends (i.e., those accounts that they follow).[19] Having collected this information, we build a directed network where each node represents a Twitter account (and where the seed accounts are a subset) and each directed edge indicates that an account befriends another. The resulting network contains 132,598 nodes and 216,472 edges. Finally, we make use of a simple label propagation model (see London and Getoor, 2013) to assign an ideological score to every non-seed account. Specifically, for every non-seed account i we assign a value of θ_i equal to the average of the ideological scores of the nodes directing toward i. Note that by construction incoming edges only come from seed accounts (for which we know their ideological scores). This network is called the "Argentine political landscape network" (see Figure 2).

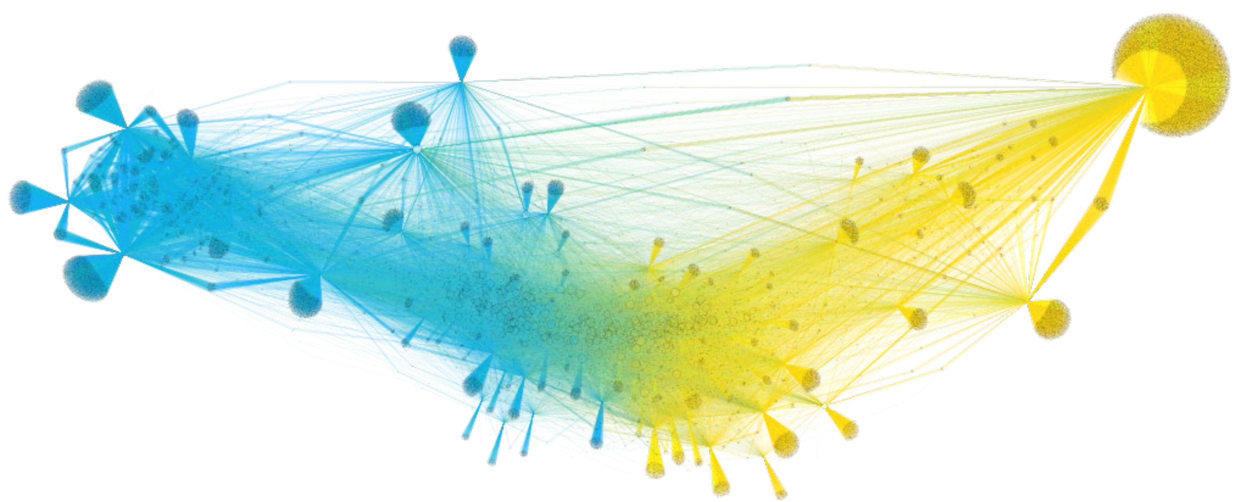

Figure 2. Argentine political landscape network.

Notes. The figure includes the 95 seed accounts and the 132,503 non-seed accounts they follow. A continuous color scale reflects users' predicted political orientation. Light blue (yellow) indicates a totally *FdT* (*JxC*) leaning account. The size of each node reflects its in-degree.

In line with previous studies (see, for example, Adamic and Glance, 2005, and Halberstam and Knight, 2016), edges between accounts with opposing ideological positions are scarce, consistent with

[19] We do this by means of the Twitter REST API. This step was carried out before starting the recruitment procedure. On average, each *FdT* leaning seed account follows 2,382 other accounts, while each *JxC* leaning seed account follows other 2,178 seed accounts.

the presence of echo chambers. Figure A2 plots the distribution of the ideological scores across the Argentine political landscape network, showing that the distribution is highly bimodal. Additionally, the structure of the network goes in line with previous work studying Argentine politics and social media (see, for example, Aruguete and Calvo, 2018).

2.b.2. *Measuring Twitter users' social media segregation and political inclinations*

Having built the Argentine political landscape network, we estimate Twitter users' political positions by analyzing the way in which they interact with this network. Specifically, we estimate two dimensions of political positions: degree of social media segregation and party preference.

Social media segregation

For every participant in the Twitter user sample, we estimate a social media segregation score by analyzing the accounts she/he follows. Note that when a Twitter user i starts following a given user j, it means she/he also starts being exposed to j's activity (i.e., tweets, retweets, quoted retweets and, to a lesser degree, likes). This means that, if user i mainly follows politically like-minded Twitter accounts, it will be immersed in a pro-attitudinal echo chamber. Taking this into consideration, for every user i, we calculate the average of the ideological scores of the accounts i follows and are included in the political network, we refer to this value as λ_i^f. If i mainly follows *FdT* leaning accounts, λ_i^f will be close to 0; if i mainly follows *JxC* leaning accounts, λ_i^f will be close to 1; and if i follows both *FdT* and *JxC* leaning accounts in a balanced way, λ_i^f will be close to 0.5. Next, we define i's *raw segregation score* (r_i) to be equal to $2 \cdot \left|\lambda_i^f - 0.5\right|$ (note that r_i varies between 0 and 1).

A potential drawback of r_i is that it does not consider the degree to which a user follows political accounts.[20] To correct for interest in politics, we define i's *politicized score* (p_i) as the number of accounts included in the political network that i follows divided by the total number of accounts i follows.[21] Then, we calculate i's *normalized segregation score* (s_i) as $r_i \cdot p_i$. This score varies between 0 and 1, where values of s_i close to 0 indicate that Twitter user i is not immersed in a political echo chamber (either because she/he does not follow politics related accounts or because she/he follows

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[20] As an illustration consider a user i, who follows 1,000 accounts, all of which are included in the political network and have an ideological score equal to 1, and a user j who follows 999 soccer-related accounts, but just a single account that is included in our political network and happens to have an ideological score equal to 1. In this case, both r_i and r_j will be equal to 1, even if i is more segregated than j. In fact, one could argue that j is not segregated at all in terms of politics, as j's Twitter interests center on other topics.

[21] An ex-post validation exercise indicates that Twitter users who answered the maximum score in Q19 (interest in politics, see Appendix D) had a mean value of p equal to 0.447, while participants who answered a lower score had a mean value of 0.327. A two-sided t-test indicates that this difference is highly significant (t = 5.56, p < 0.01). 44.37% of all Twitter users answered that maximum score in Q19.

them in a balanced way), and values close to 1 indicate that user i is highly immersed in a political echo chamber.

Finally, we classify Twitter user i as "segregated" if s_i is greater than the median value of the normalized segregation score calculated over our Twitter sample, and as "non-segregated" otherwise. Figure 3 plots for the Twitter users sample the distribution of the normalized segregation score and its constituents, the dashed line in panel C indicates the position of the normalized segregation score median value. Pre-treatment characteristics differ to a large extent according to segregation status, suggesting that segregation status may be predicted from pre-treatment characteristics (see Table A6).

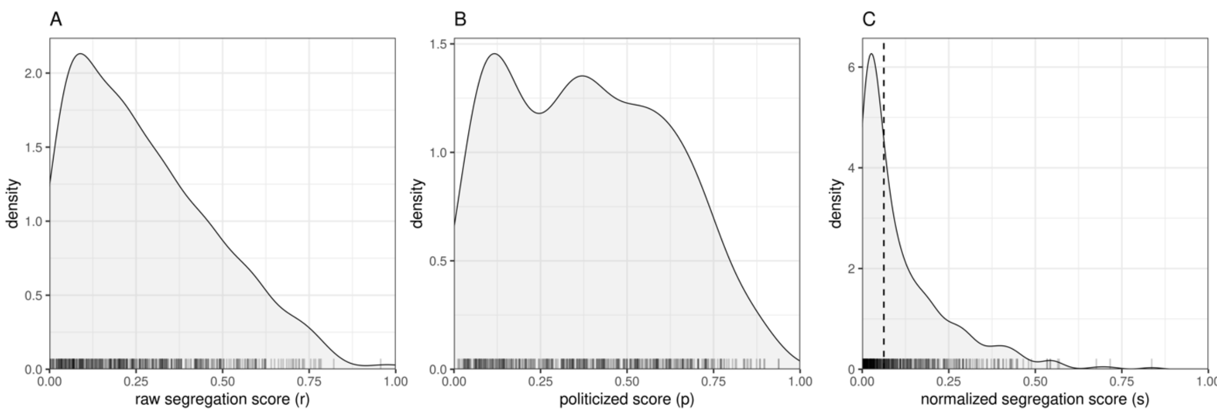

Figure 3. Distribution of normalized segregation scores and its components.
Notes. Dashed line in panel C indicates the position of the median score.

Party preference

When calculating a subset of our outcome variables (to be described in detail in Section 2.d), we need to infer if subjects lean toward the *FdT* or the *JxC* coalition. For Twitter users, we do this by analyzing their Twitter activity, specifically their "likes."[22] For every user i we estimate a party preference score (λ_i^l) equal to the median value of the ideological scores of those users included in our political landscape network whose tweets i liked.[23] In this way, if a participant i mainly liked tweets

[22] Likes are typically used as an endorsement to other tweets. The alternative is to use mentions, retweets or quoted retweets. However, taking "likes" as endorsements has three advantages. First, they are by far more common. Second, likes are less public than retweets and quoted retweets (they are not often shown in other users' feeds), so users tend to be less cautious when using them. Third, mentions and quoted retweets are often used to show opposition to tweets, whereas the vast majority of likes can be interpreted as endorsements.

[23] If the median value turned out to be equal to 0.5 (thirty cases), we replaced it by the mean value of the ideological scores. If the mean value was also equal to 0.5 (a single case), we replaced it with λ^f. Note that if a user j is liked n times by user i, θ_j counts n times when calculating λ_i^l. We also considered taking the mean value exclusively when calculating λ_i^l; however, the median value predicted in a better way the participants' vote in the primary elections (Q34 of the post-treatment questionnaires, see Appendix D).

coming from users with ideological scores close to 0 (i.e., *FdT* leaning accounts), her/his λ_i^l is close to 0, while it is close to 1 if she/he mainly liked tweets from accounts with ideological scores close to 1 (i.e., *JxC* leaning accounts).[24] Finally, for a given user i we calculate *party preference* equal to "*FdT* leaning" if λ_i^l is lesser than 0.5, and equal to "*JxC* leaning" otherwise. In our analysis, when calculating λ_i^l, we considered likes to tweets dating from June 20, 2019, up to and including October 12, 2019.

Figure 4 uses information on subjects' vote in the primary elections (which are compulsory in Argentina). It plots the distribution of λ^l and λ^f for three groups of participants: 1) Twitter users who reported having voted the *FdT* candidate in the primary elections (in light blue), 2) Twitter users who reported having voted the *JxC* candidate in the primary elections (in yellow), and 3) Twitter users who reported having voted other candidates (in gray).[25] Panel A plots participants' party preference scores calculated according to their likes (λ^l), while panel B does so according to the accounts they follow (λ^f). Note that Twitter activity is consistent with survey data on vote patterns for the primary election, and it is particularly strong for the measure that uses likes. Additionally, pre-treatment characteristics differ to a large extent across party preference, suggesting that party preference may be predicted from pre-treatment characteristics (see Table A7).

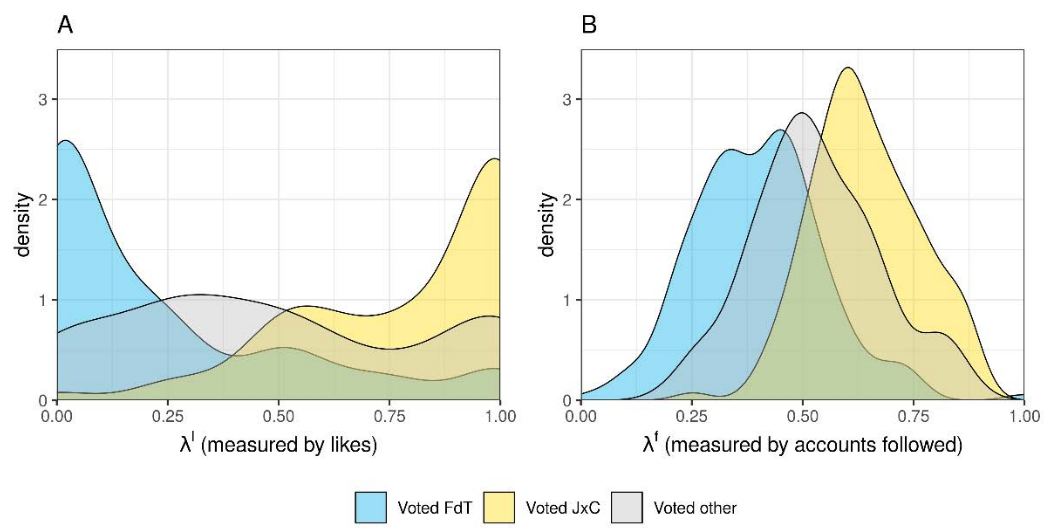

Figure 4. Distribution of Twitter users' party preference scores (likes and following).

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[24] During the period analyzed, 24 users did not like any tweet produced by an account included in the political network. For these users, we replaced λ^l with λ^f when calculating party preference.

[25] Even if the survey question on vote on the primary elections is a post-treatment question (Q34 of the post-treatment questionnaires, see Appendix D), our treatments are neutral across candidates. In fact, an ex-post analysis effectively shows no difference in reported primary election vote across treatment arms.

Notes. In panel A party preference scores are estimated by analyzing users' likes. In panel B party preference scores are estimated by analyzing users' followed accounts.

2.c. Measuring non-Twitter users' segregation status and political inclinations

Defining segregation in our sample of non-Twitter users the same way is not possible as they do not have Twitter activity. Our approach is to identify within the non-Twitter sample those subjects that, based on their pre-treatment answers, are predicted to segregate in the event of joining Twitter. We refer to them as "segregated non-Twitter users" (and "non-segregated non-Twitter users").[26]

In order to estimate predicted segregation status for non-Twitter subjects, we first train a machine learning model to predict online segregation status in the Twitter sample (calculated as described in Section 2.b.2) using as input all the ideology-related questions contained in the pre-treatment questionnaire.[27] Then, we use this model to predict non-Twitter subjects' segregation status. To estimate non-Twitter users' party preference, we followed an identical approach. We chose random forest as our main predictive model (see Hastie, Tibshirani, and Friedman, 2009).[28] Random forest excels at detecting nonlinearities and interactions in the input data, and its out-of-sample predictions commonly outperform ordinary least squares even at moderate sample sizes and with a limited number of predictive features (see Mullainathan and Spiess, 2017). The model performs reasonably well.[29] Table 1 summarizes the resulting distribution. Table A8, Table A9, Table A10 and Table A11 provide details on segregated and non-segregated participants' pre-treatment characteristics across treatment arms. Pre-treatment characteristics are balanced across treatment arms at all levels, suggesting a successful randomization.

[26] Note that non-Twitter users might still engage with social media (where they could be segregated). In fact, 56% of all participants in our non-Twitter users sample report using Facebook regularly (at least once a day).

[27] We use a rich set of ideology-related questions developed for this setting (as described in Di Tella et al., 2019, and Di Tella, Galiani, and Schargrodsky, 2021). They are described in Appendix D and they include Q14 (Messi vs. Maradona), Q15 (sentence length), Q16a (poverty and opportunities), Q16b (poverty and luck), Q16c (poverty and effort), Q17a (humans rights violations — Venezuela), Q17b (humans rights violations — USA), Q18 (Welfare state importance), Q19 (interest in politics), and Q20 (risk aversion). For each predictive feature, we imputed missing values using the sample mean (if the feature was continuous) or the mode (if the feature was categorical), and included a new variable indicating the presence of missing values.

[28] See Angrist et al. (2020), Mullainathan and Spiess (2017), and Sohnesen and Stender (2017) for examples of random forest being used in the context of applied social science research.

[29] It achieves an 80.8% accuracy in the training data when predicting online segregation status and a 61.1% validation accuracy, the model predicting party preference also achieves an 80.8% accuracy in the training data but a 71.1% validation accuracy. Validation accuracy is estimated by running 5-fold cross validation exercises (see Hastie, Tibshirani, and Friedman, 2009).

Table 1. Segregation status and party preference for three samples.

A) Segregation status	Non-segregated	Segregated
Non-Twitter users	131	110
Twitter users	224	223
Full sample	355	333

B) Party preference	*FdT* Leaning	*JxC* Leaning
Non-Twitter users	128	113
Twitter users	232	215
Full sample	360	328

2.d. Outcome and mechanism variables

We study two groups of outcomes variables (polarization indexes and variation in Twitter actions), as well as two groups of variables that we see as informing the mechanism (cortisol variation and Twitter actions during the debate). In what follows, we describe each group in detail.

Polarization indexes

Our survey included several post-treatment questions aimed at capturing different dimensions of polarization. For ease of presentation we study them in groups (but if we do not aggregate them we reach similar conclusions, as we report below). We start by building a set of five indexes that capture participants' polarization levels along standard dimensions. In all cases, these indexes are designed in such a way that higher values capture higher polarization levels. The indexes are named *Elite*, *Social Distance*, *Partisanship*, *Institutional*, and *Engagement*. Here we describe how each of them is constructed, for further details see Appendix A.

We first focus on affective polarization, that is, the dislike or distrust citizens have toward those identified with other political parties.[30] Following Druckman and Levendusky (2019), we differentiate between dislike towards party elites from dislike of other partisans. Accordingly, the *Social Distance* index is designed to capture dislike toward partisans of the opposing party, and it is calculated as the average of three components:[31] 1) the assessment of having an immediate family member marrying someone having opposite political preferences, 2) the assessment of having to spend time socializing with someone having an opposite political stance, and 3) the assessment of having to work closely with someone having an opposite political stance. And the *Elite* index captures the dislike of

[30] See Iyengar et al. (2019); Boxell, Gentzkow, and Shapiro (2020), and Rogowski and Sutherland (2016). Affective polarization has been shown to have risen in the last decade (Druckman et al., 2021) and it has been speculated to have a negative impact on democratic norms and accountability (see, for example, Graham and Svolik, 2020, and Gidron, Adams, and Horne, 2020).

[31] In all indexes, before averaging, all components are normalized so that the non-segregated Twitter-Allowed group distribution has a mean of 0 and a standard deviation of 1. Additionally, if a given component value for a given participant is missing, it is ignored when calculating the average.

outgroup party elites and it is built as the average of two components: 1) the perception that the outgroup party's presidential candidate is a threat to the well-being of Argentinians, and 2) the difference between the normalized number of positive traits participants assign to the ingroup party leader and the normalized number of positive traits subjects assign to the outgroup one.[32]

The *Partisanship* index captures the degree to which subjects are convinced of their political choice.[33] The index is calculated as the average of two components: 1) the degree to which subjects report being convinced of their future vote, and 2) the dispersion of their preferences over the different candidates, which we measure as the standard deviation calculated over the scores subjects assigned to each candidate in an exercise where participants had to distribute 100 points across each of them (see Q32 in see Appendix D). Note that evenly distributing scores between candidates is associated to a low standard deviation (i.e., low concentration in a few candidates).[34]

The *Institutional* index captures the degree to which participants distrust institutions as well as the importance they assign to loyalty over competence in executive branch appointments — a measure of tolerance to institutional weakness (see Edwards, 2001, and Egorov and Sonin, 2011). This index is related to what has been called *issue polarization* or *ideological polarization* in the related literature (see, for example, Allcott et al., 2020; Levy, 2021, and Bail et al., 2018). The index is calculated as the average of three components: 1) the difference between a score indicating how credible participants found the outgroup party committing electoral fraud in the upcoming elections and an equivalent score for the ingroup party, 2) the difference between a score indicating how much participants disagreed with a highly publicized supreme court judgement against their party and an equivalent score for a judgement against the outgroup party, and 3) a score measuring the importance given to executive branch ministers' loyalty over technical competence.

The *Engagement* index captures the degree to which participants are willing to engage in the electoral process (e.g., voting, contributing money, working or volunteering for a campaign, attending a campaign event). High political engagement has been associated to ideological extremes, particularly

[32] To identify ingroup and outgroup parties, we make use of the procedures described in Section 2.b.2 for Twitter users and Section 2.c for non-Twitter users. See Appendix A for additional details.

[33] Partisanship has been shown to correlate with polarization (see Lupu, 2015) and has been shown to be heightened when elections are approaching (see Schwalbe, Cohen, and Ross, 2020). In Allcott et al. (2020) this dimension is referred to as *vote polarization*.

[34] Given that the answers of a few participants did not add up to 100, before calculating the standard deviation, the scores were normalized in such a way that for all participants they add up to 1. This was done by means of the following expression: $s'_{i,j} = s_{i,j}/\sum_K s_{i,k}$ — where $s_{i,j}$ stand for the score participant i assigned to candidate j and where K is a set that contains the different candidates. All our main results remain robust when the dispersion scores are calculated taking as input the answers given in Q31 (scores assigned to each presidential candidate — each of them ranging from 1 to 10, see Appendix D). Results also remain robust when dispersion is measured by means of the Herfindahl-Hirschman index (a measure of market concentration commonly used to determine market competitiveness).

in voters holding unfavorable views of the opposing party (Pew Research Center, 2014b). The index is calculated as the average of two components: 1) a score indicating the willingness to audit, volunteer or donate funds to their preferred candidate, and 2) a score indicating the subject's willingness to persuade others of voting for their preferred candidate.

In addition to these five indexes, we build a series of aggregate polarization indexes. The main one, which we simply refer to as the *Combined Index*, is calculated as the average of the five polarization indexes described above.[35] To check for robustness in our results we also build three alternative versions. *Combined Index V2* is calculated as the average of the twelve components considered when calculating the *Elite*, *Social Distance*, *Partisanship*, *Institutional*, and *Engagement* indexes. Note that this version of the index gives equal weight to each component. Even though engagement has been reported to correlate with political polarization, it has also been argued that high polarization levels could discourage (i.e., turn-off) political engagement (see, Hetherington et al., 2008). For this reason, we also study the effect of excluding this dimension. *Combined Index V3* is calculated as the main *Combined Index* but excluding the *Engagement* index. *Combined Index V4* is calculated as the average of the ten components considered when calculating in *Combined Index V3*.

Variation in Twitter actions

We study two dimensions of Twitter activity: quantity and quality (labeled, respectively, Activity Level and Contact Segregation). We define *Activity Level* as the total number of original tweets, replies, mentions, retweets, quoted retweets, and likes generated by the user in the period analyzed.[36] Additionally, as baseline Twitter activity varies across participants, we study daily variation in activity levels, *ΔActivity Level* (defined as the difference between the activity level calculated over the day following the debate and the activity level calculated over the day preceding the debate).

We introduce *Contact Segregation* to capture the extent to which a subject's activity lies in an echo chamber. We construct *Contact Segregation* following a four-step procedure (which mimics the procedure described in Section 2.b.2). For a given account i, we first compute its *activity politicization score* (p_i^{act}) as the proportion of its activity (replies, mentions, retweets, quoted retweets, and likes) that is generated in response to accounts that are included in the political landscape network. Second, we calculate the mean ideological score of the accounts i interacted with and that are included in the

[35] Before being averaged each index is normalized so that the non-segregated Twitter-Allowed group distribution has a mean of 0 and a standard deviation of 1. Additionally, if a given index value for a given participant is missing, it is ignored when calculating the average. This is done for the remaining three combined indexes as well.

[36] Some users showed notably high activity levels during the period analyzed. To take this into account, we use the inverse hyperbolic sine (IHS) transformation when calculating Activity Level. $IHS(X)$ is defined as $ln(x + \sqrt{(x^2 + 1)})$. Note that the IHS transformation behaves similarly to the standard logarithmic transformation, but allows retaining non-negative-valued observations. See Burbidge, Magee, and Robb (1988) for further details.

political landscape network (we refer to this value as $\bar{\theta}_i^{act}$).[37] Third, we calculate i's *raw activity segregation score* (r_i^{act}) as $2 \cdot |\bar{\theta}_i^{act} - 0.5|$. Finally, we calculate i's *Contact Segregation* as the product of its activity politicization score and its raw activity segregation score (i.e., $p_i^{act} \cdot r_i^{act}$).[38] Since base Twitter activity varies across participants, we study variation in *Contact Segregation* around the debate, *⊿Contact Segregation* (defined as the difference between the contact segregation calculated over the day before the debate relative to that calculated over the day after).

Cortisol variation

We study changes in stress by measuring salivary cortisol.[39] We calculate cortisol variation, which we refer to as *⊿Cortisol*, as the difference between the post-treatment and the pre-treatment measurements.[40] Cortisol is commonly used as a biological marker of stress and can be reliably measured through non-invasive salivary tests (see, Kirschbaum and Hellhammer, 1989). Given that cortisol basal levels vary across subjects according to age, gender, and circadian rhythm patterns (see, Van Cauter and Kupfer, 1996), we focus on changes in cortisol during the experiment.

Twitter Actions during the debate

To interpret the Twitter-Interact group's results, we calculate *Activity Level* and *Contact Segregation* during the debate for the Twitter-Allowed and Twitter-Interact participants.

2.e. Empirical strategy

We estimate the values of a given outcome Y across treatment arms at two levels. First, at the full sample level. Second, analyzing heterogeneous effects by segregation status.[41]

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[37] If user i interacted with user j n times, θ_j counts n times when calculating this average.

[38] If a user did not interact with any account in the political landscape network, we set its contact segregation equal to 0. Note that high *Contact Segregation* scores indicate that the participants' activity was extreme in a political sense, meaning that it was closer to a political echo chamber (not necessarily their own).

[39] A growing body of evidence demonstrates that debating polarizing topics evoke feelings of anxiety and threat (see, Simons and Green, 2016) and that elections can be a source of stress (see, for example, American Psychological Association, 2020). Cortisol levels have been studied in similar contexts to ours in Ditzen et al. (2009), Dickerson and Kemeny (2004), Young (2004), Wirtz et al. (2008), Ditzen et al. (2009), Carney and Yap (2010), and Di Tella et al. (2019).

[40] Saliva samples were analyzed at ManLab laboratory. Diez et al. (2011) and Di Tella et al. (2019) used this lab to measure cortisol. Cortisol measurement is low-censored at 0.08 μg/dL (i.e., anything below 0.08 is reported at 0.08). 12 participants were excluded as they provided insufficient saliva in at least one of their two samples. As in previous work, participants with a pre/post variation in cortisol in absolute value larger than 2.5 standard deviations were excluded (10 participants).

[41] To address the possibility of correlation in the error term due to interactions between people within a classroom, standard errors are clustered at the classroom level in all regressions (see Abadie et al., 2017). Our main results remain robust when classical or HC1/robust are used (for a discussion on the topic, see King and Roberts, 2015)

When considering all participants as a whole, we estimate the following regression:

$$Y_i = \sum_{j,k} \beta_{j,k} (Twitter_{i,j} \cdot T_{i,k}) + \gamma \cdot X_i + \epsilon_i, \quad (1)$$

where Y_i is equal to the value of outcome variable Y for subject i, $Twitter_{i,j}$ stands for a set of dummy variables which indicate if participant i is a Twitter user or not ($j \in \{$*Twitter user, non-Twitter user*$\}$), $T_{i,k}$ stands for a set of dummy variables which indicate if participant i was assigned to treatment k ($k \in \{$*Documentary, Twitter-Allowed, Debate-Only, Twitter-Interact*$\}$), X_i are a set of control variables independent from treatment assignment (these include age, age^2, education years, female=1, household head=1, recruitment agency online=1, and recruitment agency offline=1), and ε_i is an error term. Before estimating Equation 1, Y and all of the control variables are normalized so that the non-segregated Twitter-Allowed group distribution has a mean of 0 and a standard deviation of 1. $\beta_{j,k}$ are the parameters of interest, which should be interpreted as the mean values of Y across treatment arms for Twitter users and non-Twitter users.

When analyzing heterogeneous effects by segregation level, we estimate the following regression:

$$Y_i = \sum_{j,k,l} \beta_{j,k,l} (Twitter_{i,j} \cdot T_{i,k} \cdot segregated_{i,l}) + \gamma \cdot X_i + \epsilon_i, \quad (2)$$

where $segregated_{i,l}$ stands for a set of dummy variables which indicate if participant i is a segregated participant or not ($l \in \{$*segregated, non-segregated*$\}$, see Section 2.b). All of the remaining variables stand for the same as in Equation 1. Again, Y and all of the control variables are normalized so that the non-segregated Twitter-Allowed group distribution has a mean of 0 and a standard deviation of 1. In this case, $\beta_{j,k,l}$ are the parameters of interest, which should be interpreted as the mean value of Y for each treatment arm for both segregated and non-segregated Twitter and non-Twitter users.

3. Results

3.a. Polarization indexes

Figure 5 presents results using our main, survey-based, polarization index combining all the data (see Table A12 and Table A13 for detailed estimates on all of the aggregate combined indexes). Estimates are presented for three samples of data. The first and second columns present estimates for the non-segregated and segregated samples respectively (obtained by fitting Equation 2 to the data), the third column presents estimates for the full sample (i.e., non-segregated and segregated subjects lumped together — estimates obtained by fitting Equation 1). Additionally, Figure 5 presents outcomes across six groups (four treatments, two of which also include non-Twitter users). Figure 6 presents results along the Elite, Social Distance, Partisanship, Institutional, and Engagement dimensions (see Table A14 and Table A15 for detailed estimates). In Figure 6, as well as in the rest of the paper, each column of panels presents estimates for the three samples (non-segregated, segregated, and full) altogether.

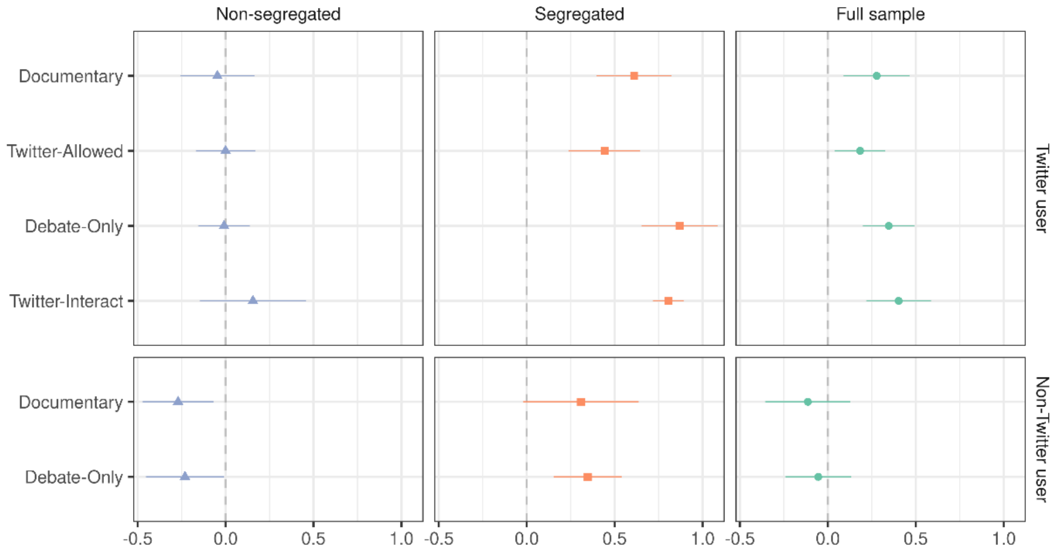

Figure 5. Aggregate polarization indexes across treatment groups

Notes: This figure presents estimated conditional mean values for each treatment group and the corresponding outcome variable. All variables are normalized so that the non-segregated Twitter-Allowed group distribution has a mean of 0 and a standard deviation of 1. Error bars reflect 90% confidence intervals (estimated by using standard errors clustered at the classroom level). See Section 2.d for variable definitions. See Table A12 and Table A13 for detailed estimates.

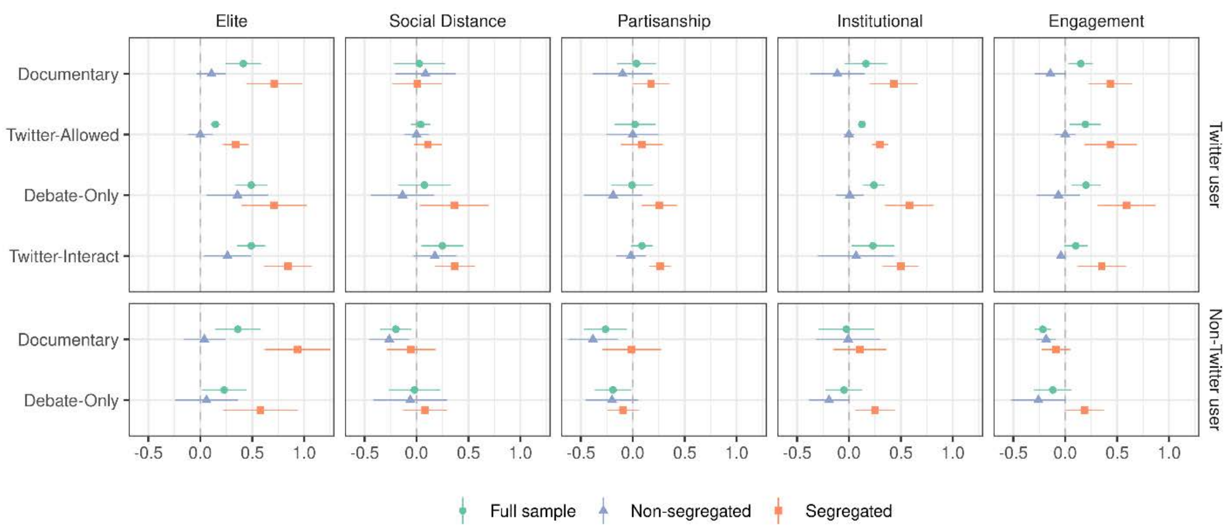

Figure 6. Individual polarization indexes across treatment groups

Notes: This figure presents estimated conditional mean values for each treatment group and the corresponding outcome variable. All variables are normalized so that the non-segregated Twitter-Allowed group distribution has a mean of 0 and a standard deviation of 1. Error bars reflect 90% confidence intervals (estimated by using standard errors clustered at the classroom level). See Section 2.d for variable definitions. See Table A14 and Table A15 for detailed estimates.

Treatment effects

Our main focus are the treatment effects. Restricting attention to the sample of non-segregated Twitter users, there are no differences in the combined polarization index for any treatment.

Restricting attention to the sample of segregated Twitter users, we note that the lowest combined polarization index that we measure is in the Twitter-Allowed treatment, although the difference with the one for the Documentary group is not statistically significant. In contrast, the difference in polarization levels between Twitter-Allowed and the other two treatments (Debate-Only and Twitter-Interact) are comfortably significant.[42] See Table A16 for detailed results.

Our measures of the different dimensions of polarization (that make up the combined index), presented in Figure 6, confirm this overall picture. For example, in the segregated sample, the level of polarization measured in Twitter-Allowed is frequently the lowest observed (in, fact, the difference is significant versus Twitter-Interact in the Elite, Social Distance and Institutional indexes, versus Debate-Only in the Elite and Institutional indexes, and versus Documentary in the Elite index). See Table A17 for detailed results.[43]

For the sample of non-Twitter users, note that aggregate polarization levels are similar across the two treatments in both the segregated and the non-segregated users' samples.[44] See Table A18 and Table A19 for detailed results.

Comparison across samples

Several comparisons across samples are of interest. The first is that within the non-Twitter sample one can observe that the segregated group is significantly more polarized than the non-segregated, suggesting polarization is not exclusively an online phenomenon (see Table A20). At the same time, note that the polarization level of the full Twitter sample is higher than those in the full non-Twitter sample in the case of the Documentary treatment. The same is true in the case of the

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[42] Interestingly, in auxiliary regressions, we find that the effects are somewhat stronger in the subsample of subjects with education below the median years of education value (although this result is obtained on a smaller sample and with a relatively crude measure based on attainment).

[43] In the non-segregated sample, the difference is significant for the Elite index in the Debate-Only and Twitter-Interact groups. Note that for segregated Twitter users there is a small increase in the Engagement index in the Debate-Only treatment and a small decrease in the Twitter-Interact group. Although we cannot reject equality, the pattern is consistent with the Twitter-Interact treatment discouraging political engagement in segregated users (see Hetherington et al., 2008).

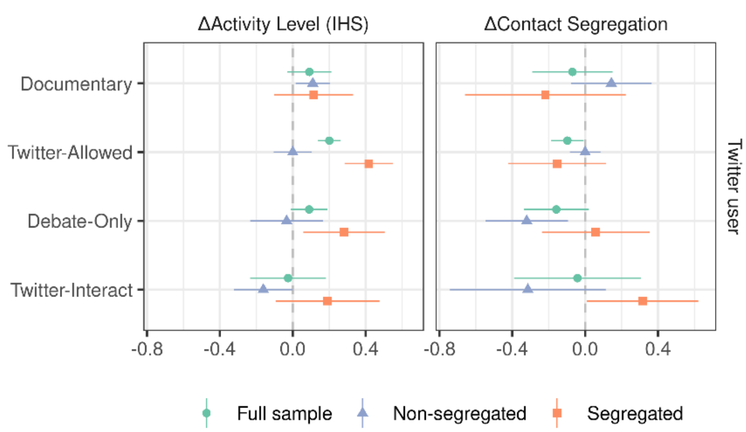
[44] At the individual index level, only for the segregated sample we observed a reduction in the Engagement index in the Documentary relative to the Debate-Only group.

Debate-Only treatment. This is driven mainly by the higher polarization of the segregated Twitter users: if attention is restricted to the segregated samples, equality in the Twitter and non-Twitter aggregate polarization indexes is rejected at the 1% level in the Debate-Only group (see Table A21).[45]

One limitation of this comparison is that it is possible that the Twitter sample is more "politicized", so the act of denying them the possibility of watching a debate that is in fact taking place causes them to answer our survey in a more polarized way.[46] In this case, one might insist on a comparison of polarization levels across the "normal" states for subjects in both samples. In other words, a comparison of the two samples in situations that are as close as possible to the way in which they would normally experience this event. For the non-Twitter sample, it is simply the Debate-Only group (under the assumption that they are not affected by the absence of their phones), with a polarization score of -0.055, s.e. 0.109. For Twitter users, the natural state is the Twitter-Allowed treatment (with a score of 0.183, s.e. 0.084). This difference is significant at the 10% level, and is driven by the somewhat lower polarization of non-segregated non-Twitter users (put differently, in normal circumstances, segregated non-Twitter users appear to be as polarized as segregated Twitter users, a result that is broadly consistent with the relatively high polarization levels offline reported in Gentzkow and Shapiro, 2011).

3.b. Variation in Twitter actions

Figure 7 summarizes variation in Twitter actions results. See Table A22 and Table A23 for detailed regression results.



[45] See Garimella and Weber, (2017) as well as Sunstein (2018) and Pariser, (2011). On the limited role of the internet in causing increases in political polarization, see Boxell, Gentzkow, and Shapiro (2017).

[46] Recall from Table 1 that the segregation score that splits the Twitter sample in half leaves a proportion of the non-Twitter sample classified as non-segregated that is higher than 0.5 (specifically, 0.54 = 131/241).

Figure 7. Variation in Twitter actions estimates across treatment groups

Notes: This figure presents estimated conditional mean values for each treatment group and the corresponding outcome variable. All variables are normalized so that the non-segregated Twitter-Allowed group distribution has a mean of 0 and a standard deviation of 1. Before being normalized, all outcome variables are expressed as first differences, where the value of the day preceding the debate is subtracted from the value of the day following the debate. Error bars reflect 90% confidence intervals (estimated by using standard errors clustered at the classroom level). See Section 2.d for variable definitions. See Table A22 and Table A23 for detailed estimates.

A reduction in *ΔActivity Level* is observed for the segregated Documentary group. We also observe a reduction in *ΔContact Segregation* for the non-segregated Debate-Only group and in the segregated Twitter-Interact group.

An interesting pattern is observed across samples for the Twitter Interact treatment. Using the variable *ΔContact Segregation*, we note that the nature of Twitter activity for non-segregated subjects tends to lie to a lesser degree in an echo chamber (i.e., they become less extreme) but the opposite happens in the segregated group (i.e., they become more extreme; statistically significant). See Table A24. The difference in these patterns is statistically different at the 1%.

3.c. Cortisol variation

From now on, we study possible mechanisms behind polarization. Figure 8 plots the results for cortisol variation. See Table A25 and Table A26 for detailed regression results.

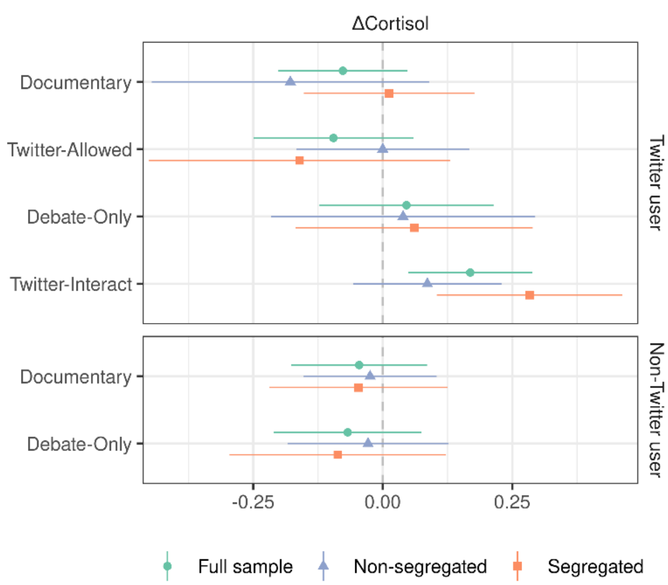


Figure 8. Cortisol variation estimates across treatment groups

Notes: This figure presents estimated conditional mean values of *ΔCortisol* for each treatment group. All variables are normalized so that the non-segregated Twitter-Allowed group distribution has a mean of 0 and a standard deviation of 1. Before being normalized, *ΔCortisol* is expressed as the first-difference between the cortisol levels of the sample provide at the end of the experiment and the one provided at the beginning. Error bars reflect 90% confidence intervals (estimated by using standard errors clustered at the classroom level). See Section 2.d for variable definitions. See Table A25 and Table A26 for detailed estimates.

Cortisol variation is similar across all treatments in the non-segregated Twitter users' sample. Restricting attention to the segregated sample, cortisol variation in the Twitter-Allowed treatment is similar to the one observed in the Documentary and Debate-Only groups, but it is significantly lower than the one observed in the Twitter-Interact treatment. This suggests that for people in echo chambers, being exposed to counter-attitudinal content coming from other Twitter accounts during a politically significant event was a cause of stress (see Table A27 for detailed results).

Cortisol variation is similar across both treatments in the non-segregated, non-Twitter users' sample. The same is true for the segregated group.

We also observe that Twitter and non-Twitter users experienced similar variations in cortisol during the experiment (see Table A28).

3.d. Twitter actions during the debate

Figure 9 plots Activity Level and Contact Segregation during the debate for the Twitter-Allowed and Twitter-Interact groups (recall that participants in the Documentary and Debate-Only groups were not allowed to use Twitter). See Table A29 and Table A30 for detailed regression results.

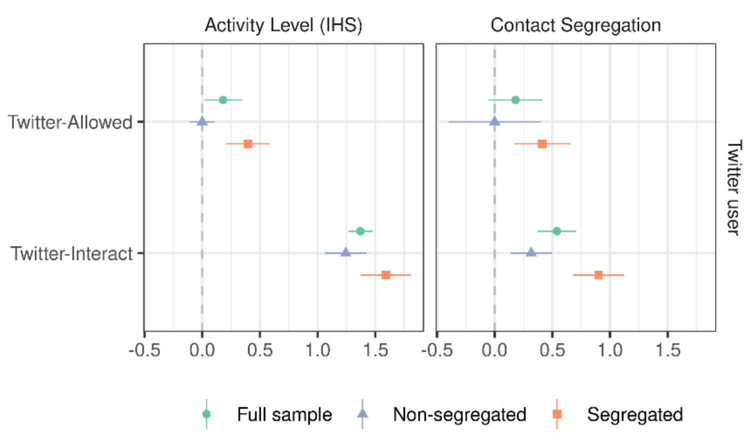


Figure 9. Twitter actions during the debate

Notes: This figure presents estimated conditional means for each treatment group and the corresponding outcome variable. All variables are normalized so that the non-segregated Twitter-Allowed group distribution has a mean of 0 and a standard deviation of 1. Error bars reflect 90% confidence intervals (estimated by using standard errors clustered at the classroom level). See Section 2.d for variable definitions. See Table A29 and Table A30 for details.

Focusing on the segregated sample, both Activity Level and Contact Segregation estimates are larger in the Twitter-Interact group than in the Twitter-Allowed group. A similar pattern is observed in the non-segregated samples estimates (although the difference in Contact Segregation is not statistically significant). Note that compliance in the Twitter-Interact treatment involved a higher level of both the quantity and quality of Twitter actions relative to normal circumstances (Twitter-Allowed). See Table A31 for detailed results.[47]

The difference observed between segregated and non-segregated participants in Activity Level and Contact Segregation for the Twitter-Allowed group (although not significant in the latter) reinforces the validity of our measure of echo chambers, as it shows that those in them are naturally more active during a politically salient event and that their activity tends to be both centered around politics and ideologically segregated. See Table A32 for detailed results.

4. Summary and discussion

Our results on the non-Twitter sample offer a simple, offline benchmark for our study. The effect of the debate, approximated by comparing the two treatments available (Debate-Only vs Documentary) suggests that the event does not change polarization levels in any of the three samples (non-segregated, segregated and full). Interestingly, the same is true for the Twitter user sample. In this case, the effect of the debate can be approximated by comparing the Documentary condition with the Twitter-Allowed treatment which is the closest we have to the "natural" state for these subjects. A reasonable interpretation is that the political event per se does not affect polarization, so that any effects that we observe are the result of the interaction of the event with social media.

The non-Twitter data also reveals that segregated users are significantly more polarized than those that are non-segregated. This suggests that offline interactions can be as polarizing as online interactions, at least in Twitter (as in Gentzkow and Shapiro, 2011). It is interesting to compare these data with the Twitter user sample. It appears that, on average, there is significantly lower polarization in the non-Twitter relative to the Twitter sample. Note that the most informative comparison involves the "natural" state in which subjects absorb the politically significant event (Debate-Only for non-

[47] The Twitter REST API provides the timestamp in which a given liked tweet was originally tweeted but not the exact time in which it was actually liked. This poses a problem for timing likes in short timespans. Some of the likes we collected could have been generated after watching the debate. Thus, we re-estimated all results presented in this section excluding likes. All results remain robust. Additionally, when likes are excluded, neither the Debate-Only nor the Documentary participants present any Twitter activity during the debate, again indicating compliance with the experiment's activities.

Twitter users and Twitter-Allowed for those that use Twitter). This comparison also suggests broadly comparable levels of polarization for segregated users across the Twitter and non-Twitter samples.[48]

Table 2 summarizes the main results of our paper, which involve the Twitter user sample. It shows that our survey-based polarization measures for non-segregated subjects across the three treatments are similar to the ones observed in Twitter-Allowed (the benchmark group). There is some evidence of lower polarization in the Debate-Only group using *⊿Contact Segregation*.

Table 2. Treatment effects summary

	Outcomes			Mechanisms		
	Combined Index	Twitter Actions (pre - post)		ΔCortisol	Twitter Actions (during the debate)	
		ΔActivity Level	ΔContact Segregation		Activity Level	Contact Segregation
Non-segregated						
Documentary	-0.046	0.110	0.144	-0.178	-	-
	(0.158)	(0.084)	(0.137)	(0.184)		
Debate-Only	-0.009	-0.034	-0.321**	0.039	-	-
	(0.128)	(0.137)	(0.142)	(0.180)		
Twitter-Interact	0.156	-0.162	-0.314	0.086	1.243***	0.317
	(0.202)	(0.112)	(0.255)	(0.130)	(0.111)	(0.213)
Segregated (in an echo chamber)						
Documentary	0.168	-0.302**	-0.064	0.173	-	-
	(0.156)	(0.141)	(0.257)	(0.180)		
Debate-Only	0.427***	-0.136	0.212	0.221	-	-
	(0.153)	(0.153)	(0.209)	(0.192)		
Twitter-Interact	0.363***	-0.226	0.468**	0.444**	1.197***	0.486***
	(0.118)	(0.190)	(0.212)	(0.184)	(0.127)	(0.139)

Notes: Standard errors clustered at the classroom level. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Treatment effects in the sample of subjects that came into the experiment already in echo chambers are positive and significant for both the Debate-Only and Twitter-Interact groups, revealing higher polarization measured in survey data relative to the benchmark group. For the Twitter-Interact group there is also an increase in *⊿Cortisol* (suggesting that the tasks involved were a source of stress for these participants) and in *⊿Contact Segregation* (suggesting that their Twitter-Interactions became more polarized). The same is broadly true for the sub-indexes which capture affective polarization (i.e., the Elite and Social Distance; not shown in Table 2, see Section 3.b). It is unlikely that the rise in polarization for the Debate-Only group was caused by the requirement to turn-off their cellphones (perhaps because these users may be particularly addicted to social media, as in Allcott, et al., 2021) because this is not observed in the Documentary group, which also turned-off their cellphones. Finally, for the Documentary group, we observe a decrease in *⊿Activity Level*.

[48] In order to connect these results to work studying online vs offline polarization, note that our measures take place at a particularly political time (around the presidential debate). There is also the challenge of calculating comparable measures of segregation across the Twitter and non-Twitter samples.

Our main result can be interpreted as identifying circumstances in which the presence of an echo chamber can be seen as de-polarizing. Why might that be? The mechanism we envisage is that people that are interested in politics "demand" echo chambers because it is helpful to them when they have to interpret a political event. For example, if people hold simplistic views of outgroup candidates, a few Twitter accounts, which can be called the "Twitter elite," might be of help by offering some nuance and guide (regarding which are good arguments, etc.). Our data shows that Twitter interactions during the debate in the Twitter-Allowed group tended to be mainly within each group's echo chamber. Higher polarization of the segregated group in the Debate-Only condition would result when the guide and nuance of the Twitter elite is absent. Higher polarization in the Twitter-Interact group would result if some of the nuance is lost when considering (and rejecting) the alternative interpretations of the event offered by outgroup members. It may also be the result of considering (and perhaps accepting) arguments offered by "weak" partisan accounts (the messages we tweeted might not be from the accounts that they usually follow). Higher cortisol levels in this condition suggest that this process is stressful. People with relatively low education would find this "service" of echo chambers more valuable.[49]

A comparison with previous work is useful. As noted above, our treatments are closely linked to two more general strategies that have been suggested to combat polarization. Moreover, two recent papers provide supporting evidence: Allcott et al. (2020) finds that deactivating Facebook during the four weeks prior to the US midterm election reduces polarization, and Levy (2021) finds that exposing Facebook users to counter-attitudinal news content decreases affective polarization. Thus, our main result can be seen as somewhat paradoxical.

By design, however, there are several differences with prior work, starting with the fact that we are interested in the reaction of people that are already polarized (i.e., in echo chambers) when the political information arrives and they interact with social media. Indeed, subjects outside echo chambers become somewhat *less* polarized according to their change in Twitter actions (*⊿Contact Segregation*), which is consistent with the findings of Levy (2021). Another basic difference with previous work is that our intervention takes place during a very short period of time (a few hours) during which a politically salient event takes place. The survey and cortisol measures are taken

[49] We find some evidence of stronger effects on the segregated with low educational attainment, although we do not have enough statistical power to make strong statements in this regard. More generally, note that our results suggest that providing counter-attitudinal data is more stressful than simply muting their echo chambers (we find higher affective polarization, higher cortisol variation, and higher contact segregation in the Twitter-Interact group). An alternative interpretation sees the disparity as result of the difference in the "dose" of information administered. Indeed, the Debate-Only treatment already exposes segregated viewers to counter-attitudinal data, so one might think of Twitter-Interact as a similar treatment in qualitative terms, only in a higher dose. Note the connection to Lord et al. (1979): both the Debate-Only and the Twitter-Interact treatments confront participants with a higher dose of conflicting data and hence provide more opportunities for the type of biased examination of the evidence that gives rise to polarization in that classic study (see, also, Taber and Lodge, 2006). Notably, our results suggest that this experience is stressful and it results in dislike of both the outgroup main candidate and of partisans (i.e., it increases affective polarization).

immediately before and after watching the debate, while changes in Twitter activity are measured the day before and the day after the debate.[50] For comparison, Allcott et al. (2020) uses a one month period, while Levy (2021) implements his Facebook intervention over two months. The political event we study can be interpreted as somewhat more intense because it is a debate involving the subjects' favorite presidential candidates, instead of the final weeks of the midterm election studied in Allcott et al. (2020). Even if these types of debates are rare, and they involve a somewhat artificial structure, they are focal points with purportedly a lot at stake, so we see them as a good setting for our study.

The setting for our study is also somewhat different from prior work. For example, our Twitter-Interact treatment involves actively engaging with Twitter messages originating in accounts located in the two main echo chambers. These accounts do not have the status, and perhaps credibility, of the subscriptions to (conservative or liberal) news outlets with which Levy (2021) treats his subjects. The messages used in the treatment exploit the "horizontal" nature of social media, where anyone can have their voices heard and not just traditional newspapers (which are costly to set up and run). Moreover, they involve a small number of "messages" from popular accounts from both sides of the ideological spectrum and we ask subjects to interact with them. While this forces them to take a more active stance, which can be viewed as somewhat artificial, it ensures that our subjects are exposed to a narrow set of counter-attitudinal information that is under our control. Reassuringly, our "backfire" result (in the Twitter-Interact and Debate-Only conditions) is observed only in people who were already in an echo chamber prior to the experiment (not people in the ideological middle).

Finally, note that society's perception of the extent of polarization might be affected by a particular set of people.[51] An interesting hypothesis is that what has changed in recent times is the sample of people from which we construct our views about polarization in society.[52] Indeed, if perceptions of polarization are influenced by the fact that Twitter is now able to capture people's raw reactions after experiencing a political event, or while debating other Twitter users that are outside their echo chamber and whom they find irritating, then our results show that this would be sampling from the group that is relatively more polarized. The behavior of the Argentine media provides an illustrative example. The day following the presidential debate, several newspapers published notes on the repercussions on social media, often citing tweets from the more extreme public figures from both

[50] The longest period over which we gather data is the 9 days prior to the debate, when people started registering for our experiment and we started following their Twitter-Interactions so that we could later classify them as segregated or non-segregated.

[51] Druckman et al. (2021a) report that high levels of out-party animus stem, in part, from misperceptions of the other party's voters, where individuals exaggerate the ideological extremity and political engagement of typical out-partisans. Pew Research Center (2019a) finds that 10% of Twitter users are responsible for 97% of all tweets about US politics.

[52] Some scholars believe that increased polarization is only an illusion, stemming from the tendency of the media to treat conflict as more newsworthy than consensus (see, for example, Fiorina et al., 2005).

sides of the political spectrum (including links to the original tweets).[53] Note that this, in turn, may induce further rounds of greater polarization in readers of these news items. Of course, the flipside of our focus on an event that may have boosted feelings of polarization in the moment is that the size of our estimated effects may overestimate the true, steady state level of polarization of these groups.

5. Conclusions

There is a growing body of work demonstrating how people live in "partisan bubbles," with little exposure to those who have a different ideological inclination. There is concern that this might foster polarization and have negative consequences for democracy, including increased prejudice and legislative stalemate. Two broad types of policy responses have been suggested. The first is to find ways of exposing people to counter-attitudinal data, and the second is to get people to reduce their consumption of social media. In this paper, we provide experimental evidence on one specific event where these two strategies did not work.

Our approach consists in designing a field experiment to observe how two groups, those inside echo chambers and those outside, react to a political event under different treatments that vary social media status in ways that mimic these two strategies. Subjects that were outside echo chambers before our study began experienced no change in polarization in all treatment arms. If anything, there is some weak evidence of a reduction in the polarization of their Twitter contacts in the counter-attitudinal condition. In contrast, subjects that started out inside echo chambers became *more* polarized when these two policies were implemented. Interestingly, the lowest level of subsequent polarization in this group was registered when they watched the debate with access to Twitter (comparable to the treatment that didn't even expose them to the political event). In other words, the lowest level of polarization for subjects in echo chambers is observed when they do what they would have done in normal (non-experimental) circumstances.

Our conjecture is that the Twitter echo chambers that subjects have formed with other like-minded Twitter users are helpful to them when they have to interpret a political event. One possible mechanism is that people's opinions tend to be simplistic, so they follow selective accounts from what could be called the "Twitter elite", in order to construct a more informed, nuanced ideology. When this contact is absent (in the Debate-Only condition) that nuance is lost. A similar thing happens in the Twitter-Interact group, when this opinion-formation exercise is contested, for example with counter attitudinal arguments and data that will ultimately be rejected.

The results raise the question of what is the appropriate benchmark against which we should frame the concern over echo chambers. An extreme position is that there has always been a subgroup of the population which, for a variety of reasons, embraces strong ideological views. While it is possible

[53] See, for example, La Nación (2019) and Infobae (2019).

that social media has intensified these views, it is far from clear that disrupting the environment they created (i.e., disrupting their echo chamber), either by introducing counter-attitudinal messages or by "recreating" a no-social-media environment, would be desirable in the sense that it reduces their polarization, at least in the short run.

One implication of our findings is related to a somewhat underappreciated fact about the increase in political polarization in the time of social media. While the evidence demonstrates that a lot of it is real, accounts of increased polarization often include reports of exchanges on social media between people with different world views as they process political events (e.g., "offensive tweet"). But if these exchanges are taking place between politicized people in different echo chambers, then their polarization level could be abnormally high.

References

Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey Wooldridge. 2017. "When Should You Adjust Standard Errors for Clustering?" Working Paper Series. https://doi.org/10.3386/w24003.

Adamic, Lada A, and Natalie Glance. 2005. "The Political Blogosphere and the 2004 U.S. Election: Divided They Blog." In *Proceedings of the 3rd International Workshop on Link Discovery*, 36–43. LinkKDD '05. New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/1134271.1134277.

Algan, Yann, Sergei Guriev, Elias Papaioannou, and Evgenia Passari. 2017. "The European Trust Crisis and the Rise of Populism." *Brookings Papers on Economic Activity*, August, 309–82. http://www.jstor.org/stable/90019460.

Allcott, Hunt, Luca Braghieri, Sarah Eichmeyer, and Matthew Gentzkow. 2020. "The Welfare Effects of Social Media." *American Economic Review* 110 (3): 629–76. https://doi.org/10.1257/aer.20190658.

Allcott, Hunt, Matthew Gentzkow, and Lena Song. 2021. "Digital Addiction," NBER Working Paper No. 28936, , no. 28936. https://doi.org/10.3386/w28936.

Ámbito. 2019. "El Rating Del Debate Presidencial: La Audiencia Viró Al Cable." *Ámbito*. https://www.ambito.com/espectaculos/debate-presidencial/el-rating-del-la-audiencia-viro-al-cable-n5059778.

American Psychological Association. 2020. "2020 Presidential Election a Source of Significant Stress for More Americans than 2016 Presidential Race."

Angrist, Josh, Pierre Azoulay, Glenn Ellison, Ryan Hill, and Susan Feng Lu. 2020. "Inside Job or Deep Impact? Extramural Citations and the Influence of Economic Scholarship." *Journal of Economic Literature* 58 (1): 3–52. https://doi.org/10.1257/jel.20181508.

Aruguete, Natalia, and Ernesto Calvo. 2018. "Redes Sociais e Política Na Argentina." *Revista Eletrônica de Estudos Integrados Em Discurso e Argumentação* 1 (16): 299–313. https://doi.org/10.17648/eidea-16-2224.

Aruguete, Natalia, Ernesto Calvo, Carlos Scartascini, and Tiago Ventura. 2021. "Trustful Voters, Trustworthy Politicians: A Survey Experiment on the Influence of Social Media in Politics." IDB Working Paper Series IDB-WP-1169. https://doi.org/10.18235/0003389.

Bail, Christopher A. 2021. *Breaking the Social Media Prism: How to Make Our Platforms Less Polarizing*. Princeton University Press. https://press.princeton.edu/books/hardcover/9780691203423/breaking-the-social-media-prism.

Bail, Christopher A, Lisa P Argyle, Taylor W Brown, John P Bumpus, Haohan Chen, M B Fallin Hunzaker, Jaemin Lee, Marcus Mann, Friedolin Merhout, and Alexander Volfovsky. 2018. "Exposure to Opposing Views on Social Media Can Increase Political Polarization." *Proceedings of the National Academy of Sciences* 115 (37): 9216–21. https://doi.org/10.1073/pnas.1804840115.

Bakshy, Eytan, Solomon Messing, and Lada A Adamic. 2015. "Exposure to Ideologically Diverse News and Opinion on Facebook." *Science* 348 (6239): 1130–32. https://doi.org/10.1126/science.aaa1160.

Baldassarri, Delia, and Andrew Gelman. 2008. "Partisans without Constraint: Political Polarization and Trends in American Public Opinion." *American Journal of Sociology* 114 (2): 408–46. https://doi.org/10.1086/590649.

Barberá, Pablo. 2015. "Birds of the Same Feather Tweet Together: Bayesian Ideal Point Estimation Using Twitter Data." *Political Analysis* 23 (1): 76–91. https://doi.org/10.1093/pan/mpu011.

Baum, Matthew A, and Tim Groeling. 2008. "New Media and the Polarization of American Political Discourse." *Political Communication* 25 (4): 345–65. https://doi.org/10.1080/10584600802426965.

Boxell, Levi, Matthew Gentzkow, and Jesse M Shapiro. 2017. "Greater Internet Use Is Not Associated with Faster Growth in Political Polarization among US Demographic Groups." *Proceedings of the National Academy of Sciences* 114 (40): 10612–17. https://doi.org/10.1073/pnas.1706588114.

———. 2020. "Cross-Country Trends in Affective Polarization." NBER Working Paper No. 26669. https://doi.org/10.3386/w26669.

Boxell, Levi, and Zachary Steinert-Threlkeld. 2021. "Taxing Dissent: The Impact of a Social Media Tax in Uganda." *Available at SSRN*, no. 3766440. https://doi.org/10.2139/ssrn.3766440.

Brown, Jacob R, and Ryan D Enos. 2021. "The Measurement of Partisan Sorting for 180 Million Voters." *Nature Human Behaviour*. https://doi.org/10.1038/s41562-021-01066-z.

Burbidge, John B, Lonnie Magee, and A Leslie Robb. 1988. "Alternative Transformations to Handle Extreme Values of the Dependent Variable." *Journal of the American Statistical Association* 83 (401): 123–27. https://doi.org/10.1080/01621459.1988.10478575.

Bursztyn, Leonardo, Georgy Egorov, Ruben Enikolopov, and Maria Petrova. 2019. "Social Media and Xenophobia: Evidence from Russia." NBER Working Paper No. 26567. https://doi.org/10.3386/w26567.

Carney, Dana R, Amy J C Cuddy, and Andy J Yap. 2010. "Power Posing: Brief Nonverbal Displays Affect Neuroendocrine Levels and Risk Tolerance." *Psychological Science* 21 (10): 1363–68. https://doi.org/10.1177/0956797610383437.

Cauter, E Van, R Leproult, and D J Kupfer. 1996. "Effects of Gender and Age on the Levels and Circadian Rhythmicity of Plasma Cortisol." *The Journal of Clinical Endocrinology & Metabolism* 81 (7): 2468–73. https://doi.org/10.1210/jcem.81.7.8675562.

Chen, Yuyu, and David Y Yang. 2019. "The Impact of Media Censorship: 1984 or Brave New World?" *American Economic Review* 109 (6): 2294–2332. https://doi.org/10.1257/aer.20171765.

Cinelli, Matteo, Gianmarco De Francisci Morales, Alessandro Galeazzi, Walter Quattrociocchi, and Michele Starnini. 2021. "The Echo Chamber Effect on Social Media." *Proceedings of the National Academy of Sciences* 118 (9). https://doi.org/10.1073/pnas.2023301118.

Clarín. 2019. "Cómo Influyó El Boca-River En El Rating de La Televisión Abierta." *Clarín*. https://www.clarin.com/espectaculos/tv/influyo-boca-river-rating-television-abierta_0_9bxtr1O_.html.

DellaVigna, Stefano, and Ethan Kaplan. 2007. "The Fox News Effect: Media Bias and Voting." *The Quarterly Journal of Economics* 122 (3): 1187–1234. https://doi.org/10.1162/qjec.122.3.1187.

Di Tella, Rafael, Lucía Freira, Ramiro H. Gálvez, Ernesto Schargrodsky, Diego Shalom, and Mariano Sigman. 2019. "Crime and Violence: Desensitization in Victims to Watching Criminal Events." *Journal of Economic Behavior and Organization* 159: 613–25. https://doi.org/10.1016/j.jebo.2017.10.005.

Di Tella, Rafael, Sebastian Galiani, and Ernesto Schargrodsky. 2021. "Persuasive Propaganda during the 2015 Argentine Ballotage." *Journal of Comparative Economics*. https://doi.org/https://doi.org/10.1016/j.jce.2021.04.007.

Dickerson Sally S; Kemeny, Margaret E. 2004. "Acute Stressors and Cortisol Responses: A Theoretical Integration and Synthesis of Laboratory Research." *Psychological Bulletin*.

Diez, Joaquín J, Daniel E Vigo, Santiago Pérez Lloret, Stephanie Rigters, Noelia Role, Danie l P Cardinali, and Daniel Pérez Chada. 2011. "Sleep Habits, Alertness, Cortisol Levels, and Cardiac Autonomic Activity in Short-Distance Bus Drivers: Differences between Morning and Afternoon Shifts." *Journal of Occupational and Environmental Medicine*. Lippincott Williams & Wilkins. https://doi.org/10.1097/JOM.0b013e318221c6de.

Ditzen, Beate, Marcel Schaer, Barbara Gabriel, Guy Bodenmann, Ulrike Ehlert, and Markus Heinrichs. 2009. "Intranasal Oxytocin Increases Positive Communication and Reduces Cortisol Levels During Couple Conflict." *Biological Psychiatry* 65 (9): 728–31. https://doi.org/https://doi.org/10.1016/j.biopsych.2008.10.011.

Druckman, James N, Samara Klar, Yanna Krupnikov, Matthew Levendusky, and John Barry Ryan. 2021a. "(Mis-)Estimating Affective Polarization." *The Journal of Politics*. https://doi.org/10.1086/715603.

———. 2021b. "Affective Polarization, Local Contexts and Public Opinion in America." *Nature Human Behaviour* 5 (1): 28–38. https://doi.org/10.1038/s41562-020-01012-5.

Druckman, James N, and Matthew S Levendusky. 2019. "What Do We Measure When We Measure Affective Polarization?" *Public Opinion Quarterly* 83 (1): 114–22. https://doi.org/10.1093/poq/nfz003.

Edwards, George C, III. 2001. "Why Not the Best? The Loyalty-Competence Trade-off in Presidential Appointments." *The Brookings Review* 19 (2): 12–16. https://doi.org/http://dx.doi.org/10.2307/20080969.

Egorov, Georgy, and Konstantin Sonin. 2011. "Dictators and Their Viziers: Endogenizing the Loyalty–Competence Trade-Off." *Journal of the European Economic Association* 9 (5): 903–30. https://doi.org/10.1111/j.1542-4774.2011.01033.x.

Enikolopov, Ruben, Alexey Makarin, and Maria Petrova. 2020. "Social Media and Protest Participation: Evidence From Russia." *Econometrica* 88 (4): 1479–1514. https://doi.org/https://doi.org/10.3982/ECTA14281.

Fergusson, Leopoldo, and Carlos Molina. 2019. "Facebook Causes Protests." *Available at SSRN*, no. 3553514. https://doi.org/10.2139/ssrn.3553514.

Fiorina, M P, S J Abrams, and J Pope. 2005. *Culture War?: The Myth of a Polarized America*. Great Questions in Politics Series. New York: Pearson Longman.

Fiorina, Morris P, and Samuel J Abrams. 2008. "Political Polarization in the American Public." *Annual Review of Political Science* 11 (1): 563–88. https://doi.org/10.1146/annurev.polisci.11.053106.153836.

Flaxman, Seth, Sharad Goel, and Justin M Rao. 2016. "Filter Bubbles, Echo Chambers, and Online News Consumption." *Public Opinion Quarterly* 80 (S1): 298–320. https://doi.org/10.1093/poq/nfw006.

Fridkin, Kim L, Patrick J Kenney, Sarah Allen Gershon, Karen Shafer, and Gina Serignese Woodall. 2007. "Capturing the Power of a Campaign Event: The 2004 Presidential Debate in Tempe." *The Journal of Politics* 69 (3): 770–85. https://doi.org/10.1111/j.1468-2508.2007.00574.x.

Garimella, Venkata Rama Kiran, and Ingmar Weber. 2017. "A Long-Term Analysis of Polarization on Twitter." *Proceedings of the International AAAI Conference on Web and Social Media* 11 (1). https://ojs.aaai.org/index.php/ICWSM/article/view/14918.

Gentzkow, Matthew, and Jesse M Shapiro. 2011. "Ideological Segregation Online and Offline." *The Quarterly Journal of Economics* 126 (4): 1799–1839. https://doi.org/10.1093/qje/qjr044.

Gidron, Noam, James Adams, and Will Horne. 2020. *American Affective Polarization in Comparative Perspective*.

Elements in American Politics. Cambridge University Press. https://doi.org/10.1017/9781108914123.

Gorodnichenko, Yuriy, Tho Pham, and Oleksandr Talavera. 2021. "Social Media, Sentiment and Public Opinions: Evidence from #Brexit and #USElection." *European Economic Review* 136: 103772. https://doi.org/https://doi.org/10.1016/j.euroecorev.2021.103772.

Graham, Matthew H, and Milan W Svolik. 2020. "Democracy in America? Partisanship, Polarization, and the Robustness of Support for Democracy in the United States." *American Political Science Review* 114 (2): 392–409. https://doi.org/10.1017/S0003055420000052.

Halberstam, Yosh, and Brian Knight. 2016. "Homophily, Group Size, and the Diffusion of Political Information in Social Networks: Evidence from Twitter." *Journal of Public Economics* 143: 73–88. https://doi.org/https://doi.org/10.1016/j.jpubeco.2016.08.011.

Hastie, T, R Tibshirani, and J H Friedman. 2009. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. 2nd ed. Springer Series in Statistics. New York, NY, USA: Springer.

Hernández, Enrique, Eva Anduiza, and Guillem Rico. 2021. "Affective Polarization and the Salience of Elections." *Electoral Studies* 69: 102203. https://doi.org/https://doi.org/10.1016/j.electstud.2020.102203.

Hetherington, Marc J, Deborah Jordan Brooks, John G Geer, and Martin P Wattenberg. 2008. "Turned Off or Turned On?: How Polarization Affects Political Engagement." In *Red and Blue Nation?*, edited by Pietro S Nivola and David W Brady, 1–54. Consequences and Correction of America's Polarized Politics. Brookings Institution Press. http://www.jstor.org/stable/10.7864/j.ctt6wpdqn.4.

Infobae. 2019. "Los Mensajes de Los Famosos En Las Redes Sobre El Debate Presidencial." *Infobae*. https://www.infobae.com/teleshow/infoshow/2019/10/14/los-mensajes-de-los-famosos-en-las-redes-sobre-el-debate-presidencial/.

Iyengar, Shanto, and Kyu S Hahn. 2009. "Red Media, Blue Media: Evidence of Ideological Selectivity in Media Use." *Journal of Communication* 59 (1): 19–39. https://doi.org/10.1111/j.1460-2466.2008.01402.x.

Iyengar, Shanto, Yphtach Lelkes, Matthew Levendusky, Neil Malhotra, and Sean J Westwood. 2019. "The Origins and Consequences of Affective Polarization in the United States." *Annual Review of Political Science* 22 (1): 129–46. https://doi.org/10.1146/annurev-polisci-051117-073034.

Iyengar, Shanto, and Sean J Westwood. 2015. "Fear and Loathing across Party Lines: New Evidence on Group Polarization." *American Journal of Political Science* 59 (3): 690–707. https://doi.org/https://doi.org/10.1111/ajps.12152.

Jackson, Matthew O. 2011. "An Overview of Social Networks and Economic Applications*." In , edited by Jess Benhabib, Alberto Bisin, and Matthew O Jackson, 1:511–85. Handbook of Social Economics. North-Holland. https://doi.org/https://doi.org/10.1016/B978-0-444-53187-2.00012-7.

Jamieson, Kathleen Hall., and David S Birdsell. 1988. *Presidential Debates: The Challenge of Creating an Informed Electorate*. New York, NY, US: Oxford University Press.

Jo, Donghee. 2020. "Better the Devil You Know : Selective Exposure Alleviates Polarization in an Online Field Experiment." *Unpublished*.

King, Gary, and Margaret E Roberts. 2015. "How Robust Standard Errors Expose Methodological Problems They Do Not Fix, and What to Do About It." *Political Analysis* 23 (2): 159–179. https://doi.org/10.1093/pan/mpu015.

Kirschbaum, Clemens, and Dirk H Hellhammer. 1989. "Salivary Cortisol in Psychobiological Research: A

Overview." *Neuropsychobiology*. Switzerland: Karger. https://doi.org/10.1159/000118611.

Kosinski, Michal, David Stillwell, and Thore Graepel. 2013. "Private Traits and Attributes Are Predictable from Digital Records of Human Behavior." *Proceedings of the National Academy of Sciences* 110 (15): 5802–5. https://doi.org/10.1073/pnas.1218772110.

La Nación. 2019. "Debate Presidencial: Mauricio Macri Advirtió Sobre El Dedo Acusador de Alberto Fernández." *La Nación*, 2019. https://www.lanacion.com.ar/politica/el-dedo-acusador-alberto-fernandez-repercutio-redes-nid2296946/.

Lelkes, Yphtach, Gaurav Sood, and Shanto Iyengar. 2017. "The Hostile Audience: The Effect of Access to Broadband Internet on Partisan Affect." *American Journal of Political Science* 61 (1): 5–20. https://doi.org/https://doi.org/10.1111/ajps.12237.

Levy, Gilat, and Ronny Razin. 2019. "Echo Chambers and Their Effects on Economic and Political Outcomes." *Annual Review of Economics* 11 (1): 303–28. https://doi.org/10.1146/annurev-economics-080218-030343.

Levy, Ro'ee. 2021. "Social Media, News Consumption, and Polarization: Evidence from a Field Experiment." *American Economic Review* 111 (3): 831–70. https://doi.org/10.1257/aer.20191777.

London, Ben, and Lise Getoor. 2013. "Collective Classification of Network Data." In *Data Classification: Algorithms and Applications*, edited by Charu Aggarwal. CRC Press. https://www.taylorfrancis.com/chapters/edit/10.1201/b17320-20/collective-classification-network-data-ben-london-lise-getoor.

Lord, Charles G, Lee Ross, and Mark R Lepper. 1979. "Biased Assimilation and Attitude Polarization: The Effects of Prior Theories on Subsequently Considered Evidence." *Journal of Personality and Social Psychology* 37 (11): 2098–2109. https://doi.org/10.1037/0022-3514.37.11.2098.

Lupu, Noam. 2015. "Party Polarization and Mass Partisanship: A Comparative Perspective." *Political Behavior* 37 (2): 331–56. https://doi.org/10.1007/s11109-014-9279-z.

McKinney, Mitchell S, and Diana B Carlin. 2004. "Political Campaign Debates." In *Handbook of Political Communication Research (1st Ed.)*, edited by Lynda Lee Kaid. New York: Routledge.

McPherson, Miller, Lynn Smith-Lovin, and James M Cook. 2001. "Birds of a Feather: Homophily in Social Networks." *Annual Review of Sociology* 27 (1): 415–44. https://doi.org/10.1146/annurev.soc.27.1.415.

Mosquera, Roberto, Mofioluwasademi Odunowo, Trent McNamara, Xiongfei Guo, and Ragan Petrie. 2020. "The Economic Effects of Facebook." *Experimental Economics* 23 (2): 575–602. https://doi.org/10.1007/s10683-019-09625-y.

Mullainathan, Sendhil, and Jann Spiess. 2017. "Machine Learning: An Applied Econometric Approach." *Journal of Economic Perspectives* 31 (2): 87–106. https://doi.org/10.1257/jep.31.2.87.

Mullainathan, Sendhil, Ebonya Washington, and Julia Azari. 2010. "The Impact of Electoral Debate on Public Opinions: An Experimental Investigation of the 2005 New York City Mayoral Election." In , edited by Ian Shapiro, Susan C Stokes, Elisabeth J Wood, and Alexander S Kirshner, 324–41. https://doi.org/10.1017/CBO9780511813146.014.

Pariser, E. 2011. *The Filter Bubble: What the Internet Is Hiding from You*. Penguin Books.

Pennec, Caroline Le, and Vincent Pons. 2019. "How Do Campaigns Shape Vote Choice? Multi-Country Evidence from 62 Elections and 56 TV Debates." NBER Working Paper No. 26572. https://doi.org/10.3386/w26572.

Pettigrew, Thomas F, and Linda R Tropp. 2006. "A Meta-Analytic Test of Intergroup Contact Theory." *Journal of Personality and Social Psychology*. Pettigrew, Thomas F.: Department of Psychology, Social Sciences II, University of California, Santa Cruz, CA, 95064, pettigr@ucsc.edu: American Psychological Association. https://doi.org/10.1037/0022-3514.90.5.751.

Pew Research Center. 2014a. *Political Polarization & Media Habits*. Washington, D.C.: Pew Research Center. https://www.journalism.org/2014/10/21/political-polarization-media-habits/.

———. 2014b. *Political Polarization in the American Public. How Increasing Ideological Uniformity and Partisan Antipathy Affect Politics, Compromise and Everyday Life*. Washington, D.C.: Pew Research Center. https://www.pewresearch.org/politics/2014/06/12/political-polarization-in-the-american-public/.

———. 2019a. *National Politics on Twitter: Small Share of U.S. Adults Produce Majority of Tweets*. Washington, D.C.: Pew Research Center. https://www.pewresearch.org/politics/2019/10/23/national-politics-on-twitter-small-share-of-u-s-adults-produce-majority-of-tweets/.

———. 2019b. *Social Media Usage in the US in 2019*. Washington, D.C.: Pew Research Center. https://www.pewresearch.org/fact-tank/2019/04/10/share-of-u-s-adults-using-social-media-including-facebook-is-mostly-unchanged-since-2018/.

Rieljan, Andres. 2020. "'Fear and Loathing across Party Lines' (Also) in Europe: Affective Polarisation in European Party Systems." *European Journal of Political Research* 59 (2): 376–96. https://doi.org/https://doi.org/10.1111/1475-6765.12351.

Rogowski, Jon C, and Joseph L Sutherland. 2016. "How Ideology Fuels Affective Polarization." *Political Behavior* 38 (2): 485–508. https://doi.org/10.1007/s11109-015-9323-7.

Schwalbe, Michael C, Geoffrey L Cohen, and Lee D Ross. 2020. "The Objectivity Illusion and Voter Polarization in the 2016 Presidential Election." *Proceedings of the National Academy of Sciences* 117 (35): 21218–29. https://doi.org/10.1073/pnas.1912301117.

Shaw, Daron R. 1999. "A Study of Presidential Campaign Event Effects from 1952 to 1992." *The Journal of Politics* 61 (2): 387–422. https://doi.org/10.2307/2647509.

Simons, Joseph J P, and Melanie C Green. 2016. "Divisive Topics as Social Threats." *Communication Research* 45 (2): 165–87. https://doi.org/10.1177/0093650216644025.

Sohnesen, Thomas Pave, and Niels Stender. 2017. "Is Random Forest a Superior Methodology for Predicting Poverty? An Empirical Assessment." *Poverty \& Public Policy* 9 (1): 118–33. https://doi.org/https://doi.org/10.1002/pop4.169.

Sunstein, Cass R. 2001. *Echo Chambers: Bush v. Gore, Impeachment, and Beyond*. Princeton, N.J.: Princeton University Press.

———. 2018. *#Republic: Divided Democracy in the Age of Social Media*. NED-New. Princeton University Press. http://www.jstor.org/stable/j.ctv8xnhtd.

Taber, Charles S, and Milton Lodge. 2006. "Motivated Skepticism in the Evaluation of Political Beliefs." *American Journal of Political Science* 50 (3): 755–69. https://doi.org/https://doi.org/10.1111/j.1540-5907.2006.00214.x.

Wirtz, Petra H, Johannes Siegrist, Ulrike Rimmele, and Ulrike Ehlert. 2008. "Higher Overcommitment to Work Is Associated with Lower Norepinephrine Secretion before and after Acute Psychosocial Stress in Men." *Psychoneuroendocrinology* 33 (1): 92–99. https://doi.org/https://doi.org/10.1016/j.psyneuen.2007.10.003.

Yang, Qi, Khizar Qureshi, and Tauhid Zaman. 2020. "Mitigating the Backfire Effect Using Pacing and Leading." arXiv preprint. https://arxiv.org/abs/2008.00049.

Young, Allan H. 2004. "Cortisol in Mood Disorders." *Stress* 7 (4): 205–8. https://doi.org/10.1080/10253890500069189.

Zhuravskaya, Ekaterina, Maria Petrova, and Ruben Enikolopov. 2020. "Political Effects of the Internet and Social Media." *Annual Review of Economics* 12 (1): 415–38. https://doi.org/10.1146/annurev-economics-081919-050239.

Appendix (Online)

A. Data construction details

Combined index (average of a, b, c, and d)

a. Elite (average of a1 and a2)
    - a1. Threat (Q. 33)
    - a2. Ingroup leader positive attributes – Outgroup leader positive attributes (Q. 29) *

b. Social Distance (average of b1, b2, and b3)
    - b1. Marriage (Q. 24a)
    - b2. Working (Q. 24b)
    - b3. Socializing (Q. 24c)

c. Partisanship (average of c1 and c2)
    - c1. Dispersion of the preferences over the presidential candidates (Q. 32)
    - c2. Convincement (Q. 30)

d. Institutional (average of d1, d2, and d3)
    - d1. Outgroup party does fraud – Ingroup party does fraud (Q. 26) *
    - d2. Court against ingroup party – Court against outgroup party (Q. 28) *
    - d3. Loyalty importance – Technically suitable importance (Q. 27)

e. Engagement (average of e1 and e2)
    - e1. Politics volunteering (Q. 25a)
    - e2. Persuade others (Q. 25b)

* To construct these variables, we use predicted party affiliation scores obtained from pre-treatment Twitter and questionnaire data.

Each Combined level variable is calculated as the average of the lower level ones. Once obtained, each average is normalized so that the non-segregated Twitter-Allowed group distribution has a mean of 0 and a standard deviation of 1.

B. Appendix Tables (Online)

Table A1. Twitter and non-Twitter users pre-treatment characteristics

	non-Twitter users	Twitter users	n	*p*-value
Sociodemographics				
Age	42.548 (0.870)	33.293 (0.527)	688	0.000
Female = 1	0.573 (0.041)	0.521 (0.024)	688	0.284
Education years	14.021 (0.142)	14.333 (0.084)	688	0.042
Household head = 1	0.585 (0.049)	0.380 (0.025)	688	0.000
Household head education years	14.117 (0.154)	14.768 (0.104)	684	0.000
Residence = City of Buenos Aires	0.556 (0.033)	0.659 (0.023)	687	0.002
Residence = Greater Buenos Aires North	0.199 (0.032)	0.139 (0.016)	687	0.101
Residence = Greater Buenos Aires West	0.145 (0.020)	0.096 (0.010)	687	0.036
Residence = Greater Buenos Aires South	0.100 (0.020)	0.101 (0.014)	687	0.959
Household size	3.100 (0.086)	3.007 (0.060)	686	0.337
Employed = 1	0.846 (0.022)	0.782 (0.019)	685	0.025
Household head employed = 1	0.958 (0.010)	0.946 (0.012)	679	0.481
Internet and social media use				
Internet at home = 1	0.958 (0.012)	0.993 (0.004)	686	0.009
Internet at work = 1	0.862 (0.025)	0.877 (0.024)	483	0.701
Has cellphone = 1	0.992 (0.006)	0.998 (0.002)	688	0.330
Times a day the cellphone is checked	35.010 (1.208)	42.724 (0.654)	685	0.000
Regular Facebook use = 1	0.560 (0.046)	0.541 (0.019)	688	0.725
Regular Twitter use = 1	0.000 (0.000)	0.855 (0.016)	688	0.000
Regular Instagram use = 1	0.432 (0.027)	0.810 (0.018)	688	0.000
Regular Whatsapp use = 1	0.975 (0.010)	0.987 (0.006)	688	0.360
Ideology and beliefs				
Messi vs. Maradona = Messi	0.337 (0.025)	0.474 (0.024)	685	0.001
Messi vs. Maradona = Maradona	0.400 (0.026)	0.258 (0.022)	685	0.000
Messi vs. Maradona = Equally good	0.263 (0.023)	0.267 (0.022)	685	0.880
Sentence length	0.436 (0.035)	0.343 (0.023)	687	0.048
Poverty: Importance of effort	6.238 (0.198)	5.648 (0.176)	677	0.028
Poverty: Importance of luck	4.774 (0.194)	4.745 (0.122)	678	0.900
Poverty: Importance of opportunities	7.909 (0.134)	7.987 (0.062)	682	0.632
Human rights violations: USA	7.595 (0.127)	8.130 (0.073)	684	0.000
Human rights violations: Venezuela	8.040 (0.166)	8.429 (0.111)	683	0.056
Welfare state importance	7.500 (0.169)	7.316 (0.093)	685	0.276
Interest in politics	7.950 (0.174)	8.578 (0.089)	685	0.002
Adverse to risk=1	0.817 (0.025)	0.776 (0.016)	687	0.150
Twitter profile when recruited				
Number of followers (log10)	-	2.222 (0.031)	447	-
Number of friends (log10)	-	2.513 (0.018)	447	-
Number of Tweets (log10)	-	1.913 (0.035)	447	-
Account age (years)	-	6.905 (0.142)	447	-
Recruitment method				
Twitter recruited	0.000 (0.000)	0.282 (0.021)	688	0.000
Recruitment agency - online panel	0.473 (0.028)	0.237 (0.021)	688	0.000
Recruitment agency - offline	0.527 (0.028)	0.481 (0.022)	688	0.201
Cortisol				
First sample cortisol level (μg/dL)	0.153 (0.006)	0.161 (0.007)	666	0.388
Political positions from pre-treatment data				
Normalized segregation score	-	0.116 (0.005)	447	-
Segregation status = segregated	0.456 (0.040)	0.499 (0.027)	688	0.426
Party preference score	-	0.484 (0.021)	447	-
Party preference = *JxC*	0.469 (0.032)	0.481 (0.028)	688	0.785

Notes: All variables correspond to pre-treatment data. "Regular Facebook use = 1" indicates that the participant uses Facebook more than once a day or during all the day long (the same applies for "Regular Twitter use = 1", "Regular Instagram use = 1" and "Regular Whatsapp use = 1"). "Segregation status = segregated" and "Party leaning = *JxC*" are calculated as described in Section 2.b. The reported *p*-value comes from a joint hypothesis *F*-test where equality of group means is tested. Standard errors clustered at the classroom level.

Table A2. Pre-treatment characteristics across recruitment groups, Twitter users

	Twitter recruited	Recruitment agency online panel	Recruitment agency offline	n	*p*-value
Sociodemographics					
Age	26.222 (0.964)	33.898 (0.751)	40.472 (1.391)	447	0.000
Female = 1	0.381 (0.042)	0.595 (0.031)	0.538 (0.047)	447	0.000
Education years	14.897 (0.205)	13.907 (0.130)	14.528 (0.219)	447	0.000
Household head = 1	0.286 (0.048)	0.381 (0.035)	0.491 (0.045)	447	0.001
Household head education years	15.440 (0.237)	14.451 (0.166)	14.613 (0.320)	444	0.010
Residence = City of Buenos Aires	0.794 (0.036)	0.626 (0.030)	0.566 (0.049)	446	0.000
Residence = Greater Buenos Aires North	0.071 (0.022)	0.140 (0.023)	0.217 (0.039)	446	0.001
Residence = Greater Buenos Aires West	0.079 (0.020)	0.107 (0.020)	0.094 (0.027)	446	0.647
Residence = Greater Buenos Aires South	0.040 (0.016)	0.126 (0.025)	0.123 (0.036)	446	0.024
Household size	2.688 (0.115)	3.158 (0.093)	3.075 (0.123)	446	0.005
Employed = 1	0.786 (0.031)	0.757 (0.027)	0.829 (0.033)	445	0.147
Household head employed = 1	0.952 (0.020)	0.948 (0.016)	0.934 (0.026)	441	0.817
Internet and social media use					
Internet at home = 1	0.984 (0.011)	1.000 (0.000)	0.991 (0.009)	447	0.190
Internet at work = 1	0.932 (0.036)	0.854 (0.025)	0.857 (0.074)	309	0.244
Has cellphone = 1	1.000 (0.000)	0.995 (0.005)	1.000 (0.000)	447	†
Times a day the cellphone is checked	43.849 (1.022)	42.430 (0.946)	41.981 (1.171)	446	0.430
Regular Facebook use = 1	0.270 (0.031)	0.605 (0.031)	0.736 (0.040)	447	0.000
Regular Twitter use = 1	0.865 (0.036)	0.912 (0.017)	0.726 (0.040)	447	0.000
Regular Instagram use = 1	0.841 (0.035)	0.837 (0.025)	0.717 (0.039)	447	0.009
Regular Whatsapp use = 1	0.992 (0.008)	0.986 (0.007)	0.981 (0.013)	447	0.657
Ideology and beliefs					
Messi vs. Maradona = Messi	0.528 (0.044)	0.479 (0.028)	0.400 (0.047)	445	0.122
Messi vs. Maradona = Maradona	0.216 (0.033)	0.256 (0.033)	0.314 (0.048)	445	0.146
Messi vs. Maradona = Equally good	0.256 (0.039)	0.265 (0.029)	0.286 (0.039)	445	0.866
Sentence length	0.136 (0.034)	0.437 (0.036)	0.396 (0.045)	446	0.000
Poverty: Importance of effort	4.671 (0.304)	6.005 (0.175)	6.107 (0.280)	442	0.000
Poverty: Importance of luck	5.190 (0.200)	4.812 (0.232)	4.067 (0.229)	443	0.000
Poverty: Importance of opportunities	8.683 (0.146)	7.784 (0.139)	7.566 (0.223)	445	0.000
Human rights violations: USA	8.556 (0.170)	8.037 (0.135)	7.811 (0.195)	446	0.027
Human rights violations: Venezuela	8.472 (0.234)	8.376 (0.137)	8.486 (0.184)	443	0.858
Welfare state importance	7.587 (0.177)	7.294 (0.159)	7.038 (0.265)	446	0.270
Interest in politics	9.127 (0.130)	8.146 (0.128)	8.792 (0.208)	445	0.000
Adverse to risk=1	0.619 (0.047)	0.842 (0.028)	0.830 (0.038)	447	0.000
Twitter profile when recruited					
Number of followers (log10)	2.302 (0.039)	2.246 (0.050)	2.079 (0.058)	447	0.008
Number of friends (log10)	2.543 (0.028)	2.510 (0.024)	2.486 (0.045)	447	0.517
Number of Tweets (log10)	1.976 (0.061)	1.955 (0.057)	1.754 (0.066)	447	0.042
Account age (years)	6.602 (0.258)	6.759 (0.214)	7.564 (0.275)	447	0.022
Cortisol					
First sample cortisol level (μg/dL)	0.174 (0.007)	0.164 (0.012)	0.136 (0.007)	434	0.000
Political positions from pre-treatment data					
Normalized segregation score	0.122 (0.013)	0.098 (0.006)	0.145 (0.013)	447	0.008
Segregation status = segregated	0.540 (0.041)	0.419 (0.031)	0.613 (0.056)	447	0.002
Party preference score	0.455 (0.041)	0.469 (0.030)	0.546 (0.049)	447	0.351
Party preference = *JxC*	0.452 (0.063)	0.460 (0.030)	0.557 (0.060)	447	0.362

Notes: All variables correspond to pre-treatment data. "Regular Facebook use = 1" indicates that the participant uses Facebook more than once a day or during all the day long (the same applies for "Regular Twitter use = 1", "Regular Instagram use = 1" and "Regular Whatsapp use = 1"). "Segregation status = segregated" and "Party leaning = *JxC*" are calculated as described in Section 2.b. The reported *p*-value comes from a joint hypothesis *F*-test where equality of group means is tested. Standard errors clustered at the classroom level. † indicates that the *F*-test could not be carried out due to invertibility problems.

Table A3. Pre-treatment characteristics across recruitment groups, non-Twitter users

	Recruitment agency online panel	Recruitment agency offline	n	*p*-value
Sociodemographics				
Age	41.583 (0.958)	43.623 (1.270)	241	0.140
Female = 1	0.504 (0.056)	0.649 (0.049)	241	0.034
Education years	13.827 (0.147)	14.237 (0.272)	241	0.205
Household head = 1	0.638 (0.050)	0.526 (0.064)	241	0.052
Household head education years	14.135 (0.192)	14.096 (0.288)	240	0.918
Residence = City of Buenos Aires	0.551 (0.038)	0.561 (0.059)	241	0.887
Residence = Greater Buenos Aires North	0.165 (0.032)	0.237 (0.051)	241	0.203
Residence = Greater Buenos Aires West	0.157 (0.032)	0.132 (0.025)	241	0.531
Residence = Greater Buenos Aires South	0.126 (0.033)	0.070 (0.026)	241	0.221
Household size	2.992 (0.134)	3.219 (0.090)	240	0.135
Employed = 1	0.858 (0.031)	0.832 (0.036)	240	0.608
Household head employed = 1	0.976 (0.013)	0.938 (0.021)	238	0.182
Internet and social media use				
Internet at home = 1	0.952 (0.020)	0.965 (0.016)	239	0.657
Internet at work = 1	0.853 (0.036)	0.873 (0.037)	174	0.690
Has cellphone = 1	0.992 (0.008)	0.991 (0.009)	241	0.942
Times a day the cellphone is checked	36.607 (1.706)	33.230 (1.694)	239	0.159
Regular Facebook use = 1	0.543 (0.063)	0.579 (0.052)	241	0.619
Regular Instagram use = 1	0.441 (0.038)	0.421 (0.047)	241	0.764
Regular Whatsapp use = 1	0.984 (0.011)	0.965 (0.016)	241	0.251
Ideology and beliefs				
Messi vs. Maradona = Messi	0.333 (0.036)	0.342 (0.050)	240	0.901
Messi vs. Maradona = Maradona	0.429 (0.042)	0.368 (0.039)	240	0.323
Messi vs. Maradona = Equally good	0.238 (0.035)	0.289 (0.037)	240	0.339
Sentence length	0.425 (0.045)	0.447 (0.049)	241	0.717
Poverty: Importance of effort	6.072 (0.202)	6.427 (0.275)	235	0.169
Poverty: Importance of luck	4.829 (0.283)	4.714 (0.188)	235	0.692
Poverty: Importance of opportunities	7.849 (0.154)	7.977 (0.175)	237	0.485
Human rights violations: USA	7.360 (0.164)	7.854 (0.189)	238	0.051
Human rights violations: Venezuela	7.857 (0.249)	8.241 (0.190)	240	0.195
Welfare state importance	7.452 (0.205)	7.553 (0.235)	239	0.716
Interest in politics	7.984 (0.196)	7.912 (0.240)	240	0.780
Adverse to risk=1	0.825 (0.038)	0.807 (0.042)	240	0.770
Cortisol				
First sample cortisol level (μg/dL)	0.153 (0.010)	0.154 (0.007)	232	0.949
Political positions from pre-treatment data				
Segregation status = segregated	0.394 (0.040)	0.526 (0.066)	241	0.078
Party preference = *JxC*	0.457 (0.047)	0.482 (0.043)	241	0.680

Notes: All variables correspond to pre-treatment data. "Regular Facebook use = 1" indicates that the participant uses Facebook more than once a day or during all the day long (the same applies for "Regular Instagram use = 1" and "Regular Whatsapp use = 1"). "Segregation status = segregated" and "Party leaning = *JxC*" are calculated as described in Section 2.b. The reported *p*-value comes from a joint hypothesis *F*-test where equality of group means is tested. Standard errors clustered at the classroom level.

Table A4. Pre-treatment characteristics across treatment arms, Twitter users

	Documentary	Twitter Allowed	Debate	Twitter Interact	n	*p*-value
Sociodemographics						
Age	34.027 (0.811)	33.936 (0.277)	31.714 (1.307)	33.500 (1.214)	447	0.409
Female = 1	0.611 (0.039)	0.482 (0.054)	0.509 (0.040)	0.482 (0.038)	447	0.074
Education years	14.575 (0.119)	14.464 (0.108)	14.009 (0.170)	14.286 (0.175)	447	0.044
Household head = 1	0.381 (0.037)	0.427 (0.067)	0.312 (0.047)	0.402 (0.030)	447	0.374
Household head education years	14.640 (0.256)	15.028 (0.168)	14.696 (0.198)	14.714 (0.145)	444	0.417
Residence = City of Buenos Aires	0.611 (0.054)	0.727 (0.019)	0.652 (0.040)	0.649 (0.045)	446	0.056
Residence = Greater Buenos Aires North	0.186 (0.033)	0.100 (0.027)	0.134 (0.027)	0.135 (0.029)	446	0.257
Residence = Greater Buenos Aires West	0.133 (0.020)	0.073 (0.023)	0.089 (0.011)	0.090 (0.020)	446	0.184
Residence = Greater Buenos Aires South	0.071 (0.026)	0.100 (0.036)	0.107 (0.026)	0.126 (0.016)	446	0.343
Household size	2.884 (0.155)	2.891 (0.055)	3.062 (0.096)	3.188 (0.088)	446	0.027
Employed = 1	0.841 (0.028)	0.778 (0.017)	0.688 (0.045)	0.821 (0.026)	445	0.015
Household head employed = 1	0.929 (0.032)	0.963 (0.013)	0.936 (0.027)	0.955 (0.008)	441	0.694
Internet and social media use						
Internet at home = 1	0.991 (0.008)	1.000 (0.000)	0.991 (0.009)	0.991 (0.008)	447	0.330
Internet at work = 1	0.907 (0.029)	0.867 (0.031)	0.829 (0.085)	0.897 (0.026)	309	0.685
Has cellphone = 1	1.000 (0.000)	1.000 (0.000)	0.991 (0.009)	1.000 (0.000)	447	†
Times a day the cellphone is checked	42.588 (0.993)	41.295 (0.970)	43.131 (1.806)	43.862 (0.920)	446	0.290
Regular Facebook use = 1	0.566 (0.035)	0.582 (0.035)	0.554 (0.017)	0.464 (0.029)	447	0.024
Regular Twitter use = 1	0.841 (0.048)	0.836 (0.019)	0.893 (0.029)	0.848 (0.020)	447	0.437
Regular Instagram use = 1	0.796 (0.026)	0.764 (0.041)	0.830 (0.039)	0.848 (0.024)	447	0.250
Regular Whatsapp use = 1	0.982 (0.011)	0.973 (0.016)	0.991 (0.009)	1.000 (0.000)	447	0.084
Ideology and beliefs						
Messi vs. Maradona = Messi	0.518 (0.044)	0.376 (0.017)	0.482 (0.036)	0.518 (0.053)	445	0.001
Messi vs. Maradona = Maradona	0.223 (0.039)	0.312 (0.031)	0.205 (0.042)	0.295 (0.040)	445	0.113
Messi vs. Maradona = Equally good	0.259 (0.049)	0.312 (0.018)	0.312 (0.043)	0.187 (0.020)	445	0.000
Sentence length	0.381 (0.048)	0.382 (0.021)	0.297 (0.055)	0.312 (0.042)	446	0.282
Poverty: Importance of effort	5.149 (0.272)	5.890 (0.156)	5.679 (0.302)	5.882 (0.494)	442	0.129
Poverty: Importance of luck	4.856 (0.223)	4.318 (0.208)	5.045 (0.214)	4.755 (0.198)	443	0.095
Poverty: Importance of opportunities	7.991 (0.140)	8.036 (0.056)	7.884 (0.147)	8.036 (0.122)	445	0.802
Human rights violations: USA	8.204 (0.152)	8.164 (0.061)	8.135 (0.152)	8.018 (0.175)	446	0.861
Human rights violations: Venezuela	8.634 (0.180)	8.373 (0.084)	8.432 (0.105)	8.273 (0.371)	443	0.594
Welfare state importance	7.389 (0.198)	7.264 (0.216)	7.369 (0.152)	7.241 (0.163)	446	0.912
Interest in politics	8.549 (0.128)	8.573 (0.227)	8.676 (0.154)	8.514 (0.186)	445	0.902
Adverse to risk=1	0.796 (0.032)	0.745 (0.030)	0.795 (0.035)	0.768 (0.027)	447	0.612
Twitter profile when recruited						
Number of followers (log10)	2.250 (0.046)	2.179 (0.061)	2.264 (0.038)	2.196 (0.084)	447	0.634
Number of friends (log10)	2.581 (0.036)	2.465 (0.026)	2.544 (0.031)	2.463 (0.014)	447	0.004
Number of Tweets (log10)	1.933 (0.058)	1.922 (0.068)	1.996 (0.080)	1.801 (0.034)	447	0.042
Account age (years)	7.152 (0.258)	6.635 (0.343)	6.587 (0.223)	7.241 (0.154)	447	0.063
Recruitment method						
Twitter recruited	0.274 (0.041)	0.291 (0.039)	0.312 (0.045)	0.250 (0.041)	447	0.762
Recruitment agency - online panel	0.257 (0.049)	0.245 (0.029)	0.241 (0.056)	0.205 (0.008)	447	0.380
Recruitment agency - offline	0.469 (0.039)	0.464 (0.054)	0.446 (0.028)	0.545 (0.040)	447	0.244
Cortisol						
First sample cortisol level (μg/dL)	0.164 (0.006)	0.186 (0.013)	0.152 (0.010)	0.142 (0.013)	434	0.078
Political positions from pre-treatment data						
Normalized segregation score	0.120 (0.010)	0.116 (0.005)	0.118 (0.013)	0.109 (0.013)	447	0.937
Segregation status = segregated	0.566 (0.046)	0.545 (0.047)	0.437 (0.051)	0.446 (0.049)	447	0.129
Party preference score	0.484 (0.035)	0.470 (0.014)	0.473 (0.030)	0.507 (0.070)	447	0.941
Party preference = *JxC*	0.513 (0.035)	0.436 (0.033)	0.509 (0.044)	0.464 (0.089)	447	0.374

Notes: All variables correspond to pre-treatment data. "Regular Facebook use = 1" indicates that the participant uses Facebook more than once a day or during all the day long (the same applies for "Regular Twitter use = 1", "Regular Instagram use = 1" and "Regular Whatsapp use = 1"). "Segregation status = segregated" and "Party leaning = *JxC*" are calculated as described in Section 2.b. The reported *p*-value comes from a joint hypothesis *F*-test where equality of group means is tested. Standard errors clustered at the classroom level. † indicates that the *F*-test could not be carried out due to invertibility problems.

Table A5. Pre-treatment characteristics across treatment arms, non-Twitter users

	Documentary	Debate	n	*p*-value
Sociodemographics				
Age	42.277 (0.740)	42.811 (1.562)	241	0.758
Female = 1	0.571 (0.064)	0.574 (0.053)	241	0.977
Education years	14.025 (0.231)	14.016 (0.171)	241	0.976
Household head = 1	0.647 (0.087)	0.525 (0.038)	241	0.199
Household head education years	14.042 (0.257)	14.190 (0.169)	240	0.630
Residence = City of Buenos Aires	0.597 (0.048)	0.516 (0.041)	241	0.206
Residence = Greater Buenos Aires North	0.193 (0.048)	0.205 (0.044)	241	0.858
Residence = Greater Buenos Aires West	0.126 (0.028)	0.164 (0.026)	241	0.324
Residence = Greater Buenos Aires South	0.084 (0.024)	0.115 (0.031)	241	0.435
Household size	3.186 (0.156)	3.016 (0.064)	240	0.313
Employed = 1	0.847 (0.037)	0.844 (0.023)	240	0.942
Household head employed = 1	0.949 (0.016)	0.967 (0.012)	238	0.392
Internet and social media use				
Internet at home = 1	0.958 (0.012)	0.959 (0.020)	239	0.965
Internet at work = 1	0.875 (0.037)	0.849 (0.035)	174	0.607
Has cellphone = 1	1.000 (0.000)	0.984 (0.010)	241	0.109
Times a day the cellphone is checked	34.811 (1.108)	35.208 (2.159)	239	0.870
Regular Facebook use = 1	0.630 (0.076)	0.492 (0.040)	241	0.106
Regular Instagram use = 1	0.429 (0.041)	0.434 (0.036)	241	0.914
Regular Whatsapp use = 1	0.983 (0.011)	0.967 (0.017)	241	0.416
Ideology and beliefs				
Messi vs. Maradona = Messi	0.347 (0.035)	0.328 (0.037)	240	0.702
Messi vs. Maradona = Maradona	0.390 (0.046)	0.410 (0.027)	240	0.709
Messi vs. Maradona = Equally good	0.263 (0.037)	0.262 (0.030)	240	0.993
Sentence length	0.403 (0.056)	0.467 (0.040)	241	0.356
Poverty: Importance of effort	5.983 (0.291)	6.492 (0.239)	235	0.178
Poverty: Importance of luck	4.629 (0.320)	4.916 (0.219)	235	0.460
Poverty: Importance of opportunities	7.886 (0.169)	7.933 (0.210)	237	0.861
Human rights violations: USA	7.530 (0.180)	7.658 (0.181)	238	0.614
Human rights violations: Venezuela	8.139 (0.160)	7.942 (0.286)	240	0.550
Welfare state importance	7.630 (0.213)	7.371 (0.257)	239	0.438
Interest in politics	7.864 (0.227)	8.033 (0.261)	240	0.627
Adverse to risk=1	0.832 (0.041)	0.802 (0.027)	240	0.542
Recruitment method				
Recruitment agency - online panel	0.529 (0.041)	0.418 (0.028)	241	0.024
Recruitment agency - offline	0.471 (0.041)	0.582 (0.028)	241	0.024
Cortisol				
First sample cortisol level (μg/dL)	0.148 (0.007)	0.158 (0.011)	232	0.455
Political positions from pre-treatment data				
Segregation status = segregated	0.445 (0.071)	0.467 (0.037)	241	0.786
Party leaning = *JxC*	0.487 (0.050)	0.451 (0.041)	241	0.573

Notes: All variables correspond to pre-treatment data. "Regular Facebook use = 1" indicates that the participant uses Facebook more than once a day or during all the day long (the same applies "Regular Instagram use = 1" and "Regular Whatsapp use = 1"). "Segregation status = segregated" and "Party leaning = JxC" are calculated as described in Section 2.b. The reported p-value comes from a joint hypothesis *F*-test where equality of group means is tested. Standard errors clustered at the classroom level.

Table A6. Pre-treatment characteristics across segregation status, Twitter users

	Non-segregated	Segregated	n	*p*-value
Sociodemographics				
Age	28.134 (0.576)	38.475 (0.770)	447	0.000
Female = 1	0.598 (0.025)	0.444 (0.035)	447	0.000
Education years	13.857 (0.127)	14.812 (0.101)	447	0.000
Household head = 1	0.295 (0.029)	0.466 (0.038)	447	0.000
Household head education years	14.641 (0.134)	14.896 (0.164)	444	0.254
Residence = City of Buenos Aires	0.641 (0.030)	0.677 (0.031)	446	0.374
Residence = Greater Buenos Aires North	0.148 (0.023)	0.130 (0.021)	446	0.557
Residence = Greater Buenos Aires West	0.099 (0.020)	0.094 (0.021)	446	0.900
Residence = Greater Buenos Aires South	0.108 (0.018)	0.094 (0.020)	446	0.599
Household size	3.174 (0.081)	2.838 (0.094)	446	0.010
Employed = 1	0.713 (0.030)	0.851 (0.018)	445	0.000
Household head employed = 1	0.941 (0.016)	0.950 (0.014)	441	0.615
Internet and social media use				
Internet at home = 1	0.996 (0.004)	0.991 (0.006)	447	0.560
Internet at work = 1	0.838 (0.034)	0.908 (0.029)	309	0.085
Has cellphone = 1	0.996 (0.004)	1.000 (0.000)	447	0.314
Times a day the cellphone is checked	42.993 (0.868)	42.455 (0.765)	446	0.586
Regular Facebook use = 1	0.518 (0.028)	0.565 (0.036)	447	0.375
Regular Twitter use = 1	0.835 (0.024)	0.874 (0.021)	447	0.210
Regular Instagram use = 1	0.911 (0.022)	0.709 (0.039)	447	0.000
Regular Whatsapp use = 1	0.991 (0.006)	0.982 (0.010)	447	0.472
Ideology and beliefs				
Messi vs. Maradona = Messi	0.529 (0.031)	0.419 (0.032)	445	0.010
Messi vs. Maradona = Maradona	0.215 (0.028)	0.302 (0.030)	445	0.027
Messi vs. Maradona = Equally good	0.256 (0.024)	0.279 (0.031)	445	0.513
Sentence length	0.330 (0.030)	0.356 (0.031)	446	0.522
Poverty: Importance of effort	5.370 (0.214)	5.923 (0.193)	442	0.003
Poverty: Importance of luck	5.014 (0.194)	4.480 (0.159)	443	0.042
Poverty: Importance of opportunities	8.162 (0.118)	7.812 (0.128)	445	0.100
Human rights violations: USA	8.117 (0.128)	8.143 (0.106)	446	0.884
Human rights violations: Venezuela	8.335 (0.145)	8.523 (0.139)	443	0.279
Welfare state importance	7.598 (0.172)	7.032 (0.154)	446	0.030
Interest in politics	8.121 (0.117)	9.036 (0.101)	445	0.000
Adverse to risk=1	0.790 (0.022)	0.762 (0.023)	447	0.372
Twitter profile when recruited				
Number of followers (log10)	2.302 (0.044)	2.142 (0.035)	447	0.003
Number of friends (log10)	2.479 (0.033)	2.547 (0.027)	447	0.168
Number of Tweets (log10)	1.870 (0.045)	1.957 (0.041)	447	0.083
Account age (years)	6.814 (0.180)	6.998 (0.169)	447	0.350
Recruitment method				
Twitter recruited	0.259 (0.027)	0.305 (0.027)	447	0.191
Recruitment agency - online panel	0.183 (0.031)	0.291 (0.028)	447	0.010
Recruitment agency - offline	0.558 (0.030)	0.404 (0.029)	447	0.000
Cortisol				
First sample cortisol level (μg/dL)	0.169 (0.008)	0.152 (0.008)	434	0.067
Political positions from pre-treatment data				
Normalized segregation score	0.024 (0.001)	0.208 (0.010)	447	0.000
Party preference score	0.443 (0.025)	0.524 (0.027)	447	0.001
Party preference = *JxC*	0.406 (0.039)	0.556 (0.034)	447	0.000

Notes: All variables correspond to pre-treatment data. "Regular Facebook use = 1" indicates that the participant uses Facebook more than once a day or during all the day long (the same applies for "Regular Twitter use = 1", "Regular Instagram use = 1" and "Regular Whatsapp use = 1"). "Party leaning = JxC" is calculated as described in Section 2.b. The reported *p*-value comes from a joint hypothesis *F*-test where equality of group means is tested. Standard errors clustered at the classroom level.

Table A7. Pre-treatment characteristics across party preference, Twitter users

	FdT	*JxC*	n	*p*-value
Sociodemographics				
Age	31.129 (0.799)	35.628 (0.934)	447	0.001
Female = 1	0.466 (0.034)	0.581 (0.033)	447	0.022
Education years	14.056 (0.104)	14.633 (0.149)	447	0.003
Household head = 1	0.345 (0.028)	0.419 (0.041)	447	0.132
Household head education years	14.590 (0.140)	14.958 (0.197)	444	0.160
Residence = City of Buenos Aires	0.659 (0.036)	0.659 (0.027)	446	0.989
Residence = Greater Buenos Aires North	0.129 (0.020)	0.150 (0.026)	446	0.553
Residence = Greater Buenos Aires West	0.099 (0.019)	0.093 (0.013)	446	0.826
Residence = Greater Buenos Aires South	0.112 (0.021)	0.089 (0.021)	446	0.456
Household size	3.100 (0.110)	2.907 (0.078)	446	0.197
Employed = 1	0.770 (0.026)	0.795 (0.033)	445	0.566
Household head employed = 1	0.956 (0.017)	0.934 (0.017)	441	0.374
Internet and social media use				
Internet at home = 1	0.996 (0.004)	0.991 (0.006)	447	0.528
Internet at work = 1	0.867 (0.034)	0.887 (0.029)	309	0.605
Has cellphone = 1	1.000 (0.000)	0.995 (0.005)	447	0.315
Times a day the cellphone is checked	42.371 (0.879)	43.107 (0.778)	446	0.477
Regular Facebook use = 1	0.504 (0.028)	0.581 (0.038)	447	0.152
Regular Twitter use = 1	0.892 (0.021)	0.814 (0.026)	447	0.022
Regular Instagram use = 1	0.841 (0.020)	0.777 (0.026)	447	0.021
Regular Whatsapp use = 1	0.987 (0.007)	0.986 (0.008)	447	0.907
Ideology and beliefs				
Messi vs. Maradona = Messi	0.420 (0.031)	0.533 (0.028)	445	0.003
Messi vs. Maradona = Maradona	0.290 (0.031)	0.224 (0.025)	445	0.071
Messi vs. Maradona = Equally good	0.290 (0.031)	0.243 (0.024)	445	0.201
Sentence length	0.273 (0.031)	0.419 (0.036)	446	0.002
Poverty: Importance of effort	4.703 (0.225)	6.664 (0.221)	442	0.000
Poverty: Importance of luck	4.887 (0.192)	4.592 (0.209)	443	0.348
Poverty: Importance of opportunities	8.645 (0.135)	7.276 (0.137)	445	0.000
Human rights violations: USA	8.453 (0.118)	7.780 (0.133)	446	0.000
Human rights violations: Venezuela	7.830 (0.155)	9.075 (0.071)	443	0.000
Welfare state importance	8.272 (0.129)	6.280 (0.193)	446	0.000
Interest in politics	8.732 (0.123)	8.411 (0.149)	445	0.123
Adverse to risk=1	0.776 (0.029)	0.777 (0.028)	447	0.985
Twitter profile when recruited				
Number of followers (log10)	2.187 (0.036)	2.261 (0.054)	447	0.272
Number of friends (log10)	2.491 (0.028)	2.538 (0.037)	447	0.387
Number of Tweets (log10)	1.934 (0.052)	1.890 (0.067)	447	0.645
Account age (years)	6.648 (0.178)	7.183 (0.172)	447	0.013
Recruitment method				
Twitter recruited	0.297 (0.035)	0.265 (0.032)	447	0.543
Recruitment agency - online panel	0.203 (0.030)	0.274 (0.036)	447	0.162
Recruitment agency - offline	0.500 (0.036)	0.460 (0.030)	447	0.408
Cortisol				
First sample cortisol level (μg/dL)	0.160 (0.006)	0.162 (0.010)	434	0.834
Political positions from pre-treatment data				
Normalized segregation score	0.104 (0.007)	0.128 (0.008)	447	0.044
Segregation status = segregated	0.427 (0.028)	0.577 (0.043)	447	0.000
Party preference score	0.170 (0.011)	0.822 (0.014)	447	0.000

Notes: All variables correspond to pre-treatment data. "Regular Facebook use = 1" indicates that the participant uses Facebook more than once a day or during all the day long (the same applies for "Regular Twitter use = 1", "Regular Instagram use = 1" and "Regular Whatsapp use = 1"). "Segregation status = segregated" is calculated as described in Section 2.b. The reported *p*-value comes from a joint hypothesis *F*-test where equality of group means is tested. Standard errors clustered at the classroom level.

Table A8. Pre-treatment characteristics across treatment arms, non-segregated Twitter users

	Documentary	Twitter Allowed	Debate	Twitter Interact	n	*p*-value
Sociodemographics						
Age	28.388 (1.199)	29.320 (0.571)	26.063 (0.993)	29.081 (1.195)	224	0.043
Female = 1	0.673 (0.061)	0.580 (0.055)	0.603 (0.052)	0.548 (0.007)	224	0.144
Education years	14.041 (0.358)	14.120 (0.177)	13.365 (0.224)	14.000 (0.097)	224	0.047
Household head = 1	0.327 (0.074)	0.380 (0.055)	0.159 (0.018)	0.339 (0.016)	224	0.000
Household head education years	14.521 (0.307)	14.720 (0.241)	14.683 (0.299)	14.629 (0.224)	223	0.964
Residence = City of Buenos Aires	0.551 (0.046)	0.740 (0.079)	0.619 (0.047)	0.656 (0.050)	223	0.174
Residence = Greater Buenos Aires North	0.224 (0.055)	0.060 (0.033)	0.175 (0.037)	0.131 (0.031)	223	0.033
Residence = Greater Buenos Aires West	0.163 (0.047)	0.100 (0.044)	0.079 (0.033)	0.066 (0.028)	223	0.341
Residence = Greater Buenos Aires South	0.061 (0.029)	0.100 (0.038)	0.111 (0.045)	0.148 (0.005)	223	0.016
Household size	2.898 (0.208)	3.020 (0.107)	3.365 (0.134)	3.323 (0.104)	224	0.052
Employed = 1	0.755 (0.056)	0.694 (0.044)	0.603 (0.052)	0.806 (0.027)	223	0.004
Household head employed = 1	0.918 (0.054)	0.959 (0.016)	0.934 (0.029)	0.951 (0.019)	220	0.815
Internet and social media use						
Internet at home = 1	1.000 (0.000)	1.000 (0.000)	0.984 (0.015)	1.000 (0.000)	224	†
Internet at work = 1	0.857 (0.069)	0.889 (0.055)	0.781 (0.093)	0.833 (0.048)	136	0.758
Has cellphone = 1	1.000 (0.000)	1.000 (0.000)	0.984 (0.014)	1.000 (0.000)	224	†
Times a day the cellphone is checked	42.857 (1.396)	42.000 (2.124)	42.540 (1.976)	44.355 (0.989)	223	0.639
Regular Facebook use = 1	0.592 (0.048)	0.620 (0.034)	0.460 (0.048)	0.435 (0.027)	224	0.000
Regular Twitter use = 1	0.776 (0.078)	0.840 (0.046)	0.857 (0.042)	0.855 (0.022)	224	0.791
Regular Instagram use = 1	0.857 (0.051)	0.920 (0.042)	0.937 (0.043)	0.919 (0.038)	224	0.668
Regular Whatsapp use = 1	0.980 (0.020)	1.000 (0.000)	0.984 (0.014)	1.000 (0.000)	224	†
Ideology and beliefs						
Messi vs. Maradona = Messi	0.592 (0.059)	0.408 (0.046)	0.587 (0.032)	0.516 (0.072)	223	0.011
Messi vs. Maradona = Maradona	0.163 (0.065)	0.306 (0.035)	0.143 (0.040)	0.258 (0.051)	223	0.014
Messi vs. Maradona = Equally good	0.245 (0.083)	0.286 (0.036)	0.270 (0.036)	0.226 (0.028)	223	0.578
Sentence length	0.286 (0.056)	0.420 (0.017)	0.302 (0.075)	0.323 (0.043)	224	0.017
Poverty: Importance of effort	4.968 (0.537)	5.551 (0.328)	5.159 (0.341)	5.754 (0.392)	220	0.538
Poverty: Importance of luck	5.574 (0.302)	4.660 (0.436)	5.270 (0.312)	4.600 (0.401)	220	0.157
Poverty: Importance of opportunities	8.354 (0.244)	8.240 (0.194)	8.222 (0.179)	7.885 (0.279)	222	0.630
Human rights violations: USA	8.367 (0.243)	8.280 (0.134)	8.161 (0.218)	7.742 (0.290)	223	0.342
Human rights violations: Venezuela	8.667 (0.259)	8.540 (0.098)	8.290 (0.106)	7.951 (0.414)	221	0.162
Welfare state importance	8.082 (0.279)	7.400 (0.543)	7.698 (0.172)	7.274 (0.233)	224	0.156
Interest in politics	8.306 (0.223)	8.120 (0.256)	8.190 (0.208)	7.902 (0.196)	223	0.561
Adverse to risk=1	0.735 (0.051)	0.760 (0.046)	0.857 (0.043)	0.790 (0.019)	224	0.257
Twitter profile when recruited						
Number of followers (log10)	2.357 (0.052)	2.291 (0.089)	2.311 (0.074)	2.259 (0.113)	224	0.827
Number of friends (log10)	2.564 (0.060)	2.453 (0.056)	2.551 (0.065)	2.361 (0.042)	224	0.017
Number of Tweets (log10)	1.852 (0.085)	1.900 (0.090)	1.966 (0.110)	1.761 (0.026)	224	0.127
Account age (years)	7.369 (0.250)	6.755 (0.492)	6.128 (0.279)	7.119 (0.238)	224	0.008
Recruitment method						
Twitter recruited	0.265 (0.058)	0.240 (0.078)	0.254 (0.028)	0.274 (0.053)	224	0.980
Recruitment agency - online panel	0.184 (0.059)	0.240 (0.072)	0.190 (0.066)	0.129 (0.031)	224	0.454
Recruitment agency - offline	0.551 (0.076)	0.520 (0.035)	0.556 (0.062)	0.597 (0.054)	224	0.693
Cortisol						
First sample cortisol level (µg/dL)	0.180 (0.014)	0.187 (0.016)	0.158 (0.013)	0.157 (0.015)	218	0.355
Political positions from pre-treatment data						
Normalized segregation score	0.022 (0.002)	0.026 (0.002)	0.024 (0.002)	0.023 (0.003)	224	0.756
Party preference score	0.399 (0.038)	0.412 (0.041)	0.450 (0.041)	0.497 (0.054)	224	0.458
Party preference = *JxC*	0.367 (0.055)	0.320 (0.084)	0.476 (0.070)	0.435 (0.076)	224	0.447

Notes: All variables correspond to pre-treatment data. "Regular Facebook use = 1" indicates that the participant uses Facebook more than once a day or during all the day long (the same applies for "Regular Twitter use = 1", "Regular Instagram use = 1" and "Regular Whatsapp use = 1"). "Segregation status = segregated" and "Party leaning = *JxC*" are calculated as described in Section 2.b. The reported *p*-value comes from a joint hypothesis *F*-test where equality of group means is tested. Standard errors clustered at the classroom level. † indicates that the *F*-test could not be carried out due to invertibility problems.

Table A9. Pre-treatment characteristics across treatment arms, segregated Twitter users

	Documentary	Twitter Allowed	Debate	Twitter Interact	n	*p*-value
Sociodemographics						
Age	38.344 (1.237)	37.783 (1.254)	38.980 (2.143)	38.980 (1.515)	223	0.927
Female = 1	0.563 (0.059)	0.400 (0.064)	0.388 (0.053)	0.400 (0.070)	223	0.115
Education years	14.984 (0.110)	14.750 (0.134)	14.837 (0.222)	14.640 (0.317)	223	0.487
Household head = 1	0.422 (0.034)	0.467 (0.098)	0.510 (0.102)	0.480 (0.044)	223	0.678
Household head education years	14.730 (0.357)	15.288 (0.299)	14.714 (0.296)	14.820 (0.251)	221	0.494
Residence = City of Buenos Aires	0.656 (0.066)	0.717 (0.044)	0.694 (0.072)	0.640 (0.059)	223	0.728
Residence = Greater Buenos Aires North	0.156 (0.044)	0.133 (0.038)	0.082 (0.044)	0.140 (0.030)	223	0.646
Residence = Greater Buenos Aires West	0.109 (0.047)	0.050 (0.042)	0.102 (0.029)	0.120 (0.037)	223	0.624
Residence = Greater Buenos Aires South	0.078 (0.035)	0.100 (0.050)	0.102 (0.029)	0.100 (0.036)	223	0.957
Household size	2.873 (0.216)	2.783 (0.164)	2.673 (0.201)	3.020 (0.106)	222	0.383
Employed = 1	0.906 (0.027)	0.847 (0.014)	0.796 (0.040)	0.840 (0.049)	222	0.108
Household head employed = 1	0.937 (0.023)	0.966 (0.018)	0.939 (0.040)	0.960 (0.024)	221	0.776
Internet and social media use						
Internet at home = 1	0.984 (0.015)	1.000 (0.000)	1.000 (0.000)	0.980 (0.018)	223	†
Internet at work = 1	0.941 (0.035)	0.854 (0.038)	0.868 (0.094)	0.972 (0.029)	173	0.086
Has cellphone = 1	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	223	0.000
Times a day the cellphone is checked	42.383 (1.495)	40.708 (1.228)	43.878 (1.962)	43.250 (1.090)	223	0.383
Regular Facebook use = 1	0.547 (0.052)	0.550 (0.069)	0.673 (0.059)	0.500 (0.088)	223	0.276
Regular Twitter use = 1	0.891 (0.051)	0.833 (0.022)	0.939 (0.026)	0.840 (0.042)	223	0.019
Regular Instagram use = 1	0.750 (0.049)	0.633 (0.098)	0.694 (0.103)	0.760 (0.040)	223	0.644
Regular Whatsapp use = 1	0.984 (0.016)	0.950 (0.030)	1.000 (0.000)	1.000 (0.000)	223	†
Ideology and beliefs						
Messi vs. Maradona = Messi	0.460 (0.050)	0.350 (0.066)	0.347 (0.066)	0.520 (0.031)	222	0.028
Messi vs. Maradona = Maradona	0.270 (0.060)	0.317 (0.070)	0.286 (0.047)	0.340 (0.046)	222	0.774
Messi vs. Maradona = Equally good	0.270 (0.041)	0.333 (0.043)	0.367 (0.080)	0.140 (0.032)	222	0.001
Sentence length	0.453 (0.059)	0.350 (0.052)	0.292 (0.062)	0.300 (0.045)	222	0.172
Poverty: Importance of effort	5.281 (0.223)	6.167 (0.085)	6.347 (0.303)	6.041 (0.652)	222	0.003
Poverty: Importance of luck	4.328 (0.287)	4.033 (0.239)	4.755 (0.233)	4.940 (0.321)	223	0.068
Poverty: Importance of opportunities	7.719 (0.322)	7.867 (0.201)	7.449 (0.165)	8.220 (0.133)	223	0.004
Human rights violations: USA	8.078 (0.240)	8.067 (0.167)	8.102 (0.179)	8.360 (0.209)	223	0.702
Human rights violations: Venezuela	8.609 (0.312)	8.233 (0.116)	8.612 (0.189)	8.673 (0.359)	222	0.232
Welfare state importance	6.859 (0.448)	7.150 (0.064)	6.938 (0.270)	7.200 (0.207)	222	0.787
Interest in politics	8.734 (0.197)	8.950 (0.212)	9.312 (0.151)	9.260 (0.108)	222	0.059
Adverse to risk=1	0.844 (0.048)	0.733 (0.036)	0.714 (0.043)	0.740 (0.042)	223	0.198
Twitter profile when recruited						
Number of followers (log10)	2.168 (0.053)	2.087 (0.055)	2.204 (0.085)	2.117 (0.085)	223	0.605
Number of friends (log10)	2.594 (0.046)	2.474 (0.014)	2.535 (0.087)	2.588 (0.030)	223	0.001
Number of Tweets (log10)	1.995 (0.074)	1.941 (0.059)	2.034 (0.079)	1.851 (0.092)	223	0.457
Account age (years)	6.986 (0.303)	6.535 (0.265)	7.178 (0.338)	7.392 (0.283)	223	0.155
Recruitment method						
Twitter recruited	0.281 (0.045)	0.333 (0.029)	0.388 (0.085)	0.220 (0.043)	223	0.118
Recruitment agency - online panel	0.313 (0.062)	0.250 (0.062)	0.306 (0.056)	0.300 (0.014)	223	0.872
Recruitment agency - offline	0.406 (0.047)	0.417 (0.075)	0.306 (0.037)	0.480 (0.053)	223	0.047
Cortisol						
First sample cortisol level (µg/dL)	0.151 (0.012)	0.184 (0.013)	0.144 (0.014)	0.122 (0.010)	216	0.003
Political positions from pre-treatment data						
Normalized segregation score	0.194 (0.009)	0.191 (0.023)	0.239 (0.017)	0.216 (0.021)	223	0.098
Party preference score	0.549 (0.049)	0.517 (0.018)	0.502 (0.032)	0.521 (0.093)	223	0.887
Party preference = *JxC*	0.625 (0.055)	0.533 (0.022)	0.551 (0.038)	0.500 (0.119)	223	0.467

Notes: All variables correspond to pre-treatment data. "Regular Facebook use = 1" indicates that the participant uses Facebook more than once a day or during all the day long (the same applies for "Regular Twitter use = 1", "Regular Instagram use = 1" and "Regular Whatsapp use = 1"). "Segregation status = segregated" and "Party leaning = *JxC*" are calculated as described in Section 2.b. The reported *p*-value comes from a joint hypothesis *F*-test where equality of group means is tested. Standard errors clustered at the classroom level. † indicates that the *F*-test could not be carried out due to invertibility problems.

Table A10. Pre-treatment characteristics across treatment arms, non-segregated non-Twitter users

	Documentary	Debate	n	*p*-value
Sociodemographics				
Age	39.970 (2.044)	42.369 (1.719)	131	0.371
Female = 1	0.561 (0.111)	0.585 (0.070)	131	0.855
Education years	13.848 (0.401)	13.846 (0.224)	131	0.996
Household head = 1	0.591 (0.109)	0.492 (0.070)	131	0.448
Household head education years	13.970 (0.552)	13.969 (0.235)	130	0.999
Residence = City of Buenos Aires	0.515 (0.050)	0.477 (0.055)	131	0.606
Residence = Greater Buenos Aires North	0.182 (0.049)	0.154 (0.046)	131	0.675
Residence = Greater Buenos Aires West	0.167 (0.058)	0.215 (0.041)	131	0.493
Residence = Greater Buenos Aires South	0.136 (0.029)	0.154 (0.042)	131	0.732
Household size	3.415 (0.243)	3.231 (0.127)	130	0.502
Employed = 1	0.864 (0.051)	0.785 (0.050)	131	0.269
Household head employed = 1	0.955 (0.026)	0.968 (0.020)	129	0.678
Internet and social media use				
Internet at home = 1	0.938 (0.025)	0.954 (0.023)	130	0.656
Internet at work = 1	0.827 (0.065)	0.902 (0.056)	93	0.383
Has cellphone = 1	1.000 (0.000)	0.985 (0.015)	131	0.303
Times a day the cellphone is checked	34.470 (2.052)	34.375 (2.721)	130	0.978
Regular Facebook use = 1	0.636 (0.085)	0.538 (0.072)	131	0.381
Regular Instagram use = 1	0.455 (0.046)	0.400 (0.063)	131	0.489
Regular Whatsapp use = 1	0.985 (0.014)	0.969 (0.030)	131	0.635
Ideology and beliefs				
Messi vs. Maradona = Messi	0.415 (0.028)	0.400 (0.041)	130	0.758
Messi vs. Maradona = Maradona	0.385 (0.057)	0.308 (0.032)	130	0.243
Messi vs. Maradona = Equally good	0.200 (0.070)	0.292 (0.049)	130	0.282
Sentence length	0.409 (0.073)	0.508 (0.050)	131	0.268
Poverty: Importance of effort	5.734 (0.349)	6.371 (0.237)	126	0.134
Poverty: Importance of luck	5.359 (0.313)	5.161 (0.253)	126	0.624
Poverty: Importance of opportunities	7.854 (0.217)	8.000 (0.340)	128	0.718
Human rights violations: USA	7.144 (0.225)	7.444 (0.331)	129	0.454
Human rights violations: Venezuela	8.068 (0.202)	7.516 (0.325)	130	0.152
Welfare state importance	7.924 (0.197)	7.738 (0.381)	129	0.665
Interest in politics	6.879 (0.426)	6.938 (0.383)	131	0.917
Adverse to risk=1	0.864 (0.053)	0.844 (0.026)	130	0.735
Recruitment method				
Recruitment agency - online panel	0.500 (0.048)	0.323 (0.071)	131	0.041
Recruitment agency - offline	0.500 (0.048)	0.677 (0.071)	131	0.041
Cortisol				
First sample cortisol level (µg/dL)	0.146 (0.008)	0.143 (0.012)	124	0.859
Political positions from pre-treatment data				
Party leaning = *JxC*	0.409 (0.041)	0.385 (0.066)	131	0.752

Notes: All variables correspond to pre-treatment data. "Regular Facebook use = 1" indicates that the participant uses Facebook more than once a day or during all the day long (the same applies for "Regular Twitter use = 1", "Regular Instagram use = 1" and "Regular Whatsapp use = 1"). "Segregation status = segregated" and "Party leaning = *JxC*" are calculated as described in Section 2.b. The reported *p*-value comes from a joint hypothesis *F*-test where equality of group means is tested. Standard errors clustered at the classroom level.

Table A11. Pre-treatment characteristics across treatment arms, segregated non-Twitter users

	Documentary	Debate	n	*p*-value
Sociodemographics				
Age	45.151 (1.209)	43.316 (2.400)	110	0.496
Female = 1	0.585 (0.052)	0.561 (0.050)	110	0.745
Education years	14.245 (0.422)	14.211 (0.247)	110	0.943
Household head = 1	0.717 (0.074)	0.561 (0.060)	110	0.105
Household head education years	14.132 (0.306)	14.439 (0.223)	110	0.420
Residence = City of Buenos Aires	0.698 (0.070)	0.561 (0.069)	110	0.167
Residence = Greater Buenos Aires North	0.208 (0.057)	0.263 (0.076)	110	0.561
Residence = Greater Buenos Aires West	0.075 (0.027)	0.105 (0.024)	110	0.408
Residence = Greater Buenos Aires South	0.019 (0.020)	0.070 (0.037)	110	0.221
Household size	2.906 (0.105)	2.772 (0.130)	110	0.427
Employed = 1	0.827 (0.038)	0.912 (0.035)	109	0.100
Household head employed = 1	0.942 (0.023)	0.965 (0.021)	109	0.475
Internet and social media use				
Internet at home = 1	0.981 (0.017)	0.964 (0.021)	109	0.539
Internet at work = 1	0.944 (0.039)	0.800 (0.049)	81	0.024
Has cellphone = 1	1.000 (0.000)	0.982 (0.017)	110	0.306
Times a day the cellphone is checked	35.236 (1.984)	36.161 (3.055)	109	0.800
Regular Facebook use = 1	0.623 (0.075)	0.439 (0.043)	110	0.035
Regular Instagram use = 1	0.396 (0.085)	0.474 (0.081)	110	0.512
Regular Whatsapp use = 1	0.981 (0.018)	0.965 (0.021)	110	0.563
Ideology and beliefs				
Messi vs. Maradona = Messi	0.264 (0.055)	0.246 (0.063)	110	0.825
Messi vs. Maradona = Maradona	0.396 (0.061)	0.526 (0.032)	110	0.060
Messi vs. Maradona = Equally good	0.340 (0.032)	0.228 (0.051)	110	0.068
Sentence length	0.396 (0.053)	0.421 (0.067)	110	0.772
Poverty: Importance of effort	6.283 (0.424)	6.625 (0.421)	109	0.568
Poverty: Importance of luck	3.731 (0.346)	4.649 (0.275)	109	0.040
Poverty: Importance of opportunities	7.925 (0.264)	7.857 (0.317)	109	0.870
Human rights violations: USA	8.019 (0.389)	7.895 (0.207)	109	0.778
Human rights violations: Venezuela	8.226 (0.207)	8.421 (0.374)	110	0.650
Welfare state importance	7.264 (0.267)	6.965 (0.348)	110	0.497
Interest in politics	9.115 (0.226)	9.281 (0.165)	109	0.557
Adverse to risk=1	0.792 (0.049)	0.754 (0.044)	110	0.561
Recruitment method				
Recruitment agency - online panel	0.566 (0.071)	0.526 (0.050)	110	0.647
Recruitment agency - offline	0.434 (0.071)	0.474 (0.050)	110	0.647
Cortisol				
First sample cortisol level (μg/dL)	0.152 (0.009)	0.174 (0.016)	108	0.218
Political positions from pre-treatment data				
Party leaning = *JxC*	0.585 (0.068)	0.526 (0.071)	110	0.550

Notes: All variables correspond to pre-treatment data. "Regular Facebook use = 1" indicates that the participant uses Facebook more than once a day or during all the day long (the same applies for "Regular Twitter use = 1", "Regular Instagram use = 1" and "Regular Whatsapp use = 1"). "Segregation status = segregated" and "Party leaning = *JxC*" are calculated as described in Section 2.b. The reported *p*-value comes from a joint hypothesis *F*-test where equality of group means is tested. Standard errors clustered at the classroom level.

Table A12. Combined indexes detailed regression estimates, full sample

	Combined Index	Combined Index V2	Combined Index V3	Combined Index V4
Non-Twitter user · Treatment: Documentary	-0.114	-0.176	-0.046	-0.123
	(0.141)	(0.132)	(0.164)	(0.151)
Twitter user · Treatment: Documentary	0.278**	0.249**	0.273**	0.234*
	(0.110)	(0.117)	(0.123)	(0.133)
Twitter user · Treatment: Twitter-Allowed	0.183**	0.194**	0.140**	0.149**
	(0.084)	(0.082)	(0.067)	(0.064)
Non-Twitter user · Treatment: Debate-Only	-0.055	-0.045	-0.013	-0.001
	(0.109)	(0.113)	(0.104)	(0.110)
Twitter user · Treatment: Debate-Only	0.346***	0.340***	0.333***	0.317***
	(0.086)	(0.084)	(0.075)	(0.082)
Twitter user · Treatment: Twitter-Interact	0.403***	0.405***	0.443***	0.435***
	(0.107)	(0.124)	(0.134)	(0.151)
Age	0.159	0.045	0.284	0.146
	(0.223)	(0.225)	(0.227)	(0.232)
Age^2	-0.021	0.049	-0.125	-0.043
	(0.189)	(0.194)	(0.196)	(0.207)
Education years	0.038	0.023	0.022	0.004
	(0.043)	(0.040)	(0.043)	(0.038)
Female=1	0.094**	0.097**	0.080*	0.080**
	(0.040)	(0.040)	(0.039)	(0.038)
Household head=1	0.044	0.054	0.011	0.021
	(0.049)	(0.046)	(0.048)	(0.044)
Recruitment agency: Online=1	-0.084	-0.092	-0.031	-0.039
	(0.060)	(0.058)	(0.063)	(0.062)
Recruitment agency: Offline=1	-0.017	-0.009	0.002	0.012
	(0.058)	(0.058)	(0.057)	(0.056)
R^2	0.106	0.089	0.101	0.076
Adj. R^2	0.088	0.071	0.084	0.059
Num. obs.	688	688	688	688
RMSE	1.061	1.066	1.092	1.088
Num. clusters	24	24	24	24

Notes. Standard errors clustered at the classroom level. ***p < 0.01; **p < 0.05; *p < 0.1.

Table A13. Combined indexes detailed regression estimates, by segregation status

	Combined Index	Combined Index V2	Combined Index V3	Combined Index V4
Non-Twitter user · Treatment: Documentary · Non-segregated	-0.270**	-0.277**	-0.250*	-0.261*
	(0.118)	(0.118)	(0.145)	(0.143)
Non-Twitter user · Treatment: Documentary · Segregated	0.307	0.166	0.411*	0.236
	(0.192)	(0.177)	(0.215)	(0.191)
Twitter user · Treatment: Documentary · Non-segregated	-0.046	-0.045	0.005	0.007
	(0.123)	(0.142)	(0.136)	(0.161)
Twitter user · Treatment: Documentary · Segregated	0.610***	0.555***	0.553***	0.478***
	(0.125)	(0.119)	(0.127)	(0.122)
Twitter user · Treatment: Twitter-Allowed · Non-segregated	-0.000	-0.000	-0.000	-0.000
	(0.099)	(0.088)	(0.098)	(0.081)
Twitter user · Treatment: Twitter-Allowed · Segregated	0.442***	0.457***	0.350***	0.361***
	(0.119)	(0.117)	(0.088)	(0.085)
Non-Twitter user · Treatment: Deabate · Non-segregated	-0.231*	-0.226	-0.166	-0.158
	(0.130)	(0.147)	(0.135)	(0.152)
Non-Twitter user · Treatment: Deabate · Segregated	0.347***	0.353***	0.340**	0.343***
	(0.113)	(0.103)	(0.129)	(0.119)
Twitter user · Treatment: Deabate · Non-segregated	-0.009	-0.018	0.017	0.004
	(0.085)	(0.078)	(0.086)	(0.089)
Twitter user · Treatment: Deabate · Segregated	0.869***	0.866***	0.798***	0.775***
	(0.126)	(0.127)	(0.135)	(0.142)
Twitter user · Treatment: Twitter-Interact · Non-segregated	0.156	0.174	0.204	0.222
	(0.176)	(0.199)	(0.211)	(0.233)
Twitter user · Treatment: Twitter-Interact · Segregated	0.805***	0.782***	0.822***	0.778***
	(0.052)	(0.051)	(0.053)	(0.038)
Age	-0.089	-0.197	0.072	-0.054
	(0.211)	(0.211)	(0.214)	(0.220)
Age^2	0.127	0.196	-0.002	0.076
	(0.180)	(0.185)	(0.185)	(0.198)
Education years	0.012	-0.002	-0.002	-0.018
	(0.044)	(0.041)	(0.042)	(0.037)
Female=1	0.132***	0.135***	0.112***	0.111***
	(0.038)	(0.039)	(0.037)	(0.038)
Household head=1	0.043	0.053	0.008	0.019
	(0.050)	(0.046)	(0.050)	(0.045)
Recruitment agency: Online=1	-0.023	-0.032	0.023	0.012
	(0.061)	(0.059)	(0.063)	(0.062)
Recruitment agency: Offline=1	0.004	0.012	0.019	0.029
	(0.055)	(0.053)	(0.054)	(0.051)
R^2	0.176	0.153	0.158	0.125
Adj. R^2	0.153	0.128	0.135	0.101
Num. obs.	688	688	688	688
RMSE	1.023	1.032	1.061	1.063
Num. clusters	24	24	24	24

Notes. Standard errors clustered at the classroom level. ***p < 0.01; **p < 0.05; *p < 0.1.

Table A14. Polarization indexes detailed regression estimates, full sample

	Elite	Social Distance	Partisanship	Institutional	Engagement
Non-Twitter user · Treatment: Documentary	0.361**	-0.199**	-0.263**	-0.025	-0.215***
	(0.129)	(0.088)	(0.122)	(0.157)	(0.047)
Twitter user · Treatment: Documentary	0.415***	0.027	0.036	0.163	0.149**
	(0.102)	(0.145)	(0.109)	(0.120)	(0.070)
Twitter user · Treatment: Twitter Allowed	0.145***	0.041	0.022	0.125***	0.194**
	(0.026)	(0.055)	(0.114)	(0.022)	(0.088)
Non-Twitter user · Treatment: Debate Only	0.230*	-0.020	-0.190*	-0.048	-0.120
	(0.126)	(0.145)	(0.103)	(0.103)	(0.106)
Twitter user · Treatment: Debate Only	0.491***	0.075	-0.007	0.239***	0.200**
	(0.091)	(0.147)	(0.118)	(0.060)	(0.083)
Twitter user · Treatment: Twitter Interact	0.491***	0.249**	0.088	0.231*	0.102
	(0.079)	(0.118)	(0.061)	(0.120)	(0.066)
Age	0.303	-0.316	0.493**	0.218	-0.221
	(0.274)	(0.197)	(0.237)	(0.185)	(0.203)
Age^2	-0.103	0.217	-0.329	-0.101	0.239
	(0.235)	(0.184)	(0.199)	(0.160)	(0.182)
Education years	0.080*	0.002	0.016	-0.039	0.058
	(0.047)	(0.036)	(0.053)	(0.039)	(0.046)
Female=1	0.101**	0.113**	-0.016	-0.011	0.078*
	(0.046)	(0.049)	(0.048)	(0.032)	(0.040)
Household head=1	-0.080	0.019	0.031	0.052	0.101*
	(0.059)	(0.033)	(0.044)	(0.042)	(0.050)
Recruitment agency: Online=1	-0.000	0.017	0.003	-0.092*	-0.167***
	(0.077)	(0.073)	(0.051)	(0.045)	(0.047)
Recruitment agency: Offline=1	-0.035	0.086	0.004	-0.055	-0.051
	(0.060)	(0.068)	(0.054)	(0.054)	(0.059)
R^2	0.160	0.037	0.041	0.064	0.073
Adj. R^2	0.143	0.018	0.022	0.046	0.055
Num. obs.	688	687	682	688	688
RMSE	1.232	1.054	1.013	0.944	0.961
Num. clusters	24	24	24	24	24

Notes. Standard errors clustered at the classroom level. ***p < 0.01; **p < 0.05; *p < 0.1.

Table A15. Polarization indexes detailed regression estimates, by segregation status

	Elite	Social Distance	Partisanship	Institutional	Engagement
Non-Twitter user · Treatment: Documentary · Non-segregated	0.039	-0.263**	-0.384**	-0.008	-0.184***
	(0.118)	(0.112)	(0.138)	(0.180)	(0.055)
Non-Twitter user · Treatment: Documentary · Segregated	0.936***	-0.052	-0.010	0.104	-0.090
	(0.185)	(0.137)	(0.165)	(0.149)	(0.081)
Twitter user · Treatment: Documentary · Non-segregated	0.108	0.086	-0.098	-0.112	-0.142
	(0.081)	(0.169)	(0.168)	(0.153)	(0.088)
Twitter user · Treatment: Documentary · Segregated	0.711***	0.007	0.175	0.430***	0.435***
	(0.157)	(0.140)	(0.104)	(0.134)	(0.124)
Twitter user · Treatment: Twitter Allowed · Non-segregated	-0.000	-0.000	-0.000	0.000	-0.000
	(0.070)	(0.068)	(0.148)	(0.030)	(0.058)
Twitter user · Treatment: Twitter Allowed · Segregated	0.340***	0.109	0.086	0.300***	0.437***
	(0.073)	(0.079)	(0.119)	(0.045)	(0.146)
Non-Twitter user · Treatment: Deabate · Non-segregated	0.060	-0.060	-0.200	-0.192	-0.258
	(0.177)	(0.208)	(0.147)	(0.114)	(0.152)
Non-Twitter user · Treatment: Deabate · Segregated	0.578**	0.083	-0.093	0.250**	0.185
	(0.210)	(0.124)	(0.086)	(0.111)	(0.110)
Twitter user · Treatment: Deabate · Non-segregated	0.358*	-0.135	-0.189	0.008	-0.066
	(0.173)	(0.178)	(0.164)	(0.077)	(0.121)
Twitter user · Treatment: Deabate · Segregated	0.709***	0.365*	0.256**	0.582***	0.593***
	(0.185)	(0.195)	(0.101)	(0.137)	(0.163)
Twitter user · Treatment: Twitter Interact · Non-segregated	0.261*	0.176	-0.018	0.069	-0.040*
	(0.134)	(0.121)	(0.084)	(0.215)	(0.023)
Twitter user · Treatment: Twitter Interact · Segregated	0.843***	0.367***	0.262***	0.496***	0.352**
	(0.135)	(0.113)	(0.061)	(0.102)	(0.137)
Age	0.155	-0.387*	0.379	0.040	-0.430**
	(0.271)	(0.194)	(0.242)	(0.200)	(0.202)
Age^2	-0.027	0.259	-0.259	0.011	0.373*
	(0.224)	(0.182)	(0.204)	(0.171)	(0.182)
Education years	0.060	-0.006	0.005	-0.056	0.040
	(0.044)	(0.035)	(0.053)	(0.039)	(0.048)
Female=1	0.126***	0.124**	-0.001	0.016	0.109***
	(0.042)	(0.050)	(0.048)	(0.032)	(0.039)
Household head=1	-0.081	0.013	0.029	0.055	0.104*
	(0.062)	(0.034)	(0.046)	(0.041)	(0.051)
Recruitment agency: Online=1	0.039	0.040	0.029	-0.051	-0.120**
	(0.080)	(0.075)	(0.055)	(0.045)	(0.049)
Recruitment agency: Offline=1	-0.027	0.096	0.015	-0.042	-0.032
	(0.065)	(0.068)	(0.055)	(0.055)	(0.058)
R^2	0.202	0.048	0.058	0.105	0.119
Adj. R^2	0.180	0.021	0.031	0.080	0.094
Num. obs.	688	687	682	688	688
RMSE	1.206	1.052	1.009	0.927	0.941
Num. clusters	24	24	24	24	24

Notes. Standard errors clustered at the classroom level. ***p < 0.01; **p < 0.05; *p < 0.1.

Table A16. Combined indexes estimated differences with respect to the Twitter-Allowed group, Twitter users

	Combined Index	Combined Index V2	Combined Index V3	Combined Index V4
Full sample				
Documentary	0.094	0.056	0.133	0.085
	(0.135)	(0.142)	(0.137)	(0.147)
Debate-Only	0.163	0.147	0.194**	0.168
	(0.111)	(0.114)	(0.093)	(0.103)
Twitter-Interact	0.220*	0.211	0.303**	0.286*
	(0.129)	(0.144)	(0.139)	(0.155)
By segregation status				
	Combined Index	Combined Index V2	Combined Index V3	Combined Index V4
Non-segregated				
Documentary	-0.046	-0.045	0.005	0.007
	(0.158)	(0.166)	(0.168)	(0.179)
Debate-Only	-0.009	-0.018	0.017	0.004
	(0.128)	(0.115)	(0.130)	(0.120)
Twitter-Interact	0.156	0.174	0.204	0.222
	(0.202)	(0.218)	(0.234)	(0.247)
Segregated				
Documentary	0.168	0.098	0.203	0.117
	(0.156)	(0.155)	(0.141)	(0.138)
Debate-Only	0.427***	0.409**	0.449***	0.414***
	(0.153)	(0.161)	(0.144)	(0.157)
Twitter-Interact	0.363***	0.325***	0.473***	0.417***
	(0.118)	(0.122)	(0.088)	(0.083)

Notes. Standard errors clustered at the classroom level. ***p < 0.01; **p < 0.05; *p < 0.1.

Table A17. Polarization indexes estimated differences with respect to the Twitter-Allowed group, Twitter users

	Elite	Social Distance	Partisanship	Institutional	Engagement
Full sample					
Documentary	0.270**	-0.014	0.014	0.038	-0.045
	(0.109)	(0.154)	(0.146)	(0.116)	(0.110)
Debate-Only	0.346***	0.034	-0.028	0.114*	0.005
	(0.089)	(0.161)	(0.151)	(0.063)	(0.117)
Twitter-Interact	0.346***	0.207	0.066	0.106	-0.092
	(0.071)	(0.128)	(0.120)	(0.113)	(0.110)
By segregation status					
	Elite	Social Distance	Partisanship	Institutional	Engagement
Non-segregated					
Documentary	0.108	0.086	-0.098	-0.112	-0.142
	(0.108)	(0.181)	(0.225)	(0.155)	(0.105)
Debate-Only	0.358*	-0.135	-0.189	0.008	-0.066
	(0.186)	(0.192)	(0.222)	(0.082)	(0.132)
Twitter-Interact	0.261*	0.176	-0.018	0.069	-0.040
	(0.150)	(0.138)	(0.172)	(0.217)	(0.063)
Segregated					
Documentary	0.371**	-0.102	0.089	0.130	-0.001
	(0.168)	(0.157)	(0.137)	(0.114)	(0.178)
Debate-Only	0.369**	0.256	0.170	0.282**	0.156
	(0.174)	(0.205)	(0.131)	(0.136)	(0.207)
Twitter-Interact	0.502***	0.258*	0.176	0.197**	-0.085
	(0.130)	(0.134)	(0.112)	(0.098)	(0.191)

Notes. Standard errors clustered at the classroom level. ***p < 0.01; **p < 0.05; *p < 0.1.

Table A18. Combined indexes estimated differences with respect to the Debate-Ony group, non-Twitter users

	Combined Index	Combined Index V2	Combined Index V3	Combined Index V4
Full sample				
Documentary	-0.059	-0.131	-0.033	-0.122
	(0.174)	(0.167)	(0.192)	(0.182)
By segregation status				
Non-segregated				
Documentary	-0.039	-0.050	-0.084	-0.103
	(0.166)	(0.174)	(0.190)	(0.194)
Segregated				
Documentary	-0.039	-0.187	0.071	-0.107
	(0.219)	(0.202)	(0.253)	(0.229)

***p < 0.01; **p < 0.05; *p < 0.1

Table A19. Polarization indexes estimated differences with respect to the Debate-Only group, non-Twitter users

	Elite	Social Distance	Partisanship	Institutional	Engagement
Full sample					
Documentary	0.131	-0.179	-0.073	0.023	-0.095
	(0.182)	(0.164)	(0.158)	(0.173)	(0.107)
By segregation status					
Non-segregated					
Documentary	-0.021	-0.203	-0.184	0.184	0.075
	(0.207)	(0.228)	(0.208)	(0.191)	(0.151)
Segregated					
Documentary	0.358	-0.135	0.083	-0.146	-0.275**
	(0.277)	(0.184)	(0.179)	(0.174)	(0.121)

Notes. Standard errors clustered at the classroom level. ***p < 0.01; **p < 0.05; *p < 0.1.

Table A20. Combined indexes estimated differences between segregated and non-segregated participants, by treatment group and Twitter usage

	Combined Index	Combined Index V2	Combined Index V3	Combined Index V4
Non-Twitter users				
Documentary	0.578***	0.443***	0.661***	0.497***
	(0.184)	(0.171)	(0.209)	(0.187)
Debate-Only	0.578***	0.579***	0.506***	0.502***
	(0.109)	(0.115)	(0.163)	(0.157)
Twitter users				
Documentary	0.657***	0.600***	0.548***	0.472***
	(0.165)	(0.167)	(0.153)	(0.152)
Twitter-Allowed	0.442***	0.457***	0.350***	0.361***
	(0.109)	(0.091)	(0.111)	(0.083)
Debate-Only	0.878***	0.884***	0.781***	0.771***
	(0.140)	(0.123)	(0.171)	(0.162)
Twitter-Interact	0.650***	0.608***	0.618***	0.556**
	(0.215)	(0.227)	(0.234)	(0.237)

***p < 0.01; **p < 0.05; *p < 0.1

Table A21. Combined indexes estimated differences between Twitter and non-Twitter users

	Combined Index	Combined Index V2	Combined Index V3	Combined Index V4
Full sample				
Documentary	0.391**	0.425**	0.319	0.358
	(0.190)	(0.199)	(0.209)	(0.222)
Debate-Only	0.401***	0.385**	0.347***	0.319**
	(0.147)	(0.157)	(0.126)	(0.138)
By segregation status				
Non-segregated				
Documentary	0.224	0.232	0.254	0.268
	(0.212)	(0.233)	(0.246)	(0.274)
Debate-Only	0.222	0.208	0.183	0.162
	(0.185)	(0.199)	(0.179)	(0.196)
Segregated				
Documentary	0.303	0.389*	0.142	0.242
	(0.204)	(0.213)	(0.203)	(0.211)
Debate-Only	0.522***	0.513***	0.458**	0.432**
	(0.166)	(0.171)	(0.184)	(0.189)

Notes. Standard errors clustered at the classroom level. ***p < 0.01; **p < 0.05; *p < 0.1.

Table A22. Variation in Twitter actions detailed regression estimates, full sample

	ΔActivity Level (IHS)	**ΔContact** Segregation
Twitter user · Treatment: Documentary	0.091	-0.070
	(0.071)	(0.129)
Twitter user · Treatment: Twitter-Allowed	0.201***	-0.098*
	(0.036)	(0.052)
Twitter user · Treatment: Debate-Only	0.090	-0.158
	(0.059)	(0.104)
Twitter user · Treatment: Twitter-Interact	-0.026	-0.042
	(0.121)	(0.203)
Age	-0.289	0.308
	(0.232)	(0.536)
Age^2	0.263	-0.227
	(0.223)	(0.477)
Education years	0.068*	-0.001
	(0.034)	(0.077)
Female=1	0.035	0.111*
	(0.054)	(0.059)
Household head=1	-0.029	-0.032
	(0.062)	(0.074)
Recruitment agency: Online=1	-0.076	-0.124
	(0.054)	(0.114)
Recruitment agency: Offline=1	-0.059	-0.067
	(0.066)	(0.116)
R2	0.028	0.014
Adj. R2	0.004	-0.011
Num. obs.	445	445
RMSE	1.010	1.475
Num. clusters	24	24

Notes. Standard errors clustered at the classroom level. ***p < 0.01; **p < 0.05; *p < 0.1.

Table A23. Variation in Twitter actions detailed regression estimates, by segregation status

	ΔActivity Level (IHS)	**ΔContact** Segregation
Twitter user · Treatment: Documentary · Non-segregated	0.110*	0.144
	(0.055)	(0.129)
Twitter user · Treatment: Documentary · Segregated	0.115	-0.218
	(0.126)	(0.257)
Twitter user · Treatment: Twitter-Allowed · Non-segregated	0.000	-0.000
	(0.061)	(0.049)
Twitter user · Treatment: Twitter-Allowed · Segregated	0.417***	-0.154
	(0.078)	(0.157)
Twitter user · Treatment: Deabate · Non-segregated	-0.034	-0.321**
	(0.117)	(0.132)
Twitter user · Treatment: Deabate · Segregated	0.281**	0.058
	(0.130)	(0.172)
Twitter user · Treatment: Twitter-Interact · Non-segregated	-0.162*	-0.314
	(0.094)	(0.249)
Twitter user · Treatment: Twitter-Interact · Segregated	0.191	0.315*
	(0.166)	(0.179)
Age	-0.427*	0.279
	(0.238)	(0.587)
Age^2	0.347	-0.218
	(0.232)	(0.510)
Education years	0.059*	-0.007
	(0.032)	(0.074)
Female=1	0.058	0.123*
	(0.055)	(0.061)
Household head=1	-0.022	-0.041
	(0.064)	(0.080)
Recruitment agency: Online=1	-0.049	-0.115
	(0.052)	(0.118)
Recruitment agency: Offline=1	-0.043	-0.069
	(0.062)	(0.119)
R2	0.048	0.033
Adj. R2	0.015	-0.000
Num. obs.	445	445
Num. clusters	1.004	1.468
RMSE	24	24

Notes. Standard errors clustered at the classroom level. ***p < 0.01; **p < 0.05; *p < 0.1.

Table A24. Variation in Twitter actions estimated differences with respect to the Twitter-Allowed group

Full sample		
	ΔActivity Level (IHS)	**ΔContact** Segregation
Documentary	-0.110	0.027
	(0.080)	(0.133)
Debate-Only	-0.111	-0.061
	(0.068)	(0.123)
Twitter-Interact	-0.227*	0.055
	(0.132)	(0.209)
By segregation status		
	ΔActivity Level (IHS)	**ΔContact** Segregation
Non-segregated		
Documentary	0.110	0.144
	(0.084)	(0.137)
Debate-Only	-0.034	-0.321**
	(0.137)	(0.142)
Twitter-Interact	-0.162	-0.314
	(0.112)	(0.255)
Segregated		
Documentary	-0.302**	-0.064
	(0.141)	(0.257)
Debate-Only	-0.136	0.212
	(0.153)	(0.209)
Twitter-Interact	-0.226	0.468**
	(0.190)	(0.212)

Notes. Standard errors clustered at the classroom level.
***p < 0.01; **p < 0.05; *p < 0.1.

Table A25. Cortisol variation detailed regression estimates, full sample

	ΔCortisol
Non-Twitter user · Treatment: Documentary	-0.046
	(0.076)
Twitter user · Treatment: Documentary	-0.077
	(0.073)
Twitter user · Treatment: Twitter-Allowed	-0.095
	(0.090)
Non-Twitter user · Treatment: Debate-Only	-0.068
	(0.083)
Twitter user · Treatment: Debate-Only	0.046
	(0.098)
Twitter user · Treatment: Twitter-Interact	0.169**
	(0.070)
Age	0.196
	(0.223)
Age^2	-0.044
	(0.194)
Education years	0.011
	(0.043)
Female=1	0.074
	(0.045)
Household head=1	0.009
	(0.036)
Recruitment agency: Online=1	-0.011
	(0.064)
Recruitment agency: Offline=1	0.021
	(0.042)
R^2	0.068
Adj. R^2	0.050
Num. obs.	666
RMSE	0.862
Num. clusters	24

Notes. Standard errors clustered at the classroom level.
***p < 0.01; **p < 0.05; *p < 0.1.

Table A26. Cortisol variation detailed regression estimates, by segregation status

	ΔCortisol
Non-Twitter user · Treatment: Documentary · Non-segregated	-0.024
	(0.075)
Non-Twitter user · Treatment: Documentary · Segregated	-0.047
	(0.100)
Twitter user · Treatment: Documentary · Non-segregated	-0.178
	(0.156)
Twitter user · Treatment: Documentary · Segregated	0.012
	(0.096)
Twitter user · Treatment: Twitter-Allowed · Non-segregated	0.000
	(0.097)
Twitter user · Treatment: Twitter-Allowed · Segregated	-0.160
	(0.170)
Non-Twitter user · Treatment: Debate · Non-segregated	-0.028
	(0.091)
Non-Twitter user · Treatment: Debate · Segregated	-0.087
	(0.122)
Twitter user · Treatment: Debate · Non-segregated	0.039
	(0.149)
Twitter user · Treatment: Debate · Segregated	0.061
	(0.134)
Twitter user · Treatment: Twitter-Interact · Non-segregated	0.086
	(0.084)
Twitter user · Treatment: Twitter-Interact · Segregated	0.283**
	(0.104)
Age	0.163
	(0.244)
Age^2	-0.020
	(0.207)
Education years	0.009
	(0.041)
Female=1	0.076
	(0.047)
Household head=1	0.011
	(0.038)
Recruitment agency: Online=1	-0.009
	(0.072)
Recruitment agency: Offline=1	0.021
	(0.046)
R^2	0.074
Adj. R^2	0.047
Num. obs.	666
RMSE	0.864
Num. clusters	24

Notes. Standard errors clustered at the classroom level.
***p < 0.01; **p < 0.05; *p < 0.1.

Table A27. Cortisol variation estimated differences with respect to the Twitter-Allowed group

Full sample	
	ΔCortisol
Documentary	0.018
	(0.111)
Debate-Only	0.141
	(0.123)
Twitter-Interact	0.264**
	(0.107)
By segregation status	
	ΔCortisol
Non-segregated	
Documentary	-0.178
	(0.184)
Debate-Only	0.039
	(0.180)
Twitter-Interact	0.086
	(0.130)
Segregated	
Documentary	0.173
	(0.180)
Debate-Only	0.221
	(0.192)
Twitter-Interact	0.444**
	(0.184)

Notes. Standard errors clustered at the classroom level.
***p < 0.01; **p < 0.05; *p < 0.1.

Table A28. Cortisol variation estimated differences between Twitter and non-Twitter users

Full sample	
	ΔCortisol
Documentary	-0.031
	(0.085)
Debate-Only	0.114
	(0.129)
By segregation status	
	ΔCortisol
Non-segregated	
Documentary	-0.154
	(0.169)
Debate-Only	0.068
	(0.191)
Segregated	
Documentary	0.059
	(0.123)
Debate-Only	0.148
	(0.124)

Notes. Standard errors clustered at the classroom level.
***p < 0.01; **p < 0.05; *p < 0.1.

Table A29. Twitter actions during the debate detailed regression estimates, full sample

	Activity Level (IHS)	Contact Segregation
Twitter user · Treatment: Twitter-Allowed	0.181*	0.181
	(0.087)	(0.124)
Twitter user · Treatment: Twitter-Interact	1.371***	0.540***
	(0.055)	(0.089)
Age	0.363	0.375
	(0.414)	(0.547)
Age^2	-0.432	-0.327
	(0.375)	(0.517)
Education years	-0.020	0.063
	(0.085)	(0.044)
Female=1	0.012	0.053
	(0.026)	(0.078)
Household head=1	0.098	-0.119
	(0.066)	(0.086)
Recruitment agency: Online=1	0.023	0.014
	(0.055)	(0.067)
Recruitment agency: Offline=1	-0.117	0.054
	(0.063)	(0.121)
R2	0.610	0.192
Adj. R2	0.593	0.158
Num. obs.	221	221
RMSE	0.810	0.910
Num. clusters	8	8

***p < 0.01; **p < 0.05; *p < 0.1

Table A30. Twitter actions during the debate detailed regression estimates, by segregation status

	Activity Level (IHS)	Contact Segregation
Twitter user · Treatment: Twitter-Allowed · Non-segregated	-0.000	0.000
	(0.057)	(0.211)
Twitter user · Treatment: Twitter-Allowed · Segregated	0.395***	0.415**
	(0.101)	(0.128)
Twitter user · Treatment: Twitter-Interact · Non-segregated	1.243***	0.317**
	(0.097)	(0.095)
Twitter user · Treatment: Twitter-Interact · Segregated	1.592***	0.901***
	(0.116)	(0.119)
Age	0.224	0.203
	(0.351)	(0.595)
Age^2	-0.362	-0.246
	(0.329)	(0.556)
Education years	-0.033	0.044
	(0.082)	(0.041)
Female=1	0.046	0.099
	(0.026)	(0.075)
Household head=1	0.118*	-0.093
	(0.055)	(0.078)
Recruitment agency: Online=1	0.050	0.045
	(0.056)	(0.075)
Recruitment agency: Offline=1	-0.106	0.060
	(0.059)	(0.104)
R2	0.627	0.246
Adj. R2	0.608	0.207
Num. obs.	221	221
RMSE	0.795	0.883
Num. clusters	8	8

Notes. Standard errors clustered at the classroom level. ***p < 0.01; **p < 0.05; *p < 0.1.

Table A31. Twitter actions during the debate estimated differences with respect to the Twitter-Allowed group

Full sample		
	Activity Level (IHS)	Contact Segregation
Twitter-Interact	1.189***	0.360***
	(0.094)	(0.113)
By segregation status		
	Activity Level (IHS)	Contact Segregation
Non-segregated		
Twitter-Interact	1.243***	0.317
	(0.111)	(0.213)
Segregated	1.197***	0.486***
Twitter-Interact	(0.127)	(0.139)

Notes. Standard errors clustered at the classroom level. ***p < 0.01; **p < 0.05; *p < 0.1.

Table A32. Twitter actions during the debate estimated differences between segregated and non-segregated participants, by treatment group

	Activity Level (IHS)	Contact Segregation
Twitter Allowed	0.395***	0.415
	(0.063)	(0.267)
Twitter Interact	0.349**	0.584***
	(0.173)	(0.070)

Notes. Standard errors clustered at the classroom level. ***p < 0.01; **p < 0.05; *p < 0.1.

C. Appendix Figures

Figure A1. Experiment's recruitment Twitter account with pinned tweet

Notes: In English, the pinned tweet reads as follows: "*Are you on Twitter and want to take part in an academic on-site study about political ideas and voter preferences on Sunday 10/13? (As a thank-you and to make up for your time, we'll give away a purchasing card to each participant) For more info, visit: <url_link>*"

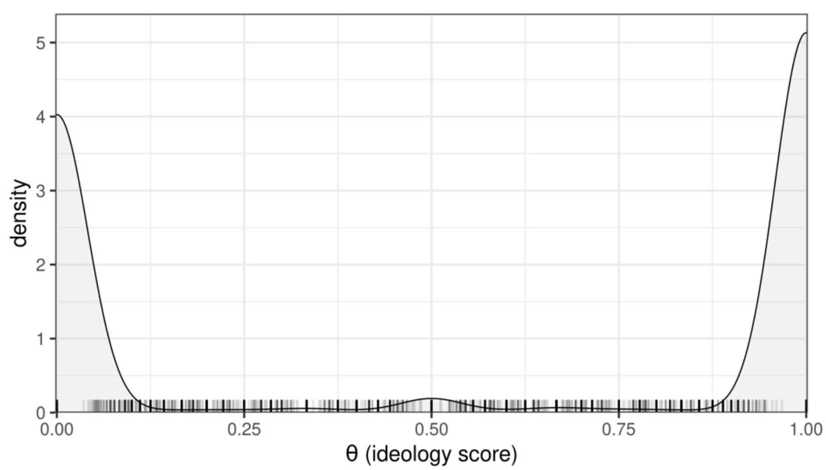


Figure A2. Ideology score (θ) distribution across the Argentine political landscape network nodes

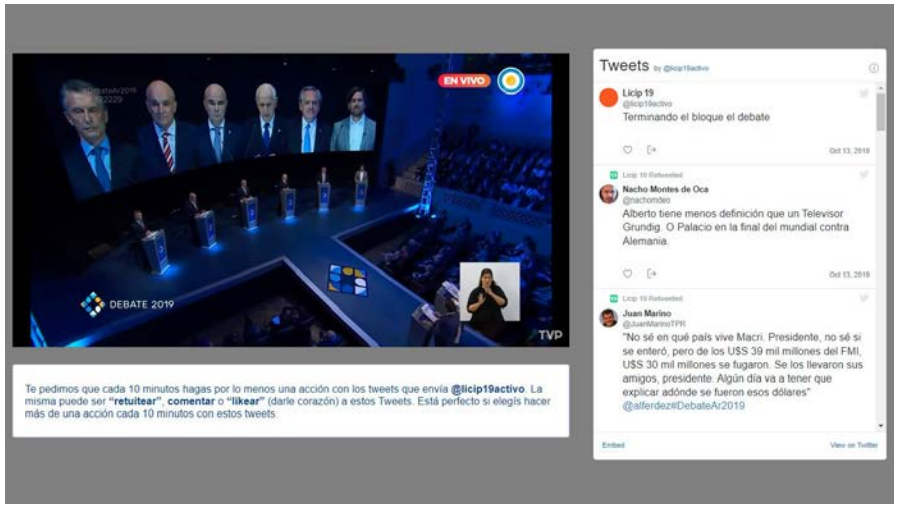


Figure A3. Twitter-Interact screen display

D. Recruitment form, pre-treatment questionnaire and post-treatment questionnaire

Recruitment form

We are seeking volunteers to take part in a study on political ideas and voter preferences. The study is not a part of an election campaign nor linked to a political party. The purpose of this initiative is to generate scientific knowledge. The study was developed by researchers at the *Laboratory for Research on Crime, Institutions, and Policies* (LICIP) of the Universidad Torcuato Di Tella.

*** When?**

If you are interested in participating in this study, you must arrive on time on Sunday, October 13th from 7.30 p.m. to 11.45 pm. Please keep in mind that the study is a 4-hour and 15 minutes commitment approximately.

*** Where?**

The study will take place at the Universidad Torcuato Di Tella (Located at Avda. Figueroa Alcorta 7350, Ciudad Autonoma de Buenos Aires, a few blocks away and across from River Plate Stadium).

*** What to expect:**

You will be asked to answer a series of questions and to observe images on screens. Meanwhile, two saliva samples will be taken to measure cortisol levels. All of your answers and the cortisol level test results will remain anonymous. Before the study implementation begins, we will ask you to sign an Informed Consent Form. The Informed Consent Form indicates that you have decided to participate in the survey, authorized two saliva samples and that you accept that your personal data will be processed in aggregated data. At no point is any personal information identifiable.

*** How will you benefit from participating in this study?**

Your participation will contribute to a better understanding of how Argentine citizens think and generate knowledge on social processes. To cover your transportation expenses and in recognition of your commitment, we will offer a $2.000 supermarket gift voucher by the end of the study. Also, we will provide snacks during the study and free transportation, if you need it, to Av. Libertador (and Juramento), and Barrancas de Belgrano. This is an interesting opportunity to get to know our university. If it is your first time visiting us, and you will also get to see up close how our researchers develop their work.

*** How to participate:**

You must be:

• Interested in taking part in these innovative ways of generating scientific knowledge.
• At least 18 years old and under 70 years.
• Eligible to vote in Argentina's presidential elections.
• We are seeking participants that are actively aware of what is going on around the world. For this reason, you must be an active Twitter user. To participate in this study, you must have opened your account before June 20, 2019, and have at least 3 tweets posted between June 20, 2019, and September 20, 2019.

If you meet the requirements outlined and you are interested in participating in this study, please click "SIGUIENTE" or "NEXT".

In order to confirm that you are indeed in a position to participate, we are going to ask you for some personal information.

Please keep in mind that the information requested on this form will only be used to recruit potential volunteers.

As stated before, if you participate in our study, all your answers will remain anonymous and will only be used for academic purposes. Our aim is not to collect specific data from any individual. We are fully committed to protect individual data and will not share any individual information.

Could you please confirm that, on Sunday, October 13, from 7.30pm to 11.45pm, you will be able to take part in the study?

Remember that this study will be conducted on site and will last 4.15 hours (approximately). It will take place at Universidad Torcuato Di Tella (UTDT). UTDT's address is 7350 Avenida Figueroa Alcorta, Ciudad Autónoma de Buenos Aires. The University's location is shown on the map below.

☐ Yes, I confirm I will participate.

Personal information

We'll ask you some personal details to confirm you're able to participate

What is your last name? ____________________

What is your first name? ____________________

How old are you? ____________________

What is your gender? (as shown on your ID)

☐ Female

☐ Male

What is your DNI (ID) number? The only reason why we request your ID is to confirm your data upon your entrance to the University. ____________________

Twitter account information

Remember we're only recruiting people who're active on Twitter.

To confirm that you're able to participate, we'll ask you some details related to your Twitter account (in case you have more than one Twitter account, choose the one you're currently more active on).

What is your Twitter account handle? As an example, we'll take Manu Ginobili (whose profile is shown below). His handle is @manuginobili. ____________________

Has your account been active since before June 20, 2019?
▢ Yes
▢ No
From June 20 thru September 20, 2019, have you tweeted or retweeted more than three messages from this account?
▢ Yes
▢ No
Are you eligible to vote for president in Argentina? Remember that one of the conditions to take part in this study is that you're eligible to vote for president in Argentina.
▢ Yes
▢ No

Follow us and let us follow you back on Twitter
To be able to DM you on Twitter and send you reminders and logistics information about the study, we ask that you follow us on Twitter. The account handle you should follow is @estudiolicip19. We'll also ask that you allow @estudiolicip19 to follow you back.
Do you follow the account with the @estudiolicip19 handle?
In case you don't, please start following it before proceeding with the questionnaire.
▢ Yes, I already follow @estudiolicip19 and will allow them to follow me back.

Contact Information
In order to confirm your participation in the study, we'll be sending you emails (only those who have previously registered and have received our confirmation can take part in the study)
What is your email address? ______________________
Please confirm your email address: ______________________
We don't intend to, but if we had to, what cellphone number could we contact you at? Please enter it as one number, that is, the area code followed by the phone number (without 15 at the beginning). For example, a valid phone number would be 1169147358. **______________________**

Thank you for your interest in participating in this exercise! We will be contacting you shortly to confirm your participation once we have verified that you are indeed in a position to participate in the exercise.
Likewise, in case you have any questions or changes in plans, you can write to us at estudioiolicip19@utdt.edu.

<u>**Pre-treatment questionnaire**</u>

Respondent #: _______ Lecture room: _________

Please answer the following questionnaire. Mark X in the appropriate boxes or answer the questions accordingly.

1. **What is your gender? (as shown on your ID):**
   □ Female
   □ Male
2. **How old are you?** …………………
3. **What is your highest level of education achieved?**
   □ Unfinished elementary school
   □ Finished elementary school
   □ Unfinished high school
   □ Finished high school
   □ Unfinished associate's degree (community college)
   □ Finished associate's degree (community college)
   □ Unfinished undergraduate school
   □ Finished undergraduate school
   □ Graduate education (master's degree, specialization, Ph.D.)
4. **Who's the main source of income in your household?** (that is, the head of household, the member that earns <u>the largest income</u>)
   - □ Me
   - □ Someone else
5. **IF YOU'RE NOT THE HEAD OF HOUSEHOLD, what is the highest level of education achieved by the head of household?**
   □ Unfinished elementary school
   □ Finished elementary school
   □ Unfinished high school
   □ Finished high school
   □ Unfinished associate's degree (community college)
   □ Finished associate's degree (community college)
   □ Unfinished undergraduate school
   □ Finished undergraduate school
   □ Graduate education (master's degree, specialization, Ph.D.)
6. **Where do you live?**
   □ City of Buenos Aires
   Which neighborhood? ______________________
   □ North of Greater Buenos Aires
   Which neighborhood? ______________________
   □ West of Greater Buenos Aires
   Which neighborhood? ______________________
   □ South of Greater Buenos Aires
   Which neighborhood? ______________________
   □ Somewhere else
   Which neighborhood? ______________________
7. **Including yourself, how many people live in your household? _______**
8. **Currently, do you have a job or are you engaged in any activity?**
   □ If so, which is it? _________________________
   □ No
9. **IF YOU'RE NOT THE HEAD OF HOUSEHOLD: does the head of household have a job or is engaged in any activity?**

□ If so, which is it? __________________________
□ No

10. **Do you have Internet…**
    10a. At home: □ Yes □ No
    10b. At work: □ Yes □ No
11. **Do you have a cellphone?**
    □ Yes
    □ No
12. **How many times a day (approximately) do you check your phone?**
    □ Less than 5 times
    □ Between 5 and 25 times
    □ Between 26 and 50 times
    □ More than 50 times
13. **Usually, do you use the following social media / messaging apps?**

	I don't have an account	I don't check it at all	Less than once a day	Once a day	More than once a day	Almost all day long
Facebook	□	□	□	□	□	□
Twitter	□	□	□	□	□	□
Instagram	□	□	□	□	□	□
WhatsApp	□	□	□	□	□	□
If it's another app, indicate which one -----------------	□	□	□	□	□	□

14. **In your opinion, who's the best soccer player: Messi or Maradona?**
    □ Messi
    □ Maradona
    □ They're equally as good.
15. **People have different ideas on the sentences criminals should receive. Consider, for instance, the case of a 20-year-old man who's been found guilty of robbery for the second time. This time, he broke into a house and stole a computer. Which sentence do you think would be most appropriate?**
    □ A fine
    □ A short sentence, less than 6 months
    □ An intermediate sentence, from 6 months to 3 years
    □ A harsh sentence, longer than 3 years
16. **Regarding people living in poverty in our country, how important do you think the following factors could be in determining their situation?**

16a. They didn't have any opportunities

Not important <-- --> Very important
□ □ □ □ □ □ □ □ □ □

16b. They didn't have any luck

Not important <-- --> Very important
□ □ □ □ □ □ □ □ □ □

16c. They didn't make an effort

Not important <-- --> Very important
□ □ □ □ □ □ □ □ □ □

17. **There is international concern about human rights violations in Venezuela and the United States. We'd like to know your opinion in both cases.**

17a. The Office of the High Commissioner for Human Rights (OHCHR), led by Michelle Bachelet, issued a report on Venezuela which states that, in this country, serious human rights violations have been committed. How believable do you think this statement could be?

Hardly believable	<--	-->	Highly believable

□ □ □ □ □ □ □ □ □ □

17b. The World Report 2019 by Human Rights Watch claims that the United States moved backward on human rights both domestically (mainly due to its migration and prison policies) and in terms of their support to foreign governments. How believable do you think this statement could be?

Hardly believable	<--	-->	Highly believable

□ □ □ □ □ □ □ □ □ □

18. **Do you believe the State should ensure the social and economic wellbeing of individuals, or do you think individuals should instead be self-sufficient and guarantee their own wellbeing through their work and involvement in the market? Where would you place yourself on the next scale?**

The State should never intervene	<--	-->	The State should always intervene

□ □ □ □ □ □ □ □ □ □

19. **How much do you care about current political affairs?**

I don't care at all	<--	-->	I really care

□ □ □ □ □ □ □ □ □ □

20. **Consider the next scenario: for personal reasons, you're in a small town outside Buenos Aires and, once there, you have to take a cab from the bus station to get to a place you don't know so well (and don't have Internet access on your cellphone). You have to choose between two companies. Company A charges you a fixed price of $480. Company B charges you per mileage. If the cab driver takes the most direct road, the ride costs $320. However, 1 out of 5 cab drivers take a detour to charge you more and, in this case, the ride would cost $640. Which of the two companies would you hire?**

□ I'd hire company A (fixed cost)
□ I'd hire company B (variable cost)

Post-treatment questionnaire

The following questionnaire was administered to participants who were allowed to use their cellphones during the debate (i.e., the Twitter-Allowed and Twitter-Interact groups). Participants who were not allowed to use their cellphones during the debate (i.e., the Documentary and Debate groups) were shown the same questionnaire but having Q22b and Q22c removed.

Respondent #: _______________ Lecture room: _____________

Please answer the following questionnaire. Mark X in the appropriate boxes or answer the questions accordingly. We'd like to ask you first some questions on what you've been watching for the past hour.

21. **Were you able to listen and watch properly the program we just showed you?** □ Yes □ No
22. **IF YOU COULDN'T WATCH IT AND LISTEN TO IT PROPERLY, why was it that you couldn't watch and listen to the program properly?**

    ____

    22b. Were you able to use your phone properly while watching the debate? □ Yes □ No

    22c. IF YOU WEREN'T, why was it that you couldn't use your phone properly?

    ____
23. **Please tell us briefly what you found most interesting about the program you've just watched:**

    ____
24. **How would you assess each of the following situations?**

    24a. Someone from my immediate family marries someone whose political preferences are opposite to mine.

I'd assess it negatively	<---------------						--------------->		I'd assess it positively
□	□	□	□	□	□	□	□	□	□

24b. Spending time socializing with someone whose political stance is opposite to mine.

I'd assess it negatively	<---------------						--------------->		I'd assess it positively
□	□	□	□	□	□	□	□	□	□

24c. Working closely with someone whose political stance is opposite to mine.

I'd assess it negatively	<---------------						--------------->		I'd assess it positively
□	□	□	□	□	□	□	□	□	□

25. **How likely are you to perform any of the following actions in the next election?**

    25a. Auditing, volunteering or donating funds to the campaign of the candidate I'll vote for.

Extremely unlikely	<---------------						--------------->		Extremely likely
□	□	□	□	□	□	□	□	□	□

25b. Having a conversation with an acquaintance, trying to persuade them to vote for the candidate you'll vote for.

Extremely unlikely	<---------------						--------------->		Extremely likely
□	□	□	□	□	□	□	□	□	□

26. **Fraud suspicions have been raised over the next election. On the one hand, *Juntos por el Cambio* has reported auditing irregularities, while *Frente de Todos* has questioned SmartMatic's vote count process. How feasible do you think the next statements could be?**

26a. Fraud in favor of Mauricio Macri - Miguel Ángel Pichetto's ticket

I wouldn't think it was fraud	<-----------------------							----------------------->	I'd think it was fraud
□	□	□	□	□	□	□	□	□	□

26b. Fraud in favor of Alberto Fernández - Cristina Fernández de Kirchner's ticket

I wouldn't think it was fraud	<-----------------------							----------------------->	I'd think it was fraud
□	□	□	□	□	□	□	□	□	□

27. **In a government, it is important for ministers to be technically equipped and follow the president's guidelines. What do think of the importance of these features when it comes to the members of the cabinet?**

27a. That they're technically equipped

Not important at all	<-----------------------							----------------------->	Extremely important
□	□	□	□	□	□	□	□	□	□

27b. That they follow the president's guidelines

Not important at all	<-----------------------							----------------------->	Extremely important
□	□	□	□	□	□	□	□	□	□

28. **In Argentina, there have been clashes between the Executive Power and the Supreme Court. What do you think of the following scenarios?:**

28a. For example, in 2008, the Supreme Court found the reform of the Council of the Magistracy submitted by president Cristina Kirchner unconstitutional. Such reform proposed a new structure of the Council and the popular election of their members. In this situation, do you think the Supreme Court has:

Not acted properly	<-----------------------							----------------------->	Acted properly
□	□	□	□	□	□	□	□	□	□

28b. There was another example this year when the Supreme Court ruled against Macri's administration and forced it to compensate provinces for the decrease in the VAT and the Profits Tax collection. In this situation, do you think the Supreme Court has:

Not acted properly	<-----------------------							----------------------->	Acted properly
□	□	□	□	□	□	□	□	□	□

29. **We now want to ask you about some positive features that, in your opinion, characterize Argentina's last two presidents. If none of them applies, please check the "She/he's none of the above" box. Please note that you can choose one feature for both (for instance, in both cases, you could answer "She/he is smart"). Also, you can avoid choosing a certain feature for both of them (for instance, not checking "She/he is brave", in both cases).**

Cristina Fernández de Kirchner
□ She's smart
□ She's hard-working
□ She's brave
□ She's honest
□ She's energetic
□ She's none of the above

Mauricio Macri
□ He's smart
□ He's hard-working
□ He's brave
□ He's honest
□ He's energetic
□ He's none of the above

30. **Regarding the candidate you think you'll vote for in the next election, on a scale of 1 to 100, how certain are you about voting for them? ………………….. (Answer with a number between 1 and 100).**
31. **What do you think about each of the following candidates as future presidents? From 1 to 10, being 1 the lowest mark and 10 the highest mark, how would you rate them?**

	Lowest									Highest	
Nicolás del Caño	□ 1	□ 2	□ 3	□ 4	□ 5	□ 6	□ 7	□ 8	□ 9	□ 10	□ ns/nc
José Luis Espert	□ 1	□ 2	□ 3	□ 4	□ 5	□ 6	□ 7	□ 8	□ 9	□ 10	□ ns/nc
Alberto Fernández	□ 1	□ 2	□ 3	□ 4	□ 5	□ 6	□ 7	□ 8	□ 9	□ 10	□ ns/nc
Juan José Gómez Centurión	□ 1	□ 2	□ 3	□ 4	□ 5	□ 6	□ 7	□ 8	□ 9	□ 10	□ ns/nc
Roberto Lavagna	□ 1	□ 2	□ 3	□ 4	□ 5	□ 6	□ 7	□ 8	□ 9	□ 10	□ ns/nc
Mauricio Macri	□ 1	□ 2	□ 3	□ 4	□ 5	□ 6	□ 7	□ 8	□ 9	□ 10	□ ns/nc

32. **In your opinion, if you had to distribute a total of 100 points among all candidates, based on their quality as future presidents, how would you allocate them? The sum of all scores should be 100.**

	Score (each between 0 and 100. The sum of all scores should be 100)
Nicolás del Caño	
José Luis Espert	
Alberto Fernández	
Juan José Gómez Centurión	
Roberto Lavagna	
Mauricio Macri	
TOTAL	100
N/A	

33. **Some people decide their vote because they consider the other candidate poses a serious threat to the country's wellbeing. When it comes to your vote, is this your case?**

No, not at all <-- --> Yes, certainly

□ □ □ □ □ □ □ □ □ □

34. **Who do you think you'll vote for in the next election that will take place on Sunday, October 27?**
    - □ Nicolás del Caño
    - □ José Luis Espert
    - □ Alberto Fernández
    - □ Juan José Gómez Centurión
    - □ Roberto Lavagna
    - □ Mauricio Macri
    - □ Blank vote
    - □ I don't know
35. **Who did you vote as presidential candidate in the midterm election that took place on August 11, 2019?**
    - □ Raúl Albarracín
    - □ Alejandro Biondini
    - □ Manuela Castañeira
    - □ Nicolás del Caño
    - □ José Luis Espert
    - □ Alberto Fernández
    - □ Juan José Gómez Centurión
    - □ Roberto Lavagna
    - □ Mauricio Macri
    - □ José Antonio Romero Feris
    - □ Blank/spoiled vote
    - □ I don't know / I don't remember
    - □ I didn't vote
36. **Would you like to share any additional comments on this survey?**

____