Greater Internet use is not associated with faster growth in political polarization among US demographic groups

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We combine eight previously proposed measures to construct an index of political polarization among US adults. We find that polarization has increased the most among the demographic groups least likely to use the Internet and social media. Our overall index and all but one of the individual measures show greater increases for those older than 65 than for those aged 18–39. A linear model estimated at the age-group level implies that the Internet explains a small share of the recent growth in polarization.

politics | polarization | Internet | social media

By many measures, Americans have become increasingly polarized in recent decades. (Both the appropriate definition of polarization and the extent of its increase are debated in the literature. See refs. 1–5 for reviews.) In 1960, ∼5% of Republicans and Democrats reported that they would "[feel] 'displeased' if their son or daughter married outside their political party"; by 2010, nearly 50% of Republicans and >30% of Democrats "felt somewhat or very unhappy at the prospect of interparty marriage" (6). The relative favorability of party affiliates toward their own party increased by >50% between 1980 and 2015 (5), and the proportion of voters voting for the same party in both presidential and House elections increased from 71% of reported voters in 1972 to 90% in 2012 (7).

Many authors link this trend to the rise of the Internet and social media. Sunstein (8) and Pariser (9) argue that the Internet may create echo chambers in which individuals receive news only from like-minded sources. Gabler (10) argues that "social media contribute to...more polarization as the like-minded find one another and stoke one another's prejudices and grievances, no matter what end of the political spectrum." Haidt (11) calls social media "one of our biggest problems" and notes that "so long as we are all immersed in a constant stream of unbelievable outrages perpetrated by the other side, I don't see how we can ever trust each other and work together again." Discussing the role of social media in the 2016 election, President Barack Obama said, "The capacity to disseminate misinformation, wild conspiracy theories, to paint the opposition in wildly negative light without any rebuttal—that has accelerated in ways that much more sharply polarize the electorate and make it very difficult to have a common conversation" (12).

In this work, we use survey data to study how trends in political polarization relate to respondents' propensities to obtain information online or from social media. Using data from the American National Election Studies (ANES), we compute eight measures of political polarization that have been proposed in past work and have increased in recent years. Examples include affect polarization (6) and straight-ticket voting (13). We do not take a stand on how polarization should be conceptualized (14) or whether polarization properly defined is in fact increasing (15, 16). Instead, we start with the measures others have put forward as evidence of rising polarization and ask whether demographic differences in these measures are consistent with an important role for the Internet and social media. This approach follows past work that analyzes demographic differences to evaluate the role of the Internet in the 2016 presidential election outcome (17).

We divide respondents according to demographics that predict Internet and social media use. The main predictor we focus on is age. We show, using data from the ANES and the Pew Research Center, that Internet and social media use rates are far higher among the young than the old, with rates of social media use in 2016 of 0.88, 0.65, and 0.30, respectively, among those aged 18–39, 40–64, and 65 and older (65+).

A normalized index of our eight polarization measures increases by 0.28 index points overall between 1996 and 2016. The increase is 0.23, 0.23, and 0.47, respectively, among those aged 18–39, 40–64, and 65+. The increase is larger for the oldest than for the youngest group in all but one of the eight measures. Using an index of predicted Internet use constructed from a broad set of demographics in the ANES, we find that the groups least likely to use the Internet experienced larger changes in polarization between 1996 and 2016 than the groups most likely to use the Internet.

To quantify the potential role of the Internet in explaining trends in polarization, we estimate a model of polarization at the age-group level, allowing for both a linear time trend and a linear effect of an age-group-level measure of Internet or social media use. Our point estimates imply that the growth in Internet use explains a small share of the trend in polarization from 1996 to 2016.

Much of the empirical evidence on the role of the Internet and social media in polarization focuses on segregation of users across information sources or social networks (18–23). Some work looks directly at online activity and political attitudes. Twitter exposure seems to moderate ideology, especially for users with diverse networks (24), and obtaining political information or experiencing cross-cutting interactions on social media

Significance

By many measures, Americans have become increasingly polarized in recent decades. We study the role of the Internet and social media in explaining this trend. We find that polarization has increased the most among the demographic groups least likely to use the Internet and social media, suggesting that the role of these factors is limited.

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Conflict of interest statement: M.G. is a member of the Toulouse Network of Information Technology, a research group funded by Microsoft. J.M.S. has, in the past, been a paid visitor at Microsoft Research and a paid consultant for a digital news startup; his spouse has written articles for several online news outlets, for which she was paid. L.B. declares no conflict of interest.

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correlates with lower polarization (25, 26). However, experimental exposure to proattitudinal and counterattitudinal news on Facebook tends to increase polarization (27). The effect of Internet access and use on political attitudes and polarization is small or mixed (28, 29). Broadband Internet access driven by state-level right-of-way legislation is associated with greater consumption of partisan media and greater partisan affect polarization (30). Obtaining news online is positively correlated with strength of partisanship (31). A metaanalysis finds evidence of a positive association between social media use and political participation, but questions the causal interpretation of much of the underlying evidence (32). See ref. 33 for a more general review on the role of the Internet in politics.

Some past work looks at demographic trends in polarization. Millennials self-declare more extreme party and ideology placements than previous generations did at the same age (34). Other work examines the interaction between age group, Internet use, and political knowledge (35).

We contribute to the literature by documenting how trends in polarization differ between groups with high and low exposure to online information and by using these differences to estimate the role of the Internet in explaining the recent rise in polarization.

Data and Measures of Polarization

Our primary sources of data are the ANES 1948–2012 Time Series Cumulative, 2008 Time Series Study, 2012 Time Series Study, and 2016 Time Series Study datasets (36–39). (Code for replication is available as *Dataset S1*. Data can be accessed via the respective institutions outlined here and in the references.)

The ANES is a nationally representative, face-to-face survey of the voting-age population that is conducted in both preelection and postelection rounds and contains numerous demographic variables and political measures. The 2012 and 2016 ANES surveys include a separate sample of respondents who completed the survey online; we drop these respondents to maintain consistency across years. We also restrict the ANES data to presidential election years.

We supplement the ANES data with survey microdata on social media use from the Pew Research Center that covers the years 2005, 2008, 2011, 2012, and 2016. We also use Pew Research Center survey microdata on Internet use in each presidential election year between 1996 and 2016 (40–47).

Our primary measures of Internet use are an indicator of Internet use from the ANES, an indicator for obtaining campaign information online from the ANES, and an indicator for social media use from the Pew Research Center. Some analysis also uses an indicator for Internet use from the Pew Research Center. *SI Appendix*, section 1 contains additional details on the construction of these indicators, including information about changes in question wording across survey waves.

Measures of Political Polarization. We calculate eight measures of polarization that have been used in past work and have increased in recent years. In each case, we try to reconstruct the measures exactly as proposed in past work and only intentionally deviate where explicitly stated. We provide an overview of each measure here, relegating additional details to *SI Appendix*, sections 1 and 2.

In computing each polarization measure, we restrict the sample to respondents with valid, nonmissing responses to each of the relevant questions used in constructing the measure. Thus, the exact sample used varies across polarization measures.

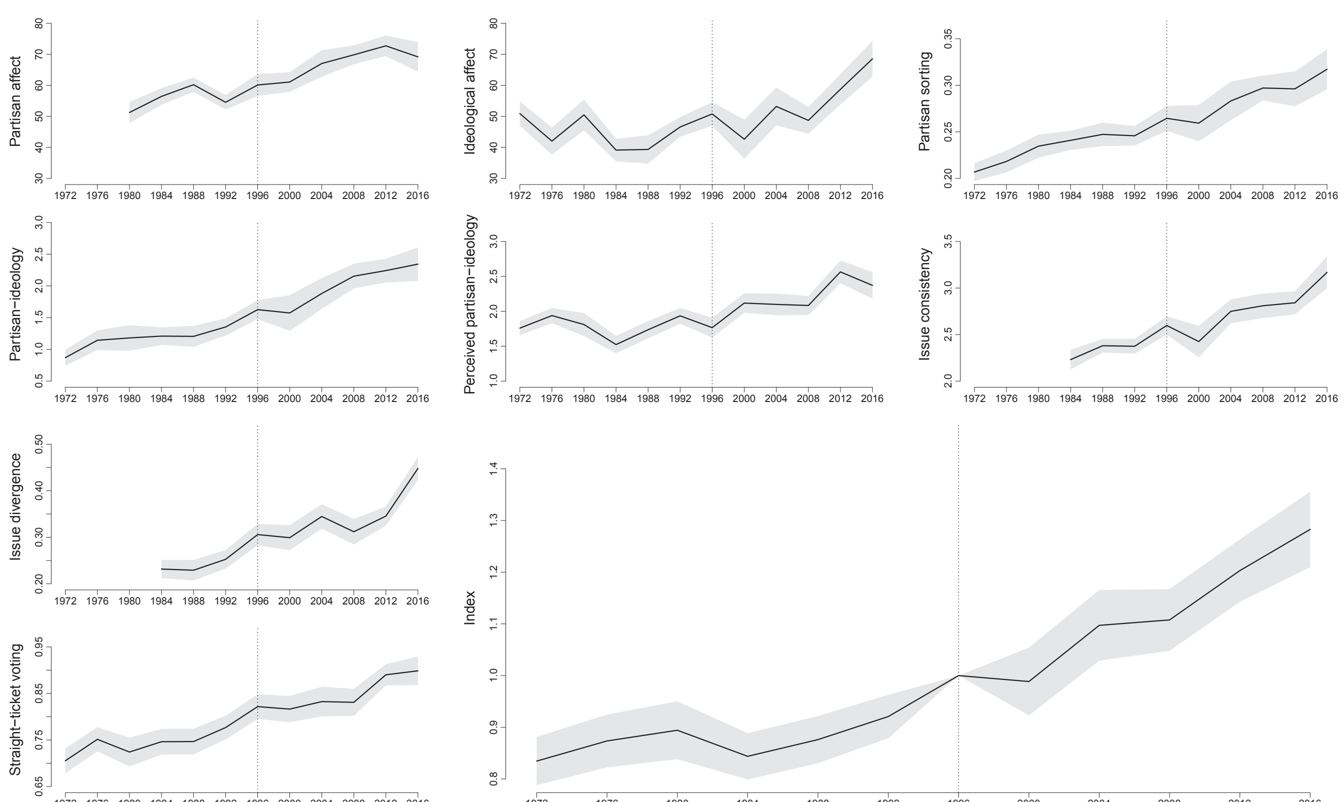

Fig. 1. Trends in political polarization. Each of the eight small plots shows the trend in a given polarization measure across time. The large plot shows the trend in the index, which is computed as the average across all polarization measures available in a given year after normalizing each measure to have a value of 1 in 1996. The shaded regions are pointwise 95% confidence intervals (CIs), constructed by using a nonparametric bootstrap with 100 replicates. Data are from the ANES. See main text for definitions and *SI Appendix*, section 3 for details on the bootstrap procedure.

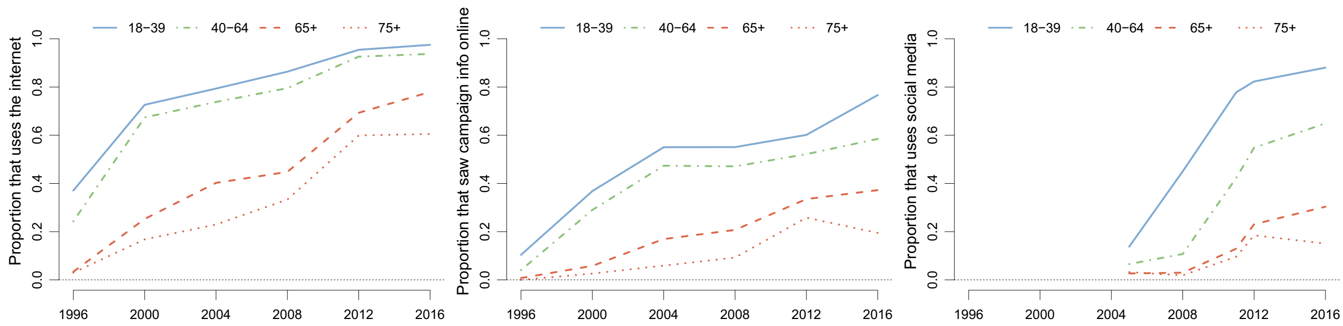

Fig. 2. Trends in Internet and social media use by age group. Each plot shows trends in Internet or social media use by age group. *Left* shows the weighted proportion of respondents that use the Internet by age group, using data from the ANES. *Center* shows the weighted proportion of respondents that obtained campaign information online by age group, using data from the ANES. *Right* shows the weighted proportion of respondents that use social media by age group, using data from the Pew Research Center. See *SI Appendix*, section 1 for details on variable construction.

We use the ANES codebook's definition of a valid, nonmissing response, except for the self-reported ideology measure, where we treat individuals who respond "Don't know" or "Haven't though much about it" as having a missing response. Observations are weighted by using the ANES survey weights unless otherwise stated.

Our first two measures of polarization use the ANES thermometer ratings of parties and ideologies to capture how respondents' feelings toward those on the other side of the political spectrum have changed over time (5, 6). The ANES thermometer scale ranges from 0 to 100, with higher values reflecting more positive feelings toward the specified group.

"Partisan affect polarization" is the sum of the mean differences, taken separately for Republicans and Democrats, between the favorability of individuals toward their own party and their favorability toward the opposite party. Leaners, respondents who initially report not having a party affiliation but who subsequently report leaning toward one party, are included with their associated parties.

"Ideological affect polarization" is the sum of the mean differences, taken separately for liberals and conservatives, between the favorability of individuals toward their own ideological group and their favorability toward the opposite ideological group. Those who identify as strict moderates on the 7-point ideological scale are excluded.

"Partisan sorting" captures the association between self-reported partisan identity and self-reported ideology (48). It is defined to be the average absolute difference between partisan identity and ideology (both measured on a 7-point scale), after weighting by the strength of partisan and ideological affiliation and transforming the measure to range between 0 (low partisan sorting) and 1 (high partisan sorting).

"Partisan-ideology polarization" is closely related to partisan sorting and captures the extent to which the self-reported ideological affiliation of Republicans and Democrats differ (1). It is defined to be the average ideological affiliation of Republicans (excluding leaners) on a 7-point liberal-to-conservative scale minus the average ideological affiliation of Democrats (excluding leaners) on the same 7-point scale.

"Perceived partisan-ideology polarization" captures the extent to which respondents perceive ideological differences between the parties (29). It is defined to be the average perceived ideology of the Republican Party minus the average perceived ideology of the Democratic Party, each on a 7-point liberal-to-conservative scale.

"Issue consistency" and "issue divergence" measure the extent to which individuals' issue positions line up on a single ideological dimension (1). Issue consistency is the average absolute value of the sum of seven responses, with each valid response defined as conservative (coded as 1), moderate (coded as 0), or liberal (coded as -1). The responses are to a question about self-reported ideology and to questions about the following six policy issues: aid to blacks, foreign defense spending, government's role in guaranteeing jobs and income, government health insurance, government services and spending, and abortion legislation. Issue divergence is the average of the unweighted correlations between these same seven responses and an indicator for Republican affiliation, among Republican and Democratic affiliates (including leaners).

"Straight-ticket voting" captures the frequency with which individuals split their votes across parties in an election (13). It is defined to be the survey-weighted proportion of voting respondents who report voting for the same party (Republican or Democratic) in both the presidential and House elections of a given year.

We define an overall index of polarization M_t equal to the average of these eight measures in year t, normalizing each measure by its value in 1996:

$$M_t = \frac{1}{|\mathcal{M}|} \sum_{m \in \mathcal{M}} \frac{m_t}{m_{1996}}.$$

Here, $\mathcal{M}$ is the set of all eight polarization measures. We also compute this index for different groups of respondents, in which

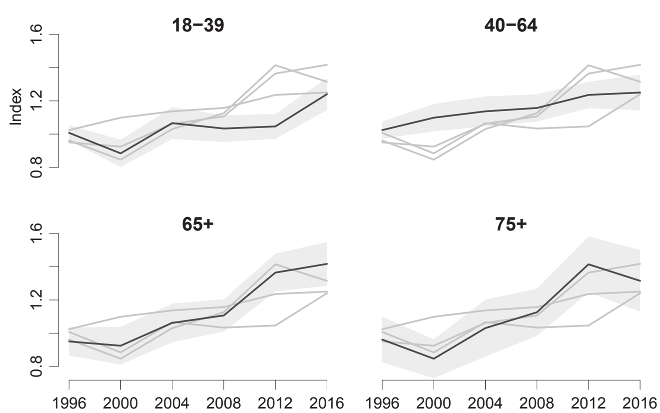

Fig. 3. Trends in polarization by age group. Each plot shows the polarization index for each of four age groups. Each plot highlights the series for one age group in bold. Shaded regions represent 95% pointwise CIs for the bold series constructed from a nonparametric bootstrap with 100 replicates. See main text for definitions and *SI Appendix*, section 3 for details on the bootstrap procedure.

Table 1. Growth in polarization 1996 to 2016

Measure	Overall	18–39	Age groups 40–64	65+	65+ minus 18–39
Partisan affect	9.1 (3.0)	4.3 (4.9)	8.9 (4.3)	13.5 (7.7)	9.27 (9.28)
Ideological affect	17.8 (3.6)	5.9 (5.7)	19.2 (6.4)	33.8 (8.4)	27.91 (10.41)
Partisan sorting	0.05 (0.01)	0.02 (0.02)	0.05 (0.02)	0.11 (0.03)	0.09 (0.04)
Partisan-ideology	0.72 (0.16)	0.70 (0.24)	0.30 (0.27)	1.58 (0.32)	0.88 (0.42)
Perceived partisan-ideology	0.61 (0.12)	0.86 (0.18)	0.38 (0.19)	0.57 (0.27)	−0.29 (0.36)
Issue consistency	0.57 (0.10)	0.55 (0.17)	0.43 (0.15)	0.88 (0.19)	0.33 (0.27)
Issue divergence	0.14 (0.02)	0.13 (0.03)	0.12 (0.03)	0.21 (0.04)	0.08 (0.05)
Straight-ticket	0.08 (0.02)	0.02 (0.04)	0.12 (0.03)	0.08 (0.03)	0.06 (0.05)
Index	0.28 (0.04)	0.23 (0.06)	0.23 (0.06)	0.47 (0.08)	0.23 (0.10)

Shown is the growth in each measure, and in the index, from 1996 to 2016. Growth is defined as the difference in value between 2016 and 1996. The "Overall" column shows the growth for the full sample. Columns "18–39," "40–64," and "65+" show the growth for members of each age group. The last column shows the difference in growth between the oldest and youngest groups. Standard errors are in parentheses and are constructed by using a nonparametric bootstrap with 100 replicates. See main text for definitions and *SI Appendix*, section 3 for details on the bootstrap procedure.

case we continue to normalize by the 1996 value in the full sample m_{1996}.

SI Appendix, Table S1 reports a correlation matrix for the individual polarization measures m_t and the index across presidential election years from 1972 to 2016.

Fig. 1 plots each measure of polarization and the index from 1972 to 2016. By design, all of the measures we include show an overall growth in polarization, with the index growing by 0.28 index points between 1996 and 2016. It is interesting to note that the index grew about as quickly in the decade before 1996 as the decade after it, a pattern also exhibited by many of the individual measures.

Trends in Internet and Social Media Use

Fig. 2 shows trends in Internet and social media use by age group between 1996 and 2016. We use the ANES or the Pew Research Center survey weights when constructing each internet measure.

Fig. 2, *Left*, shows trends in Internet use with data from the ANES. (*SI Appendix*, Fig. S1 shows the analogous trends using the Pew Research Center data.) The Internet use question was first asked in 1996, when <40% of 18–39 y olds used the Internet. This figure shows that the elderly (65+) have substantially lower levels of Internet use across all years and that the levels are even lower for those aged 75+.

Fig. 2, *Center*, shows that the contrast is even starker when looking at whether respondents obtained campaign information online; >75% of 18–39 y olds report having obtained information about the 2016 presidential campaign online, as opposed to <40% of those aged 65+ and <20% of those aged 75+.

Fig. 2, *Right*, shows trends in social media use between 2005 and 2016. As expected, older respondents have substantially lower levels of social media use than younger respondents, with a more than fourfold difference between the oldest and youngest groups in 2016.

Trends in Polarization by Demographic Group

By Age. Fig. 3 shows trends in our polarization index by age group. Table 1 provides additional quantitative detail, and *SI Appendix*, Fig. S2 shows analogous plots for the individual polarization measures. Between 1996 and 2016, polarization grew by 0.23, 0.23, and 0.47 index points, respectively, among those aged 18–39, 40–64, and 65+. Bootstrap standard errors show that we can reject, at the 5% level, the hypothesis that the increase for those aged 18–39 is equal to the increase for those aged 65+. For every measure except perceived partisan ideology, the oldest age group experienced larger changes in polarization than the youngest age group.

Focusing on partisan affect polarization, an especially important measure, we see in Table 1 that the change in partisan affect is monotone in age category, with the change among those 65+ more than three times that for 18–39 y olds.

In *SI Appendix*, Figs. S3–S5, we present plots analogous to Fig. 3 using cohorts instead of age groups, restricting the sample to males or females, restricting the sample to those who self-identify with a party, and restricting the sample to those who self-identify as being "very much interested" in the upcoming election. In *SI Appendix*, Fig. S6, we show that the trends between the 18–39 and 65+ age groups track fairly closely across the entire 1972–2016 time period.

By Predicted Internet Use. Fig. 4 shows trends in polarization according to a broad index of predicted Internet use. We suppose that

$$\Pr\left(internet_{it} = 1 | X_{it}\right) = X_{it}'\theta, \quad [1]$$

where $internet_{it}$ is the ANES indicator for Internet use for respondent i in survey year t, θ is a vector of parameters, and X_{it} is a vector of characteristics including indicators for survey year, age group, gender, race, education, and whether an

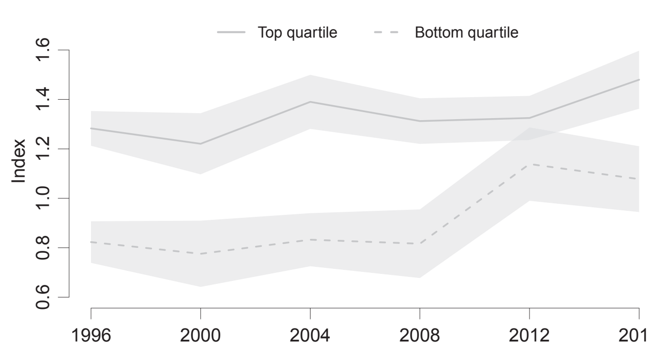

Fig. 4. Trends in polarization by predicted Internet use. The plot shows the polarization index broken out by quartile of predicted Internet use within each survey year. The bottom quartile includes values that are at or below the 25th percentile, while the top quartile includes values greater than the 75th percentile. Shaded regions represent 95% pointwise CIs constructed from a nonparametric bootstrap with 100 replicates. See main text for definitions and *SI Appendix*, section 3 for details on the bootstrap procedure.

Table 2. Proportion of linear trend explained by the Internet

Model	$(\hat{\beta}_c - \hat{\beta})/\hat{\beta}_c$	95% CI
Internet use: ANES	0.056	(−0.493, 0.604)
Internet use: Pew	−0.373	(−0.8, 0.054)
Campaign news: ANES	−0.299	(−0.765, 0.166)
Social media: Pew	−0.322	(−0.629, −0.016)

Shown is the value of $(\hat{\beta}_c - \hat{\beta})/\hat{\beta}_c$, where $\hat{\beta}_c$ and $\hat{\beta}$ are OLS estimates of the parameter β in Eq. **2**, respectively, with and without the constraint that $\rho = 0$. The equation is estimated on data from 1996 to 2016 and uses the 18–39, 40–64, and 65+ age groups. Each row shows the results for a separate Internet use variable s_t^g, which measures the proportion of respondents in the age group that either use the Internet (ANES and Pew Research Center), obtain campaign information online (ANES), or use social media (Pew Research Center). The 95% CIs are constructed by using the standard errors from a nonparametric bootstrap at the respondent level with 100 replicates. See main text for definitions and *SI Appendix*, section 3 for details on the bootstrap procedure.

individual lives in the political South. We estimate Eq. **1** using weighted least squares on the sample of the ANES respondents between 1996 and 2016 with valid responses to the questions used to construct each variable. (Coefficient estimates and variable definitions are reported in *SI Appendix*, Table S2.) We then compute predicted Internet use $\widehat{internet}_{it}$ for each respondent with valid covariate responses. Fig. 4 plots the polarization index for respondents in the first and fourth quartiles of $\widehat{internet}_{it}$ for each respective survey year t. We see that the polarization level for the top quartile (the group most likely to use the Internet) is substantially larger than that of the bottom quartile, even in 1996 when only a small percentage of the population obtained campaign information online. This is consistent with previous literature which suggests that users of the Internet and social media are a selected group (49). We find that respondents in the bottom quartile have experienced larger changes in polarization between 1996 and 2016 than respondents in the top quartile. *SI Appendix*, Fig. S2 shows analogous plots for the individual polarization measures.

Model of Internet's Impact on Polarization

To quantify the role of the Internet in explaining the rise in polarization, we consider the following linear model:

$$E(M_t^g | \alpha^g, s_t^g, t) = \alpha^g + \beta t + \rho s_t^g. \qquad [2]$$

Here, M_t^g denotes polarization for group g in year t, α^g is a group-specific intercept, β is a coefficient on a linear time trend t relative to 1996, and ρ is a coefficient on a measure s_t^g of the extent of Internet or social media use in group g in year t.

We estimate the model via ordinary least squares (OLS). Years t are the presidential election years between 1996 and 2016. Groups g are the 18–39, 40–64, and 65+ age groups.

We estimate the model with and without the constraint that $\rho = 0$. By comparing the value $\hat{\beta}_c$ estimated with the constraint to the value $\hat{\beta}$ estimated without the constraint, we arrive at an estimate $(\hat{\beta}_c - \hat{\beta})/\hat{\beta}_c$ of the share of the linear trend that can be accounted for by an effect of the Internet.

Table 2 presents the point estimate and 95% CI of the ratio $(\hat{\beta}_c - \hat{\beta})/\hat{\beta}_c$ for each of the three measures s_t^g shown in Fig. 2, plus the additional measure of internet use from the Pew Research Center. *SI Appendix*, Table S3 presents the values of all estimated parameters of Eq. **2**, with and without the constraint that $\rho = 0$.

For all Internet measures except the ANES measure of Internet use, we find that the point estimate is negative, indicating that allowing for an effect of the Internet increases the estimated time trend, and our CIs rule out the Internet explaining >17% of the linear time trend. For the ANES measure of Internet use, our point estimate indicates that the Internet explains a modest 6% of the time trend, with wide CIs that include much larger values.

SI Appendix, Figs. S7–S10 show the observed and predicted values from each unconstrained model, along with an estimated counterfactual in which we assume that s_t^g remains constant at its 1996 level throughout the time period. The counterfactuals support a limited role for the Internet in explaining the change in polarization between 1996 and 2016.

SI Appendix, Table S4 presents sensitivity analysis for the findings in Table 2 in which we successively modify two assumptions in Eq. **2**: that each group is affected only by its own Internet use, and that the effect of Internet is equal across groups.

Conclusion

Many authors point to the Internet in general and social media in particular as possible drivers of political polarization. We find that polarization has increased the most among the groups least likely to use the Internet and social media. Under appropriate assumptions, these facts can be shown to imply a limited role for the Internet and social media in explaining the recent rise in measured political polarization.

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