Mobile Internet and Political Polarization*

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December 7, 2023

Abstract

How has mobile internet affected political polarization in the United States? Using Gallup Daily Poll data covering 1,765,114 individuals in 31,499 ZIP codes between 2008 and 2017, I perform a difference-in-differences analysis and an instrumental-variable design to show that, after gaining access to 3G internet, Democratic voters became more liberal in their political views and increased their support for Democratic congressional candidates and policy priorities, while Republican voters shifted in the opposite direction. This increase in political polarization was partly determined by fake news and misinformation consumption among Republican voters and traditional news consumption among Democratic voters.

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During the past decade, the United States has experienced a significant increase in political polarization. According to Gallup, 2019 witnessed a record-setting 82-percentage-point gap in the presidential job approval rating between Republicans (89% approved of President Trump) and Democrats (7%), surpassing the previous records set by President Trump in 2018 and President Obama in 2016 (Jones, 2020). This increase in partisanship was not limited to presidential approval; according to Pew Research Center (2022), members of both political parties increasingly hold highly unfavorable views of the other side, calling it closed-minded, dishonest, and immoral. In addition to having a detrimental effect on interpersonal interactions, such political tribalism can create stalemate and undermine lawmaking (Binder, 2014).

Many observers have blamed the internet and social media for this recent rise in political polarization. In an interview with *Vox*, prominent social psychologist Jonathan Haidt describes social media in the following way: "I really believe it's one of our biggest problems. 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" (Illing, 2018).

This sentiment has been echoed in a number of recent studies that suggest social media users are, indeed, largely exposed to like-minded content (e.g., see Pariser, 2011; Flaxman, Goel and Rao, 2016; Halberstam and Knight, 2016; Lelkes, Sood and Iyengar, 2017; Sunstein, 2017; Levy, 2021; Peterson, Goel and Iyergar, 2021). However, other studies have presented contradictory evidence, showing that there is little segregation of online news consumption (Gentzkow and Shapiro, 2011; Prior, 2013; Eady et al., 2019; Guess, 2021); that the increase in polarization can partly be explained by factors unrelated to the internet (Autor et al., 2020; Boxell, 2020); that the ideological gap increased primarily among individuals who are less likely to be active internet users (Boxell, Gentzkow and Shapiro, 2017); that exposure to opposing views may not lead to moderation of one's political attitudes (Bail et al., 2018; Nyhan et al., 2023); and that social media use might actually decrease political polarization (Barberá, 2015; Beam, Hutchens and Hmielowski, 2018).

This paper addresses the debate about the effects of the internet and social media on political polarization in the United States. It is the first to analyze how the expansion of third-generation (3G) mobile networks—the first generation of mobile networks that allowed users to actively browse the internet from their smartphones, which became a major driver of social media usage (Rainie and Wellman, 2012)—affected the ideological views and policy preferences of the U.S. population. Using data from the Gallup Daily Poll covering 1,765,114 individuals living in 31,499 ZIP codes between 2008 and 2017, I show that, after the arrival of 3G internet in the ZIP code, Democratic-leaning voters became more liberal in their political views, while Republican-leaning voters became more conservative. Similarly, Democratic voters increased their support both for Democratic candidates in elections to the House of Representatives and for Democratic policy positions on abortion, gay marriage, the Affordable Care Act (ACA), and immigration. Meanwhile, Republican voters shifted in the opposite direction.

Overall, the rollout of 3G networks can account for 11.3% of the increase in polarization in political views that took place between 2008 and 2017. It can also explain 37.7% of the increase in polarization in voting behavior and 34.8% of the increase in polarization in policy preferences.

This paper also presents evidence on three novel mechanisms behind the effects of mobile internet on individuals' political preferences. First, I analyze the role of fake news and online misinformation in widening the gap between Democratic and Republican voters. Recent studies have found that online misinformation systematically favors Republicans (Benkler, Faris and Roberts, 2018; Bovet and Makse, 2019; Grinberg et al., 2019; Guess, Nyhan and Reifler, 2020), Republicans are more likely to consume online misinformation (Gonzáles-Bailón et al., 2023), and Republican politicians are more likely to share misleading content than both Democrats and the general public, with this gap increasing over time (Greene, 2022). In line with these findings, I find that, after the arrival of 3G networks, Republican-leaning voters became more likely to visit websites spreading fake news and misinformation, while there was no effect on misinformation consumption among Democratic-leaning voters. I also find that residents of Republican ZIP codes with high consumption of online misinformation at the beginning of the sample period became more conservative in their political views after the arrival of 3G networks.

Second, I analyze how news consumption from traditional media outlets affected political polarization. I find that, after mobile internet became available, Democratic voters marginally increased their consumption of traditional news and became more likely to know the names of their congressional representatives, whereas Republican voters experienced the opposite effects. I also find that, after the arrival of 3G networks, residents of Democratic ZIP codes with a high pre-3G share of traditional news consumption became more liberal in their political views. In turn, pre-3G traditional news consumption did not determine the direction of the effect of 3G on Republican voters, plausibly because of the decrease in their news interest.

Finally, another mechanism through which mobile internet affected the political preferences of the U.S. population (albeit not necessarily political polarization) is related to the insights from recent theoretical work by Bonomi, Gennaioli and Tabellini (2021), which suggests that when cultural conflict in society becomes more prominent, as it has in the United States, conflict over redistributive policies becomes muted. Thus, by increasing the salience of cultural disagreements, the expansion of mobile internet resulted in a political realignment of U.S. voters, leading voters who are poor, uneducated, and out of the labor force—who benefit most from redistribution policies supported by Democrats—to become more conservative, and voters who are wealthy, employed, and well-educated to become more liberal.

The results in this paper rely on two empirical strategies: a difference-in-differences (DiD) analysis and an instrumental-variable (IV) design. The DiD analysis uses the variation in the timing of the expansion of 3G networks across ZIP codes, controlling for geographic and time fixed effects, as well as many individual- and county-level socioeconomic characteristics. I document the absence of pretrends: the change in political views takes place only after the arrival of mobile internet, and the future availability of 3G networks is not related to political views in the ZIP code. The results are also robust to including state-year and county-year fixed effects, demonstrating that the estimates are driven by local variation in 3G availability, as well as controlling for time-varying effects of urban status, race, gender, education, income, age, and marital status. In addition, I present the results of a test developed by Oster (2017), showing that the effects of mobile internet on individuals' political views are highly unlikely to be driven by omitted-variable bias.

The IV identification strategy follows the design previously used by Manacorda and Tesei (2020) and Guriev, Melnikov and Zhuravskaya (2021). It relies on the fact that in areas with frequent lightning strikes, mobile infrastructure was rolled out more slowly—damage caused by lightning increases the costs of maintaining the infrastructure and providing telecommunication services. The IV estimates confirm the findings of the DiD analysis.

I also present two placebo exercises which demonstrate that the effects of 3G on political attitudes are driven by access to online content and not by other features on mobile infrastructure. First, I show that the previous generation of mobile networks (2G)—which allowed users to make calls and send text messages but not to actively browse the internet—did not affect individuals' political views. Second, I document that, in the short run, the expansion of 3G infrastructure had no impact on local socioeconomic conditions or migration patterns.

This paper contributes to several strands of the existing literature. First and foremost, it contributes to the extensive literature studying the effects of the internet and social media on political polarization in the United States (Gentzkow and Shapiro, 2011; Pariser, 2011; Prior, 2013; Bakshy, Messing and Adamic, 2015; Barberá, 2015; Flaxman, Goel and Rao, 2016; Halberstam and Knight, 2016; Boxell, Gentzkow and Shapiro, 2017; Lelkes, Sood and Iyengar, 2017; Spohr, 2017; Sunstein, 2017; Bail et al., 2018; Beam, Hutchens and Hmielowski, 2018; Eady et al., 2019; Allcott et al., 2020; Guess, 2021; Levy, 2021; Peterson, Goel and Iyergar, 2021; Guess et al., 2023*a*,*b*; Nyhan et al., 2023).

This literature has predominantly focused on political polarization among existing users of a particular social media platform. I complement this work by providing new evidence on how the expansion of mobile internet affected the political views, policy preferences, voting patterns, and, perhaps most importantly, online behavior of a much broader slice of the U.S. population, including individuals not present on social media. For instance, I demonstrate that mobile internet contributed to ideological segregation across social media platforms, with Democratic-leaning voters gravitating towards Twitter and Republican-leaning voters gravitating towards Facebook. I also present evidence for three novel mechanisms through which 3G internet affected the political views of the U.S. population.

This paper also contributes to the broader literature on the political effects of information technology, especially the internet and social media. The study most closely related to mine is Guriev, Melnikov and Zhuravskaya (2021), which shows that the expansion of 3G mobile internet around the globe resulted in a decrease in government approval. In addition to focusing on different political outcomes, my paper differs from this study in two important ways. First, I demonstrate that, in a polarized environment, where individuals on opposite sides of the political spectrum are exposed to different information, the direction of the mobile internet's effects on political views depends on individuals' initial position on the political spectrum. Second, I analyze the mechanisms behind these divergent effects of 3G network availability.

Another important paper studying the effects of information technology on political outcomes is Manacorda and Tesei (2020), which shows that the expansion of 2G infrastructure between 1998 and 2012 facilitated political protests during economic downturns across the African continent. However, unlike 3G infrastructure, 2G technology does not allow users to actively browse the internet. As noted above, this paper uses 2G network coverage as a placebo treatment, showing that the non-internet-related aspects of mobile network coverage have not affected political opinions in the United States.

This paper is also related to a growing literature studying the effects of the internet on electoral outcomes. Recent studies have found that in Germany (Falck, Gold and Heblich, 2014), Italy (Campante, Durante and Sobbrio, 2018), the United Kingdom (Gavazza, Nardotto and Valletti, 2019), and in Europe more generally (Guriev, Melnikov and Zhuravskaya, 2021), the availability of broadband internet has reduced voter participation in elections, possibly by crowding out news consumption with entertainment content. A number of papers have also found that the expansion of internet access has negatively affected the electoral performance of incumbent political parties (Miner, 2015; Donati, 2019; Guriev, Melnikov and Zhuravskaya, 2021) and, in Europe, contributed to the rise of populism and communitarianism (Campante, Durante and Sobbrio, 2018; Schaub and Morisi, 2019; Guriev, Melnikov and Zhuravskaya, 2021; Manacorda, Tabellini and Tesei, 2023). In the United States, greater exposure to Twitter has been shown to decrease the support for Donald Trump in the 2016 and 2020 presidential elections (Fujiwara, Müller and Schwarz, 2021). Other recent papers have also studied the effectiveness of campaign advertising on social media (Bright et al., 2020; Liberini et al., 2020) as well as the effects of social media on protest participation (Fergusson and Molina, 2019; Qin, Strömberg and Wu, 2019; Enikolopov, Makarin and Petrova, 2020), exposing corruption (Enikolopov, Petrova and Sonin, 2018; Enríquez et al., 2021), xenophobia (Bursztyn et al., 2019; Müller and Schwarz, 2021, 2022), and political contributions (Petrova, Sen and Yildirim, 2020).[1] My paper contributes to this literature by analyzing how the internet's effects on political outcomes differ depending on individuals' initial position on the political spectrum and by studying the mechanisms behind these differences. It also provides novel evidence on how the expansion of 3G internet affected individuals' news consumption and browsing activities.

Finally, this paper contributes to the rapidly expanding literature studying fake news and online misinformation (e.g., see Del Vicario et al., 2016; Allcott and Gentzkow, 2017; Faris et al., 2017; Spohr, 2017; Benkler, Faris and Roberts, 2018; Pennycook, Cannon and Rand, 2018; Allcott, Gentzkow and Yu, 2019; Bovet and Makse, 2019; Grinberg et al., 2019; Pennycook and Rand, 2019*a*,*b*; Cantarella, Fraccaroli and Volpe, 2020; Guess, Nyhan and Reifler, 2020; Pennycook and Rand, 2021; Greene, 2022). Specifically, it shows that, after 3G network coverage became available, Republican voters increased their consumption of misinformation content and, on the other hand, decreased their interest in the news from traditional media outlets. It also shows that, after the arrival of mobile internet, residents of Republican ZIP codes with high pre-3G misinformation consumption became even more conservative in their political views.

The rest of the paper is structured as follows. Section I describes the data and the identification strategy. Section II presents the effects of 3G internet on political views, policy preferences, and voting outcomes and discusses the identification assumptions underlying the estimation. Section III provides an analysis of the mechanisms behind the effects of mobile internet on political polarization. Section IV concludes.

[1] For a recent review of the literature on the political effects of the internet and social media, see Zhuravskaya, Petrova and Enikolopov (2020).

I Data and Identification Strategy

I.A Data

This subsection briefly describes the main data sources used in the analysis. Further details about these data sources, as well as a description of the secondary variables, are available in Appendix Section A.I.

Mobile network coverage.—The data on 3G and 2G network coverage come from annual maps provided by Collins Bartholomew's Mobile Coverage Explorer and cover the period from 2007 to 2019. The data consist of 1×1-kilometer binary grid cells. Figure 1 illustrates the expansion of 3G network coverage between 2008 and 2018 (i.e., the years focused on in this paper) for the contiguous United States, showing that very few locations had 3G coverage in 2008, while by 2018, 3G mobile internet had become available in most parts of the country.[2]

To combine data on mobile network coverage with the other variables used in the analysis that have ZIP-code or county-level geolocalization, I calculate the share of the ZIP codes' and counties' territory covered by mobile networks.

Gallup Daily Poll.—The paper's main outcome variables represent individuals' political preferences, the data for which come from the Gallup Daily Poll and cover the period from 2008 to 2017. The data consist of repeated cross-sectional daily polls of 1,000 respondents with geolocalization at the ZIP-code level. The main question of interest is the following: "*How would you describe your political views: very liberal, liberal, moderate, conservative, or very conservative*?" Focusing on this question enables me to analyze the divergence in Democrats' and Republicans' preferred positions on a one-dimensional ideological spectrum.[3] Other questions also ask the respondents about their political affiliation, gender, race, age, education level, marital status, and income group. After merging the Gallup Daily Poll and mobile network coverage data, the sample consists of approximately 1,765,000 observations from 31,499 ZIP codes in all 50 states and the District of Columbia.

Cooperative Congressional Election Study (CCES).—The data on individuals' policy preferences come from the CCES and cover the period from 2007 to 2019. The data consist of repeated cross-sectional annual polls of 10,000–18,000 respondents in nonelection years and 25,000–60,000 re-

[2]By definition, all grid cells that have 4G network coverage also have 3G coverage. Thus, the maps should be interpreted as showing which areas have *at least* 3G network coverage.

[3]This definition of political polarization is somewhat different from affective polarization (i.e., the tendency of one party to hold negative views towards members of the opposing party), questions about which are not included in the Gallup Daily Poll. Both these measures contain valuable information about the views of the two major U.S. parties. However, by focusing on Democrats' and Republicans' political preferences, this paper aims to analyze the ideological divergence between the two parties, which is less likely to be driven by individual events (e.g., the election of President Trump) than affective polarization and may plausibly be the root cause of affective polarization.

spondents in election years with geolocalization at the ZIP-code level. In the survey, the respondents are asked to state their opinions about whether abortion should always be legal (2007–2019), whether they support gay marriage (2008–2016), whether the Affordable Care Act should be repealed (2012–2019), and whether security along the U.S.–Mexico border should be increased (2007, 2010–2019). The dataset also includes a question about political views, similar to the one in the Gallup Daily Poll, and a variable for whom the individual voted for in current and, in certain cases, previous elections.

House election data.—The data for the 2008–2016 presidential elections and the 2008–2018 elections to the U.S. House of Representatives come from Dave Leip's Atlas of U.S. Elections. The unit of observation is a county.[4] The data include the vote shares of the Republican and Democratic candidates, the total number of ballots cast, and the number of Republican and Democratic candidates who participated in the election. To calculate turnout, I divide the number of ballots cast by the population of the county from the 2010 population census.

Comscore.—The data on individuals' internet browsing histories come from Comscore and cover the period from 2008 to 2018. For each year, the data consist of the complete time-stamped browsing histories of up to 80,000 individuals with geolocalization at the ZIP-code level. Using these data, for each ZIP code and year, I calculate the share of visits to social media websites (i.e., Facebook, Twitter), the general category of traditional news websites (e.g., CNN, Fox News), and the general category of misinformation websites among all browsing activity in the ZIP code. These shares are then normalized by their standard deviation.

A website is characterized as a misinformation website if it has been flagged as the original source of misinformation, fake news, conspiracy theories, or extremist content. In total, 171 websites fall into this category, with prominent examples including Infowars, Breitbart News, and The Gateway Pundit, among many others. A website is characterized as a traditional news website if it is the website of a U.S.-based English-language media outlet that covers national or local political events and does not fall into the categories of misinformation or sensationalist websites. In total, 301 websites fall into this category, with the three most visited websites belonging to CNN, Fox News, and the New York Times. For the full lists of websites in both of these categories and the details of how they were constructed, see Appendix Section A.II.

Lightning strike frequency.—The data on the frequency of lightning strikes come from NASA's LIS/OTD Gridded Lightning Climatology Data Collection, which presents a map of the average

[4]In Alaska, election results are not available at the county level. For this reason, Alaska is excluded from the regressions analyzing the effects of 3G internet on voting outcomes. In the non-county-level regressions, all locations in Alaska are characterized as Republican-leaning based on how the state voted in the 2008 presidential election.

annual lightning-flash rate in each 0.5×0.5-decimal-degree grid cell.[5] I use these data to calculate the average population-weighted frequency of lightning strikes in every U.S. county. Thus, the resulting variable represents the average number of people per square kilometer potentially affected by the lightning strikes.

I.B Identification strategy

To estimate the effects of mobile broadband internet on individuals' political views, I perform the following identification strategy. First, I calculate the share of the ZIP codes' territory (or counties' territory, depending on the geolocalization of the outcome variable) covered by 3G networks in that year.[6] I then estimate the following DiD model:

$$\textit{Pol. views}_{i,t} = \alpha\ \textit{3G}_{z,t} \times \textit{Pol. affiliation}_c + \mathbf{X}'_{i,c,t}\lambda + \varphi_c + \tau_t + \varepsilon_{i,t} \tag{1}$$

where i, z, c and t index individuals, ZIP codes, counties, and years, respectively. *Pol. views* represents the respondents' political views (e.g., a dummy variable for whether the respondent characterizes their views as liberal or very liberal). *3G* is the share of territory covered by 3G networks, the main explanatory variable. *Pol. affiliation* is a variable for the political affiliation of the individual's county of residence in the 2008 presidential election.[7] This definition of party membership is defined at the beginning of the sample period and, therefore, cannot be affected by individuals switching their party membership due to getting access to 3G. φ_c and τ_t are county and year fixed effects.[8] $\mathbf{X}$ is a vector of baseline individual-level and county-level controls, which include dummies for the respondents' gender, race, year of birth, education level, marital status, and income group, as well as the county's unemployment rate, log of median household income, median age, and the share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Standard errors are corrected for clusters

[5] The data can be found and are described here: https://ghrc.nsstc.nasa.gov/lightning/data/data_lis_otd-climatology.html (accessed on June 26, 2021).

[6] Given that the ZIP codes represent very small geographic areas, in the vast majority of cases, the share of the ZIP codes' territory covered by 3G is equal to either zero or one. All regression estimates are virtually identical if 3G network coverage is weighted by population density.

[7] The results are very similar if one considers the political affiliation of the individual's county of residence in the 2004 presidential election (see Appendix Table A12).

[8] The results are robust to including ZIP code fixed effects instead of county fixed effects. However, most ZIP codes have only a small number of observations per year (e.g., the average ZIP code has 5 observations per year), making the specification with ZIP code fixed effects very restrictive. At the same time, measuring 3G network coverage at the more local ZIP code level allows to precisely measure individuals' treatment status (measuring 3G network coverage at the county level is equivalent to introducing measurement error to the treatment variable).

at the level of the states and the District of Columbia.[9]

I also estimate a related DiD model, described by Specification (2), where *Pol. affiliation* represents individual-level party membership. While this regression specification utilizes a more accurate measure of individuals' political leanings, its estimates should be interpreted with caution because individuals can switch their party membership as a result of getting access to mobile internet. For this reason, the regression model that will be more commonly used throughout the paper is Specification (1).

$$\textit{Pol. views}_{i,t} = \alpha_1 \; \textit{3G}_{z,t} \times \textit{Pol. affiliation}_i + \alpha_2 \; \textit{Pol. affiliation}_i + \mathbf{X}'_{i,c,t}\lambda + \varphi_c + \tau_t + \varepsilon_{i,t} \qquad (2)$$

The main identification challenge for interpreting the DiD estimates as causal is that the expansion of 3G mobile networks could have taken place in locations that were already experiencing a change in political views before the arrival of 3G internet. To address this concern, Subsection II.B presents a number of robustness and placebo exercises, as well as the results of the test proposed in Oster (2017), all of which support the conclusion that the estimates of Specification (1) represent the causal effect of 3G internet on individuals' political views. For instance, I show that individuals' views are not affected by the future availability of mobile internet but start to change as soon as the ZIP code becomes covered by 3G networks. The results of the Oster test also show that the estimates are highly unlikely to be driven by omitted-variable bias. In addition, Subsection II.B shows that the expansion of 3G infrastructure was not correlated with changes in major local socioeconomic characteristics such as income, unemployment, poverty, or education.

To alleviate remaining concerns that the identification assumptions behind the DiD estimates might be violated, I use variation in the frequency of lightning strikes per square kilometer across U.S. counties to predict the speed of the expansion of 3G network coverage, an identification strategy used in several recent studies (e.g., see Manacorda and Tesei, 2020; Guriev, Melnikov and Zhuravskaya, 2021). The frequency of lightning strikes affects the spread of digital technologies by increasing the expected costs of building and maintaining this type of infrastructure (Andersen et al., 2012). Mobile internet towers are especially sensitive to lightning strikes, which can both cause immediate damage and result in quicker depreciation of equipment (Zeddam and Day,

[9] The standard errors are clustered at this level because, in the United States, most policies and regulations are defined at the state level. The potential alternative is to correct the standard errors for spatial and over-time correlation, as suggested in Conley (1999), Hsiang (2010), and Collela et al. (2018). However, in the main regression specifications, the sample consists of approximately 1,765,000 observations, making this calculation extremely computationally demanding and practically impossible to implement. In the regression specifications where the sample is smaller (e.g., voting behavior at the county level), I have verified that even very conservative Conley standard errors that allow for spatial correlation within a 1,000-kilometer radius and autocorrelation of 10-year temporal lags are generally smaller than the standard errors corrected for clusters at the state level.

2014; Martin, 2016). The problem can partially be addressed with surge-protection equipment, but a large swath of U.S. infrastructure is not protected. For instance, in 2017, the United States experienced 3,526 power outages affecting 36.7 million people (EATON, 2017), and its energy infrastructure received a D+ grade from the American Society of Civil Engineers (ASCE, 2017).[10] Overall, the expanion of 3G networks is likely to be slower in areas with a high frequency of lightning strikes. Thus, I use the following first-stage equation to predict 3G coverage in year t:

$$3G_{z,t} = \beta \, \mathit{Lightning\ strikes\ per\ km}^2_c \times t + \mathbf{Z}'_{z,c,t}\lambda + \varphi_c + \tau_t + \varepsilon_{z,t} \tag{3}$$

where *Lightning strikes per km* is the population-weighted frequency of lightning strikes per square kilometer, *t* is a linear time trend, and **Z** represents all the control variables, including all the baseline controls listed above, as well as separate year fixed effects for all quartiles of county population size, the log of maximum elevation in the county interacted with a time trend, and the share of the county's territory that is uninhabited interacted with a time trend. Additional controls are added to account for other factors that potentially influenced the speed of the expansion of 3G networks.

As Guriev, Melnikov and Zhuravskaya (2021) first pointed out, the availability of 3G network coverage affects internet usage in multiple ways, all of which are important for interpreting the overall effect of mobile infrastructure on political views. First, 3G network coverage increases internet use on the extensive margin by providing a connection to people who previously did not have it. Second, mobile broadband affects internet use on the intensive margin by making it easier to spend more time online. Finally, 3G availability affects *what* individuals do on the internet, facilitating engagement with social media (Rainie and Wellman, 2012) and potentially changing individuals' news consumption. To document the importance of all these factors, I use the data from Comscore and MRI Consumer Surveys to estimate the relationship between 3G network coverage and various aspects of internet usage in Republican and Democratic ZIP codes.

$$\mathit{Internet\ usage}_{z,t} = \gamma \, 3G_{z,t} \times \mathit{Pol.\ affiliation}_c + \mathbf{W}'\omega + \varphi_z + \tau_t + \varepsilon_{z,t}. \tag{4}$$

Finally, I study the mechanisms behind the 3G-driven increase in political polarization. I begin with examining the role of fake news and misinformation in determining the effects of mobile internet on the political preferences of the U.S. population. To address this question, I use the

[10] Guriev, Melnikov and Zhuravskaya (2021) find that lightning strikes affect the expansion of mobile infrastructure primarily in countries with below-median per capita income, presumably because surge-protection equipment is widely used in most rich countries. However, though the United States has above-median per capita income, the poor state of its infrastructure makes it vulnerable to damage from lightning strikes.

data from Comscore to calculate the average share of visits to misinformation websites among all browsing activities in the ZIP code in the first three years for which the data are available.[11] I then interact 3G network coverage with this measure of predisposition to misinformation consumption and estimate the following regression specification.

$$
\begin{aligned}
\textit{Pol. views}_{i,t} = \psi_1\, 3G_{z,t} \times \textit{Pol. affiliation}_c + \psi_2\, 3G_{z,t} \times \textit{Misinformation}_z \times \textit{Pol. affiliation}_c + \\
+ \psi_3\, \textit{Misinformation}_z \times \textit{Pol. affiliation}_c + \mathbf{X}'_{i,c,t}\lambda + \varphi_c + \tau_t + \varepsilon_{i,t}
\end{aligned} \tag{5}
$$

Next, I analyze the role of traditional media outlets in shaping the direction of the effects of 3G on the political views of the U.S. population. To examine this issue, I estimate a modification of Specification (5), where the measure of predisposition to misinformation consumption is replaced with a similarly-calculated measure of predisposition to consumption of traditional news.

Finally, I test another mechanism through which the expansion of mobile internet affected the political preferences of the U.S. population (although not necessarily political polarization). Recent theoretical work by Bonomi, Gennaioli and Tabellini (2021) suggests that increased cultural conflict in society should lead to less conflict over redistribution policies, resulting in a political realignment of voters. As demonstrated in Table 2 and Appendix Table A15, the arrival of 3G internet has indeed widened the cultural divide between Democrats and Republicans. Therefore, according to Bonomi, Gennaioli and Tabellini (2021), the expansion of mobile infrastructure should have also resulted in people who are poor, uneducated, and out of the labor force—the main beneficiaries of the redistribution policies supported by Democrats—becoming more conservative, and wealthy, employed, and well-educated people becoming more liberal. To test this mechanism, I present the heterogeneity of the effects of mobile internet on political views by education, income, and employment status. Specifically, I estimate Specification (1), replacing the variable for political affiliation with dummy variables for all the values of the socioeconomic characteristic of interest, controlling for all the baseline covariates, including dummies for the direct effects of all the values of the socioeconomic characteristic.

[11] The results are robust to calculating the average share of online misinformation consumption based on a smaller or larger number of years, as well as performing the same calculation for the residuals of online misinformation consumption after estimating Specification (4). The choice to focus on the first three years of the sample period is primarily based on the following two considerations. First, given the small number of individuals in each ZIP-code-year, the measure of the ZIP codes' predisposition to misinformation consumption becomes more precise when the estimates are averaged across multiple years, conditional on the distribution remaining stationary. Second, the data suggests that the share of online misinformation consumption started to increase only after 2010, while in 2008-2010, it was quite stable, suggesting that the distribution has remained stationary during those years.

II 3G Internet and Political Polarization

II.A Main Results

Table 1 presents the results of estimating the effect of 3G network coverage on individuals' political views using Specifications (1) and (2). The sample consists of approximately 1,765,000 observations from 31,499 ZIP codes in all 50 states and the District of Columbia. In Columns 1 and 2, the outcome variable is a dummy for an individual having liberal or very liberal views. Column 1 presents how the availability of 3G affected the probability of holding such views in Democratic and Republican counties. The political affiliation of the counties is based on voting outcomes in the 2008 presidential election. Counties that Obama won (lost) by a margin of at least 30 percentage points are characterized as reliably Democratic (Republican), counties that Obama won (lost) by a margin of 10 to 30 percentage points as Democratic-leaning (Republican-leaning), and the remaining counties are characterized as swing counties. Using this definition, Column 1 shows that after the arrival of mobile internet, residents of counties with mainly Democratic voters became more likely to hold liberal or very liberal political views, while in predominantly Republican counties, the effect was the opposite.

Column 2 presents the results of estimating Specification (2), which uses individual-level party membership instead of 2008 county-level voting outcomes to measure of individuals' political leanings. It shows that after the arrival of mobile internet, Democratic voters became more likely to hold liberal or very liberal views, while Republican voters became less likely to do so. Unsurprisingly, the estimates in Column 2 are larger in magnitude than those reported in Column 1—this happens because all counties consist of a mix of Democratic, Republican, and Independent voters, whose views changed in divergent directions. On the other hand, the results in Column 2 are not robust to individuals changing their party affiliation (in addition to their political views) due to getting access to mobile internet.

Columns 3 and 4 present similar results for the outcome variable of having conservative or very conservative political views.[12] After getting access to 3G internet, Democratic voters and residents of Democratic-voting counties became less likely to hold conservative political views, while Republican voters and residents of reliably Republican counties became more likely to describe themselves as conservative. The effects are stronger in Democratic counties than in Republican counties, which is explained by the fact that, similarly to Democratic voters, Independent voters

[12] Notably, the outcome variable for having conservative or very conservative political views is not perfectly collinear with the variable for holding liberal or very liberal views, because the respondents could also describe themselves as moderate.

became less conservative after the arrival of 3G network coverage. Thus, the share of Republican voters needs to be very high for the effect of mobile internet on Republican voters to dominate the effect on Democratic and Independent voters.[13]

Overall, the results in Table 1 confirm the notion that the expansion of 3G network coverage has increased political polarization.

II.B Identification Assumptions and Robustness Checks

In this subsection, I analyze a number of assumptions that need to be satisfied for the effects of mobile internet on individuals' political views to be interpreted as causal. In particular, I demonstrate that the change in political views started to take place only after the arrival of 3G networks. I also present a number of other tests and robustness checks, including the results of the IV analysis, in which the frequency of lightning strikes per square kilometer is used as an exogenous source of variation affecting the speed of the expansion of 3G networks.

State-year, county-year, and political-affiliation-year fixed effects.—A potential concern is that the change in individuals' political views may be driven not by the local availability of 3G networks but by certain state-level, county-level, or party-level factors unrelated to mobile internet. To address this concern, I estimate Specifications (1) and (2), controlling for state-year, county-year, and political-affiliation-year fixed effects (in separate regressions), which absorb all the variation from the respective sources. Table A1 in the Appendix presents the results. The estimates remain highly significant even if one controls for county-year fixed effects, which is a very demanding specification, given that counties represent small geographic areas, many parts of which experienced an increase in 3G network coverage in the same year.[14] Overall, the results in Table A1 demonstrate that it is local variation in mobile internet availability that is driving the effects on political views.

Leads of 3G network coverage.—Another potential concern is that, instead of causing individuals to change their opinions, 3G networks expanded to areas that were already experiencing a change in political views before the arrival of mobile internet. To address this concern, I estimate Specification (1), additionally controlling for the leads of 3G network coverage interacted with the

[13] In addition, as discussed in detail in Subsection III.C, residents of Republican counties primarily became more conservative in their views during the years when President Obama was in office, especially the years when, in addition to controlling the White House, Democrats controlled both chambers of Congress. In contrast, during the first years of the Trump presidency, residents of Republican counties became less conservative in their political views.

[14] In fact, the specification with county-year fixed effects generally yields regression estimates that are larger in absolute value than those in the baseline regressions, although they are also less precisely estimated. This result is likely explained by the fact that in the specification with county-year fixed effects, a larger part of the identifying variation comes from counties with many small ZIP codes, where 3G network coverage is measured most precisely.

counties' political affiliation.[15] Appendix Table A2 presents the results. If the expansion of mobile internet took place in areas that were already becoming more partisan before the arrival of 3G, then individuals' views would be correlated with the future availability of 3G network coverage. However, the results in Table A2 show that the respondents' views started to change only after mobile internet became available (i.e., the leads of 3G coverage are not correlated with individuals' political views, while the effects of contemporaneous 3G availability remain significant).

Event study.—To further demonstrate that the change in political views started to take place only after the arrival of mobile internet, I conduct an event-study analysis, in which a ZIP code is assumed to be treated when it becomes at least partly covered by 3G networks for the first time.[16] Figure 2 presents the event-study estimates for the outcome variable of holding liberal or very liberal political views in counties that Obama won in 2008 (top part of the figure) and counties that Obama lost in 2008 (bottom part of the figure).[17] The left part of the figure displays the results of estimating a standard event-study specification; the right part of figure—the estimator proposed by Sun and Abraham (2021), which is robust to potential heterogeneity in the treatment effects.[18] Appendix Table A3 reports the regression estimates.

The results indicate that neither Democrats, nor Republicans were experiencing a shift in their political views in the years before the arrival of 3G network coverage. However, after getting access to mobile internet, their views started to change, with residents of counties that Obama won in 2008 becoming more liberal and residents of counties that Obama lost in 2008 becoming more conservative. Overall, the results of the event-study analysis confirm the notion that individuals' political views started to change only after the arrival of 3G internet.

[15]More generally, because the assumption that individuals do not change their political affiliation after experiencing a shift in their views is unlikely to be satisfied, the rest of the paper focuses primarily on the political affiliation of the counties where the respondents live.

[16]Because the ZIP codes represent very small geographic areas, in the vast majority of cases, they have either no or full 3G coverage. Thus, in the first treatment year, most ZIP codes experienced a sigificant increase in the share of territory covered by 3G. The event-study results are very similar if, instead, the definition of treatment status is based on the ZIP code experiencing an increase in the share of territory covered by 3G of x percentage points, where x is any number that is greater than zero.

[17]Appendix Figure A1 presents similar estimates for the outcome variable of holding conservative or very conservative political views.

[18]As suggested in the recent literature, standard event-study estimates may place negative weights on the average treatment effects for certain groups and periods (e.g., see De Chaisemartin and D'Haultfœuille, 2020; Borusyak, Jaravel and Spiess, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021). The estimator proposed by Sun and Abraham (2021) is best suited for the data structure in this paper: *(i)* individual-level data, *(ii)* treatment at the ZIP code level, *(iii)* not all the ZIP codes appear in the sample each year. The Sun and Abraham (2021) estimator requires that one specifies a group of never-treated or last-treated observations, which serve as a comparison group for the treated units. If last-treated observations are used as a comparison group, one is also required to drop the data for the years when the last-treated observations were treated. Therefore, given that virtually all the ZIP codes in the sample ultimately get 3G network coverage, the Sun and Abraham (2021) regression specifications focus on the period from 2008 to 2013, using later-treated ZIP codes as the comparison group. As a result, these specifications have a smaller sample size than the baseline event-study regressions (see Appendix Table A3)

Sensitivity to omitted-variable bias.—To evaluate whether the effects of 3G network coverage on individuals' political views can be driven by omitted-variable bias, I follow Oster (2017) and calculate Oster's δ statistic, which shows how much more important unobservable characteristics need to be compared to observable controls to fully explain the regression results by omitted-variable bias. Appendix Table A4 reestimates the effects of 3G internet on the residents of Democratic, Republican, and swing counties as well as on self-identified Democratic, Republican, and Independent voters.[19] It also reports Oster's δs for the effects of 3G on Democratic- and Republican-leaning counties and voters, which are calculated based on the standard methodology suggested in Oster (2017).[20] The results suggest that the regression estimates are highly unlikely to be driven by omitted-variable bias. For instance, in the regression specifications with political affiliation measured at the county level, the δs for the statistically significant coefficients vary between 2.34 and 9.87, suggesting that unobserved characteristics need to be significantly more important than observed controls to make the effects on political views equal to zero. Given that observed controls include individuals' race, education, age, gender, income, and many other important individual- and county-level characteristics, all of which are well-known determinants of political views in the United States, it is very unlikely that such unobserved characteristics exist.

Time-varying fixed effects for urban status and individual characteristics.—Another potential concern is that the effects of mobile internet on Democrats' and Republicans' political views are partly determined by the change in the composition of voters that support the two parties (e.g., see Gethin, Martínez-Toledano and Piketty, 2022). To address this concern, I estimate Specifications (1) and (2), additionally controlling for year-specific fixed effect for the respondents' urban status, 10-year age group, education, income group, race, gender, and marital status. The results are reported in Appendix Table A5 and are virtually identical to those in Appendix Table A4 (none of the differ-

[19]Hereafter, counties previously characterized as "reliably Democratic/Republican" and "Democratic/Republican-leaning" are combined into one category of "Democratic/Republican-leaning" counties. The reason for the change is that the two groups generally change their views in similar ways, and a smaller number of groups increases the statistical power of the estimation. More generally, there is a tradeoff between the size of the effect on a particular group (e.g., reliably Democratic counties are likely to be more affected by 3G internet than Democratic-leaning counties, because they have more Democratic voters and fewer Republican voters) and statistical power, which depends on the number of observations in that group. Therefore, when statistical power is sufficient to highlight the differences between Democratic, Republican, and swing counties, which is the case for most estimates in this paper, I report the results for each of those groups. However, in some cases, in order to increase statistical power, I present the results for just two groups: counties that Obama won in 2008 and counties that Obama lost in 2008.

[20]In particular, to calculate the δs, as suggested in Oster (2017), I set R^2_{max}—the R-squared from a hypothetical regression of the outcome variable on all observed and unobserved controls—to be equal to $1.3\tilde{R}^2$, where $\tilde{R}^2$ is the R-squared reported in the table. In the context of the empirical exercise in this paper, this level of R^2_{max} is likely to be appropriate because the R^2 of a regression that includes ZIP-code-year fixed effects—which presents an unrealistically high upper bound of the share of variation that can be explained by observed and unobserved controls, because it assumes that a researcher can perfectly predict political views at the ZIP-code level (including the composition of the sample respondents in each ZIP-code-year)—has an R^2 that is only slightly larger than R^2_{max}.

ences are statistically significant), suggesting that the estimates are not determined by differential trends in the political views of various socioeconomic groups.

ZIP-code fixed effects.—To demonstrate that the effects of 3G network coverage on political views are not driven by time-invariant characteristics of the ZIP codes, I show that the results are robust to the inclusion of ZIP-code fixed effects. This regression specification is very restrictive, because the median number of observations in each ZIP-code-year is equal to four, and 23% of ZIP-code-years have only one observation. Nevertheless, the results in Appendix Table A6 confirm the notion that the availability of 3G internet increases political polarization, even after the inclusion of ZIP-code fixed effects.[21]

3G availability and local economic conditions.—Two potential concerns are that *(i)* the expansion of 3G networks took place primarily in areas with higher economic growth and *(ii)* the arrival of 3G could have further improved local socioeconomic conditions, potentially leading to a shift in political views. I address these concerns in the following ways. First, I analyze whether the changes in the counties' socioeconomic characteristics—namely, median household income, the unemployment rate, the share of the population receiving food assistance, the share of the population with a college degree, and the share of the population with no schooling—can predict the current or future availability of 3G networks. Specifically, I estimate the effects of these characteristics on county-level 3G network coverage in years t and $t + 1$, controlling for county and year fixed effects, as well as for the other baseline county-level controls. Columns 1 and 2 of Appendix Table A7 present the regression estimates, suggesting that none of these characteristics affected the expansion of mobile infrastructure.

Next, I analyze whether the arrival of 3G had an impact on future local socioeconomic conditions. In particular, Columns 3–5 of Appendix Table A7 present the relationship between county-level 3G network coverage in year $t - 1$ and the counties' median household income, unemployment rate, and share of the population receiving food assistance in year t, respectively. None of these outcome variables were affected by previous expansions of 3G, at least in the short run.[22]

[21] In the specification with ZIP-code fixed effects, the change in political views is measured relative to the political views in the ZIP code at the beginning of the sample period (i.e., before the arrival of 3G), whereas in the baseline specification, it is measured relative to the average political views in the county at the beginning of the sample period. Together with the fact that 2008 was a year of high support for liberal policies, this difference explains why the inclusion of ZIP-code fixed effects makes the effects of mobile internet appear more pronounced for Republican counties than Democratic counties. If the data for 2008 are excluded from the analysis, all the regression estimates become virtually the same as in Appendix Table A4 (for brevity, these results are not reported but available upon request). However, most importantly, regardless of the choice of specification, the regression estimates demonstrate a clear divergence between Democrats' and Republicans' political views.

[22] I also verified that there are no effects on the share of the population with a college degree and the share of the population with no schooling. These results are not reported, because education outcomes are unlikely to change within one year, so the nonresults for these variables are not surprising.

Thus, it is unlikely that the immediate effect of 3G availability on individuals' political views can be explained by 3G affecting local socioeconomic conditions.

Lightning strikes and the expansion of 3G networks.—To allay remaining concerns about the validity of the effects of 3G coverage on political views, I perform the IV identification strategy previously employed by Manacorda and Tesei (2020) and Guriev, Melnikov and Zhuravskaya (2021), which uses the frequency of lightning strikes to predict the speed of the expansion of 3G networks. Lightning strikes damage mobile infrastructure, often causing service interuptions and necessitating repairs. Due to the higher costs of providing and maintaining 3G infrastructure in areas with a high frequency of lightning strikes, the expansion of mobile networks is likely to be slower in those areas.

As described in Subsection I.B, I use Specification (3) to predict the speed of the expansion of 3G coverage. The first-stage relationships between 3G network coverage and the excluded instrument in counties that Obama lost and won in 2008 are reported in Columns 1 and 4 of Appendix Table A8, respectively. Appendix Figure A2 illustrates the results. In both cases, the estimates are highly significant. Columns 2 and 5 report the reduced-form relationships between the instrument and individuals' political views, and Columns 3 and 6 present the 2SLS estimates along with the first-stage F-stats for the excluded instrument.[23] The results confirm the notion that the spread of 3G internet has contributed to increasing political polarization, with Democratic voters becoming more liberal and Republican voters more conservative.

2G coverage as placebo treatment.—To demonstrate that 3G coverage affects individuals' political views through providing access to online content and not through other features of mobile networks, I use the expansion of 2G networks as a placebo treatment. 2G (or GSM) technology allows for phone calls and text messages, but it does not allow for actively browsing the internet or watching online videos. Thus, if 3G affects individuals' political views not by providing access to internet content but through other aspects of mobile networks, one would expect the effects of 2G availability to be similar to the effects of 3G. Appendix Table A9 presents the results of the placebo exercise, showing that 2G has had no effect on the political views of the respondents. This analysis confirms the notion that 3G availability affects people by providing access to online content.

Composition of the respondents.—To ensure that the results are not determined by selective attrition of the respondents in Republican- or Democratic-leaning areas, I perform the following

[23]Notably, if one analyzes the reduced-form relationship between the instrument and individuals' political views *before* the ZIP codes receive 3G network coverage, the relationship stops being statistically significant. This result should be interpreted with causion because the IV determines the timing of the expansion of mobile infrastructure (for this reason, these results are not reported). Nonetheless, the absence of a relationship between the instrument and the outcome variable prior to treatment provides suggestive evidence in support of the exclusion restriction.

analysis. First, I consider how the shares of respondents from Republican-leaning, Democratic-leaning, and swing counties evolved throughout the sample period. As illustrated in Appendix Figure A3, the three shares have remained almost perfectly stable, suggesting that the sample did not become skewed towards one of these groups. Second, I investigate whether the regression results vary for respondents that were interviewed in different ways (i.e., landline vs. cellphone).[24] The results are presented in Appendix Table A10 and are quite similar for the two groups. Thus, the estimates are not determined by the potential differences in sampling between landline and cellphone interviews. Finally, as demonstrated in Appendix Table A5, the regression results are robust to including time-varying fixed effects for the socioeconomic composition of the responents in the Gallup Daily Poll.

No effect on migration.—Another potential concern is that the arrival of mobile infrastructure might have an effect on migration to or from the affected areas, which can change the composition of the survey respondents living in a location. To alleviate this concern, I estimate the effect that the expansion of 3G internet has had on migration between the counties in the sample (i.e., the unit of analysis used to measure the political affiliation of the area), controlling for county and year fixed effects, as well as for the other baseline county-level controls. The results, reported in Appendix Table A11, show that 3G network coverage has no impact on any of the outcome variables (i.e., the in-migration, out-migration, and net-migration rates). Moreover, given that the outcome variables are measured in percentage points, the regression coefficients are very small.[25]

Vote type in past presidential elections.—As a further robustness check, I consider two alternative definitions of individuals' political affiliation. First, instead of basing the counties' political affiliation on the vote shares in the 2008 presidential election, I create a similar measure based on the 2004 presidential election (Bush vs. Kerry). Appendix Table A12 reports the result, which are very similar to those in Appendix Table A4.

Second, I consider whether the respondent voted for the Democratic or Republican presidential nominee in the last election. The advantage of this approach is that the survey respondents cannot change their vote in past presidential elections. The drawback of this approach is that, in the United States, not all adults participate in elections (in the 2008–2016 presidential elections, turnout varied between 58% and 61.6%), with turnout being higher among older, wealthier, and

[24] All Gallup Daily Poll interviews were conducted either via landline or via cellphone. Both types of interviews were conducted throughout the sample period, but the share of cellphone interviews increased over the years, reflecting both the increasing ubiquity of cellphones and the decline of landline phone use. It should be noted that cellphone usage does not require 3G network coverage.

[25] Thus, in addition to not being statistically significant, the effects are not economically meaningful. For instance, the arrival of 3G internet, on average, increases the out-migration rate by a mere 0.08%.

more-educated people and lower among minority groups.[26] The Gallup Daily Poll does not include data on votes cast in the last presidential election, so instead, I estimate Specification (2) using CCES data.[27] Appendix Table A13 presents the regression estimates, which confirm the results presented earlier in the paper.

II.C Policy Preferences and Voting Outcomes

The evidence presented in the previous subsections demonstrates that the expansion of mobile internet has had a significant effect on individuals' political views, shifting Democratic and Republican voters toward opposite ends of the political spectrum. In this subsection, I address the question of whether 3G infrastructure similarly affected policy preferences and voting outcomes.

Policy preferences.—The data on individuals' policy preferences come from the CCES dataset, which includes questions on many polarizing topics (namely, abortion, gay rights, the Affordable Care Act, and immigration). For all the policy questions, it is well known that Democrats generally stand on one side of the policy debate (e.g., abortion should be legal), while Republicans support the opposite point of view (e.g., abortion should not be legal). Therefore, under the hypothesis that 3G internet increases political polarization, individuals' policy preferences are expected to converge with the position of the party that they support.

To test this hypothesis, I estimate Specification (1), using dummies for various policy preferences as the outcome variables. Table 2 reports the results. For all the policy variables, residents of Democratic- and Republican-leaning counties shift their views in opposite directions. Thus, the expansion of 3G internet affected not only individuals' overall political views but also their attitudes toward specific policy proposals.[28]

The availability of mobile internet also affected the salience of some of the problems facing the country in the eyes of voters. The data on this question come from the Gallup Poll Social Series, where the respondents were asked to name the most important problem facing the country. Appendix Table A15 presents the results of estimating the effects of 3G internet on individuals' perceptions of whether immigration, inequality, race relations, or gun violence is the most important problem facing the country today.[29] As expected, after the arrival of 3G networks, Democratic

[26] The personalities of the presidential nominees can also affect the composition of voters who participate in a given election.

[27] The CCES dataset includes 293,587 observations that can be used in the analysis, which is six times fewer than in the Gallup Daily Poll. The substantial difference in sample size is the main reason why the Gallup Daily Poll is the main dataset used in this paper.

[28] Appendix Table A14 demonstrates that, similarly to the change in political views, individuals' attitudes toward these policies started to change only after the arrival of 3G, while the future availability of 3G is not correlated with current policy views.

[29] Individuals on different sides of the political spectrum have disparate views about the salience of these problems,

and Republican voters diverged in their views about the salience of these problems.

Voting outcomes.—To estimate the effects of mobile internet on voting outcomes, I use 2008–2018 county-level data on elections to the U.S. House of Representatives. The outcome variables of interest are the vote shares of Republican and Democratic candidates, as well as the vote margins of the Republican candidates (i.e., the vote share of the Republican candidate minus the vote share of the Democratic candidate). Columns 1–6 of Table 3 report the results of estimating Specification (1) for these outcome variables. The odd columns present the estimates for the full sample; the even columns, for the subsample of county-years with at least one Republican candidate and at least one Democratic candidate running for office. The results confirm the notion that the expansion of 3G internet increased political polarization. After the arrival of 3G, voters in Republican-leaning counties increased their support for Republican congressional candidates while proportionally decreasing the vote share of Democratic candidates; in Democratic-leaning counties, the relationship is reversed. Figure A4 illustatrates the results for the Republican and Democratic vote shares (Columns 2 and 4 of Table 3).[30]

The magnitudes of the effects are quite large, especially in Republican-leaning counties. For instance, the results in Column 2 suggest that, after the county becomes fully covered by 3G networks, the vote share of Republican candidates increases by 4.5 percentage points in Republican-leaning counties and decreases by 2.6 percentage points in Democratic-leaning counties.[31] The results in Columns 7 and 8 also suggest that the expansion of 3G internet resulted in an approximately 1-percentage-point decrease in turnout in both Democratic- and Republican-leaning counties, which is consistent with the previously documented effects of the internet on turnout in Europe (Falck, Gold and Heblich, 2014; Campante, Durante and Sobbrio, 2018; Gavazza, Nardotto and Valletti, 2019; Guriev, Melnikov and Zhuravskaya, 2021).[32] Thus, part of the effects on the vote shares of Democratic and Republican candidates might be explained by the decreases in turnout, although the impact on turnout is not sufficiently large (approximately 1 percentage point) to be

with Republican voters being more concerned about immigration and Democratic voters being more concerned about race relations, inequality, and gun safety.

[30] Appendix Table A16 demonstrates that, similarly to the change in political views and policy preferences, voting outcomes are affected by current levels of 3G coverage, not the future availability of 3G (i.e., the future availability of 3G is not correlated with current voting outcomes).

[31] The fact that, for voting outcomes, the magnitudes of the effects are larger than those for political views and policy preferences could be explained by the composition of people who vote in elections. Most notably, election turnout is consistently higher among older Americans, who generally favor Republican candidates. In turn, as shown in Appendix Table A21, 3G internet primarily increased polarization among older voters.

[32] The decrease in turnout might be driven by voters' disillusionment with the partisan nature of U.S. politics. It is also possible that the internet might decrease participation among certain groups of voters by crowding out political information with entertainment content (e.g., see Campante, Durante and Sobbrio, 2018). More generally, previous studies have shown that political participation can both increase and decrease with access to the internet (for a review of the literature, see Zhuravskaya, Petrova and Enikolopov, 2020).

fully driving the results. Overall, the results demonstrate that, in addition to causing individuals to change their political views and policy preferences, the expansion of 3G networks also induced people to change their voting behavior.

II.D 3G Coverage and Internet Usage

When interpreting the impact of mobile internet on political outcomes, it is important to note that the availability of 3G infrastructure affects several dimensions of internet usage, all of which can contribute to the overall effects of 3G. To document the importance of these factors, I estimate Specification (4) for various aspects of internet usage. Table 4 presents the results. In Column 1, I use MRI Consumer Surveys data on the share of households using the internet in the ZIP codes (measured in standard deviations) to demonstrate that the availability of 3G network coverage increased internet usage on the extensive margin in both Democratic and Republican counties.[33] The results in the rest of Table 4 are based on the data from Comscore. Columns 2 and 3 show that mobile internet coverage also affected internet usage on the intensive margin by increasing the number of websites people visit per day and the amount of time people spend online.

Columns 4–8 of Table 4 demonstrate how the availability of 3G differentially impacted *what* residents of Democratic and Republican counties do on the internet. In particular, after the arrival of 3G, residents of Democratic counties increased their usage of Twitter and decreased their usage of Facebook, possibly because of Twitter's relatively liberal content (e.g., see Fujiwara, Müller and Schwarz, 2021), whereas the effects were the opposite in Republican counties. On the other hand, Youtube usage increased both in Democratic and Republican counties, although it is likely that the two sides used it to access different types of content. Overall, the results indicate the presence of ideological segregation across social media platforms.

Next, I consider how the expansion of mobile internet affected the online consumption of traditional news and misinformation content. Specifically, in Columns 7 and 8 of Table 4, I estimate Specification (4) for the share of visits to 301 websites of traditional news media outlets (e.g., CNN, Fox News) and the share of visits to 171 websites that have been known to regularly publish false or misleading information, conspiracy theories, or extremist content (e.g., Infowars, Breitbart News).[34] The results indicate that the expansion of 3G network coverage resulted in residents of Republican counties decreasing their consumption of traditional news—possibly due to their

[33] More precisely, the outcome variable is normalized by the average within-ZIP-code standard deviation. I use the within-ZIP-code standard deviation (instead of overall standard deviations) because it reflects within-ZIP-code changes in internet use and not the heterogeneity in internet use across ZIP codes.

[34] Appendix Tables A24 and A23 present the full lists of these websites, and Appendix Section A.II describes the details of how they were constructed.

disillusionment with the mainstream media—and replacing it with misinformation content. On the other hand, residents of Democratic counties marginally increased their visits to traditional news websites, while their misinformation consumption was unaffected.[35] Appendix Table A17 presents a similar divergence between Democrats and Republicans in their visits to the websites of some of the most prominent traditional media outlets.

Finally, I use CCES data to estimate the effects of mobile internet on Democrats' and Republicans' interest in political news and their knowledge of politics. The results in Column 9 of Table 4 suggest that Republicans' 3G-driven decrease in traditional news consumption was accompanied by a decline in interest in political news, measured by them becoming less likely to say that they follow the news about the government and public affairs at least most of the time. Residents of Democratic-leaning counties did not experience a similar decline in political news interest. In turn, the estimates in Columns 10–12 of Table 4 demonstrate how the shifts in news consumption affected Democrats' and Republicans' political knowledge, measured by the probability of them knowing their congressional representative and two senators. The results indicate that residents of Democratic-leaning counties marginally increased their political knowledge, possibly as a result of more traditional news consumption, whereas residents of Republican-leaning counties became less informed about who represents them in Congress, plausibly due to the shift in their news sources and the decline in interest in political news.

Overall, as Table 4 demonstrates, the arrival of 3G internet affected multiple dimensions of internet usage. All of these dimensions are potentially important for interpreting the effects of mobile internet on Democrats' and Republicans' political views.

II.E Magnitudes of the Effects

Share of increase in political polarization explained by 3G.—To analyze the extent to which mobile internet is responsible for the increase in political polarization, I perform the following exercise. First, for each outcome variable, I consider the share of population in Democratic- and Republican-leaning counties that is aligned with the position of the dominant party in the county (e.g., the share of population that votes for the party) and calculate the change in that share between 2008 and 2018.[36] This change represents the overall increase in political polarization that took place

[35]The fact that misinformation consumption increased only in Republican areas is not surprising. During the period under consideration, the stories published on fake news and misinformation websites systematically favored Republicans (Benkler, Faris and Roberts, 2018; Bovet and Makse, 2019; Grinberg et al., 2019; Guess, Nyhan and Reifler, 2020), and Republican politicians were more willing to share misleading content with their supporters than both Democrats and the general public (Greene, 2022).

[36]For the outcome variables that did not cover the entire period from 2008 to 2018, I consider the change between the first and last years for which the data are available.

during this period. I then calculate the effect that mobile internet had on increasing the share of population that is aligned with the position of their county's dominant party. For each outcome variable, I consider the regression coefficients for the effects of 3G on the probability of holding the same views as the main party in the county, separately for Democratic- and Republican-leaning counties. Then, I multiply these estimates by the average increases in 3G network coverage that Democratic- and Republican-leaning counties experienced during the period, and I take the average of the effects on Democratic- and Republican-leaning counties, weighted by their relative sample size. The resulting variable represents the effect of mobile internet on political polarization. Finally, I calculate the share of the increase in political polarization that can be explained by mobile internet. Full details of the calculations are presented in Appendix Section A.III.

Appendix Table A18 presents the results of estimating the share of the increase in political polarization that can be explained by mobile internet. 3G network coverage can account for 11.3% of the increase in polarization in political views, 37.7% of the increase in polarization in voting behavior, and, on average, 34.8% of the increase in polarization in policy preferences.

Persuasion rates.—Following DellaVigna and Kaplan (2007) and Enikolopov, Petrova and Zhuravskaya (2011), I also calculate the persuasion rates for the effects of mobile internet on political views and voting behavior (i.e., the share of population exposed to mobile internet that is persuaded by its message). As demonstrated in Table 4, 3G coverage affects individuals' political preferences through multiple dimensions, and mobile internet should not be thought of as a "first stage" for any one variable. For this reason, it is hard to find the appropriate estimate of individuals' "exposure" to the treatment, which is one of the parameters needed to calculate the persuasion rates. To accurately measure the share of population affected by mobile broadband, while ensuring that all dimensions of internet usage are taken into account, I consider the average share of the ZIP codes' population that had a subscription to a cellular internet data plan, separately for Democratic- and Republican-leaning areas. Using this and other assumptions, the full details of which are presented in Appendix Section A.IV, I calculate the persuasion rates for the effects of 3G internet of individuals' political views, voting behavior, and policy preferences.

Appendix Table A19 presents the results. For residents of Democratic-leaning counties, the average persuasion rate is equal to $18.35/N$; for residents of Republican-leaning counties—$24.85/N$, where N represents the number of people affected by the internet per cellular-data-plan subscription (i.e., if $N = 1$, there are no spillover effects, and only one person is affected per connection; $N > 1$ indicates the presence of spillover effects).[37] These magnitudes are fully consistent

[37]These averages include the results reported in Appendix Table A19, in which the estimates are statistically significant. Full details of the calculations of the persuasion rates are presented in Appendix Section A.IV.

with the persuasion effects of the media documented in previous literature (e.g., see an overview by DellaVigna and Gentzkow, 2010).

III Mechanisms

In this section, I examine the factors that have determined the direction of the effects of 3G availability on the political preferences of the U.S. population. I begin by presenting novel evidence for a mechanism that has received growing attention in the public debate in recent years: misinformation consumption. I then analyze the role of news consumption from traditional media outlets. Finally, I present empirical evidence for 3G's role in the recent political realignments in the U.S. population, described in theoretical work by Bonomi, Gennaioli and Tabellini (2021).

III.A Misinformation, Traditional News, and Political Polarization

To analyze the role of misinformation consumption in determining the effects of 3G of individuals' political preferences, I estimate Specification (5), where 3G network coverage is interacted with the share of visits to misinformation websites among all browsing activities in the ZIP code at the beginning of the sample period. Table 5 presents the regression estimates. The results indicate that residents of Republican ZIP codes that were early adopters of misinformation consumption became less likely to hold liberal or very liberal political views (Column 1) and more likely to hold conservative or very conservative views (Column 4) after the arrival of mobile internet. Conversely, online misinformation did not affect political views in Democratic areas.

The differences in the effects of misinformation on the supporters of the two parties are not surprising. First, online conspiracy theories and fake news systematically favor Republican politicians (Benkler, Faris and Roberts, 2018; Bovet and Makse, 2019; Grinberg et al., 2019; Guess, Nyhan and Reifler, 2020), making Republican-leaning voters more predisposed to believe these stories. Second, Republican politicians have also been more likely to use the internet to share misleading content than both Democrats and the general public Greene (2022), legitimizing this content in the eyes of their supporters.

On the other hand, traditional news consumption affected the political views of Democratic-leaning voters. Specifically, Table 5 shows that residents of Democratic ZIP codes that had high levels of traditional news consumption at the beginning of the sample period became more likely to hold liberal or very liberal political views (Column 2) and less likely to hold conservative or very conservative views (Column 5) after the arrival of mobile internet.[38] Exposure to traditional news did not determine the direction of the effect of mobile internet in Republican-leaning areas, plausibly because, as demonstrated in Table 4, after the arrival of 3G network coverage, Republicans decreased both their consumption of traditional news and their interest in political news.

Overall, the results indicate that individuals' news consumption played an important role in determining the effects of mobile internet on their political views. Residents of Republican ZIP codes that were early adopters of online misinformation consumption became even more conservative in their political views after the arrival of mobile internet. In turn, residents of Democratic ZIP codes with high levels of traditional news consumption at the beginning of the sample period were particularly likely to become more liberal in their political views after 3G became available.

III.B Political Realignment of Voters

Another mechanism through which the availability of 3G affected the views of the U.S. population is related to recent theoretical work by Bonomi, Gennaioli and Tabellini (2021) and earlier work by Roemer (1998). Their work suggests that when cultural issues become more prominent, as they have in the United States since 2008, the salience of redistributive policies goes down, and conflict along this dimension is muted. As a result, the expansion of mobile internet, which increased the cultural divide among Democrats and Republicans (see Table 2), resulted in a political realignment in the United States, with voters who are poor, uneducated, and out of the labor force—who benefit the most from redistribution policies supported by Democrats—becoming more conservative, and wealthy, employed, and well-educated voters becoming more liberal.

To test this hypothesis, I present the heterogeneity of the effects of 3G internet on political views by socioeconomic characteristics such as education, income, and employment status. In the analysis, the outcome variables are regressed on 3G network coverage interacted with all the values of the socioeconomic characteristic of interest, controlling for all the baseline controls, including the direct effect of the socioeconomic characteristic. The estimates are presented in Appendix Table A20 and suggest that, after the arrival of 3G, educated, wealthy, and employed individuals became less likely to hold conservative political views and more likely to hold liberal views. In contrast, the opinions of those who are uneducated, poor, and out of the labor force shifted in the opposite direction. These results confirm the notion that the expansion of mobile internet resulted

[38] Exposure to traditional news from conservative media outlets (e.g., Fox News) does not have a different effect on individuals' political preferences. This happens because most people who follow conservative traditional media coverage also follow more liberal traditional news sources (e.g., CNN). Thus, the predominant divide is between individuals who get the news from traditional media outlets and people who distrust the "mainstream media" and, instead, consume news from less reliable sources.

in a political realignment of voters in the United States.

Notably, this realignment of voters may or may not have led to more political polarization. Specifically, if the increased salience of cultural conflict predominantly results in moderate voters shifting towards the extremes of the political spectrum, political polarization increases. On the other hand, if partisan activists are induced to move closer to the center (and potentially become moderate supporters of the party they previously opposed), polarization can also decrease.

III.C Other Heterogeneity

Age.—In previous work, Boxell, Gentzkow and Shapiro (2017) have suggested that political polarization predominantly increased among older individuals, who tend to be less active online, concluding that the internet is unlikely to be a major determinant of the recent growth in polarization. To address this debate, I present the heterogeneity of the effects of 3G network coverage by age. Specifically, I estimate Specification (1), replacing *3G* $\times$ *Pol. affiliation* with its interaction terms with dummies for the respondent being younger and older than 40.[39]

Appendix Table A21 presents the results, showing that, indeed, the expansion of mobile internet increased political polarization primarily among middle-aged and older individuals (collectively, over age 40). For those respondents, the direction of the effect of 3G on political views strongly depends on whether they lived in a Republican-leaning or Democratic-leaning county. In contrast, after the arrival of 3G, younger individuals became less likely to hold conservative political views and more likely to hold liberal political views, regardless of where they lived. Overall, the findings in Appendix Table A21 confirm those of Boxell, Gentzkow and Shapiro (2017), showing that political polarization primarily increased among older individuals. However, despite this fact, the expansion of mobile internet played an important role in widening the gap between the political views of Republican and Democratic voters.

Heterogeneity by time.—Appendix Table A22 presents the heterogeneity of the effects of 3G internet on political views by time. The results suggest that residents of Republican counties became more conservative in their political views in 2008–2009, when President Obama assumed office and Democrats controlled both chambers of Congress. In turn, in 2016–2017, when President Trump came to power and Republicans controlled both chambers of Congress, residents of both Democratic- and Republican-leaning counties became less conservative in their views.[40] The

[39] Additional controls also include non-collinear lower-level interaction terms between 3G coverage, the political affiliation of the counties, and dummies for the two age groups.

[40] The results for Republican-leaning counties are not necessarily driven by Republican voters changing their political views. Instead, it could be the case that the views of Republican voters did not change, while Democratic residents of those counties became less conservative.

findings suggest that the internet amplifies voters' reaction to events in national politics, plausibly by providing access to (partisan) information about these events. The results are fully consistent with those of Guriev, Melnikov and Zhuravskaya (2021), who show that corruption scandals led to higher corruption perception in places covered by 3G networks.

IV Conclusion

This paper analyzes how the expansion of mobile internet has increased political polarization. After 3G network coverage became available, residents of Democratic counties started holding more liberal political views and increased their support for Democratic congressional candidates and their policy priorities; residents of Republican counties shifted in the opposite direction. The expansion of 3G also affected multiple dimentions of internet usage, ranging from increasing the amount of time spent online per day to shifting the sources of individuals' news consumption.

I also present evidence for three mechanisms through which the expansion of mobile internet affected the political views of the U.S. population. In particular, I show that online misinformation resulted in Republican voters becoming more conservative in their political views after the arrival of 3G internet, while traditional media consumption had the opposite effect for Democratic voters. Finally, I show how the expansion of mobile internet resulted in a political realignment of voters in the United States, with well-educated, wealthy, and employed people becoming more liberal, and the uneducated, poor, and out of the labor force becoming more conservative.

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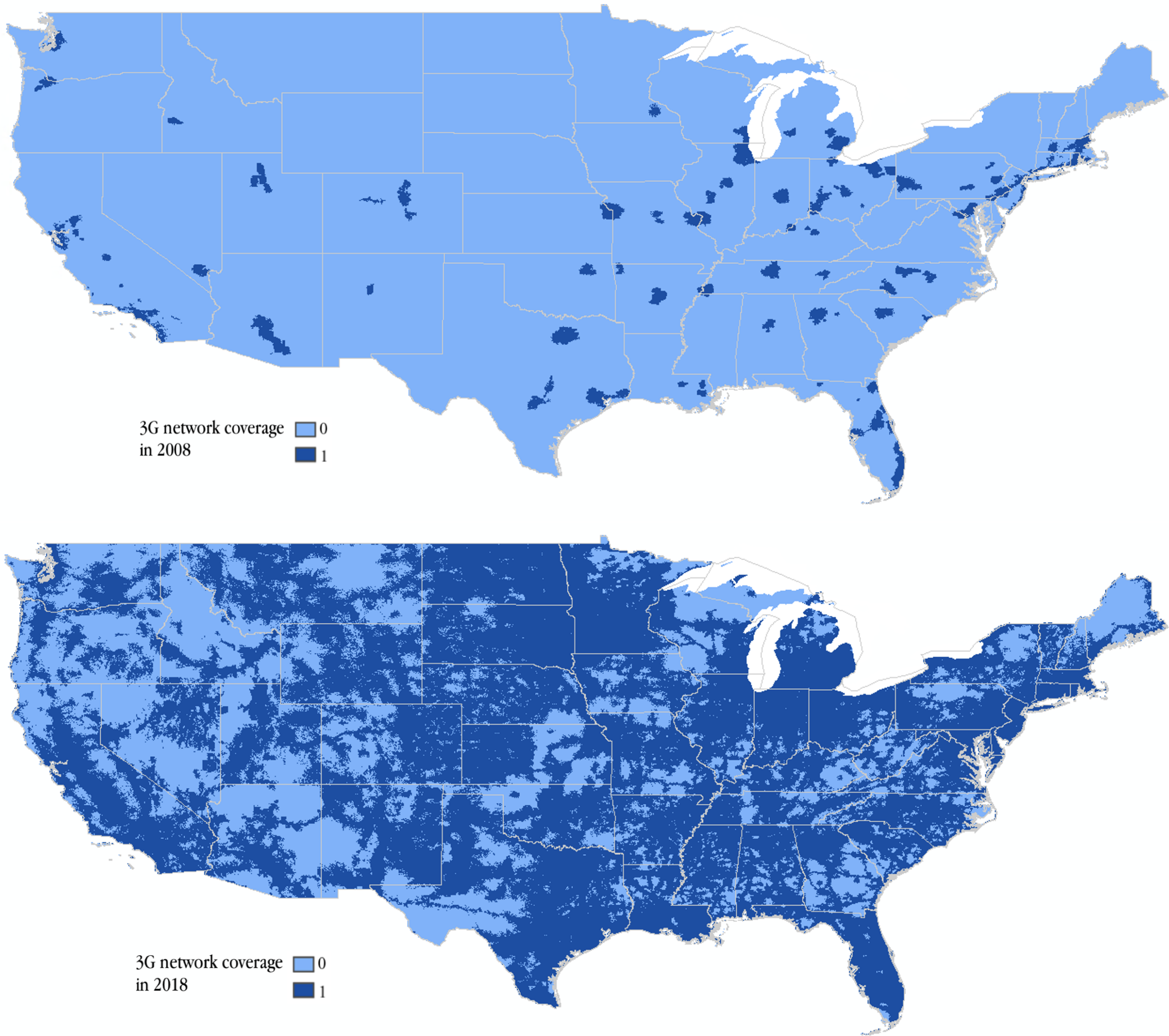

Figure 1: Expansion of 3G Network Coverage Between 2008 and 2018

Note: The two maps depict 3G network coverage for the contiguous United States in 2008 and 2018. The data consist of 1×1-kilometer binary grid cells.

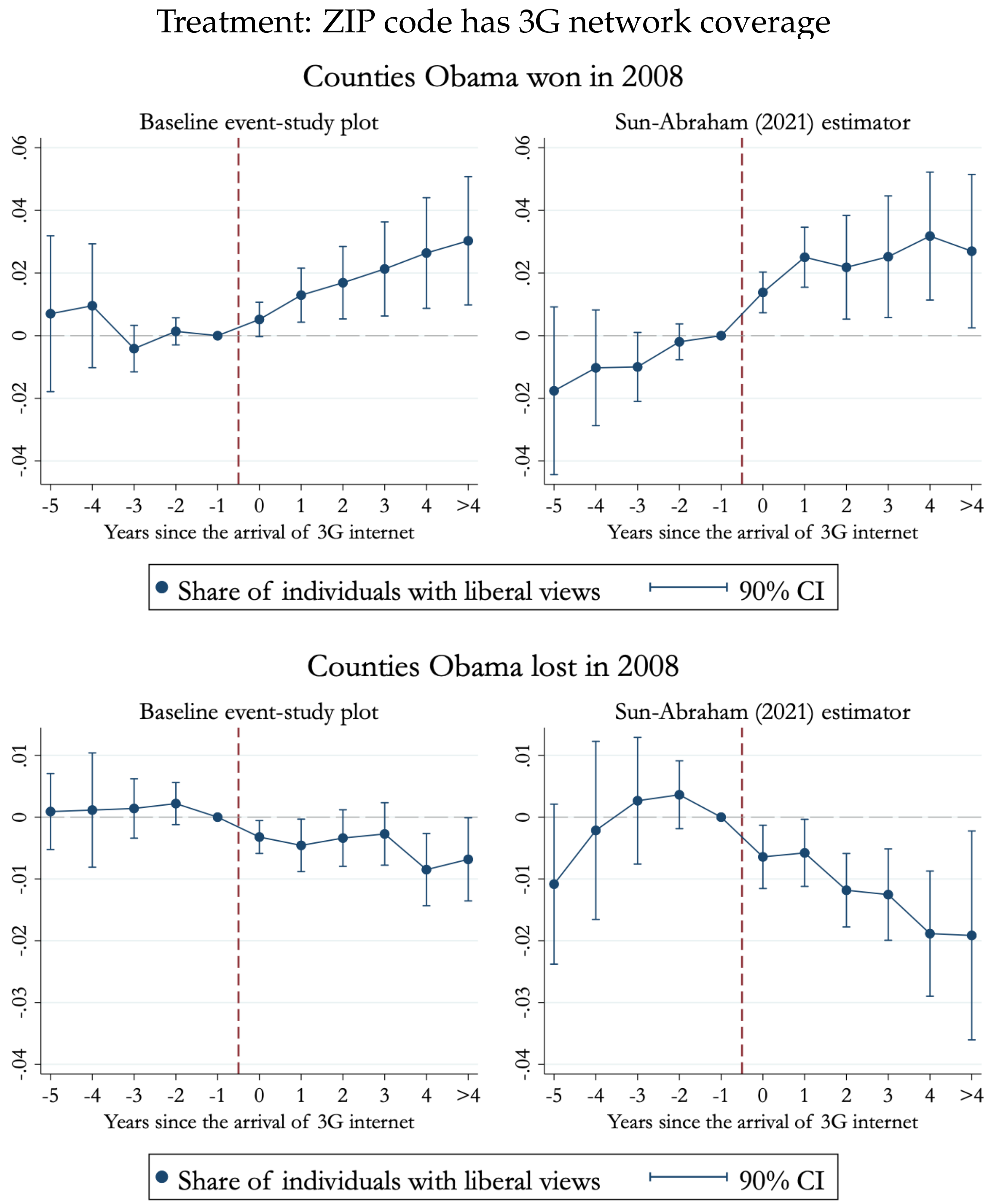

Figure 2: Event Study Analysis

Note: The figure presents an event study showing how the respondents' political views changed after the arrival of 3G internet to their ZIP code of residence. Columns 1–2 and 5–6 of Table A3 present the regression estimates. A ZIP code is defined to be treated when gets any 3G networks for the first time. The left part of the figure presents standard event-study estimates, while the right part of the figure presents the Sun-Abraham estimator.

TABLES

Table 1: 3G Internet and Political Polarization

	(1)	(2)	(3)	(4)
Dep. Var.:	Political views are:			
	Liberal or very liberal		Conservative or very conservative	
3G network coverage ×				
× Resident of reliably Democratic county	0.013**		-0.016***	
	(0.006)		(0.004)	
× Resident of Democratic-leaning county	0.008***		-0.019***	
	(0.003)		(0.003)	
× Resident of swing county	0.000		-0.007***	
	(0.002)		(0.002)	
× Resident of Republican-leaning county	-0.007***		-0.001	
	(0.002)		(0.004)	
× Resident of reliably Republican county	-0.004		0.005*	
	(0.002)		(0.003)	
× Democratic voter		0.051***		-0.017***
		(0.006)		(0.005)
× Independent voter		-0.015***		-0.019***
		(0.003)		(0.003)
× Republican voter		-0.035***		0.020***
		(0.002)		(0.003)
Observations	1,765,113	1,765,114	1,765,113	1,765,114
R-squared	0.073	0.205	0.091	0.260
Mean dep. var	0.234	0.234	0.420	0.420
Number of clusters	51	51	51	51
Number of ZIP codes	31,499	31,499	31,499	31,499
County & year FEs	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓

Note: This table presents the results of estimating Specifications (1) and (2) for respondents' self-described political views. The unit of observation is an individual. In Columns 1 and 2, the outcome variable is a dummy for whether the respondent describes their political views as liberal or very liberal; Columns 3 and 4 use a similar dummy for self-described views being conservative or very conservative. Baseline controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Other controls include a dummy variable for whether the ZIP code was fully covered by 3G networks in 2008 (i.e., the first year in the sample) and separate year fixed effects for the ZIP codes that were. In Columns 2 and 4, controls also include dummies for individuals' party affiliation. A county is assumed to be reliably Democratic if Obama won the county in 2008 by a margin of at least 30 percentage points; Democratic-leaning if Obama won the county in 2008 by a margin of 10–30 percentage points; Republican-leaning if Obama lost the county in 2008 by a margin of 10–30 percentage points; or reliably Republican if Obama lost the county in 2008 by a margin of at least 30 percentage points. Other counties are characterized as swing counties. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: 3G Internet and Policy Preferences

	(1)	(2)	(3)	(4)
Dep. Var.:	Always allow abortion	Support gay marriage	Repeal the ACA	Increase border security
3G network coverage ×				
× Resident of Democratic-leaning county	0.013**	0.037***	-0.053***	-0.029***
	(0.006)	(0.011)	(0.019)	(0.010)
× Resident of swing county	0.004	0.017	0.007	-0.019**
	(0.007)	(0.012)	(0.019)	(0.009)
× Resident of Republican-leaning county	-0.012**	-0.033***	0.027	0.017**
	(0.006)	(0.009)	(0.016)	(0.007)
Observations	394,518	316,521	278,657	356,933
R-squared	0.110	0.107	0.109	0.107
Mean dep. var	0.536	0.578	0.486	0.523
Number of clusters	51	51	51	51
Number of ZIP codes	23,216	22,450	21,375	22,614
County & year FEs	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓

Note: This table presents the results of estimating Specification (1) for the respondents' policy preferences. The unit of observation is an individual. The outcome variables are dummies for the respondents' policy preferences. Baseline controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Other controls include a dummy variable for whether the ZIP code was fully covered by 3G networks in 2008 and separate year fixed effects for the ZIP codes that were. A county is assumed to be Democratic-leaning if Obama won the county in 2008 by a margin of at least 10 percentage points, and Republican-leaning if Obama lost the county in 2008 by a margin of at least 10 percentage points; other counties are characterized as swing counties. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3: 3G Internet and Voting Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	Republican vote share (R)		Democratic vote share (D)		Republican vote margin (R-D)		Turnout	
3G network coverage ×								
× Resident of Democratic-leaning county	-5.063**	-2.577*	4.423*	2.396*	-9.486**	-4.973*	-1.516***	-1.068**
	(2.340)	(1.390)	(2.223)	(1.355)	(4.474)	(2.716)	(0.475)	(0.415)
× Resident of swing county	1.692	3.106*	-1.645	-2.913*	3.338	6.019*	-1.242**	-1.083**
	(2.058)	(1.666)	(2.012)	(1.569)	(4.021)	(3.191)	(0.481)	(0.512)
× Resident of Republican-leaning county	4.573***	4.540***	-4.530***	-4.789***	9.103***	9.329***	-0.943*	-0.753*
	(1.325)	(1.249)	(1.401)	(1.190)	(2.686)	(2.408)	(0.477)	(0.440)
Observations	18,573	16,864	18,573	16,864	18,573	16,864	18,573	16,864
R-squared	0.793	0.858	0.779	0.857	0.794	0.862	0.893	0.915
Mean dep. var	60.74	59.53	36.08	38.11	24.66	21.42	37.33	37.93
Number of counties	3,110	3,110	3,110	3,110	3,110	3,110	3,110	3,110
County & year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓
Excluding unopposed races		✓		✓		✓		✓

Note: This table presents the results of estimating Specification (1) for voting outcomes. The unit of observation is a county. The outcomes are measured in percentage points. In the odd columns, the results are reported for the full sample; in the even columns, for county-years with at least one Democrat and at least one Republican running for office. Alaska is excluded from the sample because, in Alaska, election results are not available at the county level. Baseline controls include county and year fixed effects, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Other controls include a dummy variable for whether the county was fully covered by 3G networks in 2008 (i.e., the first year in the sample) and separate year fixed effects for the counties that were. A county is assumed to be Democratic-leaning if Obama won the county in 2008 by a margin of at least 10 percentage points, and Republican-leaning if Obama lost the county in 2008 by a margin of at least 10 percentage points; other counties are characterized as swing counties. Standard errors in parentheses are corrected for clusters at the level of the states. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: 3G Internet, Online Activities, and Political Knowledge

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:				Share of visits to _____ among all webpages visited (in st. dev.):		
	Households using the internet	Websites visited per day	Minutes spent online per day	Twitter	Facebook	Youtube
3G network coverage ×						
× Resident of county Obama won in 2008	0.381*	1.877*	24.474**	0.051***	-0.066***	0.049***
	(0.197)	(0.985)	(10.687)	(0.017)	(0.022)	(0.014)
× Resident of county Obama lost in 2008	0.998***	1.879**	32.933***	-0.069***	0.061***	0.061***
	(0.153)	(0.819)	(11.489)	(0.018)	(0.019)	(0.017)
Observations	239,017	155,480	155,480	155,480	155,480	155,480
Number of ZIP codes	30,278	21,430	21,430	21,430	21,430	21,430
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
Dep. Var.:	Share of visits to _____ among all webpages visited (in st. dev.):			Respondent knows their:		
	News websites	Misinformation websites	Interest in political news	Congressional representative	First senator	Second senator
3G network coverage ×						
× Resident of county Obama won in 2008	0.020*	0.018	-0.005	0.009**	0.003	-0.001
	(0.012)	(0.012)	(0.005)	(0.004)	(0.003)	(0.003)
× Resident of county Obama lost in 2008	-0.046***	0.054***	-0.011**	-0.005**	-0.008**	-0.007**
	(0.016)	(0.015)	(0.004)	(0.003)	(0.003)	(0.003)
Observations	155,480	155,480	392,836	396,524	399,111	398,938
Number of ZIP codes	21,430	21,430	23,267	23,313	23,322	23,322

Note: This table presents how the expansion of mobile internet affected individuals' online activities and political knowledge. In Columns 1-8, the unit of observation is a ZIP code. In Columns 9-12, the unit of observation is an individual. In Column 1, the outcome variable is the share of households using the internet, measured in standard deviations. In Columns 2, the outcome variable is the number of websites visited per day. In Columns 3, the outcome variable is the number of minutes spent online per day. In Columns 4-8, the outcome variables are the share of visits to the respective website or website category among all webpages visited, measured in standard deviations. In Column 9, the outcome variable is a dummy for whether the respondent follows the news most of the time. In Columns 10–12, the outcome variables are dummies for whether the respondent knows their congressional representative and two senators. In Columns 1-8, baseline controls include ZIP code and year fixed effects. In Columns 4-8, additional controls include the log of the total number of websites visited interacted with dummies for whether Obama won or lost the county in 2008. In Columns 9-12, controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5: News, Misinformation, and Political Polarization

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Political views are:					
	Liberal or very liberal			Conservative or very conservative		
3G network coverage ×						
× Resident of county Obama won in 2008	0.007***	0.007**	0.006**	-0.016***	-0.015***	-0.015***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
× Resident of county Obama lost in 2008	-0.002	-0.002	-0.002	-0.004	-0.004	-0.004
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
3G network coverage × Pre-3G misinformation consumption in the ZIP code ×						
× Resident of county Obama won in 2008	-0.000		-0.001	-0.003		-0.002
	(0.002)		(0.002)	(0.002)		(0.003)
× Resident of county Obama lost in 2008	-0.003**		-0.003**	0.005**		0.005**
	(0.001)		(0.001)	(0.002)		(0.002)
3G network coverage × Pre-3G traditional news consumption in the ZIP code ×						
× Resident of county Obama won in 2008		0.004**	0.005**		-0.005**	-0.005**
		(0.002)	(0.002)		(0.002)	(0.002)
× Resident of county Obama lost in 2008		-0.000	0.000		0.000	-0.001
		(0.002)	(0.002)		(0.002)	(0.002)
Observations	1,734,639	1,734,639	1,734,639	1,734,639	1,734,639	1,734,639
Mean dep. var	0.234	0.234	0.234	0.418	0.418	0.418
Number of ZIP codes	25,438	25,438	25,438	25,438	25,438	25438
County & year FEs	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓

Note: This table presents the role of news and misinformation consumption in increasing political polarization. The unit of observation is an individual. The outcome variables are dummies for the respondents' political views. Baseline controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Additional controls also include a dummy variable for whether the county was fully covered by 3G networks in 2008 (i.e., the first year in the sample) and separate year fixed effects for the counties that were, the pre-3G share of people in the ZIP code that used the internet to obtain news and its interaction term with 3G network coverage. In Columns 1,3, 4, and 6, additional controls also include the direct effects of pre-3G misinformation consumption in the ZIP code, separately for counties that Obama won and lost in 2008. In Columns 2, 3, 5, and 6, additional controls also include the direct effects of pre-3G traditional news consumption in the ZIP code, separately for counties that Obama won and lost in 2008. Pre-3G misinformation and traditional news consumption in the ZIP code are measured as the averages of the respective variables in the first three years the ZIP code appears in the sample. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Online Appendix

A.I Data

This section presents information about the secondary data sources used in the analysis as well as additional information about the primary data sources.

Mobile network coverage.—The data on 3G and 2G network coverage come from maps provided by Collins Bartholomew's Mobile Coverage Explorer and cover the period from 2007 to 2019 with the exception of 2011.[41] Collins Bartholomew does not provide the data for 2011 due to a change in the company administering collection of mobile network coverage data, which prevented the data from being collected that year. Therefore, throughout the analysis, the data for 2011 are imputed as the average of the values for 2010 and 2012. The results are robust to excluding 2011 altogether.

In certain other countries, mobile network operators occasionally do not submit data to Collins Bartholomew, leading to measurement error in mobile coverage. For the United States, this issue is not relevant: the maps of mobile coverage were updated every year.

Cooperative Congressional Election Study (CCES).—The data on individual's policy preferences come the CCES and cover the period from 2007 to 2019.[42] The exact wording of the questions is the following: *(i) Do you support or oppose each of the following proposals? Always allow a woman to obtain an abortion as a matter of choice. (ii) Do you favor or oppose allowing gays and lesbians to marry legally? (iii) Congress considered many important bills over the past two years. For each of the following tell us whether you support or oppose the legislation in principle. Repeal Affordable Care Act. Would repeal the Affordable Care Act. (iv) What do you think Congress and the President should do about immigration? Increase the number of border patrol on the U.S.–Mexico border.*

Gallup Poll Social Series.—The data on individuals' opinions about the most important problem facing the country come from the Gallup Poll Social Series and cover the period from 2008 to 2018.[43] The data consist of repeated cross-sectional monthly polls of approximately 1,000 respondents with geolocalization at the ZIP-code level. The question of interest is the following: *What do you think is the most important problem facing this country today?*

SimplyAnalytics.—The data on internet and social media use come from SimplyAnalytics, a mapping application that aggregates demographic, business, and marketing data from multiple

[41]These data are described here: https://www.collinsbartholomew.com/map-data-products/vector-map-data/mobile-coverage-explorer/ (accessed on June 25, 2021).

[42]These data are described here: https://doi.org/10.7910/DVN/II2DB6 (accessed on June 26, 2021).

[43]The data are described here: https://www.gallup.com/175307/gallup-poll-social-series-methodology.aspx (accessed on June 26, 2021).

sources. The main variables of interest represent the percentage of households that in the past 30 days have *(i)* used the internet to obtain the latest news/current events, *(ii)* visited a TV network or TV show's website, *(iii)* visited YouTube.com, *(iv)* visited Facebook.com, *(v)* visited CNN.com, and *(vi)* visited FoxNews.com. Other variables also represent the percentage of households that use the internet (in general), that used the internet yesterday, and that spent more than 30 minutes on the internet yesterday. The data for all these variables come from annual MRI Consumer Surveys, which cover the period from 2011 onward.[44] These data are available at both the ZIP-code and the county levels.

PolicyMap.—The data for several county-level variables come from PolicyMap, a mapping application that aggregates data with detailed geolocalization from multiple sources. The variables obtained via PolicyMap are the following:

— *Median family income*. The data cover the period from 2008 to 2019 and were originally provided by the U.S. Department of Housing and Urban Development.

— *Unemployment rate*. The data cover the period from 2008 to 2019 and were originally provided by the Bureau of Labor Statistics Local Area Unemployment Statistics Program.

— *Share of population receiving food assistance*. The data cover the period from 2008 to 2019 and were originally provided by the U.S. Census Small Area Income and Poverty Estimates.

— *Migration data*. The data cover the period from 2008 to 2017 and were originally provided by the IRS Statistics of Income Division, County-to-County Migration Data Files.

SimplyAnalytics.—The data for several county-level control variables come from SimplyAnalytics, a mapping application that aggregates data with detailed geolocalization from multiple sources. The control variables obtained via SimplyAnalytics are the following:

— *Median age of the population*. The data cover the period from 2010 to 2018 and originally come from the American Community Survey. In order not to reduce the sample to 2010-2018, the data for 2008-2009 are imputed to have the same values as in 2010.

— *Share of population that is single*. The data cover the period from 2010 to 2018 and originally come from the American Community Survey. In order not to reduce the sample to 2010–2018, the data for 2008–2009 are imputed to have the same values as in 2010.

— *Share of population that is married*. The data cover the period from 2010 to 2018 and originally come from the American Community Survey. In order not to reduce the sample to 2010–2018, the data for 2008–2009 are imputed to have the same values as in 2010.

[44] The one exception is the variable for the percentage of households that in the last 30 days have visited FoxNews.com. This variable is available only from 2017 onward.

— *Share of population that is White, Black, and Asian*. The data cover the period from 2010 to 2018 and originally come from the American Community Survey. In order not to reduce the sample to 2010–2018, the data for 2008–2009 are imputed to have the same values as in 2010.

— *Share of population that have no schooling*. The data cover the period from 2010 to 2018 and originally come from the American Community Survey. In order not to reduce the sample to 2010-2018, the data for 2008-2009 are imputed to have the same values as in 2010.

— *Share of population that have at least a bachelor's degree*. The data cover the period from 2010 to 2018 and originally come from the American Community Survey. In order not to reduce the sample to 2010–2018, the data for 2008–2009 are imputed to have the same values as in 2010.

— *Share of population with a cellular data plan.* The ZIP-code-level data are available for 2017 and originally come from the American Community Survey. These data are not used as a control variable in any of the regression specifications. Instead, these data are used in the calculation of the persuasion rates, a detailed discussion of which is presented in Appendix Section A.IV.

A.II Website classification

Misinformation websites—To construct a comprehensive list of the major websites that have been flagged as the original source of misinformation, fake news, conspiracy theories, or extremist content, I conduct the following analysis. First, I use ChatGPT to create a list of websites known to regularly publish false or misleading content. Some prominent websites on that list include well-known purveyors of misinformation such as Infowars, Breitbart News, The Daily Stormer, The Gateway Pundit, and Natural News, among many others. I complement this list by adding the identifiable websites from Wikipedia's list of fake news websites and Snopes' Field Guide to Fake News Sites and Hoax Purveyors.[45,46]

Overall, the final list of misinformation websites consists of 171 entries, which are presented in Appendix Table A23. Consistently with the findings of the existing literature (e.g., Benkler, Faris and Roberts, 2018; Bovet and Makse, 2019; Grinberg et al., 2019; Guess, Nyhan and Reifler, 2020; Gonzáles-Bailón et al., 2023), the majority of these websites espouse a right-wing ideology and publish content that systematically favors Republican politicians.

Traditional news websites—To construct a comprehensive list of the major traditional news websites, I conduct the following analysis. Focusing on websites with at least 500 visits per year, I

[45]Wikipedia's list of fake news websites can be found here: https://en.wikipedia.org/wiki/List_of_fake_news_websites (accessed on February 17, 2023).

[46]Snopes' list of fake news websites can be found here: https://www.snopes.com/news/2016/01/14/fake-news-sites/ (accessed on February 17, 2023).

use ChatGPT to create a list of websites that can generally be categorized as news-related.[47] I then manually check the classification of all the websites on this list, refining it to include only U.S.-based English-language media outlets that *(i)* publish original news content, *(ii)* cover national or local political events, *(iii)* cannot be characterized as sensationalist or yellow press, and *(iv)* have not been flagged as the source of misinformation, fake news, conspiracy theories, or extremist content. Overall, the final list of traditional news websites consists of 301 entries, which are presented in Appendix Table A24. Some of the most visited websites on the list belong to CNN, Fox News, the New York Times, USA Today, and the Washington Post.

A.III Share of the Increase in Political Polarization Explained by 3G

To calculate the share of the change in political polarization that is driven by mobile internet, I use the following formula:

$$m = 100 \times \frac{\beta_R \, \Delta 3G_R \, w_R + \beta_D \, \Delta 3G_D \, w_D}{w_R + w_D} \times \frac{1}{\Delta P} = 100 \times \frac{\Delta P_{\mathrm{I}}}{\Delta P} \tag{6}$$

ΔP denotes the overall change in polarization (i.e., the change in the share of Democratic and Republican counties' population that holds views aligned with the views of the county's dominant party); Δ3G is the average change in 3G network coverage; β denotes the regression coefficients for 3G increasing the share of population in Democratic- and Republican-leaning counties that hold views aligned with the views of the dominant party in the county; w represents the relative sample size of Democratic- and Republican-leaning counties; and D and R index Democratic- and Republican-leaning counties, respectively. All changes represent the changes between the beginning and end of the sample period.

The first part of the formula (i.e., ΔP_{I}) represents the effect of mobile internet on political polarization; the second part of the formula (i.e., ΔP)—the overall change in political polarization. The formula can only be applied when both parts have the same sign. If, instead, $\Delta P_{\mathrm{I}} \times \Delta P < 0$, m can be calculated as the absolute value of $100 \Delta P_{\mathrm{I}} / (\Delta P - \Delta P_{\mathrm{I}})$.

Appendix Table A18 presents the results of applying Formula (6) to the outcome variables for individuals' views and voting behavior. Mobile internet can account for 11.3% of the increase in polarization in political views, 37.7% of the increase in polarization in voting behavior, and, on

[47] The cutoff of 500 is chosen to ensure that it is feasible to *(i)* perform the initial classification of all the websites using ChatGPT (which has a daily usage limit) and *(ii)* manually verify the classification of all the news-related websites within a realistic time frame. However, all the major traditional news websites have considerably more than 500 visits per year (e.g., in 2008, CNN.com was visited 421,112 times). Therefore, changes to the cutoff can only affect the inclusion of small local media outlets.

average, 34.8% of the increase in polarization in policy preferences.

A.IV Persuasion Rates

The calculations of the persuasion rates are generally based on the following baseline formula developed by DellaVigna and Kaplan (2007):

$$f = 100 \times \frac{y_T - y_C}{e_T - e_C} \times \frac{1}{1 - y_0} \tag{7}$$

where e denotes exposure to the message, y is the outcome variable, y_0 is the outcome variable in the absence of the message, and T and C index the treatment and control groups, respectively. Formula (7) was later extended by Enikolopov, Petrova and Zhuravskaya (2011) to allow for continuous variation in exposure to the message, which is the case in the setting of this paper, and take into account the effect of turnout:

$$f = 100 \times \frac{1}{1 - y_0 t_0} \left(t\frac{dy}{de} + y\frac{dt}{de} \right) \tag{8}$$

where t represents turnout, and the other notation is described above. Formula (8) can also be rewritten as

$$f = 100 \times \frac{1}{1 - y_0 t_0} \left(t\frac{dy}{dn} + y\frac{dt}{dn} \right) \frac{1}{de/dn} \tag{9}$$

where n represents 3G network coverage. The main difficulty of applying Formula (9) to the effects of 3G availability on Democratic and Republican voters is that it is not immediately clear how to measure exposure to 3G internet. On the one hand, the assumption that all residents of the ZIP code are affected by the arrival of 3G would lead to the underestimation of the persuasion rates because, in reality, it is unlikely that all invidiuals were affected. On the other hand, as shown in Subsection II.E, 3G networks have an impact on multiple dimensions of internet usage and should not be thought of as a "first-stage" for any one variable (e.g., access to the internet). The variable that represents the best measure of exposure to 3G internet is the share of the ZIP codes' population that has a subscription to a cellular data plan, the data for which are available for 2017 from SimplyAnalytics.[48] By definition, 3G network coverage is necessary for an individual to use a cellular data plan. Therefore, the share of population that has a mobile internet subscription represents the share of people that are directly affected by 3G availability.[49] Nevertheless, it is

[48]The data for other years are imputed based on a linear trend.

[49]It is potentially possible that a small number of individuals have cellular data plans even though they live in ZIP codes without 3G network coverage (e.g., if they work in a ZIP code with a 3G connection and need to use mobile internet for work). However, the share of such individuals is likely to be quite small.

possible that more than one individual is affected by each subscription. For instance, if one family member has access to mobile internet, they might share information they get online with other members of the household. Thus, one can only measure exposure to 3G internet up to a factor of N, where N represents the extent of spillover effects (i.e., if $N = 1$, there are no spillover effects, and only one person is affected per connection; $N > 1$ represents the presence of spillover effects). In the context of the United States, where most individuals can afford to get a mobile internet data plan, spillover effects are unlikely to be large, but they can still play a role in determining the magnitudes of the persuasion rates.

y_0 is measured as the average of the outcome variables after subtracting the effects of 3G internet, separately for Democratic- and Republican-voting counties. A similar strategy is used for t_0 in the election regressions.[50] The measures of dy/dn and dt/dn come from the regression estimates; y and t are represented by the average values of the respective variables. Overall, the assumptions used in the calculation of the persuasion rates are exactly the same as those used by Guriev, Melnikov and Zhuravskaya (2021).

Appendix Table A19 presents the persuasion rates of the effects of 3G internet on the preferences of Republican- and Democratic-leaning voters. For residents of Democratic-leaning counties, the average persuasion rate is equal to $18.35/N$; for residents of Republican-leaning counties, it is equal to $24.85/N$. I also calculate the confidence intervals for the persuasion rates based on recent work by Jun and Lee (2023). Given that 3G network coverage (Z_i), political views (Y_i), and exposure to the treatment (subscription to a cellular data plan, T_i) are not jointly observed, the Jun-Lee confidence intervals are not very precise. Nonetheless, the estimates of the persuasion rates fall within the Jun-Lee confidence intervals.

[50]In the survey-based regressions, turnout is assumed to be universal.

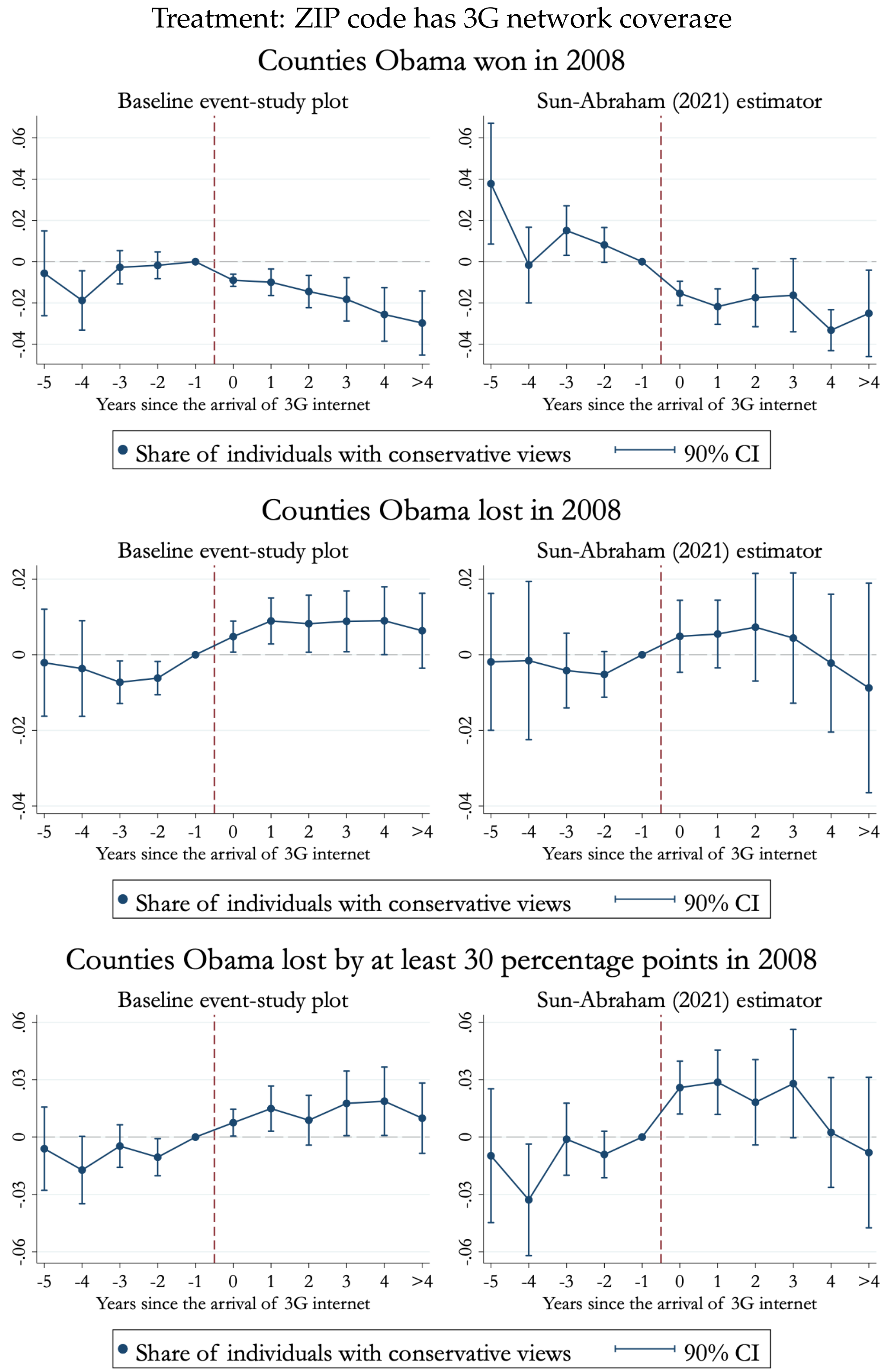

Figure A1: Event Study Analysis

Note: The figure presents an event study showing how the respondents' political views changed after the arrival of 3G internet to their ZIP code of residence. Columns 3–4 and 7–10 of Table A3 present the regression estimates. A ZIP code is defined to be treated when gets any 3G networks for the first time. The left part of the figure presents standard event-study estimates, while the right part of the figure presents the Sun-Abraham estimator.

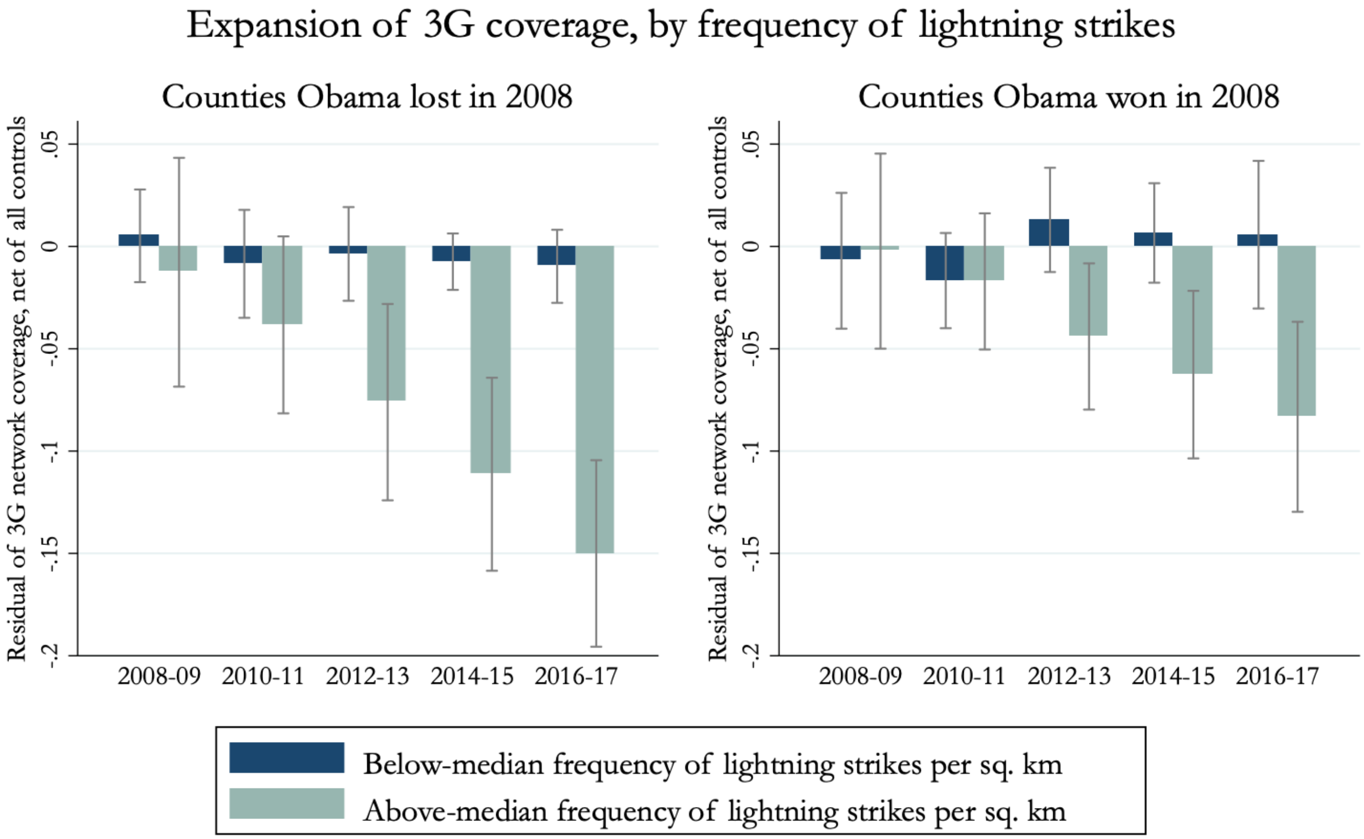

Figure A2: First stage of the IV analysis

Note: The figure illustrates the first stage of the IV analysis, described in Specification (3), showing that areas with a high frequency of lightning strikes experienced significantly slower growth in 3G network coverage. The left part of the figure illustrates the relationship in Column 1 of Table A8; the right part of the figure, the relationship in Column 4 of Table A8. The bars represent the mean residual of 3G network coverage (net of all controls) along with 95% confidence intervals. Standard errors are corrected for clusters at the level of the states and the District of Columbia.

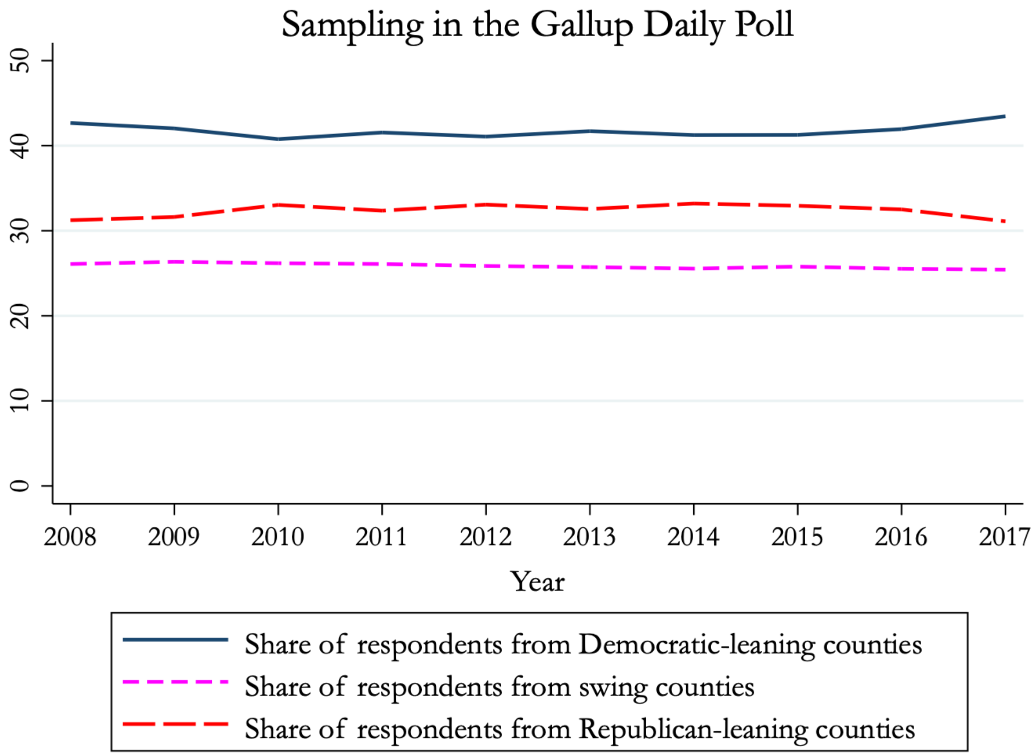

Figure A3: Sampling in the Gallup Daily Poll, by year

Note: The figure illustrates that the shares of respondents from Democratic-leaning, swing, and Republican-leaning counties have stayed stable in Gallup Daily Poll over the years.

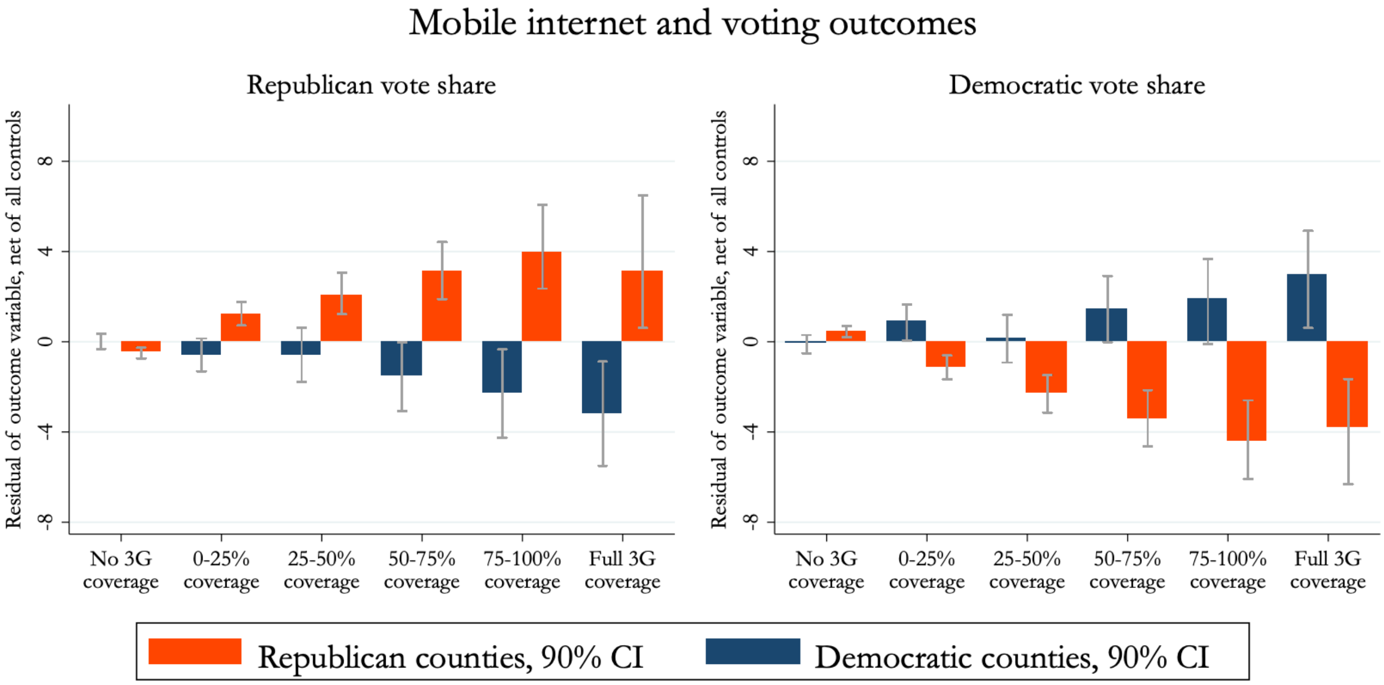

Figure A4: 3G Internet the Change in Voting Behavior

Note: The figure presents the relationship between the availability of 3G internet in a county and voting outcomes in the county. The outcome variables are the Republican and Democratic vote shares in the 2008–2018 House elections. Columns 2 and 4 of Table 3 present the regression estimates. The sample focuses on county-years when at least one Republican candidate and at least one Democratic candidate ran for office. A county is assumed to be Democratic if Obama won the county in 2008 by a margin of at least 10 percentage points; a county is assumed to be Republican if Obama lost the county in 2008 by a margin of at least 10 percentage points. The bars show the means of the outcome variable (net of all controls) along with 90% confidence intervals, which are corrected for clusters at the level of the states and the District of Columbia using 1,000 bootstrap replications, which take into account the uncertainty regarding the effects of the control variables.

Table A1: State-Year, County-Year, and Political-Affiliation-Year Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dep. Var.:	Liberal or very liberal political views						Conservative or very conservative political views					
3G network coverage ×												
× Resident of reliably Democratic county	0.013**	0.055***	0.018**				-0.016***	-0.030***	-0.017***			
	(0.006)	(0.011)	(0.008)				(0.004)	(0.010)	(0.005)			
× Resident of Democratic-leaning county	0.009***	0.037***	0.012***				-0.021***	-0.049***	-0.023***			
	(0.003)	(0.010)	(0.003)				(0.003)	(0.008)	(0.003)			
× Resident of swing county	0.002	0.011	0.005				-0.009***	-0.023***	-0.008***			
	(0.002)	(0.007)	(0.003)				(0.002)	(0.005)	(0.003)			
× Resident of Republican-leaning county	-0.006***	-0.009	-0.008***				-0.000	-0.013	0.000			
	(0.002)	(0.006)	(0.002)				(0.004)	(0.009)	(0.005)			
× Resident of reliably Republican county	-0.003	-0.013**	-0.006*				0.011***	0.006	0.006			
	(0.003)	(0.006)	(0.003)				(0.004)	(0.010)	(0.006)			
× Democratic voter				0.052***	0.059***	0.061***				-0.018***	-0.025***	-0.011*
				(0.006)	(0.008)	(0.007)				(0.005)	(0.006)	(0.006)
× Independent voter				-0.014***	-0.008**	-0.013***				-0.019***	-0.027***	-0.032***
				(0.003)	(0.003)	(0.003)				(0.003)	(0.004)	(0.003)
× Republican voter				-0.034***	-0.028***	-0.043***				0.020***	0.012***	0.028***
				(0.002)	(0.004)	(0.003)				(0.003)	(0.003)	(0.004)
Observations	1,765,113	1,764,197	1,765,113	1,765,114	1,764,198	1,765,114	1,765,113	1,764,197	1,765,113	1,765,114	1,764,198	1,765,114
R-squared	0.074	0.085	0.073	0.205	0.215	0.205	0.091	0.106	0.091	0.261	0.273	0.261
Mean dep. var	0.234	0.234	0.234	0.234	0.234	0.234	0.420	0.420	0.420	0.420	0.420	0.420
Number of clusters	51	51	51	51	51	51	51	51	51	51	51	51
Number of ZIP codes	31,499	31,458	31,499	31,499	31,458	31,499	31,499	31,458	31,499	31,499	31,458	31,499
County & year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State-year FEs	✓			✓			✓			✓		
County-year FEs		✓			✓			✓			✓	
Political-affiliation-year FEs			✓			✓			✓			✓

Note: This table presents the results of estimating Specifications (1) and (2) for respondents' political views, controlling for state-year, county-year, and political-affiliation-year fixed effects. The unit of observation is an individual. In Columns 1–6, the outcome variable is a dummy for whether the respondent describes their political views as liberal or very liberal; Columns 7–12 use a similar dummy for self-described views being conservative or very conservative. Baseline controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is male, single, married, White, Black, Asian, of multiple race, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Baseline controls also include a dummy variable for whether the ZIP code was fully covered by 3G networks in 2008 (i.e., the first year in the sample) and separate year fixed effects for the ZIP codes that were. In Columns 4–6 and 10–12, controls also include dummies for individuals' party affiliation. A county is assumed to be reliably Democratic (Republican) if Obama won (lost) the county in 2008 by a margin of at least 30 percentage points, Democratic-leaning (Republican-leaning) if Obama won (lost) by a margin of 10-30 percentage points; other counties are characterized as swing counties. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A2: Leads of 3G Network Coverage

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Political views are:					
	Liberal or very liberal			Conservative or very conservative		
3G network coverage in year t ×						
× Resident of reliably Democratic county	0.015**	0.016**	0.015**	-0.015***	-0.016***	-0.015***
	(0.007)	(0.007)	(0.007)	(0.004)	(0.005)	(0.004)
× Resident of Democratic-leaning county	0.008***	0.010***	0.008***	-0.015***	-0.017***	-0.015***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
× Resident of swing county	0.005*	0.003*	0.005*	-0.007**	-0.007**	-0.007**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
× Resident of Republican-leaning county	-0.005*	-0.006***	-0.005	0.001	0.001	0.001
	(0.003)	(0.002)	(0.003)	(0.005)	(0.004)	(0.006)
× Resident of reliably Republican county	-0.001	-0.001	-0.002	-0.002	0.002	-0.002
	(0.004)	(0.003)	(0.004)	(0.005)	(0.004)	(0.005)
3G network coverage in year t + 1 ×						
× Resident of reliably Democratic county	0.006		0.005	-0.006		-0.006
	(0.007)		(0.012)	(0.005)		(0.011)
× Resident of Democratic-leaning county	0.007		0.004	-0.009		-0.005
	(0.004)		(0.004)	(0.006)		(0.006)
× Resident of swing county	-0.004		-0.003	0.001		-0.001
	(0.004)		(0.004)	(0.004)		(0.006)
× Resident of Republican-leaning county	0.000		-0.002	-0.002		-0.000
	(0.004)		(0.005)	(0.005)		(0.007)
× Resident of reliably Republican county	-0.002		0.002	0.012		0.008
	(0.005)		(0.006)	(0.007)		(0.009)
3G network coverage in year t + 2 ×						
× Resident of reliably Democratic county		0.006	0.001		-0.005	-0.000
		(0.015)	(0.023)		(0.014)	(0.022)
× Resident of Democratic-leaning county		0.009	0.006		-0.011	-0.007
		(0.006)	(0.006)		(0.008)	(0.008)
× Resident of swing county		-0.004	-0.002		0.003	0.004
		(0.004)	(0.005)		(0.005)	(0.008)
× Resident of Republican-leaning county		0.002	0.003		-0.003	-0.003
		(0.004)	(0.005)		(0.005)	(0.005)
× Resident of reliably Republican county		-0.004	-0.005		0.009	0.004
		(0.005)	(0.006)		(0.007)	(0.008)
Observations	1,765,113	1,765,113	1,765,113	1,765,113	1,765,113	1,765,113
Mean dep. var	0.234	0.234	0.234	0.420	0.420	0.420
Number of clusters	51	51	51	51	51	51
Number of ZIP codes	31,499	31,499	31,499	31,499	31,499	31,499
County & year FEs	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓

Note: Political views are affected by the current availability of 3G coverage, not by the future availability of 3G. The unit of observation is an individual. In Columns 1–3, the outcome variable is a dummy for whether the respondent describes their political views as liberal or very liberal; Columns 4–6 use a similar dummy for self-described views being conservative or very conservative. Baseline controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. A county is assumed to be reliably Democratic (Republican) if Obama won (lost) the county in 2008 by a margin of at least 30 percentage points; Democratic-leaning (Republican-leaning) if Obama won (lost) by a margin of 10–30 percentage points; other counties are characterized as swing counties. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3: Event-Study Estimates, Democratic-Leaning and Swing Counties

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sample:	Counties Obama won in 2008				Counties Obama lost in 2008				Reliably Repub. counties	
Dep. Var.:	Liberal or very liberal		Conservative or very conservative		Liberal or very liberal		Conservative or very conservative		Conservative or very conservative	
ZIP code got 3G network coverage in:										
Year $t+5$	0.007	-0.018	-0.006	0.038**	0.001	-0.011	-0.002	-0.002	-0.006	-0.010
	(0.015)	(0.016)	(0.012)	(0.018)	(0.004)	(0.008)	(0.009)	(0.011)	(0.013)	(0.021)
Year $t+4$	0.010	-0.010	-0.019**	-0.002	0.001	-0.002	-0.004	-0.002	-0.017	-0.033*
	(0.012)	(0.011)	(0.009)	(0.011)	(0.006)	(0.009)	(0.008)	(0.013)	(0.011)	(0.018)
Year $t+3$	-0.004	-0.010	-0.003	0.015**	0.001	0.003	-0.007**	-0.004	-0.005	-0.001
	(0.005)	(0.007)	(0.005)	(0.007)	(0.003)	(0.006)	(0.003)	(0.006)	(0.007)	(0.011)
Year $t+2$	0.001	-0.002	-0.002	0.008	0.002	0.004	-0.006**	-0.005	-0.011*	-0.009
	(0.003)	(0.003)	(0.004)	(0.005)	(0.002)	(0.003)	(0.003)	(0.004)	(0.006)	(0.007)
Year t	0.005	0.014***	-0.009***	-0.015***	-0.003*	-0.006**	0.005*	0.005	0.008*	0.026***
	(0.003)	(0.004)	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.006)	(0.004)	(0.008)
Year $t-1$	0.013**	0.025***	-0.010**	-0.022***	-0.005*	-0.006*	0.009**	0.005	0.015**	0.029***
	(0.005)	(0.006)	(0.004)	(0.005)	(0.003)	(0.003)	(0.004)	(0.005)	(0.007)	(0.010)
Year $t-2$	0.017**	0.022**	-0.014***	-0.017**	-0.003	-0.012***	0.008*	0.007	0.009	0.018
	(0.007)	(0.010)	(0.005)	(0.009)	(0.003)	(0.004)	(0.005)	(0.009)	(0.008)	(0.014)
Year $t-3$	0.021**	0.025**	-0.018***	-0.016	-0.003	-0.013***	0.009*	0.004	0.018*	0.028
	(0.009)	(0.012)	(0.006)	(0.011)	(0.003)	(0.004)	(0.005)	(0.010)	(0.010)	(0.017)
Year $t-4$	0.026**	0.032**	-0.026***	-0.033***	-0.008**	-0.019***	0.009	-0.002	0.019*	0.002
	(0.011)	(0.012)	(0.008)	(0.006)	(0.004)	(0.006)	(0.005)	(0.011)	(0.011)	(0.017)
Year $t-5$ or earlier	0.030**	0.027*	-0.030***	-0.025*	-0.007	-0.019*	0.006	-0.009	0.010	-0.008
	(0.012)	(0.015)	(0.009)	(0.013)	(0.004)	(0.010)	(0.006)	(0.017)	(0.011)	(0.024)
Observations	1,009,864	656,797	1,009,864	656,797	743,914	482,713	743,914	482,713	199,086	126,843
Number of ZIP codes	14,129	13,783	14,129	13,783	17,670	16,728	17,670	16,728	5,748	5,363
Standard event study estimates	✓		✓		✓		✓		✓	
Sun-Abraham (2021) estimator		✓		✓		✓		✓		✓

Note: This table presents the event study estimates for the effects of the arrival of 3G internet on political views. A ZIP code is defined to be treated when it gets any 3G networks coverage for the first time. Odd columns present standard event-study estimates; even columns present the Sun-Abraham event-study estimator. The unit of observation is an individual. In even columns the sample is smaller because, to use last-treated ZIP codes as a valid comparison group, the Sun-Abraham estimator requires the exclusion of years when the last-treated observations were treated. As a result, in even columns, the analysis is performed for 2008-2013. In Columns 3–4 and 7–10, the outcome variable is a dummy for whether the respondent describes their political views as conservative or very conservative; Columns 1–2 and 5–6 use a similar dummy for self-described views being liberal or very liberal. Unreported controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: Oster δs for the Effects of 3G Coverage on Political Views

	(1)	(2)	(3)	(4)
Dep. Var.:	Political views are:			
	Liberal or very liberal		Conservative or very conservative	
3G network coverage ×				
× Resident of Democratic-leaning county	0.010***		-0.018***	
	(0.003)		(0.002)	
× Resident of swing county	0.000		-0.007***	
	(0.002)		(0.002)	
× Resident of Republican-leaning county	-0.006***		0.001	
	(0.002)		(0.003)	
× Democratic voter		0.051***		-0.017***
		(0.006)		(0.005)
× Independent voter		-0.015***		-0.019***
		(0.003)		(0.003)
× Republican voter		-0.035***		0.020***
		(0.002)		(0.003)
Observations	1,765,113	1,765,114	1,765,113	1,765,114
R-squared	0.073	0.205	0.091	0.260
Oster δ for 3G × Democratic political affiliation	2.335	11.391	3.269	0.989
Oster δ for 3G × Republican political affiliation	9.871	-8.787	1.756	4.664

Note: This table presents the Oster δs for the effects of 3G network coverage on individuals' political views, showing that selection on unobservable variables needs to be very high to reduce the effects of 3G coverage to zero. Following Oster (2017), I set the value of R^2_{max}—the R-squared from a hypothetical regression of the outcome variable on all observed and unobserved controls—to be equal to $1.3\tilde{R}^2$, where $\tilde{R}^2$ is the R-squared reported in the table. The unit of observation is an individual. In Columns 1 and 2, the outcome variable is a dummy for whether the respondent describes their political views as liberal or very liberal; Columns 3 and 4 use a similar dummy for self-described views being conservative or very conservative. Baseline controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Other controls include a dummy variable for whether the ZIP code was fully covered by 3G networks in 2008 (i.e., the first year in the sample) and separate year fixed effects for the ZIP codes that were. In Columns 2 and 4, controls also include dummies for individuals' party affiliation. A county is assumed to be Democratic-leaning if Obama won the county in 2008 by a margin of at least 10 percentage points, and Republican-leaning if Obama lost the county in 2008 by a margin of at least 10 percentage points; other counties are characterized as swing counties. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A5: Time-varying Fixed Effects for Urban Status and Individual Characteristics

	(1)	(2)	(3)	(4)
Dep. Var.:	Political views are:			
	Liberal or very liberal		Conservative or very conservative	
3G network coverage ×				
× Resident of Democratic-leaning county	0.012***		-0.020***	
	(0.003)		(0.003)	
× Resident of swing county	0.003		-0.010***	
	(0.002)		(0.002)	
× Resident of Republican-leaning county	-0.004**		-0.003	
	(0.002)		(0.003)	
× Democratic voter		0.053***		-0.019***
		(0.006)		(0.005)
× Independent voter		-0.013***		-0.021***
		(0.003)		(0.003)
× Republican voter		-0.035***		0.018***
		(0.002)		(0.003)
Observations	1,747,806	1,747,807	1,747,806	1,747,807
Number of ZIP codes	31,492	31,492	31,492	31,492
County & year FEs	✓	✓	✓	✓
Additional FEs	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓

Note: This table presents the results of estimating Specifications (1) and (2) for respondents' self-described political views, additionally controlling for urban-status-year, age-group-year, education-year, income-group-year, race-year, gender-year, and marital-status-year fixed effects. The unit of observation is an individual. In Columns 1 and 2, the outcome variable is a dummy for whether the respondent describes their political views as liberal or very liberal; Columns 3 and 4 use a similar dummy for self-described views being conservative or very conservative. Controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Other controls include a dummy variable for whether the ZIP code was fully covered by 3G networks in 2008 (i.e., the first year in the sample), separate year fixed effects for the ZIP codes that were, urban-status-year, age-group-year, education-year, income-group-year, race-year, gender-year, and marital-status-year fixed effects. In Columns 2 and 4, controls also include dummies for individuals' party affiliation). A county is assumed to be Democratic-leaning if Obama won the county in 2008 by a margin of at least 10 percentage points, and Republican-leaning if Obama lost the county in 2008 by a margin of at least 10 percentage points; other counties are characterized as swing counties. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: 3G Internet and Political Polarization, ZIP-Code Fixed Effects

	(1)	(2)	(3)	(4)
Dep. Var.:	Political views are:			
	Liberal or very liberal		Conservative or very conservative	
3G network coverage ×				
× Resident of Democratic-leaning county	-0.002		-0.005**	
	(0.003)		(0.003)	
× Resident of swing county	-0.006***		0.003	
	(0.002)		(0.003)	
× Resident of Republican-leaning county	-0.010***		0.011***	
	(0.002)		(0.004)	
× Democratic voter		0.045***		-0.011**
		(0.006)		(0.005)
× Independent voter		-0.018***		-0.013***
		(0.003)		(0.003)
× Republican voter		-0.036***		0.025***
		(0.002)		(0.003)
Observations	1,763,755	1,763,756	1,763,755	1,763,756
R-squared	0.099	0.222	0.113	0.275
Mean dep. var	0.234	0.234	0.420	0.420
Number of clusters	51	51	51	51
Number of ZIP codes	30,140	30,140	30,140	30,140
ZIP code & year FEs	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓

Note: This table presents the results of estimating Specifications (1) and (2) for respondents' self-described political views. The unit of observation is an individual. The number of ZIP codes is smaller than in Table 1 because ZIP codes with only one observation are automatically dropped from the sample. In Columns 1 and 2, the outcome variable is a dummy for whether the respondent describes their political views as liberal or very liberal; Columns 3 and 4 use a similar dummy for self-described views being conservative or very conservative. Controls include ZIP code and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Other controls include a dummy variable for whether the ZIP code was fully covered by 3G networks in 2008 (i.e., the first year in the sample) and separate year fixed effects for the ZIP codes that were. In Columns 2 and 4, controls also include dummies for individuals' party affiliation). A county is assumed to be Democratic-leaning if Obama won the county in 2008 by a margin of at least 10 percentage points, and Republican-leaning if Obama lost the county in 2008 by a margin of at least 10 percentage points; other counties are characterized as swing counties. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A7: 3G Network Coverage and County Socioeconomic Characteristics

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:	3G coverage in year t	3G coverage in year $t+1$	Median income in county	Unemployment rate in county	Share of population on food stamps
3G coverage in year $t-1$			-0.327	0.103	0.114
			(0.419)	(0.171)	(0.193)
Median income in county	-0.001	-0.000			
	(0.001)	(0.001)			
Unemployment rate in county	0.003	0.000			
	(0.006)	(0.007)			
Share of population on food stamps	-0.001	-0.002			
	(0.003)	(0.003)			
Share of population with no schooling	-0.002	-0.002			
	(0.006)	(0.005)			
Share of population with college degree	-0.000	-0.003			
	(0.001)	(0.002)			
Observations	34,496	34,496	34,496	34,496	34,496
Mean dep. var	0.477	0.544	56.91	6.701	14.41
Number of counties	3,139	3,139	3,139	3,139	3,139
County & year FEs	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓

Note: This table presents the relationship between 3G network coverage and the socioeconomic characteristics of the county. The unit of observation is a county. Median income is measured in thousands. Baseline controls include county and year fixed effects, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. The three outcome variables in Columns 3–5 are excluded from the list of controls in those regressions. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A8: Lightning Strikes, 3G Network Coverage, and Political Views

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Counties Obama lost in 2008			Counties Obama won in 2008		
Dep. Var.:	3G network coverage	Political views: conservative or very conservative		3G network coverage	Political views: liberal or very liberal	
Lightning strikes per km$^2 \times t$	-0.438***	-0.017***		-0.106***	-0.003**	
	(0.114)	(0.005)		(0.024)	(0.001)	
3G network coverage			0.038**			0.025*
			(0.016)			(0.014)
Anderson-Rubin 90% CI			*[0.018, 0.080]*			*[0.007, 0.058]*
Observations	749,786	749,786	749,786	1,013,599	1,013,599	1,013,599
F-stat, excluded instrument			14.68			20.42
Mean dep. var	0.621	0.506	0.506	0.791	0.282	0.282
Number of clusters	47	47	47	51	51	51
Number of ZIP codes	17,707	17,707	17,707	14,173	14,173	14,173
County & year FEs	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓	✓	✓

Note: This table presents the IV results, where 3G network coverage is predicted using the frequency of lightning strikes. The unit of observation is an individual. In Columns 1–3, the sample consists of counties that Obama lost in 2008; in Columns 4-6, the counties that Obama won in 2008. In Columns 1 and 4, the outcome variable is the share of the ZIP code's territory that has 3G network coverage; in the other columns, a dummy for whether an individual holds certain political views. The frequency of lightning strikes is measured in standard deviations. Baseline controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Additional controls used in the IV analysis include separate year fixed effects for all quartiles of county population size, the log of maximum elevation in the county interacted with a time trend, and the share of the counties' territory that is uninhabited interacted with a time trend. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. In Columns 1–3, the number of clusters is smaller because Obama won all the counties in Connecticut, the District of Columbia, Hawaii, and Vermont. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: 2G Network Coverage and Political Views

	(1)	(2)	(3)	(4)
Dep. Var.:	Political views are:			
	Liberal or very liberal		Conservative or very conservative	
2G network coverage ×				
× Counties Obama won in 2008	-0.003	-0.007	-0.003	0.001
	(0.004)	(0.005)	(0.004)	(0.004)
× Counties Obama lost in 2008	-0.002	0.003	0.002	-0.003
	(0.002)	(0.002)	(0.003)	(0.003)
3G network coverage ×				
× Counties Obama won in 2008		0.011***		-0.015***
		(0.003)		(0.003)
× Counties Obama lost in 2008		-0.004***		0.001
		(0.001)		(0.003)
Observations	1,762,802	1,762,795	1,762,802	1,762,795
Mean dep. var	0.234	0.234	0.420	0.420
Number of clusters	51	51	51	51
Number of ZIP codes	31,066	31,063	31,066	31,063
County & year FEs	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓

Note: This table presents the relationship between 2G network coverage and individuals' political views. The unit of observation is an individual. In Columns 1 and 2, the outcome variable is a dummy for whether the respondent describes their political views as liberal or very liberal; Columns 3 and 4 use a similar dummy for self-described views being conservative or very conservative. Baseline controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** p<0.01, ** p<0.05, * p<0.1.

Table A10: 3G Coverage and Political Views, Landline and Cellphone Subsamples

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Political views are:					
	Liberal or very liberal			Conservative or very conservative		
3G network coverage ×						
× Resident of Democratic-leaning county	0.010***	0.010***	0.013*	-0.018***	-0.021***	-0.020***
	(0.003)	(0.003)	(0.007)	(0.002)	(0.002)	(0.007)
× Resident of swing county	0.000	0.000	0.005	-0.007***	-0.009***	-0.008
	(0.002)	(0.002)	(0.006)	(0.002)	(0.003)	(0.006)
× Resident of Republican-leaning county	-0.006***	-0.004**	-0.010**	0.001	0.001	0.016**
	(0.002)	(0.002)	(0.005)	(0.003)	(0.004)	(0.006)
Observations	1,765,113	1,140,615	624,479	1,765,113	1,140,615	624,479
Mean dep. var	0.234	0.222	0.255	0.420	0.439	0.384
Number of ZIP codes	31,499	30,843	28,011	31,499	30,843	28,011
Full sample	✓			✓		
Subsample of landline phone interviews		✓			✓	
Subsample of cellphone interviews			✓			✓

Note: This table presents the effects of 3G network coverage on individuals' political views, separately for individuals interviewed landline phone and cellphone. The unit of observation is an individual. In Columns 1 and 2, the outcome variable is a dummy for whether the respondent describes their political views as liberal or very liberal; Columns 3 and 4 use a similar dummy for self-described views being conservative or very conservative. Baseline controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Other controls include a dummy variable for whether the ZIP code was fully covered by 3G networks in 2008 (i.e., the first year in the sample) and separate year fixed effects for the ZIP codes that were. In Columns 1 and 3, the sample consists of people interviewed via landline phone; in Columns 2 and 4—people interviewed via cellphone. A county is assumed to be Democratic-leaning if Obama won the county in 2008 by a margin of at least 10 percentage points, and Republican-leaning if Obama lost the county in 2008 by a margin of at least 10 percentage points; other counties are characterized as swing counties. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** p<0.01, ** p<0.05, * p<0.1.

Table A11: 3G Network Coverage and Migration

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	In-migration rate		Out-migration rate		Net-migration rate	
3G network coverage ×	0.121		0.079		0.042	
	(0.073)		(0.048)		(0.061)	
3G network coverage ×						
× Resident of Democratic-leaning county		0.004		0.111		-0.106
		(0.110)		(0.090)		(0.073)
× Resident of Republican-leaning county		0.129		0.037		0.093
		(0.095)		(0.058)		(0.077)
Observations	30,545	30,545	30,545	30,545	30,545	30,545
Mean dep. var	4.868	4.868	4.807	4.807	0.062	0.062
Number of counties	3,121	3,121	3,121	3,121	3,121	3,121
County & year FEs	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓

Note: This table presents the relationship between 3G network coverage and migration. The unit of observation is a county. The outcome variables are measured in percentage points. Baseline controls include county and year fixed effects, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. A county is assumed to be Democratic-leaning if Obama won the county in 2008 by a margin of at least 10 percentage points, and Republican-leaning if Obama lost the county in 2008 by a margin of at least 10 percentage points. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A12: Counties' Political Affiliation using Bush 2004 results

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Political views are:					
	Liberal or very liberal			Conservative or very conservative		
3G network coverage ×						
× Resident of county Bush lost by at least 10 percentage points in 2004	0.011**	0.012**	0.014**	-0.017***	-0.017***	-0.016***
	(0.004)	(0.005)	(0.005)	(0.003)	(0.003)	(0.004)
× Resident of county Bush won or lost by less than 10 percentage points in 2004	0.006**	0.006**	0.011***	-0.014***	-0.015***	-0.019***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
× Resident of county Bush won by at least 10 percentage points in 2004	-0.005***	-0.004**	-0.007***	-0.000	0.000	0.002
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Observations	1,745,504	1,745,504	1,745,504	1,745,504	1,745,504	1,745,504
Mean dep. var	0.233	0.233	0.233	0.420	0.420	0.420
Number of ZIP codes	31,349	31,349	31,349	31,349	31,349	31,349
County & year FEs	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓
State-year FEs		✓			✓	
Political-affiliation-year FEs			✓			✓

Note: The results are robust to using the classification of the counties' political affiliation based on the 2004 presidential election. The unit of observation is an individual. In Columns 1–3, the outcome variable is a dummy for whether the respondent describes their political views as liberal or very liberal; Columns 4–6 use a similar dummy for self-described views being conservative or very conservative. Baseline controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Columns 2 and 5 include dummies for state-year fixed effects; Columns 3 and 6 include separate year dummies for democratic, republican, and swing counties (based on the counties' vote shares in the 2004 presidential election). Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** p<0.01, ** p<0.05, * p<0.1.

Table A13: 3G Internet and Political Polarization, by Past Vote Type

	(1)	(2)	(3)	(4)
Dep. Var.:	Political views are:			
	Liberal or very liberal		Conservative or very conservative	
3G network coverage ×				
× Voted for Democratic presidential nominee in last election	0.045***	0.050***	0.008	0.001
	(0.007)	(0.008)	(0.007)	(0.007)
× Voted for Republican presidential nominee in last election	-0.017***	-0.016***	0.013*	0.021***
	(0.005)	(0.005)	(0.007)	(0.007)
Observations	293,588	293,588	293,588	293,588
Mean dep. var	0.286	0.286	0.387	0.387
Number of clusters	51	51	51	51
Number of ZIP codes	21,701	21,701	21,701	21,701
County & year FEs	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓
Political-affiliation-year FEs		✓		✓

Note: This table presents the results of estimating Specification (2) for individuals who voted for the Democratic and Republican presidential nominees in the last election. The unit of observation is an individual. In Columns 1 and 2, the outcome variable is a dummy for whether the respondent describes their political views as liberal or very liberal; Columns 3 and 4 use a similar dummy for self-described views being conservative or very conservative. Baseline controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Other controls include a dummy variable for whether the ZIP code was fully covered by 3G networks in 2008 (i.e., the first year in the sample) and separate year fixed effects for the ZIP codes that were. Observations are weighted by survey weights. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A14: Policy Preferences and Leads of 3G Network Coverage

	(1)	(2)	(3)	(4)
Dep. Var.:	Always allow abortion	Support gay marriage	Repeal the ACA	Increase border security
3G network coverage in year t $\times$				
$\times$ Resident of Democratic-leaning county	0.005	0.032**	-0.001	-0.030
	(0.008)	(0.016)	(0.046)	(0.024)
$\times$ Resident of swing county	-0.002	0.019	0.011	-0.009
	(0.009)	(0.014)	(0.029)	(0.016)
$\times$ Resident of Republican-leaning county	-0.015**	-0.031**	0.038*	0.036***
	(0.007)	(0.012)	(0.022)	(0.011)
3G network coverage in year $t+1$ $\times$				
$\times$ Resident of Democratic-leaning county	0.017	0.010	-0.058	0.004
	(0.012)	(0.016)	(0.051)	(0.033)
$\times$ Resident of swing county	0.011	-0.003	-0.010	-0.015
	(0.012)	(0.012)	(0.036)	(0.022)
$\times$ Resident of Republican-leaning county	0.004	-0.003	-0.023	-0.031*
	(0.009)	(0.013)	(0.025)	(0.018)
Observations	394,518	316,521	278,657	356,933
R-squared	0.110	0.108	0.109	0.107
Mean dep. var	0.536	0.578	0.486	0.523
Number of clusters	51	51	51	51
Number of ZIP codes	23,216	22,450	21,375	22,614
County & year FEs	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓

Note: Policy preferences are affected by current 3G network coverage, not future availability of 3G. The unit of observation is an individual. The outcome variables are dummies for the respondents' policy preferences. Baseline controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. In Columns 1, 2, and 4, additional controls include a dummy variable for whether the ZIP code was fully covered by 3G networks in 2008 and separate year fixed effects for the ZIP codes that were. In Column 3, additional controls include the same specification with 3G networks in 2012. The reason for the change is that the question about repealing the ACA was first asked in 2012. A county is assumed to be Democratic-leaning if Obama won the county in 2008 by a margin of at least 10 percentage points, and Republican-leaning if Obama lost the county in 2008 by a margin of at least 10 percentage points; other counties are characterized as swing counties. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A15: 3G Internet and the Main Problem Facing the Country

	(1)	(2)	(3)	(4)
Dep. Var.:	Main problem facing the country:			
	Immigration	Inequality	Race	Guns
3G network coverage ×				
× Resident of Democratic-leaning county	0.005	0.007***	0.001	0.001
	(0.003)	(0.002)	(0.002)	(0.001)
× Resident of swing county	-0.000	-0.003*	-0.002	-0.001
	(0.003)	(0.001)	(0.002)	(0.001)
× Resident of Republican-leaning county	0.008**	-0.004***	-0.008***	-0.003***
	(0.003)	(0.001)	(0.002)	(0.001)
Observations	105,217	105,217	105,217	105,217
R-squared	0.060	0.032	0.062	0.037
Mean dep. var	0.041	0.012	0.020	0.008
Number of clusters	51	51	51	51
Number of ZIP codes	20,392	20,392	20,392	20,392
County & year FEs	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓

Note: This table presents the results of estimating Specification (1) for the respondents' views on the most important problems facing the country. The unit of observation is an individual. The outcome variables are dummies for whether the respondent considers this problem to be the most important problem facing the country today. Baseline controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Other controls include a dummy variable for whether the ZIP code was fully covered by 3G networks in 2008 (i.e., the first year in the sample) and separate year fixed effects for the ZIP codes that were. A county is assumed to be Democratic-leaning if Obama won the county in 2008 by a margin of at least 10 percentage points, and Republican-leaning if Obama lost the county in 2008 by a margin of at least 10 percentage points; other counties are characterized as swing counties. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** p<0.01, ** p<0.05, * p<0.1.

Table A16: Voting Outcomes and Leads of 3G Network Coverage

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Republican vote share (R)		Democratic vote share (D)		Republican vote margin (R-D)	
3G network coverage in year t $\times$						
$\times$ Resident of Democratic-leaning county	-4.567**	-1.571	4.393*	1.403	-8.960**	-2.974
	(2.240)	(0.964)	(2.261)	(1.056)	(4.380)	(1.955)
$\times$ Resident of swing county	1.287	1.497	0.017	-0.770	1.271	2.267
	(1.635)	(1.281)	(1.733)	(1.207)	(3.185)	(2.305)
$\times$ Resident of Republican-leaning county	3.687**	3.900***	-3.823*	-4.703***	7.509**	8.602***
	(1.531)	(1.157)	(2.216)	(1.455)	(3.675)	(2.500)
3G network coverage in year $t+1$ $\times$						
$\times$ Resident of Democratic-leaning county	-0.377	-1.049	-0.346	1.151	-0.031	-2.200
	(2.653)	(1.569)	(2.232)	(1.575)	(4.724)	(3.099)
$\times$ Resident of swing county	0.768	2.333	-2.457	-2.911	3.225	5.245*
	(1.839)	(1.424)	(1.999)	(1.752)	(3.681)	(3.094)
$\times$ Resident of Republican-leaning county	1.352	1.061	-1.201	-0.260	2.553	1.321
	(1.485)	(1.320)	(2.380)	(1.935)	(3.730)	(3.183)
Observations	18,573	16,864	18,573	16,864	18,573	16,864
R-squared	0.793	0.858	0.779	0.857	0.795	0.862
Mean dep. var	60.74	59.53	36.08	38.11	24.66	21.42
Number of counties	3,110	3,110	3,110	3,110	3,110	3,110
County & year FEs	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓
Excluding unopposed races		✓		✓		✓

Note: Voting outcomes are affected by current 3G network coverage, not future availability of 3G. The unit of observation is a county. The outcomes are measured in percentage points. In the odd columns, the results are reported for the full sample; in the even columns, for county-years with at least one Democrat and at least one Republican running for office. Alaska is excluded from the sample because, in Alaska, election results are not available at the county level. Baseline controls include county and year fixed effects, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Other controls include a dummy variable for whether the county was fully covered by 3G networks in 2008 (i.e., the first year in the sample) and separate year fixed effects for the counties that were. A county is assumed to be Democratic-leaning if Obama won the county in 2008 by a margin of at least 10 percentage points, and Republican-leaning if Obama lost the county in 2008 by a margin of at least 10 percentage points; other counties are characterized as swing counties. Standard errors in parentheses are corrected for clusters at the level of the states. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A17: 3G Internet and Visits to Specific Websites

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	Share of visits to the website of _____ among all webpages visited (in standard deviations):							
	CNN	Fox News	MSNBC	CBS News	WSJ	NYT	WP	Conservative news websites
3G network coverage ×								
× Resident of county Obama won in 2008	0.047**	0.019	-0.002	-0.021	0.003	0.002	-0.007	0.017
	(0.018)	(0.013)	(0.018)	(0.015)	(0.013)	(0.016)	(0.015)	(0.013)
× Resident of county Obama lost in 2008	0.006	0.005	-0.061***	-0.038**	-0.028**	-0.029**	-0.065***	0.010
	(0.016)	(0.017)	(0.019)	(0.016)	(0.013)	(0.011)	(0.020)	(0.016)
Observations	155,480	155,480	155,480	155,480	155,480	155,480	155,480	155,480
Number of ZIP codes	21,430	21,430	21,430	21,430	21,430	21,430	21,430	21,430
ZIP code & year FEs	✓	✓	✓	✓	✓	✓	✓	✓

Note: This table presents how the expansion of mobile internet affected individuals' visits to specific news websites. The unit of observation is a ZIP code. The outcome variables are the share of visits to the respective website or website category among all webpages visited, measured in standard deviations. Baseline controls include ZIP code and year fixed effects. Additional controls include the log of the total number of websites visited interacted with dummies for whether Obama won or lost the county in 2008. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** p<0.01, ** p<0.05, * p<0.1.

Table A18: Share of Increase in Political Polarization Explained by 3G

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Political views	Voting	Abortion	Gay marriage	The ACA	Border security
Share of increase in political polarization explained by 3G	11.3%	37.7%	22.1%	97.6%	12.8%	6.8%
Source of results:	Tab. A4, Col. 2 and 4	Tab. 3, Col. 2 and 4	Tab. 2, Col. 1	Tab. 2, Col. 2	Tab. 2, Col. 3	Tab. 2, Col. 4
Regression estimates for Democratic counties (β_D)	0.010***	2.396*	0.013**	0.037***	0.053***	0.029***
	(0.003)	(1.355)	(0.006)	(0.011)	(0.019)	(0.010)
Regression estimates for Republican counties (β_R)	0.001	4.540***	0.012**	0.033***	0.027	0.017**
	(0.003)	(1.249)	(0.006)	(0.009)	(0.016)	(0.007)
Increase in polarization (ΔP)	0.034	7.765	0.038	0.024	0.014	0.075
Increase in 3G coverage, Democratic counties ($\Delta 3G_D$)	0.613	0.687	0.607	0.601	0.020	0.126
Increase in 3G coverage, Republican counties ($\Delta 3G_R$)	0.775	0.733	0.780	0.749	0.109	0.432
Share of Democratic counties (w_D)	0.418	0.180	0.454	0.456	0.457	0.456
Share of Republican counties (w_R)	0.323	0.575	0.287	0.284	0.284	0.284

Note: This table reports the share of the increase in poltical polarization that can be explained by mobile internet, using Formula (6). Further details of the calculations are available in Appendix Section A.III. *** p<0.01, ** p<0.05, * p<0.1.

Table A19: Persuasion Rates

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Liberal or very liberal political views			Conservative or very conservative political views		
Persuasion rate	5.33/N	15.26/N	12.89/N	19.50/N	0.87/N	30.39/N
Jun-Lee persuasion CI	[1.16, 1]	[2.23, 1]	[2.68, 1]	[4.24, 1]	[0.13, 1]	[4.55, 1]
Source of results:	Tab. A4, Col. 2	Tab. A4, Col. 2	Tab. A8, Col. 6	Tab. A4, Col. 4	Tab. A4, Col. 4	Tab. A8, Col. 3
Political affiliation:	Democratic	Republican	Democratic	Democratic	Republican	Republican
Regression estimates	0.010***	-0.006***	0.025*	-0.018***	0.001	0.038**
	(0.003)	(0.002)	(0.014)	(0.002)	(0.003)	(0.016)
Cellular coverage (*de/ds*)	0.266N	0.240N	0.263N	0.266N	0.240N	0.242N
Mean of dep. var.	0.303	0.160	0.282	0.332	0.522	0.506
Mean of 3G coverage	0.816	0.608	0.791	0.816	0.608	0.620
	(7)	(8)	(9)	(10)	(11)	(12)
Dep. Var.:	Republican vote share (R)		Democratic vote share (D)		Always allow abortion	
Persuasion rate	37.73/N	6.84/N	1.48/N	75.67/N	10.01/N	9.23/N
Jun-Lee persuasion CI	[3.59, 1]	[6.10, 1]	[3.15, 1]	[6.93, 1]	[2.97, 1]	[2.03, 1]
Source of results:	Tab. 3, Col. 2	Tab. 3, Col. 2	Tab. 3, Col. 4	Tab. 3, Col. 4	Tab. 2, Col. 1	Tab. 2, Col. 1
Political affiliation:	Democratic	Republican	Democratic	Republican	Democratic	Republican
Regression estimates	-2.577*	4.540***	2.396*	-4.789***	0.013**	-0.012**
	(1.390)	(1.249)	(1.355)	(1.190)	(0.006)	(0.006)
Effect on turnout	-1.068**	-0.753*	-1.068**	-0.753*		
	(0.415)	(0.440)	(0.415)	(0.440)		
Cellular coverage (*de/ds*)	0.245N	0.228N	0.245N	0.228N	0.327N	0.298N
Mean of dep. var.	37.12	68.78	60.56	28.76	0.615	0.427
Mean of 3G coverage	0.536	0.447	0.536	0.447	0.906	0.738
Mean of turnout	38.58	37.12	38.58	37.12		
	(13)	(14)	(15)	(16)	(17)	(18)
Dep. Var.:	Support gay marriage		Repeal the ACA		Increase border security	
Persuasion rate	33.22/N	25.53/N	28.36/N	16.57/N	16.66/N	11.02/N
Jun-Lee persuasion CI	[8.36, 1]	[4.49, 1]	[11.15, 1]	[5.43, 1]	[5.59, 1]	[3.21, 1]
Source of results:	Tab. 2, Col. 2	Tab. 2, Col. 2	Tab. 2, Col. 3	Tab. 2, Col. 3	Tab. 2, Col. 4	Tab. 2, Col. 4
Political affiliation:	Democratic	Republican	Democratic	Republican	Democratic	Republican
Regression estimates	0.037***	-0.033***	-0.053***	0.027	-0.029***	0.017**
	(0.011)	(0.009)	(0.019)	(0.016)	(0.010)	(0.007)
Cellular coverage (*de/ds*)	0.284N	0.254N	0.404N	0.373N	0.354N	0.326N
Mean of dep. var.	0.640	0.486	0.411	0.587	0.465	0.542
Mean of 3G coverage	0.888	0.692	0.973	0.879	0.950	0.894

Note: This table presents the persuasion rates of the effects of 3G internet on political outcomes. N represents the number of individuals that are affected by the internet's "message" per cellular data plan subscription (i.e., if $N = 1$, there are no spillover effects, and only one person is affected per connection; $N > 1$ indicates the presence of spillover effects). The calculation of the persuasion rates is based on the formulas in Enikolopov, Petrova and Zhuravskaya (2011), which are also reproduced in Appendix Section A.IV. Further details of the calculations are available in Appendix Section A.IV. *** p<0.01, ** p<0.05, * p<0.1.

Table A20: Heterogeneity by Education, Income, and Employment Status

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Political views are:					
	Conservative or very conservative			Liberal or very liberal		
3G network coverage ×						
× Less than high school degree	0.070***			-0.036***		
	(0.006)			(0.005)		
× High school degree	0.009**			-0.008***		
	(0.004)			(0.003)		
× Technical/Vocational school	-0.004			-0.005*		
	(0.004)			(0.003)		
× Some college education	-0.008**			0.000		
	(0.003)			(0.002)		
× College degree	-0.033***			0.013***		
	(0.003)			(0.003)		
× Post-graduate degree	-0.019***			0.011**		
	(0.004)			(0.004)		
× Income < \$24,000		0.026***			-0.015***	
		(0.003)			(0.003)	
× \$24,000 ≤ Income < \$48,000		-0.001			0.004	
		(0.003)			(0.003)	
× \$48,000 ≤ Income < \$90,000		-0.018***			0.010***	
		(0.003)			(0.002)	
× Income ≥ \$90,000		-0.031***			0.008***	
		(0.004)			(0.003)	
× Employed			-0.025***			0.009**
			(0.004)			(0.004)
× Unemployed			-0.003			-0.004
			(0.005)			(0.004)
× Out of labor force			0.018***			-0.009**
			(0.004)			(0.004)
Observations	1,765,114	1,765,114	1,244,135	1,765,114	1,765,114	1,244,135
Mean dep. var	0.420	0.420	0.421	0.234	0.234	0.235
Number of ZIP codes	31,499	31,499	30,934	31,499	31,499	30,934
County & year FEs	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓

Note: This table illustrates the heterogeneity of the effects of 3G coverage by education, income, and employment status. The unit of observation is an individual. In Columns 1–3, the outcome variable is a dummy for whether the respondent describes their political views as conservative or very conservative; Columns 4–6 use a similar dummy for self-described views being liberal or very liberal. Baseline controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Other controls include a dummy variable for whether the ZIP code was fully covered by 3G networks in 2008 (i.e., the first year in the sample) and separate year fixed effects for the ZIP codes that were. In Columns 3 and 6, controls also include dummies for individuals' employment status. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** p<0.01, ** p<0.05, * p<0.1.

Table A21: Heterogeneity by Age and Political Affiliation

	(1)	(2)
Dep. Var.:	Political views are:	
	Conservative or very conservative	Liberal or very liberal
3G network coverage $\times$ Age ≤ 40 $\times$		
$\times$ Resident of Democratic-leaning county	-0.023***	0.015***
	(0.004)	(0.004)
$\times$ Resident of swing county	-0.027***	0.005
	(0.004)	(0.004)
$\times$ Resident of Republican-leaning county	-0.032***	0.007**
	(0.006)	(0.003)
3G network coverage $\times$ Age > 40 $\times$		
$\times$ Resident of Democratic-leaning county	-0.017***	0.008**
	(0.003)	(0.004)
$\times$ Resident of swing county	-0.002	0.000
	(0.002)	(0.002)
$\times$ Resident of Republican-leaning county	0.010***	-0.008***
	(0.003)	(0.002)
Observations	1,747,806	1,747,806
Mean dep. var	0.419	0.234
Number of ZIP codes	31,492	31,492
County & year FEs	✓	✓
Baseline controls	✓	✓

Note: This table illustrates the heterogeneity of the effects of 3G network coverage by age, showing that polarization primarily increased among older individuals, which is consistent with the findings in Boxell, Gentzkow and Shapiro (2017). The unit of observation is an individual. In Column 1, the outcome variable is a dummy for whether the respondent describes their political views as conservative or very conservative; Column 2 uses a similar dummy for self-described views being liberal or very liberal. Baseline controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Other controls include non-collinear lower-level interactions between 3G network coverage, the political affiliation of the counties, and the dummies for the two age groups as well as a dummy variable for whether the ZIP code was fully covered by 3G networks in 2008 (i.e., the first year in the sample) and separate year fixed effects for the ZIP codes that were. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** p<0.01, ** p<0.05, * p<0.1.

Table A22: Heterogeneity by Time

	(1)	(2)
Dep. Var.:	Political views are:	
	Conservative or very conservative	Liberal or very liberal
Resident of Democratic county ×		
× 3G network coverage ×		
× 2008-2009	-0.015*** (0.003)	0.007* (0.004)
× 2010-2011	-0.017*** (0.004)	0.007* (0.004)
× 2012-2013	-0.025*** (0.004)	0.012*** (0.004)
× 2014-2015	-0.021*** (0.005)	0.007 (0.006)
× 2016-2017	-0.050*** (0.006)	0.030*** (0.006)
Resident of Republican county ×		
× 3G network coverage ×		
× 2008-2009	0.010* (0.005)	-0.013*** (0.002)
× 2010-2011	0.007 (0.005)	-0.002 (0.003)
× 2012-2013	-0.006 (0.005)	-0.003 (0.003)
× 2014-2015	-0.005 (0.005)	-0.001 (0.005)
× 2016-2017	-0.026*** (0.005)	0.003 (0.005)
Observations	1,765,113	1,765,113
Mean dep. var	0.420	0.234
Number of ZIP codes	31,499	31,499
County & year FEs	✓	✓
Baseline controls	✓	✓

Note: This table illustrates the heterogeneity of the effects of 3G network coverage by time. The unit of observation is an individual. In Column 1, the outcome variable is a dummy for whether the respondent describes their political views as conservative or very conservative; Column 2 uses a similar dummy for self-described views being liberal or very liberal. Baseline controls include county and year fixed effects, dummies for the respondents' gender, race, age, education level, marital status, and income group, the counties' unemployment rate, log of median household income, median age, and share of population that is single, married, White, Black, Asian, has no schooling, has at least a bachelor's degree, and is receiving food assistance. Other controls include a dummy variable for whether the ZIP code was fully covered by 3G networks in 2008 (i.e., the first year in the sample) and separate year fixed effects for the ZIP codes that were. Standard errors in parentheses are corrected for clusters at the level of the states and the District of Columbia. *** p<0.01, ** p<0.05, * p<0.1.

Table A23: List of Misinformation Websites

#	70news.wordpress.com
A	abcnews.com.co, actionnews3.com, activistpost.com, alqaida.com, americanmilitarynews.com, americannews.com, americanresistance3-0.com, americanthinker.com, amgreatness.com, amren.com, avoiceformen.com
B	beforeitsnews.com, bients.com, bipartisanreport.com, bizpacreview.com, bizstandardnews.com, bloomberg.ma, breaking-cnn.com, breitbart.com, burrardstreetjournal.com
C	cairnsnews.org, cbsnews.com.co, celebtricity.com, childrenshealthdefense.org, christiantimes.com, civictribune.com, cnn-trending.com, collective-evolution.com, conservative101.com, conservativedailynews.com, conservativedailypost.com, conservativefrontline.com, conservativestate.com, conservativetribune.com, corbettreport.com, counter-currents.com, countynewsroom.info
D	dailycaller.com, dailystormer.com, dailystormer.in, dailystormer.su, dailywire.com, davidicke.com, dcclothesline.com, denverguardian.com, disclose.tv, drudgereport.com.co
E	empireherald.com, empirenews.net, endingthefed.com, expose-news.com
F	fbnewscycle.com, fixthisnation.com, fox-news24.com, frontpagemag.com
G	gab.com, gaia.com, globalassociatednews.com, globalresearch.ca, godtoday.org, gossipmillsa.com, greatgameindia.com, guerrillanews.com, gummypost.com
H	healthimpactnews.com, highwire.com, houstonchronicle-tv.com, huzlers.com
I	ifyouonlynews.com, infowars.com
J	judicialwatch.org
L	lawenforcementtoday.com, liberalsociety.com, libertywriters.com, linkbeef.com
M	mercola.com, mintpressnews.com, mtonews.com
N	nahadaily.com, nationalenquirer.com, nationalinsiderpolitics.com, nationalreport.net, naturalblaze.com, naturalnews.com, naturalnewsradio.com, nbcnews.com.co, neonnettle.com, newobserveronline.com, newsbreakshere.com, newsbuzzdaily.com, newsexaminer.net, newsmax.com, newspunch.com, newswatch28.com, newswatch33.com, nextnewsnetwork.com, now8news.com, ntd.tv
O	oann.com, oathkeepers.org, occidentaldissent.com, occupydemocrats.com, officialproudboys.com, oneworld.press, opindia.com
P	palmerreport.com, patriotfront.us, peacedata.net, pjmedia.com, politicops.com, postcard.news, prntly.com, projectveritas.com
R	realnewsrightnow.com, redice.tv, redstate.com, reporterz.com, rilenews.com, ronpaulinstitute.org, rt.com
S	sgtreport.com, snoopack.com, sott.net, spinzon.com, sputniknews.com, stgeorgegazette.com, stormfront.org, summit.news, superstation95.com

T	theblaze.com, thebostontribune.com, theconservativetreehouse.com, thedcgazette.com, theduran.com, theepochtimes.com, thefederalist.com, thefreethoughtproject.com, thegatewaypundit.com, thegrayzone.com, thehighwire.com, thelastlineofdefense.org, thenationalpulse.com, thenewamerican.com, thenewyorkevening.com, theoccidentalobserver.net, thepoliticalinsider.com, thepredicted.com, thereporterz.com, therightscoop.com, therightstuff.biz, townhall.com, truetrumpers.com, trunews.com, truthdig.com, truthout.com
U	uconservative.com, undergroundnewsreport.com, unitedmediapublishing.com, unz.com, usadailyinfo.com, usatoday.com.co, uspostman.com
V	vdare.com, veteranstoday.com, viralmugshot.com
W	washingtonexaminer.com, washingtonpost.com.co, washingtonpress.com, westernjournal.com, whatdoesitmean.com, winningdemocrats.com, wnd.com, worldnewsdailyreport.com, worldnewsreport.com, worldtruth.tv, wtoe5news.com
Y	yournewswire.com
Z	zerohedge.com

Table A24: List of U.S. News Websites (in English)

#	10tv.com, 6abc.com, 9news.com
A	abc11.com, abc13.com, abc27.com, abc7.com, abc7chicago.com, abc7news.com, abc7ny.com, abcactionnews.com, ajc.com, al.com, americanactionnews.com, ap.org, apnews.com, arkansasonline.com, atholdailynews.com, axios.com, azcentral.com,
B	baltimoresun.com, bangordailynews.com, baynews9.com, bizjournals.com, boston.com, bostonglobe.com, bostonherald.com, buffalonews.com, businessinsider.com, buzzfeednews.com
C	cbslocal.com, cbsnews.com, charlotteobserver.com, channel3000.com, chattanoogan.com, chicagotribune.com, chron.com, chronicle.com, cincinnati.com, city-journal.org, citypages.com, clarionledger.com, cleveland.com, click2houston.com, clickondetroit.com, cnbc.com, cnn.com, columbian.com, commondreams.org, courant.com, courierpostonline.com, courier-tribune.com
D	dailyherald.com, dallasnews.com, daytondailynews.com, decaturdaily.com, democratandchronicle.com, desmoinesregister.com, denverpost.com, deseretnews.com, detroitnews.com, dispatch.com, dogonews.com
E	economist.com, elkodaily.com
F	factcheck.org, fayobserver.com, fivethirtyeight.com, forbes.com, fortune.com, fox11online.com, fox13news.com, fox13now.com, fox2detroit.com, fox2now.com, fox4kc.com, fox4news.com, fox5sandiego.com, fox59.com, fox61.com, fox6now.com, fox8.com, foxbusiness.com, foxnews.com, freebeacon.com, freep.com, ft.com
G	guardonline.com
H	hawaiinewsnow.com, heraldbulletin.com, huffingtonpost.ca, huffingtonpost.com
I	ibtimes.com, ibtimes.sg, idahostatejournal.com, ijr.com, indystar.com, inquisitr.com
J	jacksonville.com, johnsoncitypress.com, journalgazette.net, journalnow.com, jsonline.com
K	kansascity.com, kare11.com, katv.com, kcci.com, kcrg.com, kdlt.com, keloland.com, kfvs12.com, khou.com, king5.com, kmov.com, knoxnews.com, komonews.com, krdo.com, ksl.com, ksn.com, ktla.com, ktvu.com, kvia.com, kvue.com, kxan.com, ky3.com
L	lansingstatejournal.com, lasvegasnow.com, latimes.com, laweekly.com, local10.com, local12.com, lohud.com, lubbockonline.com
M	masslive.com, mcall.com, mercurynews.com, mediaite.com, miamiherald.com, miaminewtimes.com, militarytimes.com, mlive.com, mnn.com, modbee.com, motherjones.com, msnbc.com, myfox8.com, mynorthwest.com, myrtlebeachonline.com, mysanantonio.com

N	nationalinterest.org, nationalreview.com, nbcdfw.com, nbcnews.com, nbcnewyork.com, nbcphiladelphia.com, necn.com, news12.com, news4jax.com, newschannel20.com, newsday.com, newsjournalonline.com, newsobserver.com, newsok.com, newsquench.com, newsweek.com, newyorker.com, newzjunky.com, nj.com, njherald.com, nola.com, northjersey.com, npr.org, nydailynews.com, nymag.com, nytimes.com
O	observer.com, ocregister.com, omaha.com, oregonlive.com, orlandosentinel.com
P	panhandlepost.com, pennlive.com, philly.com, pix11.com, pjstar.com, politico.com, post-gazette.com, poststar.com, pressherald.com, pressofatlanticcity.com, providencejournal.com
Q	qz.com
R	rawstory.com, reviewjournal.com, reuters.com
S	sacbee.com, sandiegouniontribune.com, scnow.com, seattlepi.com, seattletimes.com, sfchronicle.com, sfgate.com, shelbystar.com, sj-r.com, slate.com, smithsonianmag.com, star-telegram.com, staradvertiser.com, startribune.com, stltoday.com, stripes.com, sun-sentinel.com, suntimes.com, syracuse.com
T	tampabay.com, tapinto.net, tbo.com, tcpalm.com, telegram.com, tennessean.com, theadvocate.com, theatlantic.com, thebatavian.com, theconversation.com, thedailybeast.com, theledger.com, thenation.com, theoaklandpress.com, therepublic.com, thestate.com, thetimesherald.com, theweek.com, theyeshivaworld.com, timesunion.com, tribdem.com, triblive.com, tucsonnewsnow.com, tulsaworld.com, turnto10.com, twincities.com
U	unionleader.com, upi.com, usatoday.com, usnews.com
V	vice.com, vicksburgpost.com, voanews.com, vosizneias.com, vox.com
W	waff.com, walb.com, washingtonpost.com, washingtontimes.com, wbur.org, wctv.tv, wcvb.com, wdbj7.com, wdrb.com, wdsu.com, wesh.com, wfaa.com, wfmynews2.com, wfmz.com, wgntv.com, wgrz.com, wftv.com, whig.com, whnt.com, wistv.com, witn.com, wivb.com, wjhg.com, wkrg.com, wkyc.com, wlwt.com, wmur.com, wnem.com, wnep.com, wnyc.org, woodtv.com, wowt.com, wpbf.com, wpxi.com, wral.com, wreg.com, wsaz.com, wsbtv.com, wset.com, wsfa.com, wsj.com, wsj.net, wsjemail.com, wsoctv.com, wsvn.com, wtae.com, wthr.com, wtop.com, wtva.com, wvgazettemail.com, wvva.com, wyff4.com