3G INTERNET AND CONFIDENCE IN GOVERNMENT*

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Abstract

How does mobile broadband internet affect approval of government? Using Gallup World Poll surveys of 840,537 individuals from 2,232 subnational regions in 116 countries from 2008 to 2017 and the global expansion of 3G mobile networks, we show that, on average, an increase in mobile broadband internet access reduces government approval. This effect is present only when the internet is not censored, and it is stronger when the traditional media are censored. 3G helps expose actual corruption in government: revelations of the Panama Papers and other corruption incidents translate into higher perceptions of corruption in regions covered by 3G networks. Voter disillusionment had electoral implications: In Europe, 3G expansion led to lower vote shares for incumbent parties and higher vote shares for the antiestablishment populist opposition. Vote shares for nonpopulist opposition parties were unaffected by 3G expansion. *JEL* codes: D72, D73, L86, P16.

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I. INTRODUCTION

What are the political implications of the expansion of mobile broadband internet around the world? Optimists argue that broadband internet improves access to independent political information, raising public awareness about quality of governance. Social media enables two-way information flows that help overcome collective-action problems in organizing protests against nondemocratic governments. For instance, in the wake of the Arab Spring of 2010–2012, the internet and social media were branded as "liberation technology" (Diamond and Plattner, 2010). Pessimists, in contrast, point out that social media makes it easy to disseminate fake news (Allcott and Gentzkow, 2017; Vosoughi, Roy, and Aral, 2018), empowers nondemocratic regimes by reducing the costs of propaganda and surveillance (Morozov, 2011; Mitchell et al., 2019), and helps populists connect to voters (Tufekci, 2018). These conjectures found empirical support in a number of studies that have analyzed the political implications of broadband internet expansion and social media penetration in single-country settings (for a recent survey of this literature, see Zhuravskaya, Petrova, and Enikolopov, 2020).

Our paper is the first to study the political effects of the expansion of third-generation (3G) mobile networks throughout the world. 3G was the first generation of mobile broadband internet that allowed users to freely browse the web from their smartphones and to stream or upload videos; it was a key driver of the rapid expansion of social media (Rainie and Wellman, 2012). We use Gallup World Poll (GWP) data on the attitudes and beliefs of approximately 840,000 individuals living in 2,232 subnational regions of 116 countries throughout the world from 2008 to 2017. We find that greater 3G availability, on average, decreases government approval. Citizens who gain access to mobile broadband internet show less support for their government: they become more aware of government corruption and less confident in the country's government institutions.

This result is consistent with conjectures of many political analysts, sociologists, and psychologists, who have argued that the growth of social media, catalyzed by the expansion of mobile broadband internet, has undermined the legitimacy of governments around the world. In his recent book *The Revolt of the Public,* a former CIA analyst Martin Gurri argues that "the rise of Homo informaticus [a citizen relying on social media for information] places governments on a razor's edge, where any mistake, any untoward event, can draw networked public into the streets... This is the situation today for authoritarian governments and liberal democracies alike. The crisis in the world [...] concerns loss of trust in government" (Gurri, 2018, p. 90). He conjectures that "the greater the diffusion of information to the public [through social media], the more illegitimate any political status quo will appear... Homo informaticus ... poses an existential challenge to the legitimacy of every government he encounters" (Gurri, 2018, p. 91). A seminal scholar of the "network society," Manuel Castells, argues in his recent book *Rupture: The Crisis of Liberal Democracy,* that the dissemination of images and videos through social media is a reason for this crisis of political legitimacy because "politics is fundamentally emotional" and "negative images are five times more effective in terms of influence than positive ones" (Castells, 2019, p.20). Similarly, a prominent social psychologist, Jonathan Haidt, with his coauthor, Tobias Rose-Stockwell, in their summary of recent research on the psychology of social media conclude that social media does not just serve as a spark for public outrage with the status quo, it also is especially "designed to make outrage contagious" (Haidt and Rose-Stockwell, 2019).

We find that the magnitude of the negative effect of the expansion of mobile broadband internet on government approval is substantial. An average-size increase in regional 3G coverage during the 2008–2017 decade resulted in 39% of an average subnational region's population gaining access to mobile broadband internet, reduced the confidence in the national government of the region's population by 2.5 percentage points (from the mean level of 51%), and increased the perception that the government is corrupt by 1.4 percentage points (from the mean of 77%).

The global setting allows us to study the heterogeneity of the effects of 3G expansion on government approval, which helps to shed light on some of the mechanisms at play. First, we show that 3G decreases government approval only when the internet is not censored. This is despite the fact that 3G networks increase internet penetration everywhere, including countries with internet censorship. This suggests that political information available online that is independent of the government makes people change their attitudes toward the government. Second, when the internet is not censored, the negative effect of 3G on government approval is stronger in countries where the government controls the traditional media, implying that mobile broadband internet becomes a major source of news when no other sources of independent political information are available. Third, we find that the effect of 3G is negative only when there is at least some corruption. The least corrupt governments (such as those of Denmark or Switzerland) suffer no drop in public approval ratings as a result of 3G expansion; in these countries, 3G expansion actually increases government approval. This evidence is consistent with Bayesian updating of public beliefs: if new information on the quality of governance made available via mobile broadband constitutes good news compared to the ex ante beliefs, 3G expansion should result in higher government approval. Fourth, we demonstrate explicitly that mobile broadband internet helps inform the public about actual corruption. Using Furceri, Papageorgiou, and Ahir (2019)'s measure of actual incidents of corruption around the world, we show that actual corruption incidents increase the public's perception of corruption more in subnational regions covered by 3G networks than in regions not covered by 3G. We also find that 3G affects the relationship between perceptions of corruption and actual corruption more in countries with relatively low overall corruptness than in countries with relatively high overall corruptness. This, again, is consistent with the Bayesian model, as each corruption episode constitutes bigger news in countries where such episodes are rare. We corroborate the result that 3G helps expose actual corruption using an alternative measure of actual corruption, which is based on revelations from the Panama Papers concerning offshore entities. Fifth, we explore individual, geographical, and over-time heterogeneity. We find that the effects are stronger for rural residents and respondents with lower socioeconomic status (measured by education and income), and weaker for younger respondents. 3G, on average, negatively affects government approval on all continents, but in Europe and Asia, the negative effect is only among rural residents (for whom the effects are stronger everywhere). The magnitude of the effect of 3G coverage on government approval is relatively stable over the observation period.

These results highlight one of the mechanisms behind the overall effect of 3G on government approval, namely, that mobile broadband internet helps expose actual misgovernance and corruption, suggesting that uncensored mobile broadband internet can be a powerful tool for political accountability. There may be other mechanisms as well. In particular, several observers suggest that social media is particularly well suited for the dissemination of false information.[1] For example, Tufekci (2018) argues that the business model of social media is likely to provide incentives to "stoke outrage, spread misinformation, and appeal to people's existing biases." We do not have data to systematically test whether the propagation of false news criticizing the government is also an important factor behind our main result. However, we do illustrate both mechanisms—that is, (i) the exposure of actual corruption and (ii) the dissemination of false narratives through platforms supported by mobile broadband internet—with three case studies: the exposure of corruption of Russia's former Prime Minister Dmitry Medvedev on YouTube in 2017; the rise to power of the Romanian "Facebook President," Klaus Iohannis, on an anti-corruption platform in 2014; and the mass dissemination of false narratives through WhatsApp by populist presidential candidate Jair Bolsonaro during Brazil's 2018 election campaign.

Finally, we examine the electoral implications of 3G expansion. To test whether the 3G-driven disillusionment of voters in their governments translates into lower vote shares for incumbent parties, we focus on Europe. Using subnational-level data on 102 parliamentary elections in 33 European democracies between 2007 and 2018, we

[1] In a recent survey of the literature, Zhuravskaya, Petrova, and Enikolopov (2020) discuss well-documented evidence of the massive spread of false stories on social media. Yet, they note there is no systematic study of whether false information is more prevalent in social networks than in the traditional media.

find that incumbent governments lost electoral support after the arrival of mobile 3G networks, corroborating our results on attitudes toward governments. The expansion of 3G coverage in an average subnational region in Europe during the 2008-2017 decade led to a 53-percentage-point increase in the share of the region's population with access to mobile broadband internet, from 37% to 90%. We show that this regional 3G expansion led to a 4.7-percentage-point decrease in the incumbent party's vote share. We then investigate what kinds of parties gained from the expansion of 3G networks. We find empirical support for the increasingly prominent hypothesis (see, e.g., Tufekci, 2018) that—in the age of social media—broadband internet empowers antiestablishment populist politicians. The decade-long expansion of 3G coverage in an average subnational region in Europe increased the vote share for right-wing populists by 4.6 percentage points and of left-wing populists by 3.6 percentage points. We also find that among opposition parties, only populist parties benefited from the expansion of 3G networks—there were no electoral gains for nonpopulist opposition parties, in general, and for Green (environmentalist) parties, in particular. Electoral support for incumbents also decreased with the expansion of 3G networks when populists were in government. We find that turnout decreased by 2 percentage points in an average region as a result of the decade of 3G expansion, which partly explains the effects on vote shares of incumbents and populists. The results, however, are statistically significant when votes cast are expressed as a share of registered voters and not of those who participated in the elections, implying that some voters did change their allegiance.

Our results suggest that, in part, the fall in incumbent governments' political approval and the rise in popularity of populist parties in Europe are two sides of the same coin. Testing for the exact mechanisms of 3G's effect on populists' vote share is beyond the scope of this paper. Why populists—but not other opposition parties—benefit politically from voter disillusionment with incumbent political elites is a promising subject for future research. Overall, we find that the existence of mobile broadband internet enables voters to become more informed about their governments, leading to a fall in government approval, particularly when other sources of independent political information are scarce or nonexistent. However, in European democracies, it also helps antiestablishment populist politicians connect to voters, an effect that cannot be fully explained by the information channel, as nonpopulist opposition parties (so far) have not benefited from 3G expansion.

Our empirical strategy relies both on difference-in-differences and instrumental-variable analyses. We use the variation in the timing of 3G expansion across different subnational regions within countries, controlling for subnational region fixed effects, year fixed effects, and a large set of potential confounders, including measures of economic development, unemployment, and democracy, as well as individual sociodemographic characteristics. We document the absence of pretrends: the future availability of mobile networks has no effect on government approval, but the effect of past 3G expansion is significant. We show that our results are robust to including country-by-year fixed effects. These results are also confirmed by an event study, in which we focus on the dynamics of government approval around sharp increases in 3G coverage. We find that such sharp increases are associated with a significant drop in government approval, with a magnitude similar to the baseline specification, and that there are no changes in government approval preceding 3G expansion into a region. We also use the techniques developed by Altonji, Elder, and Taber (2005) and Oster (2017) to show that our results are highly unlikely to be driven by omitted-variable bias. Furthermore, we apply to the 3G expansion the instrumental-variable identification strategy designed by Manacorda and Tesei (2020) for the previous generation of mobile networks (2G). The strategy relies on exogenous variation in the regional frequency of lightning strikes per area to predict the speed of expansion of regional mobile broadband internet coverage. Frequent lightning strikes hinder the rollout of telecommunication technologies because—by causing power surges—they substantially increase the costs of providing service and maintaining the infrastructure. This approach confirms the results of the difference-in-differences OLS analysis.

We also present the results for a number of placebo outcomes. In particular, we show that the relationship between mobile broadband internet and government approval is not driven by the effect of the internet on general life satisfaction or pessimism about the future. In addition, we find no impact of 3G expansion on confidence in the local police, which we consider as a placebo outcome because the performance of the local police, in contrast to that of the national government, can be observed by voters directly, without the internet.

The only other multicountry study of the political effects of expansion of telecommunications infrastructure is Manacorda and Tesei (2020), which shows that 2G mobile networks facilitated political protests during economic downturns across Africa between 1998 and 2012. Our paper differs from this important work in two fundamental ways. First, our focus is mobile broadband internet (3G), which is superior to 2G in terms of possibilities for disseminating political information. While 3G enables users to browse the internet freely and seamlessly transfer images and videos—both crucial for the growth of social media—previous-generation networks allowed only texting and very limited internet connectivity. We highlight the effect of this difference by studying 2G expansion as a placebo treatment. We find that, if anything, 2G expansion, on average, is positively correlated with government approval. Furthermore, controlling for the availability of a 2G signal does not affect our results on the effect of 3G. The results of Manacorda and Tesei (2020) on the relationship between 2G and protests in

Africa and our result on the relationship between 2G and overall government approval are not contradictory. This is because our outcome variable reflects the opinion of the majority, whereas protests are often organized by an interested minority that has more incentives than the general public to actively seek political information and self-organize. Our results suggest that it took a new generation of mobile technology for the discontent with government to spread to the general public. Second, we make use of the global coverage of the GWP data, which allows us to shed light on some of the mechanisms by showing heterogeneity with respect to internet censorship, censorship of the traditional media, overall corruptness, and actual corruption incidents.

Broadly speaking, our paper also contributes to the growing literature on the political effects of the internet and social media. Several studies (mostly focusing on single countries) have shown that access to broadband internet hurts the incumbents' political position. For example, the expansion of high-speed cable internet in Malaysia was shown to have contributed to ending the corrupt ruling coalition's 40-year monopoly on power (Miner, 2015). In South Africa, the spread of mobile internet has also shifted votes away from the ruling political party (Donati, 2019). Social media has helped to coordinate protest activity in Russia (Enikolopov, Makarin, and Petrova, 2020). Fergusson and Molina (2019) show that the addition of a new language to the Facebook interface is associated with an increase in protests in countries where this language is spoken. In Europe, the literature has focused on political participation and the rise of populists, showing the change in the effect at the time when social media emerged. Evidence from Germany (Falck, Gold, and Heblich, 2014), the United Kingdom (Gavazza, Nardotto, and Valletti, 2019), and Italy (Campante, Durante, and Sobbrio, 2018) suggests that, initially—that is, before the emergence of social media—in Europe, broadband internet crowded out political awareness with entertainment content, reducing electoral participation, without significant gains for any specific political force. Yet, beginning in 2008—when social media was born—Campante, Durante, and Sobbrio (2018) show that broadband cable internet has contributed to the rise of Italy's populist Five-Star Movement (*Movimento 5 Stelle*). This result was confirmed by Schaub and Morisi (2020) using survey data on the electoral support for populists in Italy in 2013 (Five-Star Movement) and Germany in 2017 (*Alternative für Deutschland,* AfD).

Our contribution to this literature is threefold. First, we document the effects of the expansion of mobile broadband internet on government approval across the world and show that these effects are different from those of earlier mobile technology. Second, we use our global setting to conduct comparative analyses that identify an important mechanism at play. Third, we use election data for 33 European countries over a decade to demonstrate the electoral implications of the mobile broadband internet expansion.

The rest of the paper is organized as follows. Section II presents the data and the empirical strategy. In Section III, we present the average effect of 3G expansion on government approval for the whole world and discuss the validity of our identification assumptions. Section IV presents comparative analyses. Section V explores the electoral implications of mobile broadband internet expansion in Europe. In Section VI, we illustrate our results with three country case studies. Section VII concludes.

II. DATA AND THE EMPIRICAL STRATEGY

II.A. Main variables

In this section, we briefly describe the main variables of interest. (For details about these measures, as well as descriptions of all the control variables, see Appendix Section A.)

The data on government approval come from the GWP and cover the period from 2008 to 2017. Approximately 80% of the data were collected via face-to-face interviews. The other 20% of the interviews were conducted over the telephone.[2] The exact questions about government performance in the GWP are: *"Do you have confidence in each of the following, or not: How about the national government? How about the judicial system and courts? How about the honesty of elections? Is corruption widespread throughout the government in (country), or not?"* The respondents could answer "*Yes*" or "*No*."[3] We use the responses to these four questions, also aggregating them using their first principal component and the share of positive attitudes toward the government across these four dimensions. The GWP also includes a question on individuals' internet access at home: *"Does your home have access to the internet?"*

Because we are interested in estimating the effect of mobile broadband internet availability on attitudes and beliefs, we exploit the variation in the timing of 3G expansion. (The identification strategy is discussed below.) 3G was the first generation of mobile networks that allowed users to actively browse the web on their phones, making online content, including social media, more accessible. The technology was first introduced to the public in 2001, but it took several years for most countries to adopt it. According to the International Telecommunication Union (ITU, 2019), in 2007 there were only 0.04 active mobile broadband subscriptions per capita in the world. By 2018, the figure had jumped to 0.70. Importantly, ITU data show that most of the growth in individual broadband subscriptions over the past decade, in developing

[2]Telephone interviews were conducted only in countries with at least 80% telephone coverage. This sample consists primarily of high-income OECD countries and the Arab states of the Persian Gulf. Most telephone interviews were conducted via landline telephone. In Section III.B, we show that our results are robust to limiting the sample to face-to-face interviews only.

[3]Respondents could also choose "*Refuse to answer*" or "*Do not know.*" For the four questions about government performance, the share of respondents choosing these two options varies from 6% to 11%. We have verified that the likelihood of choosing these answers is unrelated to 3G expansion.

and developed countries alike, was due to the expansion of mobile broadband internet access rather than fixed broadband (ADSL or fiber-optic cable) access. We illustrate the global growth of fixed and mobile broadband subscriptions per capita in Appendix Figure A.1.[4]

We use digital maps of global 3G network coverage from 2007 to 2018 provided by Collins Bartholomew's Mobile Coverage Explorer. These maps put together coverage data submitted by mobile network operators from around the world to the GSM Association, which represents the interests of mobile network operators worldwide. The data consist of 1×1-kilometer binary grid cells. If a grid cell is covered by 4G, it is also covered by 3G, by definition.[5] Figure I illustrates the expansion of 3G networks over the entire period of observation. It presents maps of 3G coverage in 2007 and 2018 by grid cells and the corresponding increase in the share of the subnational regions' territory covered by 3G mobile internet for countries in the GWP sample. Subnational regions are defined by the level of geolocalization provided in the GWP data.

To combine data on mobile network coverage with the GWP surveys, which have region-level localization, we calculate regional 3G coverage in each region and year defined as the weighted average across all grid-cells in each region's polygon of the value of 3G availability weighted by the population density in each grid cell. (The weights are normalized to sum up to one.)

The resulting dataset covers 840,537 individual respondents in 13,004 subnational region×year cells, from 2,232 subnational regions of 116 countries. The mean number of times the same region appears in the data is six. Over 75% of the subnational regions appear in the data for at least four years. The mean number of subnational regions per country is 16. On average, 65 respondents are surveyed in a subnational region in any particular year.

To understand the drivers and consequences of the effect of mobile broadband internet on government approval, we use independent measures of corruption, censorship of the internet, and censorship of the traditional media. We use two data sources to measure actual corruption. The first one is the International Monetary Fund's (IMF's) Global Incidents of Corruption Index (GICI) from Furceri, Papageorgiou, and Ahir (2019), which is based on text analysis of country reports, prepared by the Economist Intelligence Unit (EIU) and made available to investors on a subscription basis. The index quantifies the intensity of actual corruption by country-year. It is the result of analysis by external (EIU) experts and is distinct from the public's perception of cor-

[4] The ITU data are available at https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx (accessed on July 25, 2020).

[5] These data are available for all years except 2011. The 2011 data are unavailable due to a change in the company administering the data collection that year. We use the mean of 2010 and 2012 as a proxy for 2011 coverage. All our results are robust to excluding 2011 from the sample.

ruption. This index covers 104 countries in our sample. We use both the time-variant GICI and a measure of overall country corruptness equal to the country mean of the GICI between 2000 and 2017. The second source of data on actual corruption is based on the Panama Papers Database made available by the International Consortium of Investigative Journalists (ICIJ). For each country, we calculate the number of entities featured in the Panama Papers.[6] For the few countries that are not mentioned in the Panama Papers, we impute this number to be zero. As a baseline, we use the number of entities featured in the Panama Papers scaled by the country's population size and establish robustness to using the total number of Panama Papers entities. Then, we examine how these two measures of actual corruption—the GICI and the number of entities in the Panama Papers—interact with regional 3G coverage in explaining perceptions of corruption.

We measure censorship of the internet using Freedom House's Limits on Content score, a component of the Freedom on the Net (FOTN) index. It is available for 46 countries in our sample and ranges from 0 to 35, with higher values implying higher censorship. We use both the time-variant (contemporaneous) censorship measure available by country and year and the time-invariant country-level measure, which is calculated as the mean value of time-variant internet censorship in each country from 2015 to 2017, that is, the years with maximum cross-country variation in time-variant internet censorship. In addition to using these continuous measures of internet censorship, we also create dummy variables for a high level of censorship by using thresholds that indicate natural breaks in the distributions of the respective continuous measures (22 for the time-variant measure and 20 for the time-invariant measure). When we use the binary definition of internet censorship, we extend the sample by including observations with missing FOTN data from countries that one can be sure did not censor the internet. In particular, we assign a zero value to the time-varying dummy for high internet censorship when the FOTN data are missing and the country in that year is a democracy according to the Polity IV dataset (i.e., if the Polity2 score is 6 or above). Similarly, we assign a zero value to the time-invariant dummy when it is missing and the country is a democracy during our sample period (if the over-time mean of the Polity2 score in this country is 6 or above).[7]

The measure of censorship of the traditional media comes from Freedom House's

[6] We follow Louis-Sidois and Mougin (2020), who used the Panama Papers revelations as a shock to corruption perceptions around the world.

[7] Below, we document that our results are robust to using alternative thresholds for the definitions of the binary measures of internet censorship. We also show that the results do not depend on the imputation of zeros for democracies. The imputation is, however, reasonable because in the sample with nonmissing FOTN data, a dummy for democracy predicts the Limits on Content score to be below 22 with 99.5% probability; and all the countries with the mean Limits on Content score in 2015–2017 above 19 have an over-time mean of a Polity2 score below 6.

Freedom of the Press (FOTP) index. It is available for all 116 countries in our sample and ranges from 0 to 100, with higher values representing higher censorship. As above, we use both a contemporaneous measure and its over-time country mean.

To single out the exogenous source of variation in the speed of regional 3G expansion, we calculate the population-weighted frequency of lightning strikes per subnational region's area using the World Wide Lightning Location Network (WWLLN) dataset. This dataset provides the exact coordinates and time of all cloud-to-ground lightning strikes across the globe. We calculate the average number of lightning strikes in a subnational region per year between 2005 and 2011, weighting each of the lightning strikes by its local population density, measured using a NASA map of population density per square kilometer for each 1×1-kilometer grid cell. Then, we divide this number by the area of the subnational region. Thus, the resulting measure represents the number of people potentially affected by the lightning strikes per square kilometer in each subnational region. We deem a subnational region to have a high frequency of lightning strikes per area if the region was in the top half of the global distribution of population-weighted lightning strikes per square kilometer.

Finally, we use parliamentary election data from European democracies. Figure A.2 in the Appendix presents maps illustrating the growth in 3G-network coverage between 2007 and 2018 in Europe and the boundaries of the districts, that is, the spatial unit of observation in our European elections data. (The figure is organized similarly to Figure I.) To study the effect of 3G mobile internet expansion on the performance of incumbents and of establishment parties, we use the vote share for the party of the country's top executive at the time of the elections, as well as the combined vote share for the two parties that finished first and second in the first electoral race that occurred in each country since 2007. To analyze the performance of populist parties, we extend the panel dataset on the vote shares of populist parties in Europe from Algan et al. (2017). We classify the parties as populist or nonpopulist based on the Chapel Hill Expert Survey and on text analysis of online sources (see Guriev and Papaioannou, forthcoming, for a discussion of available classifications of populist parties). The data cover 102 elections in 33 European countries from 2007 to 2018 at the level of 398 subnational districts, for a total of 1,250 district-election observations. The mean number of elections per district is 3.25 (the median is 3), and all districts appear in the data at least twice. The data on Green parties cover 97 of the 102 considered elections because, in five elections, the Greens formed joint lists with mainstream nonenvironmentalist parties, making it impossible to measure the vote share for the Greens separately. In the Appendix, we describe these data, present the lists of populist and Green parties, and outline the methodology used to classify parties into populist and nonpopulist.

Details about the exact measures used in the analysis, summary statistics, and sources of all data are presented in Appendix Section A.

II.B. Main specifications

We estimate the effect of getting access to mobile broadband internet on individuals' beliefs. As described above, we gauge 3G availability in each subnational region (defined by the GWP localization) of each country in each year by calculating the share of the region's territory covered by 3G networks in that year, weighted by population density at each point on the map. Then, we relate attitudes toward government to 3G availability using a difference-in-differences model with region and year fixed effects:

$$(1) \qquad Gov\_approval_{irt} = \gamma_1 3G_{rt} + \gamma_2 Development_{rt} + \mathbf{X}'_{irt}\lambda + \varphi_r + \tau_t + \epsilon_{irt},$$

where i, r, and t index individuals, regions, and years, respectively. *Gov_ approval* is a dummy indicating whether the survey respondent has confidence in government. As mentioned above, we use four GWP questions to measure confidence in government. *3G* represents the share of the population in the subnational region with potential access to 3G, our main explanatory variable. φ_r and τ_t are region and year fixed effects, which control for all regional time-invariant characteristics and global time-specific shocks. *Development* represents a measure of regional economic development—an important control as 3G expansion was potentially faster in regions with high economic growth. In the baseline specification, we proxy regional economic development with the log of mean household income among GWP respondents in the region and establish robustness to using nighttime light density as an alternative measure (following Henderson, Storeygard, and Weil, 2011, 2012).[8] **X** is a vector of additional controls: age, age squared, gender, education, marital status, employment status, indicators for urban/rural place of residence, the log of the country's GDP per capita, the country's unemployment rate, and dummies for democracy and for advanced democracy.[9] In the baseline specification, standard errors are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the country in each year (to account for within-country-year correlation). We establish robustness of the results to using alternative assumptions about the variance-covariance matrix: in particular, the results are robust to correcting for spatial and over-time correlation following Conley (1999), Hsiang (2010), and Collela et al. (2018), and for

[8] In the few region-years where GWP income data are not available (less than 7% of the sample), we use nighttime light density and the country's GDP per capita to predict regional income. As discussed in Appendix Section B, the results are robust to controlling for nighttime light density. We do not use this variable in the baseline specification, because it is not comparable before and after 2014.

[9] The summary statistics are presented in Table A.1 in the Appendix.

clustering at the country level.

3G mobile service allows users to freely browse the internet from a smartphone and to use social media applications. 3G coverage affects internet use (i) on the extensive margin—by affecting the probability of getting a connection, (ii) on the intensive margin—by affecting the number of hours spent online, and (iii) qualitatively—by changing what people do online. The qualitative difference that a mobile broadband connection makes comes from the fact that a number of social media, such as WhatsApp and Telegram, are particularly well-suited for users with mobile broadband access. The ease of connection also makes a qualitative difference by engaging users in social networks (Rainie and Wellman, 2012). The vast majority of active social media users access social media applications via mobile phones, even when these applications can be accessed though a fixed internet connection.[10] All three of these margins are important for the overall effect of 3G, estimated by Specification (1). The GWP does not have data on the amount of time spent surfing the web and on social media. We can test only for the effect of 3G expansion on having access to the internet at home, as there is a question about this in the GWP. This is a very partial test of the extensive margin because (i) the GWP question does not specify whether home internet access is broadband or a slow connection, and (ii) mobile broadband internet enables people to access the internet outside their homes (e.g., if there is 3G coverage at their workplace but not at home). Nonetheless, we verify that 3G availability predicts internet access at home by estimating a difference-in-differences relationship between the respondent's internet access at home and 3G coverage in the subnational region of the respondent's residence:

$$(2) \qquad Internet\_at\_home_{irt} = \alpha_1 3G_{rt} + \alpha_2 Development_{rt} + \mathbf{X}'_{irt}\lambda + \varphi_r + \tau_t + \epsilon_{irt},$$

where $Internet\_at\_home$ denotes a dummy variable for self-reported access to the internet at home.

The two main identification assumptions for interpreting the estimation of Specification (1) of the effect of regional 3G coverage on confidence in government as causal are (i) the timing of 3G expansion is uncorrelated with other factors that may affect

[10]In 2017, out of 3.196 billion active social media users, 2.958 billion (i.e., 93%) accessed social media via mobile devices (Kemp, 2018). In 2014, this share was slightly lower, but still represented an overwhelming 81% majority (Kemp, 2015). According to YouTube, more than 70% of YouTube watch time comes from mobile devices (`https://www.youtube.com/intl/en-GB/about/press/`, accessed July 19, 2020). Twitter reports that already by 2012, two-thirds of its users were mobile, and by 2015 the share of mobile users had reached 80% (`https://www.statista.com/chart/1520/number-of-monthly-active-twitter-users/`, accessed July 19, 2020). In contrast, the growth of mobile internet use outside social media was much slower: the average share of mobile traffic was only 16% in 2013 and 50% in 2017 (`https://www.broadbandsearch.net/blog/mobile-desktop-internet-usage-statistics`, accessed July 19, 2020).

public attitudes toward government, and (ii) 3G expansion is not itself driven by the expectation of changes in government approval or by any unobserved factor that could generate a spurious correlation between government approval and 3G network coverage. These assumptions are not directly testable. However, below in Section III.A, we present a number of robustness and placebo exercises, as well as tests in the spirit of Altonji, Elder, and Taber (2005) and Oster (2017), which do suggest that the differences-in-differences results can be interpreted as causal.

To address the remaining concerns that the identification assumptions in our baseline difference-in-differences specification could be violated, we use variation in the frequency of lightning strikes per square kilometer in each subnational region to predict the speed of regional 3G expansion—the identification strategy first used by Manacorda and Tesei (2020) for 2G-network expansion in Africa. The frequency of lightning strikes has been shown to affect the diffusion of digital technologies due to an increase in the expected costs associated with voltage spikes and dips (e.g., Andersen et al., 2012). The equipment needed for mobile-phone infrastructure, including the mobile broadband networks infrastructure, is particularly sensitive to electrical surges caused by lightning strikes, which can lead both to immediate damage and to quicker depreciation of the equipment over time (Zeddam and Day, 2014; Martin, 2016). Power-surge protection can partially alleviate the problem, but it is expensive, not always effective, and less readily available outside developed countries. We predict slower 3G expansion in regions with a high frequency of population-weighted lightning strikes per square kilometer. As both the endogenous regressor (regional 3G coverage, $3G_{rt}$) and the exogenous source of variation (lightning-strike frequency per square kilometer) vary at the regional level, as a baseline, we estimate the following first-stage equation at the region-year level:

$$3G_{rt} = \delta_1[Lightning_r \times t \times Rich_{c_r}] + \delta_2[Lightning_r \times t \times Poor_{c_r}] + \mathbf{Z}'_{rt}\mu + \varphi_r + \tau_t + \epsilon_{rt}, \quad (3)$$

where $Lightning_r$ denotes a dummy indicating subnational regions with an above-median population-weighted frequency of lightning strikes per square kilometer; $Rich_{c_r}$ and $Poor_{c_r}$ are dummies indicating the countries with above- and below-median per capita income; and $\mathbf{Z}$ stands for all the other controls. We include all the region-level and country-level baseline controls described above. In addition, we control for other potential determinants of 3G expansion that can correlate with lightning-strike frequency. In particular, we extend the list of covariates to include linear time trends interacted with the subnational regions' share of territory covered by deserts, share of territory covered by mountains, maximum elevation, and dummies for each quintile of population density. To control for the fact that the initial expansion of 3G networks affects the speed of subsequent expansion, we also control for linear time trends interacted with regional 3G coverage in 2008, a dummy for whether the region had any 3G coverage in 2008, and a dummy for whether the country had any 3G coverage in 2008. We, then, estimate the second stage using predicted regional 3G coverage.

The identification assumption behind this approach is that the frequency of lightning strikes per square kilometer affects trends in government approval only through its effect on 3G expansion conditional on all other covariates. We also establish robustness to using individual-level data instead of region-year averages, an approach that places higher weight on more populous regions, as there are more observations per region in the GWP in regions with a larger population. As we show below, the results of the IV and OLS specifications are qualitatively similar; the magnitudes are somewhat larger in the IV estimation.

III. MOBILE BROADBAND INTERNET AND GOVERNMENT APPROVAL

Table I presents the results of estimating the effects of mobile broadband internet availability with the baseline difference-in-differences specification. Panel A presents the results for the full sample; Panel B, for the subsample of rural residents. Different columns of the table consider different measures of government approval as the outcome variable. The expansion of 3G networks, on average, is associated with individuals becoming more aware of government corruption and less confident in their country's government and institutions. The results are statistically significant for all four measures of government approval (Columns 1–4) and for the two aggregate measures, that is, the share of positive answers and the first-principal component of the four measures (Columns 5–6), both for the full sample and for the subsample of rural residents (Panels A and B, respectively).

In Column 1 of Appendix Table A.2, we illustrate how 3G expansion affects internet access at home. We find that 3G expansion within the respondent's region of residence significantly predicts internet availability at home. This is consistent with the observation that access to mobile broadband networks increases the extensive margin of internet use. However, 3G mobile networks have an effect on government approval above and beyond their effect on internet access at home. We show this in Columns 2 to 5 of Appendix Table A.2. The average effect of regional 3G coverage is not affected by including a dummy for having internet access at home in the list of covariates (Column 2). The effect of 3G expansion on government approval is significantly negative, both when there is and when there isn't an internet connection at home. The effect is twice as large in magnitude for individuals *without* access to the internet at home than for individuals *with* access to the internet at home (Columns 3 to 5 of Table A.2). These estimates suggest that even when people have access to the internet, getting access to *mobile* broadband internet significantly affects the way they use it.[11]

The magnitude of the effect of 3G coverage on government approval, documented in Table I, is substantial; it is particularly large for residents of rural areas. The average increase in regional 3G coverage between 2008 and 2017 across the regions in the GWP sample is 0.39. As discussed in more detail in Appendix Section C, we use this increase as the basis to understand the magnitude of the effect. For example, the estimates in Column 1 of Table I imply that in an average region 3G expansion in the last decade led to a decrease in the confidence of respondents in their country's government by 2.5 ($= -0.063 \times 0.39 \times 100$) percentage points in the full sample and by 3.5 percentage points among rural residents (from the mean levels of 51% and 54%, respectively). Similarly, as reported in Column 4, it led to a decrease in the share of people who think that the government is not corrupt by 1.4 percentage points in the full sample and 2.1 percentage points among rural residents (from the mean of approximately 22%). The results for the other measures of attitudes toward government institutions are very similar. According to the aggregate measure (Column 6, Panel A), a decade-long expansion of 3G networks in an average region led to a 2.2-percentage-point decline in government approval. (We normalize the first-principal component of the government approval variables to vary between zero and one for the ease of interpreting the magnitude of the effect.) The coefficient on the unemployment rate (measured in percentages) in the same regression is -0.010, implying that the effect of a decade-long 3G expansion has the same-size effect on government approval as a 2.2 ($= \frac{0.057 \times 0.39}{0.010}$) percentage-point rise in the national unemployment rate.

To calculate persuasion rates for the hypothetical message "do not approve of your government," one needs to make a number of important assumptions. We describe these assumptions in detail in Appendix Section C. Furthermore, one needs an estimate of the size of potential spillovers in exposure to the anti-government message from those connected to mobile internet to those who are not connected. Specifically, persuasion rates are inversely proportional to the number of people who, on average, get exposed to anti-government messages for each mobile device that is connected to the internet, which we denote by N. One could argue that, particularly in develop-

[11] As mentioned above, the estimates presented in Table I take into account both the extensive and the intensive margins of the effect of the telecommunications infrastructure on internet use, which, in turn, affects attitudes. They also take into account the qualitatively different experience of using social media on a mobile phone compared to a fixed-line connection. Therefore, a hypothetical 2SLS estimation, in which one predicts internet access at home with regional 3G coverage and then uses this prediction for estimating the effect of internet access at home on government approval would lead to a gross overestimation of the effect of the internet on government approval. Such a specification would incorrectly imply that 3G only affects the probability of having a connection to the internet at home. In reality, with the arrival of the 3G technology, people who have already been using the internet started using it more because the broadband connection is more convenient and started using it differently because 3G technology is particularly conducive to social media use.

ing countries, such spillovers are substantial. A case study that we present below in Section VI.A, about a YouTube documentary exposing corruption of Russia's Prime Minister, suggests that, indeed, people without access to the internet also get exposed to content that is available only online. As we lack the data necessary to estimate such spillovers, we can only calculate persuasion rates up to a factor of $\frac{1}{N}$. Assuming $N = 1$, that is, that there are no spillovers, we calculate the upper bound for the persuasion rates implied by the estimates for the first-principal component of the government approval variables (Column 6) to be 17.6% in the full sample and 24.2% in the sample of rural residents.

Panel A of Figure II illustrates the main result from Table I. On the horizontal axis, the figure plots the increase in regional 3G coverage in year t since 2008. The outcome variable is the residual of the first-principal component of the government approval variables in year t (after subtracting the effects of all the controls, including region and year fixed effects). Panel B provides a similar graph for the relationship between the residuals of having internet access at home in year t (again, after subtracting the effects of all the controls) and the growth in 3G coverage.[12] The graphs present the nonparametric relationship between the increase in 3G coverage and the outcome variables, along with their confidence intervals, constructed using a block bootstrap at the level of the clusters, and the data averages by equal-size bins.[13] The figure shows that, on average, 3G expansion led to a drop in government approval (Panel A) and an increase in internet access at home (Panel B).[14]

III.A. Addressing identification challenges

Can these results be interpreted as causal? In this section, we present evidence suggesting that variation in 3G coverage is plausibly exogenous. We corroborate this evidence by performing an instrumental-variable analysis, in which we use the frequency of lightning strikes per area in the subnational regions as an exogenous source

[12]To generate the outcome variables net of controls, we first regress the variable of interest on the change in regional 3G coverage since 2008 and all the controls. We then take the residuals and add to them the estimated effect of the change in regional 3G coverage since 2008. This strategy accounts for the correlation between our main explanatory variable and the other controls.

[13]To construct the confidence intervals, we first generate 55 equal-size bins for the change in regional 3G coverage since 2008. We then perform 1,000 block-bootstrap iterations, sampling at the level of the clusters. In each iteration, we save the average of the outcome variable for each of the bins and the number of observations used to construct that average. After performing 1,000 iterations, we calculate the 5th and 95th percentiles of the outcome variable for each of the bins, weighting by the number of observations in each of the bins in each iteration. Finally, we perform local polynomial smoothing (lpoly) to draw the confidence intervals, using the values of the 5th and 95th percentiles for each of the bins.

[14]Appendix Figure A.3 presents the dynamics of raw government approval and 3G coverage separately in regions with high and low average annual growth of 3G coverage, illustrating the pattern in the data behind our difference-in-differences estimates.

of variation in the speed of the expansion of 3G networks.

Country×year FEs and pretrends. To make sure that our results are not driven by differential country-level dynamics, we redo the analysis controlling for country×year fixed effects, thus, relying only on the differential expansion of 3G in different subnational regions within countries. This is a very demanding control, because it eliminates part of the relevant variation as 3G networks often expanded to all regions of a country at the same time. Nonetheless, the results (presented in Panel A of Table A.3 in the Appendix) are largely robust. After partialing out all of the country×year variation, 3G mobile internet remains an important determinant of attitudes toward government. The effect of 3G is statistically significant for five of the six measures of government approval, with the results being most precise for the two aggregate measures, which are the least noisy among the considered outcomes (Columns 5 and 6). The point estimates are smaller than in Table I, which could be explained by the fact that part of the relevant variation is not accounted for in this specification.

A major potential concern with our difference-in-differences identification strategy is that 3G networks might expand in regions with falling confidence in government. To address this concern, we examine the effects of lags and leads of regional 3G coverage. In Panel B of Table A.3 in the Appendix, we repeat the analysis presented in Panel A, but for regional 3G coverage in year $t + 1$. We find that 3G coverage next year is not significantly related to government approval this year. In Panel C of this table, we test for the equality of the magnitude of the coefficients on regional 3G coverage and its lead (presented in Panels A and B of the table, respectively). The p-values from this test indicate that we can reject equality of the effects for five of the six outcomes and, as above, the difference is most precise for the aggregate measures of government approval. This analysis suggests parallel pretrends in the specification with country-year fixed effects, i.e., when we partial out all country-level trends and shocks.

Figure III presents the point estimates along with their confidence intervals for the coefficients on several lags and leads of regional 3G coverage from the regressions with country-year fixed effects and with the first-principal component of the government approval variables as the outcome. Consistent with the parallel pretrends assumption, we find that the future availability of mobile networks has no effect on government approval, but the effect of past 3G expansions is significant for the first lag; it stays negative, but becomes insignificant, for the second lag. The p-values for the test of equality between the coefficients on the leads of 3G coverage and on 3G coverage at t presented below each point estimate show that the coefficient on 3G coverage at t is significantly larger in magnitude (in absolute value) than the coefficients on its leads.

If we do not partial out all of the country-year dynamics, a similar pretrends test would yield negative significant coefficients on the leads of regional 3G coverage in the full sample, because in many countries 3G expansion was gradual and there is a very strong, significant autocorrelation in the level of 3G coverage. To test for pretrends in government approval without country-year fixed effects, one needs to focus on cases in which there is a sharp discontinuous increase in regional 3G coverage; we do this in the next subsection.

Event study and pretrends. To further validate our pretrends analysis, we conduct an event study focusing on sharp increases in regional 3G coverage. As an event, we consider the situation (i.e., the region-year combination) in which regional 3G coverage increased by more than 50 percentage points within the previous year. By definition, this could happen only once per region, if it happens at all, provided that regional 3G coverage never falls substantially. On average, regional 3G coverage increases by 76 percentage points during the event.[15] There are 452 regions in 65 countries that experienced such a sharp increase in 3G coverage in one year between 2008 and 2018. Focusing on the sample of respondents from these regions (130,406 observations), we estimate the average dynamics of government approval around these events, that is, the sharp increases in regional 3G coverage.

The results are presented in Table II. First, we verify that our baseline relationship holds in this subsample using the first-principal component of the government approval variables as the dependent variable (Column 1). Second, instead of regional 3G coverage, we use a postevent dummy as the treatment variable (Column 2). The results are very similar to the baseline in both cases.[16] In Column 3, we present the event-study specification: we regress government approval on year dummies relative to the year of the event and all the baseline controls. In Columns 4 to 6, we repeat the same exercise in the subsample of rural residents. We find that government approval falls right after a sharp increase in regional 3G coverage (see Columns 3 and 6). All the coefficients on the postevent dummies are statistically significant and their magni-

[15] For the vast majority of regions, 3G expands monotonically. In 95% of the region-year observations, the change in 3G coverage is positive from one year to the next. Among all the subnational regions with 3G data, only 14 regions from three countries experienced sharp drops in 3G coverage from one year to another during our observation period. We exclude these regions from the event-study analysis in order to have a clean definition of the event. These regions are included in the sample for the baseline analysis. None of our results for either the baseline analysis or the event study depend on whether we include these regions or exclude them. Figure A.4 in the Appendix presents the distribution of events across years: It shows that we detect sharp increases in 3G in all years except 2011 and 2012, which is explained by the fact that the data for 2011 are interpolated, thus, by construction, there are no sharp increases in 3G coverage between 2010 and 2012. The figure also lists the countries with the events.

[16] 219 regions from 36 countries have variation in the postevent dummy in the resulting sample because the 2018 GWP data are not available and not all regions are present in the GWP data in all years. All results presented in Table II are robust both to restricting the sample only to regions with variation in the postevent dummy and to including in the sample all regions without events, that is, using the full GWP sample.

tudes are similar to those presented in Table I. In contrast, all the coefficients on the pre-event dummies are very small in magnitude and statistically indistinguishable from zero, thus, confirming the absence of pretrends. In the last two rows of the table, we present the p-values from the tests of equality of the coefficients on dummies indicating years t and $t-2$ and between the average effects for the years t and $t+1$ as compared to the average effect for years $t-2$ and $t-3$. One of four tests gives the p-value of 0.119; in all other cases, the difference in magnitudes of the effects before and after the event is significant.[17]

We illustrate these results in Panel A of Figure IV. The figure presents the coefficients on the dummies indicating the years around the event with government approval as the dependent variable (darker line, left axis). On this figure, we also illustrate the treatment in the event study by showing the coefficients on year dummies around the event with regional 3G coverage as the outcome variable (lighter line, right axis): by construction, we observe a sharp increase in 3G coverage at the event year.[18]

We also verify that the events in our event study are not associated with a concurrent change in government approval in nonevent regions of the same countries (i.e., in those regions that did not experience such a sharp increase in 3G coverage).[19]

[17] To understand the size of a pretrend that can be rejected, we follow Roth (2019) and perform the following test. We assume the presence of a linear time pretrend with slope ξ and that the coefficients on the three forwards of the event dummy are jointly normally distributed. We take the variance-covariance matrix for this distribution from the estimation of the three pre-event coefficients in the event study (Column 3 of Table II). By construction, the mean of this distribution is $(S\xi, 2\xi, \xi)$, where S is the average difference in the number of years between the period $t-1$ and each of the periods before $t-3$. Taking into account the fact that $S \geq 3$ and that the pretrend is more easily rejected for larger S, for simplicity, we set $S = 3$. Then, we search for the smallest absolute value of ξ, such that, in 90% of all realizations of the multivariate normal distribution, at least one of the pretrend coefficients is statistically significant at the 10% significance level. In particular, we take hypothetical ξ from a grid between 0 and -0.05, and for each value of ξ, we perform 100,000 random draws from the corresponding multivariate normal distribution to calculate the percentage of draws with at least one of the pretrend coefficients significant at the 10% significance level. The smallest $|\xi|$, such that in 90% of draws at least one of the pretrend coefficients is significant, is 0.0188. Thus, we are able to reject a pretrend with a slope that is larger than 0.0188 in absolute value, which is approximately equal to the absolute value of one half of the estimated treatment effect from Column 2 of Table II.

[18] Appendix Figure A.5 illustrates the dynamics of raw government approval around the event in the sample of regions for which we observe government approval both before and after the event. The figure presents the mean of government approval net of region fixed effects to account for changes in the sample composition across years.

[19] To do this, we restrict the sample to those countries where at most 60% of all GWP respondents are located in regions where the event occurred. Then, we randomly draw placebo-event regions among those that did not have an event from the country-years, in which other regions had an event. We repeat this exercise 500 times, comparing the distributions of the point estimates and their t-statistics for the effect of such placebo treatments with those for the actual treatment in the same sample of countries. The results are presented in Figure A.6 in the Appendix. We find that both the coefficient and its t-statistics from the estimation of the effect of the true event are outside of the corresponding distributions for the placebo events. We also verify that our results are not driven by influential observations. In Appendix Figure A.7, we present the residual scatterplot from the regression at the region-year level in the event-study sample. This regression is similar to the one presented in Column 2

A number of recent studies show that, in the presence of heterogeneous treatment effects, the coefficients on the leads and lags of the treatment variable in an event study might place negative weights on the average treatment effects for certain groups and periods (e.g., see Borusyak and Jaravel, 2018; Goodman-Bacon, 2018; Sun and Abraham, 2020; De Chaisemartin and D'Haultfœuille, 2020). To address this concern, following De Chaisemartin and D'Haultfœuille (2020) we use an alternative estimator that solves this issue by calculating the average of all these treatment effects.[20] The results are presented in Panel B of Figure IV. Appendix Table A.4 provides the underlying regression table. Similarly to the OLS estimation of the event study, these results indicate that government approval decreases sharply after a sharp increase in regional 3G coverage, whereas before the event, the effects are not distinguishable from zero.

2G as a placebo treatment. A potential concern is that 3G availability may affect individuals' beliefs through other mechanisms than providing access to mobile broadband internet. To address this concern, we consider the effect of the expansion of 2G networks, which allow making phone calls and sending text messages, but provide very limited internet capabilities and, in particular, do not allow browsing the internet freely or watching online videos. The key difference between 2G and 3G mobile networks is that, unlike 2G, 3G facilitates the immediate dissemination of photos and videos, which can invoke substantially stronger emotional reactions and therefore have more profound political implications than information in text form.[21] For example, the Arab Spring started after a smartphone-recorded video of the self-immolation of a street vendor, Mohamed Bouazizi, vent viral on social media (Castells, 2015, p.22). In contrast, the self-immolation a few months earlier of another street vendor, Abdesslem Trimech, had no political implications, presumably because nobody recorded it (Gurri, 2018, pp. 47-48).[22]

If individuals' beliefs were affected not by access to mobile broadband internet but rather by some other aspects of communications technology, one should expect similar effects of the expansion of 2G and 3G networks. In Table III, we show that, in

of Table II (apart from the level of aggregation). The results are robust to excluding observations that are away from the main cloud (marked on the scatterplot) or regions to which these region-year observations belong.

[20] We use the software package DID_MULTIPLEGT developed by De Chaisemartin and D'Haultfœuille (2020). Other papers (e.g., Borusyak and Jaravel, 2018; Sun and Abraham, 2020) propose similar estimators.

[21] Manuel Castells makes this point in several of his books; see, e.g., Castells (2015, p.15) and Castells (2019, p.20). The fact that videos are more powerful than text has also been shown in other contexts (e.g., Durante and Zhuravskaya, 2018).

[22] Observers also argue that the spread of information about the events in Tunisia in 2011 across the Arab states was also driven by mobile broadband internet and social media: "Most of Al Jazeera's Tunisia footage came from cell phone videos, taken by the public on the spot and communicated via Facebook. They were then re-posted online—on Al Jazeera's website, on YouTube, and on thousands of niche sites." (Gurri, 2018, p.48).

contrast to the effect of 3G presented above, the expansion of 2G networks, if anything, is associated with an *increase* in government approval (Columns 1 to 6 of Panel A), suggesting that the populace may credit the government—justifiably or not—for the construction of new infrastructure that improves its quality of life.

In Panel B of the table, we also show that controlling for 2G availability does not affect the estimates of the effect of 3G. In addition, as we show in Column 7 of Table III, unlike 3G coverage, regional 2G coverage is not related to respondents' internet access at home. These findings suggest that the negative effect of 3G on government approval is driven by its effect on mobile broadband internet access rather than by other features of the expansion of mobile networks. As we noted in the introduction, the fact that we find no negative effect of 2G on overall government approval does not contradict the findings of Manacorda and Tesei (2020), who show that 2G mobile networks facilitated protests in Africa during recessions. This is because protests are often organized by interested minorities that have more incentives to seek political information than the general public, and therefore, the expansion of 2G, which allows texting, did help these minorities to get informed and to coordinate and organize the street protests, while having no effect on the majority's opinion about the government.[23]

Variation in observables as a proxy for unobserved variation. We follow the methodologies of Altonji, Elder, and Taber (2005) and Oster (2017) to understand whether unobserved variation is likely to explain our results. First, we construct the index of observables that is the best predictor of 3G availability, by taking the fitted value from a regression of 3G on all the controls. Then, we regress our outcome variables on this index of observables, controlling for region and year fixed effects. The results are reported in Panel A of Table A.5 in the Appendix. We find that the predicted-from-observables 3G availability is not significantly related to government approval, and the point estimates have the opposite sign of the effect of 3G for four of the six outcomes, including both aggregate measures of government approval. This suggests that, at least for these four outcomes, selection on unobservables is not driving the results, under the assumption that the observables are representative of the unobservables.

Second, in Panel B of Table A.5, we report Oster's δ statistic, indicating how much more important unobservables need to be compared to observables to fully explain our results by omitted-variable bias. Following Oster (2017), we set the value of R^2_{max}—the R-squared from a hypothetical regression of the outcome on treatment and both observed and unobserved controls—to be equal to $1.3\tilde{R}^2$, where $\tilde{R}^2$ is the R-squared from the baseline estimation (Table I). In the two cases where observables should be positively selected from unobservables to explain our results (Columns 2 and 4), the

[23] Enikolopov, Makarin, and Petrova (2020) show that the expansion of the social media platform VK in Russia increased both the likelihood of protests and support for the regime.

values of δ are 5.8 and 1.6. For all the other outcomes, observables should be negatively selected from unobservables to explain our results; for these outcomes, the δs range between -4 and $-1,000$.[24] Both the magnitude and the sign of these statistics suggest that it is highly unlikely that our results are spuriously driven by unobserved variation.

The frequency of lightning strikes as an IV. Finally, we use the identification strategy proposed by Manacorda and Tesei (2020), who show that in Africa the incidence of lightning strikes predicts local trends in the expansion of 2G mobile networks. We use differences in the regional frequency of lightning strikes per square kilometer as an exogenous source of variation in the speed of the expansion of mobile broadband internet service. During thunderstorms, the electrostatic discharges can damage mobile-phone infrastructure, increasing the cost of providing mobile service. This is the case for both 2G and 3G infrastructure. For this reason, one could expect slower 3G expansion in places with a high frequency of lightning strikes. Moreover, one should expect the adoption of mobile broadband infrastructure to be more affected by lightning strikes in lower-income countries, because providers in these countries typically have fewer resources to protect equipment from being damaged—for instance, by using power-surge protection technology—or to repair it in case of damage.

As discussed in the methodology section, we predict regional 3G coverage with a linear time trend interacted with a dummy for a high frequency of lightning strikes per square kilometer in a subnational region, separately in countries with above- and below-median GDP per capita. To control for other factors that might influence the speed of 3G expansion and that can be correlated with the frequency of lightning strikes per square kilometer, we also include linear time trends interacted with the subnational regions' share of territory covered by deserts, share of territory covered by mountains, maximum elevation, and dummies for each quintile of population density. To account for differential trends in 3G expansion depending on its initial level at the beginning of the observation period, we also control for linear time trends interacted with the regions' initial (2008) level of 3G coverage and dummies for whether the region and the country had any 3G coverage in 2008.

We illustrate the first-stage and reduced-form relationships with graphs summarizing the data in the subsample of countries with below-median GDP per capita, which provides most of the variation for the IV estimation. The importance of the frequency of lightning strikes for the expansion of 3G networks is illustrated by Figure A.9 in the Appendix. It shows the evolution of regional 3G coverage separately in subnational regions with a high and low frequency of lightning strikes per square kilometer, limit-

[24] Figure A.8 in the Appendix reports the sensitivity of the value of Oster's δ to alternative assumptions about the size of $R^2_{\max}$ for the case of the aggregate government approval. It shows that even in the case of maximum possible $R^2_{\max} = 1$, Oster's $\delta = -70$.

ing the sample to countries with within-country variation in the frequency of lightning strikes. Appendix Figure A.10 illustrates how the frequency of lightning strikes per area affects government approval. The figure shows that, on average, government approval, net of all controls, decreased in subnational regions with a low frequency of lightning strikes and increased in subnational regions with a high frequency of lightning strikes.

Since both regional 3G coverage and the frequency of lightning strikes are defined at the level of subnational regions, in the main specification, we perform the regression analysis at the region-year level, using the mean of government approval in the regions as the outcome variable. Table IV reports the regression results for this specification. Column 1 of Table IV presents the first-stage relationship for the full sample. We find that the adoption of 3G technology is significantly slower in regions with a high frequency of lightning strikes per square kilometer, and that this effect is stronger—both in terms of magnitude and in terms of statistical significance—in countries with below-median income. The overall F-statistic for the excluded instruments is 21, driven mainly by the strong relationship for the countries in the lower half of the income distribution. The second stage, presented in Column 2, confirms our main result: 3G expansion leads to a significant decline in government approval. Columns 3 and 4 show the IV results for the subsample of rural residents. Because much of the first-stage variation is driven by poorer countries, in Columns 5–8 of Table IV, we repeat the analysis, focusing on the subsample of countries with below-median GDP per capita; we find similar results.[25] Table A.6 in the Appendix reports results using individual-level data, which place more weight on more populous regions. The first stage is substantially weaker in this specification: in the full sample of countries, the F-statistics for all and rural respondents are 11 and 13, respectively. The relationship between the frequency of lightning strikes per square kilometer and the expansion of 3G networks at the individual level is driven solely by countries with below-median GDP per capita. In the subsample of these countries, the F-statistics fall below 10. To address this problem, we report weak-instrument-robust Anderson-Rubin confidence intervals for the effect of 3G coverage, which show that the estimates are significant. Overall, the IV results are robust to using individual-level data despite a weaker first stage.

The magnitude of the IV estimates is substantially larger than of the OLS estimates presented in Table I. However, as most of the variation in the first stage comes from countries with below-median GDP per capita, the relevant comparison of the magnitude of the OLS and IV coefficients should come from this sample. We report the corresponding OLS estimates, keeping the same sample and the same set of controls

[25]To rule out the potential concern that the first-stage relationship is driven by a small number of outliers (Young, 2020), we verify that the results are very similar if we use bootstrap standard errors with sampling at the cluster level. The precision of the first stage is practically unaffected, and the second-stage results are slightly more precise.

as in the IV regression, in Columns 6 and 8 at the bottom of Table IV. Using these estimates as the benchmark, we find that the magnitude of the point estimates in the IV regressions is about 2.5 times as large as in the corresponding OLS regressions (e.g., -0.329 vs. -0.120, for all respondents, as reported in Column 6).

Given the results of the analyses of the validity of the OLS difference-in-differences specification presented above, it is unlikely that this difference is driven by endogeneity of regional 3G coverage. The first likely explanation for the difference in the magnitude between the OLS and IV estimates is the Local Average Treatment Effect (LATE) in the presence of heterogeneity of the effect of 3G on government approval. If mobile broadband internet has a larger effect on government approval among complier regions (regions where 3G expansion is, potentially, constrained by the frequency of strikes) than among noncomplier regions (regions where the expansion of 3G networks is not affected by lightning-strike frequency, for instance, because power-surge protection may be available), one should expect the IV estimates to be larger than the OLS estimates. It is probable that the population of the complier regions is particularly affected by political messages on social media. This may be because the ability to get power-surge protection when needed is positively correlated with the overall level of development in the region, which, in turn, is correlated with how informed the regional population is. Therefore, one could expect the population in the complier regions to be relatively less informed, making them more receptive to new political information compared to the residents of noncomplier regions.[26] The second potential source of the difference between the OLS and IV estimates is measurement error. There are several sources of such measurement error: (i) Access to mobile broadband internet is subject to numerous weather shocks, as both severe rain and wind affect connectivity (Schulman and Spring, 2011). (ii) Each year, the exact timing of the measurement of 3G network coverage does not correspond to the timing of the GWP surveys, and 3G coverage does evolve throughout the year. (iii) Providers may submit inaccurate or outdated data to the GSM Association, the ultimate source of the dataset on 3G network coverage.[27]

As with OLS, we benchmark the magnitude of the IV estimates, comparing them to the effect of unemployment. The coefficient on the unemployment rate in Column 6 of Table IV is -0.028. Hence, a decade-long increase in 3G coverage in an average

[26]We control for the overall level of regional development with region fixed effects. We cannot observe which regions are compliers because the definition of compliers involves a counterfactual level of 3G expansion under an unobserved alternative level of lightning-strikes frequency. In Appendix Section D, we describe which countries provide observations that drive the variation in the first stage, as highlighted in Appendix Figure A.11.

[27]It is possible that measurement error in 3G is nonclassical, that it is correlated with other determinants of government approval, such as governance quality. Most of this potential correlation is controlled for by region fixed effects and other covariates. If the changes in the quality of the measurement of 3G are correlated with the changes in governance quality, this could also explain the difference between the magnitudes of the OLS and IV estimates.

region of 0.39 is equivalent to a 4.6 ($= \frac{0.329 \times 0.39}{0.028}$) percentage-point increase in the national unemployment rate.

The persuasion rates implied by the IV estimates make sense only if the spillovers are substantial. In the full sample of countries, the persuasion rates are equal to $\frac{73.7}{N}$ for all residents and $\frac{80.1}{N}$ for rural residents, and in the sample of countries with below-median GDP per capita, they are $\frac{115.1}{N}$ and $\frac{133.0}{N}$, respectively. N here is the average number of people exposed to the message per smartphone with a mobile internet connection. It is reasonable to conjecture that, in complier countries, where the development of ICT is constrained by lightning strikes, N is large. (Details of the calculations and all the assumptions behind them are provided in Appendix Section C.)

Overall, the results we present in this section strongly suggest that the negative effect of 3G mobile networks on government approval can be interpreted as causal.

III.B. Robustness

Alternative assumptions about the variance-covariance matrix. Table A.7 shows that the results are robust to alternative assumptions about the correlation between the error terms. We take the specification presented in Column 6 of Panel A of Table I as the baseline (also reproduced in row 1 of Table A.7) and show in row 2 that the standard errors are only slightly larger with clusters at the country level. We then proceed to test the robustness of the results to correcting standard errors for spatial correlation following Conley (1999), Hsiang (2010), and Collela et al. (2018). In rows 3 to 8, we report the standard errors corrected for spatial correlation of the error terms within 500- and 1,000-kilometer radii with autocorrelation up to 10-year temporal lags. In all cases, the estimated effect is statistically significant at the 1% level. In addition, in Appendix Table A.8, we report the regression results for an aggregated region-level panel, in which we take simple averages of the dependent variables across individuals in each subnational region and year. As in the baseline specification, we control for the region and year fixed effects, as well as the region-level and country-level covariates (namely, we include regional-level income and the country's per capita GDP, democracy, and unemployment in the set of covariates). The results are robust.

3G coverage and population density weights. Our baseline measure of regional 3G coverage takes into account differences in population density within regions to account for the fact that mobile networks should only matter in places where people actually live. To verify that our results are not driven by any effect of population density on government approval, we conduct two exercises. First, in Panels A and B of Appendix Table A.9, we report the results of estimating Specification (1) using a measure of regional 3G coverage equal to the share of grid cells within each region and year that are covered by 3G networks (i.e., without population density weights). Second, in

Panels C and D of this table, we replicate the results presented in Table I, using the baseline measure of regional 3G coverage, but controlling for year dummies interacted with dummies for each quintile of population density. In both cases, the results are very similar to those reported in Table I, suggesting that our results are not sensitive to how we measure regional 3G coverage.

Alternative proxy for subnational economic development. In Section B of the Appendix, we show that our results are robust to using nighttime light density as an alternative proxy for regional economic development, and we discuss the properties of this control.

Robustness to excluding individual countries. We also have verified that our results are robust to excluding any one country from the sample. In particular, we conducted this exercise for the specification presented in Column 6 of Table I.

The effect over time. We explore whether the effect of 3G coverage on government approval changes over time by replacing regional 3G coverage in Specification (1) with its interaction terms with dummies for all consecutive two-year time periods in our sample. We find that the effect is stable and does not systematically change over time.[28] The results are reported in Appendix Table A.10 and illustrated in Figure A.12, which plots the over-time evolution of the effect of 3G coverage.

Subsample of observations from face-to-face interviews. For most country-years in the GWP, the data were collected via face-to-face interviews. However, in certain countries with at least 80% telephone coverage, the data were collected over the telephone. In Table A.11 in the Appendix, we show that the results are robust to excluding observations from telephone interviews and are, therefore, not driven by potential differences between the sample of respondents from in-person interviews and telephone interviews.

Balance in individual characteristics. We have checked whether the expansion of regional 3G coverage is correlated with the composition of individuals in the GWP surveys. Only a few of the large number of individual characteristics are unbalanced with respect to regional 3G expansion. We show that this imbalance does not drive our results. First, we replicate the results applying the methodology developed by Hainmueller (2012) that uses entropy balancing to reweigh observations in order to achieve balance. Second, we show that the results are robust to focusing on the subsamples without any variation in the unbalanced individual characteristics. Details of these analyses are presented in Appendix Section E.

[28] This provides further evidence that it is unlikely that there is time-specific heterogeneity in the treatment effect that could potentially lead to the standard difference-in-differences estimand being biased, as shown by Borusyak and Jaravel (2018); Goodman-Bacon (2018); Sun and Abraham (2020); De Chaisemartin and D'Haultfœuille (2020).

IV. EVIDENCE ON THE MECHANISM: COMPARATIVE ANALYSES

IV.A. Heterogeneity by censorship of the internet and of traditional media

The fact that uncensored internet can significantly undermine government popularity has not gone unnoticed by politicians, especially in nondemocratic countries. According to Freedom House, many governments have taken steps to limit internet freedom, with policies ranging from the blocking of social media and messaging apps in China, Egypt, Iran, and Russia to temporary shutdowns of mobile networks in India and Sri Lanka.[29] Yet, observers do conjecture that the internet is harder to censor than the traditional media (e.g., Diamond and Plattner, 2012).

In this section, we study whether and how the effect of 3G-network availability on individuals' attitudes toward government depends on internet censorship and on the censorship of the traditional media, (TV, radio, magazines, and newspapers).

We start by analyzing the heterogeneity of the effect of mobile broadband internet with respect to censorship of the internet. First, we add the interaction term between 3G coverage and a dummy for contemporaneous internet censorship, controlling for the direct effect of internet censorship, to our baseline difference-in-differences Specification (1). Panel A of Table V presents the results. The coefficients on 3G, indicating the effect of 3G without internet censorship, are negative and statistically significant, whereas the coefficients on the interaction term of 3G coverage with internet censorship, indicating the difference between the effects with and without internet censorship, are positive, significant for five of the six outcomes, and of similar magnitude in absolute value to the direct effect of 3G.[30]

As internet censorship is often introduced to prevent messages critical of the government from reaching the public, it is reasonable to assume that censorship is more likely when government approval is low. In that case, one should worry about a bias arising from reverse causality in this estimation. In Appendix Section F, we derive the formula for the probability limit of the estimator of the coefficient on the interaction term between 3G and internet censorship and show that it is biased downwards (toward zero) and against finding an effect. Thus, with the contemporaneous censorship dummy, we can interpret the *sign* of the effect as causal, but we are likely to underestimate the magnitude.

Panel B of Table V addresses the potential issue with reverse causality by using a time-invariant dummy for countries with internet censorship. In this estimation, we do not allow reverse causality by construction, but we introduce measurement error, as

[29]See `https://freedomhouse.org/report/freedom-net/freedom-net-2018` (accessed September 7, 2019). For academic work on internet censorship, see, e.g., King, Pan, and Roberts (2013, 2014), Qin, Stromberg, and Wu (2017), Roberts (2018), and Chen and Yang (2019).

[30]The coefficients on the direct effect of internet censorship are positive and marginally significant.

internet censorship evolves over time. The results are very similar whether we use the time-variant or the time-invariant measure. Thus, we conclude that internet censorship weakens the effect of 3G on government approval. When the internet is free, 3G coverage has a strong and statistically significant negative effect on government approval. In contrast, with internet censorship, the impact of 3G coverage on government approval is zero.[31]

Figure V illustrates these results. Panel A presents the nonparametric relationships between government approval in a region (net of all controls) and 3G expansion in this region since 2008, separately for the two groups of countries: with free internet and with censored internet, according to the time-invariant measure. The figure shows that in countries with low internet censorship (left-hand-side graph), 3G expansion is associated with lower government approval, while in countries where the internet is censored (right-hand-side graph), there is no relationship between these variables.

In Panel B of Figure V, we present the nonparametric relationships between the increase in 3G coverage since 2008 and internet access at home in the two groups of countries. Whether the internet is censored or not, the presence of 3G networks facilitates internet access at home for the population. This suggests that the difference in the effect of 3G on government approval between countries with free and with censored internet comes from the content available online rather than from internet penetration.[32]

Censoring the internet is technically difficult, due to its decentralized nature. Only a few governments restrict online content, whereas censorship of the traditional media is common throughout nondemocratic regimes. All countries with internet censorship in our sample have above-median censorship of the traditional press. In Panels C and D of Table V, we explore how the effect of 3G on government approval depends on the government's control of the traditional media. We include the interactions of 3G coverage with dummies for both internet censorship and censorship of the traditional media. As above, we use both the contemporaneous and the time-invariant measures (in Panels C and D, respectively). We define the time-variant dummy for press censor-

[31] In the Appendix, we document that these results are not driven by the choice of functional form, the threshold for defining the internet censorship dummy, or the fact that we imputed zero censorship values for democracies. In Panels A and B of Table A.12, we replicate the results of Panels A and B of Table V in the subsample of countries with nonmissing internet censorship (FOTN) data: if anything, the effects are stronger without the imputation. Panels C and D of Table A.12 show that the results are also robust to using the continuous measures of internet censorship instead of the dummies. Panel A of Figure A.13 shows that the results are robust to using alternative thresholds for the definitions of the internet censorship dummies. Panel B of this figure reports the distributions of the underlying continuous measures of internet censorship and shows that the baseline thresholds are chosen to reflect natural breaks in these distributions.

[32] Figure A.14 in the Appendix presents the corresponding nonparametric relationships, in which all controls are partialed out from the explanatory variable in addition to the dependent variable.

ship as an indicator that the FOTP index in that country and year is above the median value of this index among all countries in the sample without internet censorship, and the time-invariant measure is an indicator that the over-time mean of the FOTP index in this country is above the same median value. The coefficients on the interaction terms between 3G and the internet-censorship dummy remain positive and statistically significant in this specification, whereas the coefficients on the interaction of 3G with the dummy for above-median censorship of the traditional media are always negative and significant (for all but one outcome).[33] The coefficients on 3G coverage are also always negative, but are significant only for the aggregate measures of government approval.

The results are the same whether we use the time-variant or the time-invariant measures, which is particularly important in the case of censorship of the traditional media, because reverse causality could potentially bias the coefficient on the interaction term between 3G and censorship of the traditional media downward (away from zero), in favor of finding a negative effect. The specification with time-invariant measures of censorship is not subject to this reverse-causality problem. We illustrate the heterogeneity with respect to censorship of the traditional media in Appendix Figure A.15: focusing on countries with uncensored internet, the figure shows that the relationship between regional 3G expansion since 2008 and government approval (net of controls) is steeper in countries with above-median censorship of the traditional media compared to countries with below-median censorship of the traditional media.

Table A.13 in the Appendix replicates the entire Table V for the subsample of rural residents: the results are similar to those presented in Table V.[34]

Overall, we conclude that, with internet censorship, 3G does not affect government approval. Without internet censorship, the effect of 3G coverage on government approval is, on average, negative. The effect is stronger (more negative) when the traditional media are controlled. This evidence suggests that uncensored internet plays a particularly important role in informing the public about politics, when the traditional media do not report independent-of-the-government political information.

[33] Panels E and F of Table A.12 in the Appendix show that these results are robust to using the continuous measures of censorship of the internet and of the traditional media instead of dummies.

[34] One potential concern with the interpretation of the results about the difference in the differential effects by the censorship of the traditional media versus censorship of the internet is the potential unobserved heterogeneity between those autocratic governments that control the traditional media but not the internet and those that censor both. In particular, if the latter are more sophisticated, our results on the heterogeneity by censorship may be driven by the heterogeneity with respect to the government's sophistication. In Appendix Section G, we show that there is no correlation between the censorship-of-the-internet score and any available measure of the level of education of the political elite and their prior occupations from Gerring et al. (2019). If the sophistication of the political leadership is related to education and occupations, it is not driving our results. In the Appendix, we list countries with internet censorship.

IV.B. Is the effect of 3G always negative? Heterogeneity by country-level corruption

In theory, if the expansion of mobile broadband internet provides the public with new information about the integrity and competence of the government, the sign of the effect of 3G on government approval should depend on the relationship between the public's prior beliefs and the content received online. The expansion of 3G should decrease government approval if the new information provides a worse view of the government relative to the ex ante beliefs. However, for honest and competent governments, greater transparency may increase approval. If the new information delivers a better view of the government compared to ex ante expectations, the Bayesian public should update the assessment of the government upward. This may be the case even if online platforms disseminate predominantly negative information. For example, if social and other online media expose more damning information about governments of other countries than about one's own government, government approval may increase.

If there is no systematic bias in the information received via 3G and in the ex ante beliefs, then the negative updates by the Bayesian public should on average be balanced by the positive updates. Our results in Section III, however, indicate a statistically significant negative average impact of 3G expansion on government approval. There are two potential explanations. First, if social media is more conducive to disseminating negative information about the status quo no matter how good the government actually is and the public is unaware of this asymmetry (e.g., Castells, 2019; Haidt and Rose-Stockwell, 2019), one should expect the average effect of 3G expansion on government approval to be negative. Second, if the public's ex ante views are biased upward, for example, because the mainstream media controlled by the elites overstated the benefits of the status quo before the arrival of social media (as argued by Gurri, 2018), an increased transparency due to 3G expansion, on average, should also result in a downward shift in government approval.

To explore the heterogeneity of the impact of 3G by the actual quality of government, we use a cross-country measure of corruption constructed by IMF economists that is not based on perceptions (Furceri, Papageorgiou, and Ahir, 2019): their Global Incidents of Corruption Index (GICI) quantifies the actual corruption incidents in each country and year by measuring the share of the text of the quarterly EIU country reports devoted to corruption. In the next section, we explore within-country variation in this index over time. In this section, we use the long-term mean of this index as a measure of the overall level of corruptness in the country to understand whether and how the sign of the relationship between 3G and government approval differs in countries with high and low overall actual corruption.

We measure the overall level of the country's corruption as the country's mean of the GICI from 2000 to 2017.[35] There are 104 countries in our sample with GICI data. We divide them into 13 equal-size groups of eight countries according to their rank in the overall level of corruption.[36] We put the remaining 12 countries with missing GICI data into a separate group, denoted by "M" for missing. Then, we estimate our baseline Specification (1), but allowing the coefficient on regional 3G coverage to vary depending on which group the country is in. The results are presented in Figure VI for each of our outcome variables. The figure presents the point estimates of the coefficients on regional 3G coverage for each group, along with their 90%-confidence intervals. Even though the estimates in some of the subgroups are rather noisy, the overall picture is clear: with the exception of the least corrupt countries, the expansion of mobile broadband internet has a negative effect on government approval regardless of how corrupt the country is. In contrast, in the first group of the least corrupt countries, which consists of Denmark, Germany, Japan, the Netherlands, Norway, Sweden, Switzerland, and the United Kingdom, 3G expansion led to an increase in government approval.[37]

To ensure that the positive effect of 3G on government approval in the countries with the lowest overall corruption is not a result of pure chance, we conduct a set of 500 placebo estimations, in which we rank countries with nonmissing GICI data randomly, rather than according to the GICI, and we estimate the same specification as in Figure VI. The distribution of the t-statistics of the coefficients on the placebo group for the least corrupt countries from these regressions is presented in Appendix Figure A.16. It shows that it is extremely unlikely that the result about the effect of 3G in the countries with the least corrupt governments is just a random realization.

The results of the two heterogeneity exercises presented above—with respect to censorship and with respect to overall corruption—are consistent with the hypothesis that the consumption of political information available online is an important channel behind the political effect of 3G. However, these results provide no details on the content of such political information, in particular, whether voters are getting access to accurate political information or to false news, which—as has been shown in a number

[35] This cross-country measure is highly correlated with the various measures of quality of governance from the Worldwide Governance Indicators (WGI), which—unlike the GICI—are based on perceptions.

[36] We chose 13 groups to yield an equal number of countries in each group.

[37] The composition of this least-corrupt group is consistent with Castells (2019, p.18) who argues that "corruption is a systemic trait of contemporary politics ... with a handful of exceptions, such as Switzerland or Scandinavia (excluding Iceland)." Our results are robust to expanding the group of least corrupt countries to include Finland (the 9th least corrupt country in the world according to the index of overall corruption based on the mean of the GICI), New Zealand (10th), Belgium (11th), Portugal (12th), and Singapore (13th). The effect of 3G in the least-corrupt group becomes zero if one includes the United States, the world's 14th least corrupt country according to this index. (This is consistent with Gurri (2018), who provides extensive anecdotal evidence on how the expansion of social media has undermined the confidence in the U.S. government.) The positive and significant effect of 3G expansion in the least corrupt countries is robust to estimating the effect separately for this group of countries, instead of a full-sample estimation that allows the effect to vary by subgroup.

of studies, for example, Allcott and Gentzkow (2017); Vosoughi, Roy, and Aral (2018); Grinberg et al. (2019); Guess, Nagler, and Tucker (2019)—does get disseminated on social media. We address this question directly in the next section.

IV.C. Does mobile broadband internet help expose actual corruption?

If mobile broadband internet helps inform the public about actual corruption in government, incidents of actual corruption should translate into higher perceptions of corruption in subnational regions with greater access to mobile broadband internet. Thus, one should expect the link between actual and perceived corruption to be stronger in areas with higher 3G coverage. To test this, one needs to measure new incidents of actual corruption in a global setting. We use two alternative measures of actual corruption. The first is based on the analysis conducted by the Economist Intelligence Unit and aggregated into the GICI by Furceri, Papageorgiou, and Ahir (2019), the other is based on information from the Panama Papers, a trove of leaked documents about offshore entities.

New incidents of corruption measured with the GICI.—We consider the over-time within-country variation in the GICI as a measure of actual corruption incidents. To test whether mobile broadband internet helps expose corruption, we regress the dummy indicating whether the respondent believes that the government is *not* corrupt on the measure of actual corruption incidents (GICI) and its interaction with regional 3G coverage, controlling for the direct effect of 3G as well as all the baseline controls, including region and year fixed effects.

We find strong support for the hypothesis that the internet helps expose corruption. The results are reported in Table VI. The first two columns present the results for the full sample of countries, for which the GICI is defined, that is, including observations with zero actual corruption incidents. Columns 3 and 4 consider the subsample of country-years, in which the measure of actual corruption incidents is strictly positive, so that we rely on the variation in how much focus is given to corruption incidents in the EIU country reports, provided that corruption is among the topics covered by the report. In odd columns, we present the results for all the respondents; in even columns, for the respondents from rural areas.

The results are very similar, whether we consider all respondents or only respondents from rural areas and whether observations with zero corruption incidents are included. We find that the within-country correlation between actual corruption incidents and the perceptions of corruption is significantly higher in regions with higher 3G coverage. In regions with no 3G signal, the correlation between corruption incidents and perception that the government is not corrupt is negative but small in magnitude and is (marginally) significant only if one excludes observations with zero corruption incidents (Columns 3 and 4). In contrast, if a region has full 3G coverage, there is a large, robust, and statistically significant link between the incidence of actual corruption and its perception. According to the baseline-sample estimates (Column 1), a one-standard-deviation increase in the measure of actual corruption incidents (0.31) is associated with a 2.9-percentage-point lower perception that the government is clean in places fully covered by 3G networks, and with a nonsignificant 0.4-percentage-point lower perception that the government is clean in places without mobile broadband internet coverage. (Overall, 21.5% of respondents believe that the government is clean.) In Panel A of Figure VII, we illustrate these results by presenting the marginal effect of an increase in the index of actual corruption incidents on the respondents' perceptions that the government is not corrupt for different levels of regional 3G coverage (implied by the estimates from Column 1): the effect becomes stronger (more negative) with the increase in 3G coverage.[38] The effect of 3G expansion when there are no corruption incidents, measured by the coefficient on regional 3G coverage in Columns 1 and 2, is small in magnitude and not statistically significant, suggesting that information about corruption available online is an important channel behind the negative effect of 3G.

Columns 5 and 6 of Table VI show that these average effects mask important heterogeneity by the country's overall level of corruption. We allow the effect of the interaction between 3G coverage and actual corruption incidents as well as the direct effect of 3G to vary between two groups of countries: with above- and below-median overall corruption, measured by the long-term mean of the GICI (used in the previous section). We find that the coefficient on the triple-interaction term between 3G coverage, actual corruption incidents, and a dummy for countries with below-median overall corruption is much larger in magnitude and more significant compared to a similar interaction with a dummy for countries with above-median overall corruption. This suggests that any particular corruption incident that gets exposed via mobile broadband internet contains bigger news in countries with relatively low overall corruption. At the same time, when the index of corruption incidents is zero, 3G expansion does not significantly affect corruption perceptions when overall corruption is relatively low.

In contrast, in countries with relatively high overall corruption, having access to mobile broadband internet is associated with significantly lower perceptions of no corruption in government, even when the index of corruption incidents is zero. This can be explained by the fact that, in these countries, many corruption incidents are not reflected in the EIU reports but are exposed with the help of mobile broadband internet. In this group of countries, an increase in the index of actual corruption incidents leads to

[38]The results do not depend on the functional form of the measure of actual corruption incidents. In particular, the results are very similar if one uses $\log(GICI + 0.1)$ or $\log(GICI + 1)$ instead of using the raw GICI data.

a much smaller widening of the gap in corruption perceptions between regions covered and not covered by 3G than in countries with relatively low overall corruption. (The coefficients on the interaction terms between regional 3G coverage, a measure of actual corruption incidents, and a dummy for countries with above-median overall corruption are negative, small in magnitude, and significant only for rural residents.)[39]

In Appendix Table A.15, we show that in the subsample of European countries, mobile broadband internet also helps inform the public about corruption incidents. These results help us interpret the findings on European elections, which we present in Section V. In Columns 1 and 2, we show that—similarly to the results for the global sample presented in Table VI—in Europe, the relationship between actual and perceived corruption is stronger in those subnational regions that are covered by 3G networks compared to the subnational regions without 3G coverage. This is true both for the full sample (Column 1) and for the sample focusing on the intensive-margin variation in actual corruption that excludes country-years with zero corruption incidents (Column 2). In Column 3, we verify that 3G expansion is associated with a significant increase in internet access at home among European respondents.

New incidents of corruption measured with the Panama Papers. On April 3, 2016, the Panama Papers, 11.5 million leaked documents detailing sensitive financial information of a large number of offshore entities, were made public. These documents directly implicated many corrupt government officials around the world in tax fraud and money laundering. Although offshore accounts are not *a priori* illegal and many private individuals use them, the revelations were particularly important in exposing corruption.[40] We base our second measure of new incidents of actual corruption on the number of unique offshore entities named in the Panama Papers.

First, we estimate a specification in which we regress the respondent's perception that the government is not corrupt on the interaction between regional 3G coverage and the number of Panama Papers entities per 1,000 people in each country (i.e., we use the cross-country variation in the number of Panama Papers entities per capita, assuming that the actual corruption that gave rise to these offshore accounts can partially be observed by independent journalists and the opposition). In addition to our standard set of controls, to address the potential confounding factor that people in rich regions are more likely to know about offshore accounts than people in poor regions, we add the interaction of 3G with regional income to the set of covariates. The results are

[39]In Appendix Table A.14, we test for a pretrend in actual corruption incidents; we find no evidence of such a pretrend. In particular, we show that regional 3G coverage is not predicted by contemporaneous or past levels of actual corruption incidents (Columns 1 and 2), and the index of actual corruption incidents is not predicted by lagged regional 3G coverage (Column 3).

[40]See, e.g., the *New York Times* Editorial Board's article from April 5, 2016: https://www.nytimes.com/2016/04/06/opinion/the-PanamaPapers-sprawling-web-of-corruption.html (accessed January 19, 2020).

reported in Column 1 of Table VII. The coefficient on the interaction between regional 3G coverage and the number of Panama Papers entities per 1,000 people is negative and significant. Thus, if the revelations from the Panama Papers are a measure of the level of overall corruption, this result confirms that mobile broadband internet helps expose it. To understand the magnitude of this effect, one can compare the difference in differences between the shares of people who believe that the government is corrupt in regions covered and not covered by 3G between two hypothetical countries, such that the number of Panama Papers entities per 1,000 people differs between these countries by one standard deviation. This difference in differences is equal to 5 percentage points. Panel B of Figure VII illustrates this result by presenting the magnitude of the marginal effect of an increase in the level of actual corruption measured by the Panama Papers on the belief that the government is not corrupt by different levels of regional 3G coverage (implied by the estimates presented in Column 1 of Table VII).

Next, we factor in the date when the Panama Papers were released to the public. In particular, we estimate specifications in which we allow the effect of the interaction between regional 3G coverage and the number of Panama Papers entities per 1,000 people to vary between two time periods: before and after the Panama Papers were released. We find that the effects are negative and significant both before and after the Panama Papers were released. The effect for the period after is larger than for the period before (presented in Column 2 of Table VII), but the difference in magnitude of these coefficients is not statistically significant.

The vast majority of the entities implicated by the Panama Papers come from middle-income and rich countries. Evidently, this is not because there is less corruption in poorer countries, but instead, because corrupt officials in these countries have no access to offshore bank accounts. In addition, in many low-income countries corruption is so pervasive that people observe it directly and do not need the internet to learn about it. Thus, we exclude low-income countries from the sample in Columns 3 to 6.[41] As we show in Column 3, once low-income countries are excluded, the magnitude of the coefficient on the postrelease period becomes larger, and the difference in magnitude between the preperiod and postperiod effects becomes statistically significant (the p-values for this test are presented at the bottom of the table).

These results suggest that only part of the information contained in the Panama Papers was news to the public. Even though before the release of the Panama Papers the public did not know where corrupt officials hid their wealth, some information about the corruption of these officials was already available on the internet. For this reason, the effect of the interaction of 3G coverage with the number of Panama Papers entities

[41] We use the standard World Bank definition of low-income countries for 2015—the year before the Panama Papers revelations. The results are robust to alternative definitions of low-income countries.

is negative and statistically significant even before the leak. The difference between the coefficients from before and after the leak illustrates both the extent of surprise from the revelations of the Panama Papers and the fact that this new information was more likely to reach the public in regions covered by 3G networks.

In Column 4, we verify that these results do not rely on a linear functional form. In particular, instead of the number of Panama Papers entities per 1,000 people, we use a dummy indicating that this number exceeds 0.1, which corresponds to the top 10% of the distribution of Panama Papers entities per capita. In this specification, only the effect for the postperiod is statistically significant; the difference between the effects in the pre- and postperiods remains statistically significant.

The country ranking of the implication in the Panama Papers differs somewhat if one considers the total number of entities rather than the number of entities per capita. In particular, some large countries such as the United States and Russia have a big number of Panama Papers entities but a relatively small number of entities per capita. In Columns 5 and 6, we show that our results are robust to using the number of entities not divided by the size of country's population (factoring in that only elites have offshore accounts). Column 5 presents the results for the number of entities and Column 6 for a dummy indicating that this number is above 2000, which corresponds to the top 10% of countries in terms of the total number of Panama Papers entities per country. In all specifications, we find that the coefficients on the triple-interaction terms between regional 3G coverage, a measure of the country's exposure to the Panama Papers, and a dummy for the period after the Panama Papers were revealed are negative and significant. They are also significantly larger in magnitude than the corresponding effect for the preperiod.

To sum up, we find robust evidence that mobile broadband internet helps expose government corruption.

IV.D. Heterogeneity with respect to other country and individual characteristics, as well as placebo outcomes

We also interact regional 3G coverage with a number of other country-level and individual-level characteristics, focusing on the first principal component of government approval as the outcome variable.

Geography, income, and democracy. The first eight columns of Table A.16 report heterogeneity by continents, OECD membership, level of per capita income, and level of democracy. As above, we present the results for the full sample and for the subsample of rural residents. Columns 1 and 2 present the effect of 3G expansion separately for each continent. In the full sample, the effect is significant for Africa and the Americas and is not significant for Asia and Europe. The magnitude of the effect in European countries in the full sample is essentially zero. In contrast, in the rural subsample, the effect is significant for all the continents, including Europe, where the effect is the smallest in magnitude among all continents (but is still sizeable). Columns 3 and 4 present the results separately for OECD and non-OECD countries. The effect is significant in non-OECD countries in both samples, while in OECD countries, it is significant only in the subsample of rural residents. Columns 5 and 6 show heterogeneity by the countries' per capita income. The results in high-income countries are virtually identical to those for OECD countries; whereas in middle-income and low-income countries, the effect of 3G coverage is significant both in the full sample and the rural subsample. It is the largest in magnitude in the group of upper-middle-income countries. Columns 7 and 8 document the absence of heterogeneity with respect to the level of democracy.

In the last two columns of Table A.16, we show that censorship of the internet and of the traditional media—considered in Section IV.A above—are the most important determinants of the effect of 3G coverage on government approval: qualitatively, the results on the heterogeneity by level of censorship do not change if we control for the interaction of regional 3G coverage with dummies for continents, levels of income, and levels of democracy.

Individual socioeconomic status. Table A.17 in the Appendix tests for heterogeneity with respect to the individual characteristics of the respondents. As above, we present the results for the full sample and for the subsample of rural residents. Columns 1 and 2 show that the effects are one-and-a-half times larger for the unemployed than for the employed. Columns 3 and 4 show that there is no effect of 3G on government approval among respondents with tertiary education, in sharp contrast to the negative and significant effects for respondents with secondary education and for respondents with less than secondary education, for whom the magnitude of the effect is the largest. Columns 5 and 6 show that the attitudes of respondents whose income is above the median country income in that year are less affected by 3G expansion than the attitudes of respondents with below-median income. Finally, Columns 7 and 8 report heterogeneity with respect to age groups. The results indicate that government approval among respondents who are younger than 25 is less affected by the expansion of mobile broadband internet than among respondents of other age groups. The effect on elderly people (above 60) is similar in magnitude to the effect on middle-aged people (between 25 and 60). The individual-level heterogeneity results are essentially the same for the total population and for the rural subsample, as can be seen from the comparison of the estimates presented in the odd and even columns of Table A.17.

Life satisfaction and other placebo outcomes. In Table A.18 in the Appendix, we show that 3G did not affect attitudes unrelated to the government. In particular, we show that 3G availability is not related to life satisfaction today, the expectation about life satisfaction in five years, satisfaction with current standards of living, and beliefs about whether the standards of living are getting better. 3G coverage also has no effect on the confidence in the local police, suggesting that mobile broadband internet affects individuals' opinions about the government only for those government functions that people cannot observe directly through their day-to-day experience.

V. ELECTORAL IMPLICATIONS OF THE 3G EXPANSION

The results presented above suggest that mobile broadband internet is an important source of political information for voters. Does 3G expansion also have electoral implications? The evidence from previous literature (briefly discussed above) suggests that it does, but previous studies have addressed this question only in single-country settings. We use panel data on the election results in European democracies to examine the effects of the decade-long expansion of mobile broadband internet on the vote shares of incumbent and opposition political parties, including populist ones. We focus on Europe for two reasons. First, Europe has recently experienced a significant rise of populism (Rodrik, 2018); and we are particularly interested in whether the internet facilitates the electoral success of populist parties, as has been suggested by several observers (e.g., Gurri, 2018; Tufekci, 2018; Castells, 2019) and by previous research on Italy (e.g., Campante, Durante, and Sobbrio, 2018). Second, a conventional classification of political parties into populist and nonpopulist is not available outside Europe.

We use data on 102 parliamentary elections that took place between 2007 and 2018, covering 398 subnational districts in 33 European countries (EU-28 plus Liechtenstein, Montenegro, Northern Macedonia, Norway, and Switzerland), and we estimate regression equations analogous to Specification (1) but aggregated to the level of the subnational districts at which the election data are available. In all the specifications, we control for subnational-district and year fixed effects, as well as for a proxy for subnational district income (for which we use nighttime light density), and employ the following country-level controls: log GDP per capita, the rate of unemployment, inflation, labor-force participation, and the share of population that is 65 or older.[42]

Our aim is to test whether the relationship between 3G expansion and a decline in government approval, which we have documented above, translates into tangible electoral losses for incumbent parties. The empirical challenge is that incumbent parties change over time. We address this challenge in two ways. First, we consider how electoral support for the parties that initially were part of the establishment evolved

[42]We cannot use the IV strategy in the analysis of elections, because the frequency of lightning strikes does not have predictive power in the sample of European countries, as all of them are in the group of countries with above-median GDP per capita.

depending on the expansion of mobile broadband internet availability. For simplicity, we focus on the two largest parties in parliament from the first election during our observation period. The reason for considering two parties is that in most European democracies, the two top parties traditionally have rotated in and out of power. The advantage of this approach is that the parties that constitute the political establishment under this definition do not change over time, and we can measure their political support throughout the period.

As a more direct alternative, we consider the vote share for the ruling party, defined as the party of the country's top executive (e.g., the Prime Minister). Because the ruling parties change over time, we first make a list of all political parties that were the ruling party at any point during our observation period. Next, we track the vote share for these parties, starting from the election in which they became the incumbent to the election in which they lost their incumbency. We then pool these observations. To compare vote shares within the same incumbent parties, in addition to all the baseline covariates, we control for incumbent-party-by-district fixed effects.[43]

The results are presented in Columns 1 and 2 of Table VIII. In Column 1, the outcome is the vote share for the top two parties in the first observed election; in Column 2, it is the vote share for the incumbent party. No matter the specification, we find that 3G expansion reduces incumbents' electoral support. We illustrate this relationship in Figure VIII. The point estimates imply that the expansion of mobile broadband networks in an average subnational district over a decade resulted in a 4.7-percentage-point lower vote share for the incumbent, both when the incumbents' vote share is proxied by the vote share for the two top parties from the first election (the sample mean is 56%), and when it is measured as the vote share for the ruling party (with the sample mean of 30%).[44]

In Column 3, we reestimate the specification presented in Column 2, allowing the effect of 3G to differ between populist and nonpopulist incumbents. We find that 3G expansion leads to a decrease in the incumbents' vote share, whether or not the incumbent is populist. (There is no statistically significant difference between the coefficients on the interaction terms between district 3G coverage and dummies for populist and nonpopulist incumbents.) In Column 4, we confirm this result by showing

[43]In the first approach, our unit of observation is a subnational district in an election. In the second approach, it's an incumbent party in a subnational district in an election; namely, in those elections that led to a change of an incumbent party, there are two observations in each subnational district: one for the outgoing incumbent party and the other for the incoming incumbent party. In this specification, we control for incumbent-party-by-district fixed effects to account for geographic differences in political support for different parties. The results are the same in a less conservative specification that controls separately for district fixed effects and incumbent-party fixed effects.

[44]This magnitude is based on the following calculation: $-4.7 = -0.089 \times 0.53 \times 100$, where 0.53 is an average increase in 3G coverage for subnational districts in Europe from 2008 to 2017, as discussed in Appendix Section C, and -0.089 is the coefficient on district 3G coverage.

that populist parties that were one of the top two parties in the beginning of the period lost votes as a result of 3G expansion.

In Column 5, we show that electoral turnout decreased more in districts that got higher 3G network coverage. This result could be driven by voters getting discouraged from participating in the elections due to their disillusionment with electoral institutions, consistent with our findings based on the GWP. It also could be that potential voters lose interest in politics as a result of exposure to online entertainment.[45] Appendix Table A.19 presents the results for the incumbent vote as a share of the number of registered voters rather than of those who actually voted in the election. The magnitudes are smaller but remain statistically significant. This implies that 3G expansion did spur some voters to change their political preferences.

Factoring in voter turnout, the estimates from Columns 1 and 5 of Table VIII imply the upper bound for the persuasion rate of the message "do not vote for the ruling party" of 27%. This upper bound is calculated under the assumption of no spillovers, that only the smartphone-owner (and nobody else) gets exposed to the message delivered by the device. In European countries, such spillovers are likely to be smaller compared to the rest of the world and, particularly, compared to poor countries; yet, one cannot rule out positive spillovers, even in the European context.[46]

Taken together, these results strongly corroborate our findings on government approval from the GWP.[47] The expansion of 3G made voters more critical of their governments and resulted in worse electoral performance by the incumbents in Europe.

Which parties gain electoral support when incumbents lose it as a result of 3G expansion? In Columns 1 to 5 of Table IX, we consider the effect on the vote shares for populist and Green (environmentalist) parties. As the definitions of populist and Green parties do not change over time, the unit of observation is a subnational district in an election. First, we consider the populists' vote shares and find that 3G expansion has contributed to stronger electoral performance by populist parties in Europe. A decade-long increase in subnational district 3G coverage, on average, results in a 4.6-percentage-point higher vote share for right-wing populists and a 3.6-percentage-point higher vote share for left-wing populists (Columns 1 and 2). The effects are large relative to the mean vote shares for right-wing and left-wing populists, equal to 13.6% and 6.5%, respectively. As we show in Column 3, there is no effect on parties classified as "other populists" (those that are not classified as right-wing or left-wing). Not all

[45] Previous literature has found that political participation may increase or decrease with access to the internet depending on the setting; see a recent review of the literature by Zhuravskaya, Petrova, and Enikolopov (2020).

[46] For details of this calculation and the assumptions behind it, see Appendix Section C.

[47] As we show above, the expansion of 3G networks helped expose actual corruption incidents to European voters (see Appendix Table A.15) and led to a significant decline in government approval among European voters residing in rural areas (see Appendix Table A.16).

observers agree with the classification of populist parties into right-wing, left-wing, and other. In Column 4, we show that the results do not depend on this classification; the effects are large and statistically significant for all populists taken together. We find a 6.1-percentage-point increase in the vote share for all populists (from the mean of 26%) as a result of an average-size 3G expansion over the 2008–2017 decade.

During our observation period, populist parties were in power during some electoral terms in Bulgaria, Hungary, Italy, Montenegro, North Macedonia, Poland, Slovakia, and Slovenia. In Column 5, we exclude these countries from the sample and find a larger point estimate of the coefficient on district 3G coverage, as one would expect given that populist incumbents suffer electoral losses due to 3G expansion (see Column 3 of Table VIII).

Appendix Table A.20 reports these results with the vote share expressed as the share of registered voters. The point estimates of 3G's effects on the populists' vote (total, right-wing, and left-wing) are smaller in magnitude but remain statistically significant. The average region-level 3G expansion over the decade increased the electoral support for all populists as a share of registered voters by 2.5 percentage points (see Column 4).[48]

The baseline estimates imply the upper bound for the persuasion rate—under the assumption of no spillovers—of 10.7% for the message "vote for a populist party" (for details on how we arrive at this figure, see Appendix Section C).

Does the nonpopulist opposition also gain from 3G expansion? Column 6 of Table IX shows that 3G network availability has a precisely-estimated zero impact on the vote share for Green parties. In Column 7, we consider all the nonpopulist opposition. We define a party to be in opposition if it is not included in the current ruling coalition. Similarly to the specifications presented in Columns 2 and–3 of Table VIII, this outcome is defined for each ruling coalition, and we control for the ruling-coalition-by-district fixed effects. We find no significant effect of 3G on the nonpopulist opposition's vote share; point estimate is actually negative. Figure IX illustrates the results for the opposition parties' vote share as the outcome variable.

In the Appendix, we establish robustness of these results to excluding any single country from the sample, as reported in Figure A.17. We also present the nonparametric relationships illustrating the election results with controls partialed out from the treatment variable as well as from the outcome variables. Figure A.18 shows the results for the incumbents' vote share; Figure A.19 shows the results for the opposition.[49]

[48]The effect of 3G on the share of votes cast for populists classified as "other" becomes negative and significant, but as there are very few parties like this and there is a strong positive effect on both left-wing and right-wing populists, the overall effect for all populists remains positive and significant.

[49]We also verify that the results are robust to excluding countries with compulsory voting: Belgium, Liechtenstein, and Luxembourg.

Overall, we find that, in European democracies, only populist opposition parties benefit from the disillusionment of voters with incumbent governments as a result of 3G expansion. If exposure to online criticism of incumbents were the only mechanism behind the fall in government approval with 3G expansion, one would expect all opposition parties to benefit from this phenomenon. Explaining why populists are the ones who gained from 3G expansion in Europe is beyond the scope of this paper. The mechanism could be both coincidental and causal. For instance, it is possible that the timing of 3G expansion coincided with the time when populist messages began to strongly resonate with voters, so that they just turned to the opposition that was the most appealing to them. However, it could also be that populists messages are particularly suited to the format of social media. In particular, populists' rejection of existing democratic institutions as entrenched and serving the elites implies that they should talk directly to the voters bypassing the traditional media. Such direct contact on a large scale was made possible only with the arrival of social media. Populist messages may also be simpler, and thus, better suited for a short, catchy communication than messages of other opposition parties (see, e.g., Levy, Razin, and Young, 2020).[50]

VI. COUNTRY CASE STUDIES

In this section, we briefly discuss three case studies illustrating the possible mechanisms behind our findings from the Gallup World Poll and from the European elections. Appendix Section H provides a detailed discussion of these case studies, backs them up with descriptive evidence, and lists the sources.

VI.A. Russia 2017: YouTube video on Prime Minister's corruption

On March 2, 2017, a leading Russian opposition politician, Alexei Navalny, posted on YouTube a 50-minute documentary, *He Is Not Dimon to You* (or *Don't Call Him "Dimon"*), detailing the corruption of Prime Minister Dmitry Medvedev. Because the Kremlin controls the traditional media, the documentary was not mentioned, let alone shown, on any of Russia's TV channels; it could be viewed exclusively on YouTube. By the time Vladimir Putin removed Medvedev from the Prime Minister's job, in January 2020, the film had 35 million views on YouTube.[51]

Within one month of the film's release, Medvedev's approval rating sank to a historic low and never recovered. It was unprecedented: in ten years, Medvedev's

[50] Consider, for example, the Greens' narrative, which is substantially more complex than that of the populists. Greens call for voters to take responsibility for the planet, which requires costly policy choices. Populists, in contrast, apportion all the blame for economic and social problems to elites and foreigners, suggesting that they are the ones who should bear the costs of change.

[51] The population of Russia in 2019 was 146 million (Source: the UN's World Population Prospects 2019, accessed August 5, 2020.)

popularity had never before fallen by 10 percentage points in one month. There was no news related to Medvedev or his government that month apart from the release of the film.

According to a nationally representative survey, only two weeks after the release of the documentary, 4.5% of respondents had watched it and another 15.4% had heard about it. Both having watched the documentary and having heard about it is strongly positively correlated with respondents' self-reported internet use and with Medvedev's disapproval. One cannot establish causality in these relationships, because much of this correlation is driven by (unobserved) individual and location characteristics. It is noteworthy, however, that 9.6% of respondents who had never used the internet had some exposure to the film: 2.4% of respondents had someone else show them the film and 7.2% had heard about it from others. This indicates the importance of spillovers in the effect of the release of stories about government corruption on social media platforms: these stories reach not only those who are directly exposed but also those with whom the users of social media communicate.[52]

VI.B. Romania 2014: the election of a "Facebook President"

In democratic countries (in contrast to Russia), exposing corruption online can also have electoral consequences. In the 2014 presidential election in Romania, incumbent Prime Minister Victor Ponta lost to a former physics teacher, Klaus Iohannis, who became known as the Facebook President. The margin of victory in the second round was 8.9 percentage points, which was a major and unexpected change in the Romanian political landscape—just two years earlier, Ponta won the parliamentary election with 59% of the vote. Romania was the second-most corrupt country in the EU at that point, and the stand on anti-corruption policies was the main cleavage in Romanian politics. Iohannis won on the anti-corruption ticket.

Iohannis attributed his success to his Facebook campaign. On the election night, he wrote the following post: *"Together, we have won the battle here on Facebook! ... For the first time, the online has made a difference."* In the last two weeks of the campaign, Iohannis published eight Facebook posts per day, criticizing the status quo for corruption and emphasizing the need for change. During the campaign, Iohannis overtook Ponta in terms of followers and also strongly outperformed Ponta in terms of the number of comments, likes, and shares. A postelection survey reported that 54% of a representative sample of Romanian voters used the internet, and 93% of those internet users had a Facebook page; 70% of those respondents who used the internet

[52] In the presence of such spillovers, the calculation of the persuasion rates for the political effect of 3G expansion (see Appendix Section C) overstates the true persuasion rates, because it assumes that only those who get a mobile broadband subscription are exposed to the anti-government message.

said that the internet and social media influenced their decision to vote.[53]

VI.C. *Brazil 2018: the election of a "WhatsApp President"*

In addition to helping inform voters about misgovernance, mobile broadband internet and social media may provide a platform for disseminating misleading and outright false narratives, which can also have electoral implications.

During election campaigns in Brazil, free TV time slots are allotted to political parties based on their size and the seats in the legislature. Therefore, as an outsider in Brazilian politics, the right-wing populist candidate, Jair Bolsonaro, got virtually no access to television during the 2018 presidential election campaign. Thus, he campaigned almost exclusively online and mostly on WhatsApp, a digital social network used by 90% of Brazilian internet users. The high penetration of WhatsApp in Brazil is related to the popularity of so called "zero-rating" plans that offer free access to a limited number of social-media applications, including WhatsApp. Zero-rating plans are popular because they are affordable. Mobile subscriptions with unlimited broadband internet access are too expensive for most Brazilians.

WhatsApp, especially when accessed via zero-rating plans, is particularly well-suited for disseminating misinformation. WhatsApp messages are sent through encrypted chat groups of up to 256 members, which makes fact-checking hard for two reasons. First, WhatsApp messages are private and, therefore, not always available to fact-checkers. Second, zero-rating-plan users cannot access fact-checking information provided on non-WhatsApp platforms because of the limitations imposed by their zero-rating plan. Several sources, detailed in Appendix Section H, provide anecdotal evidence that WhatsApp was widely used to expose voters to false political narratives during the 2018 presidential election, much of which was carried out in a coordinated campaign by a network of Bolsonaro supporters. Bolsonaro won the election with 55.13% of the second-round vote.

To provide suggestive evidence of the importance of access to WhatsApp for the election results, we use cross-sectional geographic variation in mobile broadband network coverage in Brazil in 2018. We merge our 3G network availability data with the 2018 election results for Brazil's microregions (*Microrregião*).[54] We find a strong positive correlation between a microregion's 3G coverage and Bolsonaro's vote share in the second round of the election (see Appendix Figure A.24). This correlation is

[53] By 2014, Romania was almost fully covered by mobile broadband internet. Even outside Bucharest, the average share of population with access to 3G was 94%. At the time of the previous presidential election, in 2009, Romania's 3G coverage was only 10%.

[54] Across the 558 microregions, the mean 3G coverage was 28% (with the standard deviation of 24%); 22 microregions had no coverage, 166 had coverage below 10%, 104 had coverage above 50%, and 11 had 3G more than 90% coverage.

especially striking given that 3G coverage in urban areas—where the share of educated voters, who were more likely to vote against Bolsonaro—is higher than in rural areas. The slope of the correlation between 3G coverage and the electoral outcome is steep: in microregions with 3G coverage below 10%, the average vote for Bolsonaro was only 40.7%, whereas in the microregions with 3G coverage above 50%, his electoral support was 63.4%.

Overall, the three case studies illustrate how mobile broadband networks can affect government approval and lead to a fall in the incumbents' popularity.

VII. CONCLUSIONS

In this paper, we document the political effects of the expansion of mobile broadband internet throughout the world. Our analysis yields the following conclusions. The decade-long expansion of 3G networks that we studied has, on average, led to a significant reduction in government approval around the globe. However, there is substantial heterogeneity in this effect, depending on censorship of the internet, censorship of the traditional media, and overall corruptness. Government approval falls with 3G expansion only when there is no internet censorship. It is more negatively affected by the expansion of 3G networks if the traditional media are censored but the internet is not. Expansion of 3G decreases government approval if there is at least some corruption. In very few noncorrupt countries, the effect of 3G expansion on government approval is actually positive. Overall, mobile broadband internet is an important medium for providing voters with political information that is independent of the government. Part of this information is about actual corruption in government, part could be misinformation.

In Europe, the expansion of mobile broadband networks has had electoral implications. As 3G network coverage has increased, so has voters' discontent with their governments, leading to a decline in vote shares for the incumbent parties, a decrease in turnout, and electoral gains for populist parties, both on the right and on the left. On average, 3G expansion has not helped the nonpopulist opposition in Europe, including Green parties.

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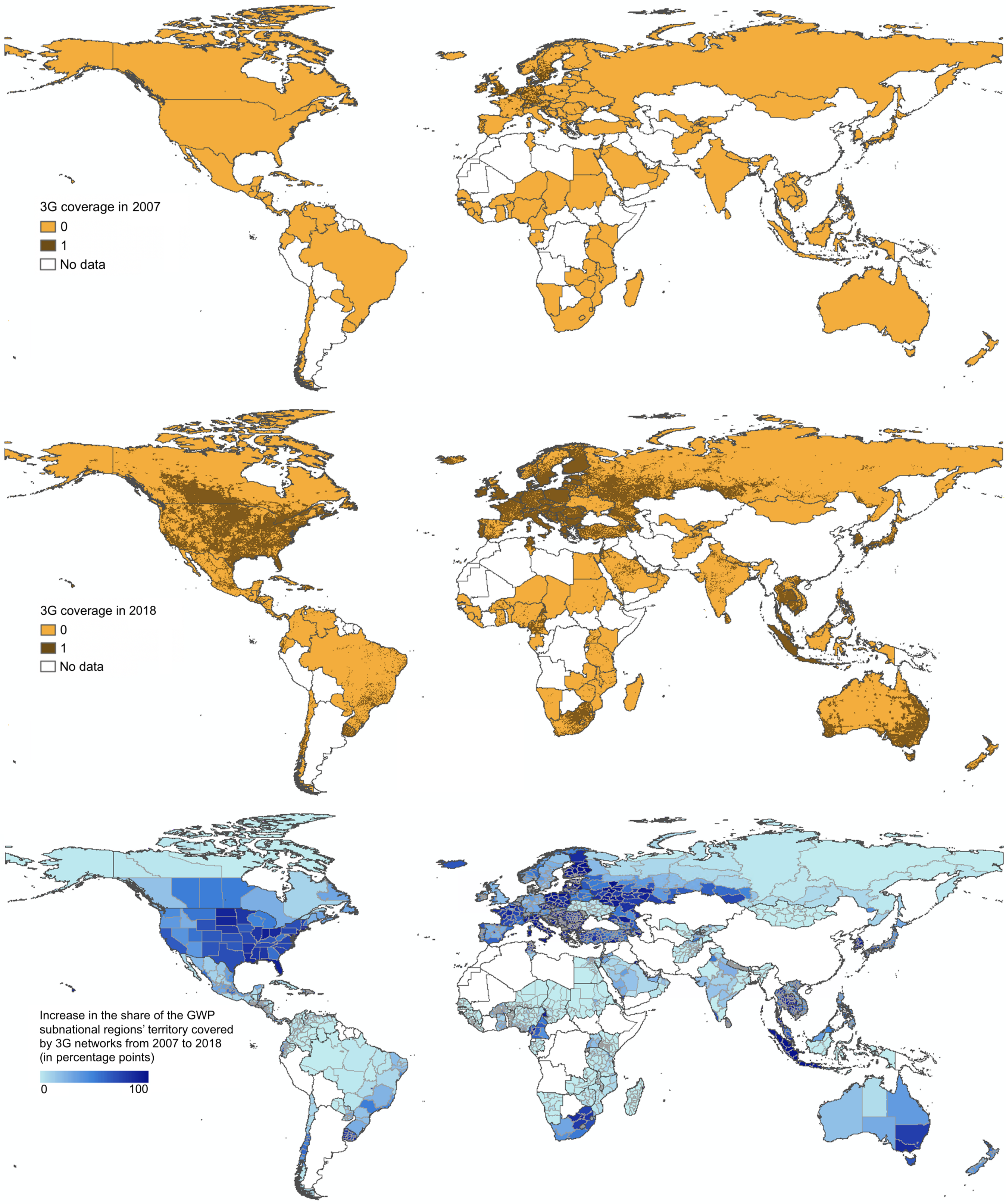


Figure I

The growth of 3G network coverage between 2007 and 2018

Note: The first two maps present 3G network coverage by grid cell in 2007 and 2018. The third map presents: (1) the boundaries of the subnational regions (the unit of localization in the GWP data) and (2) the increase in the share of each subnational region's population covered by 3G networks from 2007 to 2018. The sample consists of all countries covered by the GWP data. There are 2,232 subnational regions in the sample.

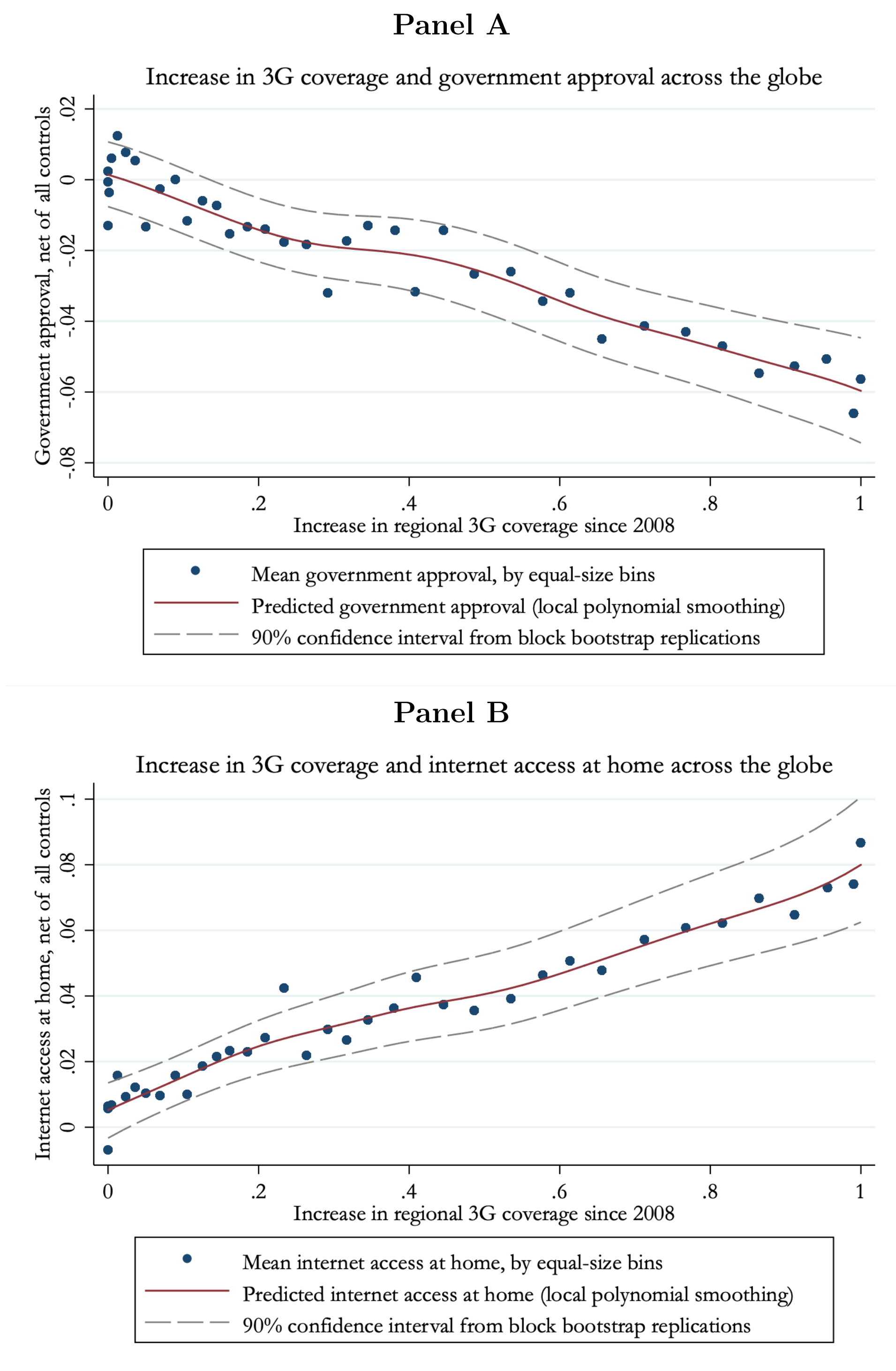


Figure II

Increase in 3G coverage and confidence in government

Note: Panel A of the figure illustrates the relationship between regional 3G coverage and government approval (Column 6 of Panel A of Table I). Panel B of the figure illustrates the relationship between the increase in regional 3G coverage and access to the internet at home (Column 1 of Panel A of Appendix Table A.2). The dots show the means of the respective outcome variables, net of all controls, by equal-size bins. The lines on the graphs show the predicted outcomes (Gaussian kernel, local polynomial smoothing). The confidence intervals are constructed by performing a block bootstrap at the level of the clusters.

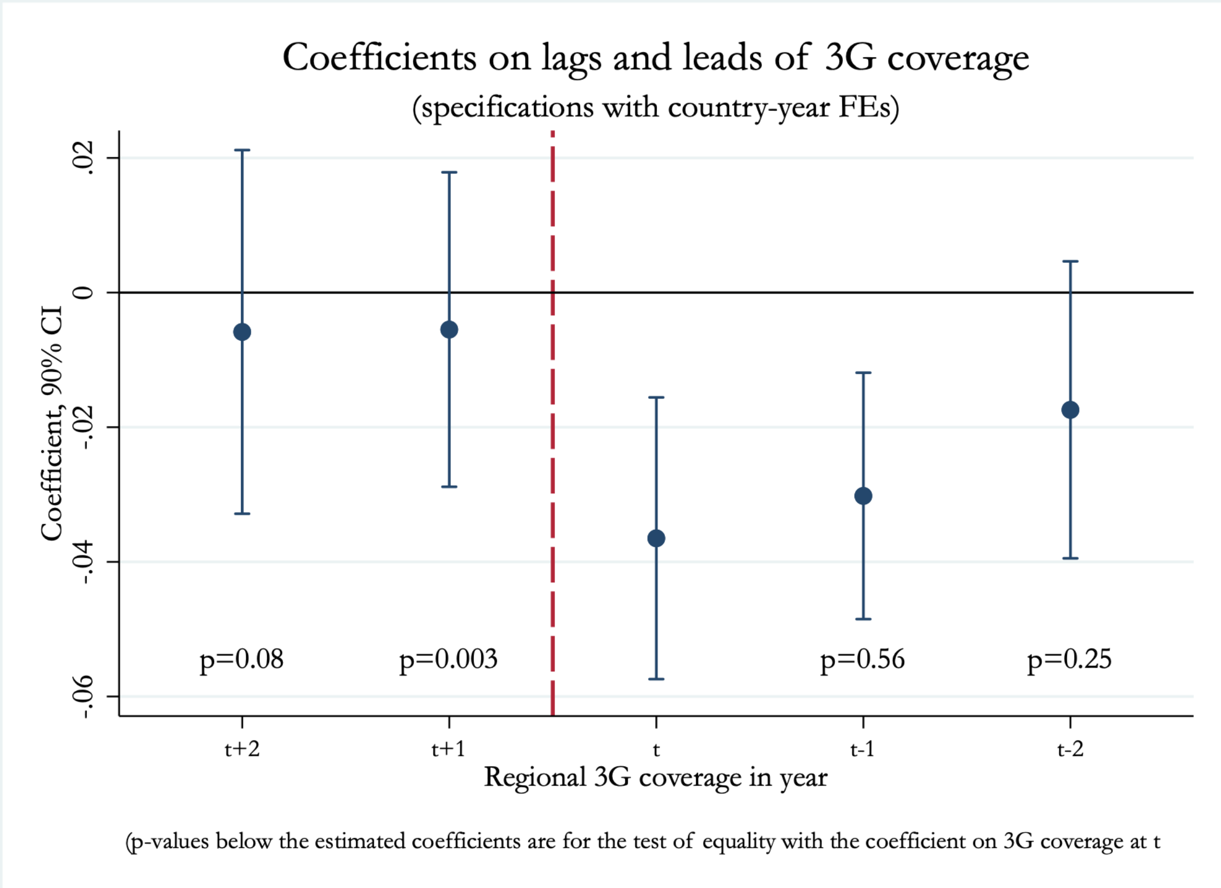


Figure III

Pretrend analysis with country × year FEs

Note: The figure presents the coefficients from the regressions of government approval on the lags and leads of 3G coverage in the full sample, controlling for country-year fixed effects and all the baseline controls. Each coefficient is from a separate regression. The results suggest that future expansions of 3G networks are not associated with current changes in government approval. The p-values below the estimates are for the test of equality of magnitudes between the respective coefficient and the coefficient on regional 3G coverage at t. The coefficients on the leads of 3G coverage are significantly smaller in absolute value than on 3G coverage at t, confirming the parallel pretrends assumption required for identification.

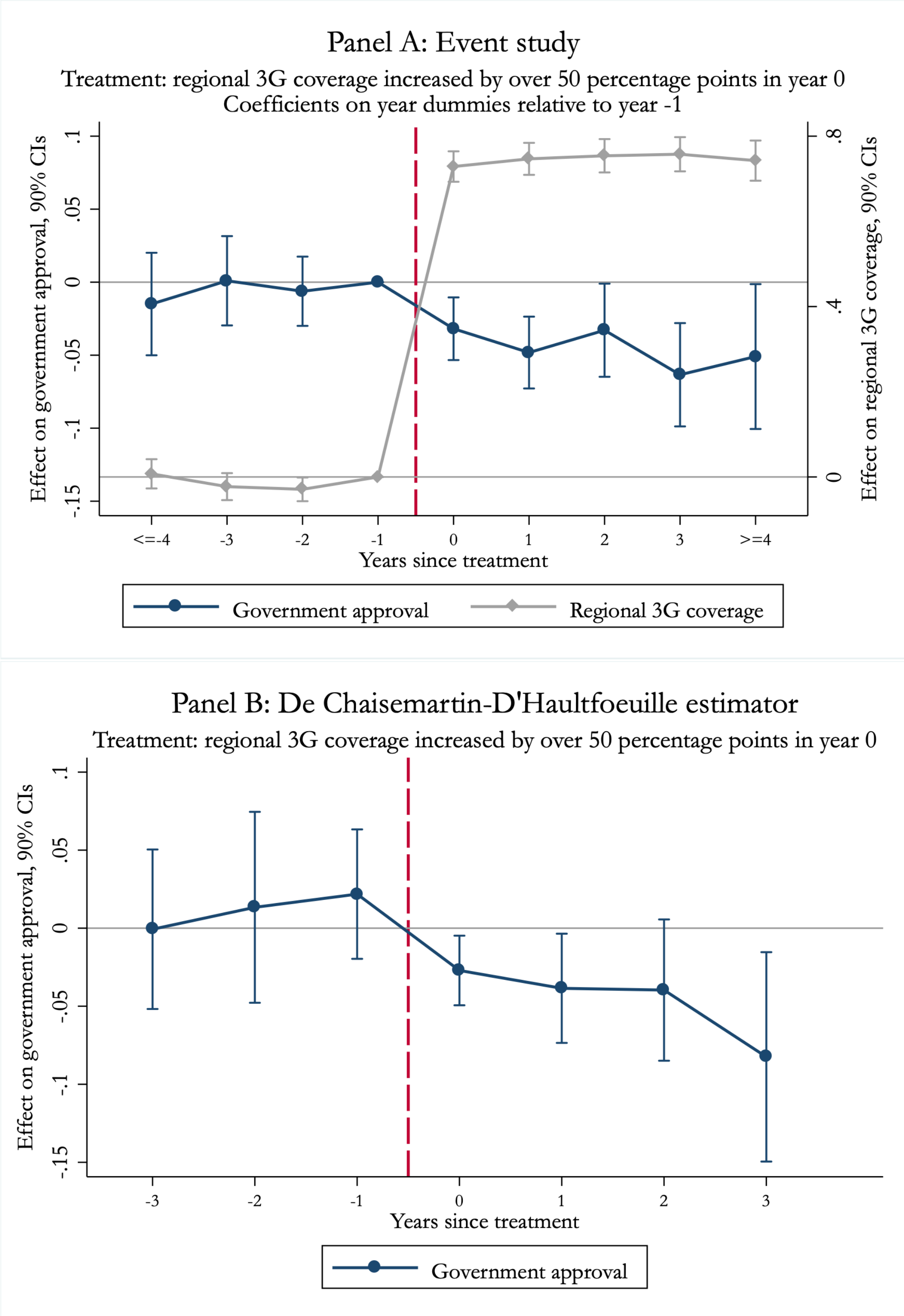


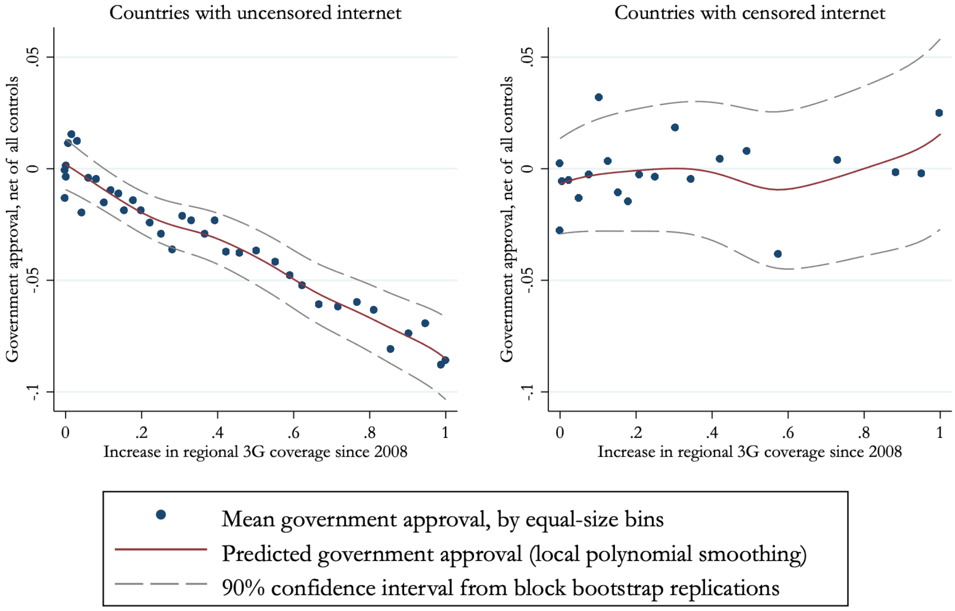
Figure IV

Event study analysis

Note: Panel A presents an event study in which government approval (left axis) and 3G coverage (right axis) are regressed on a set of year dummies around the event defined as an annual increase in regional 3G coverage of more than 50 percentage points. The regressions are run on the subsample of 452 regions in 65 countries where 3G did increase sharply in a single year between 2007 and 2018. The results of the underlying regression for government approval as outcome are presented in Column 3 of Table II. For each outcome variable, all the coefficients come from the same regression, which includes all the baseline controls and the freedom-of-the-press score in the list of covariates. Panel B presents the estimates based on the estimator proposed in De Chaisemartin and D'Haultfœuille (2020), which ensures that the average treatment effects in each group and period do not have negative weights. Both panels of the figure show that the decrease in government approval occurred after the significant expansion of 3G networks.

Panel A

Increase in 3G coverage and government approval across the globe



Panel B

Increase in 3G coverage and internet access at home across the globe

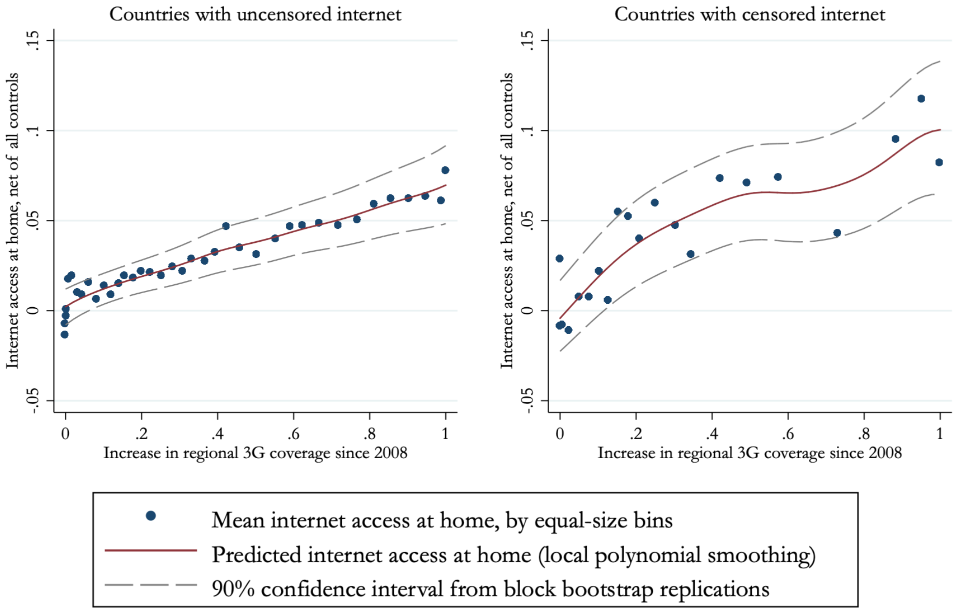


Figure V

Increase in 3G coverage and confidence in government, depending on internet censorship

Note: Panel A of the figure illustrates the results presented in Column 6 of Panel B of Table V, showing the relationship between the increase in regional 3G coverage and government approval separately for countries with and without internet censorship. Panel B of the figure illustrates the relationship between the increase in regional 3G coverage and access to the internet at home for countries with high and low levels of internet censorship. The dots show the means of the respective outcome variables, net of all controls, by equal-size bins. The lines on the graphs show the predicted outcomes (Gaussian kernel, local polynomial smoothing). The confidence intervals are constructed by performing a block bootstrap at the level of the clusters.

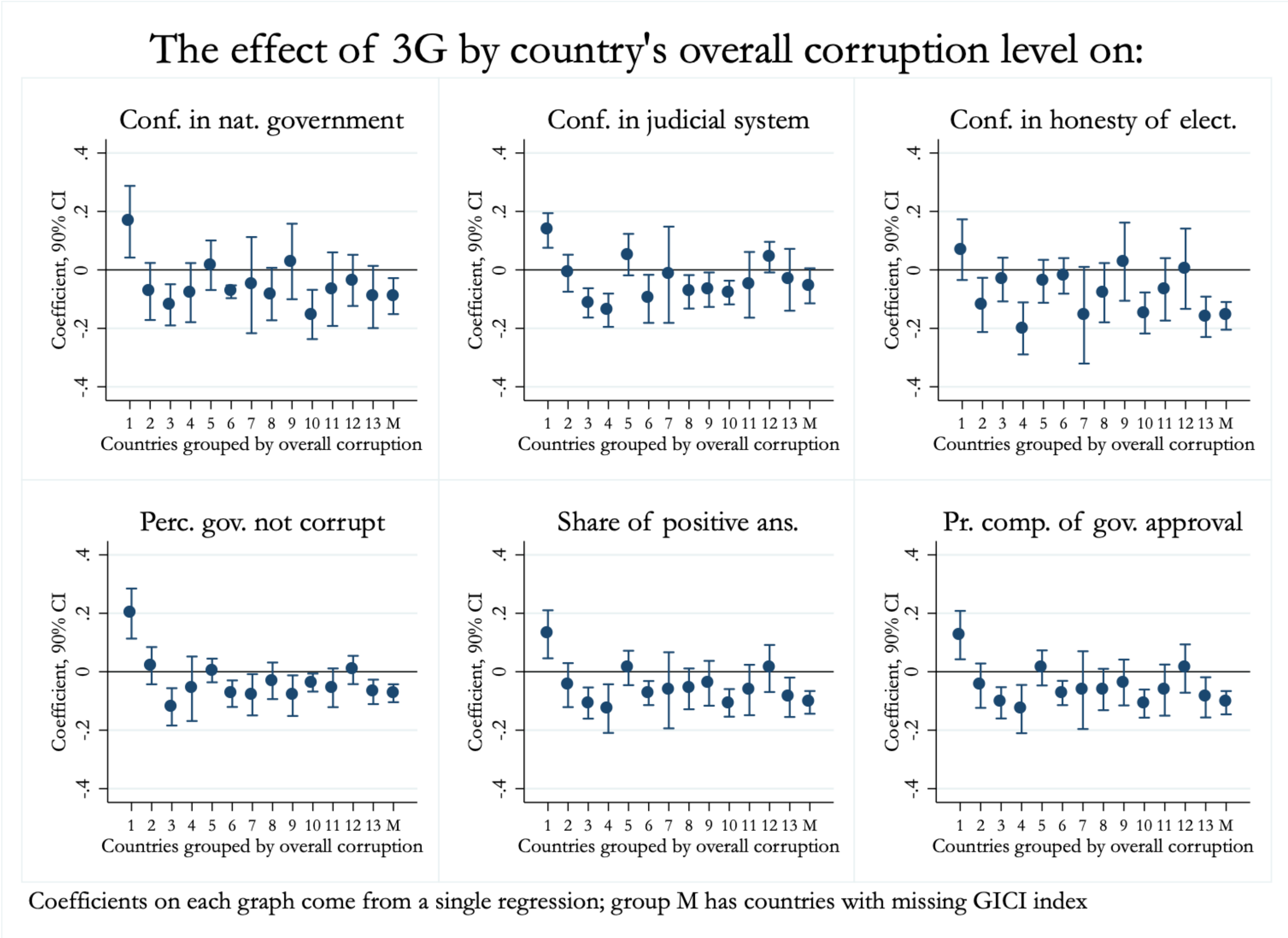
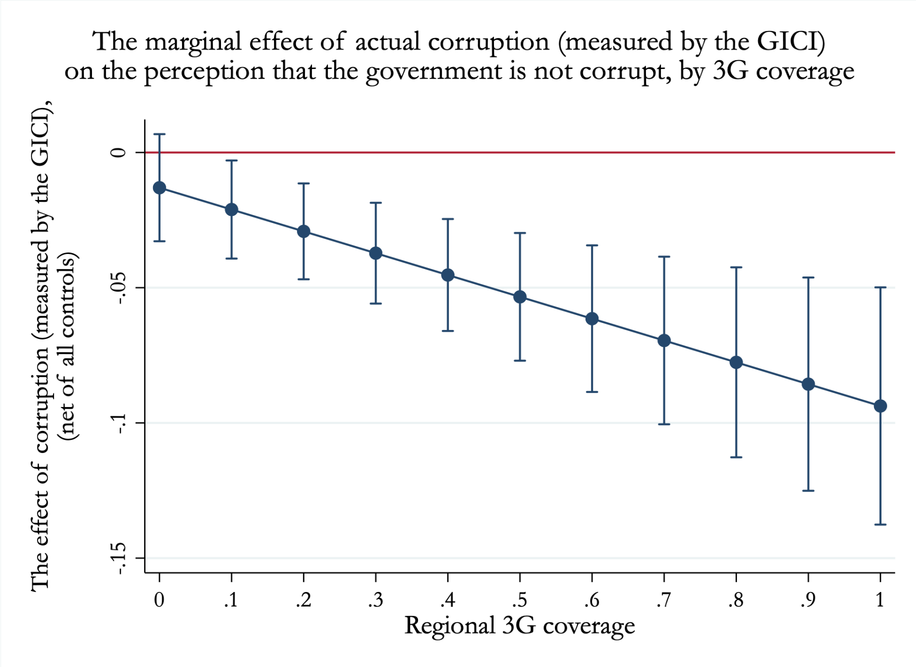


Figure VI

The effect of 3G coverage on government approval by overall corruption level

Note: The graphs present the coefficients on the interactions between regional 3G coverage and dummies for each of the 13 groups of countries, grouped by the overall level of corruption (i.e., mean GICI over 2000-2017) with 8 countries in each group. Group M has all 12 countries with missing GICI data. The graphs also present 90% confidence intervals, that are calculated from standard errors, corrected for two-way clusters at the subnational district level (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Panel A



Panel B

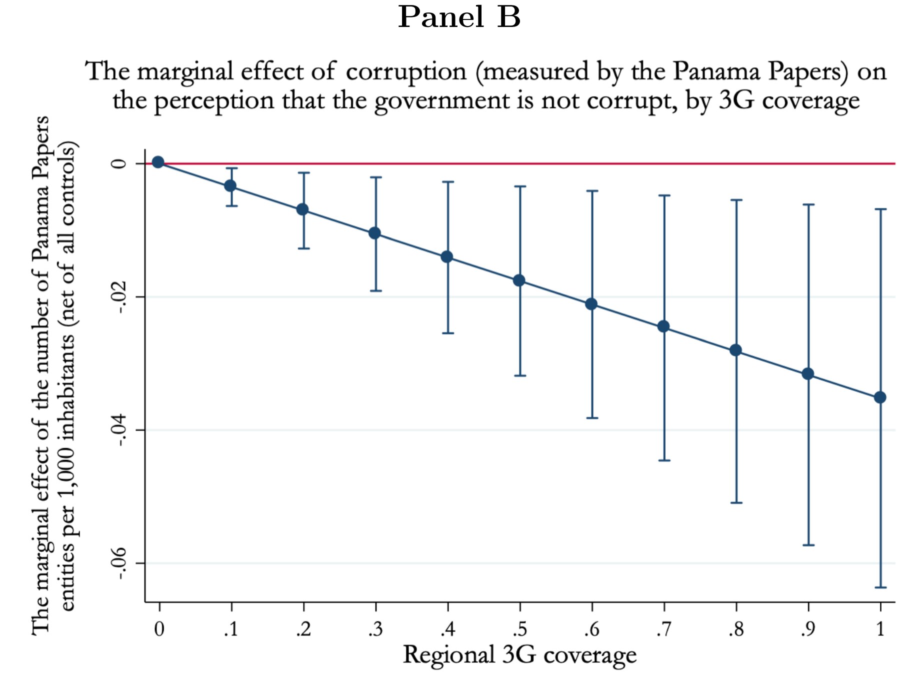


Figure VII

3G coverage and actual and perceived corruption

Note: The outcome variable is a dummy for the perception that there is no corruption in government. In Panel A, the explanatory variables are: regional 3G coverage, actual corruption incidents (GICI), their interaction term, as well as all the baseline controls, including region and year fixed effects (Column 1 of Table VI). In Panel B, the explanatory variables are: regional 3G coverage, the interaction term of regional 3G coverage and the number of entities in the Panama Papers per 1,000 people, the interaction of regional 3G coverage with regional income, as well as all the baseline controls, including region and year fixed effects (Column 1 of Table VII). The graphs present the marginal effects of an increase in actual corruption (measured by the GICI and the Panama Papers) on the perception of corruption. The graphs also present 95% confidence intervals, that are calculated from standard errors, corrected for two-way clusters at the level of the subnational districts (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation). The difference in the shape of the confidence intervals in the two graphs comes from the fact that the GICI varies both across countries and over time, whereas the Panama Papers provide information on countries at one point in time.

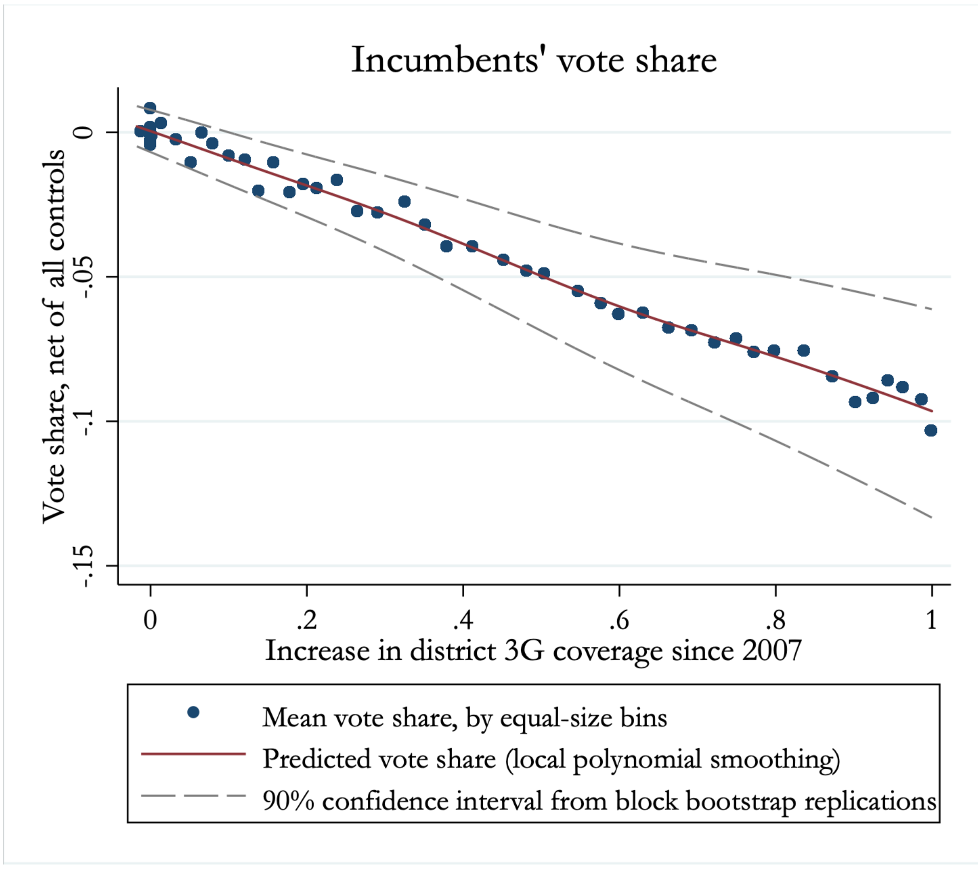


Figure VIII

Electoral implications of the expansion of 3G coverage for incumbents

Note: The figure illustrates the results presented in Column 2 of Table VIII. The dots represent the vote shares, net of all controls, by equal-size bins. The solid line on the graphs shows the predicted vote shares (Gaussian kernel, local polynomial smoothing). The 90% confidence intervals are constructed by performing a block bootstrap at the level of the clusters.

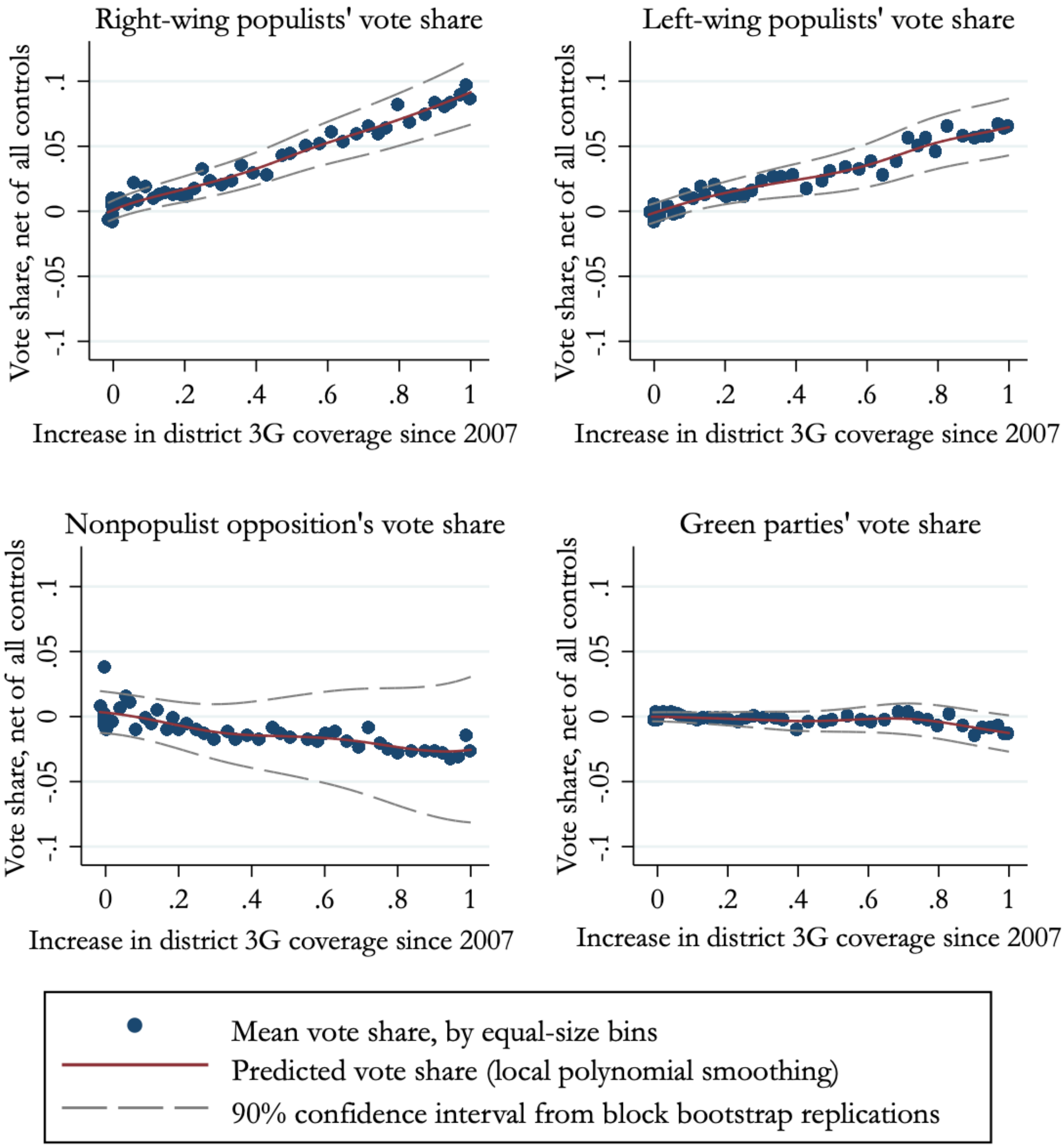


Figure IX

Electoral implications of the expansion of 3G coverage for opposition parties

Note: The plots on the first row illustrate the results presented in Columns 1 and 2 of Table IX. The plots on the second row illustrate the results presented in Columns 6 and 7 of Table IX. The dots represent the vote shares, net of all controls, by equal-size bins. The solid lines show the predicted vote shares (Gaussian kernel, local polynomial smoothing). The 90% confidence intervals are constructed by performing a block bootstrap at the level of the clusters.

Table I

The effect of mobile internet coverage on confidence in government

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Confidence in national government	Confidence in judicial system	Honesty of elections	No corruption in government	Share of questions with positive responses	1st principal component of responses
Panel A: Sample of all respondents						
Regional 3G coverage	-0.063***	-0.040***	-0.079***	-0.036**	-0.056***	-0.057***
	(0.021)	(0.015)	(0.021)	(0.014)	(0.015)	(0.015)
Observations	772,353	748,471	732,856	722,768	617,863	617,863
R-squared	0.164	0.163	0.168	0.225	0.242	0.239
Mean dep. var	0.439	0.534	0.505	0.226	0.432	0.439
Mean 3G coverage	0.397	0.381	0.383	0.383	0.381	0.381
Number of countries	111	116	112	112	110	110
Panel B: Subsample of rural residents						
Regional 3G coverage	-0.091***	-0.058***	-0.115***	-0.054***	-0.080***	-0.081***
	(0.024)	(0.017)	(0.026)	(0.016)	(0.018)	(0.018)
Observations	464,831	448,449	440,786	432,460	371,055	371,055
R-squared	0.171	0.157	0.161	0.194	0.224	0.222
Mean dep. var	0.349	0.556	0.516	0.215	0.445	0.452
Mean 3G coverage	0.329	0.314	0.316	0.316	0.311	0.311
Number of countries	110	115	111	111	109	109
Subnational region & year FEs	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. 3G internet reduces government approval. The unit of observation is an individual. Panel A reports the results for the full sample and Panel B for the subsample of respondents from rural areas. The table presents the results of the estimation of Specification (1). The dependent variables are individuals' perceptions of government and the country's institutions. Controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, and dummies for democracy status. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table II

Event-study results

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	1st principal component of the government approval responses					
Sample note 1:	Regions with a sharp increase in 3G coverage in one year in 2007-2018					
Sample note 2:	All respondents			Rural respondents		
Regional 3G coverage	-0.055***			-0.073***		
	(0.014)			(0.018)		
Post-event dummy		-0.036***			-0.052***	
		(0.012)			(0.014)	
Sharp increase in regional 3G coverage occurred in:						
Year $t+4$ or later			-0.015			-0.011
			(0.021)			(0.024)
Year $t+3$			0.001			-0.005
			(0.019)			(0.021)
Year $t+2$			-0.006			0.006
			(0.014)			(0.017)
Year t			-0.032**			-0.035**
			(0.013)			(0.015)
Year $t-1$			-0.048***			-0.066***
			(0.016)			(0.019)
Year $t-2$			-0.033*			-0.053**
			(0.019)			(0.021)
Year $t-3$			-0.063***			-0.067***
			(0.022)			(0.024)
Year $t-4$ or earlier			-0.051*			-0.061**
			(0.030)			(0.030)
Observations	130,406	130,406	130,406	66,078	66,078	66,078
R-squared	0.213	0.212	0.213	0.242	0.242	0.242
Number of countries	65	65	65	62	62	62
Number of regions	452	452	452	444	444	444
Number of countries with variation	65	36	65	62	32	62
Number of regions with variation	452	219	452	444	206	444
Subnational region & year FEs	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓
Censorship of the traditional press control	✓	✓	✓	✓	✓	✓
P-value: $\gamma[Y_t] = \gamma[Y_{t-2}]$			0.119			0.010
P-value: $(\gamma[Y_t] + \gamma[Y_{t+1}])/2 = (\gamma[Y_{t-2}] + \gamma[Y_{t-3}])/2$			0.024			0.005

Note: *** p<0.01, ** p<0.05, * p<0.1. The table presents the results of the event study. The unit of observation is an individual. The sample is comprised of individuals from regions that had a sharp increase in 3G coverage, more than 50 percentage points in the share of a subnational region's population covered by 3G in a single year, between 2007 and 2018. There are 452 regions from 65 countries like this. All regions in this sample have variation in the lags and leads of the year of the event (estimated in Columns 3 and 6). However, only 219 regions out of all regions with an event have variation in the post-event dummy within the sample, due to missing region-years in GWP data. Columns 1 to 3 report results for the full sample; Column 4 to 6—for the subsample of respondents from rural areas. The unreported controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, dummies for democracy status, and censorship-of-the-traditional-press score. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table III

The effect of 2G coverage on internet usage and confidence in government

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.:	Confidence in national government	Confidence in judicial system	Honesty of elections	No corruption in government	Share of questions with positive responses	1st principal component of responses	Internet access at home
Panel A: The effect of 2G on confidence in government and internet access at home							
Regional 2G coverage	0.045	0.031	0.098***	0.054***	0.056***	0.056**	-0.013
	(0.029)	(0.020)	(0.030)	(0.019)	(0.021)	(0.022)	(0.020)
Observations	772,353	748,471	732,856	722,768	617,863	617,863	840,537
Mean dep. var.	0.514	0.534	0.505	0.226	0.432	0.439	0.440
Panel B: The effect of 3G and 2G on confidence in government and internet access at home							
Regional 3G coverage	-0.060***	-0.038***	-0.074***	-0.032**	-0.053***	-0.053***	0.080***
	(0.020)	(0.015)	(0.020)	(0.014)	(0.015)	(0.015)	(0.017)
Regional 2G coverage	0.037	0.026	0.088***	0.049**	0.048**	0.048**	-0.002
	(0.028)	(0.019)	(0.030)	(0.019)	(0.021)	(0.021)	(0.019)
Observations	772,353	748,471	732,856	722,768	617,863	617,863	840,537
Mean dep. var.	0.514	0.534	0.505	0.226	0.432	0.439	0.440
Subnational region & year FEs	✓	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓	✓

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The table presents the effects of 2G coverage on internet usage and government support. The results suggest that, as expected, the change in 2G coverage did not increase internet access at home and, on average, increased government support. The unit of observation is an individual. Panel A reports results for the effect of 2G coverage, Panel B—similar results with 3G coverage included as a control variable. Columns 1 to 6 present the results for government approval as the outcome variables; Column 7—for a dummy for having access to the internet at home. Baseline controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, and dummies for democracy status. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table IV

Lightning strikes, 3G coverage, and government approval

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	Regional 3G coverage	1st principal component of government approval	Regional 3G coverage	1st principal component of government approval	Regional 3G coverage	1st principal component of government approval	Regional 3G coverage	1st principal component of government approval
Stage, 2SLS:	1	2	1	2	1	2	1	2
Countries in the sample:	All countries				Countries with below-median GDP per capita			
Respondents in the sample:	All	All	Rural	Rural	All	All	Rural	Rural
Regional 3G coverage		-0.283***		-0.308***		-0.329***		-0.389***
		(0.086)		(0.093)		(0.099)		(0.108)
$\mathbb{1}$[High frequency of lightning strikes per sq. km] × × Year × $\mathbb{1}$[GDP per capita below median]	-0.032***		-0.032***		-0.033***		-0.033***	
	(0.005)		(0.005)		(0.007)		(0.007)	
$\mathbb{1}$[High frequency of lightning strikes per sq. km] × × Year × $\mathbb{1}$[GDP per capita above median]	-0.010**		-0.009*					
	(0.005)		(0.005)					
Observations	12,860	12,860	11,743	11,743	5,789	5,789	5,324	5,324
Mean dep. var.	0.373	0.432	0.369	0.439	0.134	0.433	0.124	0.440
F-stat, excluded instrument		20.74		19.13		25.15		25.47
Corresponding OLS coefficient on regional 3G coverage						-0.120***		-0.158***
						(0.027)		(0.031)
Subnational region & year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Extended set of controls	✓	✓	✓	✓	✓	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. The table presents the results of an IV analysis, where the frequency of lightning strikes per sq. km. in a subnational region is used as an IV for the expansion of regional 3G coverage. The methodology follows Manacorda and Tesei (2020). High frequency of lightning strikes per sq. km is defined by the subnational region being in the top half of the distribution of lightning strikes per sq. km. Odd columns present the results of the first stage. Even columns—the results of the second stage. Columns 1 to 4 present the results for all the countries in the sample; Columns 5 to 8—for the subsample of countries with below-median GDP per capita. The unit of observation is a subnational region. Controls include the region's average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, dummies for democracy status, and linear time trends interacted with the subnational regions' share of territory covered by deserts, share of territory covered by mountains, maximum elevation, dummies for each quintile of population density, 3G coverage in 2008, a dummy for whether the region had any 3G coverage in 2008, and a dummy for whether the country had any 3G coverage in 2008. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table V

The effect of 3G coverage on government approval, depending on the level of internet censorship and on the level of censorship of the traditional media

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Confidence in national government	Confidence in judicial system	Honesty of elections	No corruption in government	Share of questions with positive responses	1st principal component of responses
Panel A: Time-variant dummy for internet censorship						
Regional 3G coverage	-0.100***	-0.057***	-0.117***	-0.054***	-0.081***	-0.082***
	(0.023)	(0.016)	(0.021)	(0.016)	(0.016)	(0.016)
Regional 3G coverage ×	0.105**	0.037	0.173***	0.054*	0.093***	0.094***
× Internet censorship dummy	(0.041)	(0.029)	(0.043)	(0.029)	(0.034)	(0.035)
Internet censorship dummy	0.068**	0.042*	0.053*	0.011	0.045*	0.046*
	(0.033)	(0.024)	(0.031)	(0.023)	(0.027)	(0.028)
Observations	656,015	631,606	618,480	613,737	521,632	521,632
R-squared	0.157	0.166	0.157	0.234	0.238	0.235
Panel B: Time-invariant dummy for internet censorship						
Regional 3G coverage	-0.098***	-0.055***	-0.124***	-0.056***	-0.081***	-0.082***
	(0.025)	(0.018)	(0.023)	(0.017)	(0.018)	(0.018)
Regional 3G coverage ×	0.091**	0.027	0.201***	0.056***	0.084***	0.085***
× Dummy: countries with internet censorship	(0.043)	(0.028)	(0.043)	(0.021)	(0.031)	(0.032)
Observations	648,705	624,264	611,221	606,955	515,365	515,365
R-squared	0.157	0.166	0.158	0.235	0.239	0.235
Panel C: Time-variant dummies for internet censorship and above-median press censorship						
Regional 3G coverage	-0.032	-0.027	-0.089***	-0.026	-0.046**	-0.047**
	(0.029)	(0.020)	(0.024)	(0.021)	(0.020)	(0.020)
Regional 3G coverage ×	0.157***	0.059**	0.195***	0.078**	0.121***	0.123***
× Internet censorship dummy	(0.044)	(0.030)	(0.046)	(0.031)	(0.035)	(0.036)
Regional 3G coverage ×	-0.116***	-0.051**	-0.046	-0.049*	-0.059**	-0.060**
× Above-median press censorship dummy	(0.034)	(0.023)	(0.030)	(0.025)	(0.025)	(0.025)
Internet censorship dummy	0.057*	0.037	0.049	0.005	0.039	0.040
	(0.032)	(0.024)	(0.031)	(0.023)	(0.027)	(0.027)
Above-median press censorship dummy	0.123***	0.023	0.070**	0.059**	0.068***	0.069***
	(0.034)	(0.021)	(0.030)	(0.025)	(0.023)	(0.023)
Observations	656,015	631,606	618,480	613,737	521,632	521,632
R-squared	0.158	0.166	0.158	0.234	0.239	0.236
Panel D: Time-invariant dummies for internet censorship and above-median press censorship						
Regional 3G coverage	-0.040	-0.019	-0.109***	-0.025	-0.052**	-0.053**
	(0.032)	(0.024)	(0.026)	(0.023)	(0.023)	(0.023)
Regional 3G coverage ×	0.154***	0.066**	0.218***	0.089***	0.115***	0.117***
× Dummy: countries with internet censorship	(0.050)	(0.033)	(0.050)	(0.025)	(0.037)	(0.037)
Regional 3G coverage ×	-0.117***	-0.072**	-0.031	-0.061**	-0.057*	-0.058*
× Dummy: countries with above-median press censorship	(0.043)	(0.032)	(0.038)	(0.030)	(0.031)	(0.032)
Observations	648,705	624,264	611,221	606,955	515,365	515,365
R-squared	0.157	0.166	0.158	0.235	0.239	0.236
Subnational region & year FEs	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The unit of observation is an individual. The dependent variables are individuals' perceptions of government and the country's institutions. Panels A and C use time-variant measures of censorship, whereas Panels B and D use time-invariant measures. Unreported controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, and dummies for democracy status. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table VI

The relationship between actual and perceived corruption

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Perception of no corruption in government					
Sample:	All	Rural	All	Rural	All	Rural
Regional 3G coverage × Actual corruption incidents	-0.081***	-0.101***	-0.059**	-0.062**		
	(0.025)	(0.030)	(0.024)	(0.029)		
Regional 3G coverage × Actual corruption incidents × × Country with below-median overall corruption					-0.222***	-0.243***
					(0.035)	(0.041)
Regional 3G coverage × Actual corruption incidents × × Country with above-median overall corruption					-0.030	-0.039*
					(0.020)	(0.024)
Regional 3G coverage	-0.014	-0.025	-0.019	-0.037*		
	(0.016)	(0.019)	(0.016)	(0.020)		
Regional 3G coverage × × Country with below-median overall corruption					0.005	0.002
					(0.021)	(0.026)
Regional 3G coverage × × Country with above-median overall corruption					-0.033*	-0.057***
					(0.019)	(0.020)
Actual corruption incidents	-0.013	-0.013	-0.017*	-0.021*	-0.015	-0.017
	(0.010)	(0.012)	(0.010)	(0.012)	(0.010)	(0.012)
Observations	691,872	414,346	581,944	354,966	691,872	414,346
R-squared	0.226	0.192	0.151	0.126	0.227	0.193
Subnational region & year FEs	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓
Sample excludes observations with zero corruption incidents			✓	✓		

Note: *** p<0.01, ** p<0.05, * p<0.1. The outcome variable is a dummy for the perception that there is no corruption in government. Actual corruption incidents stand for the IMF's Global Incidents of Corruption Index (GICI). The unit of observation is an individual. Unreported controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, and dummies for democracy status. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table VII

3G coverage, the number of entities in the Panama Papers, and perceived corruption

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Perception of no corruption in government					
Countries in the sample:	All countries		Excluding low-income countries			
Regional 3G coverage ×						
× Number of Panama Papers entities per capita	-0.035**					
	(0.014)					
× Number of Panama Papers entities per capita × Before Panama Papers		-0.031**	-0.033**			
		(0.014)	(0.014)			
× Number of Panama Papers entities per capita × After Panama Papers		-0.037**	-0.048***			
		(0.018)	(0.017)			
× 𝟙[Top 10% of countries by Panama Papers entities per capita] × Before Panama Papers				-0.045		
				(0.033)		
× 𝟙[Top 10% of countries by Panama Papers entities per capita] × After Panama Papers				-0.100**		
				(0.040)		
× Number of Panama Papers entities × Before Panama Papers					-0.012***	
					(0.004)	
× Number of Panama Papers entities × After Panama Papers					-0.017***	
					(0.005)	
× 𝟙[Top 10% of countries by Panama Papers entities] × Before Panama Papers						-0.092***
						(0.028)
× 𝟙[Top 10% of countries by Panama Papers entities] × After Panama Papers						-0.174***
						(0.038)
Regional 3G coverage	-0.027*	-0.017	-0.015	-0.015	-0.012	-0.008
	(0.014)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
Regional 3G coverage × After Panama Papers		-0.011	-0.001	0.003	-0.002	0.000
		(0.014)	(0.014)	(0.014)	(0.014)	(0.015)
Observations	722,768	722,768	620,827	620,827	620,827	620,827
R-squared	0.225	0.226	0.232	0.232	0.232	0.232
p-value β(Before Panama Papers) = β(After Panama Papers)		*0.490*	*0.055**	*0.058**	*0.073**	*0.0095****
Subnational region & year FEs	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓
All lower-level interactions	✓	✓	✓	✓	✓	✓
Interactions of 3G and regional income	✓	✓	✓	✓	✓	✓

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The outcome variable is a dummy for the perception that there is no corruption in government. "Number of Panama Papers entities" is the number of entities from a country in the Panama Papers. "Number of Panama Papers entities per capita" is the number of entities from a country in the Panama Papers per 1,000 inhabitants. "Before Panama Papers" and "After Panama Papers" are dummies indicating whether the GWP interview took place before or after the release of the Panama Papers to the public. The unit of observation is an individual. Controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the region's average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, dummies for democracy status, the Freedom of the Press score, and the interactions of regional 3G coverage with the region's average level of income. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table VIII

The effect of 3G coverage on incumbents' electoral performance in Europe

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:	Vote share of:				
	Top 2 parties from the 1st election	Ruling party (the party of the Prime Minister)		Populist parties if they are among top 2 parties from the 1st election	Turnout
Unit of observation:	District-year	District-year-incumbent		District-year	District-year
District 3G coverage	-0.089**	-0.089***		-0.090**	-0.038***
	(0.045)	(0.031)		(0.036)	(0.012)
District 3G coverage × Populist party			-0.120**		
			(0.050)		
District 3G coverage × Nonpopulist party			-0.084***		
			(0.032)		
Observations	1,234	1,536	1,536	341	1,250
R-squared	0.889	0.917	0.917	0.982	0.968
Mean dep. var.	0.561	0.304	0.304	0.329	0.656
Mean 3G coverage	0.649	0.645	0.645	0.655	0.647
District & year FEs	✓			✓	✓
Incumbent-by-district & year FEs		✓	✓		
Baseline controls	✓	✓	✓	✓	✓
Excl. countries without populists among top 2 in the 1st election				✓	

Note: *** p<0.01, ** p<0.05, * p<0.1. The 3G expansion led to a decrease in the vote share for incumbent parties. This is true for both nonpopulist and populist incumbent parties. In Columns 1, 4, and 5, the unit of observation is a subnational district in an election. In Columns 2-3, the unit of observation is an incumbent party in a subnational district in an election. The data in Column 5 cover 102 parliamentary elections in 33 European countries (this is the full panel). In Columns 1, 2, and 3, Romania is excluded because, in Romania, after the first election, the top 2 parties merged with other large parties. In Columns 2-3, Switzerland is excluded because, in Switzerland, the position of the president rotates among the parties in the ruling coalition. In Column 4, the sample is restricted to countries that had populist parties among the top 2 parties in the first election. Controls include the country's unemployment rate, labor-force participation rate, inflation rate, log of GDP per capita, the share of population over 65 years old, and the subnational district's average nighttime light density. As the nighttime light density data for 2007-2013, 2014, and 2015-2018 come from different sources (DMSP-OLS, a combination of DMSP-OLS and VIIRS, and VIIRS, respectively), we interact the measure of nighttime light density with a dummy for each of those time periods. Standard errors presented in parentheses are corrected for two-way clusters at the level of the subnational districts (to account for over time correlation) and at the level of the countries in each year (to account for within-country-year correlation).

Table IX

The effect of 3G coverage on the opposition's electoral performance in Europe

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.:	Vote share of:						
	Right-wing populists	Left-wing populists	Other populists	All populists	All populists	Green parties	Nonpopulist opposition
Unit of observation:	District-year	District-year	District-year	District-year	District-year	District-year	District-year-ruling coalition
District 3G coverage	0.086***	0.067***	-0.038	0.115***	0.129***	-0.007	-0.030
	(0.024)	(0.022)	(0.024)	(0.039)	(0.042)	(0.012)	(0.053)
Observations	1,250	1,250	1,250	1,250	1,002	1,141	1,566
R-squared	0.961	0.876	0.934	0.924	0.813	0.870	0.904
Mean dep. var	0.136	0.065	0.060	0.260	0.189	0.039	0.431
Mean 3G coverage	0.647	0.647	0.647	0.647	0.648	0.636	0.654
District & year FEs	✓	✓	✓	✓	✓	✓	
Ruling-coalition-by-district & year FEs							✓
Baseline controls	✓	✓	✓	✓	✓	✓	✓
Excl. countries with populists in power					✓		

Note: *** p<0.01, ** p<0.05, * p<0.1. The expansion of 3G networks led to an increase in both right-wing and left-wing populists' vote share, but not in the vote share for green parties or the nonpopulist opposition in general. In Columns 1 to 6, the unit of observation is a subnational district in an election. In Column 7, the unit of observation is the ruling coalition in the subnational district in an election. The data in Columns 1-5 cover 102 parliamentary elections in 33 European countries (the full panel). In Column 6, there are fewer observations than in Columns 1-5 because in five elections (Spain in 2015-2016, Croatia in 2015-2016, and Greece in 2015) Green parties formed join lists with large non-Green parties, making it impossible to determine what share of the votes went to the Green parties and what to their partners. Column 5 excludes all countries, in which populists were a ruling party at some point during the sample period: Bulgaria, Hungary, Italy, Montenegro, North Macedonia, Poland, Slovakia, and Slovenia. In Column 7, the election results for Switzerland and Romania are excluded because, in Switzerland, all the major parties are a part of the ruling coalition, and in Romania, after the first election, the parties in the ruling coalition merged with parties outside of the ruling coalition. Controls include the country's unemployment rate, labor force participation rate, inflation rate, log of GDP per capita, the share of population over 65 years old, and the regions' average level of nighttime light density. As the nighttime light density data for 2007-2013, 2014, and 2015-2018 come from different sources (DMSP-OLS, a combination of DMSP-OLS and VIIRS, and VIIRS, respectively), we also interact the measure of nighttime light density with a dummy for each of those time periods. Standard errors presented in parentheses are corrected for two-way clusters at the level of the subnational district (to account for over time correlation) and at the level of the countries in each year (to account for within-country-year correlation).

ONLINE APPENDIX FOR
3G INTERNET AND CONFIDENCE IN GOVERNMENT

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A. Data description

In this section, we present the details about the data. Table A.1 presents the summary statistics of all the variables used in the analysis.

Gallup World Poll. The main outcome variables that measure attitudes toward the incumbent government, as well as individual-level internet access at home, come from the Gallup World Poll (GWP), annual worldwide surveys conducted by Gallup.[55] These data cover individuals in 160 countries between 2008 and 2017 with localization at the subnational region level. The GWP surveys before 2008 cannot be used for our analysis because the data on the localization of respondents were not collected. About 80% of the interviews were conducted face-to-face. In particular, this is the case in Central and Eastern Europe, Latin America, former Soviet states, nearly all of Asia, and Africa. The other 20% of the interviews were conducted over the telephone, which only happened in countries with at least 80% telephone coverage, i.e., primarily in high-income OECD countries and the Arab states of the Persian Gulf. Telephone interviews were mostly conducted via landline telephone.

As discussed in the main text, the exact questions about government performance in the GWP are: *"Do you have confidence in each of the following, or not: How about the national government? How about the judicial system and courts? How about the honesty of elections? Is corruption widespread throughout the government in (country), or not?"* The respondents could answer "*Yes*" or "*No*". We use the responses to these four questions as well as their first principal component and the average share of positive attitudes to the government along these four dimensions. The question on internet access at home is formulated as follows: *"Does your home have access to the internet?"* The GWP surveys also inquire about a wide range of individual characteristics, which we use as control variables in the analysis.

Mobile network coverage. The data on the main explanatory variable, namely, mobile broadband (3G) networks come from Collins Bartholomew's Mobile Coverage Explorer. As a placebo, we also use data on 2G mobile networks from the same source.[56] These data assemble maps submitted by individual mobile network operators from all around the world to the GSM Association, representing the interests of mobile

[55]These data are described here: https://www.gallup.com/analytics/232838/world-poll.aspx (accessed on May 22, 2019).

[56]These data are described here: https://www.collinsbartholomew.com/map-data-products/vector-map-data/mobile-coverage-explorer/ (accessed on May 22, 2019).

network operators worldwide. The data on mobile network coverage are available for 159 countries and territories during the years between 2007 and 2018 at the level of 1x1 km binary grid cells, with the exception of 2011. Due to a change in the company administering the collection of mobile network coverage data, the data for 2011 was not collected. For this reason, we impute the data for 2011 by taking the average of the values in 2010 and 2012. (The results are robust to excluding 2011 from the sample.) As shown in Figure I, mobile-network information on some countries is missing; in particular, this is the case for a number of large countries, such as Algeria, Argentina, Bolivia, China, Pakistan, and Peru. Furthermore, as Collins Bartholomew explained to us, occasionally (although rarely) some mobile network operators do not submit data to the GSM Association, which leads to measurement error in 3G coverage. This measurement error could be classical in nature, i.e., idiosyncratic, or it could be non-classical, i.e., it could correlate with the determinants of our main outcome of interest, namely, government approval. In both cases, the IV estimates correct for this potential measurement error.

To combine mobile network coverage data with the GWP surveys, we calculate the share of the GWP subnational regions' population that lives in areas covered by mobile networks. In particular, for each region and year, we calculate the mean of the grid-cell value of the mobile network availability across all grid cells in each region's polygon using weights for population density in each grid cell. The weights are normalized by the average population density in the region, so that the weights sum up to one.[57] We refer to the resulting measures as regional 3G or 2G coverage—they measure the shares of region's population with access to 3G and 2G networks. Then, we merge them to the data from the GWP.

The resulting dataset used in the analysis covers 840,537 individuals in 2,232 subnational regions of 116 countries between 2008 and 2017. The number of countries is below that in the GWP due to the missing data on mobile network coverage for 38 countries and on the level of democracy—an important control variable discussed below—for another 6 countries.

European elections. To study the electoral implications of the expansion of mobile broadband internet, we use data on the voting results of parliamentary elections in European democracies at the subnational level. We compile data on 102 parliamentary elections that took place in 33 European countries during the period of 2007-2018. The data come from the following sources. First, we use the European Election Database

[57]The proxy for population density at the resolution of 0.1×0.1 decimal degrees comes from the NASA dataset. These data are available at: https://neo.sci.gsfc.nasa.gov/view.php?datasetId=SEDAC_POP (accessed on May 22, 2019). We then impose on this map a grid with the resolution that matches the resolution of the 3G coverage maps (i.e., 1×1 kilometer) assuming that the population density is constant within each 0.1×0.1 decimal degree cell.

provided by the Norwegian Centre for Research Data (NSD).[58] Second, for the elections not covered by the European Election Database, we use data from the Election Resources on the Internet website compiled by Manuel Alvarez-Rivera.[59] Finally, for the elections not covered by either of the two databases, we collect data from the national election statistics websites. The 33 considered countries are EU-28 plus Liechtenstein, Montenegro, Northern Macedonia, Norway and Switzerland (the full list of countries is presented in Figure A.17). The data cover 398 subnational districts.[60] For each election, we collect party-specific election results. For each electoral term in each country, we also collect information on the party of the top executive (e.g., Prime Minister) and compile the list of all parties which enter the ruling coalition at every point in time. These data allow us to track the vote share of the incumbent and of the opposition.

To analyze whether populist parties have benefited from the expansion of 3G internet, we expand the dataset on populist parties in Europe previously used by Algan et al. (2017). To classify the parties' ideologies, we use the Chapel Hill Expert Survey and complement it with text analysis of online sources. In particular, for each of the political parties that participated in parliamentary elections in Europe between 2007 and 2018, we analyze the text of its Wikipedia pages and the sources referenced by Wikipedia. If a party is characterized as "populist" or its policy platform as "populism," the party is classified as populist. Parties are classified as right-wing populist and left-wing populist, when the words "populist" or "populism" are used in one sentence with "right-wing" and "left-wing." In addition, all populist partied with ideology described as "far-right" and "far-left" were coded as "right-wing" and "left-wing," respectively. All populist parties that were not characterized as right-wing or left-wing, were included in the category of "other populists." The list of all populist political parties in Europe according to this classification is presented below in Table A.26.

We also collect data on which parties have Green (environmentalist) ideology. In five elections in our sample (Spain in 2015-2016, Croatia in 2015-2016, and Greece in 2015), Green parties formed joint lists with other large non-Green parties, making it impossible to measure the Green vote share. Thus, these five elections are excluded from the analysis of Green parties vote share. The list of all Green parties used in the analysis is presented below in Table A.27.

We merge the elections data to the data on 3G networks using the same procedure as with the GWP.

Democracy and censorship. The data on the level of democracy come from the

[58]The data are available at: https://nsd.no/european_election_database (accessed on February 7, 2020).

[59]The data are available at: http://electionresources.org/ (accessed on February 7, 2020).

[60]For Lithuania, the election data are reported at the level of electoral constituencies, which often transcend the boundaries of Lithuania's counties (the unit of analysis that would be consistent with the size of the other districts in our sample). Therefore, we aggregate the data for the constituencies in the way that matches the map of counties to the greatest extent possible.

Polity2 score of the Polity IV dataset.[61] These data are available at the country-year level. In all regressions, we control for a dummy indicating that a country in this particular year is a democracy (Polity2 $\geq$ 6) and a dummy that a country in this particular year is an advanced democracy (Polity2 ≥ 8).

The data on internet censorship come from the Limits on Content Index, which is a component of Freedom House's Freedom on the Net index.[62] These data are available at the country-year level, but cover only 46 counties in our sample during the period from 2009 to 2017. This index varies from 0 to 35 with the mean of 14 and the median of 12. (Higher values imply higher censorship.) In addition to the continuous measure of Limits on Content, we construct a dummy for a high level of internet censorship. A country in a particular year is considered to have high internet censorship if its Limits on Content score is 22 or above.[63] A country is considered to have low internet censorship either if it has the Limits on Content score below 22 or, in cases when Freedom House did not calculate the Limits on Content score for that country, if the Polity2 score from the Polity IV dataset is six or above (i.e., classified as a democracy by Polity IV). The inclusion of democracies as countries with low censorship allows us to increase the size of the sample. Among democracies that have nonmissing Limits on Content score, all with the exception of Thailand in 2011 had a score below 22. Thailand in 2011 had a Limits on Content score of 23. In 2014, Thailand's Polity2 score decreased from 7 to -3. The resulting dummy for high/low internet censorship is defined for 100 countries in our sample.

In addition to the time-dependent measure of internet censorship, we also create a time-invariant variable, representing the countries' overall level of online censorship. To define this variable, we use the average of the countries' Limits on Content Index in 2015-2017.[64] We also define a dummy for a high overall level of internet censorship. A country is considered to have high overall censorship on the net if the average of its Limits on Content scores in 2015-2017 is 20 or more.[65] A country is considered to have low overall internet censorship if it has the average Limits on Content score below 20 or, in cases when the average Limits on Content score for that country is not available, if the average Polity2 score for that country is six or above (classified as a democracy

[61] It is available at: http://www.systemicpeace.org/inscrdata.html (accessed on May 22, 2019).

[62] The index is described here: https://freedomhouse.org/report/freedom-net-methodology (accessed on May 22, 2019).

[63] Panel B of Figure A.13 shows that there is a natural break in the distribution of the Limits on Content score at 22. Our results are robust to using other thresholds for defining the dummy for a high level of internet censorship as shown in Panel A of Figure A.13.

[64] For earlier years, the Limits on Content Index is defined only for a small subset of countries.

[65] Panel B of Figure A.13 shows that there is a natural break in the distribution of the average Limits on Content score at 20. We verify that the results are robust to using other thresholds for defining the dummy for a high level of the overall internet censorship, as presented in Panel A of Figure A.13.

by Polity IV).

We also use the data from Freedom House's Freedom of the Press index.[66] This index varies from 0 to 100 with higher values implying lower press freedom. As the Freedom of the Press index increases with censorship of the traditional media, we refer to it as the "Censorship of the traditional media score."

Actual corruption. The data on actual corruption incidents come from the IMF's Global Incidents of Corruption Index (GICI) which uses text analysis of the Economist Intelligence Unit's country reports to measure the prevalence of corruption in a particular country in a particular year that the Economist Intelligence Unit considers to be important enough to be described to investors (Furceri, Papageorgiou, and Ahir, 2019). These data cover 143 countries around the globe annually since 1996. Note that this measure is distinct from corruption perceptions, as the Economist Intelligence Unit bases these reports on its own country research. The index of actual corruption (GICI) is defined for each country×year. In some regression specifications, we also consider the countries' overall level of corruption. We calculate this time-invariant measure as the average value of the GICI index for each country in 2000-2017.

We use the GICI index in two alternative samples. The baseline specification uses the entire sample. We also also report results using only a the subset of country×years in which the report mentions corruption at least once (i.e., $GICI > 0$). Namely, provided that the report mentions corruption, we use the extent to which the report focuses on it as a measure of importance of actual corruption incidents. The reason for this sample restriction is that corruption may not be a topic of the Economist Intelligence Unit's reports in two cases: 1) if there were no corruption incidents worth mentioning, and 2) if corruption is very high but widely known, and therefore, is not considered as useful information for investors. As we report in the main text, the results are robust to using both samples.

The number of entities in the Panama Papers comes from the dataset constructed by the International Consortium of Investigative Journalists.[67] We divide the number of entities in each country by the country's population in 2015 (in thousands). We also show that the results are robust to using the total number of entities (without dividing it by the country's population).

Night lights. We use remote sensing techniques to proxy for economic development using high-resolution data on nighttime light density (i.e., luminosity) following Henderson, Storeygard, and Weil (2011, 2012). The data on nighttime light density come from DMSP-OLS and VIIRS. The DMSP-OLS data span until 2013.[68] The VI-

[66] These data are available here: https://freedomhouse.org/report-types/freedom-press (accessed on May 22, 2019).

[67] These data are described and can be downloaded here: https://offshoreleaks.icij.org/pages/database (accessed on January 1, 2020).

[68] They are described here: https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html

IRS data are available for 2015-2016.[69] We impute nighttime light density in 2014 by taking an average of VIIRS in 2015 and DMSP-OLS in 2013; and in 2017 and 2018 by using the value from VIIRS in 2016. The mean level of nighttime light density, weighted by population density, is calculated for each subnational region and year in our sample. As the nighttime light density data in 2008-2013, 2014, and 2015-2017 come from different sources, and are not directly comparable, we allow the effect of nighttime light density to vary in each of these periods. The incomparability of the nighttime light density data in different sub-periods under study is the reason why we do not include these measures as a baseline control in the GWP regressions. Below, in Appendix Section B, we establish robustness of the results to adding nighttime light density interacted with pre- and post-2014 dummies to the set of covariates.

Frequency of lightning strikes. We use the World Wide Lightning Location Network (WWLLN) dataset for the IV estimation.[70] These data provide the exact coordinates and time of all detected cloud-to-ground lightning strikes for the entire globe. Using these data, we calculate the average annual number of lightning strikes per subnational region's area between January 1st, 2005 and December 31st, 2011, weighting each lightning strike by population density in the 1×1 kilometer grid cell where the lightning strike occurred.[71] By weighting the lightning strikes by population density, we ensure that they reflect the number of individuals potentially affected by lightning strikes. To be precise, the equation that describes the population-weighed frequency of lightning strikes per square kilometer in a subnational region r, $\overline{L_r}$, is:

$$\overline{L_r} = \frac{1}{A_r} \sum_{j}^{A_r} L_j d_j, \tag{4}$$

where j indexes all 1×1 kilometer grid cells in region r. A_r is the subnational region's area size, i.e., the number of 1×1 kilometer grid cells. L_j is the average annual number of lightning strikes in grid cell j. d_j is population density (per square kilometer) in the grid cell j, by definition equal to the total population of grid cell j. Our instrument is a dummy for regions with a high frequency of lightning strikes per area defined as being in the top one-half of the global distribution of the population-weighed number

(accessed on May 22, 2019).

[69] They are described here: `https://ngdc.noaa.gov/eog/viirs/download_dnb_composites.html` (accessed on May 22, 2019).

[70] These data are collected by the University of Washington and are available under a license agreement from `http://wwlln.net` (accessed on July 20, 2020).

[71] We focus on the period from 2005 to 2011—i.e, the first half of the sample period covered by the WWLLN data, available for 2005-2018—to avoid a potential concern that the frequency of lightning strikes has changed in the later years due to climate change (e.g., Aich et al., 2018) and, therefore, is not representative of the lightning frequency from the earlier years. As ICT companies need to plan ahead their infrastructure expansion, longer-term lightning frequency is likely a better measure of their plans.

of lightning strikes per square kilometer ($\overline{L_r}$) across all subnational regions.[72]

Other variables. The global maps of deserts and mountain ranges are based on World Land-Based Polygon Features, available from Stanford University's Digital Repository.[73] The global map of elevation at 30×30 arcsecond resolution comes from the GMTED2010 dataset; it was created by the U.S. Geological Survey (USGS) and the National Geospatial-Intelligence Agency (NGA).[74] In addition, we hand-collect data on smartphone penetration by country-year from multiple sources ranging from surveys conducted by Pew Research Center to estimates of multiple marketing research firms and telecommunication consultancies. We list the sources of these data at the end of the Appendix. We also use the data on the number of active mobile broadband subscriptions per capita from the World Telecommunication/ICT Indicators database (WTI) provided by the International Telecommunication Union.[75]

B. Results on government approval controlling for nighttime light density

In the baseline specification, we control for the level of economic development with the log of the average income in each of the subnational regions in that year.[76] In several countries and years, the GWP did not collect income data at all. In order to include these countries in the data set, we predict the level of income at the subnational region level for these countries and years using nighttime light density and GDP per capita data. First, in the sample where all the data are available, we regress the log of the average GWP regional income on log regional nighttime light density and log GDP per capita, controlling for year and country fixed effects. Both nighttime light density and per capita GDP have positive and highly significant coefficients. Then, we make an out-of-sample prediction for the log of the average GWP regional income where the GWP income data are missing while the data on nighttime light density and GDP per capita are available. As data from DMSP-OLS and VIIRS are not directly comparable, we perform this procedure separately for the years in which DMSP-OLS data are available (2008-2013), for the years in which VIIRS data are available (2015-

[72]Note that we cannot use the alternative dataset on global lightning strikes available from NASA (`https://ghrc.nsstc.nasa.gov/lightning/`). The reason is that NASA satellites use optical imaging to locate lightning strikes, a type of technology that is best suited to detect in-cloud lightning but which does not detect most cases of cloud-to-ground lightning. In turn, cloud-to-ground lightning strikes are much more important in affecting mobile infrastructure than in-cloud lightning. As a result, when using the NASA dataset, the first stage relationship is too weak.

[73]The data are described and can be downloaded here: `https://purl.stanford.edu/bh326sc0899` (accessed on September 17, 2020).

[74]The data are described and can be downloaded here: `https://topotools.cr.usgs.gov/gmted_viewer/viewer.htm` (accessed on July 16, 2020).

[75]These data are described and can be purchased here: `https://www.itu.int/en/ITU-D/Statistics/Pages/publications/wtid.aspx` (accessed on July 25, 2020).

[76]Income data are available only for a subset of the GWP respondents even when this question was asked, and therefore, controlling for individual income substantially reduces the number of observations.

2016), and for 2014, the year for which we impute nighttime light density by taking an average of VIIRS in 2015 and DMSP-OLS in 2013.

To show that our results are robust to alternative measures of economic development, we re-do the analysis using nighttime light density data as a measure of economic development instead of log average income from the GWP. As data from DMSP-OLS and VIIRS are not directly comparable, we also include an interaction term of nighttime light density and a dummy for the years for which the data come from VIIRS and an interaction term of nighttime light density and a dummy for 2014, the year for which we impute nighttime light density by taking an average of VIIRS in 2015 and DMSP-OLS in 2013. Table A.21 presents the results. They are similar to those presented in Table I.

C. Magnitudes and persuasion rates

Relevant variation in regional 3G coverage. In order to interpret the magnitude of the effect, it is useful to understand the scope of the variation in regional 3G coverage. The standard deviation of regional 3G coverage in our GWP sample is 0.4. This number reflects both cross-sectional and over-time variation. The standard deviation of the residual of regional 3G coverage after partialing out region fixed effects is 0.18. However, we are interested in the cumulative effect of the 3G expansion throughout the sample period, i.e., between 2008 and 2017. Panel A of Appendix Figure A.20 presents the distribution of the change in regional 3G coverage between 2008 and 2017 across the regions in the sample. The mean increase in regional 3G coverage over 10 years across all the regions in the sample is 0.39. We use this figure as the basis to calculate the average effect of the 3G expansion on government approval. The estimates presented in the last column of Table I imply that an average region witnessed a decline in government approval of 2.2 percentage points and of 3.2 percentage points among its rural residents as a result of the expansion of mobile broadband internet.

Our analysis of the electoral implications of the 3G expansion uses European data. The standard deviation of 3G coverage in the election sample is 0.346. Once the subnational district fixed effects are partialled out, the standard deviation falls to 0.26. The mean increase in regional 3G coverage over 10 years (2008-2017) across all the subnational districts in the election sample is 0.53. We take this figure as the basis to calculate the average effect of the 3G expansion on election outcomes. For example, the estimates presented in the first column of Table VIII imply that the top two establishment parties lost 4.7 percentage points of electoral support in an average subnational district in Europe over the last decade due to the expansion of 3G coverage. In Panel B of Appendix Figure A.20, we present the distribution of the change in regional 3G coverage between 2008 and 2017 across the subnational districts in the election sample.

Assumptions behind persuasion rates calculations. To compare the magnitude of these effects to those from other persuasive communications studied in the literature, we calculate the persuasion rates relying on the formula developed by DellaVigna and Kaplan (2007):

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

where f stands for the persuasion rate, y is the behaviour of interest, e is exposure, subscripts T and C stand for treatment and control groups, respectively. y_0 is the share of subjects who would adopt the behaviour of interest in a hypothetical case of no message. This formula was extended by Enikolopov, Petrova, and Zhuravskaya (2011) to the case of continuous variation in exposure allowing for both persuasive and dissuasive effect on turnout (denoted by t). It yields the rate of persuasion for an infinitesimally small change in exposure to the message, de:

$$f = 100 \times \frac{1}{1 - y_0 t_0} \left(t\frac{dy}{de} + y\frac{dt}{de} \right). \tag{5}$$

In order to apply this formula to the estimates of the effect of regional 3G coverage on government approval, one needs to make several assumptions. First and foremost, one needs to define what one means by exposure, i.e., explain how the change in regional 3G coverage affects users exposure to the messages critical of the government that make them approve of the government less. I.e., we need to define how the change in regional 3G coverage (denoted by s) affects exposure. Then, (5) can be re-written as:

$$f = 100 \times \frac{1}{1 - y_0 t_0} \left(t\frac{dy}{ds} + y\frac{dt}{ds} \right) \frac{1}{{}^{de}/_{ds}}. \tag{6}$$

Many observers have noted that mobile broadband internet has changed the way people use the internet, including for political information. For example, WhatsApp group messages, which as we discuss in Section VI, were used by Jair Bolsonaro for political campaigning, only could be accessed with a mobile phone with a broadband connection. As discussed in the main text (see, for instance, footnote 10), the vast majority of users of Twitter, Facebook, and Youtube platforms access them through a mobile phone. Also, those who use these platforms on mobile phones rather than on other devices, use them more actively. Furthermore, the fact that mobile broadband internet can be accessed at any point in time leads to the fact that people are more likely to get exposed to political information at the time when they are most interested in it, which potentially could make them more receptive to the message.

Thus, we deem access to mobile broadband internet as related to—but distinct from—access to the internet at home or at work. We use the GWP's question *"Does your home have access to the internet?"* to illustrate this. In Column 1 of Appendix Table A.2, we show that the expansion of 3G networks is significantly associated with an increased access to the internet at home. However, as discussed in the main text, Columns 2 to 5 of the table show that 3G networks have an effect on government approval above and beyond its effect on internet access at home. This suggests that even when people have access to the internet, getting access to *mobile* internet significantly affects the way people use it. Thus, our goal is to measure the effect of gaining access specifically to *mobile* broadband internet.

Second, network availability is necessary but not sufficient for accessing social-media mobile applications. To get connected, one also needs a smartphone and a subscription. There are no data in the GWP on smartphone ownership or mobile subscriptions that would cover a sufficient number of countries or years. Thus, to understand how the expansion of 3G network coverage translated into the use of mobile broadband internet, we use two additional data sources. (i) We hand-collect data on smartphone penetration by country-year from multiple sources ranging from surveys conducted by Pew Research Center to estimates of multiple marketing research firms and telecommunication consultancies. These data cover only a subset of our country-year observations. The resulting dataset covers 63 countries with 318 country-year observations, and a median country is included 4 times between 2008 and 2017. Out of these countries, 58 are included in our most restrictive GWP sample, (i.e., Column 6 of Table I).[77] (ii) The data on the number of active mobile broadband subscriptions per capita come from the World Telecommunication/ICT Indicators database (WTI) provided by the International Telecommunication Union. This variable is also available at the country-year level and covers almost all country-year observations in our sample.[78]

In Panel A of Appendix Figure A.21, we present the cross-country averages of the difference between the country's smartphone penetration (left-hand side graph) and active mobile broadband subscriptions per capita (right-hand side graph), on the one hand, and the share of the country's population covered by 3G networks, on the other hand.[79] The mean differences along with their confidence intervals are plotted

[77]Sources that were used to collect these data often do not specify their definition of adult population, for which they report smartphone penetration. It is quite likely that this definition varies across sources, which makes the resulting data very noisy.

[78]5% of regions in our dataset come from countries where all regions had 3G coverage below 4% in 2017 according to our primary source of data, Collins Bartholomew's Mobile Coverage Explorer dataset. Yet, among these countries, several have a non-negligible number of active mobile broadband subscriptions in 2017 according to the International Telecommunication Union's (ITU) data. We have verified that our results do not change if we consider a subsample of countries with the maximum regional 3G coverage above 4%. The number of observations is 12% smaller in these regressions, but all the results go through.

[79]We calculate the share of the country's population covered by 3G networks in the same way as

separately for each year. The right-hand side graph shows that the number of active subscriptions to mobile broadband was never significantly smaller than the share of population covered by 3G. In the early years of the 3G rollout, the number of subscriptions was slightly lower than 3G coverage (although the difference is not statistically significant), but in the later years, the number of per-capita subscriptions became higher than the share of population with 3G coverage, suggesting that in the later periods some users have multiple contracts. In a number of developed countries, by the end of the period, the total number of active mobile broadband subscriptions became larger than the size of the population. In contrast, the penetration of smartphones, on average, was smaller than the country's 3G coverage throughout the entire period and this difference is statistically significant and particularly sizeable before 2015. Only in the last three years of the observation period, smartphone penetration has (almost fully) caught up with 3G coverage. Overall, the users' ability to connect to mobile broadband infrastructure could be constrained by the slow adoption of smartphones, particularly at the beginning of the period.

In Appendix Table A.22, we explore the within-country over-time correlation between 3G coverage, on the one hand, and smartphone penetration and per capita active mobile broadband subscriptions, on the other hand. This correlation is strong and significant both in the whole sample (as reported in Columns 1, 2, 5 and 6) and in the subsample of countries with below-median per capita GDP (Columns 3, 4, 7, and 8). The point estimates are similar irrespective of whether we use the full available sample or restrict the sample to countries present in the GWP data (as can be seen from the comparison of odd and even columns). Panel B of Figure A.21 illustrates the residual scatterplots in the full sample.

The estimated coefficients reflect the correlation between an increase in 3G coverage in a country and a concurrent increase in the use of the individual means of connecting to mobile internet using 3G. The point estimates are somewhat smaller in magnitude for smartphone penetration than for mobile broadband subscriptions, consistent with the fact that smartphone penetration, on average, is smaller, and, therefore, is likely to be a more constraining factor in connecting users to mobile broadband internet. In addition, for each dependent variable, the point estimates in the subsamples of poor countries are smaller than those for rich and poor countries together, which is consistent with the conjecture that individual constraints in getting access to mobile broadband are higher in poorer countries.[80]

To find ${}^{de}\!/_{ds}$, one needs to take these individual constraints into account. Let us denote the point estimates from Columns 1-4 of Table A.22 by ${}^{dp}\!/_{ds}$, where p stands for "penetration of smartphones." ${}^{de}\!/_{ds}$ can be proxied by ${}^{dp}\!/_{ds}$ under the assumption

regional 3G coverage but using country rather than subnational region polygons.

[80]Most of the differences between these point estimates are not statistically significant.

that the only person, who gets exposed to the message delivered by mobile broadband internet through a smartphone, is the owner of this smartphone. However, in many settings, smartphone users are likely to share what they learn on social media about their governments with family, friends, and co-workers, who have no access to a device that can connect to mobile broadband internet. Our case study on the Youtube film about corruption of Russia's Prime Minister Dmitry Medvedev shows that such spillovers can be substantial. It is reasonable to conjecture that in developing countries spillovers are higher because families are larger than in developed countries and because it is also more likely that several co-workers share the same mobile device to connect to the internet. If these spillovers exist within the subnational regions, the change in exposure associated with a unit change in 3G coverage can be proxied by the following product:

$$\frac{de}{ds} = \frac{dp}{ds} \times N, \tag{7}$$

where N is the number of people who get exposed to the message per smartphone ($N \geq 1$). If there are no spillovers, $N = 1$. As we have no data to estimate N, we calculate the persuasion rates up to a factor of $\frac{1}{N}$.

Third, we have verified that there is no significant relationship between the expansion of regional 3G coverage and the share of respondents who chose *"Do not know"* and/or *"Refuse to answer"* on the questions about government approval. Thus, there is no need to take into account selection into answering these questions in applying the formula for persuasion in government disapproval (which otherwise would have been similar to turnout). Thus, for the estimates of the persuasion rates for GWP data, $t = t_0 = 1$ and $dt = 0$.

Forth, to apply the formula, one needs to find a proxy for y_0. The graph presented on the top left corner of Figure A.3 in the Appendix shows that there is a lot of fluctuations in government approval unrelated to the 3G expansion and a significant amount of heterogeneity both in the initial levels and the expansion of 3G across regions. There is no clean control group because a significant share of regions already had substantial 3G coverage in 2008. This makes finding a proxy for y_0 challenging. Thus, we use the overall sample means for the respective outcome variables and subtract from them the effect of 3G, proxied by the product of mean regional 3G coverage times the marginal effect of 3G coverage on the outcome of interest. This is a crude, but most robust proxy for the behaviour of interest in the absence of mobile broadband internet. (We report these sample means at the bottom of each relevant table).

Finally, $\frac{dy}{ds}$ comes directly from the point estimates of the effect of regional 3G coverage on outcomes.

Estimates of the persuasion rates of mobile broadband internet on government disapproval. Under the assumptions presented above, the OLS point estimates presented in the last column of Table I imply the following persuasion rate for the message *"Disapprove of your government"* for all the respondents and for respondents who live in rural areas, respectively:

$$f_{All}^{OLS} = 100 \times \frac{1}{0.439 + 0.381 \times 0.057} \times 0.057 \times \frac{1}{0.702 \times N} = \frac{17.6}{N}\%,$$

$$f_{Rural}^{OLS} = 100 \times \frac{1}{0.452 + 0.311 \times 0.081} \times 0.081 \times \frac{1}{0.702 \times N} = \frac{24.2}{N}\%.$$

0.439 and 0.452 are sample means of government approval (= 1−government disapproval). 0.057 and 0.081 are the marginal effects of the 3G expansion on government disapproval (equal to the negative of the effects on government approval). 0.381 and 0.311 are mean 3G coverage in the samples of all respondents and of respondents from rural areas. (All these figures are reported in Table I.) 0.702 is our estimate of $\frac{dp}{ds}$ from Column 1 of Table A.22.[81]

The instrumental variable estimation, presented in Table IV, implies the following persuasion rates in the full sample of countries:

$$f_{All}^{IV} = 100 \times \frac{1}{0.439 + 0.381 \times 0.283} \times 0.283 \times \frac{1}{0.702 \times N} = \frac{73.7}{N}\%,$$

$$f_{Rural}^{IV} = 100 \times \frac{1}{0.452 + 0.311 \times 0.308} \times 0.308 \times \frac{1}{0.702 \times N} = \frac{80.1}{N}\%,$$

where 0.283 and 0.308 are point estimates of the marginal effects of the 3G expansion on government disapproval from Table IV and the rest of the numbers are as above.

The IV estimates in the subsample of countries with below-median GDP per capita imply:

$$f_{All\ Poor}^{IV} = 100 \times \frac{1}{0.433 + 0.134 \times 0.329} \times 0.329 \times \frac{1}{0.599 \times N} = \frac{115.1}{N}\%,$$

$$f_{Rural\ Poor}^{IV} = 100 \times \frac{1}{0.440 + 0.124 \times 0.389} \times 0.389 \times \frac{1}{0.599 \times N} = \frac{133.0}{N}\%.$$

[81] We take the estimates from Columns 1 and 3 to proxy for $\frac{dp}{ds}$, respectively, in the full sample and the sample of poor countries because these estimates are based on a larger number of observations than those in Columns 2 and 4.

0.433 and 0.440 are sample means of government approval (= 1−government disapproval). 0.329 and 0.389 are the point estimates in the corresponding IV estimation. 0.134 and 0.124 are mean 3G coverage in the samples of all respondents and of respondents from rural areas among poor countries. 0.599 is the estimate of $\frac{dp}{ds}$ from Column 3 of Table A.22.

The persuasion rates from the IV estimation clearly point to the presence of spillovers in complier countries as the IV estimates represent the LATE for compliers. Indeed, in complier countries, where the expansion of 3G mobile networks depends on the frequency of lightning strikes, it is plausible that several people get exposed to the message from one smartphone. Figure A.22 presents the value of the persuasion rates for each of the key estimations depending on the size of the spillovers.

Estimates of the persuasion rates of mobile broadband internet on election outcomes. In the case of elections with several parties, Equation (6) trivially extends to the case of exposure to a negative campaigning message persuading voters not to vote for a particular party (the vote for this political party is denoted by ν):

$$f = 100 \times \frac{1}{\nu_0 t_0} \left(-t\frac{d\nu}{ds} - \nu\frac{dt}{ds} \right) \frac{1}{{de}/{ds}}. \tag{8}$$

As above, we use proxy ν_0 and t_0 by their respective overall sample means and subtract from them the effect of 3G, proxied by the product of mean district 3G coverage and the marginal effect of 3G coverage on ν and t. We apply this formula to the effect of 3G on voting against the establishment parties (the top two parties at the beginning of the period):

$$f^{Top2} = 100 \times \frac{0.656 \times 0.089 + 0.561 \times 0.038}{(0.561 + 0.089 \times 0.647)(0.656 + 0.038 \times 0.647)} \times \frac{1}{0.702 \times N} = \frac{27.0}{N}\%.$$

0.656 is the mean turnout. 0.561 is the mean vote for the establishment parties. 0.089 is the marginal effect of 3G on the establishment parties vote share with the minus sign. 0.038 is the marginal effect of 3G on turnout with the minus sign. 0.647 is the mean of 3G coverage in the sample of European regions. (See bottom of Table VIII.) 0.702 is the estimate of $\frac{dp}{ds}$ (reported in Table A.22).

The persuasion rate of the message *"Vote for a populist party"* from Equation (6) is:

$$f^{Populists} = 100 \times \frac{0.656 \times 0.115 - 0.260 \times 0.038}{1 - (0.260 - 0.115 \times 0.647)(0.656 + 0.038 \times 0.647)} \times \frac{1}{0.702 \times N} = \frac{10.7}{N}\%.$$

0.260 is the mean vote for the populist parties. 0.115 is the marginal effect of 3G on populists' vote share. As above, 0.656 is the mean turnout. −0.038 is the marginal effect of 3G on turnout. 0.647 is the mean 3G coverage in the sample of European regions. (All these figures are reported in Tables VIII and IX.) 0.702 is the estimate of

$\frac{de}{ds}$ (reported in Table A.22).

As in Europe, families are smaller than in many other parts of the world, particularly in developing countries, it is likely that spillovers are smaller and N is close to one.

D. Countries that drive the variation in the first stage

In Figure A.11 in the Appendix, we present the residual scatter plot behind the first-stage relationship reported in Column 5 of Table IV. Panel A marks the country and year of potentially influential region-year observations. We have verified that the exclusion of these observations or all observations from these regions does not affect the results. Panel B highlights the observations that generate the negative slope of the first stage relationship, which are our best proxy for complier observations. Importantly, only a subset of these observations are compliers, as some are "always takers" and some are "never takers" that happen to fit the estimated relationship. Then, we single out those regions that have all region-year observations in the highlighted quadrants. These regions are the best empirical proxy for complier regions one could get.

The sample of countries with below-median GDP per capita consists of 52 countries, of which 27 are in Africa, 15 in Asia, 8 in the Americas, and 2 countries are in Europe (i.e., Moldova and Ukraine). Out of these 52 countries, the following 19 countries have at least one "complier" region with a high frequency of lightning strikes per square kilometer: Benin, Burkina Faso, Cameroon, Chad, Congo (Kinshasa), El Salvador, Guatemala, Honduras, India, Indonesia, Kenya, Malawi, Mozambique, Nepal, Nigeria, Senegal, Tanzania, Vietnam, and Zimbabwe. And the following 7 countries have at least one region "complier" region with a low frequency of lightning strikes per area: Armenia, Burkina Faso, Moldova, Mongolia, Namibia, Niger, and Tunisia.

E. Checking for balance in individual characteristics

We check whether the expansion of regional 3G coverage is correlated with the composition of individuals in the GWP surveys. In Column 1 of Appendix Table A.23, we present the balance test. In particular, we regress regional 3G coverage—our main treatment variable—on the set of individual characteristics controlling for region and year fixed effects. In Column 2, we repeat this analysis with a binary treatment variable. In particular, we use the post-event dummy, i.e., the dummy for a region experiencing a greater than 50 percentage points increase in 3G coverage in one year that was considered in the event-study exercise, as the dependent variable in Column 2. In both cases, we find that the treatment (continuous or binary) is not significantly correlated with the majority of the individual characteristics. But individuals' education, age, and marriage status have a significant association with the 3G expansion. (Coefficients on age and age squared do not show up as statistically significant individually, but they are jointly significant, as reported at the bottom of the table.) To test whether this misbalance drives our results, we follow Hainmueller (2012) and use entropy balancing to re-weight observations so that regions that experienced treatment (i.e., had an increase in 3G coverage of more than 50 percentage points) and those that did not have the same mean and variance of all the individual-level characteristics after subtracting region and year fixed effects. We use the post-event dummy as treatment in this exercise because this methodology can only be used in the case of binary treatment. In Column 3 of Table A.23, we show that re-weighting leads to a balanced sample: there is no significant relationship between the treatment dummy and any of the individual-level characteristics.

Columns 4 and 5 illustrate the effect of the unbalanced individual characteristics on our estimates. In particular, we present the results of the estimation of the effect of the treatment on government approval before and after the re-weighting. The results are very similar, suggesting that misbalance does not drive our results.

In Columns 6 and 7 of Table A.23, we take an alternative approach to demonstrate that misbalance is not driving our results. We show robustness of the effect of the "post-event" treatment dummy on government approval in subsamples with no variation in the unbalanced covariates. Specifically, Column 6 shows the effect of the post-event treatment dummy on government approval in the subsample of married individuals without a high school degree and Column 7—in the subsample of unmarried individuals without a high school degree.[82] In both cases, we control for the full set of dummies for each specific age (with one year intervals) to account for potential changes in the age composition of the respondents. In both columns, we find a strong relationship between the treatment dummy and government approval.[83]

Overall, these results strongly suggest that the composition of individuals in the GWP surveys is not driving the relationship between regional 3G coverage and government approval.

F. Reverse causality in internet censorship

It is possible that internet censorship is endogenous to government approval, i.e., censorship is introduced when government approval is low in order to increase government approval. In this section, we show that such reverse causality leads to a downward bias in estimating the effect of the interaction between internet censorship and mobile broadband internet signal availability on government approval.

Assume that 3G coverage, denoted by I for "internet," and censorship, denoted

[82] As demonstrated in Table A.17, educated individuals are less affected by the expansion of regional 3G coverage.

[83] We also verified that we get exactly the same results using the continuous treatment variable, regional 3G coverage.

by C for "censorship," affect government approval according to the following simple structural relationship:

$$y = \beta_0 + \beta_1(1 - \alpha C)I + \varepsilon, \tag{9}$$

where y represents government approval, β_0 is government approval in the absence of the internet, $\beta_1 < 0$ is a parameter that represents the effect of uncensored internet on government approval, $\alpha > 0$ is a parameter that denotes the sensitivity of the probability of blocking critical messages to the level of censorship, and ε is the error term. αC is the probability of blocking a potential critical message about the government available on the internet. Thus, $(1 - \alpha C)$ is the probability that this critical message is available on the internet. Equation (9) can also be rearranged in the following way:

$$y = \beta_0 + \beta_1(1 - \alpha C)I + \varepsilon = \beta_0 + \beta_1 I - \alpha\beta_1 CI + \varepsilon = \beta_0 + \beta_1 I + \beta_2 CI + \varepsilon, \tag{10}$$

where $\beta_2 = -\alpha\beta_1 > 0$.

Now suppose that censorship is higher when government approval is lower:

$$C = \tilde{C} - \lambda y + u. \tag{11}$$

$\tilde{C}$ is the level of internet censorship that is exogenous to government approval, and $\lambda > 0$ is the sensitivity of censorship to government approval; u is white noise. The structural causal relationship between I, C and Y is still given by Equation (10). Apart from the reverse causality problem (11), all the standard OLS assumptions are assumed to be satisfied. If we had an instrumental variable for censorship that is exogenous to approval ($\tilde{C}$), we would have been able to consistently estimate β_2 from (10) using 2SLS. However, we only observe C and estimate (10) using OLS. From the formula for the OLS estimator, we get:

$$\hat{\beta}_2^{OLS} = \frac{\left(\sum_{i=1}^N I \sum_{i=1}^N CI^2 - \sum_{i=1}^N I^2 \sum_{i=1}^N CI\right)\sum_{i=1}^N y + \left(\sum_{i=1}^N I \sum_{i=1}^N CI - N\sum_{i=1}^N CI^2\right)\sum_{i=1}^N Iy + \left(N\sum_{i=1}^N I^2 - \sum_{i=1}^N I \sum_{i=1}^N I\right)\sum_{i=1}^N CIy}{N\sum_{i=1}^N I^2 \sum_{i=1}^N C^2I^2 + 2\sum_{i=1}^N I \sum_{i=1}^N CI^2 \sum_{i=1}^N CI - \sum_{i=1}^N CI \sum_{i=1}^N CI \sum_{i=1}^N I^2 - \sum_{i=1}^N I \sum_{i=1}^N I \sum_{i=1}^N C^2I^2 - N\sum_{i=1}^N CI^2 \sum_{i=1}^N CI^2} =$$

$$= \beta_2 + \frac{\left(\sum_{i=1}^N I \sum_{i=1}^N CI^2 - \sum_{i=1}^N I^2 \sum_{i=1}^N CI\right)\sum_{i=1}^N \varepsilon + \left(\sum_{i=1}^N I \sum_{i=1}^N CI - N\sum_{i=1}^N CI^2\right)\sum_{i=1}^N I\varepsilon + \left(N\sum_{i=1}^N I^2 - \sum_{i=1}^N I \sum_{i=1}^N I\right)\sum_{i=1}^N CI\varepsilon}{N\sum_{i=1}^N I^2 \sum_{i=1}^N C^2I^2 + 2\sum_{i=1}^N I \sum_{i=1}^N CI^2 \sum_{i=1}^N CI - \sum_{i=1}^N CI \sum_{i=1}^N CI \sum_{i=1}^N I^2 - \sum_{i=1}^N I \sum_{i=1}^N I \sum_{i=1}^N C^2I^2 - N\sum_{i=1}^N CI^2 \sum_{i=1}^N CI^2}.$$

$$\operatorname*{plim}_{N\to\infty}\left[\beta_2 + \frac{\left(\sum_{i=1}^N I \sum_{i=1}^N CI^2 - \sum_{i=1}^N I^2 \sum_{i=1}^N CI\right)\sum_{i=1}^N \varepsilon + \left(\sum_{i=1}^N I \sum_{i=1}^N CI - N\sum_{i=1}^N CI^2\right)\sum_{i=1}^N I\varepsilon + \left(N\sum_{i=1}^N I^2 - \sum_{i=1}^N I \sum_{i=1}^N I\right)\sum_{i=1}^N CI\varepsilon}{N\sum_{i=1}^N I^2 \sum_{i=1}^N C^2I^2 + 2\sum_{i=1}^N I \sum_{i=1}^N CI^2 \sum_{i=1}^N CI - \sum_{i=1}^N CI \sum_{i=1}^N CI \sum_{i=1}^N I^2 - \sum_{i=1}^N I \sum_{i=1}^N I \sum_{i=1}^N C^2I^2 - N\sum_{i=1}^N CI^2 \sum_{i=1}^N CI^2}\right] =$$

$$= \beta_2 + \frac{\left(E[I]E[CI^2] - E[I^2]E[CI]\right)E[\varepsilon] + \left(E[I]E[CI] - E[CI^2]\right)E[I\varepsilon] + \left(E[I^2] - E[I]E[I]\right)E[CI\varepsilon]}{E[I^2]E[C^2I^2] + 2E[I]E[CI^2]E[CI] - E[CI]E[CI]E[I^2] - E[I]E[I]E[C^2I^2] - E[CI^2]E[CI^2]} =$$

$$= \beta_2 + \frac{\mathrm{Var}[I]}{D}E[CI\varepsilon],$$

where $D = E[I^2]E[C^2I^2]+2E[I]E[CI^2]E[CI]-E[CI]E[CI]E[I^2]-E[I]E[I]E[C^2I^2]-E[CI^2]E[CI^2]$. Note that:

$D > 0$ because it is the determinant of the variance-covariance matrix,
$\mathrm{Var}[I] > 0$ because it is the variance, and
$E[CI\varepsilon] < 0$ because:

$$E[CI\varepsilon] = E\left[\frac{(\tilde{C} - \lambda\beta_0 - \lambda\beta_1 I - \lambda\varepsilon + u)I\varepsilon}{1 + \lambda\beta_2 I}\right] = -\lambda E\left[\frac{I\varepsilon^2}{1 + \lambda\beta_2 I}\right] < 0.$$

Therefore,

$$\frac{\mathrm{Var}[I]}{D}E[CI\varepsilon] < 0$$

and

$$\operatorname*{plim}_{N\to\infty}\left[\hat{\beta}_2^{\;OLS}\right] < \beta_2.$$

Thus, with reverse causality, the coefficient on the interaction term between 3G and internet censorship is biased downward, i.e., toward zero, and the true effect is even stronger than the one estimated by OLS.

G. Censorship of the internet and the education and occupations of the political elites

As we described in footnote 34, one potential concern with the interpretation of the results about the difference in the differential effects by the censorship of the traditional media vs. the censorship of the internet is the potential unobserved heterogeneity between those autocratic governments that control the traditional press but not the internet, and those that censor both. In particular, if the latter are more sophisticated, our results on the heterogeneity by censorship may be driven by the heterogeneity with respect to the government's sophistication. We use the data collected by Gerring et al. (2019) on the education of the world's political elites to address this concern to the extent to which sophistication of governments is correlated with the level of education and prior occupations of the political leadership. We find no correlation between the censorship of the internet score and any available measure of the level of education of the political elite (such as the share of those with a graduate degree, a post-graduate degree, or a PhD; the share of those proficient in English, and the share with Western education) or prior occupation of the political elite (such as the share with a military background, the share with an engineering, math, or computer science background; share with white collar occupations), once the level of democracy (Polity2) is controlled for. The censorship of the traditional media score is significantly (negatively) correlated with the share of political elites with Western education controlling for the level of democracy. If one also controls for the censorship of the internet, this correlation disappears. We also checked that controlling for the interaction terms between education and occupation of the country leadership does not change our results. Table A.24 presents the results of the cross-country regressions in which the censorship of the internet (Panel A) and the censorship of the traditional press (Panel B) are related to the education and occupations of the political elites controlling for the level of democracy and the censorship of the other domain. These results suggest that, if the sophistication of the political leadership is related to education and occupations, it is not driving our results. The list of countries that censor the internet according to our time-invariant internet censorship dummy is as follows: Bahrain, Belarus, Russia, Rwanda, Saudi Arabia, Thailand, Turkey, United Arab Emirates, Uzbekistan, and Vietnam. Countries that do not censor internet, but have a comparable level of traditional-press censorship are Armenia, Azerbaijan, Cambodia, Egypt, Honduras, Jordan, Kyrgyzstan, Malaysia, Singapore, Sri Lanka, Sudan, Venezuela, Zambia, and Zimbabwe.

H. Details of case studies

Russia 2017. The internet is an especially important source of political information in countries with censored traditional media. On March 2, 2017, a 50-minute documentary film entitled "He Is Not Dimon to You" describing the corruption of Prime Minister Dmitry Medvedev was posted on YouTube. The film detailed a network of foundations and businesses directly or indirectly controlled by Medvedev and produced evidence that Medvedev owned a large palace near Moscow, a historical palace in Saint-Petersburg, a skiing resort in the Caucasus, a manor on the Volga River, two wineries (in Russia and in Italy), and two yachts. Google searches for "He Is Not Dimon to You" and "Medvedev" skyrocketed immediately after the release of the film. The film was discussed by the few remaining independent newspapers and radio stations (there is no independent TV in Russia) and on digital social networks.

None of the three Russia's leading pollsters asked any questions about the film; however, there is some information about Medvedev's approval ratings around the time of the film's release. One of the three leading polling firms, pro-government FOM, stopped publishing Medvedev's ratings after the release of the film. The second one, government-owned VCIOM, did not report the approval ratings but asked respondents whether various politicians, including Medvedev, act in the interest of society as a whole or in the interest of a narrow group of people. One month after the film's release, the share of respondents agreeing with the statement that Medvedev is "acting in the interest of society as a whole" dropped from 61 to 49 percent, whereas the share of individuals saying that he is "acting in the interest of a narrow group" increased from 18 and 25 percent. Levada Center, Russia's only truly independent polling firm, continued monthly surveys of Medvedev's approval ratings. According to Levada's data, one month after the film became available, Medvedev's approval ranking sank from 52 to 42 percent, while the disapproval ranking jumped from 47 to 57%.[84] As a result, Medvedev's rating was at its historic low within one month of the film's release. Never before had Medvedev's popularity experienced such a large decline within one month.[85] Medvedev's approval rating never recovered and stayed below 50 percent throughout his remaining time in office. When Medvedev was removed from the Prime Minister's job in January 2020, his approval rating was at 38 percent.[86]

The only survey which directly traced the viewership of the film was carried out by Alexei Navalny's Anti-Corruption Foundation (FBK)—the team who created the film. The survey of a representative sample of voting-age Russians was administered by phone two weeks after the film's release on YouTube (from March 14 to March 24). The survey included standard questions on the approval of Putin and Medvedev as well as questions about the film.[87] At the time of this survey, 4.5 percent of respondents said that they had already watched the film, 15.4 percent said that they had heard at least something about the film, while 80 percent had not even heard about it. By definition, those who watched the film had to have access to the internet (as it was only available on YouTube). Access to the internet was also a strong predictor of having heard of the film. Appendix Figure A.23 shows that among those who have heard about the film but have not watched it, 77% used the internet every day. This is only slightly lower than the respective 86% among those who watched the film and significantly higher than 58% among those who had not heard about the film.[88]

As shown in Column 1 of Appendix Table A.25, daily internet use is associated with an increase in the likelihood of having heard about the film of 11 percentage points. This effect is tantamount to more than doubling the probability of having heard about

[84] https://www.levada.ru/en/ratings/, accessed on May 25, 2020.

[85] Levada had been tracking Medvedev's approval since 2007, when Medvedev, then the first deputy prime minister was hinted as a presidential candidate; he then served as president in 2008-12 and then as prime minister in 2012-20.

[86] It is worth noting that these approval ratings may seem high for a democracy, but they are very low for an autocracy with total government control of all major traditional media and substantial internet censorship.

[87] The respondents were asked about their attitude toward Medvedev with a 4-point Likert scale, with the following possible responses: "negative," "rather negative," "rather positive," and "positive." Many refused to answer the question but among those who gave an answer, 74 percent were "rather positive" or "positive."

[88] The survey included six categories of the frequency of internet use ("Never," "At most monthly," "Twice a month," "Once a week," "2-3 times a week," "Daily"). We focus on a dummy for daily use of the internet. 62% respondents reported that they use the internet daily. The correlations are robust to using more flexible categorizations.

the film, i.e., shifting it from 9 percent among those who use the internet rarely or never to 20 percent among daily internet users. Both having watched the film and having only heard about it is associated with having a significantly more negative attitude toward Medvedev. As shown in Column 2, those who had watched the film were 36 percentage points less likely to be "positive" or "rather positive" toward Medvedev relative to the respondents who have not heard about the film. Similarly, people who just heard about the film but have not watched it were 18 percentage points less likely to be "positive" or "rather positive" toward Medvedev. Of course, these correlations can be explained by self-selection into seeking the information about the film. They, however, are robust to controlling for basic socio-economic characteristics as well as prior voting behavior and (as shown in Column 3) the attitude toward Vladimir Putin, which explains a lot of the variation in the attitude toward Medvedev and should control for at least some of this selection.

Romania 2014. While in Russia the publication of information about corruption on YouTube helped to reduce the approval rating of the political leadership, in more democratic countries, the dissemination of critical information on social media also had electoral consequences. This can be illustrated with an example of the political campaign by the winner of the 2014 presidential election in Romania, Klaus Iohannis, who subsequently became known as the "Facebook President" (Patrut, 2015, 2017).

In the first round of the election, the incumbent Prime Minister, Victor Ponta, came first with 40% of the total vote, while Iohannis came second with 30%. At the time of the first round, Iohannis was also behind Ponta in two-way polls—which until two days before the second round predicted a 55:45 outcome in favor of Ponta (Csala, 2014). In the second round, however, Iohannis won with 54.5% of the vote. As we mentioned in the main text, he himself attributed this success to his Facebook campaign. A post-election survey by the Romanian Institute for Assessment and Strategy reported that 54% of a representative sample of Romanian voters used the Internet and 93% of them used Facebook. 70% of internet users said that the internet and social networks influenced their decision to vote (Patrut, 2015).[89]

Iohannis joined Facebook only in May 2014, whereas the incumbent, Ponta, had a Facebook page since 2010. At the time of the first round, Iohannis was behind Ponta in terms of Facebook followers (484 vs. 659 thousand, Tănase, 2015). However, between the two rounds Iohannis almost doubled the number of followers and overtook Ponta (848 vs. 715 thousand, Tănase, 2015).[90] He also strongly outperformed Ponta in terms of comments, likes and shares (Csala, 2014, Tănase, 2015). In these last two weeks of the campaign, Iohannis published 8 posts per day (Androniciuc, 2016). During

[89]In 2014, 7 out of 20 million Romanians were Facebook users, making Facebook a particularly influential social network (Patrut, 2015).

[90]Later on, Iohannis became the first European politician to reach one million followers on Facebook (Androniciuc, 2018).

the election campaign, Iohannis became the leader of the anti-corruption movement (Mungiu-Pippidi, 2018).

Facebook was especially effective at reaching out to Romanians residing abroad. These citizens received their information on Romanian politics via the internet. Romanians living abroad constituted 20% of Iohannis's Facebook followers (for Ponta, the respective number was 10%, Patrut, 2015). While Iohannis got 53% of the vote within the country, he obtained between 89 and 96 percent in major destinations of Romanian emigrants in Western countries (Tănase, 2015). Their turnout in the second round was 2.5 times as high as in the first round or in the second round of the previous presidential election in 2009. The expat voters accounted for 3% of the total vote which was important but not decisive. However, the impact of these voters was much larger: in the survey conducted by the Romanian Institute for Assessment and Strategy, 42% said that they had a family member or a friend abroad whose vote advice was decisive (Patrut, 2015). This is also an indication of the potential importance of spillovers in the political effects of social media.

Brazil 2018. In addition to informing voters about misgovernance and corruption, mobile broadband internet and social media also provide a platform for disseminating misleading and outright false narratives, often promoted by populist politicians. A notable example is the 2018 presidential election in Brazil, when WhatsApp contributed to the victory of a far-right candidate Jair Bolsonaro.

Due to regulations favoring insiders, during the campaign, Bolsonaro only got 1% of the total TV time devoted to political campaigning, whereas his main opponent had 19%, and the candidate with the most air time had 44% (Evangelista and Bruno, 2019). Thus, he had to roll out a digital campaign. Unlike the "Facebook President" Iohannis, Bolsonaro became a "WhatsApp President" (dos Santos, 2018). WhatsApp is a mobile messaging/social network application owned by Facebook and used by about 120 million Brazilians.[91] The popularity of WhatsApp in Brazil, as discussed in the main text, is related to the spread of so called "zero-rating" plans (Evangelista and Bruno, 2019). Three-quarters of internet users in Brazil had a connection though such plans (Belli, 2018).

In order to use these "zero-rating" plans, one needs to have access to 3G. In 2018, there was substantial geographic variation in access to mobile broadband internet. We use it to show a strong correlation between 3G coverage and Bolsonaro's vote share in the second round of the election (Appendix Figure A.24). Importantly, 3G coverage is higher in urban than in rural areas, where the share of educated voters, who were more likely to vote against Bolsonaro, is also higher than in rural areas (Barros and Santos Silva, 2019).

Bolsonaro's "digital populism" (Cesarino, 2019) combined both the anti-corruption

[91] In 2018, this represented almost 90 percent of Brazilian internet users (Machado, 2018).

narrative related to the grand corruption scandals in the ruling Workers' Party (PT) and a set of false accusations against PT's leadership. The concerns regarding corruption were certainly legitimate. A large corruption scandal, known as Operation Car Wash, that involved the national oil company Petrobras and many top-ranking government officials, resulted in a multi-year investigation and the impeachment of President Dilma Rousseff (from PT). She was succeeded by her vice-president Michel Temer who also was found to be involved in the scandal. He refused to resign but his popularity was so low that he did not stand for re-election in 2018. PT then nominated a popular ex-president Lula da Silva (Rousseff's predecessor). However, he too was convicted on corruption charges and was disqualified from running in 2018. The leadership of the main opposition party, PSDB (which was in power before PT and whose candidate came a close second in the previous presidential election) was also implicated in Operation Car Wash. Not surprisingly, corruption became the most important issue in Brazilian politics. Even in times of double-digit unemployment, surveys would indicate corruption as Brazilians' top concern (Winter, 2018).

In addition to relying on a legitimate anti-corruption narrative, Bolsonaro also used social media to attack PT with falsehoods and misinformation. As we discuss in the main text, WhatsApp is a platform that is particularly well-suited for spreading false narratives because messages are shared and reshared through encrypted chat groups, in which the information can only be viewed by group members. It is estimated that there were hundreds of thousands of WhatsApp groups in Brazil in 2018 (Tardáguila et al., 2018).[92] A study of 100,000 WhatsApp political images circulating in 347 chat groups has identified 50 most shared images (Tardáguila et al., 2018). Out of these 50, 28 images were completely false or misleading; only 4 were truthful. Another study of WhatsApp groups showed that misleading images were much more likely to be shared: while misinformation images represented only 1% of all unique shared images, they were shared by 5.7% users, and reached 44% of groups monitored by the researchers (Resende et al., 2019).

A part of the dissemination of misleading political images was carried out in a coordinated campaign by a network of Bolsonaro supporters (Evangelista and Bruno, 2019). A leading Brazilian newspaper *Folha de S. Paulo* discovered the illegal marketing contracts where businesses paid marketing agencies for mass-messaging of pro-Bolsonaro misinformation. Later, WhatsApp recognized that such mass-messaging broke its own rules (Campos Mello, 2019).

[92]Facebook which owns WhatsApp has invested substantial resources in fact-checking in Brazil; however, these fact-checking efforts were focused on Facebook social network and not on WhatsApp (Nalon, 2018).

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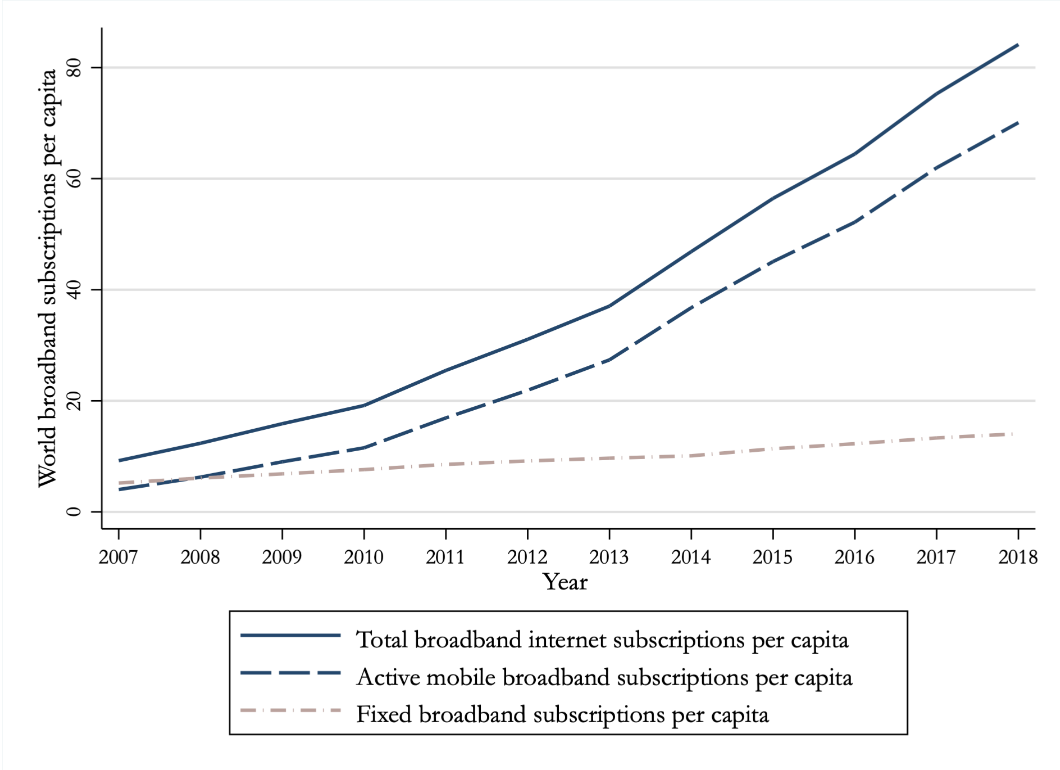
Panel A: World



Panel B: Developing and developed countries

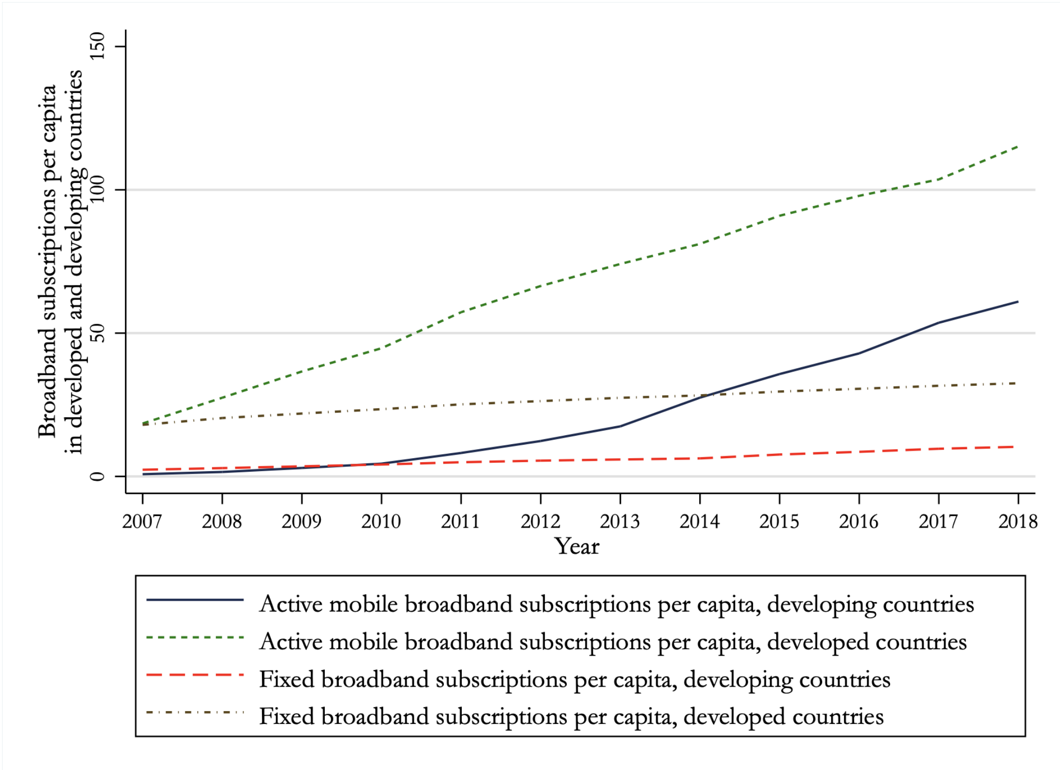


Figure A.1

Time series of active mobile and fixed broadband subscriptions per capita globally

Note: The figure presents the evolution of the number of active mobile and fixed broadband subscriptions per capita in the entire world and separately in developed and developing countries. Source: ITU. `https://www.itu.int/en/ITU-D/Statistics/Documents/statistics/2019/ITU_Key_2005-2019_ICT_data_with%20LDCs_28Oct2019_Final.xls`, (accessed on July 25, 2020).

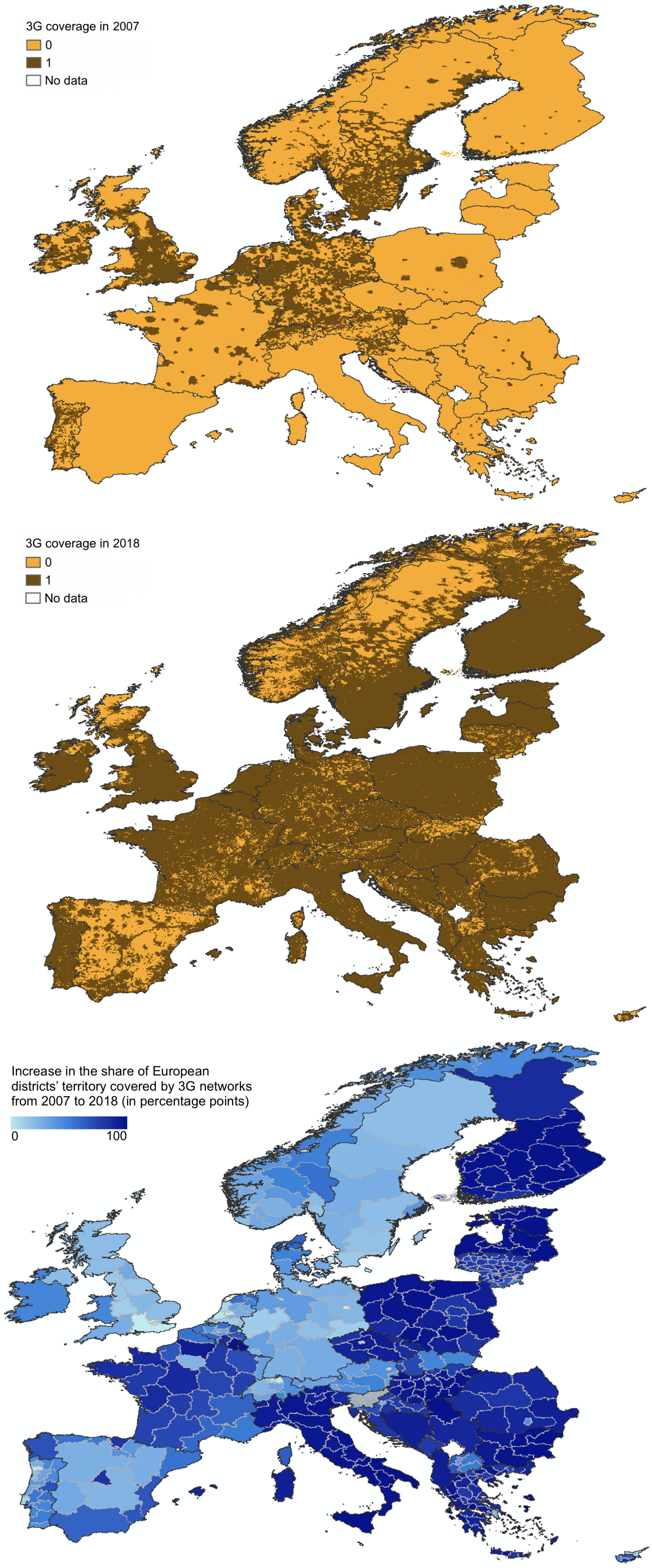


Figure A.2

The growth of 3G network coverage between 2007 and 2018 in Europe

Note: The first two maps present 3G network coverage by grid cell in 2007 and 2018 for the European countries. The third map presents: 1) the boundaries of the districts, which are the spatial unit of observation in the elections data and 2) the increase in the share of the district's population covered by 3G networks from 2007 to 2018. The sample consists of European countries. There are 398 districts in the sample.

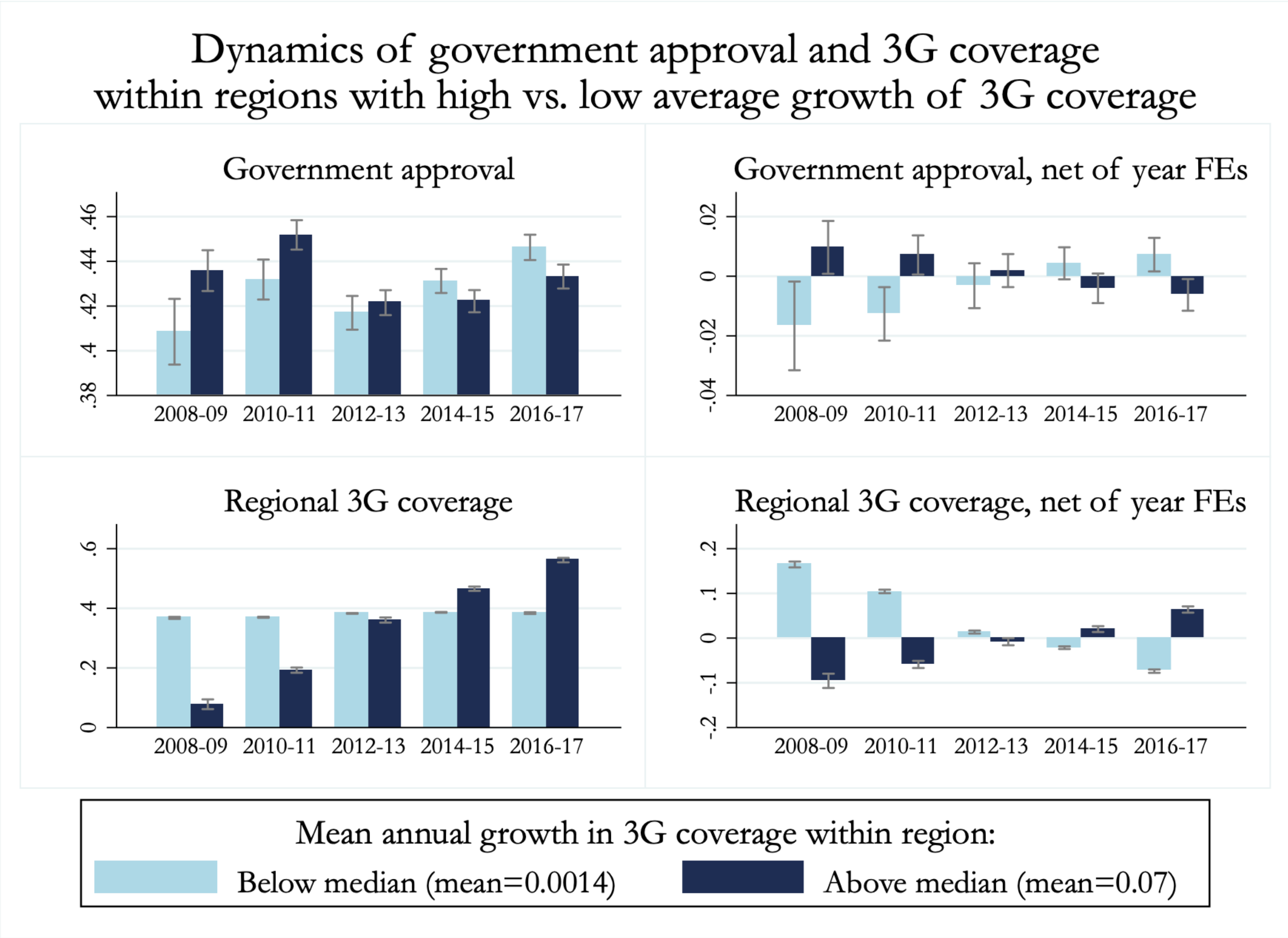


Figure A.3

Dynamics of government approval and 3G coverage in regions with high and low growth in 3G

Note: The figure presents the mean of government approval and the mean of regional 3G coverage by year, separately for regions with below-median and above-median average annual growth of 3G coverage. We partial out region fixed effects from all presented series to take into account changes in the sample composition as not all regions appear in the data in all years. Graphs on the left present raw dynamics and graphs on the right present the dynamics net of year fixed effects. We calculate the average within-region annual growth of 3G coverage by regressing 3G coverage on linear trend and taking the point estimate of the estimated coefficient.

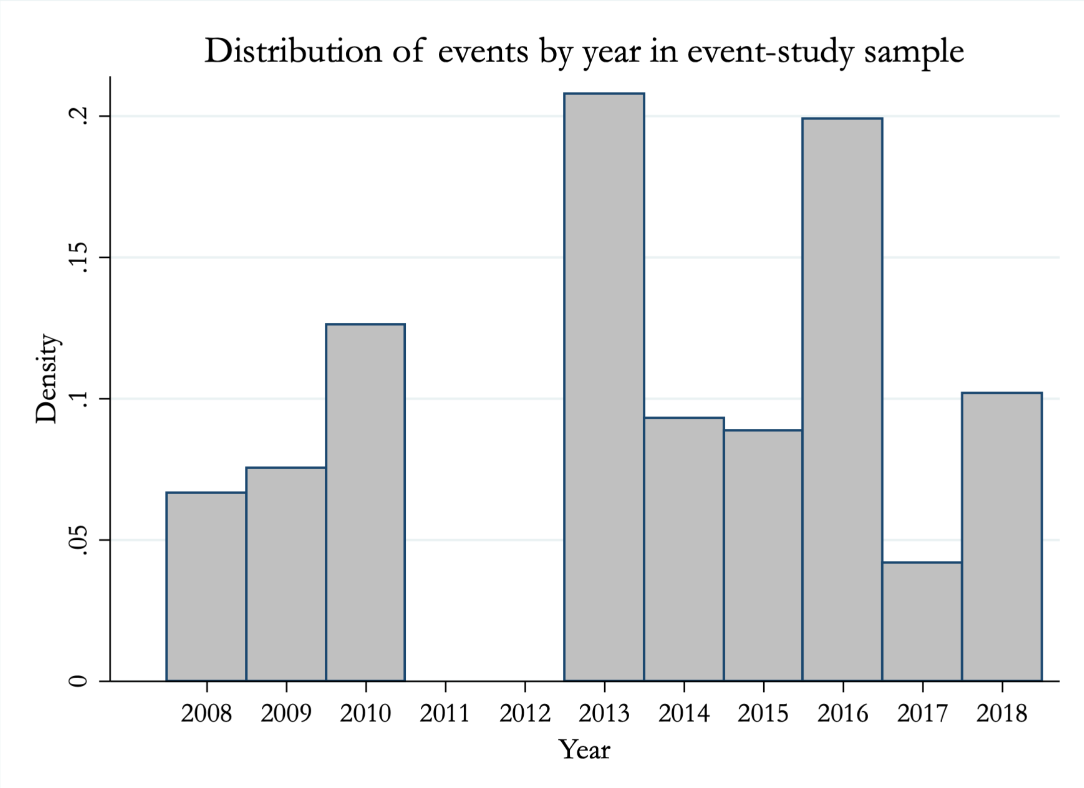


Figure A.4
Event-study sample across years

Note: The figure presents the distribution of regions with events across years. There are 452 event-regions in 65 countries between 2008 and 2018. Below we list countries with events in each year. The number in parentheses indicates the number of regions with an event in this country and year.

2008: Italy (14)†, South Korea (4)†, Spain (11)†, United States (1)†
2009: Georgia (1), Japan (5), Malaysia (9), South Korea (11), Tajikistan (1), Luxembourg (5)†, Serbia (1)†, United States (1)†
2010: Indonesia (8), Israel (1), Netherlands (2), Russia (1), Sri Lanka (4), United States (3), Brazil (1)†, Bulgaria (6)†, Chile (1)†, Dominican Republic (11)†, Egypt (3)†, Estonia (1)†, Finland (1)†, Indonesia (3)†, Ireland (7)†, Mexico (1)†, Slovakia (3)†
2013: Armenia (5), Mauritius (9), Panama (1), Paraguay (2), Tunisia (17), Venezuela (1), Hungary (3)†, Tunisia (5)†, Vietnam (51)†
2014: Guatemala (1), Moldova (29), Azerbaijan (1)†, Kenya (1)†, Moldova (5)†, Montenegro (2)†, Niger (1)†, Serbia (1)†, Suriname (1)†
2015: Burkina Faso (5), Chad (1), Congo Brazzaville (2), Ghana (1), Lesotho (5), Lithuania (6), Uruguay (19), Tanzania (1)†
2016: El Salvador (2), Russia (1), Thailand (39), Trinidad & Tobago (11), Jamaica (10)†, Thailand (27)†
2017: Benin (5), Cambodia (3), Cyprus (4), Czech Republic (1), Mozambique (1), Namibia (1), Nigeria (1), Benin (2)†, Swaziland (1)†
2018: Cambodia (3)†, Cameroon (9)†, El Salvador (2)†, India (4)†, Indonesia (4)†, Kyrgyzstan (1)†, Nepal (3)†, Russia (11)†, Tanzania (4)†, Turkey (5)†

† indicates the events that contribute to the definition of lags or leads of the event year in estimating the event-study relationship (Columns 3 and 6 of Table II), but there is no variation in the dummy for "post-event" within these regions in the GWP sample. Thus, in Columns 2 and 5 of Table II, these regions only contribute to estimating the coefficients on control variables, such as year effects. There are 219 regions from 36 countries with variation in the post-event dummy. The difference stems from the fact that not all countries and regions are present in GWP in all years and GWP data are not available for 2018. The results are robust to excluding the regions without variation in the post-event dummy from the event-study sample.

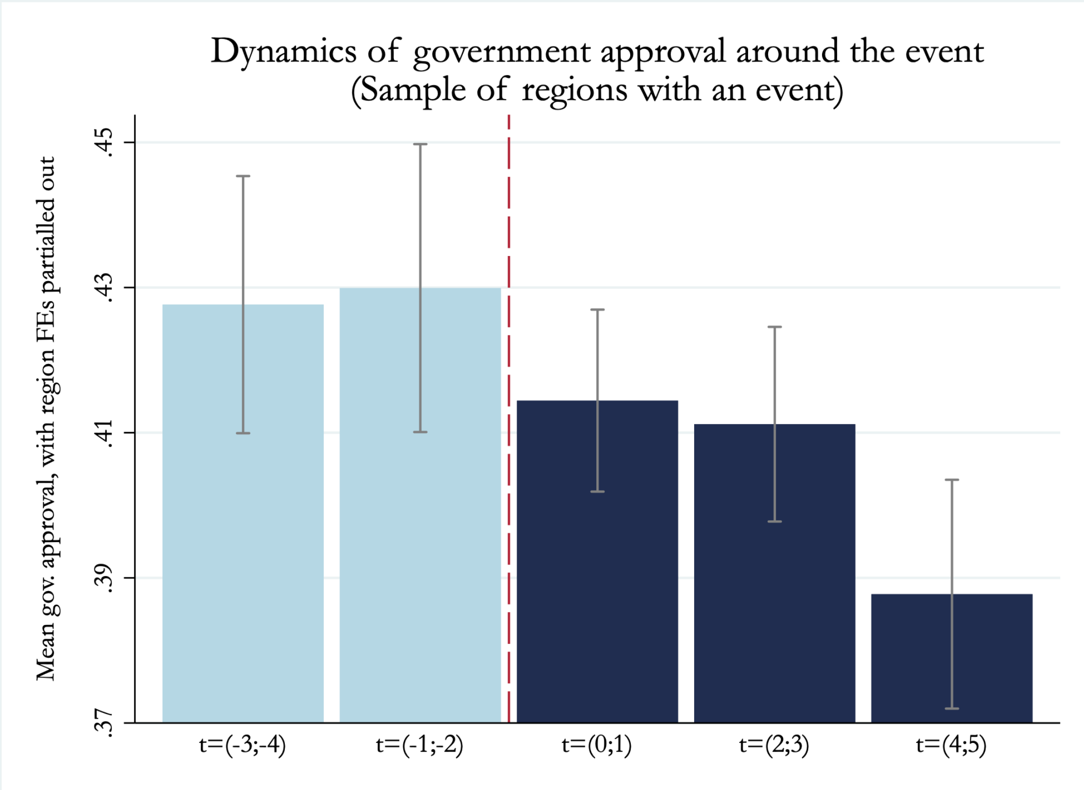


Figure A.5

Raw dynamics of government approval around the events

Note: The figure presents the dynamics of the mean of government approval (net of region fixed effects) for years before and after the event in the sub-sample of regions with variation in the treatment dummy within the sample. We partial out region fixed effects to take into account changes in the sample composition as not all regions appear in the data in all years. Dashed vertical line indicated the time of the event (the increase of the regional 3G coverage by at least 50 percentage points in one year).

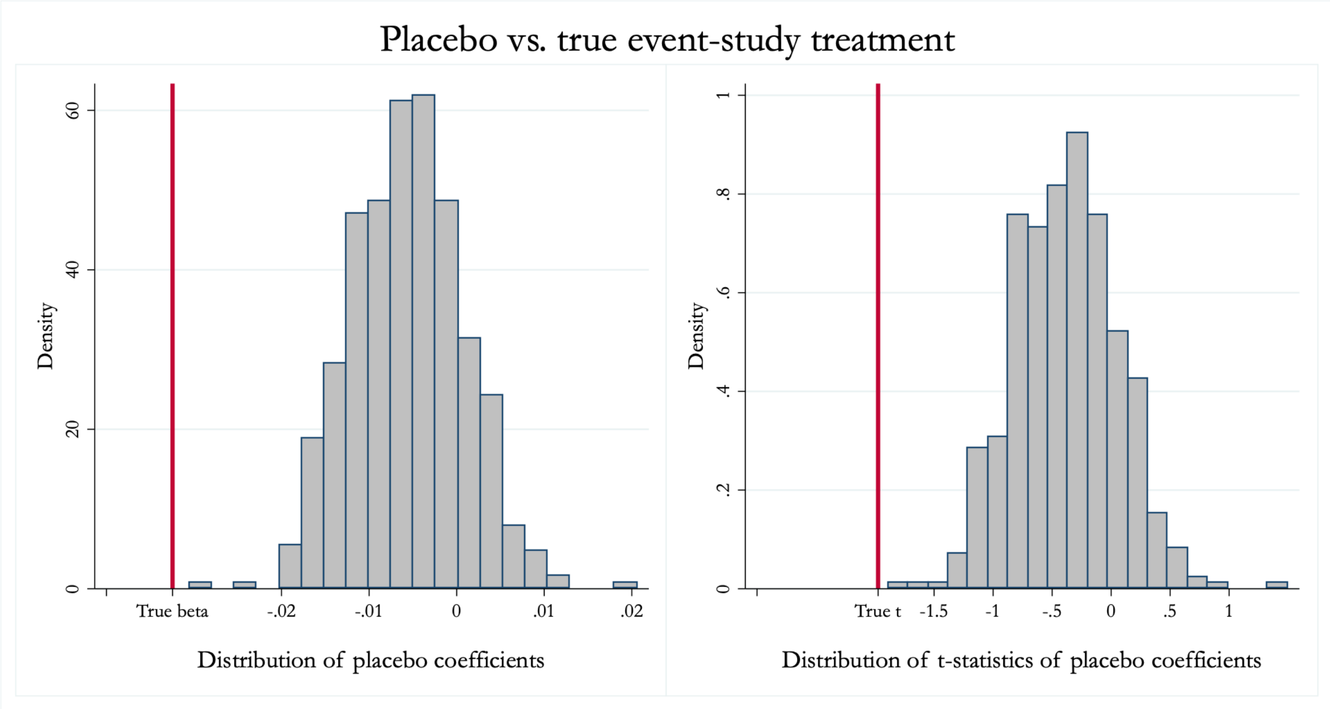


Figure A.6

Event study treatments are not associated with a concurrent decline in government approval in other regions of the same countries in the same year

Note: The figure compares the results of for the post-event dummy in the event-study sample to the results from placebo treatments—500 random draws from the same countries and years as the actual events, but from regions that did not experience the event. In the event study, event is defined as the region experiencing an increase in 3G coverage of more than 50 percentage points in a single year. Thus, placebo events consider regions from the same countries and years that did not experience an increase in 3G coverage of more than 50 percentage points. To ensure that regions with the event are comparable to the placebo regions, we exclude country-years when at least 60% of the regions in the country had an event. The thick vertical lines indicate the result for the real events in this subsample for the specification similar to the one presented in Column 2 of Table II. Without this sample restriction, the difference between results for the actual and for the placebo events is even bigger. The left panel presents the point estimates, the right panel—the t-statistics. For the true events, the mean value of the increase in regional 3G coverage is 76 percentage points of the region's territory (with the standard deviation of 16.5). For the placebo treatments, the mean increase in regional 3G coverage is 13 percentage points (with the standard deviation of 15).

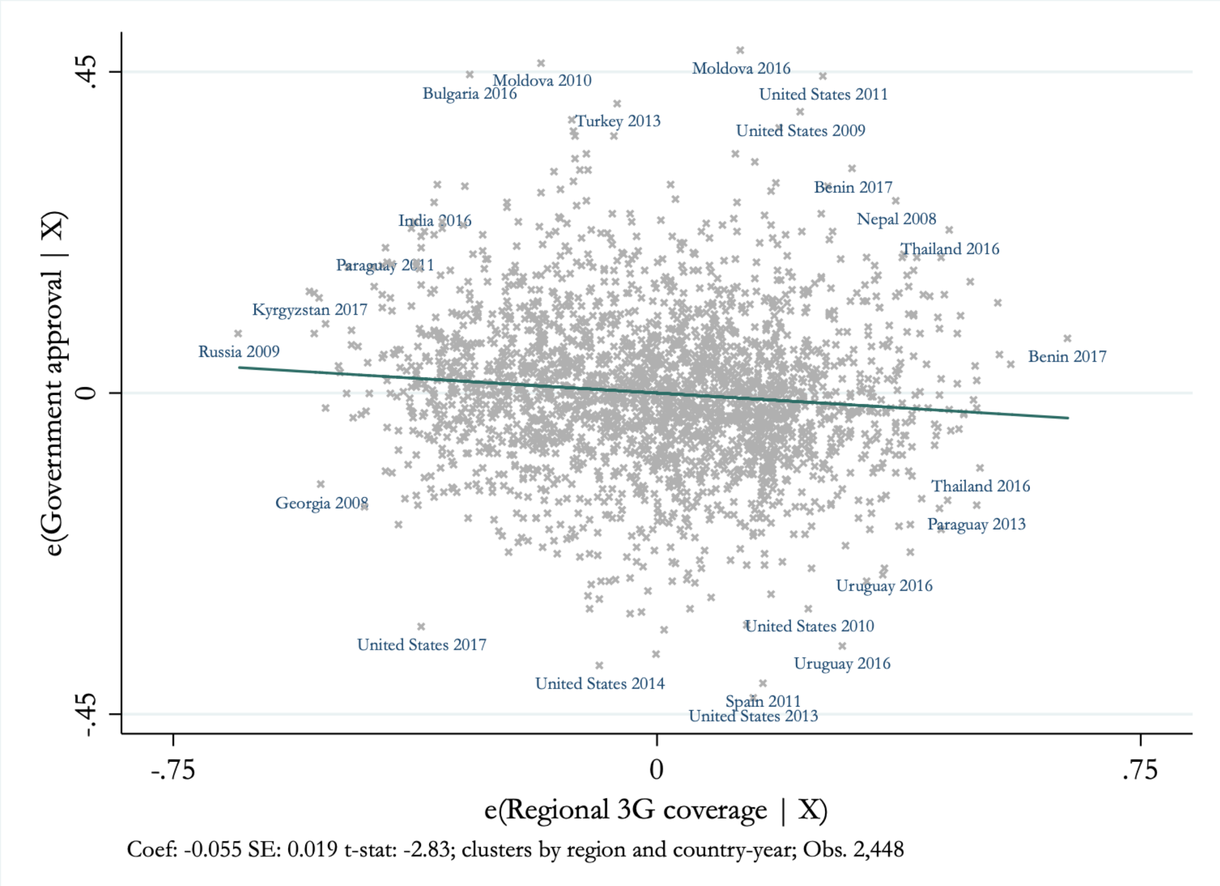


Figure A.7

Residual scatter plot of government approval and regional 3G coverage at the region-year level in the event-study sample

Note: The figure presents the residual scatter plot from estimating a specification, similar to the one presented in Column 2 of Table II, but at the region×year level. An observation is a region×year. We verified that the results do not change if we exclude the regions with observations marked on the figure and if we exclude the observations marked on this figure, leaving the rest of the observations for the same regions in the sample.

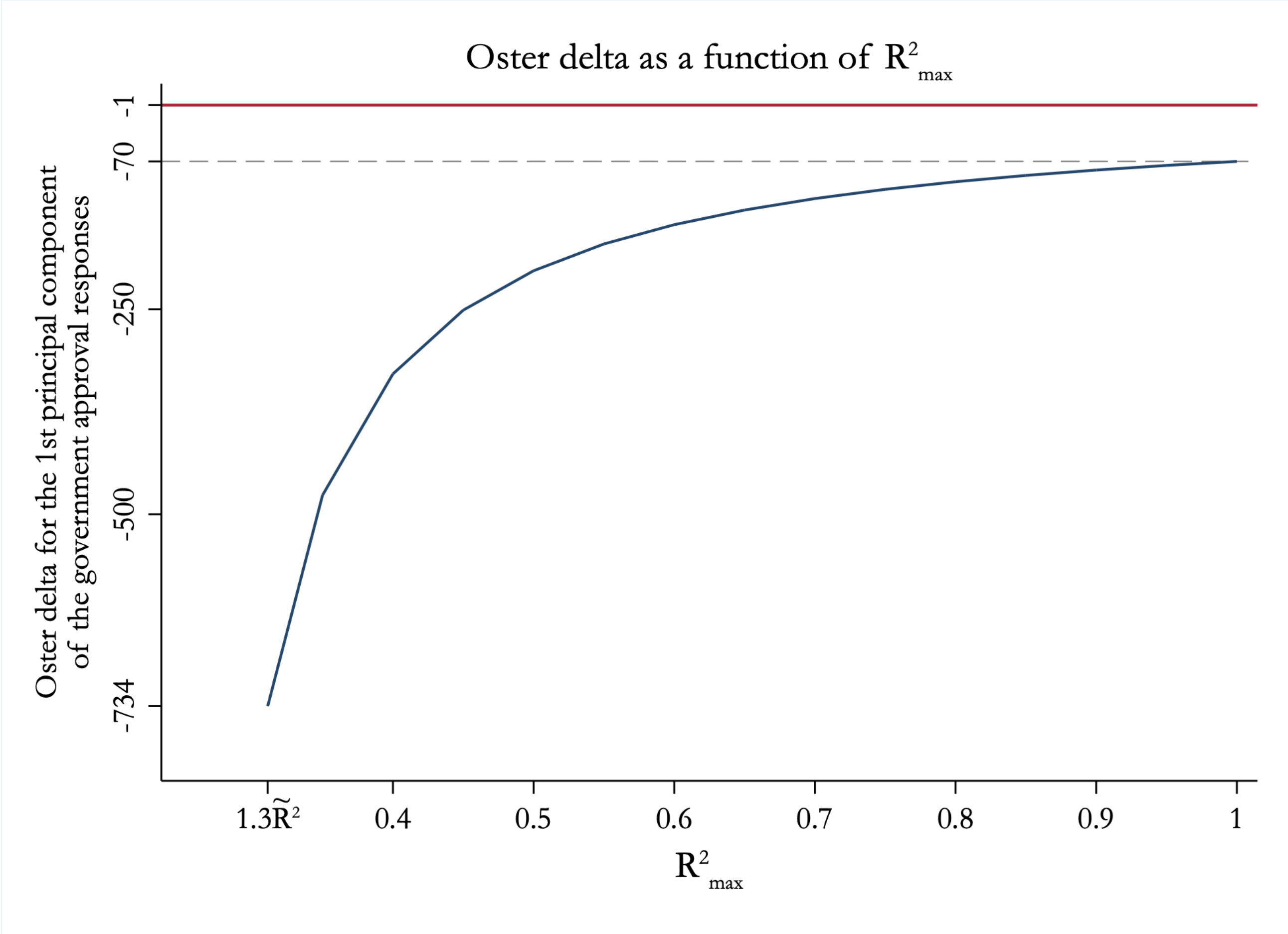


Figure A.8

Robustness of Oster's δ to alternative assumptions about $R^2_{\max}$

Note: The figure presents the value of Oster's δ as a function of $R^2_{\max}$ from $R^2_{\max} = 1.3\tilde{R}^2$, where $\tilde{R}^2$ is the R-squared from Table I, to $R^2_{\max} = 1$. The dependent variable is the 1st principal component of government approval.

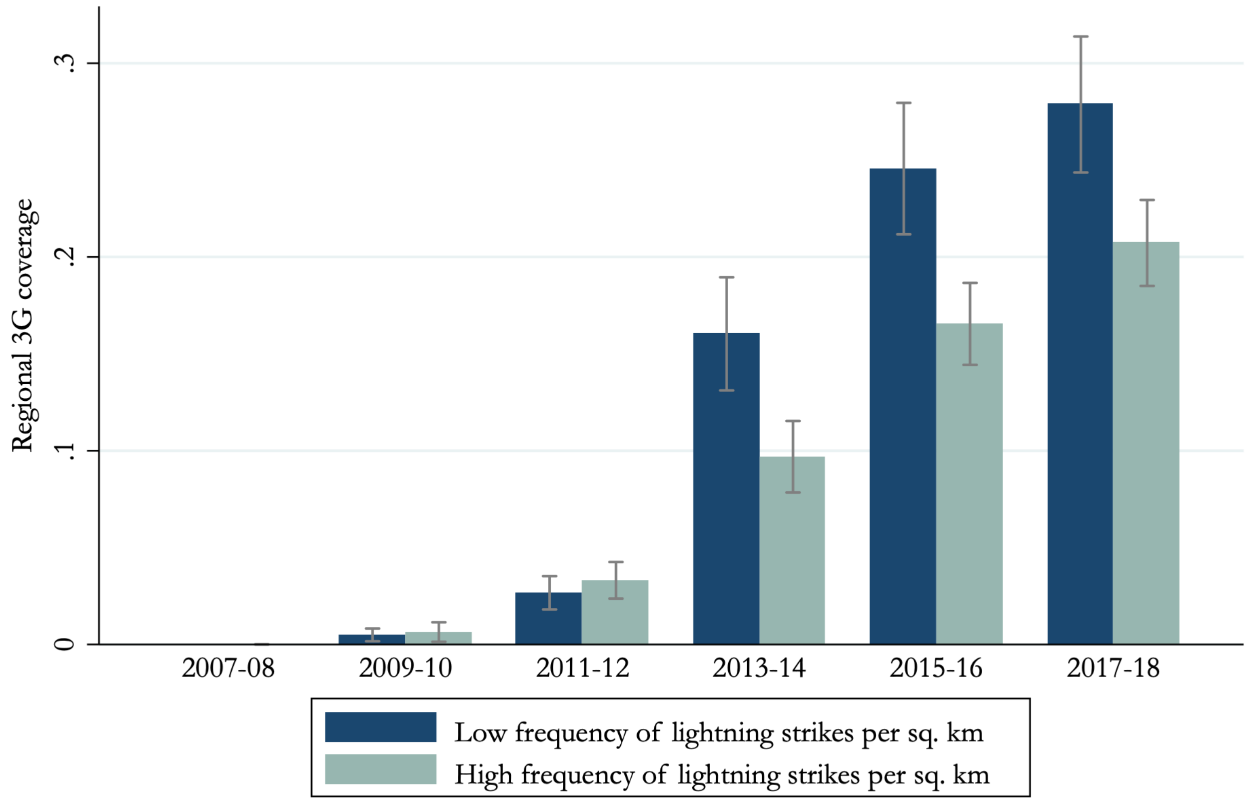


Figure A.9

Growth in regional 3G coverage by frequency of lightning strikes per area, region-year level

Note: The figure illustrates the relationship between regional 3G coverage and the frequency of lightning strikes per area. In particular, it presents the evolution of regional 3G coverage in subnational regions with a high frequency of lightning strikes per sq. km and in subnational regions of the same countries with a low frequency of lightning strikes per sq. km. The sample consists of countries with below-median GDP per capita that have within-country variation in the frequency of lightning strikes per sq. km.

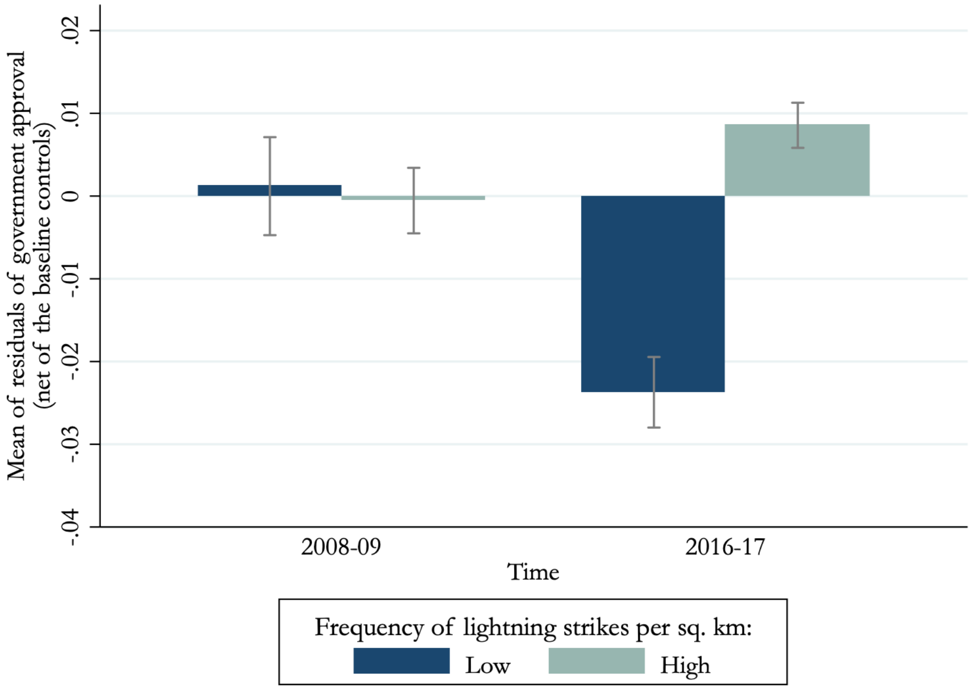


Figure A.10

Lightning strikes and the change in government approval
among countries with below-median GDP per capita

Note: The figure illustrates the reduced-form relationship behind the 2SLS estimation presented in Columns 5 and 6 of Table IV. The results are based on the sample of countries with below-median GDP per capita. The vertical axis presents mean government approval net of all controls, including region and year fixed effects. The graph also presents the 90% confidence intervals with robust standard errors.

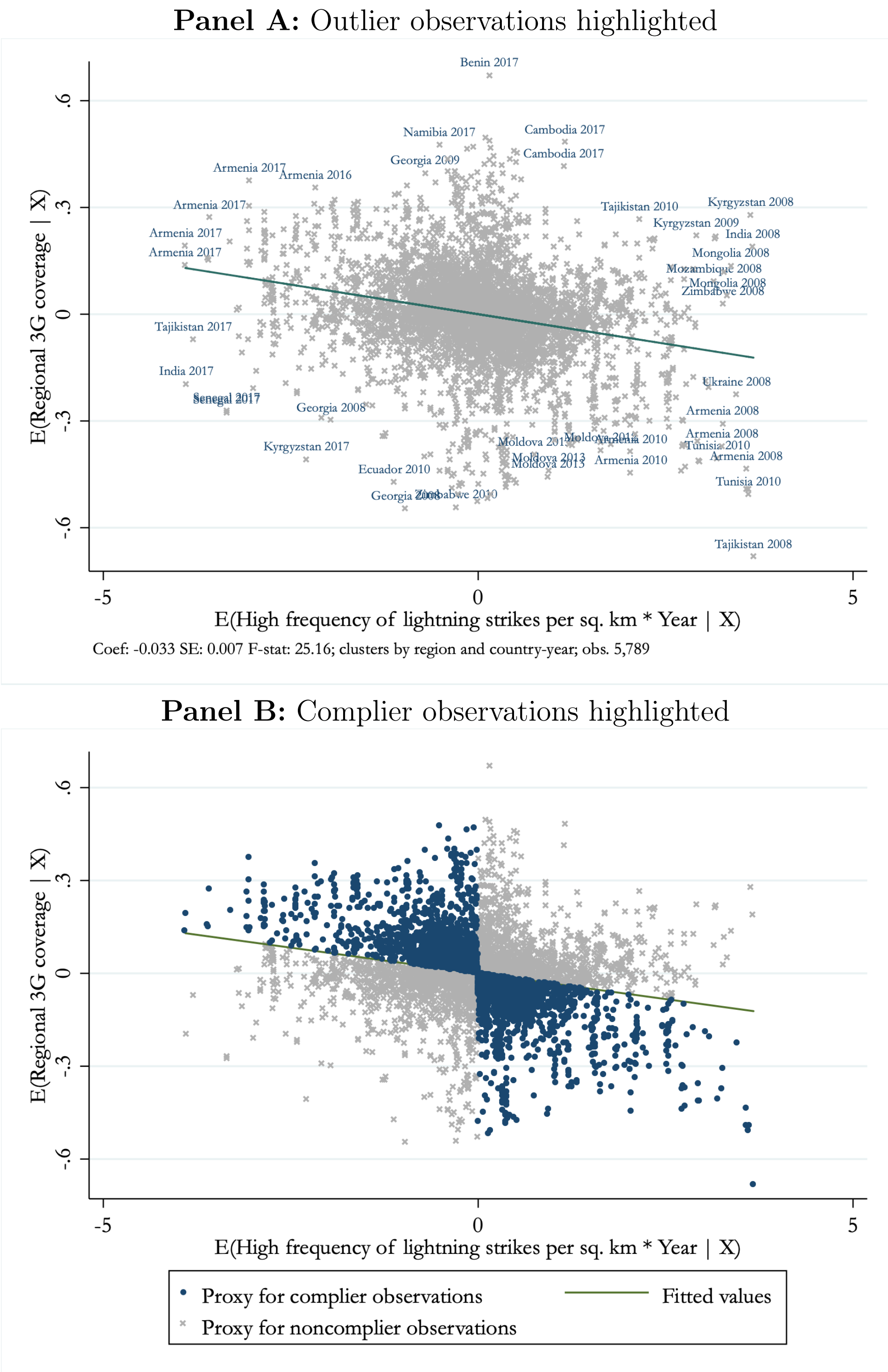


Figure A.11

Residual scatter plot of regional 3G coverage and a dummy for a high frequency of lightning strikes per square kilometer interacted with a time trend, region-year level

Note: The figure presents the residual scatter plot of the first-stage relationship from Column 5 of Table IV between regional 3G coverage and a dummy for a high frequency of lightning strikes per square kilometer interacted with a time trend. The sample consists of countries with below-median GDP per capita. In Panel A, we highlight the observations that are relatively far away from the cloud. We have verified that excluding the region-year observations that are highlighted on this graph or excluding regions with observations that are highlighted on this graph does not affect the results of either the first or the second stage. In Panel B, we highlight the observations that are driving the first stage. We deem them as a proxy for complier observations: only a subset of these observations are compliers, as some are "always takers" and "never takers" that happen to fit the estimated relationship.

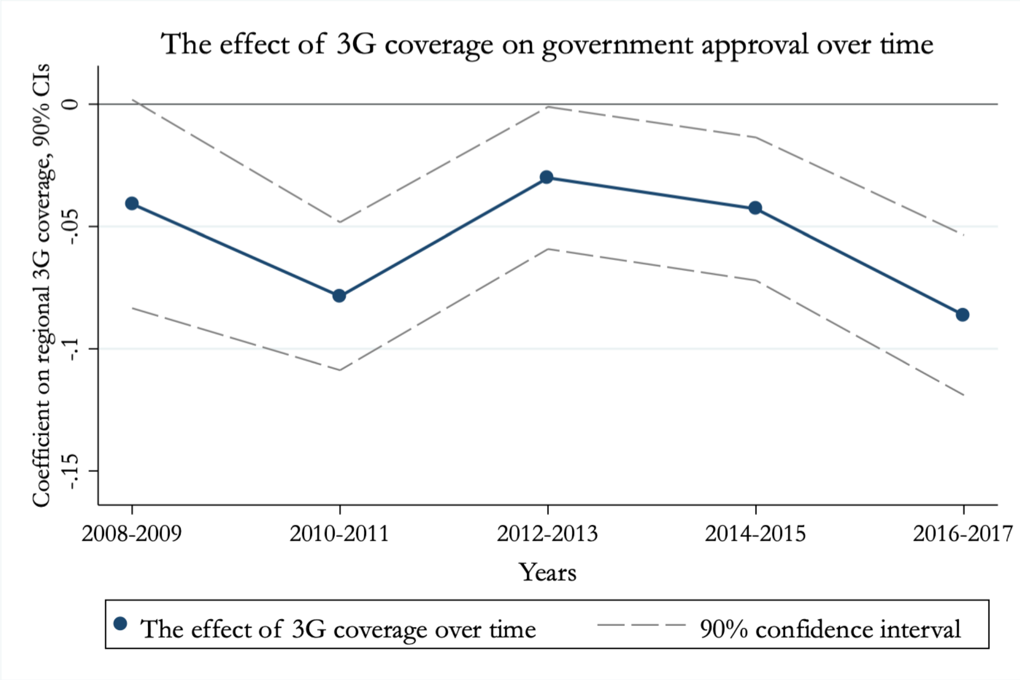
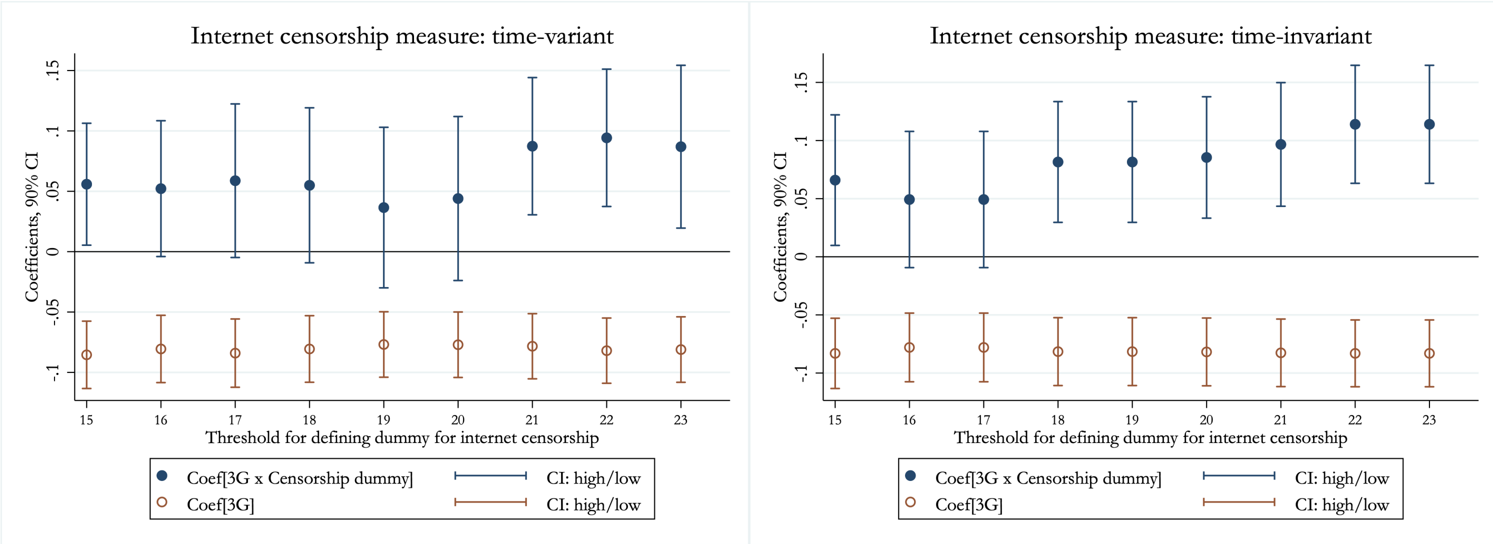


Figure A.12

3G coverage and government approval, by time period

Note: The figure presents the results presented in Column 1 of Table A.10. The standard errors used to construct the confidence intervals are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Panel A: Robustness to using other thresholds of internet censorship in regression



Panel B: The baseline thresholds are natural breaks in the distributions of continuous measures of internet censorship

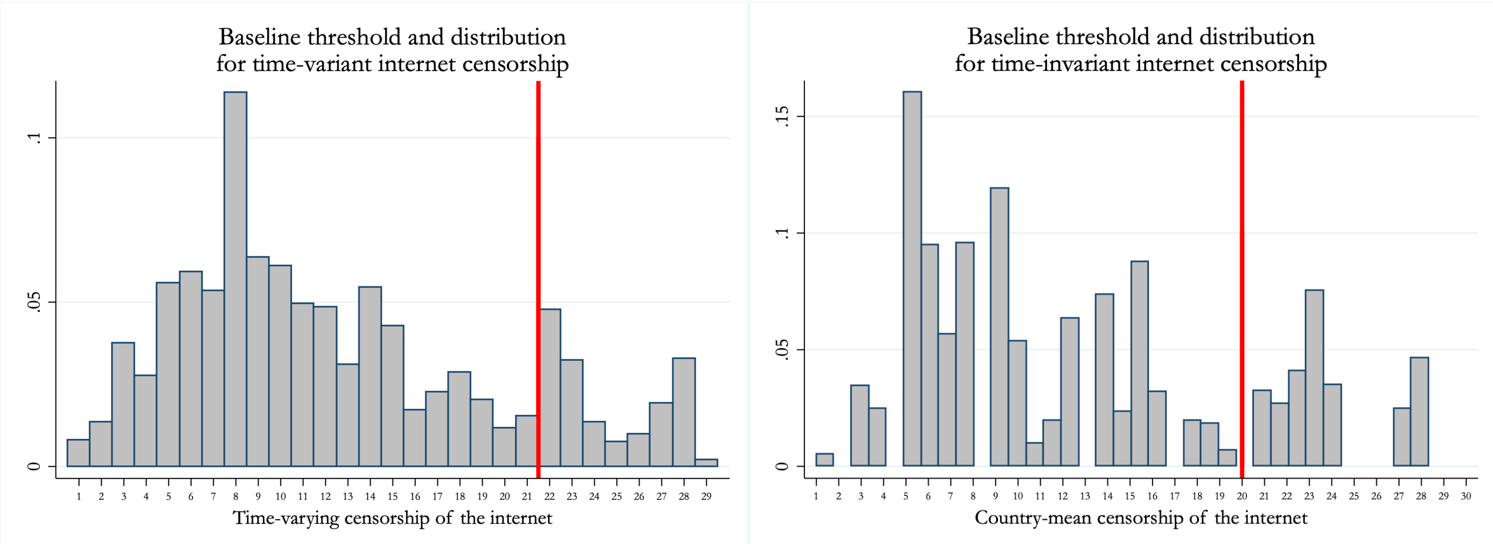


Figure A.13

The choice of threshold for the dummy for internet censorship

Note: Panel A of the figure presents the robustness of the results from Column 6 of Panels A and B of Table V to different thresholds for the definition of dummies for internet censorship. Panel B of the figure present the distributions of the continuous measures of internet censorship to illustrate the choice of the baseline thresholds. The baseline threshold for the time-variant dummy corresponds to the 90th percentile of the distribution of the internet censorship score. The baseline threshold for the time-invariant dummy corresponds to the 85th percentile of the distribution of the time-invariant internet censorship score. Countries that fall above the baseline threshold of 20 are listed in the Appendix Section G.

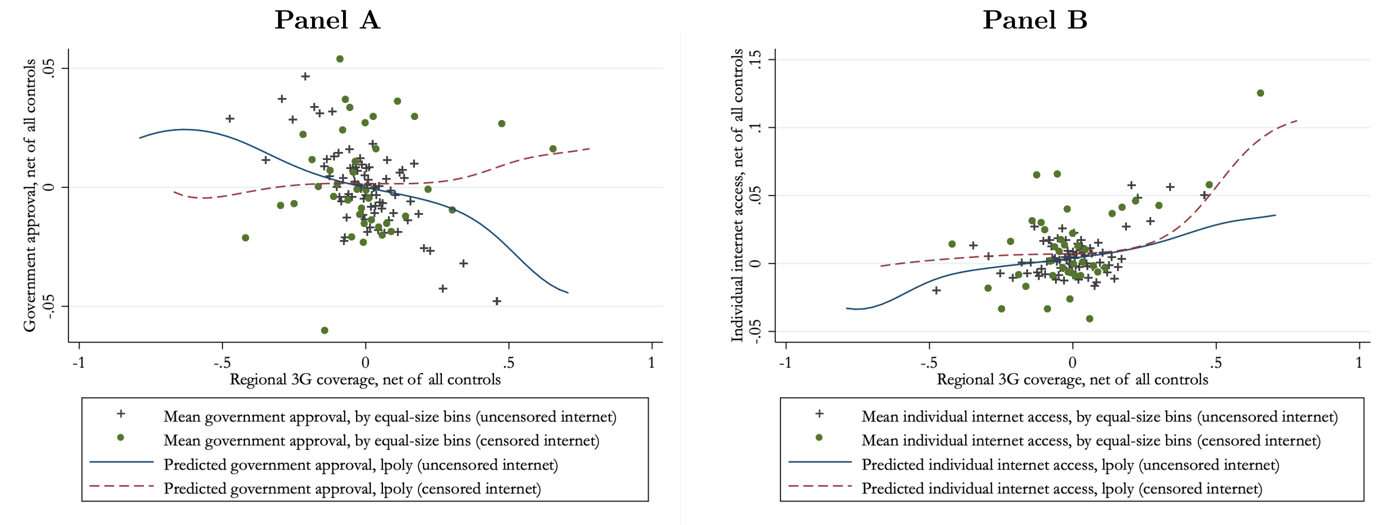


Figure A.14

3G coverage, confidence in government, and internet access at home in countries with censored and uncensored internet, net of all controls

Note: Panel A of the figure illustrates the nonparametric (local polynomial smoothing) relationship between government approval and regional 3G coverage in countries with and without internet censorship from Column 6 of Panel B of Table V. To construct this figure, we regress the government approval and regional 3G coverage variables on all the other controls and plot the relationship between the residuals, separately for countries with and without internet censorship. The dots show the means of the respective outcome variables , net of all controls, by equal-size bins. The lines on the graphs show the predicted outcomes (Gaussian kernel, local polynomial smoothing). Similarly, Panel B of the figure illustrates the nonparametric (local polynomial smoothing) relationship between internet access at home and regional 3G coverage in countries with high and low censorship.

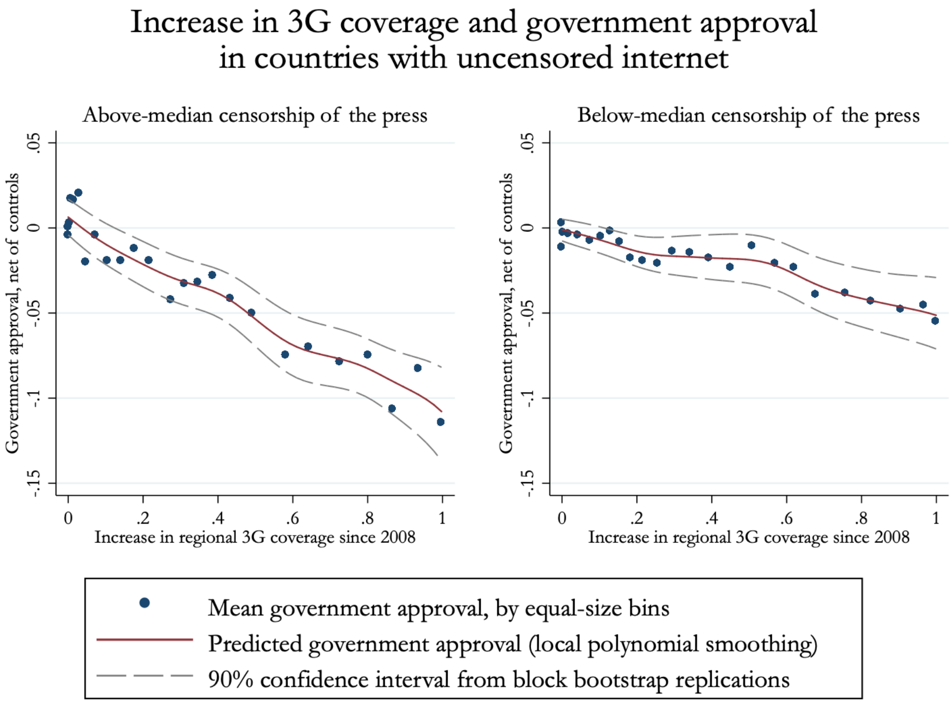


Figure A.15

3G coverage and government approval in countries with uncensored internet, depending on censorship of the traditional press

Note: Uncensored 3G internet decreases government approval more in countries with high censorship of the traditional press. The figure illustrates the results from Column 6 of Panel D of Table V. The left-hand side of the figure illustrates the nonparametric (local polynomial smoothing) relationship between government approval and regional 3G coverage for countries with uncensored internet and above-median censorship of the traditional press; the right-hand side—the same relationship for countries with uncensored internet and below-median censorship of the traditional press. The effects of all the other controls are subtracted prior to estimating the nonparametric relationship. The dots show the means of the respective outcome variables , net of all controls, by equal-size bins. The solid lines on the graphs show the predicted outcomes (Gaussian kernel, local polynomial smoothing).

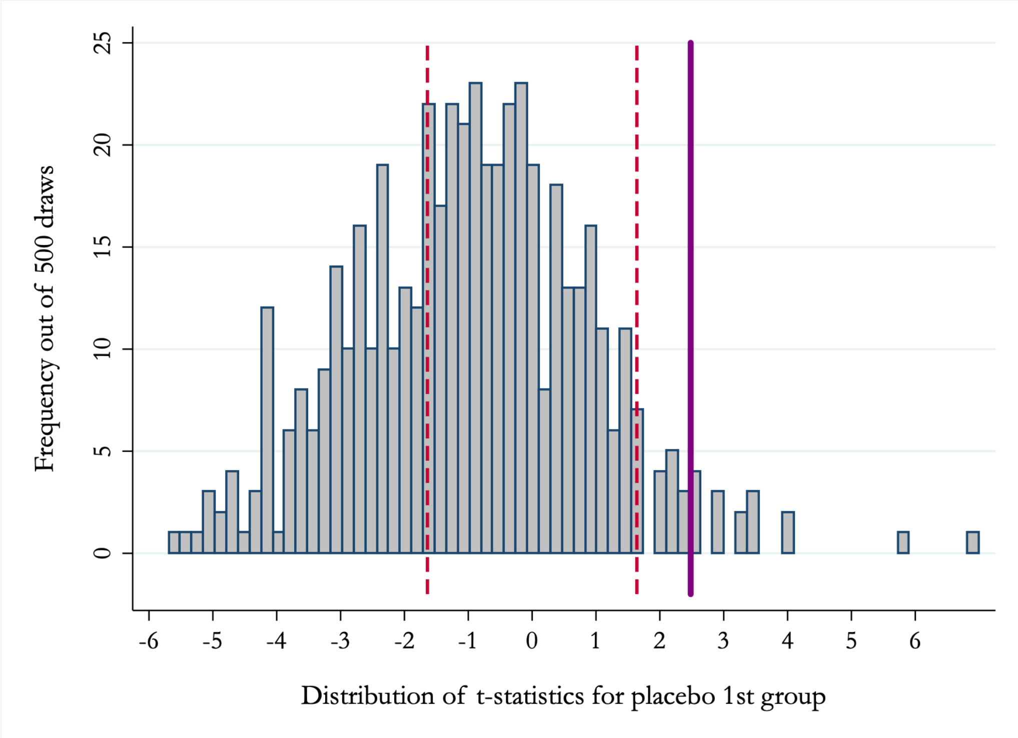


Figure A.16

Results of the placebo for the heterogeneity w.r.t. overall corruption level, in which countries are randomly allocated to groups

Note: The figure presents the distribution of the t-statistic for the coefficient on the interaction term between 3G coverage and a dummy for the top group, in the same specification as in Figure VI, but as a result of 500 draws in which countries are randomly allocated among the 13 groups with nonmissing GICI index, instead of the allocation according to the level of GICI index. Dashed vertical lines indicate the 10%-significance thresholds for the negative and positive effect. Thick solid line indicates the true t-statistic for the effect of 3G in the group of least corrupt countries.

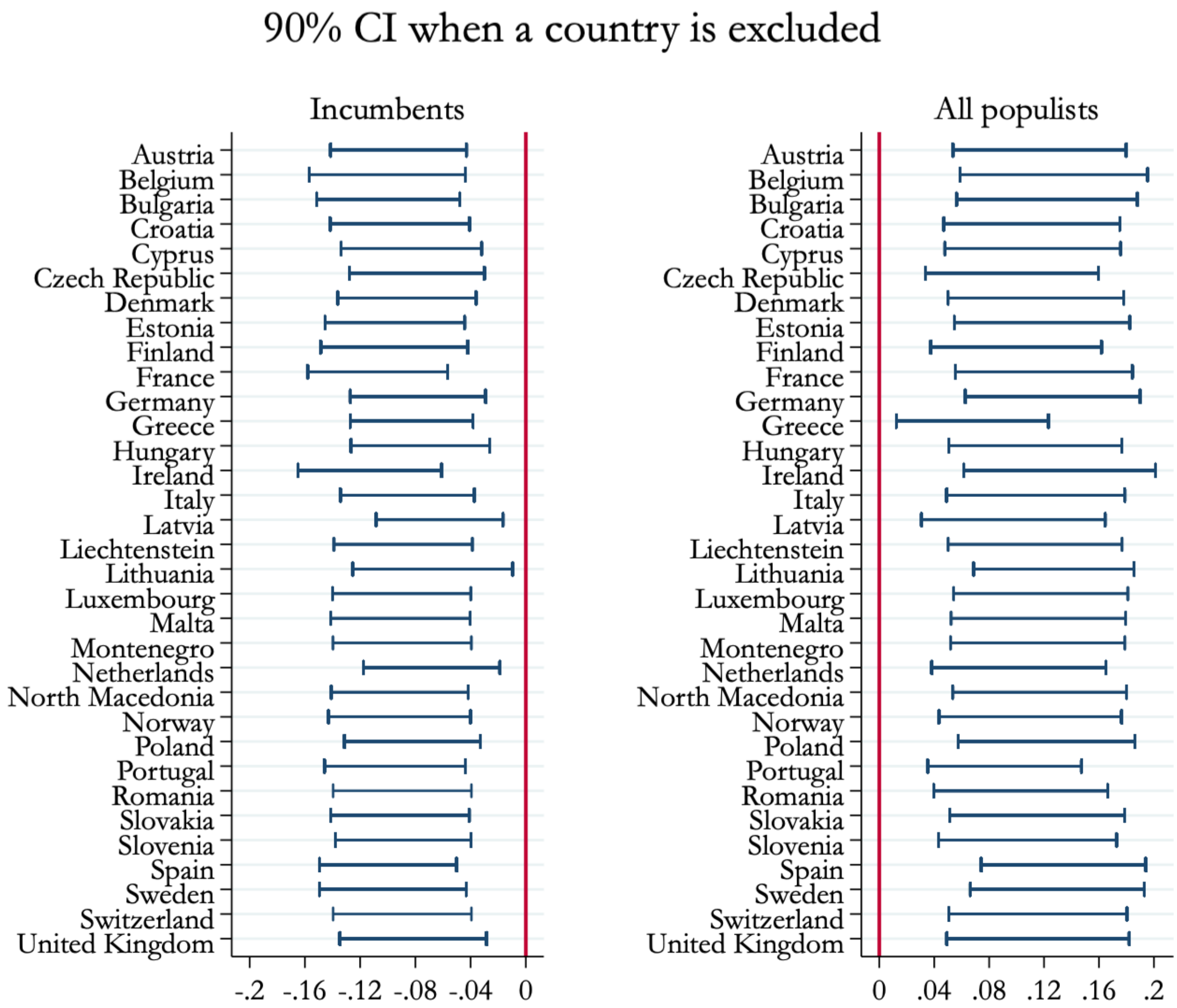


Figure A.17
The confidence interval for the effect of 3G internet on election results in Europe when the countries are excluded one by one

Note: The figure presents the 90% confidence intervals for the effect of 3G internet on the incumbents' and populists' vote shares—the regression specifications in Column 2 of Table VIII and Column 4 of Table IX, respectively—when all the countries are excluded one by one. The results are robust to the exclusion of any single country.

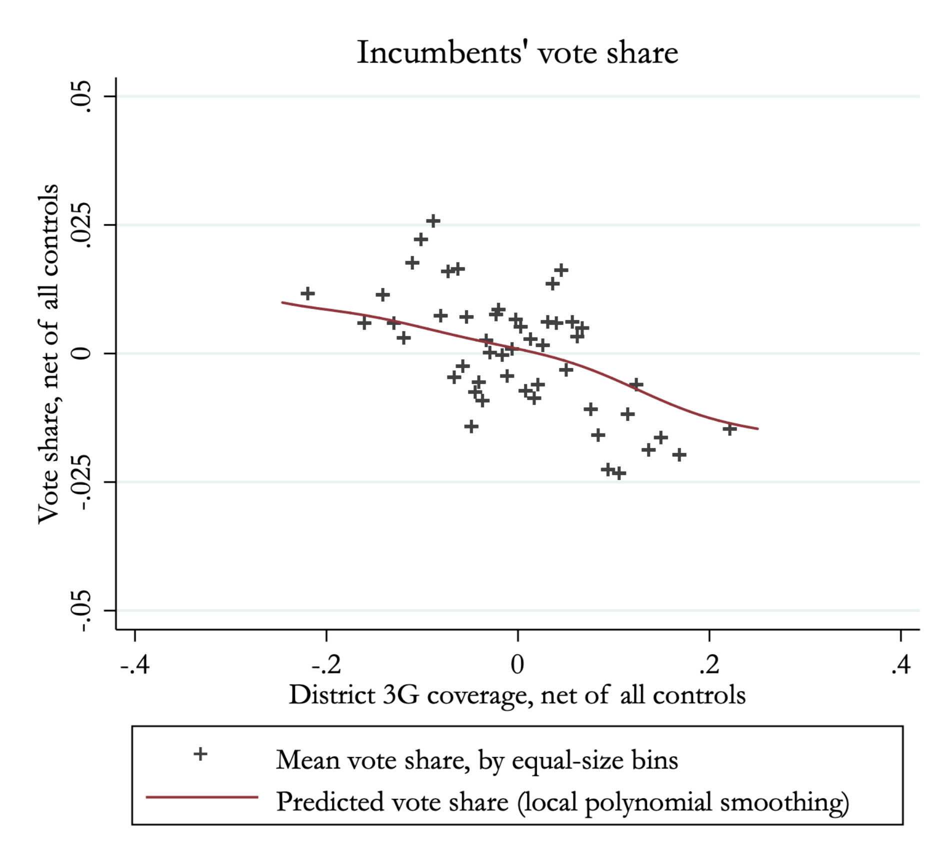


Figure A.18

3G coverage and the vote share of incumbent parties, net of all controls

Note: The figure presents the nonparametric (local polynomial smoothing) relationship between regional 3G coverage and the vote share of incumbent parties (net of all controls), illustrating the result presented in Column 2 of Table VIII. To construct this figure, we regress the vote share and regional 3G coverage on all the other controls and plot the relationship between the residuals. The dots show the means of the respective outcome variables , net of all controls, by equal-size bins. The lines on the graphs show the predicted outcomes (Gaussian kernel, local polynomial smoothing).

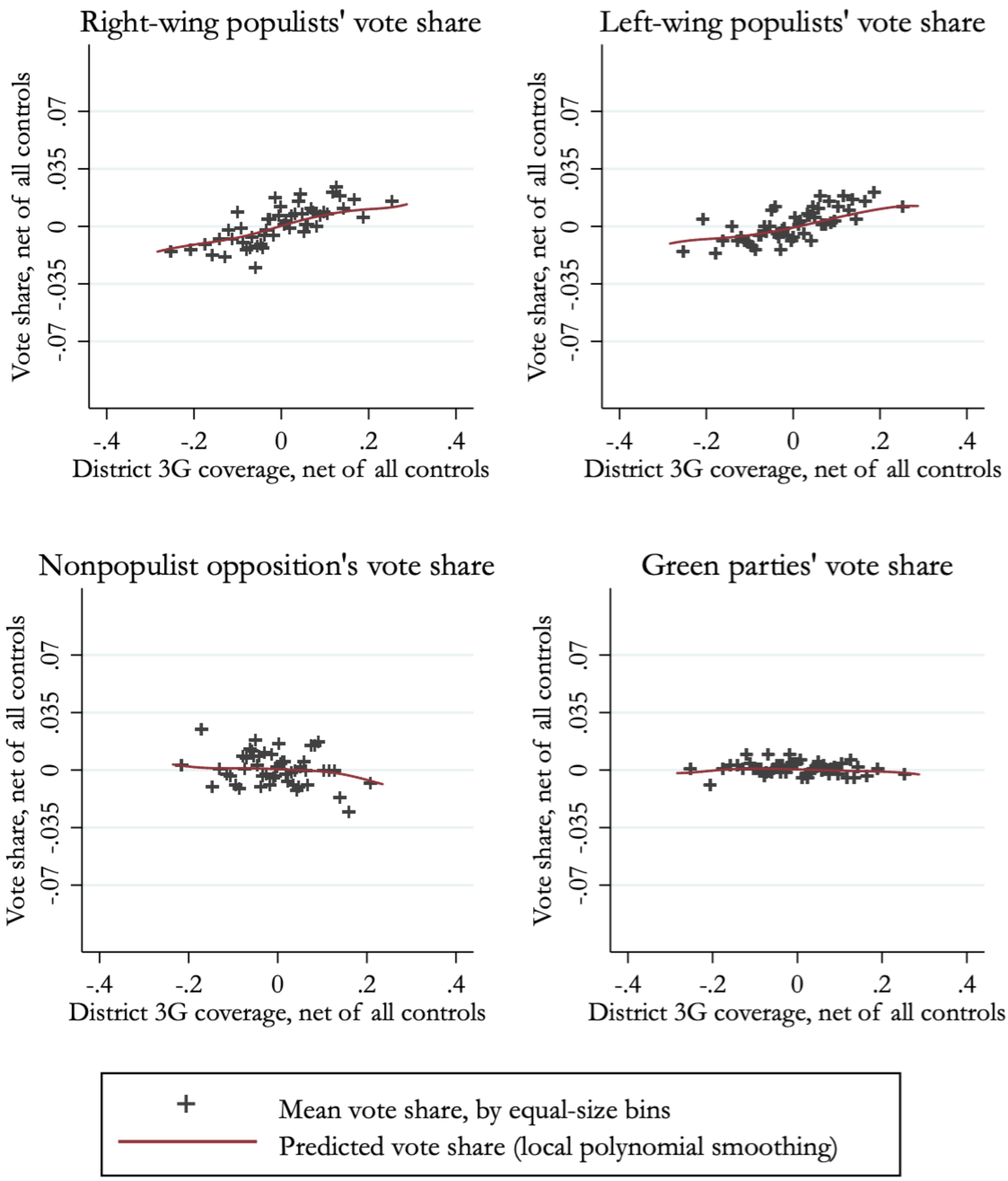
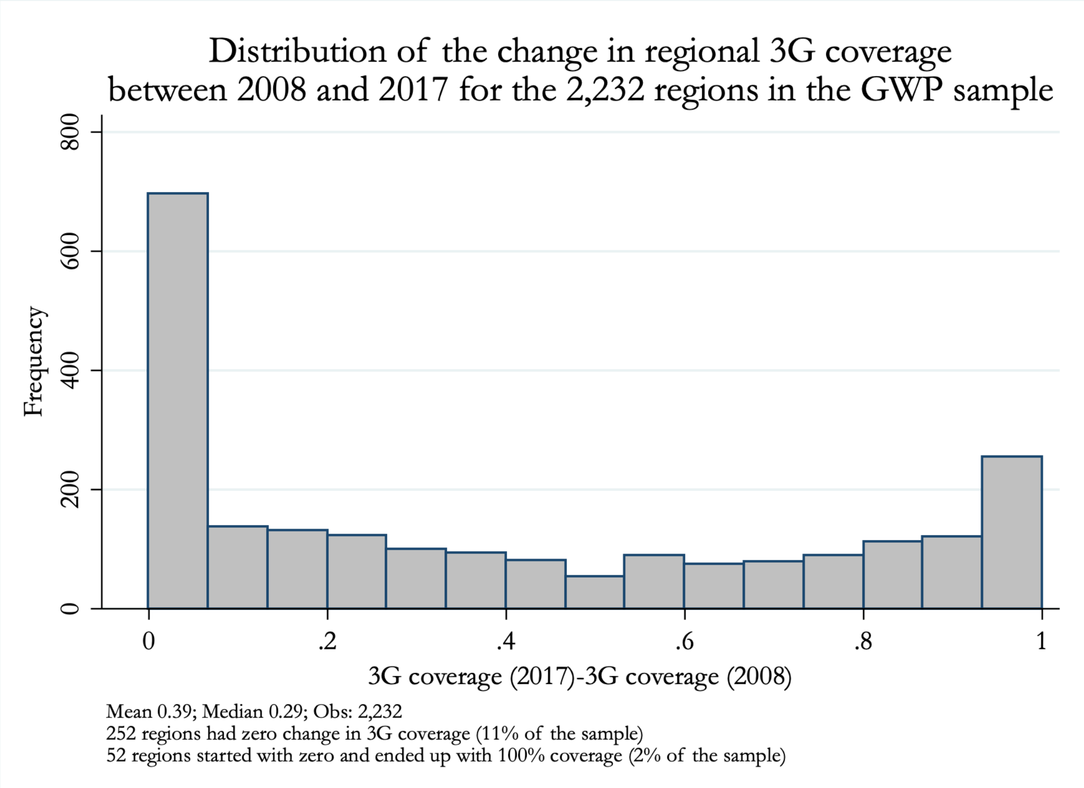


Figure A.19

3G coverage and the vote share of opposition parties, net of all controls

Note: The figure presents the nonparametric (local polynomial smoothing) relationship between regional 3G coverage and the vote share of right-wing populists, left-wing populists, the nonpopulist opposition, and green parties (net of all controls), illustrating the results presented in Columns 1, 2, 6, and 5 of Table IX, respectively. To construct this figure, we regress the respective vote shares and regional 3G coverage on all the other controls and plot the relationships between the residuals. The dots show the means of the respective outcome variables , net of all controls, by equal-size bins. The lines on the graphs show the predicted outcomes (Gaussian kernel, local polynomial smoothing).

Panel A



Panel B

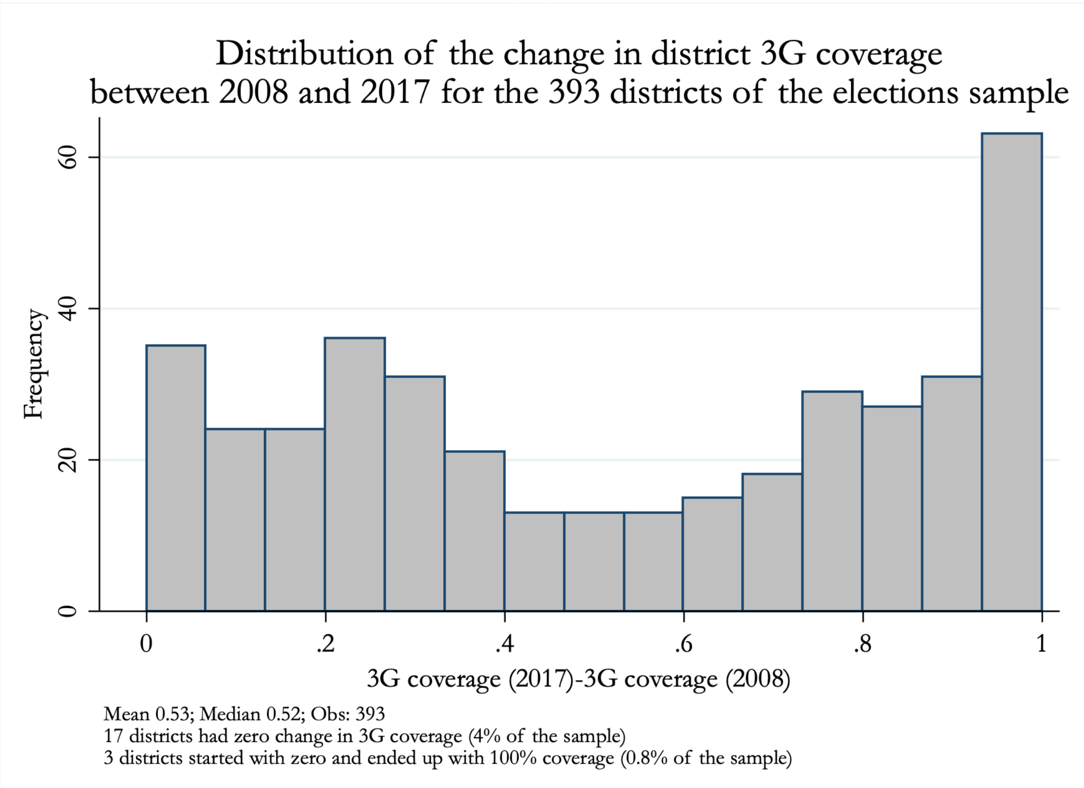
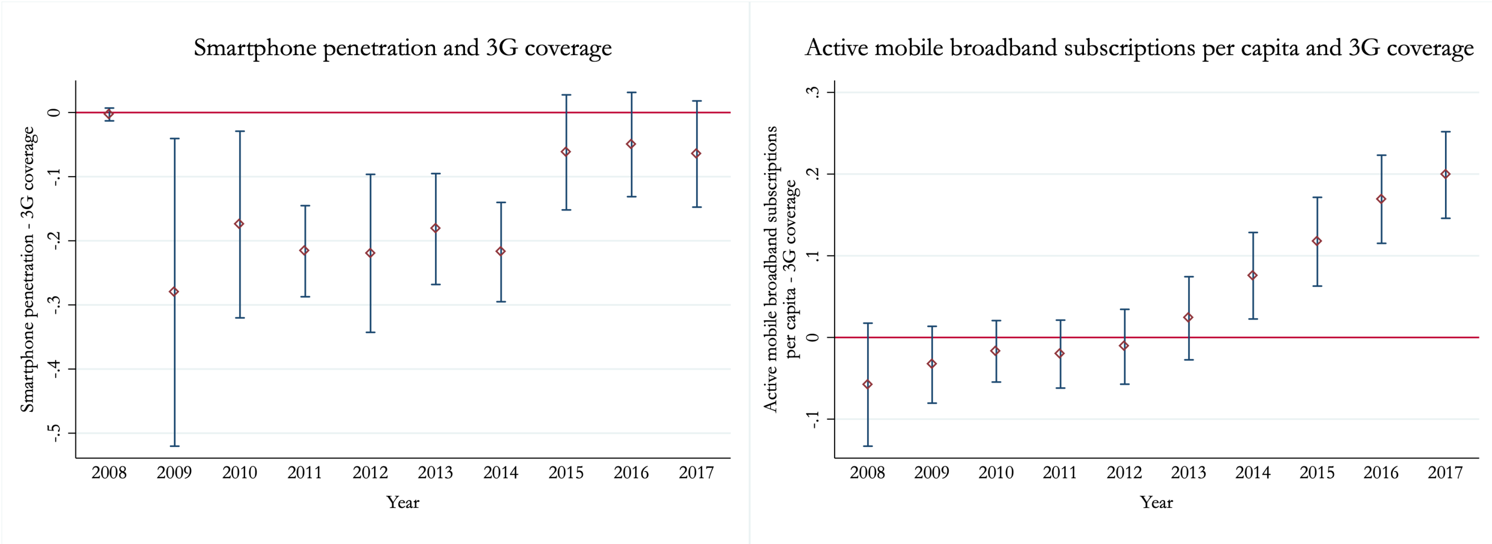


Figure A.20

Change in regional 3G coverage between 2008 and 2017

Note: The figure presents the difference in regional 3G coverage between 2017 and 2008 across regions in the sample in Panel A and across subnational districts in the election sample in Panel B.

Panel A: Cross-country mean of the difference between:



Panel B: Residual scatter plots, after partialing out country fixed effects, between:

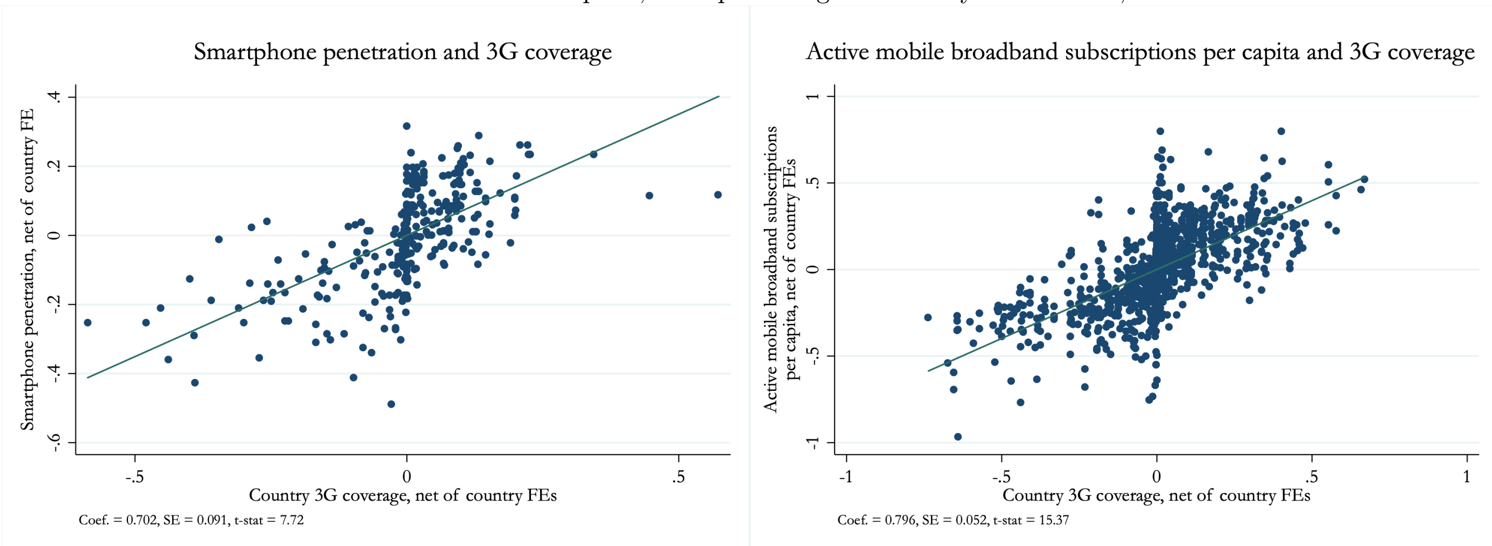


Figure A.21

The correlation between 3G coverage and individual means of accessing mobile broadband

Note: Panel A of the figure presents the cross-country mean by year of the difference between the country's penetration of smartphones (left) and active mobile broadband subscriptions per capita (right) and the country's 3G coverage along with 95% confidence intervals. It shows that, on average, smartphone penetration lagged behind 3G coverage before 2015. In contract, the number of mobile broadband subscriptions per capita was never significantly smaller than 3G coverage. Panel B presents the scatter plots behind the relationships presented in Columns 1 and 5 of Table A.22.

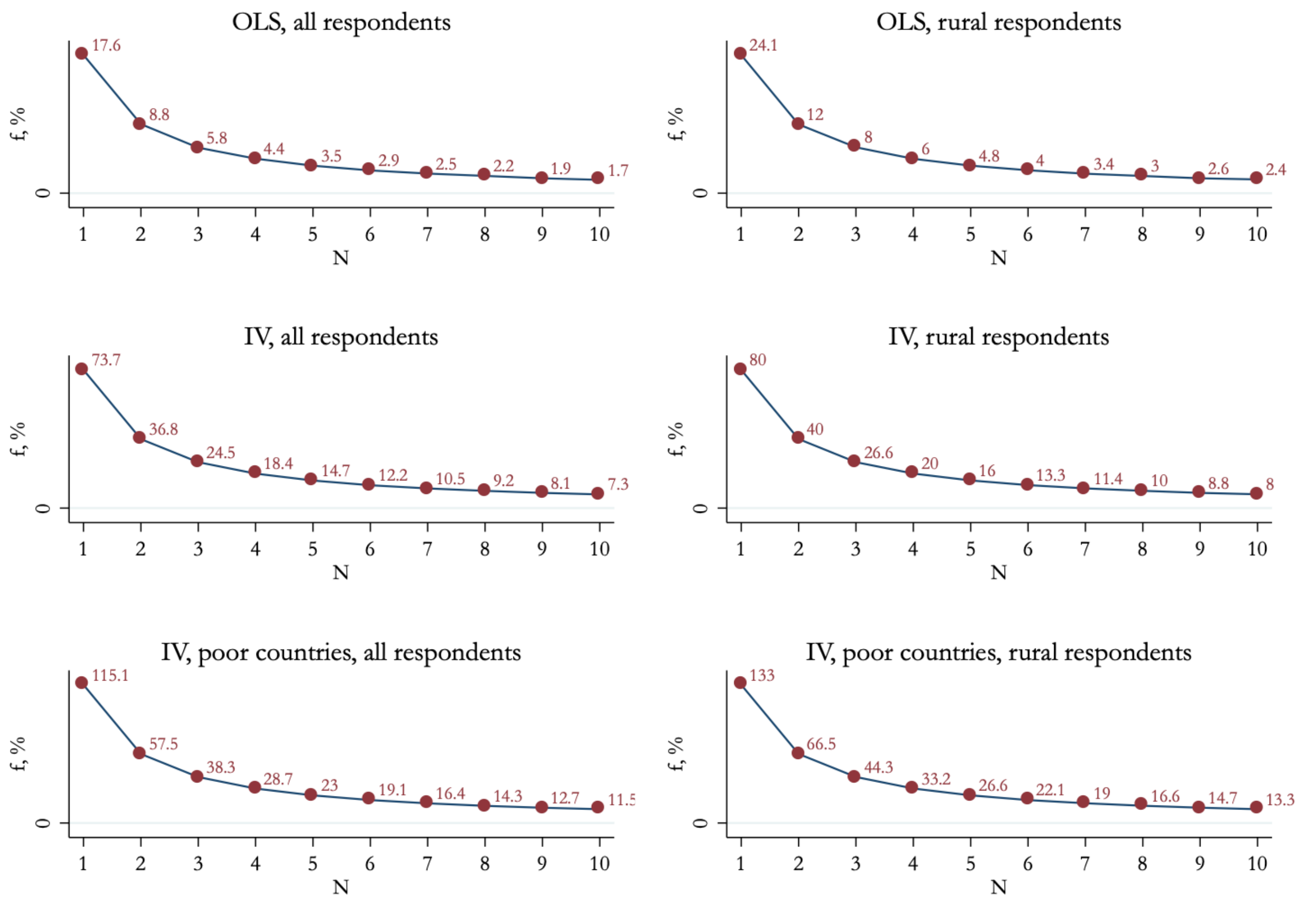


Figure A.22
Persuasion rates as a function of N, the number of people,
who get exposed to the message per smartphone

Note: The figure reports the persuasion rates implied by different estimations using GWP data, depending on the assumption about the size of the spillovers. N represents the number of individuals exposed to the message per smartphone.

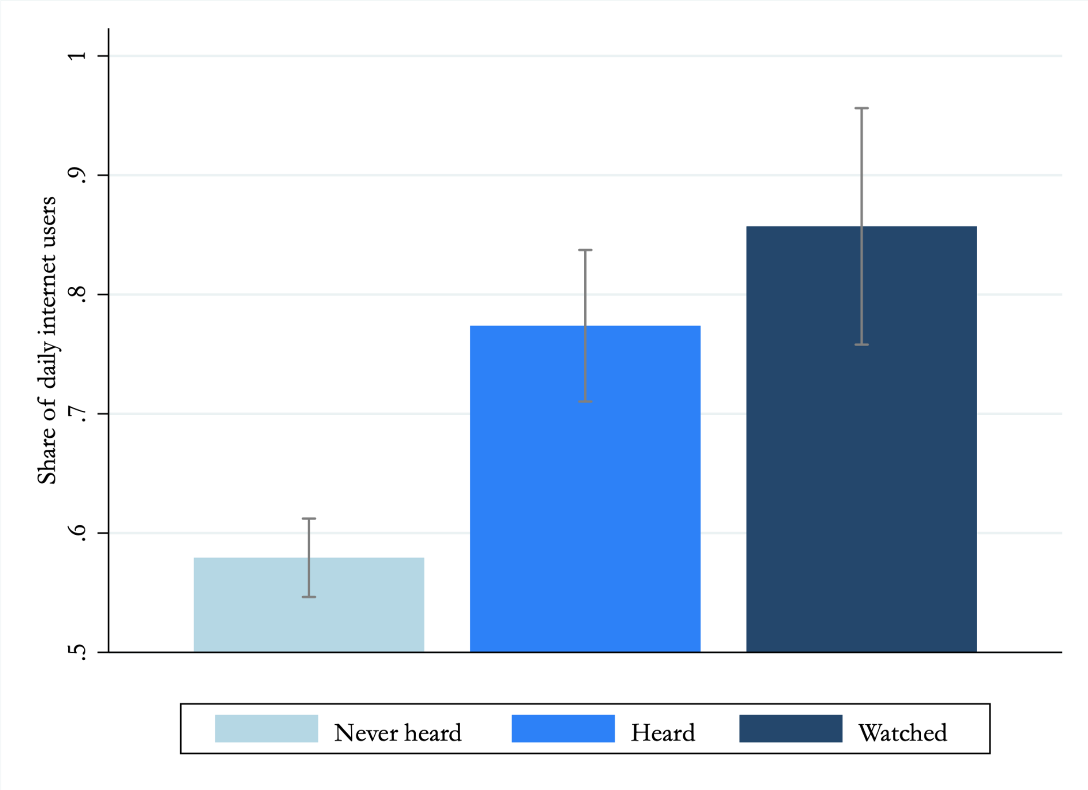


Figure A.23

Internet use and exposure to the film "He Is Not Dimon to You"

Note: The figure presents the share of daily internet users among those who had never heard of the film "He Is Not Dimon to You", those who had heard about it but had not watched it, and those who had watched it.
Sources: FBK survey, authors' calculations.

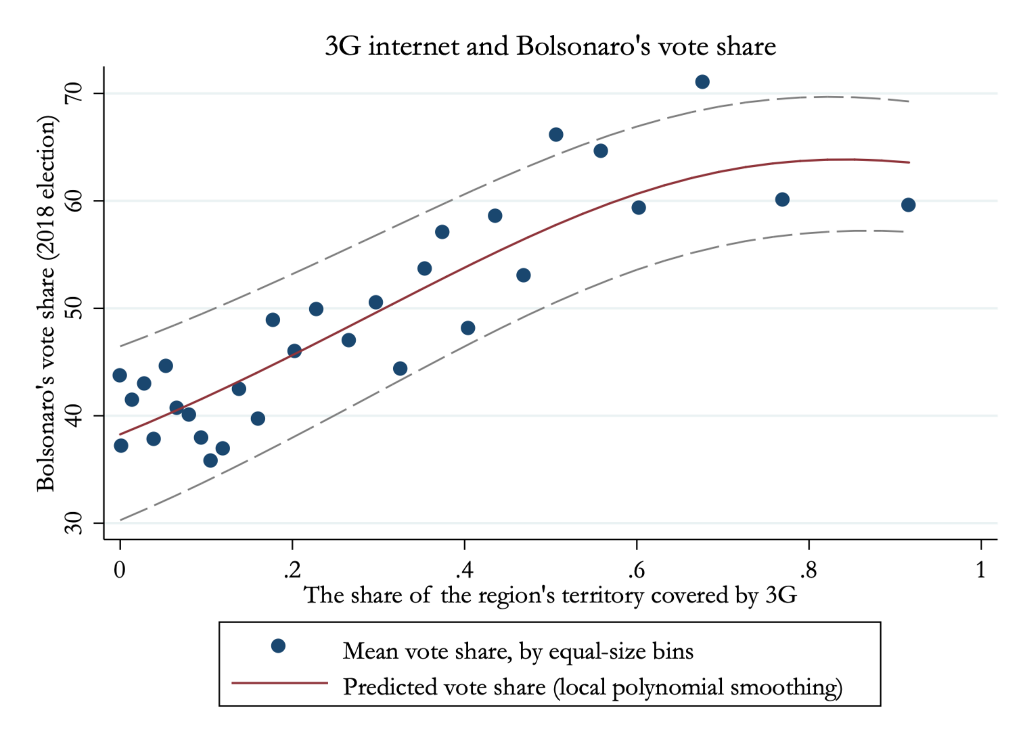


Figure A.24

3G coverage and Jair Bolsonaro's vote share in the second round of the 2018 presidential election

Note: The figure illustrates the nonparametric (local polynomial smoothing) relationship between microregion 3G coverage and Jair Bolsonaro's vote share in the second round of the 2018 presidential election. The data from 558 Brazilian microregions are aggregated into 30 equal-size bins. The solid line shows the predicted outcome (Gaussian kernel, local polynomial smoothing).

Table A.1
The summary statistics of the variables used in the analysis

	Mean	SD	Observations	Source of data
Panel A: GWP dataset				
Regional 3G coverage	0.395	0.401	840,537	Collins Bartholomew
Regional 2G coverage	0.781	0.310	840,537	Collins Bartholomew
Internet access at home	0.440	0.496	840,537	GWP
Confidence in national government	0.514	0.500	772,353	GWP
Confidence in judicial system	0.534	0.499	748,471	GWP
Honesty of elections	0.505	0.500	732,856	GWP
No corruption in government	0.226	0.418	722,768	GWP
Share of positive government approval responses	0.432	0.348	617,863	GWP
1st principal component of government approval responses	0.439	0.352	617,863	GWP
Internet censorship (Limits on Content score)	11.838	6.009	378,534	Freedom House
Dummy for low censorship	0.949	0.220	715,303	Freedom House and Polity IV
Freedom of the Press score	46.603	21.255	840,537	Freedom House
Polity2 score ≥ 8	0.541	0.498	840,537	Polity IV
Polity2 score ≥ 6	0.694	0.461	840,537	Polity IV
Index of actual corruption (GICI)	0.272	0.307	801,487	IMF
The Panama Papers' entities per 1,000 people	0.241	1.528	840,537	ICIJ
Log average regional income	8.309	1.220	840,537	GWP
Log nighttime light density (from DMSP-OLS)	1.484	2.050	430,017	DMSP-OLS (2008-2013)
Log nighttime light density (from VIIRS)	-0.788	2.632	191,648	VIIRS (2015-2016)
Unemployment rate	7.361	5.382	840,537	World Bank
Log GDP per capita	9.323	1.141	840,537	World Bank
Dummy for below-median GDP per capita	0.491	0.500	617,863	World Bank
Dummy for high frequency of lightning strikes per sq. km	0.596	0.491	617,863	WWLLN
Dummy for high frequency of lightning strikes per sq. km (sample of countries with below-median GDP per capita)	0.725	0.447	303,601	WWLLN
Unemployed	0.059	0.236	840,537	GWP
Employment status not known	0.426	0.494	840,537	GWP
Female	0.541	0.498	840,537	GWP
Age	41.901	17.776	840,537	GWP
Number of children	1.178	1.834	840,537	GWP
Married	0.573	0.495	840,537	GWP
Divorced	0.065	0.247	840,537	GWP
Widow[er]	0.079	0.269	840,537	GWP
Highest level of education = high school	0.531	0.499	840,537	GWP
Highest level of education = tertiary	0.161	0.368	840,537	GWP
Urban status = large city	0.307	0.461	840,537	GWP
Urban status = suburb of large city	0.096	0.295	840,537	GWP
Urban status = rural location	0.597	0.490	840,537	GWP
Panel B: European elections dataset				
District 3G coverage	0.647	0.346	1,250	Collins Bartholomew
Incumbents' vote share	0.304	0.127	1,536	National election statistics
Top 2 parties' from the 1st election vote share	0.561	0.181	1,242	National election statistics
Top 2 parties' from the 1st election vote share (sample of populist parties)	0.329	0.148	341	National election statistics
Right-wing populists' vote share	0.136	0.173	1,250	National election statistics
Left-wing populists' vote share	0.065	0.101	1,250	National election statistics
Other (unclassified) populists' vote share	0.060	0.125	1,250	National election statistics
All populists' vote share	0.260	0.203	1,250	National election statistics
Green parties' vote share	0.039	0.051	1,250	National election statistics
Nonpopulist opposition's vote share	0.431	0.193	1,566	National election statistics
Turnout	0.656	0.115	1,250	National election statistics
Log GDP per capita	10.427	0.364	1,250	World Bank
Unemployment rate	10.442	6.334	1,250	World Bank
Labor force participation	71.559	4.971	1,250	World Bank
Inflation rate	1.808	1.995	1,250	World Bank
Share of population over 65 years	17.369	2.691	1,250	World Bank
Log nighttime light density (DMSP-OLS)	2.405	0.785	801	DMSP-OLS (2007-2013)
Log nighttime light density (VIIRS)	0.302	1.191	391	VIIRS (2015-2016)

Table A.2
Regional 3G coverage, internet access at home, and government approval

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:	Internet access at home	1st principal component of government approval			
Sample:	All	All	All	Internet access at home: No	Yes
Panel A: Sample of all respondents					
Regional 3G coverage	0.080***	-0.056***	-0.073***	-0.071***	-0.035**
	(0.017)	(0.015)	(0.016)	(0.019)	(0.015)
Internet access at home		-0.010***	-0.023***		
		(0.002)	(0.004)		
Regional 3G coverage × × Internet access at home			0.033***		
			(0.008)		
Observations	840,537	617,863	617,863	347,809	269,981
R-squared	0.482	0.239	0.240	0.212	0.291
Panel B: Subsample of rural residents					
Regional 3G coverage	0.083***	-0.080***	-0.098***	-0.097***	-0.044***
	(0.017)	(0.018)	(0.019)	(0.022)	(0.016)
Internet access at home		-0.013***	-0.027***		
		(0.003)	(0.004)		
Regional 3G coverage × × Internet access at home			0.036***		
			(0.009)		
Observations	501,957	371,055	371,055	242,933	128,032
R-squared	0.502	0.223	0.223	0.213	0.266

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. 3G internet is associated with higher probability of having internet at home and it reduces government approval with or without access to the internet at home. The unit of observation is an individual. Panel A reports the results for the full sample and Panel B for the subsample of respondents from rural areas. Column 1 presents the results of the estimation of Specification (2), and Columns 2–5 present the results of the estimation of variants of Specification (1). The dependent variable in Column 1 is a dummy for having access to the internet at home. The dependent variable in Columns 2–5 is the aggregate measure of government approval. In Column 4, the sample is comprised of individuals without internet access at home and in Column 5—with internet access at home. Controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, and dummies for democracy status. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table A.3

The effect of 3G internet at t and $t+1$ on confidence in government at t, controlling for country×year fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Confidence in national government	Confidence in judicial system	Honesty of elections	No corruption in government	Share of questions with positive responses	1st principal component of responses
Panel A: Robustness to controlling for country×year FEs: The effect of 3G coverage in year t						
Regional 3G coverage at t	-0.016	-0.029*	-0.056***	-0.036***	-0.037***	-0.036***
	(0.017)	(0.017)	(0.016)	(0.013)	(0.013)	(0.013)
Mean dep. var.	0.439	0.534	0.505	0.226	0.432	0.439
Observations	772,353	748,471	732,856	722,768	617,863	617,863
Number of countries	111	116	112	112	110	110
Panel B: Test for a pre-trend: the effect of the lead of the 3G coverage						
Regional 3G coverage at $t+1$	0.015	-0.012	-0.021	-0.006	-0.006	-0.005
	(0.017)	(0.018)	(0.019)	(0.014)	(0.014)	(0.014)
Mean dep. var.	0.514	0.534	0.505	0.226	0.432	0.439
Observations	772,353	748,471	732,856	722,768	617,863	617,863
Number of countries	111	116	112	112	110	110
Panel C: Test for a pre-trend: p-value of the test for the equality of the effects of 3G coverage and its lead						
p-value	0.038	0.160	0.027	0.012	0.003	0.003
Subnational region & country×year FEs	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. 3G internet has a significant negative effect on government approval even after controlling for the country-by-year fixed effects. Next year's expansion of 3G networks is not correlated with the change in government approval today, suggesting that the parallel trends assumption holds. Panel C presents the results of the test of equality of the effects of 3G and its lead. The unit of observation is an individual. Controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, and the regions' average level of income. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table A.4
De Chaisemartin - D'Haultfœuille event-study results

	(1)	(2)
Dep. Var.:	1st principal component of the government approval responses	
Sample note 1:	Regions with a sharp increase in 3G coverage in one year in 2008-18	
Sample note 2:	All respondents	Rural respondents
Sharp increase in regional 3G coverage occurred in:		
Year $t+3$	-0.001	-0.015
	(0.029)	(0.033)
Year $t+2$	0.013	0.057
	(0.035)	(0.038)
Year $t+1$	0.022	0.031
	(0.025)	(0.030)
Year t	-0.027**	-0.033*
	(0.014)	(0.020)
Year $t-1$	-0.039*	-0.093***
	(0.021)	(0.025)
Year $t-2$	-0.040	-0.078***
	(0.027)	(0.028)
Year $t-3$	-0.082**	-0.081**
	(0.039)	(0.040)
Observations	130,406	66,078
Number of countries	65	62
Number of regions	452	444
Subnational region & year FEs	✓	✓
Baseline controls	✓	✓
Censorship of the traditional press control	✓	✓
P-value: $\gamma[Y_t] = \gamma[Y_{t-1}]$	0.087	0.085
P-value: $(\gamma[Y_t] + \gamma[Y_{t+1}])/2 = (\gamma[Y_{t-1}] + \gamma[Y_{t-2}])/2$	0.052	0.000

Note: *** p<0.01, ** p<0.05, * p<0.1. The table presents the estimates of the De Chaisemartin - D'haultfœuille event-study estimator. The unit of observation is an individual. The sample is comprised of individuals from regions that had a sharp increase of more than 50 percentage points in the share of subnational region's population covered by 3G in a single year, between 2008-2018. There are 452 regions from 65 countries like this. All regions in this sample have variation in the lags and leads of the year of the event. However, only 219 regions out of all regions with an event have variation in the post-event dummy within the sample due to missing region-years in the GWP data. Columns 1 reports the results for the full sample; Column 2—for the subsample of respondents from rural areas. The unreported controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, dummies for democracy status, and the censorship of the traditional press score. Standard errors in parentheses are corrected for clusters at the level of the subnational regions.

Table A.5

Altonji-Elder-Taber test and Oster test

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Confidence in national government	Confidence in judicial system	Honesty of elections	No corruption in government	Share of questions with positive responses	1st principal component of responses
Panel A: Altonji-Elder-Taber test						
Predicted from observables regional 3G coverage	0.119	-0.074	0.150	-0.039	0.030	0.031
	(0.322)	(0.200)	(0.321)	(0.202)	(0.238)	(0.241)
Panel B: Oster test						
Oster δ for $\gamma_1 = 0$	-4.22	5.83	-5.84	1.63	-1012.00	-733.97

Note: *** p<0.01, ** p<0.05, * p<0.1. Panel A presents the results of the ATE test, showing that the variation from the control variables does not explain the effect of regional 3G coverage on government approval. The estimation involves a two-stage procedure. First, regional 3G coverage is predicted using all the control variables as well as the subnational region and year fixed effects. Controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the region's average level of income, the log of the country's GDP per capita, the country's unemployment rate, and dummies for democracy status. The government approval variables are then regressed on the predicted level of regional 3G coverage, controlling for the subnational region and year fixed effects but not the additional controls. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation). Panel B presents the δs from the Oster test, showing that selection on unobservable variables needs to be very high to reduce the effect of regional 3G coverage to zero. Following Oster (2017), we set the value of $R^2_{\max}$—the R-squared from a hypothetical regression of the outcome on treatment and both observed and unobserved controls—to be equal to $1.3\tilde{R}^2$, where $\tilde{R}^2$ is the R-squared from Table I.

Table A.6

Lightning strikes, 3G coverage, and government approval (individual level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	Regional 3G coverage	1st principal component of government approval	Regional 3G coverage	1st principal component of government approval	Regional 3G coverage	1st principal component of government approval	Regional 3G coverage	1st principal component of government approval
Stage, 2SLS:	1	2	1	2	1	2	1	2
Countries in the sample:	All countries				Countries with below-median GDP per capita			
Respondents in the sample:	All	All	Rural	Rural	All	All	Rural	Rural
Regional 3G coverage		-0.319***		-0.320***		-0.374**		-0.398**
		(0.105)		(0.101)		(0.171)		(0.165)
Anderson-Rubin 90% confidence interval						*[-0.877,-0.113]*		*[-0.765,-0.124]*
𝟙[High frequency of lightning strikes per sq. km] × × Year × 𝟙[GDP per capita below median]	-0.025***		-0.027***		-0.019**		-0.022***	
	(0.005)		(0.005)		(0.008)		(0.007)	
𝟙[High frequency of lightning strikes per sq. km] × × Year × 𝟙[GDP per capita above median]	-0.008		-0.008					
	(0.005)		(0.005)					
Observations	617,863	617,863	371,055	371,055	303,601	303,601	213,460	213,460
F-stat, excluded instrument		11.11		13.05		6.65		9.71
Corresponding OLS coefficient on regional 3G coverage						-0.107***		-0.153***
						(0.026)		(0.027)
Subnational region & year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Extended set of controls	✓	✓	✓	✓	✓	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. The table presents the results of an IV analysis, where the frequency of lightning strikes per sq. km. in a subnational region is used as an IV for the expansion of regional 3G coverage. The methodology follows Manacorda and Tesei (2020). High frequency of lightning strikes per sq. km is defined by the subnational region being in the top half of the distribution of lightning strikes per sq. km. Odd columns present the first stage. Even columns—the results of the second stage. Columns 1-4 present the results for all the countries in the sample; Columns 5-8—for the subsample of countries with below-median GDP per capita. The unit of observation is an individual. Controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the region's average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, dummies for democracy status, and linear time trends interacted with the subnational regions' share of territory covered by deserts, share of territory covered by mountains, maximum elevation, dummies for each quintile of population density, 3G coverage in 2008, a dummy for whether the region had any 3G coverage in 2008, and a dummy for whether the country had any 3G coverage in 2008. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table A.7

Robustness to alternative assumptions about variance-covariance matrix

Dependent variable: 1st principal component of the measures of government approval		
	Assumptions about variance-covariance matrix:	Regional 3G coverage
Coefficient		-0.057
(1)	Baseline: 2-way clusters by region and country-year	(0.015)***
(2)	Clusters by country	(0.019)***
	Conley correction for spatial correlation within:	
(3)	- 500km and 1 temporal lag	(0.013)***
(4)	- 500km and 5 temporal lags	(0.014)***
(5)	- 500km and 10 temporal lags	(0.014)***
(6)	- 1,000km and 1 temporal lag	(0.014)***
(7)	- 1,000km and 5 temporal lags	(0.014)***
(8)	- 1,000km and 10 temporal lags	(0.015)***
Observations		617,863

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The table shows that the results are robust to clustering by country and adjusting the standard errors to spatial correlation at 500 and 1,000 km radii with 1, 5, and 10-year temporal lags.

Table A.8

Robustness to using region-year averages as the unit of analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Region-year mean of the following variable:					
	Confidence in national government	Confidence in judicial system	Honesty of elections	No corruption in government	Share of questions with positive responses	1st principal component of responses
Panel A: Means taken across all respondents in each region-year						
Regional 3G coverage	-0.064***	-0.041**	-0.090***	-0.029**	-0.057***	-0.058***
	(0.022)	(0.016)	(0.024)	(0.014)	(0.016)	(0.017)
R-squared	0.611	0.655	0.617	0.756	0.686	0.682
Observations	13,055	13,192	12,913	13,179	12,860	12,860
Panel B: Means taken across rural residents only						
Regional 3G coverage	-0.073***	-0.063***	-0.106***	-0.034**	-0.073***	-0.074***
	(0.016)	(0.018)	(0.028)	(0.017)	(0.019)	(0.019)
R-squared	0.574	0.593	0.563	0.706	0.632	0.628
Observations	11,991	12,079	11,823	12,075	11,743	11,743
Subnational region & year FEs	✓	✓	✓	✓	✓	✓
Region- and country-level controls	✓	✓	✓	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is a subnational region in a year. Panel A reports the results for the region-year averages for the full sample, Panel B—for the subsample of respondents from rural areas. The outcome variables are the regional-level perceptions of government and the country's institutions. Controls include the region's average level of income, the log of the country's GDP per capita, the country's unemployment rate, and two dummies for the country's democracy status. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation). Several region×year observations in this sample are not part of our baseline sample, which consists of 13,004 region×year observations, because of the absence of the individual-level controls, not included in this estimation.

Table A.9

Robustness to using regional 3G coverage without population weights and to controlling for population-density-specific time effects

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Confidence in national government	Confidence in judicial system	Honesty of elections	No corruption in government	Share of questions with positive responses	1st principal component of responses
Panel A: Robustness to using regional 3G coverage without population weights: Sample of all respondents						
Regional 3G coverage, no population-density weights	-0.060***	-0.039**	-0.078***	-0.034**	-0.054***	-0.054***
	(0.021)	(0.015)	(0.021)	(0.014)	(0.016)	(0.016)
R-squared	0.164	0.163	0.168	0.225	0.242	0.239
Observations	772,353	748,471	732,856	722,768	617,863	617,863
Mean dep. var.	0.514	0.534	0.505	0.226	0.432	0.439
Number of countries	111	116	112	112	110	110
Panel B: Robustness to using regional 3G coverage without population weights: Subsample of rural residents						
Regional 3G coverage, no population-density weights	-0.089***	-0.057***	-0.117***	-0.053***	-0.079***	-0.080***
	(0.024)	(0.017)	(0.026)	(0.016)	(0.018)	(0.018)
R-squared	0.171	0.157	0.161	0.194	0.224	0.222
Observations	464,831	448,449	440,786	432,460	371,055	371,055
Mean dep. var.	0.539	0.556	0.516	0.215	0.445	0.452
Number of countries	110	115	111	111	109	109
Panel C: Robustness to controlling for population-density-specific time effects: Sample of all respondents						
Regional 3G coverage	-0.067***	-0.038**	-0.080***	-0.039***	-0.057***	-0.058***
	(0.021)	(0.015)	(0.021)	(0.014)	(0.016)	(0.016)
R-squared	0.164	0.164	0.168	0.226	0.243	0.240
Observations	772,353	748,471	732,856	722,768	617,863	617,863
Mean dep. var.	0.514	0.534	0.505	0.226	0.432	0.439
Number of countries	111	116	112	112	110	110
Year FEs interacted with quintiles of population density	✓	✓	✓	✓	✓	✓
Panel D: Robustness to controlling for population-density-specific time effects: Subsample of rural residents						
Regional 3G coverage	-0.091***	-0.053***	-0.110***	-0.057***	-0.079***	-0.079***
	(0.024)	(0.017)	(0.025)	(0.015)	(0.018)	(0.018)
R-squared	0.171	0.157	0.161	0.195	0.225	0.223
Observations	464,831	448,449	440,786	432,460	371,055	371,055
Mean dep. var.	0.539	0.556	0.516	0.215	0.445	0.452
Number of countries	110	115	111	111	109	109
Year FEs interacted with quintiles of population density	✓	✓	✓	✓	✓	✓
Subnational region & year FEs	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. Panels A and B of the table replicate the results from Table I, replacing the baseline measure of regional 3G coverage with one that does not use population density weights. Panels C and D of the table replicate the results from Table I, adding year dummies interacted with quintiles of population density to the list of covariates. The unit of observation is an individual. Panels A and C report the results for the full sample and Panels B and D for the subsample of respondents from rural areas. The dependent variables are perceptions of government and the country's institutions. Baseline controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, and dummies for democracy status. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table A.10
The effect of 3G coverage on government approval over time

	(1)	(2)
Dep. Var.:	1st principal component of the measures of government approval	
Sample:	All	Rural
Regional 3G coverage in 2008-2009	-0.041	-0.059**
	(0.026)	(0.029)
Regional 3G coverage in 2010-2011	-0.078***	-0.086***
	(0.018)	(0.023)
Regional 3G coverage in 2012-2013	-0.030*	-0.033*
	(0.018)	(0.020)
Regional 3G coverage in 2014-2015	-0.043**	-0.067***
	(0.018)	(0.019)
Regional 3G coverage in 2016-2017	-0.086***	-0.122***
	(0.020)	(0.022)
Observations	617,863	371,055
R-squared	0.240	0.223
Subnational region & year FEs	✓	✓
Baseline controls	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is an individual. Column 1 reports results for the full sample; Column 2—for the subsample of respondents from rural areas. Controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, and dummies for democracy status. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table A.11
The effect of 3G coverage on government approval,
subsample of observations from face-to-face interviews

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Confidence in national government	Confidence in judicial system	Honesty of elections	No corruption in government	Share of questions with positive responses	1st principal component of responses
Panel A: Sample of all respondents						
Regional 3G coverage	-0.071***	-0.045***	-0.096***	-0.039**	-0.064***	-0.065***
	(0.022)	(0.016)	(0.023)	(0.015)	(0.017)	(0.017)
R-squared	0.178	0.170	0.162	0.164	0.229	0.229
Observations	602,934	601,597	586,328	577,484	491,068	491,068
Mean dep. var.	0.530	0.523	0.468	0.182	0.410	0.418
Number of countries	89	94	90	90	88	88
Panel B: Subsample of rural residents						
Regional 3G coverage	-0.104***	-0.068***	-0.135***	-0.060***	-0.094***	-0.095***
	(0.026)	(0.019)	(0.028)	(0.017)	(0.019)	(0.020)
R-squared	0.180	0.163	0.157	0.122	0.211	0.212
Observations	373,069	369,126	361,598	354,219	302,873	302,873
Mean dep. var.	0.558	0.551	0.485	0.173	0.427	0.436
Number of countries	88	93	89	89	87	87
Subnational region & year FEs	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. Panels A and B of the table replicate the results from Table I for the subsample of country-years in the GWP, for which the data was collected via face-to-face interviews. The unit of observation is an individual. Panel A reports the results for the full sample and Panel B for the subsample of respondents from rural areas. The dependent variables are individuals' perceptions of government and the country's institutions. Controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, and dummies for democracy status. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table A.12

Robustness of the heterogeneity w.r.t. internet censorship
to alternative definitions of internet censorship

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Confidence in national government	Confidence in judicial system	Honesty of elections	No corruption in government	Share of questions with positive responses	1st principal component of responses
Panel A: Time-variant dummy for internet censorship in sub-sample of countries with nonmissing content limits data						
Regional 3G coverage	-0.152***	-0.086***	-0.122***	-0.081***	-0.105***	-0.107***
	(0.034)	(0.023)	(0.032)	(0.025)	(0.024)	(0.025)
Regional 3G coverage × ×Internet censorship dummy	0.175***	0.083***	0.189***	0.089***	0.133***	0.135***
	(0.043)	(0.029)	(0.045)	(0.030)	(0.033)	(0.034)
Internet censorship dummy	0.054*	0.028	0.049	0.005	0.037	0.038
	(0.032)	(0.023)	(0.033)	(0.022)	(0.026)	(0.027)
Observations	338,027	331,304	320,685	322,892	267,141	267,141
R-squared	0.176	0.174	0.160	0.193	0.235	0.234
Panel B: Time-invariant dummy for internet censorship in sub-sample of countries with nonmissing content limits data						
Regional 3G coverage	-0.162***	-0.087***	-0.141***	-0.088***	-0.110***	-0.112***
	(0.040)	(0.027)	(0.037)	(0.027)	(0.029)	(0.029)
Regional 3G coverage × ×Dummy for countries with internet censorship	0.177***	0.069**	0.220***	0.092***	0.125***	0.127***
	(0.052)	(0.035)	(0.052)	(0.027)	(0.039)	(0.040)
Observations	338,027	331,304	320,685	322,892	267,141	267,141
R-squared	0.175	0.174	0.159	0.193	0.234	0.233
Panel C: Time-variant continuous measure of internet censorship						
Regional 3G coverage	-0.190***	-0.108***	-0.215***	-0.083**	-0.129***	-0.131***
	(0.059)	(0.035)	(0.055)	(0.037)	(0.042)	(0.043)
Regional 3G coverage × ×Internet censorship score	0.072**	0.039**	0.106***	0.025	0.047*	0.048*
	(0.033)	(0.019)	(0.034)	(0.023)	(0.028)	(0.028)
Internet censorship score	0.063	0.034	0.006	0.031	0.027	0.028
	(0.039)	(0.025)	(0.044)	(0.028)	(0.034)	(0.034)
Observations	338,027	331,304	320,685	322,892	267,141	267,141
R-squared	0.176	0.174	0.159	0.193	0.234	0.233
Panel D: Time-invariant continuous measure of internet censorship						
Regional 3G coverage	-0.231***	-0.134***	-0.262***	-0.112***	-0.160***	-0.163***
	(0.067)	(0.040)	(0.063)	(0.041)	(0.050)	(0.051)
Regional 3G coverage × ×Mean internet censorship score	0.089**	0.048**	0.137***	0.037*	0.063**	0.065**
	(0.035)	(0.021)	(0.036)	(0.019)	(0.029)	(0.030)
Observations	338,027	331,304	320,685	322,892	267,141	267,141
R-squared	0.175	0.174	0.159	0.193	0.234	0.233
Panel E: Time-variant continuous measures of censorship online and offline						
Regional 3G coverage	0.070	-0.008	-0.093	-0.038	0.021	0.023
	(0.091)	(0.050)	(0.081)	(0.048)	(0.058)	(0.059)
Regional 3G coverage × × Internet censorship score	0.199***	0.075**	0.223***	0.089***	0.127***	0.129***
	(0.047)	(0.035)	(0.055)	(0.031)	(0.038)	(0.038)
Regional 3G coverage × × Censorship of the press score	-0.064***	-0.020	-0.043**	-0.022*	-0.039***	-0.039***
	(0.020)	(0.013)	(0.018)	(0.012)	(0.013)	(0.013)
Controls for direct effects of censorship	✓	✓	✓	✓	✓	✓
Observations	338,027	331,304	320,685	322,892	267,141	267,141
R-squared	0.190	0.181	0.171	0.202	0.248	0.247
Panel F: Time-invariant continuous measures of censorship online and offline						
Regional 3G coverage	0.020	-0.097	-0.120	0.029	-0.036	-0.038
	(0.098)	(0.063)	(0.090)	(0.058)	(0.072)	(0.073)
Regional 3G coverage × × Mean internet censorship score	0.226***	0.068*	0.220***	0.113***	0.140***	0.143***
	(0.056)	(0.038)	(0.058)	(0.038)	(0.048)	(0.048)
Regional 3G coverage × × Mean press censorship score	-0.071***	-0.010	-0.041*	-0.039**	-0.037**	-0.038**
	(0.023)	(0.016)	(0.022)	(0.015)	(0.018)	(0.018)
Observations	338,027	331,304	320,685	322,892	267,141	267,141
R-squared	0.176	0.174	0.159	0.193	0.234	0.233
Subnational region & year FEs	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The unit of observation is an individual. Panels A, C, and E use time-variant measures of censorship, whereas Panels B, D, and F use time-invariant measures. The results presented in Panels E and F are robust to including a triple interaction term between 3G coverage and both censorship measures. The coefficients on this triple interaction term are small and statistically insignificant. Unreported controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, and dummies for democracy status. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation). Internet censorship score is the Limits on Content score divided by 10. Press censorship score is the Freedom of the Press score divided by 10.

Table A.13

The effect of 3G coverage on government approval, depending on the level of censorship of the internet and on the level of censorship of the traditional media in the subsample of rural residents

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Confidence in national government	Confidence in judicial system	Honesty of elections	No corruption in government	Share of questions with positive responses	1st principal component of responses
Panel A: Time-variant dummy for internet censorship						
Regional 3G coverage	-0.134***	-0.083***	-0.163***	-0.079***	-0.112***	-0.114***
	(0.029)	(0.020)	(0.027)	(0.019)	(0.020)	(0.021)
Regional 3G coverage × × Internet censorship dummy	0.154***	0.080**	0.241***	0.065**	0.137***	0.139***
	(0.044)	(0.039)	(0.032)	(0.030)	(0.034)	(0.035)
Internet censorship dummy	0.037	0.021	0.041	0.003	0.027	0.028
	(0.033)	(0.023)	(0.026)	(0.023)	(0.024)	(0.024)
Observations	387,537	372,315	365,515	361,210	307,391	307,391
R-squared	0.166	0.161	0.151	0.210	0.224	0.222
Panel B: Time-invariant dummy for internet censorship						
Regional 3G coverage	-0.127***	-0.078***	-0.163***	-0.079***	-0.110***	-0.111***
	(0.029)	(0.020)	(0.028)	(0.019)	(0.021)	(0.021)
Regional 3G coverage × × Dummy: countries with internet censorship	0.119***	0.048	0.237***	0.069***	0.117***	0.118***
	(0.043)	(0.034)	(0.040)	(0.023)	(0.030)	(0.031)
Observations	381,397	366,178	359,444	355,545	302,162	302,162
R-squared	0.166	0.161	0.151	0.212	0.225	0.223
Panel C: Time-variant dummies for internet censorship and above-median press censorship						
Regional 3G coverage	-0.044	-0.051**	-0.122***	-0.037*	-0.066***	-0.067***
	(0.032)	(0.023)	(0.030)	(0.021)	(0.023)	(0.024)
Regional 3G coverage × × Internet censorship dummy	0.230***	0.108***	0.277***	0.101***	0.178***	0.181***
	(0.047)	(0.040)	(0.039)	(0.032)	(0.035)	(0.036)
Regional 3G coverage × × Above-median press censorship dummy	-0.149***	-0.056**	-0.068**	-0.069**	-0.078***	-0.079***
	(0.037)	(0.024)	(0.034)	(0.028)	(0.026)	(0.027)
Internet censorship dummy	0.027	0.017	0.037	-0.001	0.022	0.023
	(0.032)	(0.023)	(0.026)	(0.023)	(0.023)	(0.024)
Above-median press censorship dummy	0.127***	0.012	0.067*	0.065**	0.066**	0.066**
	(0.036)	(0.022)	(0.035)	(0.029)	(0.025)	(0.026)
Observations	387,537	372,315	365,515	361,210	307,391	307,391
R-squared	0.167	0.161	0.151	0.211	0.224	0.223
Panel D: Time-invariant dummies for internet censorship and above-median press censorship						
Regional 3G coverage	-0.056	-0.045*	-0.145***	-0.044**	-0.075***	-0.076***
	(0.034)	(0.026)	(0.031)	(0.022)	(0.025)	(0.025)
Regional 3G coverage × × Dummy: countries with internet censorship	0.196***	0.083**	0.256***	0.107***	0.154***	0.156***
	(0.051)	(0.038)	(0.049)	(0.029)	(0.036)	(0.037)
Regional 3G coverage × × Dummy: countries with above-median press censorship	-0.144***	-0.065*	-0.035	-0.071**	-0.069**	-0.070**
	(0.046)	(0.033)	(0.043)	(0.031)	(0.033)	(0.033)
Observations	381,397	366,178	359,444	355,545	302,162	302,162
R-squared	0.167	0.161	0.151	0.212	0.225	0.223
Subnational region & year FEs	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is an individual. Panels A and C use time-variant measures of censorship, whereas Panels B and D use time-invariant measures. Unreported controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, and dummies for democracy status. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table A.14
Checking for pre-trends in corruption incidents

	(1)	(2)	(3)
Dep. Var.:	Regional 3G coverage		Actual corruption incidents
Actual corruption incidents	-0.001		
	(0.024)		
Actual corruption incidents, lag		-0.015	
		(0.024)	
Regional 3G coverage, lag			0.055
			(0.045)
Observations	727,935	727,935	727,935
R-squared	0.844	0.844	0.520
Subnational region & year FEs	✓	✓	✓
Baseline controls	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. The index of actual corruption incidents is based on the IMF's Global Incidents of Corruption Index (GICI). The unit of observation is an individual. Unreported controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, and dummies for democracy status. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table A.15

The relationship between actual corruption incidents (GICI) and perceived corruption in Europe

	(1)	(2)	(3)
Dep. Var.:	Perception of no corruption in government		Internet access at home
Sample:	Respondents in European countries		
Regional 3G coverage	0.011	0.022	0.048**
	(0.024)	(0.024)	(0.021)
Regional 3G coverage × Actual corruption incidents	-0.075**	-0.068*	
	(0.038)	(0.037)	
Actual corruption incidents	-0.038*	-0.030	
	(0.022)	(0.021)	
Observations	197,500	127,667	277,764
R-squared	0.329	0.157	0.370
Subnational region & year FEs	✓	✓	✓
Baseline controls	✓	✓	✓
Sample excludes observations with zero corruption incidents		✓	

Note: *** p<0.01, ** p<0.05, * p<0.1. In Columns 1 and 2, the outcome variable is a dummy for the perception that there is no corruption in government. In Columns 1 and 2, we replicate the results presented in Columns 1 and 3 of Table VI, showing that 3G internet helps expose corruption in the subsample of European countries. In Column 3, the outcome variable is a dummy for internet access at home. In this column, we estimate Specification (2) for the subsample of European countries. Actual corruption incidents stands for the IMF's Global Incidents of Corruption Index (GICI). The unit of observation is an individual. All columns use the sample of all respondents. Controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, and dummies for democracy status. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table A.16

Heterogeneity with respect to the country's geography, income, and democracy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. Var.:	The 1st principal component of the measures of government approval									
Sample:	All	Rural	All	Rural	All	Rural	All	Rural	All	Rural
Regional 3G coverage × Africa	-0.067**	-0.086**							0.157	0.243
	(0.026)	(0.039)							(0.119)	(0.172)
Regional 3G coverage × Asia & Oceania	-0.030	-0.050*							0.056	0.044
	(0.026)	(0.029)							(0.115)	(0.181)
Regional 3G coverage × Europe	-0.011	-0.042*							0.299*	0.379
	(0.021)	(0.022)							(0.169)	(0.262)
Regional 3G coverage × North and Central America	-0.167***	-0.199***							0.151	0.221
	(0.039)	(0.046)							(0.181)	(0.280)
Regional 3G coverage × South America	-0.173***	-0.208***							0.109	-0.015
	(0.045)	(0.063)							(0.163)	(0.272)
Regional 3G coverage × OECD			-0.023	-0.043*					-0.103	-0.059
			(0.025)	(0.025)					(0.063)	(0.116)
Regional 3G coverage × non-OECD			-0.068***	-0.085***					0.000	0.000
			(0.015)	(0.020)					(0.000)	(0.000)
Regional 3G coverage × High income country					-0.033	-0.046**			-0.151	-0.200*
					(0.025)	(0.025)			(0.063)	(0.116)
Regional 3G coverage × Upper-middle income country					-0.105***	-0.124***			-0.035	-0.062
					(0.027)	(0.029)			(0.049)	(0.076)
Regional 3G coverage × Lower-middle or low income country					-0.043**	-0.059**			0.000	0.000
					(0.021)	(0.029)			(0.000)	(0.000)
Regional 3G coverage × Perfect democracy							-0.042*	-0.060**	0.191	0.077
							(0.022)	(0.024)	(0.167)	(0.171)
Regional 3G coverage × Democracy (excluding perfect democracies)							-0.058***	-0.085***	-0.040	-0.095
							(0.022)	(0.024)	(0.065)	(0.082)
Regional 3G coverage × Nondemocracy							-0.064***	-0.068**	0.000	0.000
							(0.023)	(0.031)	(0.000)	(0.000)
Regional 3G coverage × Internet censorship score									0.182***	0.279***
									(0.049)	(0.067)
Regional 3G coverage × Censorship of the press score									-0.063***	-0.089***
									(0.022)	(0.031)
Observations	617,863	371,055	617,863	371,055	617,863	371,055	617,863	371,055	267,141	158,813
R-squared	0.242	0.226	0.242	0.225	0.242	0.225	0.242	0.225	0.242	0.220
Subnational region & year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls for the direct effect of censorship of the press	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Control for the direct effect of internet censorship									✓	✓

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The unit of observation is an individual. Unreported controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, dummies for democracy status. "Perfect democracy" is a dummy for 2008-2017 mean Polity2 score equal to 10; "Nondemocracy" is a dummy for this mean below 6. In addition to these baseline controls, we control flexibly for the censorship of the traditional press (by adding 20 dummies, corresponding to every 5 points in Freedom of the Press score), an important determinant of government approval as demonstrated in Table V. We, however, omit the control for internet censorship in all but the last two columns because it exists only for a subset of countries. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation). Internet censorship score is the Limits on Content score divided by 10. Press censorship score is the Freedom of the Press score divided by 10.

Table A.17

Heterogeneity with respect to the respondent's education, employment status, income, and age

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	The 1st principal component of the measures of government approval							
Sample:	All	Rural	All	Rural	All	Rural	All	Rural
Regional 3G coverage	-0.048***	-0.065***	-0.081***	-0.096***	-0.070***	-0.084***	-0.058***	-0.075***
	(0.015)	(0.018)	(0.016)	(0.019)	(0.015)	(0.017)	(0.015)	(0.018)
Regional 3G coverage × Unemployed	-0.023***	-0.027***						
	(0.007)	(0.008)						
Regional 3G coverage × Employment status missing	-0.015***	-0.015***						
	(0.005)	(0.006)						
Regional 3G coverage × Tertiary education			0.082***	0.103***				
			(0.013)	(0.015)				
Regional 3G coverage × Secondary education			0.020**	0.019**				
			(0.008)	(0.009)				
Regional 3G coverage × Income above country median					0.038***	0.043***		
					(0.003)	(0.004)		
Regional 3G coverage × Income missing					-0.018	-0.019		
					(0.031)	(0.038)		
Regional 3G coverage × Age below 25							0.013***	0.019***
							(0.004)	(0.006)
Regional 3G coverage × Age above 60							-0.006	-0.003
							(0.006)	(0.006)
Observations	617,863	371,055	617,863	371,055	617,863	371,055	617,863	371,055
R-squared	0.242	0.225	0.242	0.226	0.242	0.226	0.242	0.225
Subnational region & year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓
Controls for the effect of censorship of the press	✓	✓	✓	✓	✓	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is an individual. Odd columns report results for the full sample and even columns for the subsample of respondents from rural areas. Unreported controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, dummies for democracy status. Controls for the effect of censorship of the press stand for 20 dummies corresponding to every 5 points in the Freedom of the Press score. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table A.18

The effect of 3G coverage on life satisfaction and on confidence in the local police (placebo outcomes)

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:	Current level of life satifaction Range: 0-10	Expected level of life satisfaction in 5 year Range: 0-10	Satisfied with standard of living Range: 0-1	Standard of living getting better Range: 1-3	Confidence in local police Range: 0-1
Panel A: Sample of all respondents					
Regional 3G coverage	0.079	0.016	0.009	-0.024	0.009
	(0.063)	(0.074)	(0.012)	(0.028)	(0.014)
Observations	922,399	858,368	865,001	861,972	755,852
Mean dep. var.	5.560	6.794	0.621	2.157	0.664
Panel B: Subsample of rural residents					
Regional 3G coverage	0.039	-0.015	0.000	0.010	-0.020
	(0.082)	(0.103)	(0.015)	(0.031)	(0.015)
Observations	528,126	490,372	499,787	505,678	456,173
Mean dep. var.	5.278	6.581	0.592	2.138	2.137
Subnational region & year FEs	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. The table shows that 3G internet did not affect individuals' attitudes toward their life or toward the *local* police, suggesting that access to the internet did not make individuals more negative about the things with which they were already familiar. The unit of observation is an individual. Controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, and dummies for democracy status. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table A.19
The effect of 3G coverage on the incumbent's vote as a share of registered voters in Europe

	(1)	(2)	(3)	(4)
Dep. Var.:	Vote share (as a share of registered voters) of:			
	Top 2 parties from the 1st election	Ruling party (the party of the Prime Minister)		Populist parties if they are among top 2 parties from the 1st election
Unit of observation:	District-year	District-year-incumbent		District-year
District 3G coverage	-0.068**	-0.066***		-0.082***
	(0.030)	(0.020)		(0.028)
District 3G coverage × Populist party			-0.104***	
			(0.033)	
District 3G coverage × Nonpopulist party			-0.059***	
			(0.020)	
Observations	1,234	1,536	1,536	341
R-squared	0.903	0.925	0.926	0.970
Mean dep. var.	0.370	0.201	0.201	0.203
District & year FEs	✓			✓
Incumbent-by-district & year FEs		✓	✓	
Baseline controls	✓	✓	✓	✓
Excl. countries without populists among top 2 parties in the 1st election				✓

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The expansion of 3G networks led to a decrease in the vote share of incumbent parties. This is true for both nonpopulist and populist incumbent parties. The table replicates the results of Table VIII but uses the share of votes relative to the number of registered voters (instead of actual voters). In Columns 1, 4, and 5, the unit of observation is a subnational district in an election. In Columns 2-3, the unit of observation is an incumbent party in a subnational district in an election. In Columns 1, 2, and 3, the sample does not include Romania because, in Romania, after the first election, the top 2 parties merged with other large parties. In Columns 2 and 3, the sample does not include Switzerland because, in Switzerland, the position of the president rotates among the parties in the ruling coalition. In Column 4, the sample is restricted to countries that had populist parties among the top 2 parties in the first election. Controls include the country's unemployment rate, labor force participation rate, inflation rate, log of GDP per capita, the share of population over 65 years old, and the subnational district's average level of nighttime light density. As the nighttime light density data for 2007-2013, 2014, and 2015-2018 come from different sources (DMSP-OLS, a combination of DMSP-OLS and VIIRS, and VIIRS, respectively), we interact the measure of nighttime light density with a dummy for each of those time periods. Standard errors presented in parentheses are corrected for two-way clusters at the level of the subnational districts (to account for over time correlation) and at the level of the countries in each year (to account for within-country-year correlation).

Table A.20
The effect of 3G coverage on the opposition's vote as a share of registered voters in Europe

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.:	Vote share (as a share of registered voters) of:						
	Right-wing populists	Left-wing populists	Other populists	All populists	All populists	Green parties	Nonpopulist opposition
Unit of observation:	District-year	District-year	District-year	District-year	District-year	District-year	District-year-ruling coalition
District 3G coverage	0.043***	0.032***	-0.028*	0.047*	0.060**	-0.008	-0.038
	(0.016)	(0.012)	(0.014)	(0.025)	(0.025)	(0.007)	(0.031)
Observations	1,250	1,250	1,250	1,250	1,002	1,141	1,566
R-squared	0.954	0.877	0.946	0.923	0.808	0.879	0.920
Mean dep. var	0.087	0.040	0.039	0.166	0.122	0.026	0.285
District & year FEs	✓	✓	✓	✓	✓	✓	✓
Ruling coalition-by-district&year FEs							✓
Baseline controls	✓	✓	✓	✓	✓	✓	✓
Excl. countries with populists in power					✓		

Note: *** p<0.01, ** p<0.05, * p<0.1. The expansion of 3G networks led to an increase in both right-wing and left-wing populists' vote share, but not in the vote share of green parties or the nonpopulist opposition in general. The table replicates the results of Table IX but uses the share of votes relative to the number of registered voters (instead of actual voters). In Columns 1-6, the unit of observation is a subnational district in an election. In Column 7, the unit of observation is a ruling coalition in a subnational district in an election. The data in Columns 1-5 cover 102 parliamentary elections in 33 European countries (the full panel). In Column 6, there are fewer observations than in Columns 1-5 because in five elections (Spain in 2015-2016, Croatia in 2015-2016, and Greece in 2015) Green parties formed join lists with large non-Green parties, making it impossible to determine what share of votes went to the Green parties and what to their partners. Column 5 excludes all countries, in which populists were a ruling party at some point during the sample period: Bulgaria, Hungary, Italy, Montenegro, North Macedonia, Poland, Slovakia, and Slovenia. In Column 7, the election results for Switzerland and Romania are excluded because, in Switzerland, all the major parties are a part of the ruling coalition, and in Romania, after the first election, the parties in the ruling coalition merged with parties outside of the ruling coalition. Controls include the country's unemployment rate, labor force participation rate, inflation rate, log of GDP per capita, the share of population over 65 years old, and the regions' average level of nighttime light density. As the nighttime light density data for 2007-2013, 2014, and 2015-2018 come from different sources (DMSP-OLS, a combination of DMSP-OLS and VIIRS, and VIIRS, respectively), we also interact the measure of nighttime light density with a dummy for each of those time periods. Standard errors presented in parentheses are corrected for two-way clusters at the level of the subnational districts (to account for over time correlation) and at the level of the countries in each year (to account for within-country-year correlation).

Table A.21

The effect of 3G on confidence in government, controlling for log nighttime light density instead of log average regional income

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Confidence in national government	Confidence in judicial system	Honesty of elections	No corruption in government	Share of questions with positive responses	1st principal component of responses
Panel A: All respondents						
Regional 3G coverage	-0.058***	-0.033**	-0.062***	-0.039***	-0.049***	-0.050***
	(0.021)	(0.014)	(0.020)	(0.015)	(0.015)	(0.015)
Observations	771,483	747,624	731,993	721,945	617,104	617,104
Mean dep. var.	0.514	0.533	0.505	0.226	0.432	0.439
Number of countries	111	116	112	112	110	110
Panel B: Respondents from rural areas						
Regional 3G coverage	-0.076***	-0.045***	-0.087***	-0.056***	-0.066***	-0.067***
	(0.024)	(0.017)	(0.025)	(0.016)	(0.018)	(0.018)
Observations	463,990	447,631	439,952	431,665	370,324	370,324
Mean dep. var.	0.538	0.556	0.516	0.215	0.444	0.452
Number of countries	110	115	111	111	109	109
Subnational region & year FEs	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓
Nighttime light density instead of income	✓	✓	✓	✓	✓	✓

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The unit of observation is an individual. Panel A reports results for the full sample and Panel B for the subsample of respondents from rural areas. The dependent variables are individuals' perceptions of government and the country's institutions. Controls include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of nighttime light density, the log of the countries' GDP per capita, the countries' unemployment rate, and dummies for democracy status. As the nighttime light density data for 2008-2013, 2014, and 2015-2017 come from different sources (DMSP-OLS, a combination of DMSP-OLS and VIIRS, and VIIRS, respectively), we also interact the measure of nighttime light density with a dummy for each of those time periods. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table A.22
Within-country correlation between 3G coverage, smartphone penetration, and active mobile broadband subscriptions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	Smartphone penetration				Active mobile broadband subscriptions per capita			
Countries in the sample:	All countries		Below-median income		All countries		Below-median income	
GWP countries only:		✓		✓		✓		✓
3G coverage	0.702***	0.674***	0.599***	0.561***	0.796***	0.788***	0.618***	0.623***
	(0.091)	(0.087)	(0.128)	(0.101)	(0.052)	(0.054)	(0.083)	(0.092)
Observations	318	295	70	67	1,113	954	472	419
R-squared	0.756	0.754	0.525	0.524	0.757	0.772	0.545	0.575
Mean dep. var	0.391	0.378	0.144	0.136	0.404	0.388	0.183	0.177
Mean 3G coverage	0.528	0.533	0.129	0.131	0.348	0.341	0.114	0.117
Number of countries	63	58	14	13	127	109	57	51
Country FEs	✓	✓	✓	✓	✓	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is a country-year. Columns 1, 2, 5, and 6 present the results for both rich and poor countries. Columns 3, 4, 7, and 8 present the results for countries with below-median GDP per capita. Odd columns present results for all the countries, for which there are data on both 3G coverage and the respective dependent variable, while even columns restrict to the sample of countries present in the GWP sample. Standard errors in parentheses are corrected for clusters at the level of the countries.

Table A.23
Balance in individual-level characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.:	Regional 3G coverage	Post-event dummy		1st principal component of government approval responses			
Sample:	All	All	All	All	All	No high school degree	
						Married	Unmarried
Hainmueller (2012) weighting:	No	No	Yes	No	Yes	No	No
Post-event dummy				-0.036***	-0.031***	-0.059***	-0.035**
				(0.011)	(0.012)	(0.016)	(0.014)
Female	0.000	0.002	0.002				
	(0.001)	(0.001)	(0.001)				
Married	-0.003**	-0.002*	-0.002				
	(0.001)	(0.001)	(0.002)				
Divorced	0.000	0.002	0.001				
	(0.002)	(0.002)	(0.003)				
Widow[er]	-0.001	-0.000	-0.001				
	(0.002)	(0.002)	(0.002)				
Number of children/10	0.002	0.003	0.006				
	(0.003)	(0.003)	(0.004)				
Age/10	-0.000	-0.001	-0.001				
	(0.001)	(0.002)	(0.002)				
Age^2/1,000	0.002	0.002	0.002				
	(0.002)	(0.002)	(0.002)				
High school degree	0.007***	0.004***	0.001				
	(0.001)	(0.001)	(0.001)				
Tertiary education	0.008***	0.005***	0.000				
	(0.002)	(0.002)	(0.002)				
Unemployed	-0.000	0.003	0.002				
	(0.002)	(0.002)	(0.003)				
Employment status missing	-0.000	-0.001	-0.001				
	(0.002)	(0.004)	(0.003)				
Large city	0.003	-0.004	-0.003				
	(0.003)	(0.003)	(0.004)				
Suburb of large city	0.003	0.002	0.007				
	(0.005)	(0.005)	(0.006)				
Small town or village	0.001	-0.004	-0.001				
	(0.003)	(0.003)	(0.004)				
Observations	840,537	840,537	840,537	617,863	617,863	116,111	73,138
Mean dep. var	0.395	0.117	0.235	0.439	0.439	0.486	0.458
Number of countries	116	116	116	110	110	110	110
Subnational region & year FEs	✓	✓	✓	✓	✓	✓	✓
Re-balanced sample			✓		✓		
Age fixed effects						✓	✓
p-value for age and age^2	0.002	0.025	0.220				

Note: *** p<0.01, ** p<0.05, * p<0.1. Column 1 of the table presents the relationship between regional 3G coverage and the individual-level characteristics. Column 2 of the table presents the relationship between a dummy for a region having experienced an increase in 3G coverage of more than 50 percentage points in one year and the individual-level characteristics. Column 3 replicates the results from Column 2 after re-weighting the observations using entropy balancing following Hainmueller (2012). Columns 4 and 5 present the relationship between the post-event dummy and government approval before and after re-weighting the observations, respectively. Columns 4 and 5 present the relationship between the post-event dummy and government approval in the subsamples of married and unmarried individuals without a high school degree, respectively, additionally controlling for age fixed effects. The unit of observation is an individual. Controls in Columns 4-7 include age, age squared, gender, marital status, dummies for high school and university education, employment status, urban status, the regions' average level of income, the log of the countries' GDP per capita, the countries' unemployment rate, and dummies for democracy status. Standard errors in parentheses are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Table A.24

The correlation between censorship and education and occupations of political elites

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(9)	(10)	(11)
Panel A: Characteristics of the political leadership and the censorship of the internet score										
Dep. Var.:	Average censorship of the internet									
Share of political leadership with the following characteristics:										
Speaks English	0.100									
	(1.179)									
College degree or higher		0.150								
		(2.828)								
Postgraduate degree or higher			1.011							
			(1.863)							
Ph.D. degree				4.634						
				(3.095)						
Western education					0.109					
					(1.909)					
Military education						7.181				
						(11.556)				
Degree in engineering, math or computer science							3.298			
							(6.877)			
White collar occupation								0.965		
								(2.649)		
Media-industry occupation									3.292	
									(6.586)	
Political occupation										-1.388
										(1.954)
Average Polity2 score	-0.504***	-0.504***	-0.505***	-0.494***	-0.502**	-0.476**	-0.488***	-0.514***	-0.459**	-0.512***
	(0.181)	(0.182)	(0.180)	(0.181)	(0.193)	(0.191)	(0.179)	(0.187)	(0.221)	(0.181)
Average censorship of the traditional press	0.152***	0.152***	0.154***	0.154***	0.153**	0.149***	0.152***	0.148***	0.152***	0.144***
	(0.052)	(0.051)	(0.052)	(0.051)	(0.059)	(0.049)	(0.049)	(0.054)	(0.051)	(0.052)
Observations	42	42	42	42	42	42	42	41	41	41
R-squared	0.736	0.736	0.737	0.748	0.736	0.739	0.736	0.731	0.732	0.734
Mean dep. var	12.93	12.93	12.93	12.93	12.93	12.93	12.93	13.09	13.09	13.09
Panel B: Characteristics of the political leadership and the censorship of the traditional press										
Dep. Var.:	Average censorship of the traditional press									
Share of political leadership with the following characteristics:										
Speaks English	-0.323									
	(3.429)									
College degree or higher		-2.445								
		(9.016)								
Postgraduate degree or higher			-5.208							
			(6.926)							
Ph.D. degree				-7.749						
				(8.521)						
Western education					-7.988					
					(5.273)					
Military education						3.880				
						(27.081)				
Degree in engineering, math or computer science							-3.776			
							(14.353)			
White collar occupation								5.694		
								(6.295)		
Media-industry occupation									-6.140	
									(10.128)	
Political occupation										-3.923
										(5.256)
Average Polity2 score	-1.682***	-1.682***	-1.640***	-1.632***	-1.706***	-1.671***	-1.695***	-1.723***	-1.749***	-1.698***
	(0.398)	(0.389)	(0.403)	(0.394)	(0.464)	(0.392)	(0.423)	(0.422)	(0.399)	(0.405)
Average censorship of the internet	1.268***	1.266***	1.272***	1.328***	1.192**	1.260***	1.274***	1.213***	1.267***	1.203***
	(0.395)	(0.385)	(0.393)	(0.403)	(0.450)	(0.396)	(0.388)	(0.418)	(0.405)	(0.403)
Observations	42	42	42	42	42	42	42	41	41	41
R-squared	0.736	0.736	0.737	0.748	0.736	0.739	0.736	0.731	0.732	0.734
Mean dep. var	12.93	12.93	12.93	12.93	12.93	12.93	12.93	13.09	13.09	13.09

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The table presents the correlations between the country's censorship of the internet, censorship of the press, and the characteristics of the country's political leadership. Average censorship of the internet is the mean of the Limits on Content score. Average censorship of the traditional press is the mean of the Freedom of the Press score. Robust standard errors in parenthesis.

Table A.25
Internet use, exposure to the "He Is Not Dimon to You" film and attitudes toward Medvedev

	(1)	(2)	(3)
Dep. Var.:	Heard about the film	Positive attitude toward Medvedev	
Watched the film		-0.364***	-0.319***
		(0.080)	(0.076)
Heard about the film		-0.178***	-0.157***
		(0.055)	(0.048)
Attitude toward Putin			0.665***
			(0.083)
Daily internet user	0.115***	-0.118**	-0.119***
	(0.036)	(0.045)	(0.039)
Voted for Putin 2012	0.019	0.145***	0.068*
	(0.028)	(0.040)	(0.039)
Age	0.020*	-0.060***	-0.060***
	(0.011)	(0.013)	(0.013)
Female	-0.017	0.109***	0.079**
	(0.026)	(0.035)	(0.034)
Urban	0.034	-0.068**	-0.060**
	(0.027)	(0.033)	(0.028)
Education group	0.020***	-0.025***	-0.014
	(0.007)	(0.009)	(0.009)
Income group	0.018	0.052***	0.035**
	(0.012)	(0.018)	(0.017)
Observations	973	685	683
R-squared	0.119	0.231	0.329
Mean dep.var	0.159	0.743	0.742

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The table presents the relationship between internet use, exposure to the "He Is Not Dimon to You" film, and attitudes toward Medvedev. Column 1 presents the relationship between the probability of hearing about the film and individual characteristics. Columns 2 and 3 present the relationship between having watched or heard about the film and the attitude toward Medvedev. An observation is an individual. Robust standard errors in parentheses.

Table A.26
The classification of populist political parties in Europe

Country	Right-wing populists	Left-wing populists	Unclassified populists
Austria	FPÖ–Freedom Party of Austria (2008, 2013, 2017), BZÖ–Alliance for the Future of Austria (2008, 2013), Team Stronach (2013)	List Peter Pilz (2017)	List Roland Düringer - My Vote Counts (2017)
Belgium	VB–Flemish Interest (2007, 2010, 2014), LDD–Libertarian, Direct, Democratic (2007, 2010, 2014), PP–People's Party (2010, 2014), FN—National Front (2007, 2010)		
Bulgaria	Attack (2009, 2013, 2014), National Front for the Salvation of Bulgaria (2013), IMRO–Bulgarian National Movement (2013), Patriotic Front (2014), Bulgaria without Censorship (2014), United Patriots (2017), Volya Movement (2017)	BSP–Bulgarian Socialist Party (2009, 2013, 2014, 2017)	GERB (2009, 2013, 2014, 2017), Order, Law and Justice (2009, 2013), National Movement for Stability and Progress (2009), People's Voice (2013, 2014)
Croatia	HSP–Croatian Party of Rights (2007, 2011, 2015, 2016), HDSSB–Croatian Democratic Alliance of Slavonia and Baranja (2007, 2011, 2015, 2016), Croatian Party of Rights Dr. Ante Starčević (2011)	Croatian Labourists–Labour Party (2011)	Human Shield (2015, 2016), Labour and Solidarity Party (2015, 2016)
Cyprus	ELAM–National Popular Front (2011, 2016)		Citizens' Alliance (2016), DIKO–Democratic Party (2011, 2016)
Czech Republic	Dawn of Direct Democracy (2013), Freedom and Direct Democracy (2017)	Party of Citizens' Rights–Zemanovci (2010, 2013)	VV–Public Affairs (2010), ANO 2011 (2013, 2017)
Denmark	Danish People's Party (2007, 2011, 2015)		
Estonia	Conservative People's Party of Estonia (2015)		Estonian Centre Party (2007, 2011, 2015), ERL–Estonian People's Union (2007, 2011)
Finland	Finns Party (2007, 2011, 2015)		
France	FN–Front National (2007, 2012, 2017), Debout la France (2017)	La France Insoumise (2017)	
Germany	National Democratic Party of Germany (2009, 2013, 2017), The Republicans (2009), Alternative for Germany (2013, 2017)	Die Linke (2009, 2013, 2017)	Die Partei (2017)
Greece	LA.O.S.–Popular Orthodox Rally (2007, 2009, 2012), Golden Dawn (2012, 2015), ANEL–Independent Greeks (2012, 2015)	SYRIZA–Coalition of the Radical Left (2007, 2009, 2012, 2015), Popular Unity (2015)	
Hungary	FIDESZ–Hungarian Civic Union (2010, 2014, 2018), JOBBIK–Movement for a Better Hungary (2010, 2014, 2018), MDF–Hungarian Democratic Forum (2010)		
Ireland		Sinn Féin (2007, 2011, 2016)	

Italy	FdI–Brothers of Italy (2013, 2018), LN–Northern League (2008, 2013, 2018), Casa-Pound Italia (2018)	Civil Revolution (2013), Power to the People (2018)	M5S–Five Star Movement (2013, 2018), PdL–The People of Freedom (2008, 2013), IdV–Italy of Values (2008), Forza Italia (2018)
Latvia	NA–National Alliance (2010, 2011, 2014, 2018), For Latvia from the Heart (2014, 2018), Who owns the State? (2018)		
Liechtenstein	The Independents (2013, 2017)		
Lithuania	TT–Party "Order and Justice" (2008, 2012, 2016), JL–"Young Lithuania" (2008, 2012), Coalition "Against corruption and poverty" (2016)	SLF–Socialist People's Front (2012)	National Resurrection Party (2008), DP+j–"Labour party + Youth" (2008), Labour Party (2012, 2016), The Way of Courage (2012, 2016)
Luxembourg	Alternative Democratic Reform Party (2009, 2013, 2018)	KPL–Communist Party of Luxembourg (2009, 2013, 2018)	
Malta			
Montenegro	Movement For Changes (2009), Serbian National List (2009), Democratic Front (2012, 2016)		European Montenegro (2009, 2012), Democratic Party of Socialists (2016)
Netherlands	Party for Freedom (2010, 2012, 2017), Forum for Democracy (2017)	Socialist Party (2010, 2012, 2017)	50PLUS (2012, 2017)
Norway	Progress Party (2009, 2013, 2017)		Centre Party (2009, 2013, 2017)
Northern Macedonia	VMRO-DPMNE (2008, 2011), United for Macedonia (2011)		
Poland	Self-Defense (2007), Law and Justice (2007, 2011, 2015), League of Polish Families (2007), Kukiz'15 (2015)		Palikot's Movement (2011)
Portugal		B.E.–Left Bloc (2009, 2011, 2015)	CDS–People's Party (2009, 2011, 2015), Democratic Republican Party (2015)
Romania	Greater Romania Party (2008, 2012), New Generation Party–Christian Democratic (2008)	People's Party–Dan Diaconescu (2012)	
Slovakia	Slovak National Party (2010, 2012, 2016), L'SNS–Kotleba–People's Party Our Slovakia (2010, 2012, 2016), We Are Family (2016)	SMER–Direction (2010, 2012, 2016)	HZDS–People's Party–Movement for a Democratic Slovakia (2010, 2012), 99perc (2012)
Slovenia	Slovenian Democratic Party (2008, 2011, 2014, 2018), Slovenian National Party (2008, 2011, 2014, 2018), Lipa–Party Lime Tree (2008)		LMS–List of Marjan Šarec (2018)
Spain	Platform for Catalonia (2011), Vox (2015, 2016)	PODEMOS (2015, 2016)	Convergence and Union (2008, 2011), Citizens–Party of the Citizenry (2015, 2016)

Sweden	Sweden Democrats (2010, 2014, 2018)		
Switzerland	Swiss People's Party (2007, 2011, 2015), Federal Democratic Union (2007, 2011, 2015), Swiss Democrats (2007, 2015), Ticino League (2007, 2011, 2015), Geneva Citizens' Movement (2011, 2015)	Solidarity (2007, 2015)	
United Kingdom	UKIP (2010, 2015, 2017), British National Party (2010), DUP–Democratic Unionist Party (2010, 2015, 2017)		

Note: Years, when parties participated in the parliamentary elections, are in parentheses.

Table A.27
Green political parties in Europe

Country	**Green parties**
Austria	The Greens—The Green Alternative (2008, 2013, 2017)
Belgium	Ecolo (2007, 2010, 2014), Groen! (2007, 2010, 2014)
Bulgaria	
Croatia	ZZK–Green-Yellow Coalition (2007), Croatian HSLS–Croatian Social Liberal Party (2011), HSS–Croatian Peasant Party (2011)
Cyprus	Ecological and Environmental Movement (2011, 2016)
Czech Republic	Green Party (2010, 2013, 2017)
Denmark	Unity List—Red-Green Alliance (2007, 2011, 2015), The Alternative (2015)
Estonia	Estonian Greens (2007, 2011, 2015)
Finland	Green League (2007, 2011, 2015)
France	The Greens (2007, 2012, 2017)
Germany	Alliance 90/The Greens (2009, 2013, 2017)
Greece	Ecologist Greens (2007, 2009, 2012)
Hungary	
Ireland	Green Party (2007, 2011, 2016)
Italy	
Latvia	Union of Greens and Farmers (2010, 2011, 2014, 2018), The Progressives (2018)
Liechtenstein	
Lithuania	Lithuanian Farmers and Greens Union (2008, 2012, 2016), Lithuanian Green Party (2016)
Luxembourg	The Greens (2009, 2013, 2018)
Malta	Democratic Alternative (2008, 2013, 2017)
Montenegro	
Netherlands	Green Left (2010, 2012, 2017)
Norway	Green Party (2013, 2017)
Northern Macedonia	
Poland	
Portugal	PCP-PEV–Unitary Democratic Coalition (2009, 2011, 2015)
Romania	Ecologist Party of Romania (2008, 2012)
Slovakia	Green Party (2012, 2016)
Slovenia	Greens of Slovenia (2008, 2011, 2014, 2018)
Spain	Initiative for Catalonia Greens–United and Alternative Left (2008, 2011), Equo (2011)
Sweden	Green Party (2010, 2014, 2018)
Switzerland	Green Party (2007, 2011, 2015), Green Liberal Party (2007, 2011, 2015)
United Kingdom	Green Party (2010, 2015, 2017)

Note: Years, when parties participated in the parliamentary elections, are in parentheses.

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