

3G Internet and Confidence in Government*

Sergei Guriev[†]Ⓐ Nikita Melnikov[‡]Ⓐ Ekaterina Zhuravskaya[§]

This draft: March 2020

First draft: June 2019

Abstract

How does broadband internet affect government approval? Using surveys of 840,537 individuals from 2,232 subnational regions in 116 countries in 2008-2017 from the Gallup World Poll and the global expansion of 3G mobile networks, we show that an increase in broadband mobile internet access reduces government approval. This effect is present only when the internet is not censored and is stronger when traditional media is censored. 3G internet helps expose actual corruption in government: revelations of the Panama Papers and corruption incidents translate into higher perceptions of corruption in regions covered by 3G networks. The disillusionment of voters with governments had electoral implications: In Europe, the expansion of mobile internet led to a decrease in the vote shares of incumbent parties and an increase in the vote shares of the antiestablishment populist opposition, but not of the nonpopulist opposition, whose political support was unaffected by the expansion of 3G networks.

Keywords: Government approval, 3G, Mobile, Internet, Corruption, Populism

*We thank Philippe Aghion, Oriana Bandiera, Timothy Besley, Filipe Campante, Mathieu Couttenier, Ruben Durante, Thomas Fujiwara, Davide Furceri, Irena Grosfeld, Andy Guess, Brian Knight, Ilyana Kuziemko, John Londregan, Marco Manacorda, Chris Papageorgiou, Maria Petrova, James Robinson, Seyhun Orcan Sakalli, Andrey Simonov, David Strömberg, Maria Micaela Sviatschi, Alwyn Young, the participants of seminars in Princeton University, Paris School of Economics, Sciences Po, Bocconi University, New Economic School, London School of Economics, and Annual Workshop of CEPR RPN on Populism, Kyiv Conference on Corruption, IIES/SNS International Policy Talks, Social Media Economics Workshop in ENS Lyon, and the Annual Globalisation Seminar at the School of Business and Management (Queen Mary University in London) for helpful comments. We also thank Antonela Miho and Etienne Madinier for excellent research assistance. The authors wish to thank the World Wide Lightning Location Network (<http://wwlln.net>), a collaboration among over 50 universities and institutions, for providing the lightning location data used in this paper. All authors contributed equally to the paper.

[†]Sciences Po, Paris, France, and CEPR. sergei.guriev@sciencespo.fr.

[‡]Princeton University, Princeton, NJ, United States. melnikov@princeton.edu.

[§]Paris School of Economics (EHESS), Paris, France, and CEPR. ezhuravskaya@gmail.com.

1 Introduction

What are the political implications of the expansion of broadband internet around the world? Optimists argue that the internet improves access to independent political information, while social media helps overcome collective action problems by allowing two-way information flows. Thus, the new information and communication technology promotes public awareness of government corruption and helps opposition activists to organize and resist non-democratic governments. For instance, in the wake of the Arab Spring of 2010-2012, the internet was branded a “liberation technology” (Diamond and Plattner, 2010). Pessimists, in contrast, point out that the internet facilitates the dissemination of fake news (Allcott and Gentzkow, 2017; Vosoughi, Roy and Aral, 2018), empowers non-democratic regimes by reducing costs of propaganda and surveillance (Mitchell et al., 2019; Morozov, 2011), and helps populists to connect to voters through social media (Tufekci, 2018). These conjectures found empirical support in a number of studies, which have analyzed the political implications of the broadband internet expansion in a single-country setting (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 introduction of broadband mobile (3G) internet access throughout the world. Prior to this paper, the only multi-country study of the political effects of the expansion of telecommunications infrastructure is Manacorda and Tesei (forthcoming), which shows that the second-generation (2G) mobile networks, that allowed texting and a very limited internet connectivity, facilitated political protests during economic downturns across Africa between 1998 and 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 across all continents in 2008-2017 to show that the expansion of 3G mobile internet infrastructure leads to a significant increase in internet use and, on average, decreases government approval. The public that gains access to broadband mobile internet becomes more aware of government corruption and less confident in the country’s government institutions. The magnitudes are substantial: the expansion of 3G coverage from having no signal to full coverage of an average subnational region reduces the confidence of this region’s residents in their national government by 6 percentage points (from the mean level of 51 percent) and increases the perception that the government is corrupt by 4 percentage points (from the mean of 77 percent).

The global setting allows us to shed light on one of the mechanisms behind this average effect by documenting heterogeneity across countries. First, we show that 3G decreases government approval only when the internet is not censored. This is despite the fact that 3G increases internet use everywhere, and in particular, in countries

with internet censorship. This suggests that it is the independent-of-the-government political information available online that makes people change their attitudes toward 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 the internet becomes a major source of news when there are no other sources of independent political information. Third, we demonstrate explicitly that the internet helps inform the public about corruption. [Furceri, Papageorgiou and Ahir \(2019\)](#) collected a measure of actual incidents of corruption in national governments for a large number of countries. Using their measure, we show that the perceptions of corruption among residents of subnational regions covered by 3G networks are more receptive to the occurrence of actual corruption than the perceptions of individuals from regions that do not have access to 3G networks. We also verify that mobile internet helps expose corruption using an alternative measure of actual corruption based on revelations from the Panama Papers leak of information about offshore entities. Fourth, we explore individual, geographical, and over-time heterogeneity. We find that the effects are stronger for rural residents, for respondents with lower socio-economic status measured by education and income, and weaker for younger respondents. 3G negatively affects government approval on all continents, but in Europe, this is only the case among rural residents (for whom the effects are stronger everywhere); and in Asia the effect is significant only if one excludes countries with internet censorship (particularly prevalent on this continent). The magnitude of the effect of 3G coverage on government approval is stable over our observation period. Taken together, our comparative analyses suggest that uncensored internet can be a powerful tool of political accountability.

Finally, we examine the electoral implications of the 3G internet expansion. To test whether the internet-driven disillusionment of voters with their governments translates into lower vote shares of incumbent parties, we use subnational-level data on 102 parliamentary elections in 33 European democracies between 2007 and 2018. We focus on Europe for three reasons. First, it is a set of broadly comparable democracies. Second, during this period, the rise of populism was particularly pronounced in Europe ([Rodrik, 2018](#)). And third, for Europe, there is a conventional classification of political parties into populist and nonpopulist.

We find that incumbent governments lose electoral support after the arrival of mobile 3G networks, corroborating our results for the attitudes toward governments. On average, moving from no to full 3G coverage in a subnational region results in an 8.9 percentage point decrease in the incumbent party’s vote share. We then investigate what kinds of parties gain from the expansion of 3G networks. We find strong 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 expansion of 3G coverage in a subnational region from no signal to full coverage increases the vote share of right-wing populists by 8.6 percentage points and of left-wing populists by 6.7 percentage points. We also find that only populist opposition parties benefit from the expansion of 3G networks: there are no electoral gains from the mobile internet expansion for the nonpopulist opposition, in general, and for Green (environmentalist) parties, in particular. Importantly, electoral support for the incumbents also decreases with the expansion of 3G networks when populists are in government. We find that turnout, on average, decreases by 3.8 percentage points after an increase from no to full 3G coverage, which can partly explain the effects on the vote shares of the incumbents and populists. However, we find that the results are also 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 the incumbent governments’ political approval and the rise of the popularity of populist parties are two sides of the same phenomenon. Testing for the exact mechanisms of the effect of 3G on the populists’ vote share is beyond the scope of this paper. Why it is the populists—and not other opposition parties—who benefit politically from the voters’ disillusionment with the incumbent political elites, caused by the 3G expansion, should be the subject of future research. Overall, we find that broadband mobile internet helps inform voters about their governments, leading to a fall in government approval, particularly, when there are no other sources of independent political information. 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 other nonpopulist opposition parties do not benefit from the 3G expansion.

Our empirical strategy relies both on difference-in-differences and instrumental-variables analyses. We use the variation in the timing of the expansion of 3G mobile networks across different subnational regions within countries, controlling for subnational region fixed effects, year fixed effects, and a large set of potential confounds, including measures of economic development, unemployment, democracy, as well as individual socio-demographic characteristics. We document the absence of pre-trends: the future availability of mobile networks has no effect on government approval, but the effect of past 3G expansions is significant. We show that our results are robust to including country-by-year fixed effects. These results are 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 reduction in government approval with a magnitude similar to the baseline specification; and

there are no changes in government approval preceding the 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 use the instrumental-variables identification strategy designed by [Manacorda and Tesei \(forthcoming\)](#) that relies on the variation in the regional frequency of lightning strikes to predict the speed of the expansion of regional mobile internet coverage. This approach confirms the results of the difference-in-differences OLS analysis.

To address a potential concern that the 3G technology may affect individual attitudes through channels other than broadband internet access, we use the expansion of 2G mobile networks as a placebo treatment. 3G was the first generation that allowed users to freely browse the web from their smartphones. We show that, if anything, 2G, on average, is *positively* correlated with government approval and that controlling for the availability of a 2G signal does not affect our results.¹ We also present the results for a number of placebo outcomes. In particular, we show that the relationship between broadband mobile internet and government approval is not driven by the effect of the internet on general life satisfaction or pessimism about the future.

Our paper contributes to the growing literature on the political effects of the internet. Several studies (mostly, focusing on individual countries) have shown that access to the internet hurts the incumbents' political position. For example, the expansion of high-speed cable internet in Malaysia was shown to have helped end 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, 2017](#)). Social media helped to coordinate protest activity across Africa ([Manacorda and Tesei, forthcoming](#)) and in Russia ([Enikolopov, Makarin and Petrova, forthcoming](#)). Similarly, [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 of the emergence of social media. The evidence from Germany ([Falck, Gold and Heblich, 2014](#)), the UK ([Gavazza, Nardotto and Valletti, 2019](#)), and Italy ([Campante, Durante and Sobbrío, 2018](#)) suggests that, initially, i.e., before the emergence of social media, in Europe, broadband internet had crowded out political awareness with entertainment content, reducing electoral participation, without any significant gains of any specific political force. Yet, starting with 2008, i.e., the time of the introduction of social me-

¹[Manacorda and Tesei \(forthcoming\)](#) show that, in Africa, 2G facilitated protests during recessions. The two results are not in contradiction because protests are often organized by a minority. [Enikolopov, Makarin and Petrova \(forthcoming\)](#), for instance, demonstrate that social media in Russia increased both the likelihood of protests and the support for the regime.

dia, [Campante, Durante and Sobbrío \(2018\)](#) show that broadband cable internet has contributed to the rise of the populist Five Star Movement in Italy. This result was confirmed by [Schaub and Morisi \(2019\)](#) using survey data on the electoral support for populists in Italy in 2013 (Five Star Movement) and in Germany in 2017 (AfD). Our analysis covers the period between 2007 and 2018 and, thus, corresponds to the time when social media was rapidly expanding.

Our contribution to the literature is three-fold. First, we document the political effects of broadband internet for a large set of countries across the world. Second, the comparative analysis allows us to shed light on one of the mechanisms: we show that uncensored internet is a vehicle for getting independent-of-the-government political information to voters, which is particularly effective when traditional media is not free. Third, we use election data for 33 European countries over a decade to show that incumbent parties lost political support as a result of the expansion of 3G mobile internet, while the populist opposition—both on the right and on the left—gained votes. The nonpopulist opposition did not receive any electoral benefits due to the expansion of access to 3G networks.

The rest of the paper is organized as follows. Section 2 presents the data and the empirical strategy. In Section 3, we present the average effect of the expansion of 3G networks on government approval for the whole world and discuss the validity of our identification assumptions. Section 4 presents the comparative analysis, which demonstrates that the negative information about the government available online is an important mechanism behind the overall effect. Section 5 explores the electoral implications of the mobile internet expansion. Section 6 concludes.

2 Data and the empirical strategy

2.1 The main variables

In this section, we briefly describe the main variables of interest, relegating details about these measures as well as the description of all the control variables to the Appendix Section A.1.

The data on government approval come from the GWP and cover the period from 2008 to 2017. 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 and also aggregate 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: *“Does your home have access to the internet?”*

We are interested in estimating the effect of the internet on attitudes and beliefs. Yet, individual beliefs may affect the decision to connect to the internet, and other factors, such as the level of development, may impact both government approval and internet availability. To overcome these endogeneity problems, we exploit the plausibly exogenous variation in the timing of the expansion of third-generation—3G—mobile networks. (We discuss the plausibility of the identification assumptions below.)

3G was the first generation of mobile networks that allowed users to actively browse the web on their phones, making the internet more accessible and convenient to use. 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), only 4% of the world’s population had mobile broadband subscriptions in 2007. The following years witnessed significant growth in mobile internet users, reaching 70.1% of the global population by 2018. Importantly, ITU data show that most of the growth in individual internet usage both in developing and developed countries over the last decade was due to the expansion of broadband mobile internet access rather than cable (ADSL or fibre-optic cables) internet.²

We use annual maps of global 3G network coverage from 2007 to 2018 provided by Collins Bartholomew’s Mobile Coverage Explorer. The data consist of 1km×1km binary grid cells. Figure 1 illustrates the expansion of 3G networks over the entire period of observation. It presents the 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.

After combining the data sources, 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 6. Over 75% of the subnational regions appear in the data for 4 years or more. 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 internet’s effect on government approval, we use independent measures of corruption, censorship of the internet, censorship of the traditional press. We use two measures of actual corruption. The first one is the International Monetary Fund’s (IMF’s) Global Incidents of Corruption

²The ITU data are available at <https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx> (accessed on November 13, 2019).

Index (GICI) from [Furceri, Papageorgiou and Ahir \(2019\)](#), which is based on text analysis of country reports, prepared by the Economist Intelligence Unit (EUI) and made available to investors on a subscription basis. The index quantifies the intensity of actual corruption across countries over time. It is the result of analysis by external (EUI) experts and is distinct from the corruption perceptions of the public. This index covers 97 countries in our sample. The second measure is based on the Panama Papers Database made available by the International Consortium of Investigative Journalists (ICIJ). In particular, for each country, we calculate the number of entities featured in the Panama Papers. For the few countries, which are not mentioned in the Panama Papers, we impute this number to be zero. 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. In addition to a continuous measure of internet censorship, we also create a dummy for censored internet which equals one if the Limits on Content score is 22 or above and zero if the score is below 22. In order to expand the sample, we also set the dummy for censored internet to zero if a country does not have FOTN data but in that year the country is a democracy according to the Polity IV dataset (i.e., if the Polity2 score is 6 or above). In the sample with non-missing FOTN data, a dummy for democracy predicts the Limits on Content score to be below 22 with 99.5% probability.

The measure of censorship of traditional media comes from Freedom House’s 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.

To single out the exogenous source of variation in the speed of the expansion of regional 3G network coverage, we calculate the frequency of lightning strikes per sub-national region using the World Wide Lightning Location Network (WWLLN) dataset.

Finally, we use parliamentary election data from European democracies. [Figure A1](#) in the Appendix presents maps illustrating the growth in 3G networks coverage between 2007 and 2018 in Europe and the boundaries of the districts, i.e., the spatial unit of observation in our European elections data. (The figure is organized similarly to [Figure 1](#).) To study the effect 3G mobile internet on the performance of the incumbents and of the establishment parties, we use the vote share of the party of the country’s top executive at the time of the elections, as well as the combined vote share of the two parties that came 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. \(2017\)](#).

The classification of parties into populist and nonpopulist is based on the Chapel Hill Expert Survey and on text analysis of online sources. The data cover 102 elections in 33 European countries in 2007-2018 at the level of 398 subnational districts. There are 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 out 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. We describe these data, present the lists of populist and Green parties, and outline the methodology used to classify parties into populist and nonpopulist in the Appendix.

The details about the exact measures used in the analysis, summary statistics, and sources of all data are presented in the Appendix Section [A.1](#).

2.2 The main specifications

We estimate the effect of being connected to broadband mobile internet on individuals' beliefs. We gauge 3G mobile networks availability ($3G$) 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 the availability of 3G mobile networks using a difference-in-differences model with region and year fixed effects (Specification 1):

$$Gov_approval_{irt} = \gamma_1 3G_{rt} + \gamma_2 Development_{rt} + \mathbf{X}'_{irt} \lambda + \varphi_r + \tau_t + \epsilon_{irt}. \quad (1)$$

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 different GWP questions to measure confidence in government. $3G$ represents the share of 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 the expansion of 3G networks 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 the GWP respondents in the region and establish robustness to using nighttime light density as an alternative measure (following [Henderson, Storeygard and Weil, 2011, 2012](#)).³ \mathbf{X} is a vector of additional controls:

³In the few region-years where the 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 the Appendix Section [A.2](#), the results are robust to controlling for nighttime light

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.⁴ 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 country level 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 clustering at the country level.

3G mobile service allows users to freely browse the internet from the smartphone. As a result, 3G coverage affects internet use on the extensive margin—by affecting the probability of having a connection—and on the intensive margin—by affecting the number of hours spent online. Both of these margins are important for the overall effect of 3G, estimated by Specification (1). As the GWP does not have data on the amount of time spent surfing the web, we can only test for the extensive-margin effect. In particular, we verify that the availability of 3G mobile networks predicts individual internet access by estimating a difference-in-differences relationship between the respondent’s internet access and 3G coverage in the subnational region of the respondent’s residence (Specification 2):

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

where *Internet* denotes a dummy variable for self-reported access to the internet.

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 as follows: i) the timing of the expansion of 3G mobile networks affects individuals’ attitudes toward government only through its effect on individuals’ access to the internet and ii) the expansion of 3G mobile networks is not itself driven by the expectation of changes in government approval or by any unobserved factor that can generate a spurious correlation between government approval and 3G network coverage. These assumptions are not directly testable. However, below in Section 3.1 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 density. We do not use this variable in the baseline specification because it is not comparable before and after 2014.

⁴Summary statistics are presented in Table A1 in the Appendix.

baseline differences-in-differences specification could be violated, we use the variation in the frequency of lightning strikes among the subnational regions to predict the speed of the expansion of regional 3G coverage—the identification strategy first used by [Manacorda and Tesei \(forthcoming\)](#) for the 2G network expansion in Africa. In particular, we estimate the following equation as the first stage to predict $3G_{irt}$:

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

where $Lightning_r$ denotes a dummy indicating subnational regions with a high frequency of lightning strikes; $Rich_{c_r}$ and $Poor_{c_r}$ are dummies indicating the countries with above- and below-median per capita income; $\tau_t^{R,P}$ denotes year fixed effects, separate for countries with above- and below-median per capita income; and \mathbf{Z} stands for all the baseline controls described above. The identification assumption behind this approach is that the frequency of lightning strikes affects trends in government approval only through its effect on the expansion of 3G mobile network coverage. As shown below, the results of the IV and OLS specifications are qualitatively similar, and the magnitudes are somewhat larger in the IV estimation.

3 Mobile internet and government approval

Table 1 presents the results of estimating the effects of mobile 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. In Column 1, the outcome variable is individual internet access (Specification 2). We find that the expansion of 3G networks within the respondent’s region of residence strongly predicts individual internet access. Conditional on all covariates, on average, moving from zero 3G availability in a region to full 3G coverage increases the probability of an individual being connected to the internet by 8.0 percentage points when considering the entire sample (Panel A) and by 8.3 percentage points when focusing on rural areas (Panel B). (The effects are highly significant in both samples.)

Columns 2 to 7 of Table 1 consider different measures of government approval as the outcome variables. 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 different measures of government approval (Columns 2-5) and for the two aggregate measures, i.e., the share of positive answers and the first principal component of the four measures (Columns 6-7), both for the full sample and the subsample of rural residents (Panels A and B).

The magnitude of the effects is sizeable in the full sample; and it is particularly large for residents of rural areas. For example, the estimates in Column 2 imply that, on average, the expansion of 3G networks from zero to full coverage in a region decreases the confidence of respondents in their country’s government by 6 percentage points in the full sample and by 9 percentage points for rural residents (from the mean levels of 51% and 54%, respectively). Similarly, as reported in Column 5, it decreases the share of people who think that the government is not corrupt by 3.6 percentage points in the full sample and 5.4 percentage points for rural residents (from the mean of approximately 22%). The results for the other measures of attitudes toward government institutions are very similar. (Note that we normalize the first principal component of the government approval variables to vary between zero and one for the ease of the interpretation of the magnitude of the effect.) The persuasion rate for the hypothetical message “do not approve of your government” implied by the estimate for the first principal component of the government approval variables (Column 7) is 10.2% in the full sample and 14.8% in the sample of rural residents.⁵

Figure 2 illustrates these results. On the horizontal axis, the two panels of the figure plot the increase in the share of a subnational region’s territory covered by 3G in year t since 2008. In Panel A, 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); in Panel B—the residual of individual internet use in year t (similarly, after subtracting the effects of all the controls).⁶ 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.⁷ The figure shows that in an average region, the expansion of 3G

⁵As mentioned above, the estimates presented in Columns 2-7 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. Thus, a 2SLS estimation, in which one predicts individual internet access with regional 3G coverage and then uses this prediction for estimating the effect of individual internet access on government approval would lead to an overestimation of the effect. Such a specification incorrectly implies that 3G only affects the probability of connecting to the internet. In reality, with the arrival of 3G technology, people who have already been using the internet before started using it more because the broadband connection is more convenient.

⁶To 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 other controls.

⁷To 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 percentile for each of

coverage led to a drop in government approval (Panel A) and an increase in internet use (Panel B).

3.1 Addressing identification challenges

Can these results be interpreted as causal? In this section, we present evidence suggesting that the 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 in the subnational regions as an exogenous source of variation in the speed of the expansion of 3G networks.

Country×year FEs.—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 A2 in the Appendix) are largely robust. After partialling 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 5 out of 6 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 1, which could be explained by the fact that part of the relevant variation is not accounted for in this specification.

Pre-trends.—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 A2 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 related to government approval this year, suggesting parallel pre-trends.

Panel A of Figure 3 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 pre-trends 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.

Event study.—To validate our pre-trends analysis further, we also conduct an

the bins.

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 past year. By definition, in each region, this could only happen once, if it happens at all, provided that regional 3G coverage never falls substantially. There are 422 regions in 63 countries which experienced such a sharp increase in 3G coverage in one year.⁸ Focusing on the sample of respondents from these regions (116,932 observations), we regress the first principal component of the government approval variables on year dummies relative to the year of the event and all the baseline controls. The results are presented in Appendix Table A3 separately for the full sample and for the subsample of rural residents. The results are similar in both samples.

We illustrate the results for the full sample in Panel B of Figure 3. 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). We find that government approval falls right after a sharp increase in regional 3G coverage. All the coefficients on the post-event dummies are statistically significant and their magnitudes are similar to those presented in Table 1. 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 pre-trends. Panel B of Figure 3 also illustrates 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.⁹

2G as a placebo treatment.—A potential concern is that 3G availability may affect individuals’ beliefs through other mechanisms than providing access to 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

⁸For the vast majority of regions, 3G expands monotonically. In 95% of region \times year observations, the change 3G is positive from one year to the next. Among all 2,232 subnational regions in the sample, 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.

⁹We 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). In order to do this, we confine 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 200 times and compare 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 A2 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.

very limited internet capabilities and, in particular, do not allow browsing the internet freely. Indeed, in Column 1 of Table 2, we show that, unlike 3G coverage, regional 2G coverage is not related to respondents’ internet access. If individuals’ beliefs were affected not by internet access but by some other aspects of the expansion of the communications technology, one should expect similar effects of the expansion of 2G and 3G networks. In Table 2, we show that, in contrast to the effect of 3G presented above, the expansion of 2G networks, if anything, is associated with an *increase* in government approval (as shown in Columns 2 to 7 of Panel A), suggesting that the population may credit the government—justifiably or not—for the construction of new infrastructure. In Panel B of the table, we also show that controlling for 2G availability does not affect the estimates of the effect of 3G. These findings suggest that the negative effect of 3G on government approval is driven by its effect on internet access rather than by other features of the expansion of mobile networks.

Variation in observables as a proxy for unobserved variation.—We follow the methodologies of Altonji, Elder and Taber (2005) and Oster (2017) to understand how important the effect of unobservables needs to be 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 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 A4 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 4 out of 6 outcomes, including both aggregate measures of government approval. This suggests that, at least for these 4 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 A4, 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. In the two cases where observables should be positively selected from unobservables to explain our results (Columns 2 and 4), the 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 δ s range between -4 and $-1,000$. 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 stability of 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. The results are reported in Appendix Table A5 and illustrated in Figure A3, which plots the over-time

evolution of the effect of 3G coverage. There is no systematic change in the effect over time. The stability of the effect is important for the validity of our estimation strategy, as in those cases when the treatment effect changes over time, the standard difference-in-differences estimand may be biased, as shown by [Goodman-Bacon \(2018\)](#).

The frequency of lightning strikes as an IV.—Finally, we use the identification strategy proposed by [Manacorda and Tesei \(forthcoming\)](#), who show that in Africa the incidence of lightning strikes predicts local trends in the expansion of 2G mobile networks. During thunderstorms, the electrostatic discharges can damage mobile-phone infrastructure, increasing the cost of mobile-service provision. This is the case for both 2G and 3G infrastructure. For this reason, one could expect a slower expansion of mobile-phone coverage in places with a high frequency of lightning strikes. Importantly, the adoption of mobile technology is likely to be affected by lightning strikes primarily in lower-income countries, because providers in these countries typically have fewer resources to protect mobile-network infrastructure from being damaged—for instance, by using power-surge protection technology—or to repair it in case of damage.

For identification, we use differences in the regional frequency of lightning strikes as an exogenous source of variation in the speed of the expansion of mobile internet service. In particular, we predict regional 3G coverage with a linear time trend interacted with a dummy for a high frequency of lightning strikes in a subnational region, separately in countries with above- and below-median GDP per capita. We deem a subnational region to have a high frequency of lightning strikes if, during our observation period (2008-2017), the region was in the top quartile of the global distribution of lightning strikes per subnational region.¹⁰ As the excluded instruments are triple interactions—between the time trend, the frequency of lightning strikes, and the country’s income group—to control for potential differences in trends between richer and poorer countries, we allow the year fixed effects to differ for the two groups of countries.

Column 1 of Table 3 presents the first stage for the full sample. We find that the adoption of 3G technology is significantly slower in regions with a high frequency of lightning strikes but only in countries with below-median income. In countries with above-median GDP per capita, there is no significant relationship between the frequency of lightning strikes and the expansion of 3G networks. The overall F-statistic for the excluded instruments is 10.5, but it is driven solely by the strong relationship for the countries in the lower half of the income distribution. The second stage, presented

¹⁰Under this definition, the number of lightning strikes per day in a median region with a high frequency of lightning strikes is 100; whereas it is 4 in a median region with a low frequency of lightning strikes. The IV results are broadly robust to changing the cutoff for the high frequency of lightning strikes, e.g., to the top one-third or top one-half of the distribution of lightning strikes per subnational region.

in Column 2, confirms our main result that the expansion of regional 3G coverage leads to a significant decline in government approval. Columns 3 and 4 show the IV results for the subsample of rural residents. The results are qualitatively similar, but the F-statistic for the excluded instruments is below the conventional threshold for a strong instrument. As all of the first-stage variation is driven by poorer countries, in Columns 5-8, we repeat the analysis focusing on the subsample of countries with below-median GDP per capita. In this sample, the first-stage relationships are sufficiently strong and the estimated effects in the second stage are statistically significant both for all the respondents and for the respondents from rural areas.¹¹ We illustrate the reduced-form relationship for all respondents in countries with below-median GDP per capita in Figure A4 in the Appendix. The figure shows that, on average, government approval, net of all the baseline controls, decreased between 2008 and 2017 in subnational regions with a low frequency of lightning strikes and increased in subnational regions with a high frequency of lightning strikes.

The lack of variation in the first stage among richer countries implies that the point estimates from the second stage in the full sample reflect the Local Average Treatment Effect (LATE) for the group of lower-income countries. Thus, the magnitudes of these estimates should be compared to the OLS for the sample of countries with below-median GDP per capita. We report these estimates in Columns 6 and 8 at the bottom of the table. The magnitude of the point estimates in the IV regressions is about twice as large as in the corresponding OLS regressions. Given the results of the analyses of the validity of the OLS difference-in-differences specification presented above, the difference in the magnitude between the OLS and IV estimates is likely due to measurement error in our main explanatory variable rather than endogeneity.¹²

Overall, the results presented in this section strongly suggest that the negative

¹¹In order 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 bootstrapped standard errors with sampling at the level of the clusters. The precision of the first stage is practically unaffected and the second-stage results are slightly more precise.

¹²Assuming no heterogeneity in the effect of 3G on government approval, measurement error can fully explain the difference between the OLS and IV estimates in the sample of countries with below-median income if 51% of the total variance in the access to 3G mobile internet service is due to measurement error. There are several potential sources of such measurement error. For example, access to mobile internet is subject to numerous weather shocks, as both severe rain and wind affect connectivity (Schulman and Spring, 2011). In addition, providers may submit inaccurate or outdated data to the GSM Association, the ultimate source of our dataset on mobile network coverage. Furthermore, the difference between the OLS and IV estimates could be due to the heterogeneity of the effect of 3G within the sample of countries with below-median GDP per capita. In particular, IV would yield higher point estimates than OLS if 3G has a larger effect on government approval among complier regions (i.e., those regions where the 3G expansion can potentially be constrained by the frequency of lightning strikes) than among noncomplier regions (i.e., those regions where the expansion of 3G networks is not affected by lightning frequency, for instance, because of the availability of power-surge protection)—just as is the case for poorer compared to richer countries.

effect of 3G mobile networks on government approval can be interpreted as causal.

3.2 Robustness

Alternative assumptions about the variance-covariance matrix.—Table A6 shows that the results are robust to alternative assumptions about the correlation between the error terms. We take the specification presented in Column 7 of Panel A of Table 1 as the baseline (also reproduced in row 1 of Table A6) 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.

Aggregating the attitudes data to the subnational-region level.—Appendix Table A7 reports 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.

Alternative proxy for subnational economic development.—In Section A.2 of the Appendix, we show that our results are robust to using nighttime light density as an alternative proxy for regional economic development and 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 7 of Table 1.

4 Evidence on the mechanism

4.1 Comparative analysis: censorship of the internet and of the traditional media

The fact that uncensored internet can significantly undermine government popularity has not gone unnoticed by politicians, especially in non-democratic countries. According to Freedom House, many governments have taken steps to limit internet freedom, with policies ranging from the blockage of social media and messaging apps in China, Egypt, Iran, and Russia to temporary shutdowns of mobile networks in India

and Sri Lanka.¹³ 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 networks availability on individuals' attitudes toward government depends on internet censorship and on the censorship of the traditional media, such as TV, radio, and newspapers. We operationalize this by adding interaction terms between 3G coverage and the measures of censorship online and offline to our baseline difference-in-differences specification (1), controlling for the direct effects of these two types of censorship.

We start by considering the heterogeneity of the main effect with respect to the censorship of the internet, which we measure using the Limits on Content component of the FOTN index. Panels A and B of Table 4 present the results. In Panel A, we use an internet censorship dummy; in Panel B—a continuous internet censorship index. The results are similar in both panels: the coefficients on the interaction terms of 3G with the internet censorship measures are positive and statistically significant, so that internet censorship weakens the effect of 3G on government approval. If the internet is free, 3G coverage has a strong and statistically significant negative effect on government approval. In contrast, in countries with internet censorship, the impact of 3G coverage on government approval is zero or even positive. Figure 4 illustrates these findings. Panel A presents the nonparametric relationships between the change in government approval in a region (net of all controls) and the increase in 3G coverage in this region since 2008, separately for countries with free internet and with censored internet. The figure shows that in countries with low internet censorship (left-hand-side graph), the expansion of 3G 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, we present the nonparametric relationships between the increase in 3G coverage since 2008 and internet use in the two groups of countries. Irrespective of whether the internet is censored, the presence of 3G networks facilitates internet access for the population. The difference in the effect of 3G on government approval between countries with free and with censored internet, thus, comes from the content available online rather than from the internet penetration.¹⁴

In Panel C of Table 4, we include the interactions of 3G with both internet censorship and with censorship of the traditional media (the FOTP index). We find that the coefficients on the interactions of 3G with internet censorship remain positive and statistically significant, whereas the coefficients on the interactions of 3G with cen-

¹³See <https://freedomhouse.org/report/freedom-net/freedom-net-2018> (accessed on September 7, 2019). For academic work on internet censorship, see, for instance, [King, Pan and Roberts \(2013, 2014\)](#), [Qin, Stromberg and Wu \(2017\)](#), [Roberts \(2018\)](#), and [Chen and Yang \(2019\)](#).

¹⁴Figure A5 in the Appendix presents the corresponding nonparametric relationships, in which all controls are partialled out from the explanatory variable in addition to the dependent variable.

sorship of the traditional press are negative (and significant for 5 out of 6 outcomes). Thus, for sufficiently low levels of internet censorship, the effect of 3G coverage on government approval is negative; and it is stronger (i.e., more negative) when traditional media is censored. We illustrate this result in Appendix Figure A6: focusing on countries with uncensored internet, it shows that the relationship between the increase in regional 3G coverage since 2008 and government approval (net of controls) is steeper in countries with above-median censorship of the traditional press compared to countries with below-median censorship of the traditional press. This suggests that uncensored internet plays a particularly important role in informing the public about politics, when traditional media does not report independent-of-the-government political information.¹⁵

Heterogeneity with respect to other country and individual characteristics.—We also interact regional 3G coverage with a number of other country-level characteristics and with individual-level variables. Table A9 in the Appendix reports heterogeneity by continents, OECD membership, and the levels of income and democracy. We present the results of each specification for the full sample (Columns 1, 4, 7, and 10), for the subsample of countries with uncensored internet (Columns 2, 5, 8, and 11), and for the subsample of rural residents (Columns 3, 6, 9, and 12). In addition to the baseline controls, we control flexibly for the censorship of the traditional press (by adding 20 dummies, corresponding to every 5 points in the Censorship of the Press Score), an important determinant of government approval as demonstrated in Table 4. We, however, omit the control for internet censorship because it exists only for a subset of countries.

Columns 1-3 present the effect of the expansion of 3G separately for each continent. In the full sample, the effect is significant for the African continent and each of the Americas and is not significant for Asia and Europe. However, Asia is the continent with the highest number of countries with internet censorship: 11 out of 16 such countries are in Asia. In Column 2, we show that the effect is significant for Asia (as well as for Africa and the Americas), once we focus on countries with low internet censorship. In the rural subsample (Column 3), the effect is significant for all continents, including Europe, where the effect is the smallest in magnitude among all continents, but is still sizeable: the expansion of 3G networks from no signal to full coverage in an average European region is associated with a 4.2-percentage-point lower government approval among its rural residents.

Columns 4-6 present the results separately for OECD and non-OECD countries. The effect is economically and statistically significant in non-OECD countries: We

¹⁵Table A8 in the Appendix replicates Table 4 for the subsample of rural residents; the results are similar to those presented in Table 4.

observe 6.8 and 8.5 percentage point decreases in government approval as a result of an increase in 3G availability from zero to full coverage in the sample of total population and in the subsample of rural residents, respectively. Similarly to the results for Europe, the effect for OECD countries is significant only for rural residents. The difference between the results for rural and urban areas may be explained by the differences in the availability of offline sources of political information. The remainder of Table A9 (Columns 7 to 12) shows that there is no significant heterogeneity with respect to per capita GDP or the level of democracy, measured by the Polity2 score.

Table A10 in the Appendix tests for heterogeneity with respect to the individual characteristics of the respondents. Odd columns present the results for the full sample and even columns for the subsample of rural residents. Columns 1 and 2 show that the effects are significantly stronger for the unemployed than for the employed (−7.1 percentage points vs. −4.8 percentage points, respectively, according to the estimates presented in Column 1). Columns 3 and 4 show that there is no effect of 3G on government approval among respondents with tertiary education, in sharp contrast with the negative and significant effects for respondents with secondary education and for respondents with education below secondary, 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 the expansion of 3G than those of the 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 years old is less affected by the expansion of mobile internet than among respondents of other age groups. The effect on the elderly (above 60) is similar in magnitude to the effect on the middle-aged (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 odd and even columns of Table A10.

Overall, the results of all our heterogeneity exercises are consistent with the hypothesis that the consumption of political information available online is an important channel behind the political effect of 3G. However, the analyses presented above do not provide any information on the content of such political information, in particular, whether voters get access to accurate political information or to false news, which—as was shown in a number of studies (e.g., Allcott and Gentzkow, 2017; Vosoughi, Roy and Aral, 2018; Guess, Nagler and Tucker, 2019; Grinberg et al., 2019)—do get disseminated on social media. We address this question directly in Section 4.2.

Life satisfaction and other placebo outcomes.—In Table A11 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 5 years, satisfaction with the current standards of living, and beliefs about whether standards of living are getting better. 3G coverage also has no effect on the confidence in the *local* police, suggesting that internet access affects individuals’ opinions about the government only for those government functions that people cannot observe directly through their day-to-day experience.

4.2 Does mobile internet help expose actual corruption?

In this section, we test the conjecture that mobile internet helps inform the public about actual cases of corruption in government. If so, incidents of actual corruption should translate into higher perceptions of corruption more in subnational regions with greater access to mobile internet. In other words, 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 the incidence of actual corruption in a global setting. It is challenging, as the vast majority of cross-country measures of corruption rely on perceptions. We use two alternative measures of actual corruption. The first one is based on the analysis conducted by the Economist Intelligence Unit; the other one—on the information from the leaked documents about offshore entities, known as the Panama Papers.

The Global Incidents of Corruption Index.—[Furceri, Papageorgiou and Ahir \(2019\)](#) are the first to construct a measure of actual corruption that covers the entire world and is unrelated to perceptions—the IMF’s Global Incidents of Corruption Index (GICI). This index quantifies the importance of actual corruption in each country and year by measuring the share of the text of the annual EIU country reports devoted to corruption. We define the index of actual corruption incidents by taking the logarithm of the GICI plus 0.1 to make the distribution of the resulting index resemble a normal distribution.¹⁶ We regress the dummy indicating whether the respondent believes that the government is *not* corrupt on the index of actual corruption incidents 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 to the public. The results are reported in Columns 1 to 4 of Table 5. The first two columns consider the subsample of country×years, in which the index of actual government corruption 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

¹⁶As discussed in Appendix Section A.1, our results do not depend on the functional form. In particular, they are robust to using the raw GICI index and to adding 1 instead of 0.1 before performing the log transformation. As shown below, the results are robust to using the samples with and without zero GICI.

is among the topics covered by the reports. Columns 3 and 4 present robustness of the results to using the full sample of country×years, for which the GICI index is defined, i.e., including observations with zero actual corruption incidents.¹⁷ Columns 1 and 3 show the results for all the respondents; Columns 2 and 4—for the respondents from rural areas (the results are very similar). We find that the correlation between actual corruption incidents and the perceptions of corruption does increase with 3G coverage. In regions with no 3G signal, the correlation between the index of actual corruption and the perception that the government is not corrupt is negative but small in magnitude and significant only in one out of four specifications (Column 2). 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 index of the intensity of actual corruption (0.65) is associated with a 2.2-percentage-point lower perception that the government is clean in places fully covered by 3G networks, and with a non-significant 0.06-percentage-point lower perception that the government is clean in places without mobile internet coverage. (Overall, 18.3% of respondents believe that the government is clean.) In Figure 5, we illustrate these results by presenting the marginal effect of an increase in the index of actual corruption incidents on respondents’ perceptions that the government is not corrupt for different levels of regional 3G coverage (implied by estimates from Column 1): This effect becomes stronger (more negative) with the increase in 3G coverage.

In Columns 5 to 7 of Table 5, we test for a pre-trend in actual corruption and find no evidence of such a pre-trend. In particular, we show that regional 3G coverage is not predicted by contemporaneous or past levels of actual corruption incidents (Columns 5 and 6), and the index of actual corruption is not predicted by lagged regional 3G coverage (Column 7).

In Appendix Table A12, we show that mobile internet also helps inform the public about actual corruption, measured by the GICI, in the subsample of European countries. (These results help us interpret the findings on European elections, which we present in Section 5.) In Column 1, we verify the first stage by showing that the expansion of 3G is associated with a significant increase in internet usage among European respondents. In Columns 2 and 3, we show that—similarly to the results for the global sample presented in Table 5—in Europe, the relationship between actual

¹⁷As discussed in Appendix Section A.1, when considering the whole world, focusing on the intensive margin of the discussions of corruption incidents in the EIU country reports makes more sense because, in very corrupt countries, the pervasiveness of corruption is well known to investors and, therefore, the EIU reports may focus on other aspects of the investment climate in those countries. The fact that the results are robust suggests, however, that, after partialling out the fixed effects, the variation in the index of actual corruption is meaningful in both samples.

and perceived corruption is stronger in those subnational regions that are covered by the 3G networks compared to the subnational regions without 3G coverage. This is true both for the sample focusing on the intensive-margin variation in actual corruption that excludes country×years with zero corruption incidents (Column 2), and for the full sample without such a restriction (Column 3).¹⁸

The Panama Papers.—On April 3, 2016, the Panama Papers, i.e., 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 from around the world in tax fraud and money laundering. Although offshore accounts are not *a priori* illegal and many private individuals use them, the Panama Papers revelations were particularly important in exposing corruption.¹⁹ We base our second measure of actual corruption on the number of unique offshore entities featured 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 cross-country variation in the number of Panama Papers entities per capita, assuming that this variation reflects the underlying level of corruption, which can partially be observed by independent journalists and the opposition). In all the regressions, we include our standard set of controls, including region and year fixed effects. To control for the potential confounding factor that people in rich regions are more likely to have knowledge 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 reported in Column 1 of Table 6. 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 underlying level of corruption, this result confirms that mobile internet helps expose corruption. 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 differ between these countries by one standard deviation. This difference in differences is equal to 5 percentage points. Panel B of Figure 5 illustrates this result by presenting the magnitude of the marginal effect of an increase in the level of corruption measured by the Panama Papers on the belief

¹⁸Note that the extensive-margin variation is more meaningful in Europe than in the whole world because the level of corruption in Europe is substantially lower than in some developing countries.

¹⁹See, for instance, 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 on January 19, 2020).

that the government is not corrupt by different levels of regional 3G coverage (implied by the estimates presented in Column 1 of Table 6.)

As the next step, we take into account 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 revelations. The effect for the period after is larger than for the period before (as presented in Column 2 of Table 6), but the difference in magnitude of these coefficients is not statistically significant.

The vast majority of 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 do not have 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.²⁰ As shown in Column 3, once low-income countries are excluded, the magnitude of the coefficient on the post-release period becomes larger, and the difference in magnitude between the pre-period and post-period effects becomes statistically significant (the p-value for this test is presented at the bottom of the table).

These results suggest that only a 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 of the 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 is significantly negative in the before period. The difference between the coefficients from before and after the scandal 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 post-period is statistically significant; the difference between the effects in pre- and post-periods remains statistically significant.

The ranking of exposure to the Panama Papers differs somewhat if one considers

²⁰We 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.

the total number of entities rather than the number of entities per capita. In particular, some large countries such as the US or Russia have a great 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. 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 the 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 pre-period.

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

5 Electoral consequences of 3G internet

The results above suggest that mobile internet is an important source of political information for voters. Does the expansion of internet access have electoral implications? The evidence from the previous literature (briefly discussed above) suggests that it does, but previous studies addressed this question in a single-country setting. We use panel data on election results in European democracies to examine the electoral effects of the expansion of mobile internet in the last decade. As mentioned above, we focus on Europe for several reasons. First, European democracies are broadly comparable. Second, Europe has recently experienced a significant rise of populism ([Rodrik, 2018](#)); we are particularly interested in whether the internet facilitates the electoral success of populist parties, as was suggested by many observers (e.g., [Tufekci, 2018](#)) and by previous research on Italy (e.g., [Campante, Durante and Sobbrío, 2018](#)). Furthermore, 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 estimate regression equations analogous to Specification (1) but aggregated to the level of the subnational districts, at which the elections data are available. In all specifications, we control for subnational-district and year fixed effects as well as a proxy for subnational district income (for which we use the best measure available to us, namely, nighttime light density), and 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.²¹

Our aim is to test whether the relationship between the expansion of 3G networks and a decline in government approval, which we have documented above, translates into tangible electoral losses for the incumbent parties. The empirical challenge is that the incumbent parties change over time. We address this challenge in two ways. First, we consider how the electoral support of the parties that initially were part of the establishment evolved depending on the expansion of mobile 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 of the ruling party, defined as the party of the country's top executive (i.e., 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 in time during our observation period. Next, we track the vote share of 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 together. In order 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.²²

The results are presented in Columns 1 and 2 of Table 7. In Column 1, the outcome is the vote share of the top two parties in the first observed election; in Column 2, it is the vote share of the incumbent party. Irrespective of the specification, we find that the expansion of 3G mobile networks reduces the incumbents' electoral support. We illustrate this relationship in Figure 6. The point estimates imply that an expansion of mobile networks from zero to full 3G coverage in a subnational district results in a 9-percentage-point lower vote share of the incumbent, both when the incumbents' vote share is proxied by the vote share of the two top parties from the first election (the sample mean is 56%), and when it is measured as the vote share of the ruling party (with the sample mean of 30%).

²¹We cannot use the IV strategy in the analysis of elections because lightning frequency 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.

²²In the first approach, the unit of observation is a subnational district in an election. In the second approach—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 \times 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.

In Column 3, we reestimate the specification presented in Column 2, allowing the effect to differ between populist and nonpopulist incumbents. We find that the expansion of 3G networks leads to a decrease in the incumbents' vote share irrespective of whether 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 that populist parties that were among the top two parties in the beginning of the period lost votes as a result of the expansion of mobile internet.

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 to participate in elections due to their disillusionment with the electoral institutions, consistent with our findings based on the Gallup World Poll. It also could be the case that potential voters lose interest in politics as a result of exposure to online entertainment.²³ Appendix Table A14 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 as a result of the expansion of mobile internet, some voters did change their political preferences. Taking turnout into account, the estimates (from Column 2 of Table A14) imply the persuasion rate of 8.2% of the message “do not vote for the ruling party.”

Taken together, these results strongly corroborate our findings on government approval from the Gallup World Poll.²⁴ The expansion of 3G mobile networks made voters more critical of their governments and resulted in worse electoral performance of the incumbents in Europe.

Which parties gain electoral support when incumbents lose it as a result of the 3G expansion? In Columns 1 to 5 of Table 8, we consider the effect on the vote shares of 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 share and find that the expansion of 3G networks has contributed to a stronger electoral performance of populist parties in Europe. Moving from zero to full 3G coverage, on average, results in an 8.6-percentage-point higher vote share of right-wing populists and a 6.7 percentage-point higher vote share of left-wing populists (Columns 1 and 2). The effects are large

²³Previous literature has found that political participation may increase or decrease with access to the internet depending on the setting; see literature review by [Zhuravskaya, Petrova and Enikolopov \(2020\)](#).

²⁴As shown above, the expansion of 3G networks led to a significant decline in government approval among European voters in rural areas (see Table A9). In Appendix Table A12, we also show that 3G has helped expose actual corruption incidents to the European voters.

relative to the mean vote shares of right-wing and left-wing populists, equal to 13.6% and 6.5%, respectively. As shown in Column 3, there is no effect on parties classified as “other populists” (i.e., those that are not classified as right-wing or left-wing). Not all 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 and the effects are large and statistically significant for all populists taken together. We find an 11.5-percentage-point increase in the vote share of all populists as a result of 3G expanding from no signal to full coverage (from the mean of 26%).

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 the 3G expansion (see Column 3 of Table 7).

Appendix Table A15 reports these results with the vote share expressed as the share of registered voters. The point estimates of the effects of 3G on the populists’ vote (total, right-wing, and left-wing) are smaller in magnitude, but remain statistically significant. The expansion of 3G availability from no signal to full coverage in a subnational district increases the electoral support of all populists as a share of registered voters by 4.7 percentage points (see Column 4), implying the persuasion rate of 5.6% of the message “vote for a populist party.”²⁵

Does the nonpopulist opposition also gain from the 3G expansion? Column 6 of Table 8 shows that 3G network availability has a precisely-estimated zero impact on the vote share of 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 2-3 of Table 7, 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, and the point estimate is actually negative. Figure 7 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 A9. We also present the nonparametric relationships illustrating the election results with controls partialled out from the treatment variable as well as from the outcome variables. Figure A7 shows the results

²⁵The 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 also when the vote is expressed as a share of registered voters.

for the incumbents' vote share; Figure A8—for the opposition.²⁶

Overall, we find that, in European democracies, only populist opposition parties benefit from the disillusionment of voters with incumbent governments as a result of the expansion of access to broadband mobile internet. If exposure to online criticism of incumbents were the only mechanism behind the fall in government approval with the expansion of internet access, one would expect all opposition parties to benefit from this phenomenon. Explaining why populists are the ones who gained from the mobile internet 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 the 3G expansion coincided with the time when the populist message resonated most with voters, so that they just turned to the opposition that was the most appealing to them. However, it could also be that the populists' message is particularly suited to the format of social media. In particular, the populists' rejection of the existing democratic institutions as entrenched and serving the elites implies that they should talk directly to the voters bypassing traditional media. Such direct contact on a large scale was made possible only with the arrival of social media. Furthermore, the populists' message may be simpler, and thus, better suited for a short and catchy communication than messages of other opposition parties.²⁷

6 Conclusions

This paper documents the political effects of the expansion of 3G mobile internet in a global setting. Our analysis yields the following main conclusions. The expansion of mobile internet networks in the last decade has, on average, led to a significant reduction in government approval across the world. However, there is substantial heterogeneity in this effect with respect to the censorship of the internet and of the traditional media. Government approval falls with the expansion of 3G only when there is no internet censorship. However, government approval is more affected by the expansion of 3G networks if the traditional media is censored, but the internet is not. Broadband mobile internet is an important medium for providing voters with independent-of-the-government political information; in particular, it helps expose incidents of actual corruption to the public.

In Europe, the expansion of 3G mobile networks has had electoral implications.

²⁶We also verify that the results are robust to excluding countries with compulsory voting: Belgium, Liechtenstein, and Luxembourg.

²⁷Consider, 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 the economic and social problems to the elites and foreigners, suggesting that those are the ones who should bear the costs of change.

As 3G increases discontent with the government, the incumbent parties' vote shares decline. These electoral losses of incumbent parties are accompanied with a decrease in turnout and with electoral gains for populist parties, both on the right and on the left of political spectrum. The 3G expansion has not helped the nonpopulist opposition, including the environmentalist parties.

Our comparative analysis shows that providing unbiased political information to voters is an important channel through which the internet affects attitudes toward incumbent governments. However, the results for the European elections suggest that informing the public is not the only channel behind the political effects of the 3G expansion, as only populist opposition parties have capitalized on the fall in government approval associated with an increase in broadband mobile internet use.

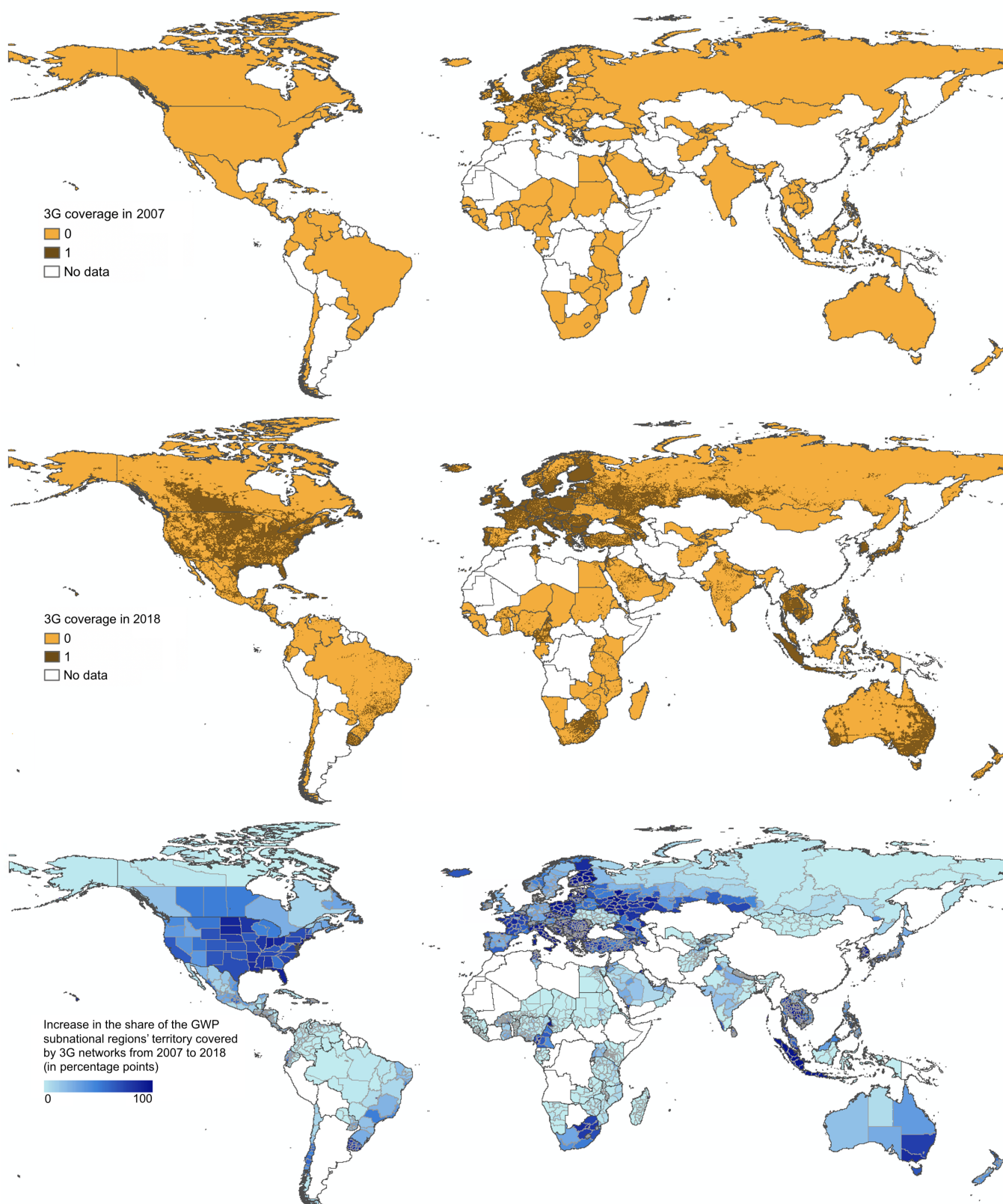
References

- Algan, Yann, Sergei Guriev, Elias Papaioannou, and Evgenia Passari.** 2017. "The European Trust Crisis and the Rise of Populism." *Brookings Papers on Economic Activity*, 309–382.
- Allcott, Hunt, and Matthew Gentzkow.** 2017. "Social Media and Fake News in the 2016 Election." *Journal of Economic Perspectives*, 31(2): 211–236.
- Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber.** 2005. "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools." *Journal of Political Economy*, 113(1): 151–184.
- Campante, Filipe, Ruben Durante, and Francesco Sobbrío.** 2018. "Politics 2.0: The Multifaceted Effect of Broadband Internet on Political Participation." *Journal of the European Economic Association*, 16(4): 1094–1136.
- Chen, Yuyu, and David Yang.** 2019. "The Impact of Media Censorship: 1984 or Brave New World?" *American Economic Review*, 109(6): 2294–2332.
- Collela, Fabrizio, Rafael Lalive, Seyhun Orcan Sakalli, and Mathias Thoenig.** 2018. "Inference with arbitrary clustering." University of Lausanne, Mimeo.
- Conley, T.G.** 1999. "GMM estimation with cross sectional dependence." *Journal of Econometrics*, 92(1): 1–45.
- Diamond, Larry, and Marc F. Plattner.** 2010. "Liberation Technology." *Journal of Democracy*, 21: 69–83.
- Diamond, Larry, and Marc F. Plattner,** ed. 2012. *Liberation Technology: Social Media and the Struggle for Democracy (A Journal of Democracy Book)*. Johns Hopkins University Press.

- Donati, Dante.** 2017. “Mobile Internet access and political outcomes: Evidence from South Africa.” Universitat Pompeu Fabra, Mimeo.
- Enikolopov, Ruben, Alexey Makarin, and Maria Petrova.** forthcoming. “Social Media and Protest Participation: Evidence from Russia.” *Econometrica*.
- Falck, Oliver, Robert Gold, and Stephan Heblich.** 2014. “E-lections: Voting Behavior and the Internet.” *American Economic Review*, 104(7): 2238–65.
- Fergusson, Leopoldo, and Carlos Molina.** 2019. “Facebook Causes Protests.” Universidad de los Andes. mimeo.
- Furceri, Davide, Chris Papageorgiou, and Hites Ahir.** 2019. “Global Incidents of Corruption Index.” IMF.
- Gavazza, Alessandro, Mattia Nardotto, and Tommaso Valletti.** 2019. “Internet and Politics: Evidence from U.K. Local Elections and Local Government Policies.” *The Review of Economic Studies*, 86(5): 2092–2135.
- Goodman-Bacon, Andrew.** 2018. “Differences-in-Differences with Variation in Treatment Timing.” NBER Working Paper No. 25018.
- Grinberg, Nir, Kenneth Joseph, Lisa Friedland, Briony Swire-Thompson, and David Lazer.** 2019. “Fake News on Twitter during the 2016 U.S. Presidential Election.” *Science*, 363(6425): 374–378.
- Guess, Andrew, Jonathan Nagler, and Joshua Tucker.** 2019. “Less than You Think: Prevalence and Predictors of Fake News Dissemination on Facebook.” *Science Advances*, 5(1): eaau4586.
- Henderson, Vernon, Adam Storeygard, and David Weil.** 2011. “A Bright Idea for Measuring Economic Growth.” *American Economic Review*, 101(3): 194–199.
- Henderson, Vernon, Adam Storeygard, and David Weil.** 2012. “Measuring Economic Growth from Outer Space.” *American Economic Review*, 102: 994–1028.
- Hsiang, Solomon.** 2010. “Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America.” *Proceedings of the National Academy of Sciences*, 107(35): 15367–15372.
- ITU.** 2019. *Measuring digital development. Facts and figures 2019*. ITUPublications: Geneva, Switzerland.
- King, Gary, Jennifer Pan, and Margaret E. Roberts.** 2013. “How Censorship in China Allows Government Criticism but Silences Collective Expression.” *American Political Science Review*, 107(2 (May)): 1–18.
- King, Gary, Jennifer Pan, and Margaret E. Roberts.** 2014. “Reverse-Engineering Censorship in China: Randomized Experimentation and Participant Observation.” *Science*, 345(6199): 1–10.

- Manacorda, Marco, and Andrea Tesei.** forthcoming. “Liberation Technology: Mobile Phones and Political Mobilization in Africa.” *Econometrica*.
- Miner, Luke.** 2015. “The unintended consequences of Internet diffusion: Evidence from Malaysia.” *Journal of Public Economics*, 132(C): 66–78.
- Mitchell, Amy, Jeffrey Gottfried, Sophia Fedeli, Galen Stocking, and Mason Walker.** 2019. “Many Americans Say Made-Up News Is a Critical Problem That Needs To Be Fixed | Pew Research Center.” Pew Research Center.
- Morozov, Evgeny.** 2011. “The Net Delusion: The Dark Side of Internet Freedom.” *Public Affairs, New York*.
- Oster, Emily.** 2017. “Unobservable Selection and Coefficient Stability: Theory and Evidence.” *Journal of Business & Economic Statistics*, 37(2): 187–204.
- Qin, Bei, David Stromberg, and Yanhui Wu.** 2017. “Why Does China Allow Freer Social Media? Protests versus Surveillance and Propaganda.” *Journal of Economic Perspectives*, 31(1): 117–140.
- Roberts, Margaret E.** 2018. *Censored: Distraction and Diversion Inside China’s Great Firewall*. Princeton University Press.
- Rodrik, Dani.** 2018. “Populism and the economics of globalization.” *Journal of International Business Policy*, 1(1-2): 12–33.
- Schaub, Max, and Davide Morisi.** 2019. “Voter mobilization in the echo chamber: Broadband internet and the rise of populism in Europe.” Collegio Carlo Alberto. mimeo.
- Schulman, Aaron, and Neil Spring.** 2011. “Pingin’ in the Rain.” *Internet Measurement Conference (IMC)*. <https://cseweb.ucsd.edu/~schulman/docs/imc11-thunderping.pdf>.
- Tufekci, Zeynep.** 2018. “How social media took us from Tahrir Square to Donald Trump.” MIT Technology Review.
- Vosoughi, Soroush, Deb Roy, and Sinan Aral.** 2018. “The spread of true and false news online.” *Science*, 359: 1146–1151.
- Young, Alwyn.** 2020. “Consistency without Inference: Instrumental Variables in Practical Application.” London School of Economics. mimeo.
- Zhuravskaya, Ekaterina, Maria Petrova, and Ruben Enikolopov.** 2020. “Political Effects of the Internet and Social Media.” *Annual Review of Economics*, 12. DOI: <https://doi.org/10.1146/annurev-economics-081919-050239>.

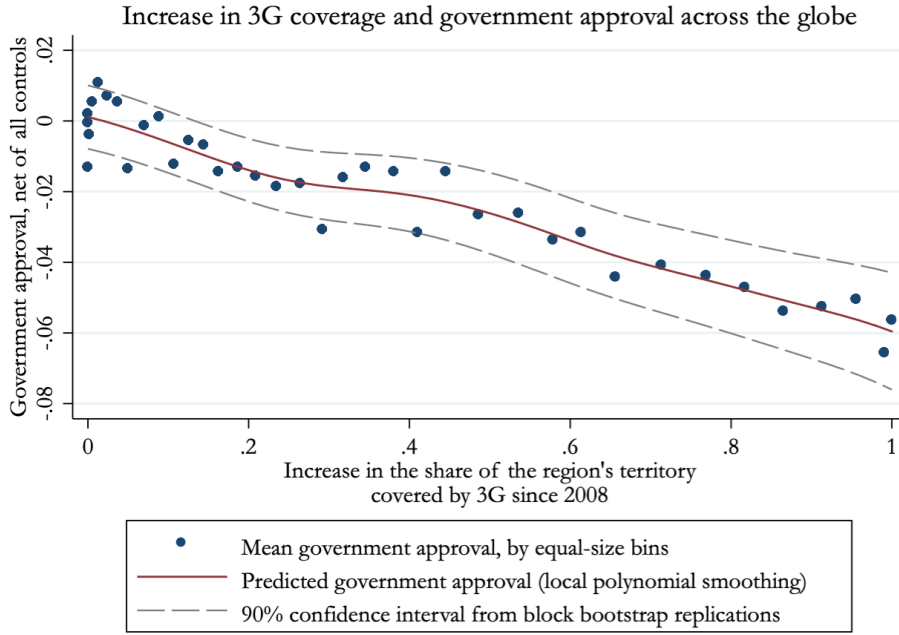
Figure 1: The growth of 3G network coverage between 2007 and 2018



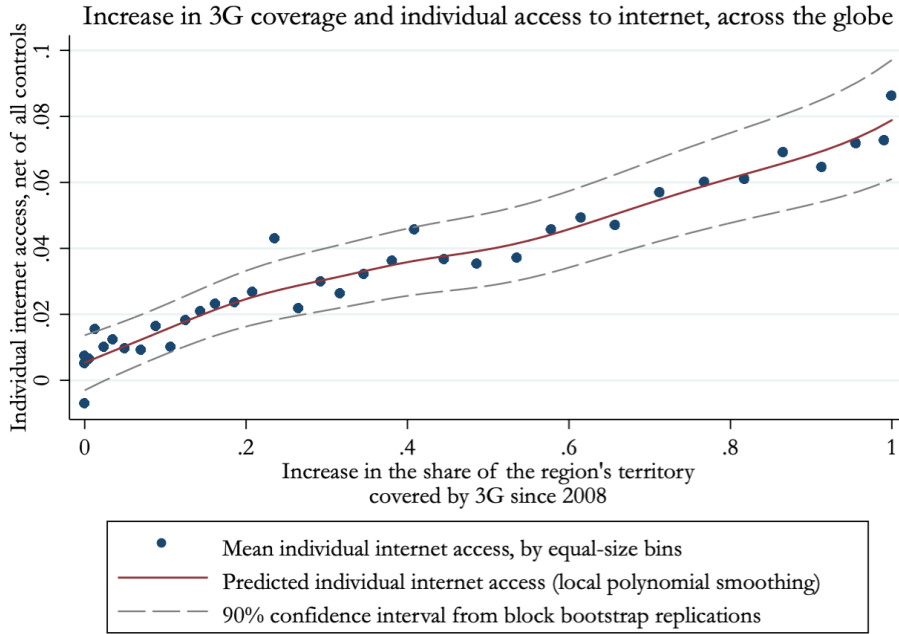
Note: The first two maps present 3G network coverage by grid cell in 2007 and in 2018. The third map presents: 1) the boundaries of the subnational regions, the unit of localization in the GWP data and 2) the increase in the share of the subnational regions' territory covered by 3G networks from 2007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

Figure 2: Increase in 3G coverage and confidence in government

Panel A

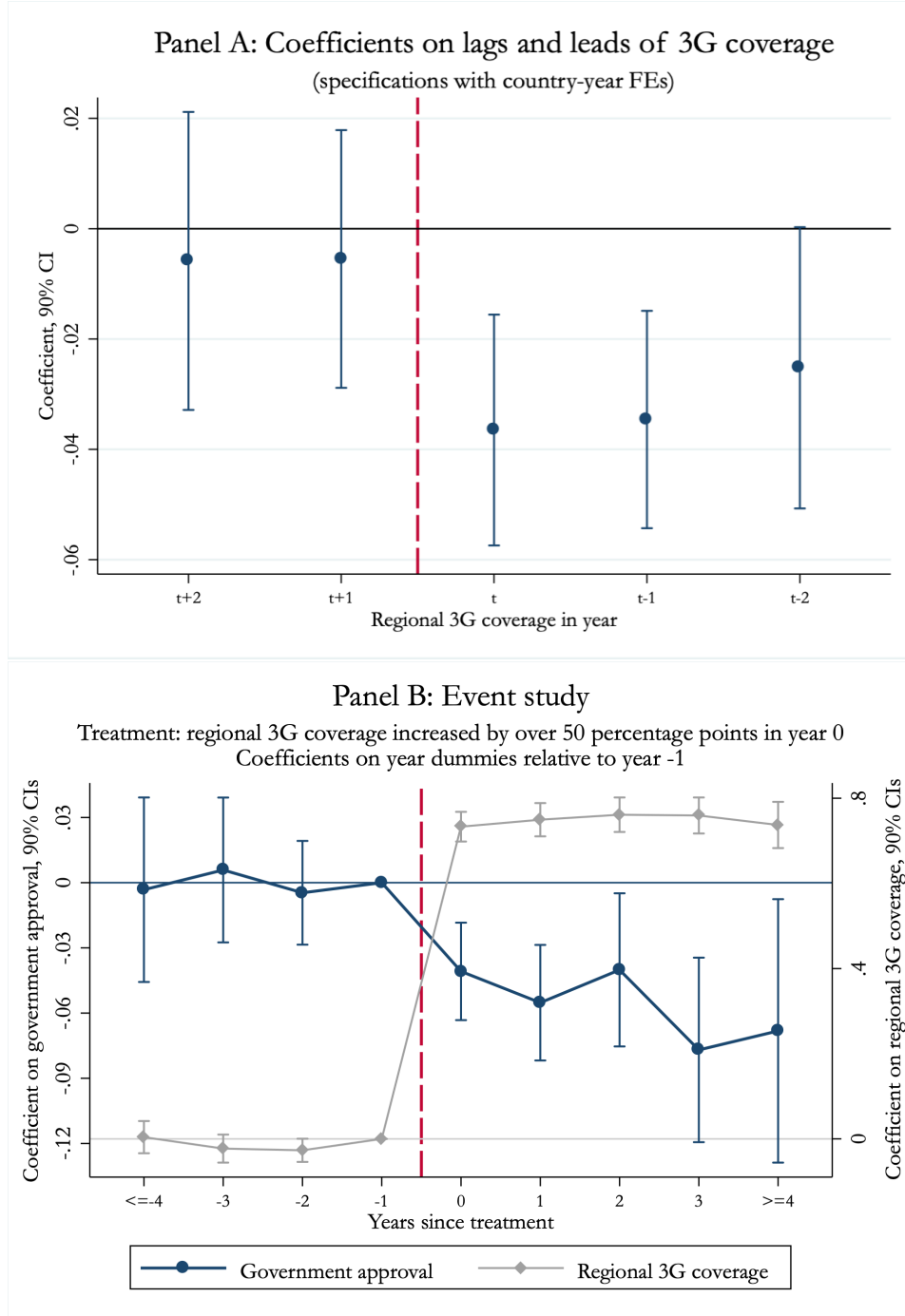


Panel B



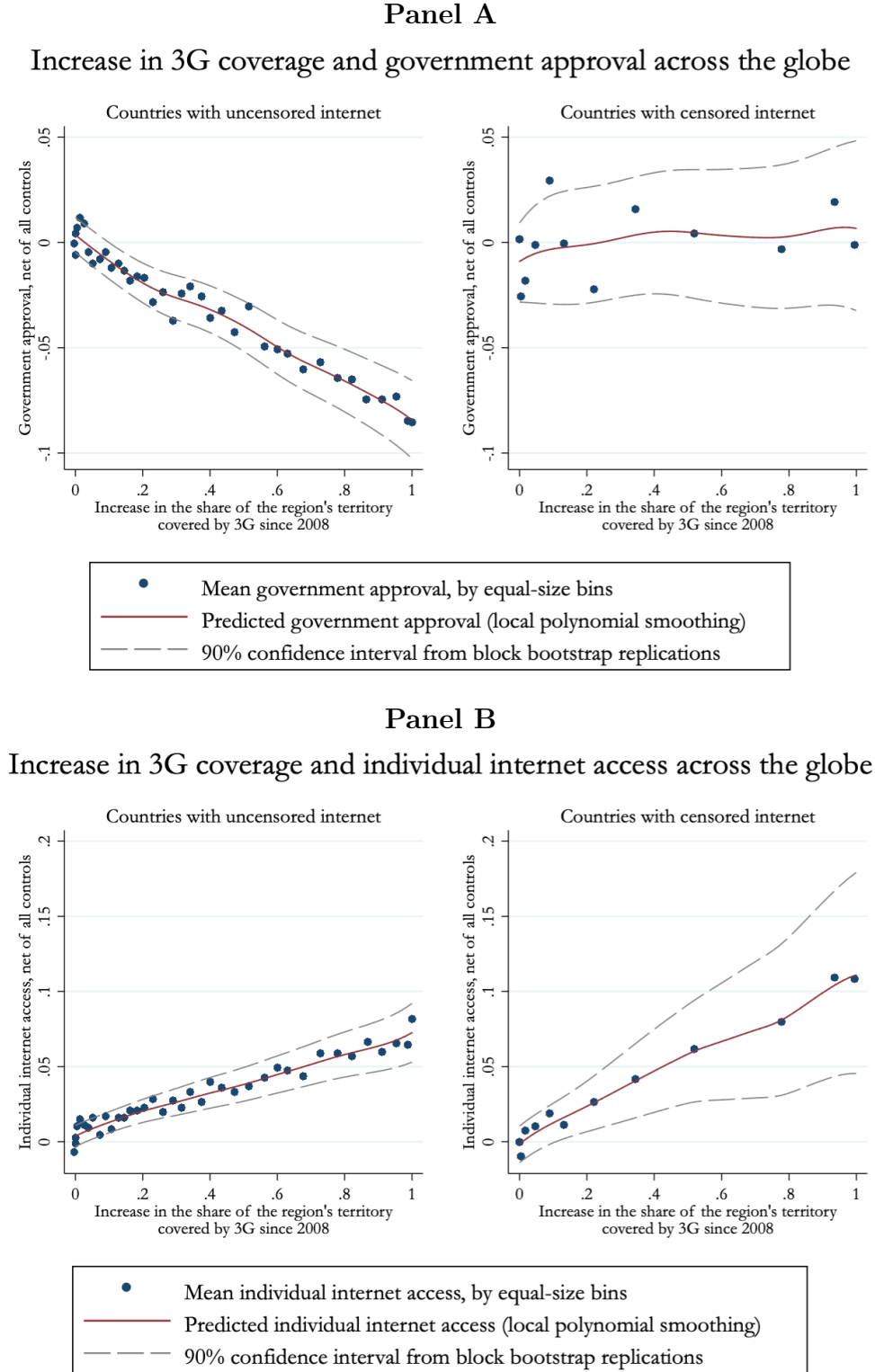
Note: Panel A of the figure illustrates the relationship between regional 3G coverage and government approval (Column 7 of Panel A of Table 1). Panel B of the figure illustrates the relationship between the increase in regional 3G coverage and individual internet access (Column 1 of Panel A of Table 1). The dots show the means of the respective outcome variables net of all the 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 3: Pre-trend analysis



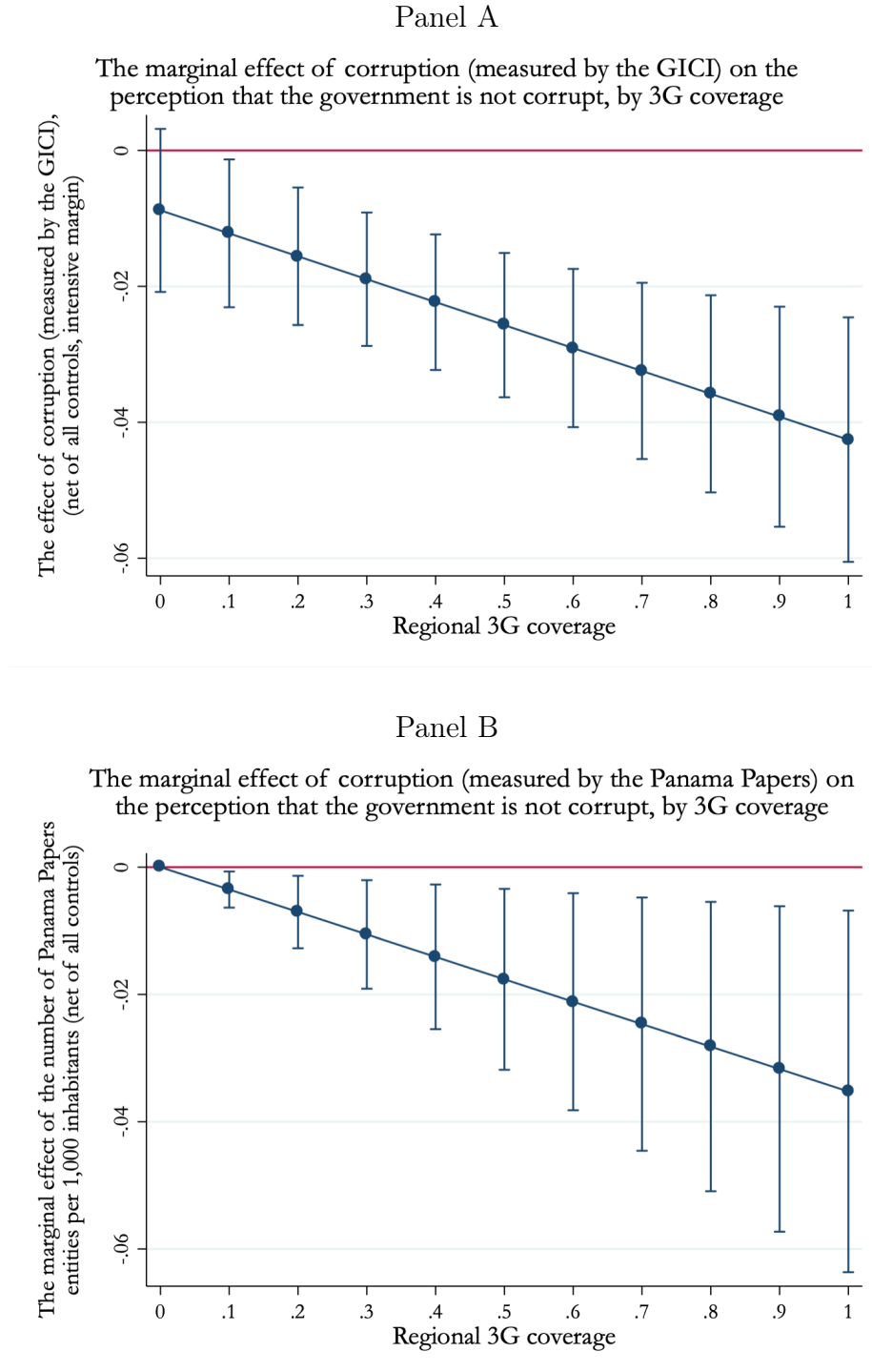
Note: Panel A presents the coefficients from the regressions of government approval on the lags and leads of 3G coverage in the full sample, controlling for country-year fixed effects and all the baseline controls. Each coefficient is from a separate regression. Panel B presents an event study, in which government approval (left axis) and 3G coverage (right axis) are regressed on a set of year dummies around treatment defined as an annual increase in regional 3G coverage of more than 50 percentage points. The regressions are run on the subsample of 422 regions in 63 countries, where 3G did increase sharply once over the sample period. The number of observations is 116,932. 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. Both panels of the figure show that future expansions of 3G networks are not associated with current changes in government approval, confirming the parallel pre-trends assumption required for identification.

Figure 4: Increase in 3G coverage and confidence in government, depending on internet censorship



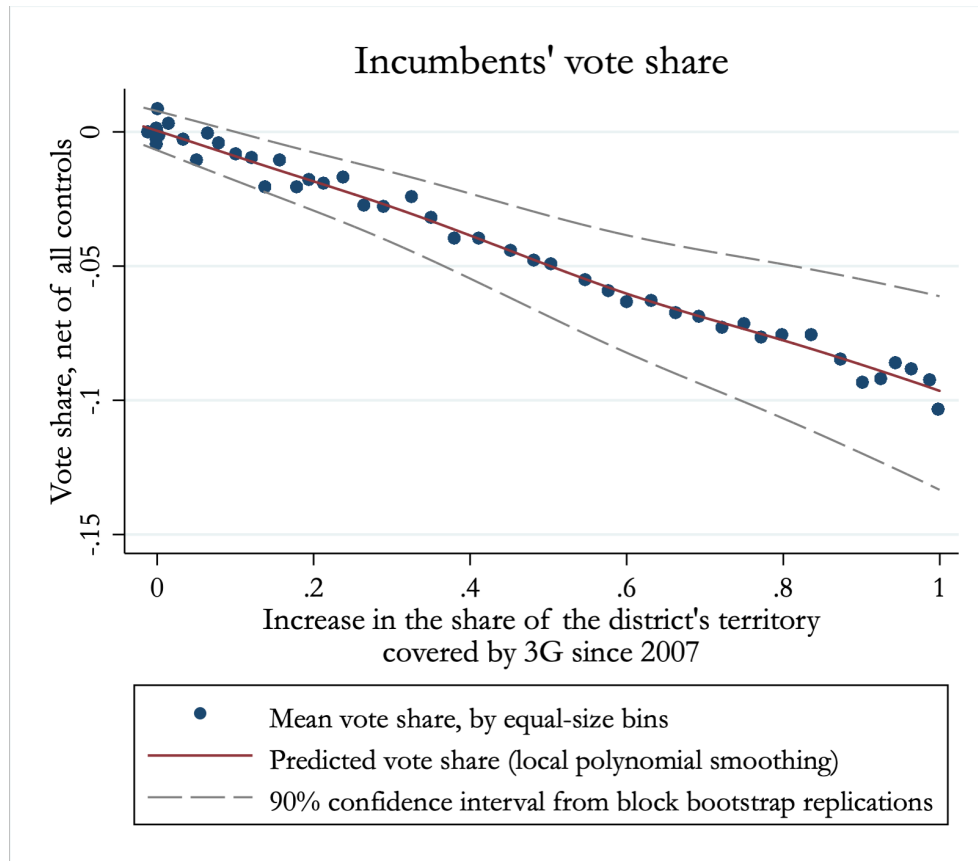
Note: Panel A of the figure illustrates the results presented in Column 6 of Panel A of Table 4, showing the relationship between the increase in regional 3G coverage and government approval separately for countries with high and low levels of censorship of the internet. Panel B of the figure illustrates the relationship between the increase in regional 3G coverage and individual internet access (as in Column 1 of Panel A of Table 1) for countries with high and low levels of internet censorship. The dots show the means of the respective outcome variables net of all the 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 5: 3G network coverage, actual and perceived corruption



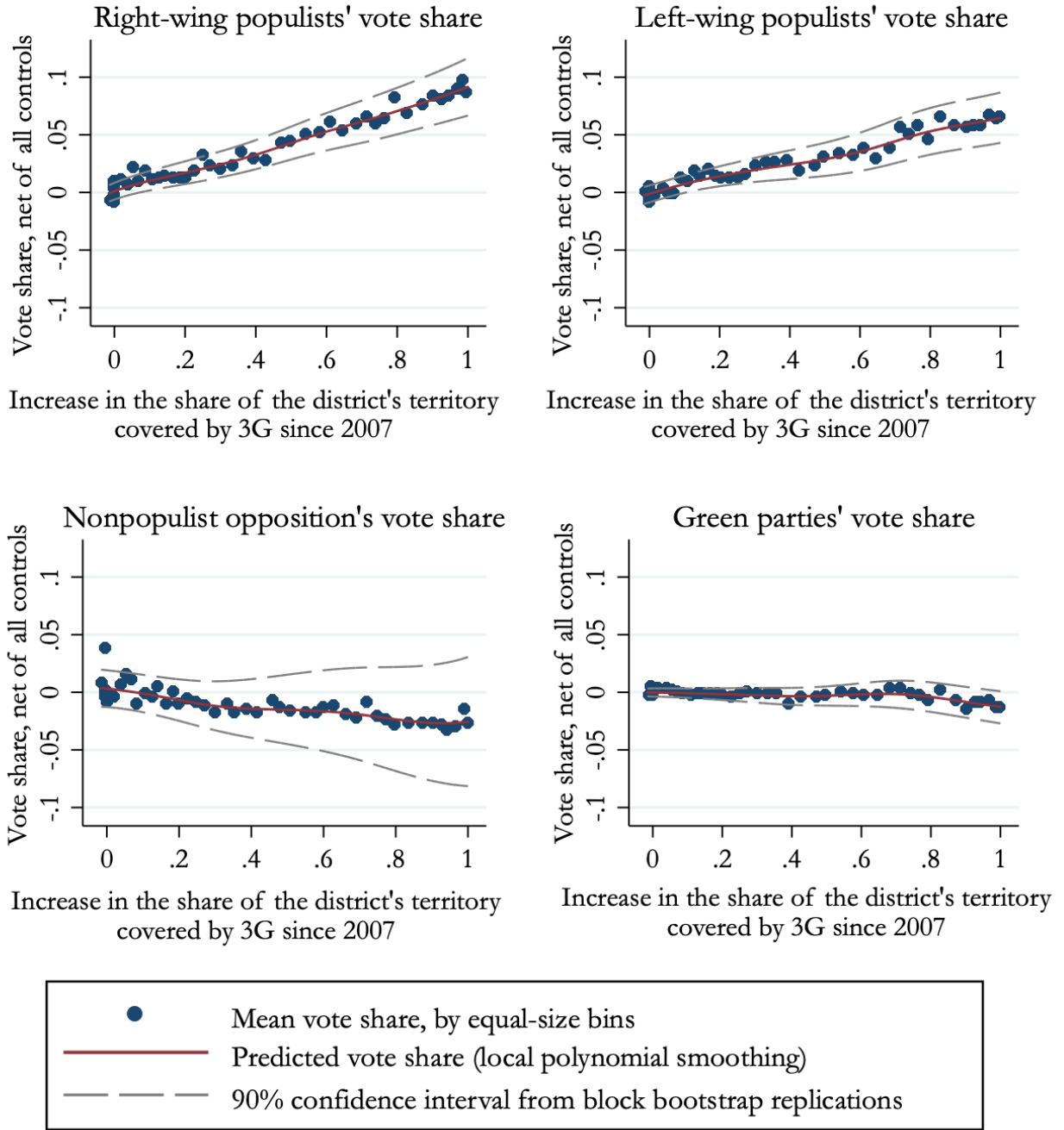
Note: The outcome variable is a dummy for the perception that there is no corruption in government. In Panel A, the explanatory variables are: regional 3G coverage, log actual corruption (measured by the GICI), their interaction term, as well as all the baseline controls, including region and year fixed effects. The index of actual corruption is based on the IMF's Global Incidents of Corruption Index (GICI). 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. 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 6: Electoral implications of the expansion of 3G coverage: Incumbents



Note: The figure illustrates the results presented in Column 2 of Table 7. The dots represent the vote shares net of all the 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 7: Electoral implications of the expansion of 3G coverage: Opposition



Note: The plots on the first row illustrate the results presented in Columns 1 and 2 of Table 8. The plots on the second row illustrate the results presented in Columns 6 and 5 of Table 8. The dots represent the vote shares net of all the controls by equal-size bins. The solid lines on the graphs 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 1: The effect of the internet on confidence in government

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|--|---|---|----------------------------------|-------------------------|--------------------------------|--|--|
| <i>Dep. Var.:</i> | Individual access to the internet | 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 | 0.080*** (0.017) | -0.063*** (0.021) | -0.040*** (0.015) | -0.079*** (0.021) | -0.036** (0.014) | -0.056*** (0.015) | -0.057*** (0.015) |
| R-squared | 0.482 | 0.164 | 0.163 | 0.168 | 0.225 | 0.242 | 0.239 |
| Observations | 840,537 | 772,353 | 748,471 | 732,856 | 722,768 | 617,863 | 617,863 |
| Mean dep. var. | 0.440 | 0.514 | 0.534 | 0.505 | 0.226 | 0.432 | 0.439 |
| Number of countries | 116 | 111 | 116 | 112 | 112 | 110 | 110 |
| Panel B: Subsample of rural residents | | | | | | | |
| Regional 3G coverage | 0.083*** (0.017) | -0.091*** (0.024) | -0.058*** (0.017) | -0.115*** (0.026) | -0.054*** (0.016) | -0.080*** (0.018) | -0.081*** (0.018) |
| R-squared | 0.502 | 0.171 | 0.157 | 0.161 | 0.194 | 0.224 | 0.222 |
| Observations | 501,957 | 464,831 | 448,449 | 440,786 | 432,460 | 371,055 | 371,055 |
| Mean dep. var. | 0.350 | 0.539 | 0.556 | 0.516 | 0.215 | 0.445 | 0.452 |
| Number of countries | 115 | 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. Column 1 presents the results of the estimation of Specification 2, and Columns 2–7 present the results of the estimation of Specification 1. The dependent variable in Column 1 is a dummy for individual access to the internet. The dependent variables in Columns 2–7 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 2: The effect of 2G coverage on internet usage and confidence in government

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|----------------------------------|-------------------------|--------------------------------|--|--|
| <i>Dep. Var.:</i> | Individual access to the internet | 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: The effect of 2G on internet access and confidence in the government | | | | | | | |
| Regional 2G coverage | -0.013 (0.020) | 0.045 (0.029) | 0.031 (0.020) | 0.098*** (0.030) | 0.054*** (0.019) | 0.056*** (0.021) | 0.056** (0.022) |
| Observations | 840,537 | 772,353 | 748,471 | 732,856 | 722,768 | 617,863 | 617,863 |
| Mean dep. var. | 0.44 | 0.514 | 0.534 | 0.505 | 0.226 | 0.432 | 0.439 |
| Panel B: The effect of 3G and 2G on internet access and confidence in the government | | | | | | | |
| Regional 3G coverage | 0.080*** (0.017) | -0.060*** (0.020) | -0.038*** (0.015) | -0.074*** (0.020) | -0.032** (0.014) | -0.053*** (0.015) | -0.053*** (0.015) |
| Regional 2G coverage | -0.002 (0.019) | 0.037 (0.028) | 0.026 (0.019) | 0.088*** (0.030) | 0.049** (0.019) | 0.048** (0.021) | 0.048** (0.021) |
| Observations | 840,537 | 772,353 | 748,471 | 732,856 | 722,768 | 617,863 | 617,863 |
| Mean dep. var. | 0.440 | 0.514 | 0.534 | 0.505 | 0.226 | 0.432 | 0.439 |
| 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 individual internet usage 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. Column 1 presents the results for individual access to the internet, Columns 2-7—for government approval. Other 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 3: Lightning strikes, 3G coverage, and government approval

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|-------------------------|---|-------------------------|---|--|---|-------------------------|---|
| <i>Dep. Var.:</i> | 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 |
| <i>Stage, 2SLS:</i> | 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 |
| <i>Countries in the sample:</i> | All countries | | | | Countries with below-median GDP per capita | | | |
| <i>Respondents in the sample:</i> | All | All | Rural | Rural | All | All | Rural | Rural |
| Regional 3G coverage | | -0.227** (0.097) | | -0.313** (0.138) | | -0.245** (0.106) | | -0.359** (0.149) |
| 1[High frequency of lightning strikes] × Year × × 1[GDP per capita below median] | -0.029*** (0.006) | | -0.022*** (0.006) | | -0.026*** (0.006) | | -0.020*** (0.005) | |
| 1[High frequency of lightning strikes] × Year × × 1[GDP per capita above median] | 0.001 (0.006) | | -0.001 (0.007) | | | | | |
| Observations | 617,863 | 617,863 | 371,055 | 371,055 | 303,601 | 303,601 | 213,460 | 213,460 |
| F-stat, excluded instrument | | 10.52 | | 7.31 | | 19.31 | | 13.99 |
| Corresponding OLS estimate on regional 3G coverage | | | | | | -0.119*** (0.027) | | -0.166*** (0.029) |
| Subnational region FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Baseline controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FEs separately for countries with below- and above-median GDP per capita | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Note: *** p<0.01, ** p<0.05, * p<0.1. The table presents the results of an IV analysis, where the the frequency of lightning strikes in a subnational region is used as an IV for the expansion of regional 3G coverage. The methodology follows [Manacorda and Tesei \(forthcoming\)](#). High frequency of lightning strikes is defined by the subnational region being in the top quartile of the distribution of lightning strikes. 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 separate year dummies for countries with below- and above-median GDP per capita. 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 4: 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

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|-----------------------------------|-------------------------------|----------------------|-----------------------------|--|--------------------------------------|
| <i>Dep. Var.:</i> | 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: Dummy for high internet censorship | | | | | | |
| Regional 3G coverage | -0.100*** (0.023) | -0.057*** (0.016) | -0.117*** (0.021) | -0.054*** (0.016) | -0.081*** (0.016) | -0.082*** (0.016) |
| Regional 3G coverage × Censored internet dummy | 0.105** (0.041) | 0.037 (0.029) | 0.173*** (0.043) | 0.054* (0.029) | 0.093*** (0.034) | 0.094*** (0.035) |
| 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: Continuous measure of internet censorship | | | | | | |
| Regional 3G coverage | -0.190*** (0.059) | -0.108*** (0.035) | -0.215*** (0.055) | -0.083** (0.037) | -0.129*** (0.042) | -0.131*** (0.043) |
| Regional 3G coverage × Censorship of the internet | 0.072** (0.033) | 0.039** (0.019) | 0.106*** (0.034) | 0.025 (0.023) | 0.047* (0.028) | 0.048* (0.028) |
| 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 C: Continuous measure of internet censorship and continuous measure of censorship of the traditional press | | | | | | |
| Regional 3G coverage | -0.226*** (0.056) | -0.099** (0.042) | -0.294*** (0.065) | -0.140*** (0.039) | -0.159*** (0.045) | -0.160*** (0.045) |
| Regional 3G coverage × Censorship of the internet | 0.199*** (0.047) | 0.075** (0.035) | 0.223*** (0.055) | 0.089*** (0.031) | 0.127*** (0.038) | 0.129*** (0.038) |
| Regional 3G coverage × Censorship of the traditional media | -0.064*** (0.020) | -0.020 (0.013) | -0.043** (0.018) | -0.022* (0.012) | -0.039*** (0.013) | -0.039*** (0.013) |
| 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 |
| Subnational region & year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Baseline controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Censorship controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Censorship of the internet significantly reduces the effect of 3G internet on government approval, while censorship of the traditional media significantly increases it. The unit of observation is an individual. The dependent variables are individuals' perceptions of government and the country's institutions. Censorship of the internet is measured using the Limits on Content component of the Freedom on the Net (FOTN) index. In Panel A, it is used as a dummy which is equal to one if the Limits on Content index is 22 or above and zero if the Limits on Content index is below 22 or if the Limits on Content index is unavailable but a country is a democracy according to the Polity IV dataset (i.e., if the Polity2 score is 6 or above). Censorship of the traditional press is measured using Freedom House's Freedom of the Press score (with 0 = free press and 100 = fully censored press). The mean of the latter is subtracted before creating the interaction with 3G coverage. All regressions include the measure of internet censorship itself (either the dummy, Panel A, or the continuous Limits on Content index, Panel B and Panel C). In Panel C, we also include dummies for all levels of censorship of the traditional media in order to flexibly control for it. Other 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 5: The relationship between actual and perceived corruption;
checking for pre-trends in corruption

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|--|---|----------------------|----------------------|----------------------|--|-------------------------------|------------------|
| <i>Test:</i> | Relationship between actual and perceived corruption | | | | Pre-trends in corruption incidents? | | |
| <i>Dep. Var.:</i> | Perception of no corruption in government | | | | Regional 3G coverage | Index of actual corruption | |
| <i>Sample:</i> | All | Rural | All | Rural | All | All | All |
| Regional 3G coverage \times Index of actual corruption | -0.034*** (0.011) | -0.031** (0.014) | -0.042*** (0.010) | -0.052*** (0.012) | | | |
| Index of actual corruption | -0.009 (0.006) | -0.012* (0.007) | -0.006 (0.006) | -0.006 (0.006) | -0.008 (0.014) | | |
| Regional 3G coverage | -0.074*** (0.019) | -0.090*** (0.021) | -0.088*** (0.019) | -0.118*** (0.020) | | | |
| Index of actual corruption, lagged | | | | | | -0.014 (0.013) | |
| Regional 3G coverage, lagged | | | | | | | 0.066 (0.108) |
| Observations | 581,944 | 354,966 | 691,872 | 414,346 | 727,935 | 727,935 | 702,013 |
| R-squared | 0.151 | 0.127 | 0.227 | 0.193 | 0.844 | 0.844 | 0.571 |
| Subnational region & year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Baseline controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Sample extended to cases of zero corruption | | | ✓ | ✓ | | | |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. In Columns 1-4, the outcome variable is a dummy for the perception that there is no corruption in government. In Columns 5 and 6, the outcome variable is regional 3G coverage. In Column 7, the outcome variable is the index of actual corruption incidents. The index of actual corruption incidents is based on the IMF's Global Incidents of Corruption Index (GICI), see the Appendix for details. In Columns 1-2 and 5-7, we use the baseline variation in the index of actual corruption, i.e., restricting the sample to country \times year observations with strictly positive GICI. In Columns 3 and 4, we document robustness to extending the sample to all country \times years with defined 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 6: 3G coverage, the number of entities in the Panama Papers, and perceived corruption

| | (1) | (2) | (3) | (4) | (5) | (6) |
|--|---|---------------------|--------------------------------|---------------------|----------------------|----------------------|
| <i>Dep. Var.:</i> | Perception of no corruption in government | | | | | |
| <i>Countries in the sample:</i> | 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** (0.014) | -0.033** (0.014) | | | |
| × Number of Panama Papers entities per capita × After Panama Papers | | -0.037** (0.018) | -0.048*** (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) |
| <i>p-value $\beta(\text{Before Panama Papers}) = \beta(\text{After Panama Papers})$</i> | | 0.490 | 0.055* | 0.058* | 0.073* | 0.0095*** |
| 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 |
| 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 7: The effect of 3G coverage on the incumbents' electoral performance in Europe

| | (1) | (2) | (3) | (4) | (5) |
|--|--|--|---|---------------------|----------------------|
| <i>Dep. Var.:</i> | 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 | |
| <i>Unit of observation:</i> | District-year | District-year-incumbent | District-year | District-year | |
| District 3G coverage | -0.089** (0.045) | -0.089*** (0.031) | | -0.090** (0.036) | -0.038*** (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 |
| 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 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. 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 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 8: The effect of 3G coverage on the opposition's electoral performance in Europe

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|--|-------------------------|------------------------|--------------------|---------------------|---------------------|-------------------|------------------------------------|
| <i>Dep. Var.:</i> | Vote share of: | | | | | | |
| | Right-wing populists | Left-wing populists | Other populists | All populists | All populists | Green parties | Nonpopulist opposition |
| <i>Unit of observation:</i> | District-year | District-year | District-year | District-year | District-year | District-year | District-year- ruling coalition |
| District 3G coverage | 0.086*** (0.024) | 0.067*** (0.022) | -0.038 (0.024) | 0.115*** (0.039) | 0.129*** (0.042) | -0.007 (0.012) | -0.030 (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 |
| 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. In Columns 1-6, 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).

A Online Appendix

A.1 Data description

In this section, we present the details about the data. Table A1 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, come from the Gallup World Poll (GWP), annual worldwide surveys conducted by Gallup.²⁸ 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. Most interviews are conducted face to face. In particular, this is the case in Central and Eastern Europe, most of Latin America, former Soviet states, nearly all of Asia, the Middle East and Africa. The rest of the interviews are conducted via telephone, which only happens in countries where telephone penetration is over 80%.

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 individuals’ internet access 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, 3G mobile networks come from Collins Bartholomew’s Mobile Coverage Explorer. As a placebo, we also use data on 2G mobile networks from the same source.²⁹ 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. Despite the large number of countries included in the dataset, as shown in Figure 1, 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.

To combine mobile network coverage data with the GWP surveys, we calculate the share of the subnational region’s territory covered by mobile networks at the level of localization of the GWP data, weighted by population density at each point on the

²⁸These data are described here: <https://www.gallup.com/analytics/232838/world-poll.aspx> (accessed on May 22, 2019).

²⁹These data are described here: <https://www.collinsbartholomew.com/map-data-products/vector-map-data/mobile-coverage-explorer/> (accessed on May 22, 2019).

map.³⁰ We perform this procedure separately for each subnational region and year, for which both the GWP and mobile coverage data are available. We then merge the shares of region’s territory covered by 3G and by 2G to the data from the GWP.

The resulting dataset used in the analysis covers 840,538 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 the 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 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 provided by the Norwegian Centre for Research Data (NSD).³¹ 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.³² 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 A9). The data cover 398 subnational districts.³³ 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-

³⁰The proxy for population density 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).

³¹The data are available at: <https://nsd.no/european-election-database> (accessed on February 7, 2020).

³²The data are available at: <http://electionresources.org/> (accessed on February 7, 2020).

³³For 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.

wing populist, when the words “populist” or “populism” are used in one sentence with “right-wing” and “left-wing.” In addition, all populist parties 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 A16.

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 A17.

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 Polity2 score of the Polity IV dataset.³⁴ 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 ($\text{Polity2} > 5$) and a dummy that a country in this particular year is an advanced democracy ($\text{Polity2} > 7$).

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.³⁵ These data are available at the country-year level, but cover only 46 countries 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. In addition to the continuous measure of Limits on Content, we construct a dummy for a high level of online censorship. A country in a particular year is considered to have high censorship on the net if its Limits on Content score is 22 or above. A country is considered to have low internet censorship 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, corresponding to the level of a democracy. The inclusion of democracies as countries with low censorship allows us to increase the size of the sample. Among democracies that have non-missing 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 2015, Thailand’s Polity2 score decreased from 7 to -3. The resulting dummy for high/low censorship is defined for 100 countries in our sample.

We also use data from Freedom House’s Freedom of the Press index.³⁶ As the

³⁴It is available at: <http://www.systemicpeace.org/inscrdata.html> (accessed on May 22, 2019).

³⁵The index is described here: <https://freedomhouse.org/report/freedom-net-methodology> (accessed on May 22, 2019).

³⁶These data are available here: <https://freedomhouse.org/report-types/freedom-press> (ac-

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. We define the index of actual corruption as $\ln(0.1 + GICI)$ for each country \times year. The reason behind this transformation is that it makes the distribution of the resulting index resemble a normal distribution. Our results are fully robust to using the raw GICI index as well as adding 1 instead of 0.1 to the GICI before taking the logarithm. We use this measure in two alternative samples. The baseline sample uses only for the subset of country \times 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. We also report results using the entire sample that includes country \times years with zero corruption incidents according to the GICI. 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.³⁷ 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 2013.³⁸ The VIIRS data are available for 2015-2016.³⁹ We impute nighttime light density in 2014 by

cessed on May 22, 2019).

³⁷These data are described and can be downloaded here: <https://offshoreleaks.icij.org/pages/database> (accessed on January 1, 2020).

³⁸They are described here: <https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html> (accessed on May 22, 2019).

³⁹They are described here: https://ngdc.noaa.gov/eog/viirs/download_dnb_composites.html (accessed on May 22, 2019).

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 the Appendix Section A.2, 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.—Finally, we use the World Wide Lightning Location Network (WWLLN) dataset to measure the frequency of lightning strikes per region during our observation period.⁴⁰ These data provide the exact coordinates and time of all detected lightning strikes for the entire globe. We calculate the total number of lightning strikes per subnational region between the January 1st, 2008 and the December 31st, 2017. We then define a region to have a high frequency of lightning strikes if it falls in the the top quartile of the global distribution of the number of lightning strikes across subnational regions.⁴¹

A.2 GWP results 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.⁴² 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

⁴⁰The data are available from the University of Washington at <http://wwlln.net>.

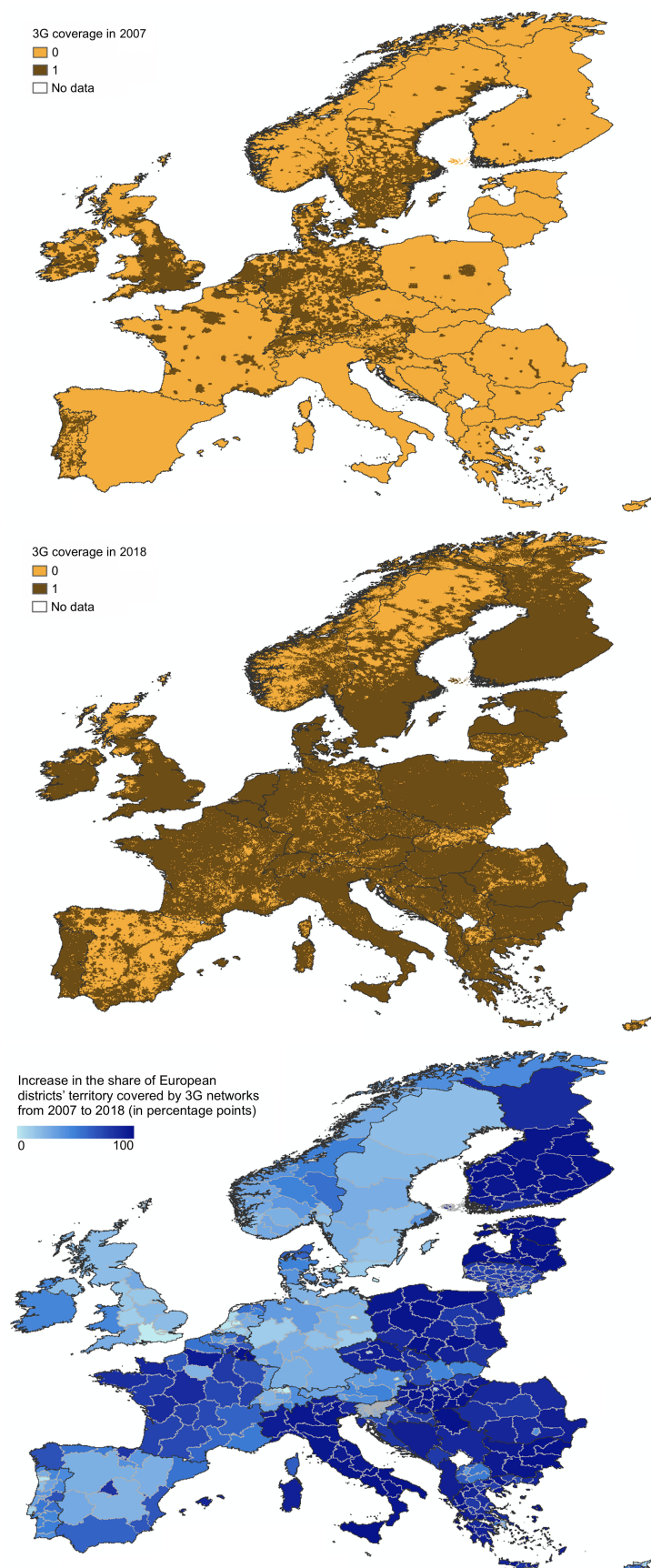
⁴¹Note we cannot use the alternative dataset on global lightning strikes available from NASA (<https://ghrc.nsstc.nasa.gov/lightning/>). The reason is that NASA satellites use optical imaging to locate lightning strikes, a type of technology that is best suited to detect in-cloud lightning but which 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.

⁴²Income 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.

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 (2015-2016), 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.

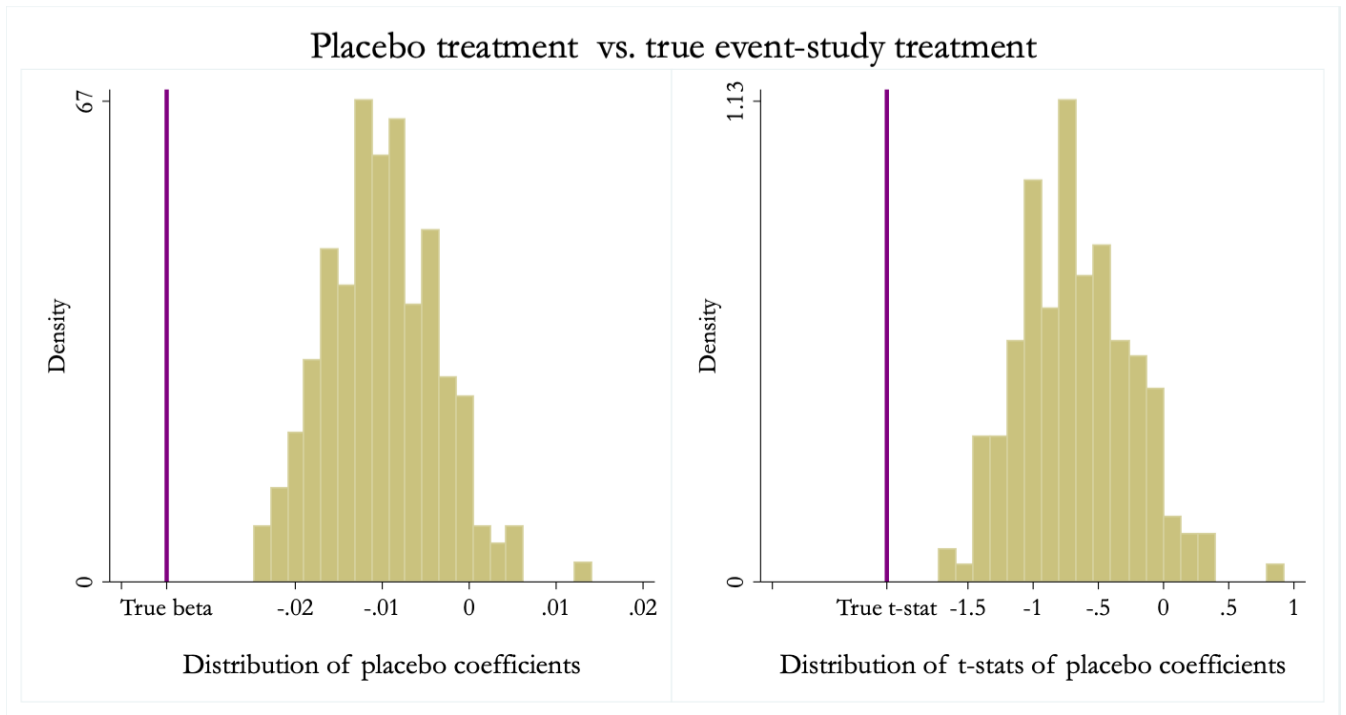
To show that our results are robust to alternative measures of economic development, we re-do the analysis using nighttime light density data as a measure of economic development instead of log average income from the GWP. As data from DMSP-OLS and VIIRS are not directly comparable, we also include an 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 [A13](#) presents the results. They are similar to those presented in Table [1](#).

Figure A1: The growth of 3G network coverage between 2007 and 2018 in Europe



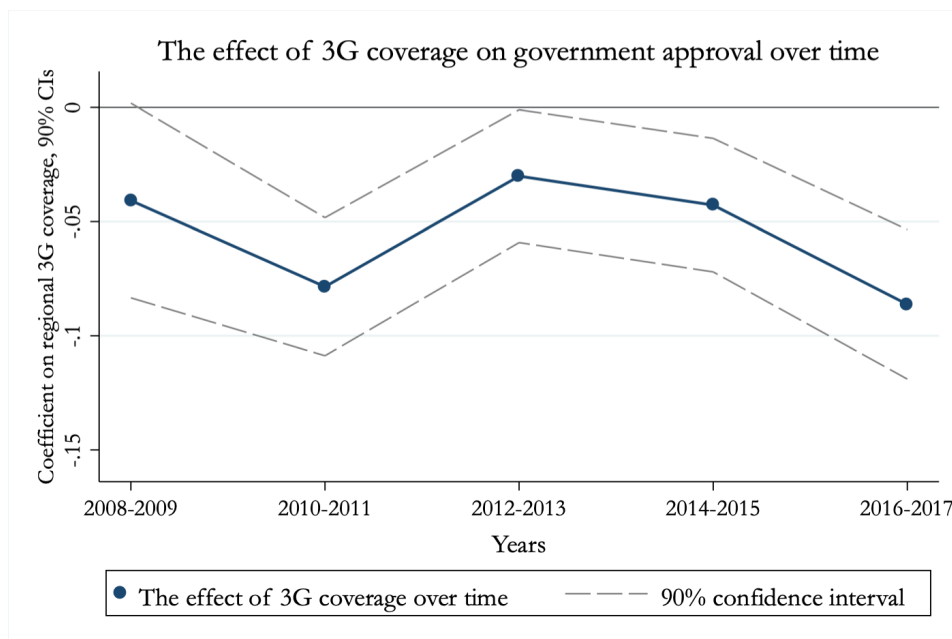
Note: The first two maps present 3G network coverage by grid cell in 2007 and 2018 for the European countries. The third map presents: 1) the boundaries of the districts, which are the spatial unit of observation in the elections data and 2) the increase in the share of the districts' territory covered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

Figure A2: Event study treatments are not associated with a concurrent decline in government approval in other regions of the same countries in the same year



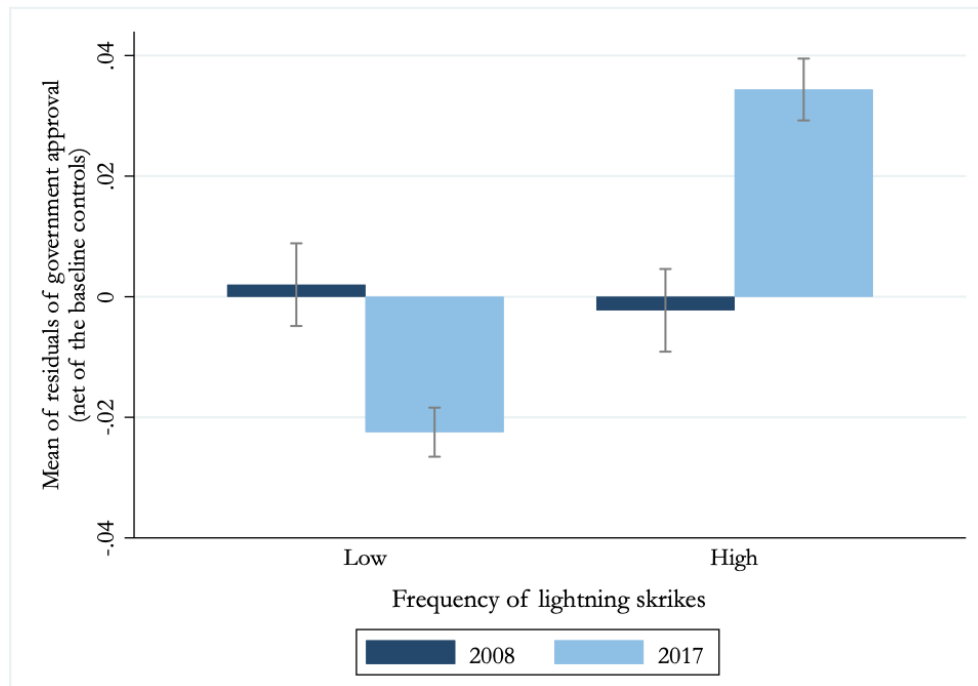
Note: The figure compares the results of the event study (presented in Figure 3) to the results from placebo treatments—200 random draws from the same countries and years as the actual events, but from regions that did not experience the event. In the event study, treatment status is defined as the region experiencing an increase in 3G coverage of more than 50 percentage points. Thus, placebo treatments 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 the treated regions are comparable to the placebo regions, we exclude country-years when at least 60% of the regions in the country were treated. Without this restriction, the difference between actual and placebo treatments is even more significant. 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 12 percentage points of the region’s territory (with the standard deviation of 16).

Figure A3: 3G coverage and government approval, by time period



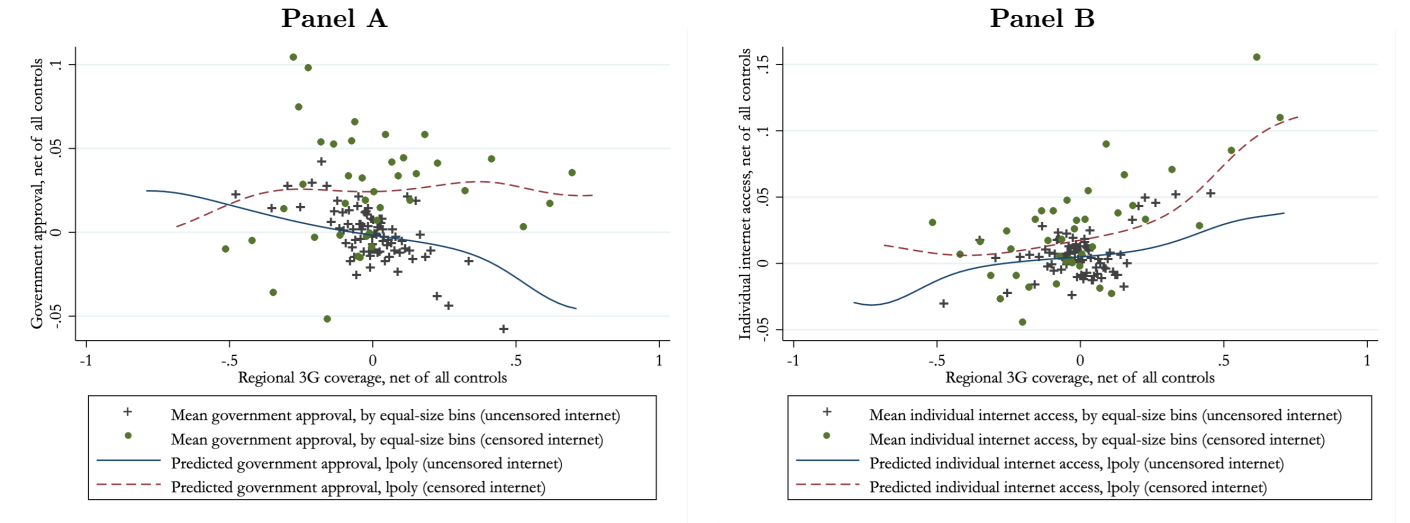
Note: The figure presents the results presented in Column 1 of Table A5. The standard errors used to construct the confidence intervals are corrected for two-way clusters at the level of the subnational regions (to account for correlation over time) and at the level of the countries in each year (to account for within-country-year correlation).

Figure A4: Lightning strikes and the change in government approval among countries with below-median GDP per capita



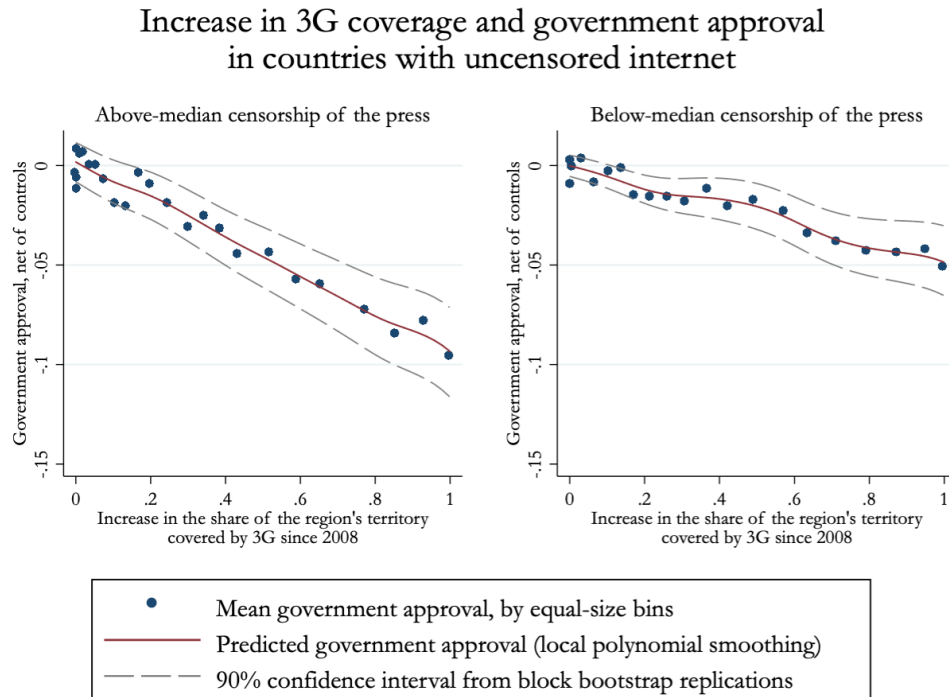
Note: The figure illustrates the reduced-form relationship behind the 2SLS estimation presented in Columns 5 and 6 of Table 3. The results are based on the sample of countries with below-median GDP per capita. The vertical axis presents mean government approval net of the baseline controls, including region and year fixed effects. The graph also presents the 90% confidence intervals with robust standard errors.

Figure A5: 3G coverage, confidence in government, and individual internet access in countries with censored and uncensored internet, net of all controls



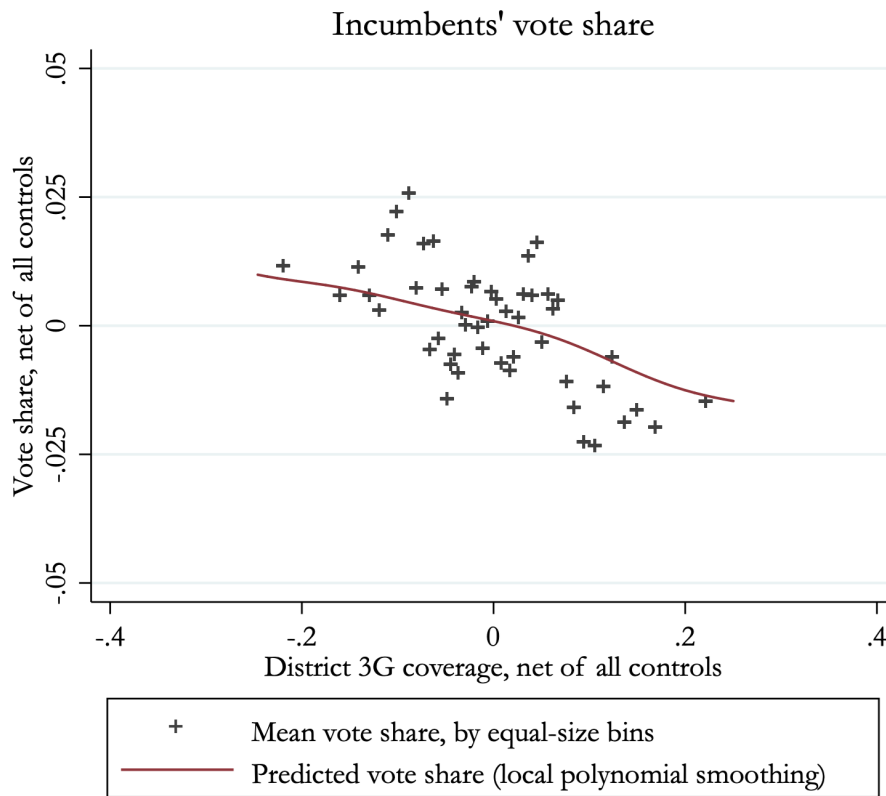
Note: Panel A of the figure illustrates the nonparametric (local polynomial smoothing) relationship between government approval and regional 3G coverage in countries with high and low censorship from Column 6 of Panel A of Table 4. To construct this figure, we regress the government approval and regional 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 the 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 individual internet access and regional 3G coverage in countries with high and low censorship.

Figure A6: 3G coverage and government approval in countries with uncensored internet, depending on censorship of the traditional press



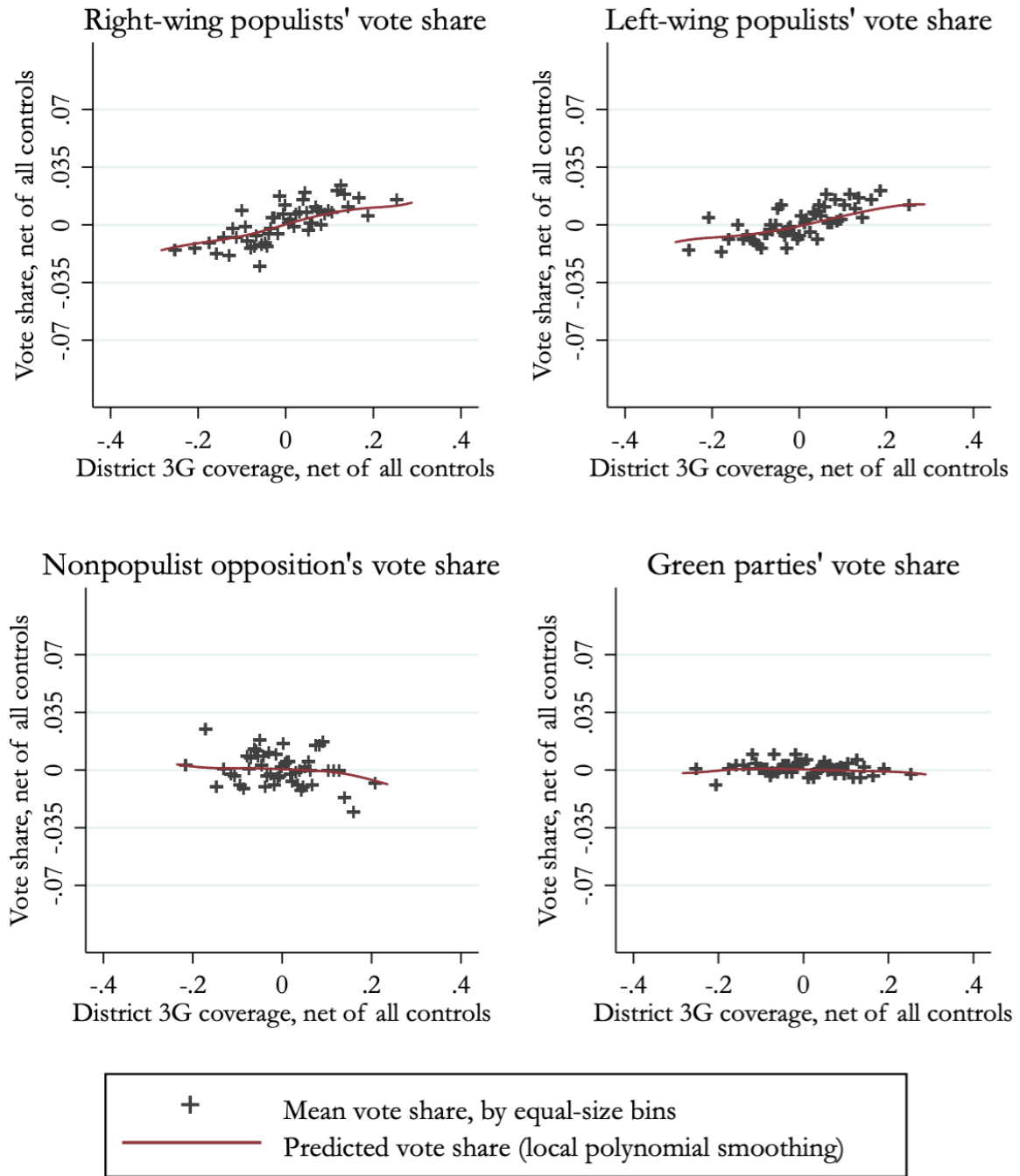
Note: Uncensored 3G internet decreases government approval more in countries with high censorship of the traditional press. The figure illustrates the results from Column 6 of Panel C of Table 4. The left-hand side of the figure illustrates the nonparametric (local polynomial smoothing) relationship 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 the controls by equal-size bins. The solid lines on the graphs show the predicted outcomes (Gaussian kernel, local polynomial smoothing).

Figure A7: 3G coverage and the vote share of incumbent parties, net of all controls



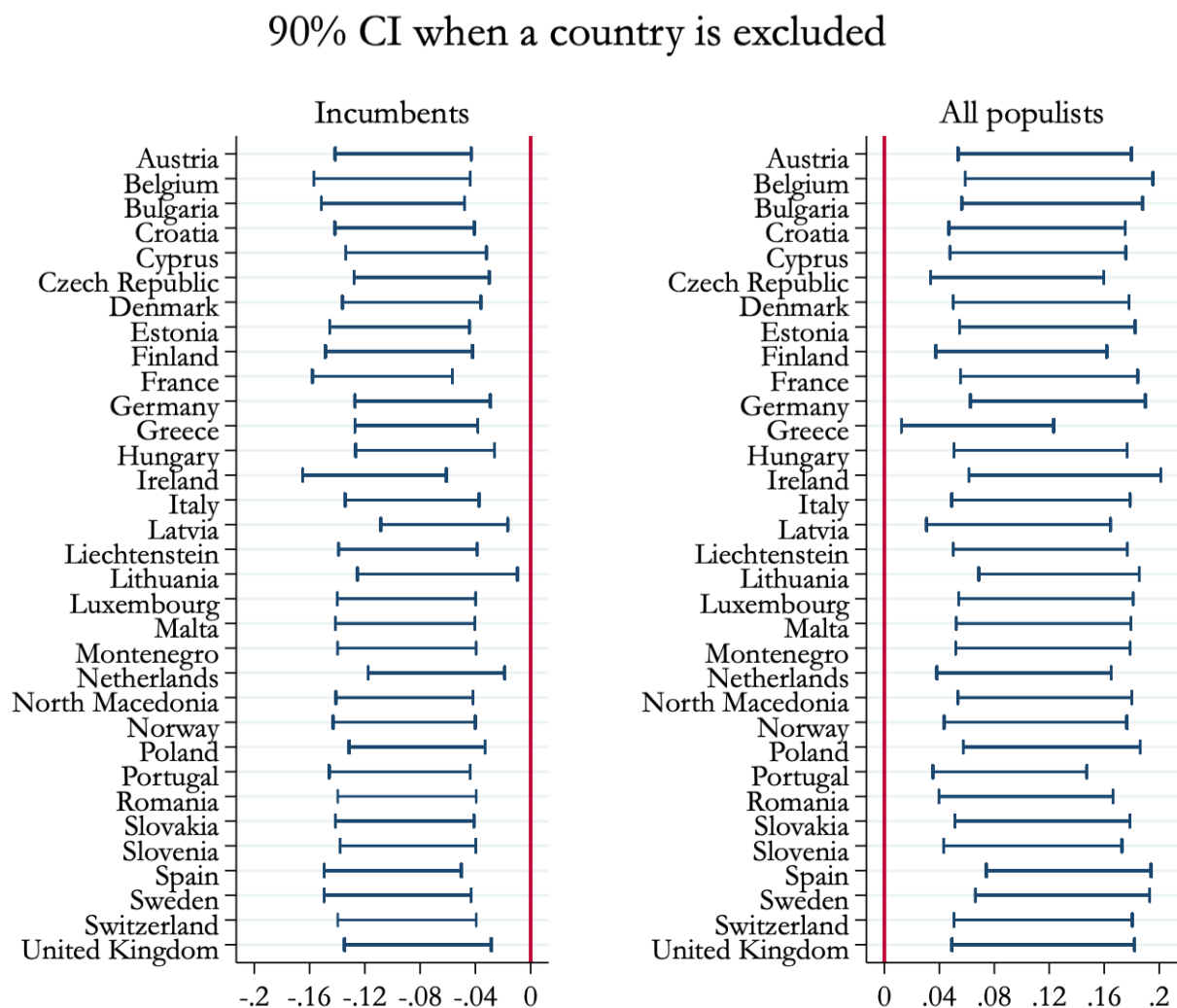
Note: The figure presents the nonparametric (local polynomial smoothing) relationship between regional 3G coverage and the vote share of incumbent parties (net of all controls), illustrating the result presented in Column 2 of Table 7. To construct this figure, we regress the vote share and regional 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 the controls by equal-size bins. The lines on the graphs show the predicted outcomes (Gaussian kernel, local polynomial smoothing).

Figure A8: 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 8, 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 the controls by equal-size bins. The lines on the graphs show the predicted outcomes (Gaussian kernel, local polynomial smoothing).

Figure A9: 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 7 and Column 4 of Table 8, respectively—when all the countries are excluded one by one. The results are robust to the exclusion of any single country.

Table A1: 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 | 840,538 | Collins Bartholomew |
| Regional 2G coverage | 0.781 | 0.310 | 840,538 | Collins Bartholomew |
| Individual access to the internet | 0.440 | 0.496 | 840,538 | GWP |
| Confidence in national government | 0.514 | 0.500 | 772,354 | 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 |
| Censorship (Limits on Content score) | 11.840 | 6.009 | 378,534 | Freedom House |
| Dummy for low censorship | 0.949 | 0.220 | 715,304 | Freedom House and Polity IV |
| Freedom of the Press score | 46.602 | 21.255 | 840,538 | Freedom House |
| Polity2 score > 7 | 0.541 | 0.498 | 840,538 | Polity IV |
| Polity2 score > 5 | 0.694 | 0.461 | 840,538 | Polity IV |
| Index of actual corruption, $\log(GICI + 1)$ | -1.275 | 0.752 | 801,488 | IMF |
| The Panama Papers' entities per 1,000 people | 0.245 | 1.553 | 840,538 | ICIJ |
| Ln average regional income | 8.309 | 1.220 | 840,538 | GWP |
| Ln nighttime light density (from DMSP-OLS) | 1.484 | 2.050 | 430,017 | DMSP-OLS (2008-2013) |
| Ln nighttime light density (from VIIRS) | -0.788 | 2.632 | 191,648 | VIIRS (2015-2016) |
| Unemployment rate | 7.361 | 5.382 | 840,538 | World Bank |
| Ln GDP per capita | 9.323 | 1.141 | 840,538 | World Bank |
| Dummy for below-median GDP per capita | 0.491 | 0.500 | 617,863 | World Bank |
| Dummy for high frequency of lightning strikes | 0.352 | 0.478 | 617,863 | WWLLN |
| Dummy for high frequency of lightning strikes (sample of countries with below-median GDP per capita) | 0.427 | 0.495 | 303,601 | WWLLN |
| Unemployed | 0.059 | 0.236 | 840,538 | GWP |
| Employment status not known | 0.426 | 0.494 | 840,538 | GWP |
| Female | 0.541 | 0.498 | 840,538 | GWP |
| Age | 41.901 | 17.776 | 840,538 | GWP |
| Number of children | 1.178 | 1.834 | 840,538 | GWP |
| Married | 0.573 | 0.495 | 840,538 | GWP |
| Divorced | 0.065 | 0.247 | 840,538 | GWP |
| Widow[er] | 0.079 | 0.269 | 840,538 | GWP |
| Highest level of education = high school | 0.531 | 0.499 | 840,538 | GWP |
| Highest level of education = tertiary | 0.161 | 0.368 | 840,538 | GWP |
| Urban status = large city | 0.307 | 0.461 | 840,538 | GWP |
| Urban status = suburb of large city | 0.096 | 0.295 | 840,538 | GWP |
| Urban status = rural location | 0.597 | 0.490 | 840,538 | 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 |
| Turnout | 0.656 | 0.115 | 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 |
| Ln 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 |
| Ln nighttime light density (DMSP-OLS) | 2.405 | 0.785 | 801 | DMSP-OLS (2007-2013) |
| Ln nighttime light density (VIIRS) | 0.302 | 1.191 | 391 | VIIRS (2015-2016) |

Table A2: 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) |
|--|-----------------------------------|-------------------------------|----------------------|-----------------------------|--|--------------------------------------|
| <i>Dep. Var.:</i> | 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 (0.017) | -0.029* (0.017) | -0.056*** (0.016) | -0.036*** (0.013) | -0.037*** (0.013) | -0.036*** (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 (0.017) | -0.012 (0.018) | -0.021 (0.019) | -0.006 (0.014) | -0.006 (0.014) | -0.005 (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 |
| 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. Tomorrow's expansion of 3G networks is not correlated with the change in government approval today, suggesting that the parallel trends assumption holds. 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 A3: Event study results

| | (1) | (2) |
|---|---|----------------------|
| <i>Dep. Var.:</i> | 1st principal component of the measures of government approval | |
| <i>Sample note 1:</i> | Regions with a sharp increase in 3G coverage in one year during the sample period | |
| <i>Sample note 2:</i> | All respondents | Rural respondents |
| Sharp increase in 3G coverage occurred in: | | |
| Year $t + 4$ or later | -0.003 (0.026) | 0.011 (0.028) |
| Year $t + 3$ | 0.006 (0.020) | 0.005 (0.022) |
| Year $t + 2$ | -0.005 (0.015) | 0.011 (0.017) |
| Year t | -0.041*** (0.014) | -0.046*** (0.015) |
| Year $t - 1$ | -0.055*** (0.016) | -0.075*** (0.019) |
| Year $t - 2$ | -0.040* (0.021) | -0.064*** (0.023) |
| Year $t - 3$ | -0.077*** (0.026) | -0.086*** (0.028) |
| Year $t - 4$ or earlier | -0.068* (0.037) | -0.089** (0.036) |
| Observations | 116,932 | 59,691 |
| R-squared | 0.222 | 0.248 |
| Number of countries | 63 | 60 |
| Number of regions | 422 | 417 |
| Subnational region & year FEs | ✓ | ✓ |
| Baseline controls | ✓ | ✓ |
| Censorship of the traditional press control | ✓ | ✓ |

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. The table presents the results of the event study, where the event is defined as an increase of more than 50 percentage points in the share of subnational region's territory covered by 3G in a single year. Other 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 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 A4: Altonji-Elder-Taber test and Oster test

| | (1) | (2) | (3) | (4) | (5) | (6) |
|--|---|----------------------------------|-------------------------|--------------------------------|--|--|
| <i>Dep. Var.:</i> | 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 (0.322) | -0.074 (0.200) | 0.150 (0.321) | -0.039 (0.202) | 0.030 (0.238) | 0.031 (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 δ s 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_{\max} —the R-squared from a hypothetical regression of the outcome on treatment and both observed and unobserved controls—to be equal to $1.3\tilde{R}$, where \tilde{R} is the R-squared from Table 1.

Table A5: The effect of 3G coverage on government approval, over time

| | (1) | (2) |
|-----------------------------------|---|----------------------|
| <i>Dep. Var.:</i> | 1st principal component of the measures of government approval | |
| <i>Sample:</i> | All | Rural |
| Regional 3G coverage in 2008-2009 | -0.041 (0.026) | -0.059** (0.029) |
| Regional 3G coverage in 2010-2011 | -0.078*** (0.018) | -0.086*** (0.023) |
| Regional 3G coverage in 2012-2013 | -0.030* (0.018) | -0.033* (0.020) |
| Regional 3G coverage in 2014-2015 | -0.043** (0.018) | -0.067*** (0.019) |
| Regional 3G coverage in 2016-2017 | -0.086*** (0.020) | -0.122*** (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 A6: 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 A7: Robustness to using region-year averages as the unit of analysis

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|--|---|---|----------------------------------|-------------------------|--------------------------------|--|--|
| <i>Dep. Var.:</i> | Region-year mean of the following variable: | | | | | | |
| | Individual access to the internet | 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 | 0.051*** (0.015) | -0.064*** (0.022) | -0.041** (0.016) | -0.090*** (0.024) | -0.029** (0.014) | -0.057*** (0.016) | -0.058*** (0.017) |
| R-squared | 0.886 | 0.611 | 0.655 | 0.617 | 0.756 | 0.686 | 0.682 |
| Observations | 13,878 | 13,055 | 13,192 | 12,913 | 13,179 | 12,860 | 12,860 |
| Panel B: Means taken across rural residents only | | | | | | | |
| Regional 3G coverage | 0.051*** (0.017) | -0.073*** (0.016) | -0.063*** (0.018) | -0.106*** (0.028) | -0.034** (0.017) | -0.073*** (0.019) | -0.074*** (0.019) |
| R-squared | 0.860 | 0.574 | 0.593 | 0.563 | 0.706 | 0.632 | 0.628 |
| Observations | 12,746 | 11,991 | 12,079 | 11,823 | 12,075 | 11,743 | 11,743 |
| Subnational region & year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Region- and county-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. Column 1 presents the effect for the share of people with access to the internet, and Columns 2–7 for 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 A8: The effect of 3G coverage on government support, depending on the level of censorship of the internet and of the traditional media, subsample of rural residents

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|-----------------------------------|-------------------------------|----------------------|-----------------------------|--|--------------------------------------|
| <i>Dep. Var.:</i> | 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: Dummy for high internet censorship | | | | | | |
| Regional 3G coverage | -0.134*** (0.029) | -0.083*** (0.020) | -0.163*** (0.027) | -0.079*** (0.019) | -0.112*** (0.020) | -0.114*** (0.021) |
| Regional 3G coverage × Censored internet dummy | 0.154*** (0.044) | 0.080** (0.039) | 0.241*** (0.032) | 0.065** (0.030) | 0.137*** (0.034) | 0.139*** (0.035) |
| 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: Continuous measure of internet censorship | | | | | | |
| Regional 3G coverage | -0.241*** (0.073) | -0.144*** (0.043) | -0.267*** (0.068) | -0.122*** (0.040) | -0.171*** (0.052) | -0.174*** (0.053) |
| Regional 3G coverage × Censorship of the internet | 0.087** (0.038) | 0.051** (0.023) | 0.115*** (0.038) | 0.025 (0.026) | 0.054* (0.031) | 0.055* (0.031) |
| Observations | 200,349 | 195,949 | 190,566 | 190,752 | 158,813 | 158,813 |
| R-squared | 0.175 | 0.163 | 0.153 | 0.155 | 0.209 | 0.210 |
| Panel C: Continuous measure of internet censorship and continuous measure of censorship of the traditional press | | | | | | |
| Regional 3G coverage | -0.340*** (0.074) | -0.203*** (0.063) | -0.427*** (0.083) | -0.190*** (0.042) | -0.263*** (0.055) | -0.267*** (0.056) |
| Regional 3G coverage × Censorship of the internet | 0.279*** (0.060) | 0.162*** (0.051) | 0.331*** (0.069) | 0.101*** (0.037) | 0.207*** (0.046) | 0.212*** (0.047) |
| Regional 3G coverage × Censorship of the traditional media | -0.082*** (0.025) | -0.044** (0.018) | -0.071*** (0.024) | -0.021 (0.013) | -0.057*** (0.015) | -0.058*** (0.016) |
| Observations | 200,349 | 195,949 | 190,566 | 190,752 | 158,813 | 158,813 |
| R-squared | 0.189 | 0.169 | 0.166 | 0.164 | 0.224 | 0.225 |
| Subnational region & year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Baseline controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Censorship controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table replicates the results of Table 4 in the subsample of rural residents. The unit of observation is an individual. The dependent variables are individuals' perceptions of government and the country's institutions. Censorship of the internet is measured using the Limits on Content component of the Freedom on the Net (FOTN) index. In Panel A, it is used as a dummy which is equal to one if the Limits on Content index is 22 or above and zero if the Limits on Content index is below 22 or if the Limits on Content index is unavailable but a country is a democracy according to the Polity IV dataset (i.e., if the Polity2 score is 6 or above). Censorship of the traditional media is measured using Freedom House's Freedom of the Press score. The mean of the latter is subtracted before creating the interaction with 3G coverage. All regressions include the measure of internet censorship itself (either the dummy, Panel A, or the continuous Limits on Content index, Panel B and Panel C). In Panel C, we also include dummies for all levels of censorship of the traditional press. Other 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 A9: Heterogeneity with respect to the country's geography, income, and democracy

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|--|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| <i>Dep. Var.:</i> | The 1st principal component of the measures of government approval | | | | | | | | | | | |
| <i>Sample:</i> | All | All | Rural | All | All | Rural | All | All | Rural | All | All | Rural |
| Regional 3G coverage × Africa | -0.067** (0.026) | -0.061** (0.031) | -0.086** (0.039) | | | | | | | | | |
| Regional 3G coverage × Asia & Oceania | -0.030 (0.026) | -0.108*** (0.028) | -0.050* (0.029) | | | | | | | | | |
| Regional 3G coverage × Europe | -0.011 (0.021) | -0.014 (0.023) | -0.042* (0.022) | | | | | | | | | |
| Regional 3G coverage × North and Central America | -0.167*** (0.039) | -0.201*** (0.033) | -0.199*** (0.046) | | | | | | | | | |
| Regional 3G coverage × South America | -0.173*** (0.045) | -0.160*** (0.043) | -0.208*** (0.063) | | | | | | | | | |
| Regional 3G coverage × OECD | | | | -0.023 (0.025) | -0.022 (0.029) | -0.043* (0.025) | | | | | | |
| Regional 3G coverage × non-OECD | | | | -0.068*** (0.015) | -0.098*** (0.014) | -0.085*** (0.020) | | | | | | |
| Regional 3G coverage | | | | | | | -0.054*** (0.014) | -0.075*** (0.015) | -0.069*** (0.019) | -0.056*** (0.016) | -0.090*** (0.019) | -0.064*** (0.022) |
| Regional 3G coverage × Ln GDP per capita (demeaned) | | | | | | | -0.015 (0.014) | -0.008 (0.017) | -0.014 (0.017) | | | |
| Regional 3G coverage × Polity 2 (demeaned) | | | | | | | | | | -0.000 (0.003) | 0.003 (0.004) | -0.004 (0.004) |
| Observations | 617,863 | 505,133 | 371,055 | 617,863 | 505,133 | 371,055 | 617,863 | 505,133 | 371,055 | 617,863 | 505,133 | 371,055 |
| R-squared | 0.242 | 0.238 | 0.226 | 0.242 | 0.238 | 0.225 | 0.242 | 0.238 | 0.225 | 0.242 | 0.238 | 0.225 |
| Subnational region & year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Baseline controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Censorship of the traditional press controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Only countries without internet censorship | | ✓ | | | ✓ | | | ✓ | | | ✓ | |

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is an individual. Columns 1, 4, 7, and 10 present the results for the full sample, Columns 2, 5, 8, and 11—for the subsample of countries with uncensored internet, and Columns 3, 6, 9, and 12—for the subsample of rural residents. 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 20 dummies corresponding to every 5 points in the Censorship 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 A10: Heterogeneity with respect to the respondent's education, employment status, income, and age

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|--|--|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| <i>Dep. Var.:</i> | The 1st principal component of the measures of government approval | | | | | | | |
| <i>Sample:</i> | All | Rural | All | Rural | All | Rural | All | Rural |
| Regional 3G coverage | -0.048*** (0.015) | -0.065*** (0.018) | -0.081*** (0.016) | -0.096*** (0.019) | -0.070*** (0.015) | -0.084*** (0.017) | -0.058*** (0.015) | -0.075*** (0.018) |
| Regional 3G coverage × Unemployed | -0.023*** (0.007) | -0.027*** (0.008) | | | | | | |
| Regional 3G coverage × Employment status missing | -0.015*** (0.005) | -0.015*** (0.006) | | | | | | |
| Regional 3G coverage × Tertiary education | | | 0.082*** (0.013) | 0.103*** (0.015) | | | | |
| Regional 3G coverage × Secondary education | | | 0.020** (0.008) | 0.019** (0.009) | | | | |
| Regional 3G coverage × Income above country median | | | | | 0.038*** (0.003) | 0.043*** (0.004) | | |
| Regional 3G coverage × Income missing | | | | | -0.018 (0.031) | -0.019 (0.038) | | |
| Regional 3G coverage × Age below 25 | | | | | | | 0.013*** (0.004) | 0.019*** (0.006) |
| Regional 3G coverage × Age above 60 | | | | | | | -0.006 (0.006) | -0.003 (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 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Censorship of the traditional press controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

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, and 20 dummies corresponding to every 5 points in the Censorship 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 A11: The effect of 3G coverage on life satisfaction and on confidence in the local police (placebo outcomes)

| | (1) | (2) | (3) | (4) | (5) |
|--|--|---|--|--|---|
| <i>Dep. Var.:</i> | Current level of life satisfaction 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 (0.063) | 0.016 (0.074) | 0.009 (0.012) | -0.024 (0.028) | 0.009 (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 (0.082) | -0.015 (0.103) | 0.000 (0.015) | 0.010 (0.031) | -0.020 (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 towards their life or towards 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 A12: The relationship between actual corruption (GICI) and perceived corruption in Europe

| | (1) | (2) | (3) |
|--|--------------------------------------|--|----------------------|
| <i>Dep. Var.:</i> | Individual access to the internet | Perception of no corruption in government | |
| <i>Sample:</i> | Respondents in European countries | | |
| Regional 3G coverage | 0.048** (0.021) | -0.043* (0.024) | -0.063** (0.029) |
| Regional 3G coverage \times Index of actual corruption | | -0.045*** (0.015) | -0.044*** (0.014) |
| Index of actual corruption | | -0.006 (0.010) | -0.009 (0.011) |
| Observations | 277,764 | 127,667 | 197,500 |
| R-squared | 0.370 | 0.157 | 0.330 |
| Subnational region & year FEs | ✓ | ✓ | ✓ |
| Baseline controls | ✓ | ✓ | ✓ |
| Sample extended to cases of zero corruption | | | ✓ |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. In Column 1, the outcome variable is a dummy for individual internet access. In Columns 2 and 3, the outcome variable is a dummy for the perception that there is no corruption in government. In the first column, we estimate Specification 2 for the subsample of European countries; and in Columns 2 and 3, we replicate the results presented in Columns 1 and 3 of Table 5, showing that 3G internet helps expose corruption in the subsample of European countries. 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. 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 A13: 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) | (7) |
|--|---|---|----------------------------------|-------------------------|--------------------------------|--|--|
| <i>Dep. Var.:</i> | Individual access to the internet | 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 | 0.092*** (0.017) | -0.058*** (0.021) | -0.033** (0.014) | -0.062*** (0.020) | -0.039*** (0.015) | -0.049*** (0.015) | -0.050*** (0.015) |
| Observations | 839,642 | 771,483 | 747,624 | 731,993 | 721,945 | 617,104 | 617,104 |
| Mean dep. var. | 0.441 | 0.514 | 0.533 | 0.505 | 0.226 | 0.432 | 0.439 |
| Number of countries | 116 | 111 | 116 | 112 | 112 | 110 | 110 |
| Panel B: Respondents from rural areas | | | | | | | |
| Regional 3G coverage | 0.086*** (0.017) | -0.076*** (0.024) | -0.045*** (0.017) | -0.087*** (0.025) | -0.056*** (0.016) | -0.066*** (0.018) | -0.067*** (0.018) |
| Observations | 501,091 | 463,990 | 447,631 | 439,952 | 431,665 | 370,324 | 370,324 |
| Mean dep. var. | 0.350 | 0.538 | 0.556 | 0.516 | 0.215 | 0.444 | 0.452 |
| Number of countries | 115 | 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. Column 1 presents the results of the estimation of Specification 2, Columns 2-7 present the results of the estimation of Specification 1. The dependent variable in Column 1 is a dummy for individual access to the internet. The dependent variables in Columns 2-7 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 A14: The effect of 3G coverage on the incumbent's vote as a share of registered voters in Europe

| | (1) | (2) | (3) | (4) |
|--|--|--|---|----------------------|
| <i>Dep. Var.:</i> | 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 | |
| <i>Unit of observation:</i> | District-year | District-year-incumbent | District-year | |
| District 3G coverage | -0.068** (0.030) | -0.066*** (0.020) | | -0.082*** (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 7 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 A15: 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) |
|--|--|------------------------|--------------------|-------------------|--------------------|-------------------|------------------------------------|
| <i>Dep. Var.:</i> | 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 |
| <i>Unit of observation:</i> | District-year | District-year | District-year | District-year | District-year | District-year | District-year- ruling coalition |
| District 3G coverage | 0.043*** (0.016) | 0.032*** (0.012) | -0.028* (0.014) | 0.047* (0.025) | 0.060** (0.025) | -0.008 (0.007) | -0.038 (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 8 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 A16: 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) | | |

Table A17: 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 HSLŠ–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) |