Mobile Internet access and political outcomes: Evidence from South Africa

Dante Donati[†]
Universitat Pompeu Fabra

This version: March 2018
Most recent version available here

Abstract

Does mobile Internet arrival affect individuals' voting behavior in developing countries? I provide an empirical answer to this question looking at the South African municipal elections results between 2000 and 2016. I exploit the temporal and geographical variation in 3G Internet coverage to estimate its impact on (1) the vote shares of the major parties, (2) voter turnout, (3) electoral competition and (4) protests. Using a high-resolution newly constructed dataset along with a Diff-in-Diff and 2SLS estimation, I show that in 2016 Internet availability caused a reduction in the vote share of the ruling party by almost 7 pp. The main opponents have gained from the Internet arrival. Political competition and number of protests increased. Results are robust to different model specifications, and alternative estimators. Then, I develop an extensive analysis of the potential mechanisms. A triple difference estimator is used to assess the role of the Internet in providing information on corruption and administrative scandals. I find that in localities more exposed to the scandals the impact of 3G arrival is larger. Finally, I conduct a spatial analysis to study how the surrounding environment influences the impact digital information has on opinions towards the incumbent. I show that Internet penetration fosters convergence of preferences over space.

Keywords: Corruption, Media, Mobile Internet, Municipal elections, Political outcomes.

[†]I thank seminar attendants at Universitat Pompeu Fabra and Toulouse School of Economics. I am grateful to Ruben Durante, Ruben Enikolopov, Frederico Finan, José García-Montalvo, Nicola Gennaioli, Fabrizio Germano, Saumitra Jha, Eliana La Ferrara, David Nagy, Maria Petrova, Giacomo Ponzetto, Nandan Rao, Marta Reynal-Querol, Alessandro Tarozzi and Carlos Velasco Rivera for their comments and useful insights. I acknowledge financial support from LEAP Bocconi (Laboratory for Effective Anti-Poverty Policies) for the purchasing of data on mobile Internet coverage.

1. Introduction

In the past few decades, Information and Communications Technology (ICT) has transformed the world. By connecting people and places, ICT has played a vital role in the national, regional and global development, and it holds significant promise for the future (World Bank, 2006). At the same time, the Internet can also be seen as a powerful political tool that allows people to access additional/new information, to overcome collective action and coordination problems, and foster political change. Indeed, some scholars (McChesney, 2007) have argued that the world is experiencing a "communication revolution", an idea that relates to the presumed democratizing role of the Internet, which relax media ownership rules in the traditional media sector. Furthermore, more recently the Internet has also led to the birth of a novel and particularly popular news platform, that is social media. The main novelty social media bring to the society is the horizontal flow of information between individual users. The information role of social media might also be amplified by the possibility of being literally "constantly on line", thanks to the expansion of the 3G mobile Internet accompanied by the growing usage of the smartphones.

Can the provision of high-speed mobile Internet affect political participation and political outcomes in developing countries? If yes, what are the most plausible mechanisms which drive the phenomenon? This essays seeks to answer these questions looking at the mobile Internet expansion that took place between 2000 and 2016 in South Africa.

The topic is particularly relevant for different reasons. First, recent political events and subsequent scandals, such as the alleged Russian interference in the 2016 US election[1], or the presumed Cambridge Analytica link with President Trump's campaign[2] and the Brexit[3], have demonstrated how the Internet in general, and social media in particular, might be powerful tools to influence politics in the developed world. Second, mobile Internet penetration (as well as social media usage) is constantly and rapidly growing in developing countries. Here, the fall in prices of data bundles and smartphones, combined with a widening share of young people are driving the widespread adoption of the mobile technology, yet digital divide is still a prominent issue. This means that Internet usage increases both in the intensive and extensive margins. Third, developing countries offer peculiar institutional and political backgrounds, which make the analysis of the arrival of new technologies particularly interesting[4]. For instance, the current ruling party of South Africa, that is the African National Congress (ANC), has dominated the scene since 1994. Only in the more recent elections its rivals experienced a notably increase in popularity. Finally, understanding the mechanisms through which the Internet plays a role in fragile settings might reveal helpful insights on its potential use as a monitoring tool. At the same time, this might incentivize political accountability, economic efficiency, and the the design and implementation of new policies on transparency.

Identifying the causal impact of mobile Internet access on political outcomes is challenging. In particular, compared to the literature on radio and TV coverage[5], in this

[1] For a comprehensive timeline of the events, see "Russia, Trump, and the 2016 U.S. Election". Council on Foreign Relations. 26 February 2018.

[2] "Leaked: Cambridge Analytica's blueprint for Trump victory". The Guardian. 23 March 2018.

[3] "The Cambridge Analytica files: the story so far". The Guardian. 26 March 2018.

[4] The Internet has been identified as a driving factor behind the protests and revolutions involving the middle-eastern countries (Arab Spring). See, for instance, Steinert-Threlkeld et al. (2015).

[5] See Olken (2009), Enikolopov et al. (2011), La Ferrara et al. (2012) and Durante et al. (2017), among others.

case it is harder to exploit technological features of the transmitters to find an exogenous source of variation. Internet coverage is far from random, yet it reflects the result of private operators' decision problem on if and where to install the technology. In this process, demand side factors play a fundamental role (Buys at al., 2009).

In this paper I attempt to tackle endogeneity issues related to the Internet coverage adopting two complementary strategies: a Diff-in-Diff estimation and a 2SLS approach. In the first case, I exploit the gradual temporal and geographical expansion of 3G Internet coverage along with the change in political outcomes across 35,000 partitions of voting districts between the 2006 and 2016 Municipal Elections. The second strategy exploits the variation in terrain ruggedness and its differential impact (pre- vs post-2005, i.e. the year in which 3G rollout started) on the number of years each locality has been covered by the new technology. To conduct the research, I rely on a granular measure of Internet coverage and a newly-constructed dataset containing geo-referenced information at the (sub)voting district-year level on political outcomes, protests, population density, luminosity as a proxy for GDP, and additional information on socio-demographic characteristics, infrastructure, geography and expenditure.

I then perform a variety of robustness checks to alleviate concerns on identification. Firstly, in order to provide evidence in favor of the parallel trend assumption, I run placebo regressions. I find that the change in coverage between 2006 and 2016 does not predict any political outcome between 2000 and 2006. Moreover, findings from the implementation of the Altonji, Elder and Taber (2005) procedure strengthen the Diff-in-Diff approach. Secondly, I perform some checks on the exogeneity of my instrument. I show that (1) before 2006, terrain ruggedness does not predict any political outcomes; (2) the presence of the mining industry (which is highly correlated with ruggedness) does not affect the outcomes between 2006 and 2016.

My findings show that Internet access was particularly detrimental for the popularity of the ruling party. In fact, a unitary increase in Internet coverage led to a drop in the share of votes for the ANC by approximately 7 percentage points (pp) in 2016. This is almost 10% of the mean of ANC vote share in 2006. By contrast, the main ANC opponent, the Democratic Alliance (DA), benefited from Internet coverage by roughly 3 pp. At the same time, smaller and newly formed parties, like the Inkatha Freedom Party (IFP) and the Economic Freedom Fighters (EFF), gained approximately 4 pp, overall.

Mobile coverage is found to have no significant effect on voter turnout, while its impact on the number of parties running in the district is positive. This seems to suggest that 3G availability encouraged political competition. Lastly, mobile Internet led to a rise in the number of protests against a typically political entity, such as a government institution. This might indicate that network availability (1) provided information which intensified grievance and willingness to complain and (2) favored coordination among individuals.

Then, I develop an extensive analysis of the potential mechanisms that may drive the observed relationships. I conduct an analysis of heterogeneity of the effects across sub-samples of the original dataset to examine which segments of the population are more likely to be affected by Internet coverage. Results show that localities with higher education and where traditional ICT and media penetration were higher in 2000 exhibit larger effects. I complement this study with a triple difference estimator to shed light on the role of the Internet in providing information on (1) the financial administration of the municipal money (political accountability and corruption scandals) and (2) administrative issues with the social turmoil and violent events that followed the mining strikes in 2012.

This analysis reveals that among localities with high level of corruption-related expenditure, a unitary increase in coverage caused a further reduction in the votes for the ANC party of almost 1 pp. Meanwhile, small and newly formed parties gained: their vote share and the propensity of running increased in these localities. Similarly, in places where the mining industry played a prominent role, 3G availability led to an additional fall in ANC share of approximately 2.7 pp. Interestingly, in this case voters decided either to support the second biggest party, the DA, or preferred not to vote. Overall, this analysis points out the information role the Internet played in exposing corruption and administrative scandals within the incumbent party, and the subsequent diverse reaction of voters' behavior. At the same time, the persuasive power of online information damaging the ANC leader is higher when individuals share ethnic affinity with him.

Finally, I conduct a spatial analysis to understand how ex-ante political preferences of neighboring districts directly affect (1) the political outcomes of a locality and (2) the way 3G coverage impacted on them. Firstly, I show that places where ANC vote share in 2000 was between 20 and 60% are those driving the negative effect of mobile coverage on the popularity of the incumbent. In fact, the Internet did not play significant role in those districts where affection towards the ANC was large in the past. Secondly, I illustrate that heterogeneity across past voting habits disappears when one replicates the analysis on two distinct groups of municipalities: those where ANC share was overall above and below the median in 2000. This suggests that beliefs in the surrounding environment matter for the way information affects a locality more than its own prior political preferences. Lastly, I construct an index of spatial divergence of preferences towards ANC and employ it in a triple difference estimation. I show that proximity to a larger share of people who do not support the incumbent has both direct and indirect effects on the political outcomes of a locality. The former is the result of social interaction between people with diverse opinions: localities surrounded by a larger mass of individuals who used to dislike the ANC will vote less for the party. The latter works through information segregation: the vote for the incumbent drops even more when the neighbors do not support ANC and the locality has Internet coverage. This may suggest that online information is partially filtered by the neighbor, and this fact leads to convergence of preferences over space: opinions of neighboring districts with ex-ante different beliefs become more alligned when 3G is present.

To the best of my knowledge, this is the first paper to assess and measure the relevance of spatial divergence in preferences on the way online information impacts on voting behavior. In addition, it is also the first work trying to combine mobile Internet availability with its potential role in exposing corruption and conveying information on political accountability.

The paper relates to the literature in the political economy of media that has tried to analyze the potential impact of the diffusion of broadband internet and digital ICTs on various forms of political participation and mobilization. For instance, the pioneering work by Falk et al. (2014) studies Internet and voting behavior in Germany. The authors show that the Internet had a negative impact on turnout and, at the same time, its availability crowded out TV viewership but not newspaper readership. A more recent paper by Campante et al. (2016) addresses the phenomenon from a broader perspective, emphasizing the potential underlying mechanisms for Italian politics. The findings support the idea that access to the Internet provides exit opportunities for voters dissatisfied with mainstream politics: turnout decreases in the short term. However, the Internet is consequently used as a political tool to reach out and recruit these individuals by newly formed parties. Since my paper focuses on municipal elections it also relates to the work by Gavazza et al. (2016), which looks at the impact of Internet penetration on local policies in the UK. Exploting exogenous variation in rainfall, the authors show that turnout, local expenditure and taxes are negatively affected by Internet penetration. Most interestingly, heterogeneity analysis displays that the negative effect on turnout is significant only for low-educated or low-aged localities. This is consistent with the idea that the Internet affected political outcomes only for those individuals that mainly utilize it as a source of entertainment.

However, all previous works focus exclusively on developed economies. Developing countries, given their peculiar political and institutional background and their fragile traditional media environment may exhibit different patterns. Overall, empirical evidence on Internet availability and politics in these countries is limited and my paper contributes to fill this gap. A recent paper by Miner (2015) studies the impact of landline internet penetration in Malaysia on pro-government vote. Among other things, the author shows that areas with higher landline internet penetration experienced higher turnout and lower share of votes for the ruling coalition. Conversely, in my case I take advantage of the availability of granular data on 3G coverage and restrict the attention on mobile technology rather than landline network. Under this aspect my work offers an additional novel contribution to the current literature. The paper also relates to the study of Manacorda and Tesei (2016), which is the first one using the same data on mobile coverage, yet with a different purpose. In fact, the authors find support for the liberation technology argument that digital mobile ICT fosters political mobilization.

Since my paper exclusively focuses on the recent diffusion of mobile Internet, it closely relates to the use and spread of social media, and their influence on politics. Experimental evidence by Bond et al. (2012) demonstrates the ability of online Facebook messages on political mobilization to directly influence real-world voting behavior. Enikolopov et al. (2016) show that the penetration of the Russian online social network (VK) increased protests and pro-governmental support. Allcott and Gentzkow (2017) analyzes the role of fake news in social media in the 2016 US election. Moreover, Ferraz and Finan (2008) and Enikolopov at al. (2018) illustrate the role of traditional media and social media, respectively, in divulge information on corruption, while Chen and Yang (2018) analyze the effects of providing citizens with access to an uncensored Internet in authoritarian regimes.

My work also draws insights from the literature on traditional media and its impact on voting behavior (DellaVigna and Kaplan, 2007; Enikolopov, Petrova, and Zhuravskaya, 2011; Gentzkow, Shapiro, and Sinkinson, 2011; Gentzkow, Petek, Shapiro, and Sinkinson, 2015; Chiang and Knight, 2011), violence and ethnic tensions (Yanagizawa-Drott, 2014; DellaVigna, Enikolopov, Mironova, Petrova, and Zhuravskaya, 2014; Adena, Enikolopov, Petrova, Santarosa, and Zhuravskaya, 2015), and policy outcomes (Strömberg, 2004; Eisensee and Strömberg, 2007; Snyder and Strömberg, 2010). Other papers also study ideological segregation online (Gentzkow and Shapiro, 2011; Halberstam and Knight, 2016; Gentzkow, Shapiro, and Taddy, 2016). The paper also relates to the literature on the impact of technology adoption (e.g., Dittmar, 2011; Cantoni and Yuchtman, 2014) and the effects of ICT on development (Elbers and Lanjouw, 2001; Grace, Kenny & Qiang, 2004). Finally, I draw from Acemoglu and Asuman (2011) for an overview on opinion dynamics in social networks.

The remainder of this paper is structured as follows. Section 2 describes the political background. Section 3 provides descriptive evidence on the Internet and the overall media market. Section 4 outlines the empirical strategy. Section 5 describes the data. Section 6 shows the empirical results. Section 7 draws the conclusions.

2. Political background

Since the end of apartheid in 1994 the African National Congress (ANC) has dominated South Africa's politics. The ANC is the ruling party in the national legislature, as well as in eight of the nine provinces. The ANC received 62.15%[6] of the votes during the 2014 general election. Until December 2017, the party has been led by Jacob Zuma, who has served as President of South Africa since May 9, 2009. After his resignation on February 15, 2018, Cyril Ramaphosa was elected President of the Republic. The main challenger to the ANC's rule is the Democratic Alliance, which received 22.23% of the votes in the 2014 election. The newly formed Economic Freedom Fighters (EFF), led by expelled ANC Youth League leader Julius Malema, contested its first municipal election since its formation in 2013 and received 6.35% of the votes in the general election.

Local government in South Africa consists of municipalities of various types. The largest metropolitan areas are governed by metropolitan municipalities, while the rest of the country is divided into district municipalities, each of which consists of several local municipalities. In 2016, there were 8 metropolitan municipalities, 44 district municipalities and 205 local municipalities. The councils of metropolitan and local municipalities are elected by a system of mixed-member proportional representation every 5 years. The following table depicts the overall results of the currently major 4 parties in the last 4 municipal ballots.

Table 1: South African municipal election results

Party name	2000	2006	2011	2016
African National Congress (ANC)	59.4%	64.82%	61.95%	53.9%
Democratic Alliance (DA)	22.1%	16.24%	23.94%	26.9%
Inkatha Freedom Party (IFP)	9.1%	7.5%	3.57%	4.25%
Economic Freedom Fighters (EFF)		Formed in 2013		8.19%

Source: IEC of South Africa

The streaking feature that emerges from the figures is the gradual decline in the ANC vote share after 2006, which has been accompanied by an increase in popularity of the DA. In particular, between 2006 and 2016 ANC lost approximately 11 percentage points (pp), while DA gained the same. Establishing any trend for the newly formed EFF is impossible, yet this party receive about 8% in the last municipal elections.

Understanding what might have driven the decline in ANC popularity and support is difficult. A possible explanation can be found in the various administration and corruption scandals that have emerged in the country during the last years, most of them in relation to the figure of former President Zuma[7].

On August 10, 2012, at the Marikana platinum mine, rock drillers began a wildcat strike seeking for a pay raise. The strike occurred beside a backdrop of antagonism and violence between the National Union of Mineworkers (NUM), affiliated to the ANC, and its emerging rival, the Association of Mineworkers and Construction Union (AMCU). On August 16, members of the South African Police Service opened fire on a group of

[6]This and the following numbers come from the Independent Electoral Commission (IEC) of South Africa, http://www.elections.org.za

[7]For an overview, see "The trials of Jacob Zuma". BBC. 15 December 2017.

strikers. On that day, 34 miners were killed, and at least 78 were wounded [8]. The incident was considered to be the single most lethal use of force by South African security forces against civilians since the apartheid era [9] Its economic impact was not negligible: South Africa's economy shrank by 0.6% in the first quarter only because of this strike. [10]. South African media showed graphic footage and photos of the shootings, while the headlines included "Killing Field", "Mine Slaughter", and "Bloodbath". International media (such as Reuters and Al Jazeera) questioned whether the mine's links to the ruling ANC constituted an "economic apartheid" [11]. A 52-minute awarded documentary about the events titled Miners Shot Down was also produced. While AMCU blamed the NUM and the police for the massacre, Frans Baleni, the general secretary of the NUM defended the police action at the Kaya FM radio station, saying: "The police were patient, but these people were extremely armed with dangerous weapons" [12]. Opposition parties and other political leaders criticized the police and called for Zuma to resign because of the controversy over the shooting. Meanwhile, some black people felt betrayed by "their" party: "I won't vote for the ANC next time because they failed the people. My family always voted ANC but we don't trust it any more" [13].

Other scandals have emerged more recently. A major campaign issue during the 2016 election was corruption within the ANC, in particular President Zuma's relationship with the Gupta family [14] and funding for the construction of his home at Nkandla. At the same time, after the elections, new scandals came out [15]. In January 2017 the ANC was taken to court by a South African public relations expert, TV and radio personality Sihle Bolani for some work done during the elections. According to court papers filed in the High Court in Johannesburg, the ANC planned to spend R50 million (almost $3.8 million) on a covert campaign targeting opposition parties in the 2016 local government elections. In particular, a covert team, initially known as the War Room, intended to "disempower DA and EFF campaigns" and set a pro-ANC agenda using a range of media, without revealing the ANC's hand. Apparently, one of the most widely adopted strategy behind the fake campaign was the use of fake posters, such as the one targeting EFF electorate depicted in Figure 11 in the appendix.

In the first months of 2018, growing pressure on Zuma led him to resign as President of South Africa. Facing a motion of no confidence in parliament, Zuma announced his resignation on 14 February 2018[16], and was succeeded by Ramaphosa the next day.

The overall disclosure and circulation of information on the previously mentioned phenomena was likely to produce negative consequences on the popularity of the leading party, which was considered directly involved in those facts. Traditional media (e.g.

[8] "South Africa mine killings: Jacob Zuma announces inquiry". BBC News. 17 August 2012.

[9] "South African police open fire as striking miners charge, killing and wounding workers". The Washington Post. Associated Press. 16 August 2012.

[10] "End of South Africa's platinum mine strike signals end of ANC domination". The Guardian. 25 June 2014.

[11] "South Africa's economic apartheid". Al Jazeera. 12 September 2012.

[12] "Mine Strike Mayhem Stuns South Africa as Police Open Fire". The New York Times. 16 August 2012.

[13] "Marikana mine shootings revive bitter days of Soweto and Sharpeville". The Guardian. 7 September 2012.

[14] An Indian-South African business family which owns a business empire spanning computer equipment, media and mining.

[15] For instance, see http://amabhungane.co.za/article/2017-01-24-inside-the-ancs-black-ops-election-campaign

[16] "Time's up: Jacob Zuma has resigned". Mail&Guardian. 14 February 2018.

radio, TV and newspapers) constitute one way through which scandals could potentially reach out to the people. However, the information provided by these media is usually filtered according to the political slant of the outlet, the opinions of its public and the institutional environment. In fact, according to the World Press Freedom Index, South Africa is ranked 31^{st} out of 180, denouncing a fragile media independence. In particular, "coverage of certain subjects involving the ruling ANC, government finances, or state-funded improvements to President Zuma's personal home are either off limits or provoke a hostile reaction from the authorities" [17].

Similar restrictions are unlikely to hold for new media, which are promoted by the diffusion of the Internet and are broadly identified with social media and online information and communication platforms (e.g. Facebook, Twitter, WhatsApp, Wikipedia, YouTube, etc.). As a consequence, availability of the Internet becomes a fundamental source of complementary and potentially relevant information from the voters' perspective. In addition, by their nature, online platforms have the power of creating viral circulation of news, amplifying their effects and boosting their persuasive power.

This paper seeks to find a plausible explanation for the trends depicted in Table 1 in the increase in Internet access and use of social media that, similarly to other countries, South Africa experienced between 2005 and 2016. In particular, I argue that individuals in covered areas had the chance of accessing new, free and relatively unbiased (local and international) information through the Internet. This, in turns, should impact on their political participation, attitudes and voting preferences. The potential mechanism behind this assumption would entail that Internet access helped voters in both (1) accessing information on ANC corruption and social scandals and (2) realizing that some news about competitors were fake. This mechanism implies that in areas with higher Internet coverage people decided to punish the ruling party and vote for alternative candidates or refuse to vote. Therefore, one should expect to observe a negative impact of Internet coverage on the ANC vote share. By contrast, effects on other parties are more difficult to predict.

3. The Internet in South Africa

In terms of Internet access, South Africa is one of the most technologically advanced countries on the African continent. Nevertheless, there is still large spatial variation in Internet coverage within the country, with overall urban areas enjoying more connectivity than rural places.

South African Internet market is mainly dominated by three private Internet service providers (ISPs) with more or less homogenous market shares (Figure 12 in the appendix). The country has experienced a sharp increase in Internet usage since 2006: users as percentage of the population were around 5% in 2006, while they were more than 50% in 2016 (Figure 13a in the appendix). The average price for 1GB of prepaid data was about \$7 in 2016, that is almost 1.8% of the average monthly per capita GNI. This makes South Africa one of the country with the lowest prices in the Southern African Development Community. No sharp drop in tariffs has occurred. At the same time, fixed broadband Internet subscribers per 100 people remain below 4 (Figure 13b in the appendix), and they mostly live in large cities where landline is available. Therefore, the rest (and most)

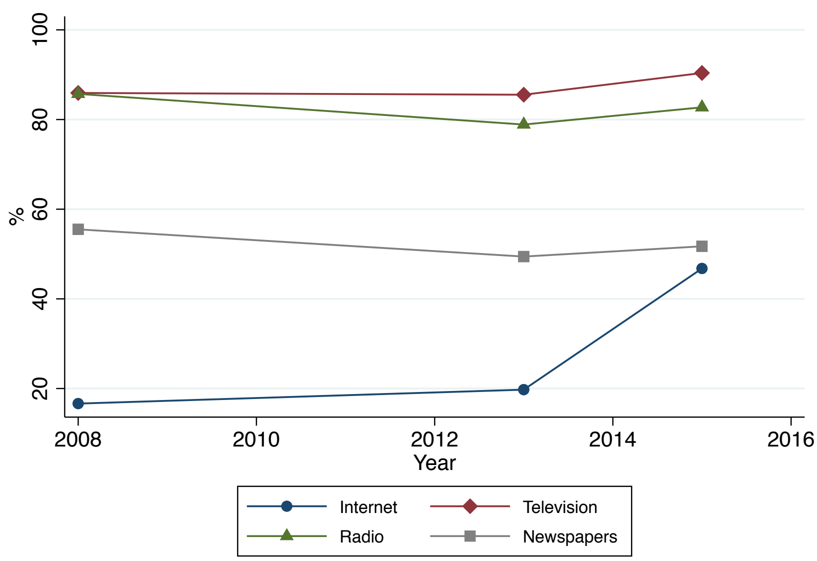
[17] http://www.rsf.org

of Internet users rely on mobile technologies. As a matter of fact, if we look at the number of mobile cellular subscriptions per 100 people (Figure 13c in the appendix) we can observe that after 2008 people started subscribing for a second line. As expected, the temporal variation in the usage was accompanied by a significant spatial expansion of mobile Internet coverage between 2006 and 2015 (Figure 14 in the appendix). By contrast, 2G (GSM) coverage has remained mostly stable over the past 12 years.

According to the 2016 annual report from We Are Social (https://wearesocial.com), an independent agency that monitors internet activity combining data from various qualified sources, almost 26.8 million people (50%) were active Internet users in January 2016. 13 million of them (24%) were active social media users, and 10 million (19%) were active mobile social users (Figure 15 in the appendix). The majority (92%) of South Africa's adult population owns a phone whether dumb, feature or smartphone. Smartphones represent the biggest share of this majority at 60%. Only 18% owns a laptop or a desktop computer, and 7% a tablet. The average South African spends just under 5 hours a day online (assuming time spent online at work is also counted). Average daily time spent on the Internet via a mobile phone is about 3 hours, and the time spent on any social media is just less than 3 hours. Note how time spent on social media and watching TV are almost exactly the same amount. This may be due to what the digital world calls using a "second screen", that is, tweeting, Whatsapping or Facebooking etc., while watching something on TV. Figure 15 in the appendix also reports the top ten most popular social media among South Africans, with WhatsApp and Facebook holding to the top two spots. Most of Facebook's users in South Africa are between the ages of 20 and 29 (41%). Senior citizens above the age of 60 account for 7% of users.

Previous literature (such as Gavazza et. al 2016) has documented the existence of a substitution effect of Internet arrival on the use of traditional media in order to access information. Did this happen in South Africa? Figure 1 below is based on the elaboration of Afrobarometer data and helps us answering this question.

Figure 1: Regular users by type of media (to access information)



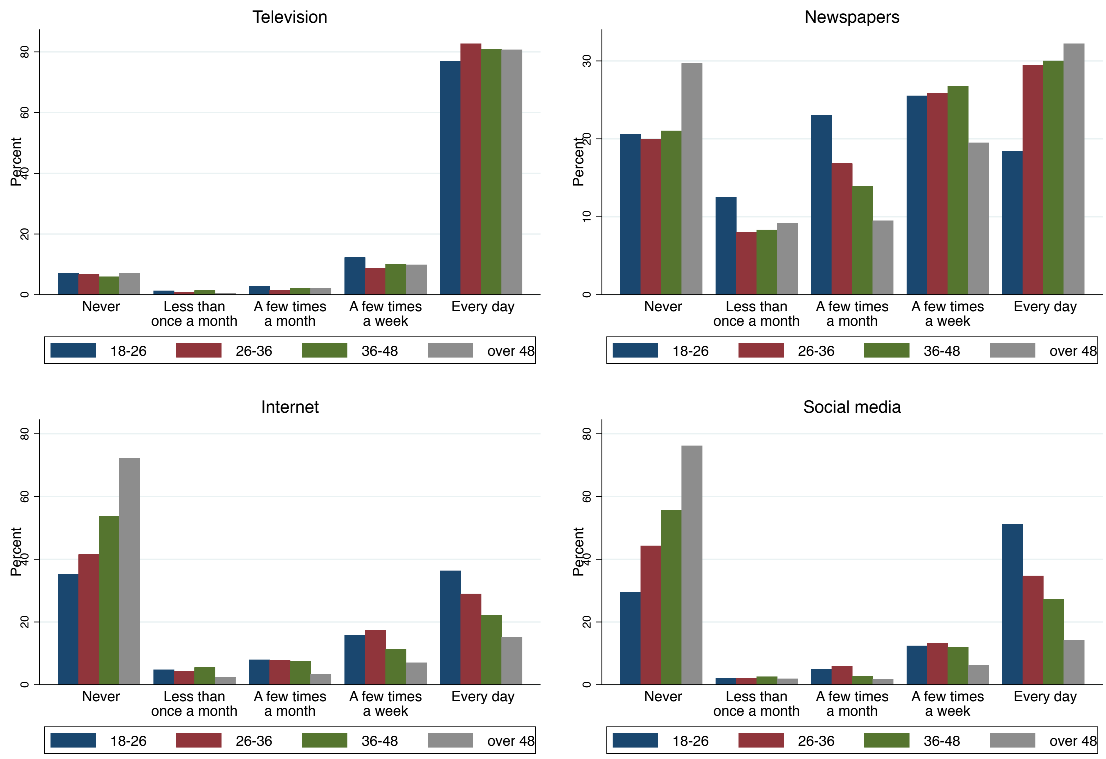
Notes: Author's own calculations based on Afrobarometer.

Regular users are defined as those individuals that use the media as a source of information at least a few times a week. As expected, Internet usage rose between 2008 and

and 2015, and it sharply increased between 2013 and 2015. Meanwhile, at least on the extensive margin, it seems that the Internet did not crowd out traditional media. Newspapers readership only marginally decreased, while the use of radio and TV remained almost constant over the last years. This does not mean that habits towards media usage did not change. Indeed, on the intensive margin, traditional media usage probably went down.

Is there heterogeneity in the use of these media across different age categories? Figure 2 below addresses this point for year 2015.

Figure 2: Use of media across age groups



Notes: Author's own calculations based on Afrobarometer.

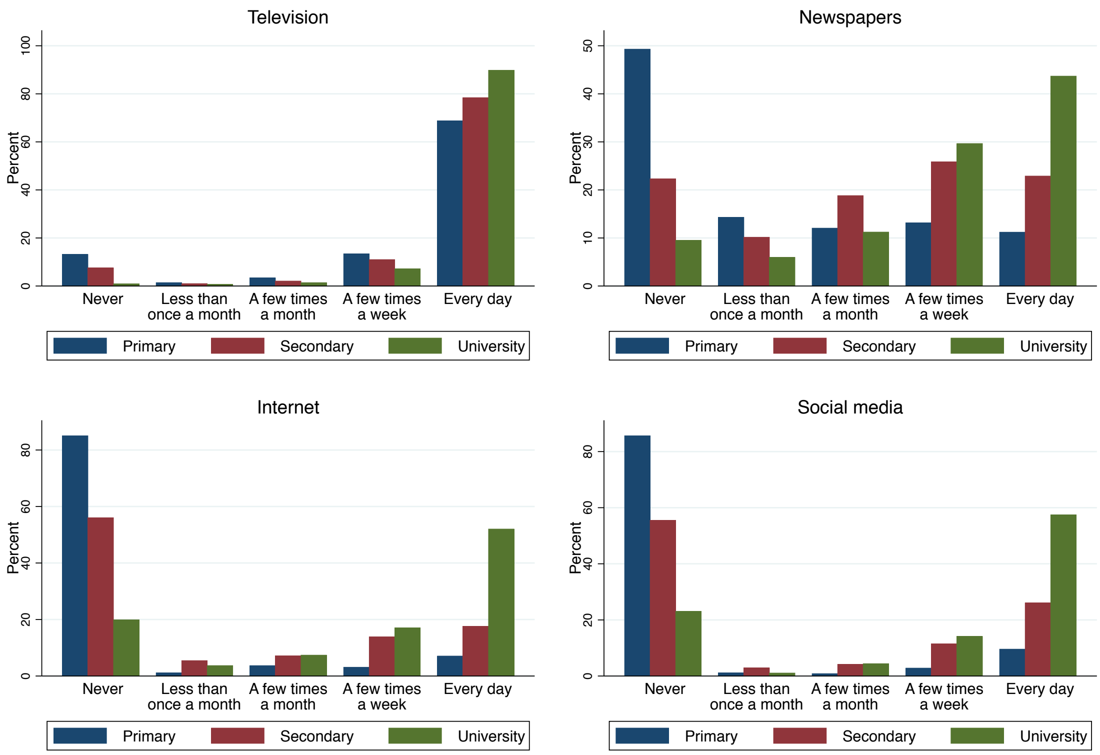
For each type of media[18] the charts depict the frequency of its usage by age group (age quartiles). As expected, the use of television does not vary substantially across different age categories, with approximately 80% of the people in each age group watching TV to get information on a daily basis. The situation slightly differs for newspapers. Here we can see that relatively old people are more likely to read newspapers every day and, at the same time, they are also more likely not to read them at all. Apparently, as people get older their choice on readership gets more polarized.

As on the Internet and social media usage the picture is remarkably different. Here the reader might observe that only relatively young people use the Internet or the social media as source of information on a regular basis. Most importantly a large fraction of old people (almost 80%) never access information through this type of media. These charts suggest that we should expect to find a larger effect of Internet coverage in those places with higher proportion of youth, as they represent the segment of the population that most likely utilizes this type of media.

[18]Radio is excluded for the sake of conciseness, yet its statistics are very similar to the ones on TV.

What about heterogeneity across education levels? Figure 3 below reports the frequency in media usage by different education categories.

Figure 3: Use of media across educational groups

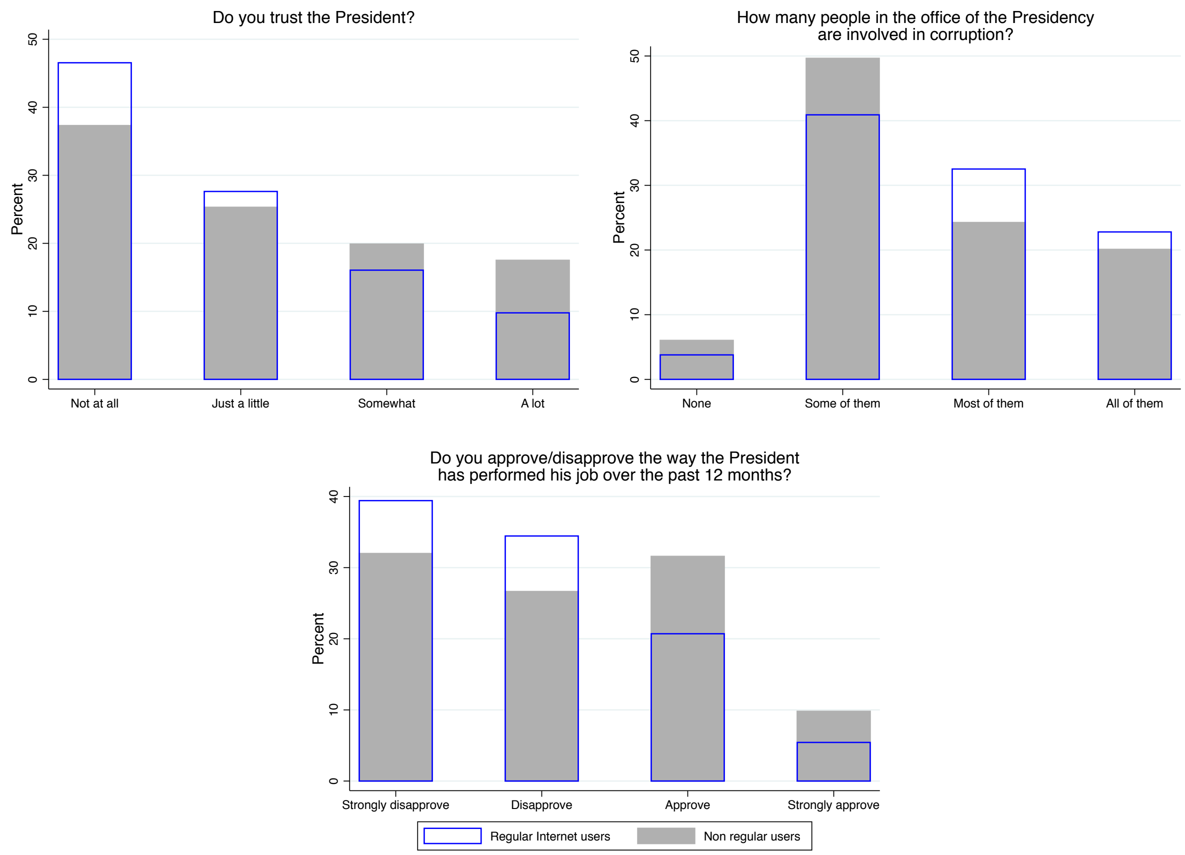


Notes: Author's own calculations based on Afrobarometer.

Information through television is accessible from all the groups in a pretty similar way. However, for newspaper the situation is different, with the majority of university graduates reading newspapers every day. By contrast, almost 50% of low-educated individuals never read newspapers. Similar patters appear when we look at Internet and social media usage across different education groups. In particular, above 80% of the people with primary education never use these media. Meanwhile, almost 50% of highly-educated individuals use them every day. The reasons explaining these patterns are not revealed by this simple analysis, yet one may think that higher education is associated with higher usage through income. In other words, only richer (i.e. highly educated) individuals can afford to buy the necessary technology (smartphone, laptop, Internet subscription, etc.). Overall, these figures might imply that the expected effect of Internet coverage is larger in places where the average level of education is also higher.

The previous figures show that a non-negligible proportion of individuals, especially if young and educated, were used to access information through the Internet and social media in 2015. If this new source of information actually played a role in revealing to the people about corruption scandals inside the ruling party, then one might expect to observe heterogeneous opinions towards the former ANC leader and President across Internet users and non users. Figure 4 below shows the answers to three questions on the President and his office for two distinct categories: regular Internet users (those that use the media as a source of information at least a few times a week) and non-regular users.

Figure 4: Opinions towards the presidency by Internet usage



However, Internet usage is likely to be correlated with various individual characteristics. To partially address this issue, I run separate regressions instrumenting Internet usage with actual 3G coverage and controlling for different socio-economic covariates. Table 2 below shows the results of this exercise for answers to different questions.

Table 2: OLS and 2SLS: Opinions by Internet usage

	Any party affection		ANC affection		ANC vote		Trust president	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Internet user	-0.000	-0.340	-0.046	-0.547*	-0.070*	-0.604*	-0.069**	-0.234
	(0.020)	(0.290)	(0.033)	(0.319)	(0.038)	(0.331)	(0.031)	(0.352)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

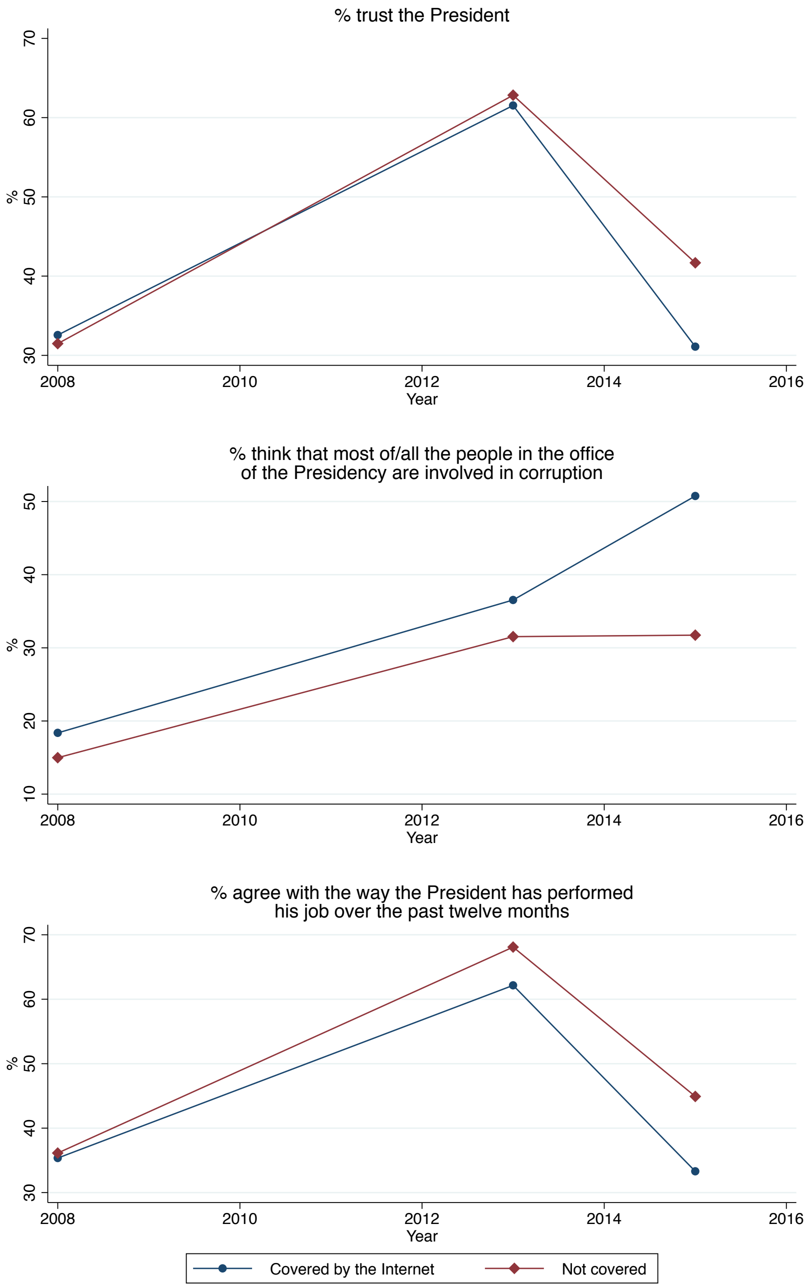
	Trust ruling party		Performance President		Corruption President		Opposition silenced	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Internet user	-0.070*	-0.655**	-0.110***	-0.444	0.053**	0.736**	0.044	0.886***
	(0.040)	(0.324)	(0.025)	(0.351)	(0.026)	(0.305)	(0.027)	(0.298)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wald F-stat		14.8		14.8		14.8		14.8
Observations	2376	2376	2376	2376	2376	2376	2376	2376

Notes - Standard errors in parentheses clustered at the village level. The Kleibergen-Paap rk Wald F statistic is reported. Province fixed effects included in all regressions. Controls include TV, radio and newspaper usage, occupational status, age, education, religion, distance from closest provincial capital/major city. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

General affection towards politics is not influenced by Internet usage, while ANC affection is. As expected, respondents who use the Internet more regularly are less likely to vote for the ANC and to trust the President and the ruling party. In addition, these people are more likely to disapprove the way the President performed his job in the last year and to think that most of the people in his office are involved in corruption. Finally, they are more willing to think that opposition parties are silenced by the incumbent.

A robustness check for the previous correlations can be performed looking at trends in the answers to these questions across individuals with and without Internet access. To carry out this exercise I aggregate the previously depicted possible answers and create a binary indicator. Figure 5 shows the results. In 2008, individuals living in areas with potential access to the Internet had similar opinions to those with no access. As expected, divergence in opinions across the two groups enlarges over time. This is consistent with two facts: (1) actual Internet usage was low in 2008 and it increased over time; (2) many political and corruption scandals emerged in more recent years. Therefore, it seems that the simple fact of living in an area with Internet access in 2008 does not imply divergence in opinions towards the incumbent.

Figure 5: Trends in the opinions towards the presidency by Internet coverage



Notes: Author's own calculations based on Afrobarometer.

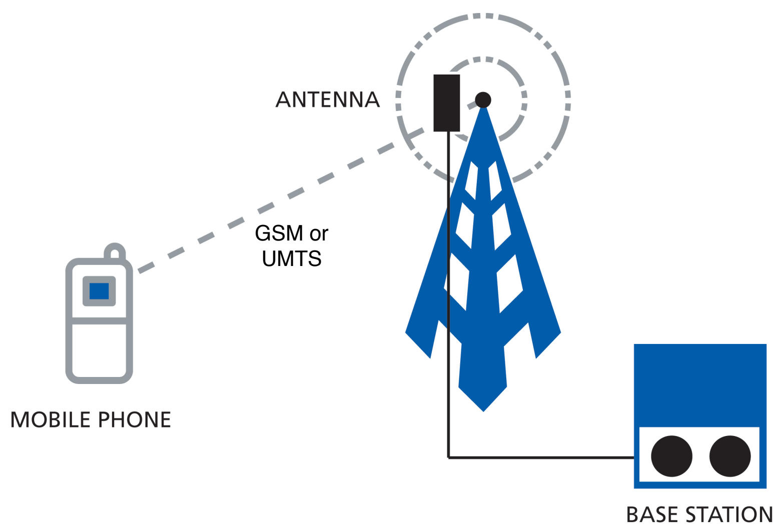
The descriptive evidence reported in this section partially sheds light on the potential mechanisms that may drive the causal relationship between Internet coverage and political outcomes. In particular, 3G coverage leads to higher Internet usage, often through smartphones, especially among the young and more educated generation. In turn, this fosters social media penetration and access to information via browsing in areas where 3G is present. Availability of new media amplifies the circulation of those news that damage the incumbent party. Voters take the new information into account to make educated political choices: their opinions and trust towards ANC are affected, and this is likely to impact their behavior at the ballots.

4. Empirical strategy

4.1 Determinants of 3G coverage

The rollout of 3G mobile network in South Africa started around 2005. At that time, existing antennas were already supporting the 2G (GSM) wireless communication technology, which enabled mobile phone calls and very limited data usage. 3G technology is an extension of GSM and is designed to offer faster data access speeds and network efficiencies for mobile Internet and multimedia applications. The following image describes the basic way any mobile phone network works.

Figure 6: Mobile phone technology



The primary job of a cell tower is to elevate antennas that transmit and receive radio-frequency signals from mobile devices. Wires run from the antenna to base station equipment, typically located at ground level in sealed telecom equipment cabinets. Components of the base station include transceivers, which enable the transmission and reception of radio signals through the antennas.

Two main differences exist between a 2G and a 3G mobile network infrastructure. The first one has to deal with the number of antennas (towers) required to provide signal to a specific population. Specifically, more 3G antennas are needed to cover the same number of connections that one 2G repeater could support alone. The second difference lies in the equipment installed in the base station. Therefore, supplanting 2G with 3G technology requires at least two changes: (1) installation of additional towers in new sites;

(2) updating the technology in existing sites. For 3G technology, there are two favored technical approaches – Enhanced Data rates for GSM Evolution (EDGE) and Universal Mobile Telecommunications System (UMTS). UMTS requires that carriers completely replace their existing base station equipment to offer 3G services, while EDGE does not. In South Africa, all mobile operators rely on UMTS, meaning that a replacement process has occurred.

In this paper I seek to identify the causal impact of Internet penetration on political outcomes. For this purpose, I will exploit the temporal and spatial variation in coverage and ballot results that occurred over the period 2000-2016. However, Internet allocation is far from random, yet it reflects market-based calculations and profit optimization choices performed by the private ISPs. Endogeneity issues are perhaps less severe than when considering landline Internet, being the mobile technology relatively more difficult to restrain in a given precise area by its electromagnetic nature. However, the decisions on the region a private operator aims at targeting and the site and year in which the transmitter is located are likely endogenous. At a basic level, the site must be adjacent to a road for physical access, with availability of electrical power and telecommunications network connectivity.

A World Bank report by Buys at al. (2009) studies the determinants of disparities in cell phone coverage in Sub-Saharan Africa in order to understand the predictors of mobile internet coverage. The report highlights that both demand and supply side factors play a role. Among other things, it shows that places with larger potential market size (as measured by per capita income), lower elevation and smoother terrain characteristics are significant determinants of better coverage.

Following a similar approach, I analyze the determinants of 3G availability in South Africa. Internet coverage can be measured in a twofold way: (1) looking at the share of area covered (i.e. penetration); (2) considering the number of years of coverage for each locality. I take both measures into account and regress them on a series of socio-demographic, economic and geographical characteristics. Therefore, I estimate a fixed-effects model that predicts coverage based on these characteristics. In the estimation I use years 2000, 2006, 2011 and 2016, i.e. those coinciding with the local municipal elections. Table 13 in the appendix shows the results. The share of area covered is positively associated with population density, urbanization, education, presence of a road, and cellphone penetration in 2000, among other things. At the same time, mean age, distance from provincial capitals and main cities, and terrain ruggedness negatively predicts penetration. Similar associations hold when considering the number of years of coverage.

4.2 Baseline specification

The baseline empirical strategy of this paper relies on a Diff-in-Diff approach that exploits the high-resolution features of the data at the voting sub-district level. The main specification I estimate is the following:

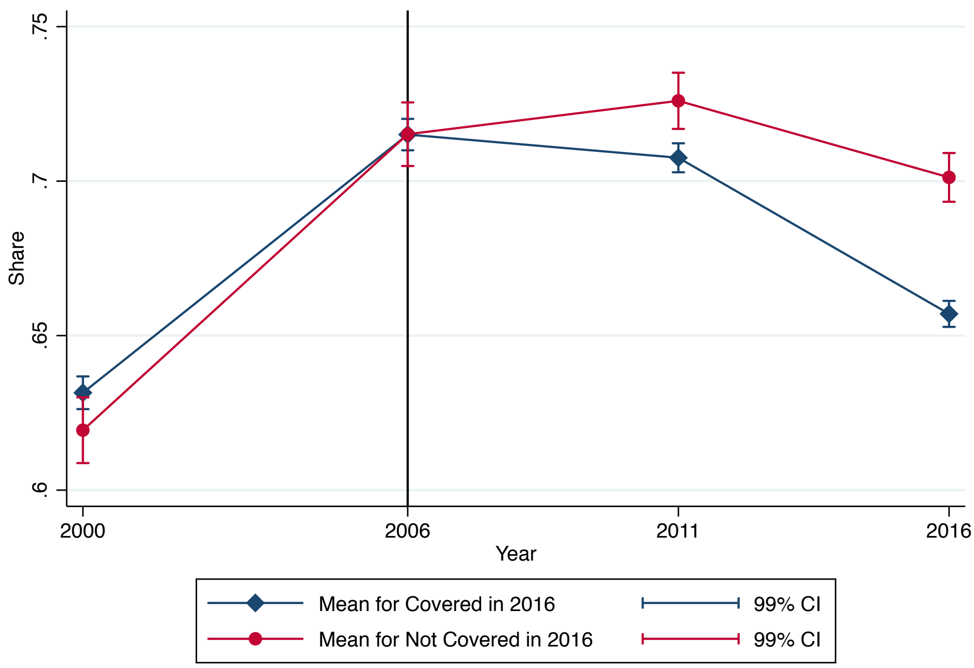
$$y_{it} = \beta_0 C_{it} + \sum_{j=2011}^{2016} (\beta_{1j} C_{it} * \mathbb{1}(t=j)) + \mathbf{x}_{it}^{'} \beta_2 + \mathcal{P}(\mathbf{w}_i * \theta_t)^{'} \beta_3 + \mu_i + \theta_t + \varepsilon_{it} \qquad (1)$$

Where i is the index for voting sub-districts, and t is the year level time index, such that $t = 2006, 2011, 2016$. In fact, the baseline analysis focuses on the period 2006 to 2016 to carry out causal inference, and exploits the first two electoral rounds (2000-2006) to conduct placebo checks. C stands for *Coverage*, which is the mean Internet coverage of each locality. Vector $\mathbf{x}$ contains time variant controls such as the log of luminosity and population density, urbanization rate, average education and age. Vector $\mathbf{w}$ contains pre-determined time constant variables measured in 2000 and geographical controls. I interact these covariates with year dummies, and also include 5^{th}-order polynomials. Finally, μ and θ represent voting sub-district and year fixed effects, respectively. Variable y is alternatively the vote share of ANC, DA and other parties combined, voter turnout, average number of parties and average number of protests.

Specification reported in (1) allows me to account for various sources of potential endogenity. In particular, voting district fixed effects account for time invariant unobserved factors that may affect the outcome and may also be correlated with Internet coverage. The year dummies capture instead the time trend in the outcomes that is common to all localities. Finally, I allow demand and supply side factors to have different impacts on the outcome over time by interacting pre-determined controls with time dummies. I cluster standard errors at the level of the smallest (temporally) stable union of voting sub-districts to account for both cross-sectional and temporal correlation in the errors.

In equation (1), coefficient β_0 captures the average difference in y between covered and non-covered localities at the baseline year, i.e. 2006. In order for $\beta_{1,2011}$ and $\beta_{1,2016}$ to consistently identify the average treatment effect of Internet coverage on the outcomes of interest the parallel trend assumption must hold. In other words, in the absence of Internet coverage, treated and untreated localities should exhibit common trends. Although it is impossible to provide a formal proof for this assumption, I will conduct a placebo experiment regressing electoral outcomes in 2000-2006 on lagged-Internet coverage measured in 2006-2016. Results from such a procedure are in favor of the parallel trend assumption if *Lagged Coverage* does not significantly predict any political outcome over the period 2000-2006. A graphical inspection of pre-trends can also be helpful.

Figure 7: ANC SHARE BY 3G COVERAGE



Notes: Districts covered in 2006, metropolitan areas, province capitals and larger cities are excluded.

Figure 7 reports the mean share of ANC party over time for two subgroups of localities, those with Internet coverage (i.e. $Coverage > 0$) and those not covered in 2016. To draw the figure, I exclude localities that were covered by 3G in 2006 and drop metropolitan areas and provincial capitals. In addition, I shift the lines so that in 2006 the averages for the two groups exactly matches. This is done to better inspect existence of specific trends in ANC share before the arrival of the 3G technology.

The figure shows that in covered localities ANC lost disproportionately more than in other districts. In particular, this loss is amplified between 2011 and 2016, that is when the supply of scandals and social media penetration became higher. Most importantly, there seems to be supporting evidence to exclude the presence of specific pre-trends in ANC share before 2006. Overall, the picture is in favor of the parallel trend assumption.

Finally, I conduct a test following the standard AET (Altonji, Elder and Taber 2005) procedure. This approach uses the degree of selection on observed variables as a guide to the degree of selection on the unobservables. Specifically, in my context I regress the outcome variables on the "endogenous" component of coverage, that is the one explained by geographical and socio-economic observables. If the coefficient on predicted coverage is not statistically significant or it has opposite sign compared to the baseline regressions, then this suggest that unobservables should play a limited role in the baseline results .

4.3 Alternative specifications

In order to provide extra evidence on the impact of mobile Internet coverage on political outcomes I perform a robustness analysis based on alternative approaches.

The first one involves the use of a pre-matching estimator. In particular, I rely on propensity score matching to estimate the likelihood of being sufficiently covered (i.e. $Coverage \geq 0.5$) by 3G in 2011 and 2016 given socio-economic and geographical observables measured in 2000. I use one match per observations, meaning that each treated locality is matched with another one from the control. The treatment effect is computed by taking the average of the difference between the observed and potential outcomes for each locality.

The second approach relies on a 2SLS estimation. In this case, I instrument the "Number of years of Coverage" since 2005 with exogenous variation in (the log of) terrain ruggedness interacted with a dummy which equals 1 if $year > 2005$. Several technical reports and papers highlight how the site where an antenna is built must be adjacent to a road for physical access, with availability of electrical power and telecommunications network connectivity (Harris, 2011; GSMA report, 2015; Aker and Mbiti, 2010, among others). When the rollout of the 3G started in South Africa, i.e. around 2005, phone companies had to verify that locations met these physical requirements before building antennas. At the same time, they had to expand the network to reach additional areas. Ceteris paribus, phone companies initially avoided localities with geographical characteristics associated with higher costs —namely, steeper slopes, and distance from a main road and major urban centers—. Conditional on economic development, population density, distance from cities, and other geographical controls, terrain ruggedness is the factor that best explains the time of 3G arrival in a location. This is also visible in the exploratory analysis reported in column 2 of Table 13 in the appendix. In particular, $log(ruggedness)$ matters for the timing of mobile Internet penetration only after 2006. Therefore, I rely on the following 2SLS procedure:

$$
\begin{aligned}
&1^{st}\ Stage: \quad YC_{it} = \pi_0 \left(log(Rugg) * \mathbb{1}(Year > 2005) \right)_{it} + \mathbf{z}_{it}^{'}\pi_1 + \mu_i + \theta_t + u_{it} \\
&2^{nd}\ Stage: \quad y_{it} = \gamma_0 \hat{YC}_{it} + \mathbf{z}_{it}^{'}\gamma_1 + \mu_i + \theta_t + \varepsilon_{it}
\end{aligned} \tag{2}
$$

where $t = 2000,\ 2006,\ 2011,\ 2016$ and YC_{it} stands for the number of years since 2005 district i has had at least half of its area covered by 3G (i.e. $Coverage_{it} \geq 0.5$). $Rugg$ stands for ruggedness, and its measured by the standard deviation of elevation. Vector $\mathbf{z}$ contains time variant controls and time invariant variables interacted with year fixed effects.

In order for the instrument to be valid, two conditions have to be satisfied. Firstly, it has to be relevant. One can easily investigate relevance by looking at the $Wald\ F-statistic$ from the 1^{st} stage. In particular, since in my case the i.i.d. assumption is dropped and I cluster the standard errors, I will consider the $Kleibergen - Paap\ rk\ Wald\ F - statistic$.

The second condition is exogeneity. This requires that the correlation between ruggedness and any relevant omitted voting district's characteristics did not change around 2005, other than through the availability of the Internet. Although it is impossible to develop a formal proof for this assumption, I will conduct a series of exercises to provide supporting evidence.

4.4 Testing the mechanisms

To obtain some suggestive evidence on which potential mechanisms could drive the causal relationship between Internet and political outcomes, I develop an extensive heterogeneity analysis. The basic idea behind this analysis is to draw from the descriptive evidence of section 3 along with the insights from the political scenario described in section 2 and then examine if and how Internet coverage plays a different role across various socio-economic conditions and across regions differently exposed to social and political scandals. This analysis is conducted in two different ways, which exploit alternative features of the data.

The first strategy to study the potential mechanisms simply relies on the analysis of heterogeneous treatment effects. In particular, I split the original sample in various sub-samples according to observable and possibly relevant characteristics measured in 2000.

These include income (luminosity), education and age to study differential effects of 3G across distinct socio-economic conditions. According to section 2 one should expect to observe a larger impact in localities with higher education rates and percentage of youth, being highly-educated and young individuals those who are more likely to own a digital device and to use it more regularly. Moreover, I look at population density and urbanization rate to assess potential heterogeneity across rural and urban areas. Finally, I consider ownership of devices and traditional media (cellular, phone, TV and Radio) to study differences among localities with a diverse technological take-up. One idea is that circulation of information is lower in more isolated localities, hence one may expect a higher impact of Internet arrival there. However, the effect of the Internet depends on the way individuals use it. Therefore, it might be that in localities where traditional media penetration was scarce, individuals who suddenly got access to the web used it for different purposes than accessing information. If this is the case, then final effects are difficult to predict.

For each characteristic I use the median value to split the original sample in two groups. Hence, for each group I run regression (1) in order to understand which characteristics are more suitable to explain the observed relationship.

The second strategy is based on a triple-difference estimation (DDD). This has a twofold purpose. On the one hand, a DDD estimation provides a further tool to tackle potential endogeneity of Internet coverage. On the other hand, it gives additional insights on the information role of the Internet. In fact, the strategy exploits the spatial variation in the probability of exposure to administrative and corruption scandals. Specifically, I take advantage of two sources of variation.

First, I exploit variation in irregular and unauthorized expenditure per capita across municipalities to construct a proxy for corruption at the municipal level. The idea is that in regions where this expenditure is higher, the probability of scandals is also higher. In the last years the National Treasury funded an initiative called Municipal Money. This is a free, impartial and politically neutral online tool to find out about how municipal funds are spent. Every individual can access this information on the web. A screenshot of the web page is reported in Figure 16 in the appendix. In addition, in order to give a sense on how the demand for information on corruption has increased over time, the same figure depicts Google trends for searches of the word "corruption". As expected, in recent years searches for corruption have increased significantly. Overall, this is a consequence of the rise in both Internet penetration and supply of corruption-related scandals. If the Internet is used as a source of information, then one should expect to find significantly larger effects of *Coverage* in municipalities with a higher level of irregular expenditure per capita.

Second, I rely on the surge in mining strikes to take advantage of the spatial variation in social and economic discontent. Localities where the mining industry played a relevant role were more likely to be affected by the long-lasting negative consequences of the strikes. In addition, as explained in details in section 2, the ANC party shared the blame for the accidents and for the inadequate administration of the events. Therefore, among places exposed to the mining industry, i.e. those that suffered most from the strikes, one may expect the Internet to play a bigger role in shaping individuals' opinions. In fact, opinions towards the incumbent are likely to be affected by (1) direct personal experience of the brutality of the events and (2) availability of persuasive information on the accidents. In particular, finding larger effects of *Coverage* on political outcomes in these places would support the idea that either voters have voluntarily used the Internet to retrieve information, or they indirectly got exposure to it.

To empirically examine the information channel I estimate the following regression:

$$\begin{aligned} y_{it} = \quad & \beta_0 C_{it} + \beta_1 C_{it} * \theta_t + \mathbf{x}_{it}' \beta_2 + \mathcal{P}(\mathbf{w}_i * \theta_t)' \beta_3 + \\ & \beta_4 C_{it} * \theta_t * E_i + \beta_5 C_{it} * E_i + \beta_6 \theta_t * E_i + \mu_i + \theta_t + \varepsilon_{it} \end{aligned} \tag{3}$$

where the usual notation applies with the only difference that for this analysis I focus only on the 2011 and 2016 electoral waves. The main reason is that data on municipal expenditure are available for years after 2011, and information on the gross value added (GVA) from the mining sector is measured in 2009. At the same time, it is true that mining accidents and scandals occurred much more frequently after 2011. Therefore, in equation (3), θ_t is a dummy equal to 1 if the year is 2016, meaning that the baseline is set in 2011.

E is a time invariant variable that represents overall exposure to either corruption or mining strikes, alternatively. Specifically, when E stands for corruption, it is measured by the sum of irregular and unauthorized audited municipal expenditure per capita in years 2012 to 2015. Otherwise, when E stands for exposure to mining events, it is proxied by the per capita GVA from mining and quarrying, for each district. Note that standalone E is omitted from (3) because of the inclusion of districts fixed effects. The main coefficient of interest is β_4, the one associated to the triple-interaction term. According to the political scenario presented in section 2 and the descriptive evidence presented in section 3, a negative and significant β_4 when y is the ANC share would provide evidence in favor of the information channel: in places where availability of scandal events was higher people with Internet access gained exposure to additional facts and changed their political opinions.

4.5 Spatial analysis

The spatial analysis takes advantage of the geo-referenced features of the dataset to understand whether the political environment affects the way Internet coverage impacts on political behavior. The analysis draws from the idea that preferences and beliefs of the neighbor N of voting district i have a direct and indirect influence on voting outcomes in i. The direct effect is the result of social interaction: closer individuals interact more and, in turn, this shapes their beliefs. The indirect effect works through information segregation over space: the online/offline information that individuals in i are exposed to is partially filtered by N_i.

I seek to disentangle the two effects and assess their final impact on spatial convergence (or divergence) of political preferences. It is reasonable to imagine that this effect also depends on the prior beliefs of i with respect to those of N_i. Without loss of generality, I use the vote share of ANC in 2000 as a proxy for prior beliefs of each district and its neighbor. This way, pro- vs anti-incumbent preferences measure beliefs, and reflect the polarized South African political scenario. To define the neighbors I rely on 1^{st} order Queen contiguity spatial weight matrix. According to this procedure, two districts are neighbors if they share any part of a common border. Hence, for each district i, I use the weight matrix to compute the average ANC share in the neighbor, i.e. ANC_{N_i}. Then, I construct a relative measure of beliefs' divergence, or $Spatial\ Isolation$ (SI), according to the following formula

$$Spatial\ Isolation_i = ANC_i - ANC_{N_i}, \tag{4}$$

where, by construction, $SI_i \in [-1, 1]$, $\forall\ i$.

Whenever SI is close to zero, then we are in presence of clusters: individuals geographically close to each others have aligned beliefs (either they like or dislike the incumbent). By contrast, when SI approaches the extremes, then heterogeneity in beliefs is high. This means that, on average, in these localities individuals are more exposed to diverse opinions towards the incumbent.

Finally, one should consider if the information provided by 3G is compatible with the beliefs in i and/or N_i. In this specific context, it is likely that online information is damaging the image of the incumbent party, as I will show in section 6. This implies that as SI approaches to 1, online information is more aligned with N_i'dominant beliefs and less with those of i, and vice versa.

To disentangle the social interaction and information segregation effects I interact $Coverage$ with SI, and estimate a DDD regression as shown in (2), where now $E_i =$

SI_i. Overall, a higher SI means that a smaller share of people around i likes ANC, relative to i. In this setting, coefficient β_6 would capture the social interaction effect on i' political behavior of being closer to a neighbor which is more likely to be anti-incumbent. Coefficient β_5, i.e. the one on the triple interaction term, instead captures the extra role of Internet coverage in amplifying (or reducing) the social interaction effect. In particular, if β_5 and β_6 have the same sign, then this would provide supporting evidence on the existence of online spatial information segregation.

5. Data and descriptive statistics

5.1 Dataset construction and sources

The research is based on a newly-assembled dataset containing time-varying and geo-referenced information on political outcomes (vote share of the main parties, political turnout, number of parties and protests), 3G mobile Internet coverage, economic development (as measured by luminosity at night), population density, urbanization and a variety of socio-demographic indicators (education, age, youth population and media ownership) measured at the voting district level. In addition, each observation contains time constant information on average elevation (m), terrain ruggedness (m^2), average terrain slope, area (km^2), a dummy variable indicating the presence of a major road, river and mining, and the distance (km) from the closest provincial capital or city with more than 1 million inhabitants.

The construction of the dataset involved two steps.

Step 1. Firstly, I create new geographical units of analysis. In fact, data on political outcomes come at a very disaggregated level, that is the voting district. However, the boundaries and the number of these districts change over time. The Municipal Demarcation Board of South Africa[19], which provided me with the demarcation data, is in charge, among other things, of the determination and redetermination of municipal wards boundaries for the elections. The Board is an independent authority. Its status is protected by section 3 of The Local Government: Municipal Demarcation Act, 1998, and various judgments by the Constitutional Court. As stated in their website, the main driver of demarcation redeterminations is the increasing or decreasing number of voters.

In 2000 there were 14,988 voting districts, 18,872 in 2006, 20,857 in 2011 and 22,612 in 2016. Hence, the first step was to create a stable geographically and time invariant unit of observation. This has two purposes: on the one hand it allows comparability of electoral outcomes over time, on the other hand it solves the problem of endogenous change in the district boundaries. There are to possible ways of creating new units of observations.

The first method focuses on the union of all neighboring districts whose boundaries change over time: I use an algorithm that combine neighboring and mutable voting districts until it reaches a stable aggregation. The output provides new entities that represent the smallest aggregations of districts whose borders are constant between 2000 and 2016. These are approximately 3,800 clusters, much less than the initial number of voting districts.

The second method, instead, is based on the intersection of initial districts. The procedure is exemplified in Figure 17 in the appendix. The spatial intersection of two initial voting districts whose common border changes over time gives birth to three new entities.

[19]http://www.demarcation.org.za

For each entity/year I assign the political outcome of the voting district from which it originated, for the respective year. This procedure creates about 43,000 observations per year.

The two methodologies produce two distinct datasets: the number and size of the observations largely differ. The first method has the advantage of measuring the political outcome more accurately, as it is simply the sum of the outcome in the initial districts. However, the dimension of the new entities is critical. Most of them are large in size and, in turn, Internet coverage ends up being imprecisely measured. In particular, for each large observation, it becomes impossible to distinguish who is covered and who is not. In this setting, the granularity of my measure of 3G coverage becomes, somehow, useless. Therefore, to better take advantage of the high-resolution of the data, I decide to focus on the second procedure. The 43,000 observations/year have much smaller dimensions, hence it becomes possible to precisely attribute average Internet penetration to each of them. Then, to account for correlation in the errors induced by the intersection process, I cluster the standard errors at the level of the smallest stable aggregation, as depicted by the dashed line in Figure 17 in the appendix. The procedure provides larger, hence more conservative, standard errors. At the same time, in order to alleviate the suspect of endogenous change in the borders, I replicate the baseline estimation only for those districts whose boundaries remained almost constant over time.

Step 2. For each of the 43,000 units I calculate zonal statistics (mean and standard deviation) of the above mentioned variables using the GIS toolbox. The following list contains details on the sources I used.

Administrative data on political outcomes for municipal elections come from the Independent Electoral Commission (IEC) of South Africa. These data are freely available on the IEC website[20]. However, only the most recent shape-files are available online. I obtained the comprehensive set of shape-files for all years since 2000 directly from the IEC office. Voting data contains information on the total number of potential voters, the actual number of those who actually voted, and the number of votes each party got in each voting district. I used the number of potential voters as a proxy for population for each voting district.

Data on Internet coverage come from Collins Mobile Coverage Explorer[21], a web based roaming coverage map service made available through Collins Bartholomew's partnership with the GSMA[22]. See Manacorda and Tesei (2016) for a recent application of the data. Using the latest mapping technology, the company combines up-to-date world base maps with unique mobile network coverage data provided by operators from around the world. These maps are then delivered to network operators to help them tell their users where they can use their phones when abroad. The data that have been licensed collate, for all years between 2007 and 2015 (with the exception of 2010), the most recent submission during that year from all member operators in each country. The dataset comes in GIS vector format and for each country provides 2G, 3G and 4G coverage, separately: each pixel has value 1 if covered, 0 otherwise. In South Africa the geographical precision varies from year to year, with a maximum pixel size of 1km by 1km (up to almost 200m x 200m in the most recent version). I exploit only 3G coverage data since there is practically no variation in 2G or 4G technologies between 2007 and 2015: almost all places had 2G

[20]http://www.elections.org.za

[21]http://www.collinsbartholomew.com/mobile-coverage-maps/mobile-coverage-explorer/

[22]https://www.gsma.com

already before 2007, almost no place had 4G in 2015 (nor before). To proxy coverage in 2016 I use Internet coverage in 2015, as this depicts the situation up to December of that year. Similarly, I use coverage in 2007 to proxy internet penetration in 2006. Measurement error associated to this approximations should be small. On the one hand, municipal elections in 2016 were held on the 3rd of August. The assumption is that 3G coverage did not change abruptly in the months right before elections. If it did, my estimate would represent a lower-bound for the actual effect. On the other hand, in the initial years (2007-2009), changes in penetration were extremely marginal. Therefore, is it reasonable to assume that infrastructure status between 2006 and 2007 does not significantly differ.

Luminosity (nigh-light) is used as a proxy for economic development. These data are collected by the Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS) satellite program and is maintained and processed by the National Oceanic and Atmospheric Administration (NGDC 2010, Baugh et al. 2009). They are available for download in GIS vector format on the NGDC website[23]. I use data until 2013, which is the last available year. Each pixel (1 square kilometer) in the luminosity data is assigned a digital number (DN) representing its luminosity. The DNs are integers that range from 0 to 63. The higher this number is, the greater the economic activity in the pixel is. The reader may look at Pinkovskiy and Sala-i-Martin (2016) for a recent application of this dataset as a proxy for GDP in Africa. Unfortunately, being these data available only up to 2013 I had to predict nigh-light for 2015/16. I exploited linear extrapolation by assuming for each observation a constant growth rate between 2011 and 2015, using the observed growth experienced between 2011 and 2013.

I rely on the PRIO/Uppsala Armed Conflict Location and Event (ACLED)[24] dataset to measure actual discontent towards politics. The dataset provides information on a variety of characteristics for any kind of conflict event. I restrict the attention to unilateral actions perpetrated by rioters/protesters. This category of events includes demonstrations against a typically political entity, such as a government institution. The event is coded as involving protesters, when it is non-violent; and as involving rioters if the demonstrators employ violence. However, I disregard this distinction: I merge the two categories and refer to them all together as protests. Moreover, I consider only events that took place in the election years and in the preceding one. So, for instance, for year 2000 I use events that happened in 1999 and 2000. Finally, for each locality/year, I compute the total sum of protests.

Data on education, monthly income, age distribution, urbanization and TV/radio/phone and cellphone ownership at the municipality level come from the 2001 and 2011 population Census. These data are freely available from the official website of Statistics South Africa[25]. Information comes at a very disaggregated unit of analysis, called Small Area level: in 2001 and 2011 there were approximately 56,000 and 85,000 of such Small Areas, respectively. I use zonal statistics to compute the average quantity of the variables of interest for each observational unit/year. Since information on 2006 and 2016 does not exist, I interpolate and extrapolate the quantities, respectively, so to create a balanced panel for each locality. Note that I use the 2001 census wave as a proxy for socio-economic characteristics in year 2000.

[23]http://www.ngdc.noaa.gov/eog/dmsp/downloadV4composites.html

[24]http://www.acleddata.com

[25]http://www.statssa.gov.za

For each municipality I retrieve information on the total income and capital expenditure[26] and on the level of irregular and unauthorized expenditure[27] available on the audited financial statements produced by the Department of National Treasury[28]. In this case I consider data from 2012 to 2015, being these the only years for which the information is available.

Data on elevation and ruggedness (as measured by the standard deviation of the elevation) at similar resolution come from the Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010). The dataset is hosted by the Earth Resources Observation and Science (EROS)[29]. Moreover, shapefiles containing information on major cities, main roads and waterways come from Open Street Map[30]. Data on mining presence come from the Mineral Resources Data System (MRDS)[31]. Information on Gross Value Added from mining and quarrying in 2009 comes from the economic sector maps provided by Quantec and accessible online on the Geospatial Analysis Platform[32]. Finally, geographic data on major ethnic groups come from the GREG database[33].

The analysis is conducted after cleaning the dataset and considering only observations that are farer than 15 km from the closest provincial capital or city with more that 1 million inhabitants[34], and such that their population density in 2000 was lower than the 95^{th} percentile. This is mainly done in order to avoid contagion effects due to (1) the possible, yet fairly negligible expansion of the landline broadband Internet, and (2) presence of Wi-Fi connections. In fact, excluding the major urban agglomerations mitigates potential confounding effects that may create biased results. Finally, to increase the precision of my estimates I neglect localities with no population and exclude the largest 1% in terms of area (km^2). Hence, out of a total of 43,014 observations, overall 8,026 are dropped. Nevertheless, including these observations in the analysis does not substantially alter the magnitude of the estimated coefficients.

5.1 Descriptive statistics

Table 3 provides the descriptive statistics for the final sample. The main variables of interest are displayed for the years 2000, 2006, 2011 and 2016. Note that the table also reports the statistics for socio-demographic and economic variables measured in 2001 (or 2011 for Radio and TV ownership). As a general rule, I reported the first year for which the information was available. Moreover, the mean total GVA and GVA from mining and quarrying is calculated at the district level, while expenditure data on corruption come at the municipality level. In the latter case, the total number of observations corresponds to the number of municipalities, i.e. 234. Between 2006 and 2016 Internet penetration rose

[26]For income I use the Statement of Financial Performance: how a municipality has spent money and received income; for capital I use expenditure on purchase, repair and renewal of capital assets.

[27]Specific expenditure amounts from audited financial results, recorded in the notes to the annual financial statements of each municipality.

[28]https://www.municipaldata.treasury.gov.za

[29]https://www.topotools.cr.usgs.gov/gmted_viewer/

[30]https://www.openstreetmap.org

[31]https://www.mrdata.usgs.gov/mrds/

[32]https://www.gap.csir.co.za/download-maps-and-data

[33]https://www.icr.ethz.ch/data/greg/

[34]These are Bhisho, Bloemfontein, Cape Town, Durban, East London, Johannesburg, Kimberley, Nelspruit, Pietermaritzburg (Ulundi), Pietersburg (Polokwane), Port Elizabeth, Pretoria and Richards Bay.

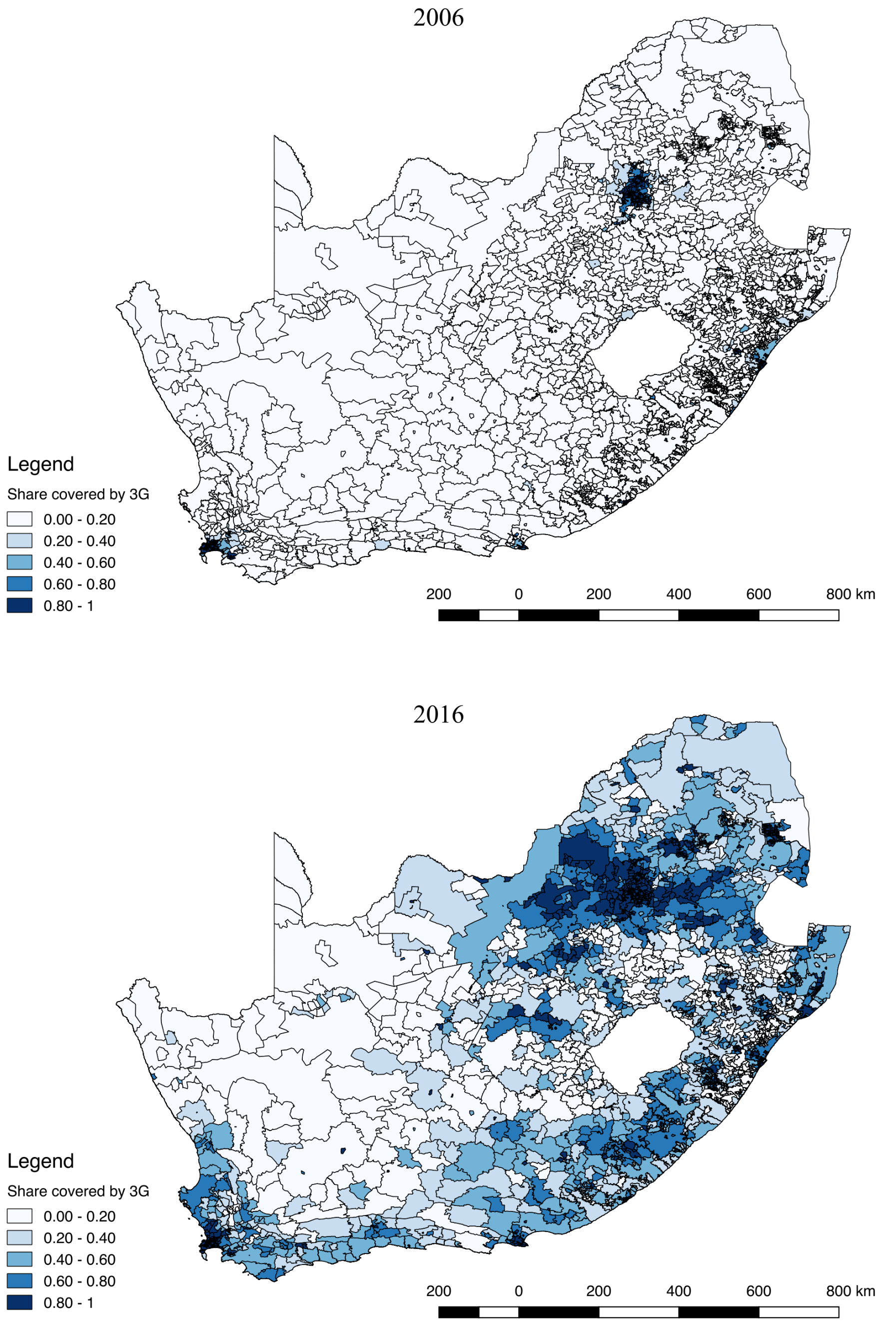
by 50 percentage points. Figure 8 below shows the spread of 3G coverage for the entire country over space and time.

Table 3: Descriptive statistics: final sample

Variabe	Year	Obs	Mean	Median	Std. Dev.	Min	Max
Coverage	2000	34988	0.00	0	0	0	0
Coverage	2006	34988	0.10	0	0.29	0	1
Coverage	2011	34988	0.22	0	0.38	0	1
Coverage	2016	34988	0.60	0.71	0.41	0	1
ANC share	2000	34590	0.60	0.70	0.29	0	1
ANC share	2006	34615	0.68	0.80	0.28	0	1
ANC share	2011	34986	0.68	0.78	0.26	0	1
ANC share	2016	34970	0.63	0.69	0.24	0	1
DA share	2000	27789	0.15	0.04	0.23	0	1
DA share	2006	31187	0.10	0.02	0.19	0	1
DA share	2011	34071	0.13	0.03	0.22	0	1
DA share	2016	34970	0.14	0.03	0.23	0	1
Other parties share	2000	33071	0.26	0.13	0.28	0	1
Other parties share	2006	34437	0.20	0.10	0.24	0	1
Other parties share	2011	34604	0.17	0.09	0.21	0	.99
Other parties share	2016	34970	0.21	0.16	0.17	0	1
Turnout	2000	34632	0.51	0.51	0.15	0	1
Turnout	2006	34619	0.53	0.53	0.13	0	1
Turnout	2011	34988	0.57	0.58	0.12	0	1
Turnout	2016	34988	0.57	0.57	0.11	0	1
N. of parties	2000	34632	4.56	4	2.54	2	14
N. of parties	2006	34619	6.57	6	3.78	2	23
N. of parties	2011	34988	7.96	7	4.23	2	33
N. of parties	2016	34988	9.92	9	5.48	3	36
N. of protests	2000	34988	0.000	0	0.02	0	2
N. of protests	2006	34988	0.001	0	0.04	0	4
N. of protests	2011	34988	0.003	0	0.07	0	6
N. of protests	2016	34988	0.019	0	0.36	0	27
Luminosity	2000	34988	9.09	2.65	15.09	0	63
Pop. density	2000	34988	725.35	275.20	1001.46	.002	4797
Urbanization rate	2001	34988	0.12	0	0.30	0	1
Years of schooling	2001	34988	4.95	4.75	1.79	0	16
Age	2001	34988	26.28	25.80	5.55	0	82.5
Youth share (14<age<30)	2001	34988	0.27	0.27	0.08	0	1
Phone (share of households)	2001	34988	0.11	0.04	0.16	0	1
Cellphone (share of households)	2001	34988	0.20	0.16	0.16	0	1
TV (share of households)	2011	34988	0.45	0.45	0.28	0	1
Radio (share of households)	2011	34988	0.52	0.57	0.24	0	1
GVA from mining (Millions, Rpc)	2009	34988	0.04	0.00	0.40	0	28
Total GVA (Millions, Rpc)	2009	34988	0.47	0.08	1.86	0	110
Corruption expenditure (Rpc)	2011-2014	234	3961	1510	13701	0	204008
Total expenditure (Rpc)	2011-2014	234	18416	15866	15079	2257	100333
Elevation (m)		34988	921.62	976.08	469.29	0	2546
Ruggedness (m^2)		34988	38.79	23	45.39	0	551
Area (km^2)		34988	20.14	2.58	61.52	.25	654
Distance from city (km)		34988	123.05	112.13	74.61	15	646
Road		34988	0.11	0	0.31	0	1
River		34988	0.04	0	0.20	0	1
Mine		34988	0.01	0	0.10	0	1

Notes - Population is proxied by the number of potential voters. GVA is gross value added, Rcp stands for Rounds per capita.

Figure 8: Mobile internet penetration



6. Results

6.1 Main findings

This section describes the main findings of this paper. Results for the baseline specification described in equation (1) are reported in Panel A of Table 4. The coefficients of interest are those on the interaction terms ($Coverage * 2016(2011)$). The table also reports the standalone coefficients on $Coverage$, which captures average differences in the dependent variables between covered and non covered localities at baseline, i.e. in 2006. For the sake of conciseness I report only the specification that includes the full set of controls and a polynomial function of some of them.

Table 4: The impact of mobile internet coverage on political outcomes

Panel A: Diff-in-Diff; years 2006 to 2016; whole sample

	ANC share	DA share	Other parties	Turnout	(log) N. of parties	N. of protests
	(1)	(2)	(3)	(4)	(5)	(6)
Coverage*Year 2016	-0.067***	0.027***	0.041***	0.005	0.062**	0.024***
	(0.015)	(0.008)	(0.014)	(0.009)	(0.030)	(0.009)
Coverage*Year 2011	-0.033***	0.024***	0.012	0.005	0.005	0.011*
	(0.010)	(0.007)	(0.009)	(0.007)	(0.024)	(0.006)
Coverage	0.032***	-0.018**	-0.013	-0.009	-0.023	-0.020**
	(0.010)	(0.008)	(0.010)	(0.007)	(0.025)	(0.010)
Voting District FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
All controls	✓	✓	✓	✓	✓	✓
Polynomial	✓	✓	✓	✓	✓	
Mean in 2006	0.683	0.100	0.202	0.529	6.571	0.001
Observations	103728	98871	103177	103752	103752	103770
Adj. R-squared	0.753	0.848	0.717	0.514	0.815	0.133

Notes - Standard errors in parentheses clustered at the smallest stable aggregation of voting districts. Controls in all columns include: time varying information on (log) luminosity and (log) population density, urbanization rate, years of schooling, age and share of youth; these variables measured in 2000 interacted with time dummies; presence of mine, road, river, slope index, (log) elevation, (log) ruggedness, (log) area and (log) distance from closest city interacted with time dummies. Columns 1, 2 and 3 include (log) number of parties and turnout in 2000 interacted with time dummies. Column 4 includes (log) number of parties in 2000 interacted with time dummies. Column 5 includes turnout in 2000 interacted with time dummies. Column 6 includes ANC share and all previous variables measured in 2000 interacted with time dummies. A 5^{th} order polynomial function of socio-demographic, economic and geographic variables is included in columns 1 to 5. Voting district and year fixed effects are included in all specifications. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

Panel B: Propensity Score Matching; years 2006 to 2016; whole sample

	ΔANC share	ΔDA share	ΔOther parties	ΔTurnout	Δ(log) N. of parties	ΔN. of protests
	(1)	(2)	(3)	(4)	(5)	(6)
ATE in 2016						
Covered vs. Not	-0.052***	-0.006	0.046***	-0.004	0.052***	0.013***
	(0.005)	(0.010)	(0.004)	(0.003)	(0.014)	(0.003)
ATE in 2011						
Covered vs. Not	-0.037***	0.026***	0.026***	-0.004	-0.030*	0.002**
	(0.010)	(0.009)	(0.005)	(0.006)	(0.018)	(0.001)
Observations	34482	30675	33959	34488	34488	34590

Notes - Robust Abadie-Imbens standard errors in parentheses. A locality is considered Covered in a given year if Coverage≥0.5 in that year. In all columns the propensity of being Covered is estimated using (log) luminosity, (log) population density, urbanization rate, years of schooling, age and share of youth measured in 2000; presence of mine, road, and river, slope index, (log) elevation, (log) ruggedness, (log) area and (log) distance from closest city. Columns 1, 2 and 3 include (log) number of parties and turnout in 2000. Column 4 includes (log) number of parties in 2000. Column 5 includes turnout in 2000. Column 6 includes ANC share and all previous variables measured in 2000. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

Panel C: Diff-in-Diff; years 2006 to 2016; localities with mostly stable demarcations

	ANC share	DA share	Other parties	Turnout	(log) N. of parties	N. of protests
	(1)	(2)	(3)	(4)	(5)	(6)
Coverage*Year 2016	-0.139***	0.067***	0.068***	0.014	0.238***	0.119*
	(0.022)	(0.018)	(0.018)	(0.012)	(0.038)	(0.071)
Coverage*Year 2011	-0.052***	0.065***	-0.012	-0.003	0.074**	0.089**
	(0.019)	(0.016)	(0.015)	(0.012)	(0.035)	(0.039)
Coverage	0.070***	-0.056***	-0.010	-0.007	-0.157***	-0.116*
	(0.019)	(0.017)	(0.014)	(0.011)	(0.031)	(0.068)
Voting District FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
All controls	✓	✓	✓	✓	✓	✓
Polynomial	✓	✓	✓	✓	✓	
Observations	8181	8010	8163	8181	8181	8172
Adj. R-squared	0.816	0.919	0.763	0.620	0.864	0.167

Notes - The sample includes only localities that experienced at maximum 2 changes in their demarcations between 2000 and 2016. These represent almost 8% of the initial sample. All Notes from Panel A apply here. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

A sensitivity analysis of the results to different specifications is reported in Table 14 in the appendix. In addition, Table 15 in the appendix reports the results from the same specification including the 2000 electoral wave, which therefore becomes the baseline year.

In line with my expectations, column (1) shows that Internet coverage was detrimental for the incumbent party. The coefficients suggest that a unitary increase in coverage – i.e. moving from 0 to 100% of the area covered by the Internet – causes ANC share to drop by approximately 6.7 and 3.3 percentage points in 2016 and 2011, respectively. These are almost 10 and 5% of the mean of the dependent variable in 2006, respectively. Note that at baseline, places with higher mobile Internet penetration where more willing to vote for the incumbent, compared to those with no coverage. This fact seems to suggest that the presence of ANC did not prevent the arrival of the Internet.

Columns (2) and (3) depict the situation for the rivals, in particular the Democratic Alliance (DA) and the combination of all other parties. In 2016, the arrival of the Internet seems to benefit both the categories: DA share rises by almost 3 pp, while other parties gain 4 pp. These are almost 30 and 20% of their means in 2006, respectively. Notice that the incumbent's loss is perfectly compensated by the sum of the opponents' gains. Column (4) suggests that, despite its positive coefficient, voter turnout is not significantly affected by 3G coverage in any year. In other words, Internet penetration does not affect political participation.

Column (5) seeks to understand the importance of 3G network for local political competition. The latter is measured using the number of parties running in a given district. The coefficient of interest suggests that in 2016 mobile Internet coverage leads to a 6% increase in the number of parties. This means that the new technology may (1) promote the proliferation of new parties and (2) encourage the existing parties to run in new places. Overall, voters and politicians face increased competition.

Finally, column (6) analyses the effect of 3G availability on protests against a typically political entity. The aim is to demonstrate that voters behavior at ballots reflects general discontent, which is partially captured by public demonstrations. Results show that in 2016 Internet availability causes the number of protests to rise by 0.024, that is 24 times the mean of the dependent variable in 2006. Note that approximately half of the increase takes place in 2011. The number of protests can rise for at least two, complementary, reasons: (1) 3G provides relatively new information that persuade people to voice their opinions and publicly show their dissatisfaction; (2) mobile Internet is an effective coordination tool that helps individuals to organize their public life. Although my analysis cannot disentangle the contribution of each channel, it shows that in South Africa 3G Internet has positive effect on public engagement. This is also supported by the absence of negative effects on turnout.

In order to confirm the previous findings I enrich the analysis using a Propensity Score Matching estimation. Results from this approach are shown in Panel B. Not surprisingly, both signs and magnitudes of the estimated Average Treatment Effects are consistent with those from the baseline analysis. Moreover, to alleviate concerns about endogenous changes in boundaries, I replicate the baseline estimation only for those localities whose demarcations remained fairly stable over time. In fact, one potential concern is that Internet coverage may be correlated with strategic re-demarcation interventions which, in turn, affect political outcomes. Hence, I restrict the attention to those localities that experienced at maximum 2 changes in their borders between 2000 and 2016[35]. These represent around 8% of the sample. Results are shown in Panel C. All estimated coefficients

[35] I choose this threshold in order to have sufficient power (observations) for the tests. However, restricting the attention to districts that did not experience any change yields even larger coefficients.

are much larger than those from the baseline analysis. This seems to point out that places where boundary modifications occurred more frequently – i.e. those where concerns on endogeneity are higher – are not spuriously amplifying the magnitudes, and that baseline estimations on the full sample represent a lower bound.

The following table provides results for the 2SLS estimation described in equation (2). In this case the main independent variable is the total number of years since 2005 a locality has been sufficiently covered by 3G (i.e. $Coverage \geq 0.5$). For the sake of comparison, the table also provides OLS estimation coefficients. The analysis takes all four electoral waves into account so to exploit the differential impact, around 2005, that terrain ruggedness has on political outcomes through the arrival of the 3G technology. Overall, results are in line with the baseline findings for all variables except for the DA share. Therefore, an additional year of 3G coverage leads to a decrease in the vote share for the incumbent, and to a rise in the popularity of other (smaller) parties, apart from the Democratic alliance. In fact, the 2SLS output seems to provide no particular evidence on its gain from mobile Internet. In addition, more years of coverage favor voter turnout, political competition and public demonstrations against government institutions .

Table 5: THE IMPACT OF NUMBER OF YEARS OF COVERAGE ON POLITICAL OUTCOMES

OLS and 2SLS; years 2000 to 2016; whole sample

	ANC share		DA share		Other parties	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Years of coverage	-0.008***	-0.051***	0.003***	-0.010	0.005***	0.052***
	(0.002)	(0.016)	(0.001)	(0.007)	(0.002)	(0.017)
Voting District FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Polynomial	✓		✓		✓	
log(ruggedness)*Post		-0.303***		-0.351***		-0.302***
1st stage Wald F-stat		126.4		121.8		106.5
Observations	138318	138318	126661	126661	136259	136259
Adj. R-squared	0.719	0.659	0.810	0.794	0.724	0.619
	Turnout		N. of parties		N. of protests	
	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Years of coverage	0.000	0.013*	0.074**	0.602***	0.002***	0.007**
	(0.001)	(0.007)	(0.031)	(0.137)	(0.001)	(0.003)
Voting District FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Polynomial	✓		✓			
log(ruggedness)*Post		-0.307***		-0.375***		-0.309***
1st stage Wald F-stat		127.5		187.7		122.3
Observations	138384	138384	138384	138384	138360	138360
Adj. R-squared	0.406	0.377	0.848	0.813	0.096	0.092

Notes - Standard errors in parentheses clustered at the smallest stable aggregation of voting districts. Controls in columns 1, 3, 5, 7, 9 and 11 are the same as those included in the baseline specification. Controls in columns 2, 4, 6, 8, 10 and 12 are the same with the exceptions of road and river presence, slope index, (log) elevation and (log) ruggedness, which are excluded because of their high correlation with the instrument. Coefficient on the instrumental variable from the first stage regression and the respective Kleibergen-Paap rk Wald F-statistic are reported. Post is a dummy which equals 1 if Year>2005. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

Overall, the magnitudes of the estimated coefficients are quite impressive, and their signs seem to support the hypothesized mechanisms. In other words, it can be that more voters in localities covered by the Internet decided to punish the incumbent party because of the type of information they received thorough the web. Although this specification is not informative on the exact mechanism behind this relationship, it provides general supporting evidence for the role the Internet played in the municipal elections. The analysis developed in section 6.3 will try to analyze to what extent the additional information on corruption and administration scandals that voters received through the web might have driven the results.

6.2 Robustness

Before the examination of the potential mechanisms I perform some additional exercises to prove the robustness of the applied methodologies and the respective estimates.

To convince the reader that the estimated coefficients actually capture causal effects, placebo estimations are extremely useful. In particular, the idea behind this exercise is to regress the outcome variables observed in the years before the expansion of the mobile technology (2000-2006) on Internet coverage between years 2006 and 2016. If the parallel trend assumption holds, then one should find no effects of lagged coverage on political variables. Table ? provides evidence in favor of the parallel trend assumption: coefficients on Lagged Coverage interacted with the time dummy are not statistically different from zero for all the variables of interest. This evidence rules out the potential presence of divergent pre-trends in the outcome variables across covered and not covered localities.

Table 6: PLACEBO ESTIMATES

Diff-in-Diff; years 2000 to 2006; whole sample

	ANC share	DA share	Other parties	Turnout	(log) N. of parties	N. of protests
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Coverage*2006	-0.017	0.011	0.005	-0.013	-0.016	-0.002
	(0.016)	(0.008)	(0.014)	(0.009)	(0.028)	(0.002)
Lagged Coverage	-0.001	-0.002	0.002	0.003	0.006	0.002
	(0.013)	(0.008)	(0.011)	(0.008)	(0.019)	(0.002)
Voting District FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Polynomial	✓	✓	✓	✓	✓	
Observations	68,884	54,684	65,588	68,976	68,976	69,180
Adj. R-squared	0.792	0.809	0.825	0.383	0.869	0.000

Notes - Standard errors in parentheses clustered at the smallest stable aggregation of voting districts. To compute Lagged Coverage for each locality I assign the value of coverage in 2006 to year 2000, and the value of coverage in 2016 to year 2006. Same controls as those included in the baseline specification are included here. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

I then perform a standard AET test. This strategy is useful in cases in which doubt remains about the exogeneity of the treatment variable. The approach uses the degree of selection on observables as a guide to the degree of selection on the unobservables. In particular, it involves two steps. Firstly, I regress Internet coverage on a bunch of potentially relevant predictors and then I calculate its fitted values. I use OLS linear predictions from the regression of *Coverage* on economic, socio-demographic and geographic variables. Secondly, I regress political outcomes between 2006 and 2016 on the predicted coverage and its interaction with time dummies to assess the extent to which its plausibly endogenous component may affect these outcomes. The following table shows the results from the second step[36].

[36]The outcome for the first step is shown in Table 13 in the appendix.

Table 7: AET PROCEDURE

Diff-in-Diff; years 2006 to 2016; whole sample						
	ANC share	DA share	Other parties	Turnout	(log) N. of parties	N. of protests
	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Coverage*2016	0.294***	-0.108*	-0.179**	-0.217***	0.559***	-0.281***
	(0.078)	(0.064)	(0.090)	(0.052)	(0.183)	(0.048)
Predicted Coverage*2011	0.430***	-0.063	-0.355***	-0.151***	0.275	-0.219***
	(0.081)	(0.061)	(0.095)	(0.054)	(0.188)	(0.043)
Predicted Coverage	-0.403***	0.050	0.355***	0.305***	-0.480**	0.168***
	(0.078)	(0.066)	(0.092)	(0.050)	(0.204)	(0.034)
Voting District FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Subset of controls	✓	✓	✓	✓	✓	✓
Observations	103,728	98,871	103,177	103,752	103,752	103,770
Adj. R-squared	0.741	0.844	0.702	0.477	0.801	0.131

Notes - Standard errors in parentheses clustered at the smallest stable aggregation of voting districts. Controls include (log) ruggedness, (log) distance from closest city, radio, TV and phone ownership measured in 2000 and interacted with time dummies. Predicted coverage is the linear prediction of the share of area covered by 3G in each district. The prediction is based on economic, socio-demographic and geographic variables. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

The coefficients on predicted coverage interacted with time dummies have opposite signs with respect to those from the baseline analysis. This is true for all political variables, with the exception of column (5). The procedure suggests that the component of 3G coverage explained by observables is not driving the baseline results. Therefore, assuming that selection on observables is informative about selection on unobservables, the findings seem to alleviate the concern that relevant omitted variables matter for the results. By contrast, coefficient on the (log of) number of parties is not in line with this claim: in fact, the effect of 3G coverage seems to be driven by observable characteristics and this may rise some concerns about the role of unobservables in this case.

All together, findings from tables 6 and 7 along with the visual inspection of pre-trends depicted in Figure 7, provide enough evidence on the robustness of the baseline analysis. At the same time, additional checks on the validity of the 2SLS estimation can be performed. In this case, exogeneity of the instrumental variable is the major concern. In particular, a reasonable claim is that ruggedness interacted with time may affect political outcomes through different channels, other than coverage. In order to show that this is unlikely to be the case, I adopt a twofold strategy.

Firstly, I perform some placebo checks: for those localities not covered by 3G in 2006, I regress the outcomes of interest between 2000 and 2006 on $log(Ruggedness) * \mathbb{1}(Year = 2006)$. With this exercise, I try to assess if terrain ruggedness impacts on political outcomes through channels different from the Internet. Results depicted in Panel A of Table 8 seem to rule out this possibility.

Secondly, I analyse whether the presence of a mine, which is correlated with terrain ruggedness, can explain the observed 2SLS results. In Panel B of Table 8, column (1) shows the strong correlation between ruggedness and mining. Hence, in columns (2-6) I depict results from regressing political variables on mining interacted with Post. This specification allows me to detect the existence of a differential impact of mining on politics around 2005. Overall, results confirm that this should not be the case. In fact, the coefficient is statistically significant only for turnout, yet its sign is opposite to the one estimated in the 2SLS approach. Hence, the evidence reported so far should alleviate concerns on potential endogeneity of the instrumental variable.

Table 8: Instrumental validity checks

Panel A: Diff-in-Diff; years 2000 to 2006; only localities with no 3G coverage in 2006

	ANC share	DA share	Other parties	Turnout	(log) N. of parties	N. of protests
	(1)	(2)	(3)	(4)	(5)	(6)
log(Ruggedness)*2006	0.001	-0.002	0.001	-0.002	-0.004	-0.000
	(0.003)	(0.002)	(0.003)	(0.002)	(0.006)	(0.000)
Voting District FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Polynomial	✓	✓	✓	✓	✓	
Observations	59,626	45,612	56,410	59,714	59,714	59,634
Adj. R-squared	0.786	0.735	0.833	0.354	0.820	0.001

Notes - Standard errors in parentheses clustered at the smallest stable aggregation of voting districts. Localities covered by 3G in 2006 are excluded from the analysis. Same controls as those included in the baseline specification are included here. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

Panel B: Diff-in-Diff; years 2000 to 2016; whole sample

	Mine presence	ANC share	DA share	Other parties	Turnout	(log) N. of parties	N. of protests
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(Ruggedness)	0.003***						
	(0.001)						
Mine Presence*Post		-0.011	0.005	0.006	-0.019**	0.014	0.022
		(0.014)	(0.012)	(0.008)	(0.009)	(0.020)	(0.017)
Municipality FE	✓						
Voting District FE		✓	✓	✓	✓	✓	✓
Year FE		✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓
Polynomial		✓	✓	✓	✓	✓	
Observations	34,988	138,318	126,661	136,259	138,384	138,384	138,216
Adj. R-squared	0.063	0.724	0.810	0.731	0.406	0.845	0.095

Notes - Standard errors in parentheses clustered at the smallest stable aggregation of voting districts. Column 1 shows results from a cross-sectional regression for year 2000. Controls in column 1 include economic, socio-demographic and geographic variables. Same controls as those included in the baseline specification are included in columns 2-6. Post is a dummy which equals 1 if Year>2005. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

6.3 Mechanisms

Results of section 6.1 are in line with some of the findings of Miner (2016) for Malaysia. Specifically, they seem to agree with the fact that Internet access can jeopardize the reputation and weaken the popularity of the ruling parties in developing countries.

This incidentally leads to the following question: why do we observe these effects? Does this mean that traditional media are biased towards the incumbent? Where do the effects come from? Answering these questions is quite challenging, and it requires knowledge about substitution effects among different media, on what people exactly do with the new technology, and which segments of the population are mostly affected by it. The analysis of heterogeneity of treatment effects across various subsamples can reveal some insights on the mechanisms behind the observed relations. Hence, I consider the following dimensions: income (luminosity), average years of schooling, share of young people, population density, urbanization, phone and traditional media ownership. The first variable is a proxy for general well-being, while the second and the third ones exploit heterogeneity in Internet adoption rates. The fourth and fifth quantities look at the importance of different urbanization paths, while the sixth and seventh ones explore diverse adoption rates of analogical communication technologies. Finally, the last two variables capture potential heterogeneous effects across places with different levels of news circulation.

For each of them, I use the value of the median at baseline (in 2000) in order to create two categories. Table 9 provides the results for this analysis.

Table 9: Analysis of heterogeneity

	ANC share (1)	DA share (2)	Other parties (3)	Turnout (4)	(log) N. of parties (5)
High luminosity	-0.082***	0.029***	0.056***	0.007	0.087***
	(0.021)	(0.009)	(0.017)	(0.010)	(0.030)
Low luminosity	-0.090**	0.029	0.037	0.056***	0.004
	(0.043)	(0.032)	(0.038)	(0.019)	(0.098)
High schooling	-0.081***	0.033***	0.050***	0.002	0.067**
	(0.017)	(0.009)	(0.014)	(0.007)	(0.028)
Low schooling	-0.039	0.002	0.031	0.024	0.034
	(0.026)	(0.012)	(0.028)	(0.018)	(0.050)
High youth	-0.074***	0.019**	0.056***	-0.001	0.093***
	(0.018)	(0.008)	(0.015)	(0.009)	(0.031)
Low youth	-0.047***	0.034**	0.013	0.013	0.025
	(0.018)	(0.014)	(0.017)	(0.010)	(0.031)
High density	-0.061***	0.019**	0.042***	0.002	0.067**
	(0.017)	(0.008)	(0.016)	(0.009)	(0.030)
Low density	-0.093***	0.048***	0.049***	0.010	0.069**
	(0.021)	(0.013)	(0.016)	(0.012)	(0.031)
High urbanization	-0.070***	0.035***	0.038***	0.009	0.057*
	(0.016)	(0.012)	(0.014)	(0.009)	(0.032)
Low urbanization	-0.068***	0.027**	0.043**	0.002	0.077**
	(0.022)	(0.011)	(0.021)	(0.012)	(0.039)
High cellphone	-0.070***	0.029***	0.044***	-0.000	0.075***
	(0.019)	(0.009)	(0.016)	(0.008)	(0.026)
Low cellphone	-0.053**	0.009	0.042	0.027**	0.067
	(0.024)	(0.014)	(0.026)	(0.014)	(0.060)
High phone	-0.088***	0.039***	0.049***	0.005	0.098***
	(0.014)	(0.010)	(0.012)	(0.008)	(0.031)
Low phone	-0.027	0.005	0.027	-0.006	0.011
	(0.023)	(0.008)	(0.024)	(0.014)	(0.031)
High radio	-0.095***	0.039***	0.058***	-0.005	0.090***
	(0.015)	(0.009)	(0.012)	(0.008)	(0.024)
Low radio	-0.019	0.004	0.016	0.014	0.034
	(0.020)	(0.009)	(0.020)	(0.012)	(0.035)
High TV	-0.081***	0.033***	0.049***	-0.003	0.083***
	(0.015)	(0.009)	(0.012)	(0.007)	(0.027)
Low TV	-0.041*	0.002	0.040*	0.014	0.035
	(0.024)	(0.010)	(0.023)	(0.014)	(0.040)

Notes - Each cell reports the result of a single OLS regression on mutually exclusive sub-samples (pair of rows). Each sub-sample is identified using as threshold the median value of the variable. Only the estimated coefficient on Coverage*2016 is reported for conciseness. Same controls as those included in the baseline specification are included here. Standard errors in parentheses clustered at the smallest stable aggregation of voting districts. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

The table shows that income and education matter for the overall effect of coverage on all political variables but ANC share. In fact, while it is true that places with a lower schooling rate do not drive the results, the same is not true for poorer localities. There is no visible difference in the impact of coverage on ANC vote across different income categories. As on the vote share of the rivals, the magnitude for low income localities is still meaningful and the statistical insignificance seems to be driven by the large standard errors. By contrast, greater and significant effects for places with higher schooling rates are in line with the descriptive evidence of section 3: more educated people tend to be regular Internet users. At the same time, the findings may support the idea that difference in usage habits matter, with less educated individuals using the new technology more for entertaining purposes rather than to gather information.

As on the share of young people, results are less clear. For columns (1), (3) and (5), they confirm the idea that impacts are larger for the young generation because of its higher adoption rate. This is not the case for the effect on DA share. Hence, it seems that the effect of coverage interacts with the generational differences in preferences for alternative parties, with younger people more willing to vote for smaller or newly formed parties.

Results for population density and urbanization rate are interesting. Internet coverage is found to have quite similar effects on all outcomes across the sub-groups. If anything, places with lower density display overall larger coefficients than those with higher density. This seems to point out a larger scope for 3G arrival in villages rather than bigger cities.

Less surprising is the heterogeneity across cellphone and phone ownership in 2000. Phones adoption in the past is likely to be correlated with today smartphones' penetration. This might explain the different effects across the two groups. Finally, the Internet is found to have different effects across places with diverse traditional media adoption rates. This points out the coexistence of at least two channels for those places where radio and tv penetration is higher: (1) these localities are also richer, that is the people can afford the new technology and this explains the observed heterogeneity; (2) in these places, individuals are more used to be exposed to offline information and when the Internet arrives they exploit it to get even more. By contrast, the people who do not own traditional media have lower political engagement: they do not use the new technology to gather information.

Overall, the previous analysis suggests that income, education and penetration of traditional ICTs matter for the impact of 3G on political outcomes. However, a caveat of this analysis is given by its difficulty in isolating the exact source of any observed heterogeneous effect. That is, interactions and overlaps between different variables confound the study and make it difficult to understand if heterogeneity comes from diverse adoption rates (income), way of using the technology (habits) or persuasion.

In order to partially circumvent this issue and better identify the information role that 3G played in South Africa, I develop a triple difference framework and estimate equation (3). The main findings of section 6.1 are in line with the idea that the additional information – i.e. the online content – is, somehow, damaging the reputation of the ANC party. Specifically, correlational evidence of section 4 exhibits that Internet users are more likely to think that most of the people in the office of the President are involved in corruption, among other things. Is it really possible that the ANC party lost votes because a segment of the population was informed about the overall unsatisfactory administration and corruption scandals?

The following table seeks to provide some causal evidence on this. Panel A of Table 10 shows results from a triple difference estimation where I exploit the difference in corruption-related expenditure per capita across municipalities as an additional source of variation. In places where this irregular expenditure is higher, voters are more likely to be exposed to corruption scandals, especially if they are covered by the Internet. That is, among localities with similar corruption level, those with coverage should exhibit an additional drop in the ANC vote share, being their inhabitants more likely to know about the scandals.

Table 10: The information channel

Panel A: Diff-in-Diff-in-Diff, years 2011 to 2016, whole sample

	ANC share	DA share	Other parties	Turnout	(log) N. of parties	N. of protests
	(1)	(2)	(3)	(4)	(5)	(6)
Corruption*Coverage*2016	-0.010***	-0.001	0.010***	0.001	0.022**	0.001
	(0.003)	(0.002)	(0.004)	(0.001)	(0.010)	(0.003)
Expenditure*Coverage*2016	-0.000	0.008	-0.004	-0.009*	-0.012	-0.009
	(0.011)	(0.005)	(0.012)	(0.005)	(0.035)	(0.007)
Voting District FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
All controls	✓	✓	✓	✓	✓	✓
Polynomial	✓	✓	✓	✓	✓	
Observations	69,224	67,404	68,506	69,264	69,264	69,180
Adj. R-squared	0.790	0.904	0.699	0.605	0.819	0.210

Notes - Standard errors in parentheses clustered at municipality level. Corruption is the log of total irregular and unauthorized municipal expenditure per capita in 2012 to 2015. Expenditure is the log of income and capital municipal expenditure per capita in 2012 to 2015. All other interactions are included but not reported for conciseness. Same controls as those included in the baseline specification are included here. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

Panel B: Diff-in-Diff-in-Diff, years 2011 to 2016, whole sample

	ANC share	DA share	Other parties	Turnout	(log) N. of parties	N. of protests
	(1)	(2)	(3)	(4)	(5)	(6)
Mining*Coverage*2016	-0.027**	0.023*	0.002	-0.022**	-0.016	0.012
	(0.011)	(0.013)	(0.010)	(0.011)	(0.029)	(0.014)
GVA*2016	0.001	0.001*	-0.002**	-0.001**	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Voting District FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
All controls	✓	✓	✓	✓	✓	✓
Polynomial	✓	✓	✓	✓	✓	
Observations	69,224	67,404	68,506	69,264	69,264	69,180
Adj. R-squared	0.790	0.904	0.699	0.605	0.815	0.209

Notes - Standard errors in parentheses clustered at the smallest stable aggregation of voting districts. Mining is the per capita Gross Value Added from mining and quarrying of the locality. GVA is the per capita Gross Value Added from all sectors. All other interactions are included but not reported for conciseness. Same controls as those included in the baseline specification are included here. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

The figures support the hypothesized channel. Column (1) reports the results for the ANC vote share. The coefficient on the triple-interaction term ($Corruption * Coverage * 2016$) is negative and statistically significant at the 10% significance level. Its magnitude suggests that, among localities with high level of corruption-related expenditure, a unitary increase in coverage causes a reduction in the votes for the ANC party of almost 1 pp. If one exclusively focuses on municipalities where the ANC was ruling (which are anyway the majority) the magnitude of the coefficient does not significantly vary[37]. At the same time, the major gainers from the corruption scandals are smaller and newly formed parties (in fact, the DA vote share is not affected). Finally, the number of parties increases.

In Panel B I exploit variation in the relevance of the mining industry as a proxy for exposure to the consequences of the mining strikes and the subsequent social turmoil. The idea is that in localities where the mining industry plays a prominent role, (1) the people are more likely to make web searches to understand the causes of the disorders and the responsibilities of those involved; (2) individuals are easier to persuade by the online information, as their personal involvement is higher. Column (1) shows the main result: the coefficient on the triple-interaction term ($Mining * Coverage * 2016$) is negative and statistically different from zero. Its magnitude suggests that, in localities where mining

[37]Results available upon request

industry is prominent, a unitary increase in coverage causes a reduction in the votes for the ANC party of almost 2.7 pp. The sign is in line with the previous statement and points out the role of mobile internet in denouncing administrative scandals. Differently from corruption, mining issues seem to favor the second biggest party, i.e. the DA. This perhaps suggests that individuals trust more consolidated parties when they face administrative issues, while they prefer new or small political entities when corruption is seen as the main problem. At the same time, the number of parties remains unchanged, yet overall disaffection towards politics seems to increase, as voter turnout goes down.

In general, the analysis confirms the prior that individuals are likely to use mobile Internet also to access additional information and that exposure to these facts makes them change their political opinions and behavior. The incumbent party always loses from this, while the rivals gain. Interestingly, who benefits most depends on the type of scandals.

To conclude this section I study ethnicity, and its interaction with coverage. Although South Africa offers a large variety of ethnic groups, I decide to focus on one of them: the Zulu tribe. With approximately 10-12 million people, this is the largest ethnic group of South Africa. Two distinct strands of Zulu nationalism competed for dominance in the ANC over the last 100 years: the conservative one, and the one progressive and more inclusive of other communities. Former President Jacob Zuma belongs to the Zulu people, and his election as ANC President in 2007 signifies the triumph of the conservative wing of Zulu nationalism[38]. In his battle with former President Thabo Mbeki, Zuma has exploited his Zulu traditions. In particular, he was able to explicitly mobilized voters in KwaZulu Natal – the Zulu province – to support him on the basis of his Zulu-ness, rather than performance in government and in the party. More recently, Zuma took advantage of his ethnic origins to cover-up poor personal choices, indiscretions and wrong behavior [39]– and portraying those who oppose such poor behavior of being opposed to African 'traditions' or 'culture'.

Table 11: ETHNICITY AND PERSUASION

Diff-in-Diff-in-Diff, years 2006 to 2016, whole sample

	ANC share (1)	DA share (2)	Other parties (3)	Turnout (4)	(log) N. of parties (5)	N. of protests (6)
Zulu*Coverage*2016	-0.161***	-0.004	0.163***	-0.039***	0.045	-0.031
	(0.027)	(0.017)	(0.021)	(0.014)	(0.051)	(0.022)
Zulu*2016	0.279***	-0.023***	-0.257***	0.064***	-0.181***	-0.008
	(0.014)	(0.007)	(0.015)	(0.007)	(0.033)	(0.006)
Coverage*2016	-0.001	0.025***	-0.023*	0.019**	0.017	0.027**
	(0.013)	(0.008)	(0.012)	(0.009)	(0.027)	(0.011)
Voting District FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
All controls	✓	✓	✓	✓	✓	✓
Polynomial	✓	✓	✓	✓	✓	
Observations	103,062	98,209	102,513	103,086	103,086	103,104
Adj. R-squared	0.781	0.847	0.756	0.523	0.824	0.133

Notes - Standard errors in parentheses clustered at the smallest stable aggregation of voting districts. Zulu is a dummy which equals 1 if Zulu is the main ethnic group of the voting district. All other interactions are included but not reported for conciseness. Same controls as those included in the baseline specification are included here. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

A plausible hypothesis is that information on corruption and administrative scandals related to the figure of Jacob Zuma may have specific persuasive power for those individ-

[38]"Zuma and Zulu nationalism". Pambazuka News. 19 December 2012.

[39]"Jacob Zuma President of South Africa". Encyclopædia Britannica. Last update: 19 March 2018.

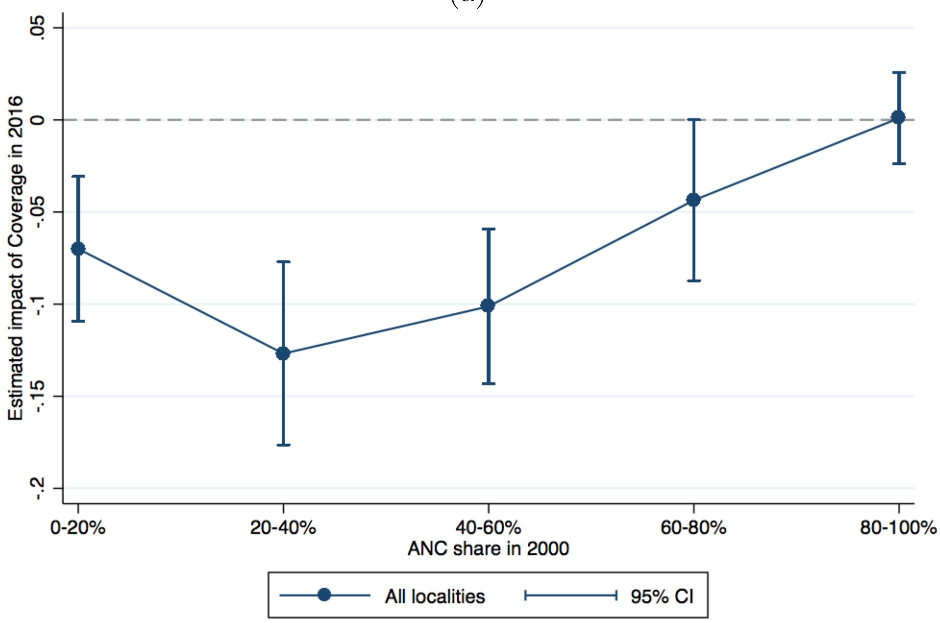
uals who share ethnic and linguistic traits with him. Hence, I exploit ethnicity to assess the persuasive strength of online information in the South African context. I replicate the triple difference estimation where I consider interactions between the belonging to the Zulu tribe with 3G coverage of a locality. Table 11 shows the results. Interestingly, the Zulu people are driving the effect of 3G coverage on ANC and Other parties shares. In particular, column (1) suggests that the Internet causes a drop in ANC share in those regions where the Zulu people are the majority, while it does not in the non-Zulu localities. Meanwhile, coefficient on the double interaction term ($Zulu * 2016$) supports the idea that Zuma was able to gather large support from his ethnic group. Therefore, it seems that for those individuals who share ethnic affinity with Zuma, online information leads to divergence of preferences towards the ANC and its leader. At the same time, Zulu people with Internet access either prefer to vote for smaller parties (column 3) or they do not vote (column 4). By contrast, political participation in Zulu localities with no 3G coverage increases, while political competition goes down. Overall, these results are in line with the idea that persuasion of online information damaging the leader is higher when individuals share common ethnic and cultural traits with him.

6.4 Spatial analysis

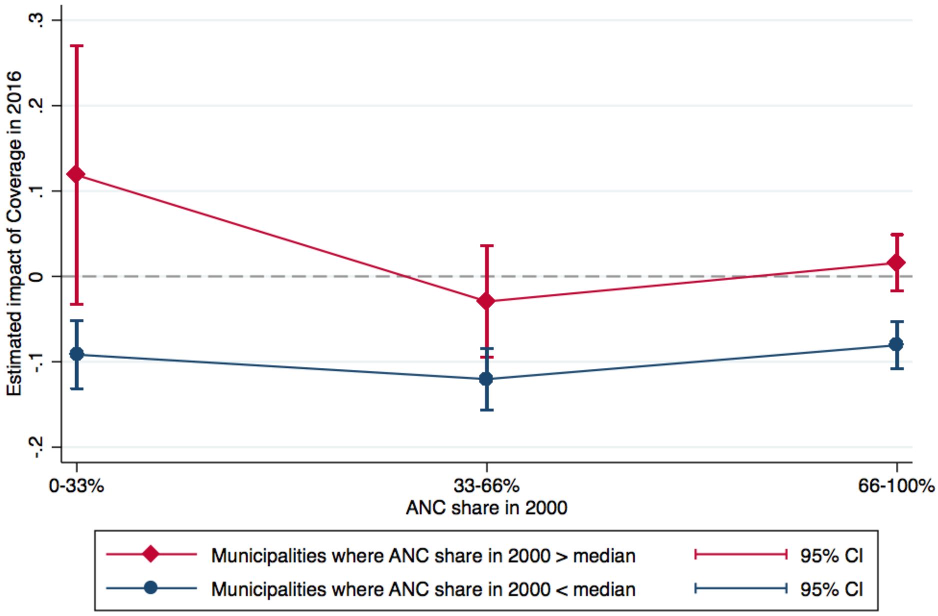
In section 6.1, I demonstrated that mobile Internet arrival damages the popularity of the ANC and favors the opponents. In section 6.3, I provided evidence supporting the conjecture that at least part of the impact is due to the online information that the Internet conveys. Therefore, I reasonably claimed that such information was harmful for the incumbent. The goal of this section is to assess the role of neighbors' prior beliefs towards the ANC on the spread and impact of online information in a locality. One can argue that prior preferences of the locality itself matter. Indeed, the first exercise of this section is meant to study heterogeneity effects of 3G across different priors towards the incumbent. In particular, for each locality I exploit the ANC vote share in 2000 as a proxy for the overall ex ante preferences. Then, according to them I split the sample in 5 categories and estimate the baseline regression for each group. Figure 9 (a) below shows the variation of the coefficient of interest when ANC share is the dependent variable.

Figure 9: Loss in ANC share across different past voting behavior

(a)



(b)

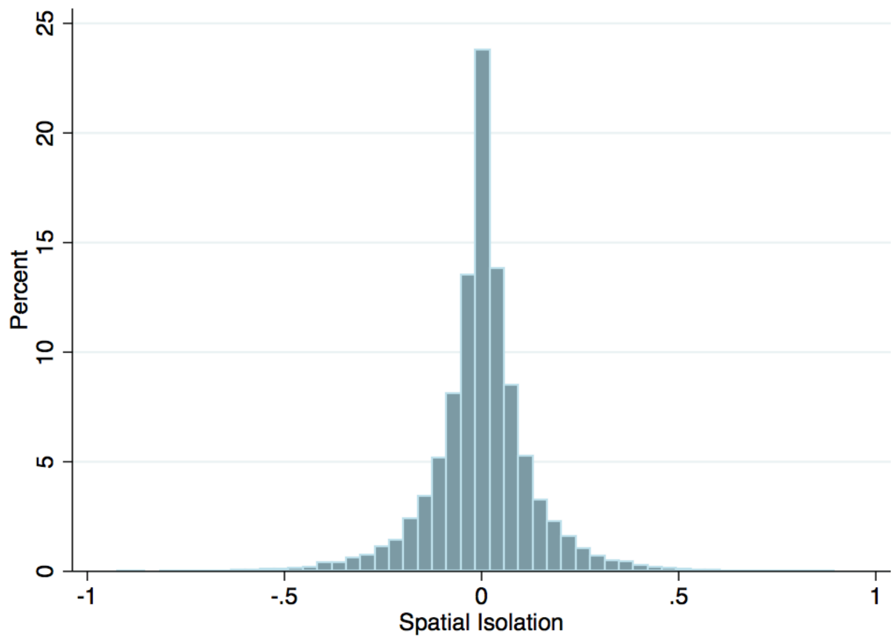


The impact of 3G on the incumbent vote share is found to vary significantly across localities with different ex ante political preferences. In particular, in localities where ANC supporters were by large the majority of the people, the availability of online information does not affect voting behavior in 2016. Instead, the persuasive power of the Internet is the largest for those places where the percentage of ANC supporters was between 20 and 60 in 2000. This is in line with the idea that where diversity in the dominant opinion is used to be low, information advising against that opinion has little potential for persuasion. This might happen because of online information segregation (i.e. these people receive partial information) and/or because they do not believe certain messages.

However, heterogeneity across diverse past political habits is attenuated when one replicates the analysis on two separate groups of municipalities: those where the average ANC share in 2000 was above and below the median value (66%). Figure 9 (b) shows that municipalities where ANC was not used to be very popular are driving the results, independently on the ex ante political preferences of the single locality. In fact, notice that 3G coverage has a negative and sizable impact also in places that (1) had more than 66% of the people supporting the incumbent and (2) they lie in a municipality where ANC share was below the median in 2000. By contrast, municipalities with higher ANC affection do not exhibit these patterns. Here, 3G coverage does not produce significant change in voters' behavior. Hence, the figure suggests that the surrounding political environment could matter for both diffusion (segregation) and persuasive power of online information.

To better investigate the interaction between prior beliefs of one locality and the prevailing political preferences of its neighbors, I construct an index which measures relative belief's divergence over space. In particular, I follow the formula described in (4) and name the index *Spatial Isolation* (with respect to preferences towards ANC). Figure 10 below shows the distribution of the index over the sample.

Figure 10: Histogram of Spatial Isolation index



The histogram is symmetric with respect to the origin and approximate a standard Normal distribution, with thinner tails and a larger mass in the middle. Location i is said to be spatially isolated when either i supports the ANC and the neighbors do not, or vice versa. Hence, isolated localities lies in the tails of the above distribution, where the value of the index approaches the extremes. By contrast, spatial isolation is low in the middle: here we are in presence of spatial clusters with respect to preferences towards the incumbent. People with similar preferences tend to be closer over space.

The index is useful because it provides a relative and continuous measure of beliefs' divergence. In particular, given i's preferences, a higher value of the index (i.e. SI approaching 1) means that the share of ANC supporters around i is shrinking. Therefore, one can exploit this measure and its interaction with 3G coverage to assess the role of social interaction and information segregation on political outcomes. In particular, I estimate the triple difference equation described in (3), where $E = SI$. Table 11 describes the results.

The coefficient capturing the direct role of offline exchange of opinions between individuals (i.e. social interaction) is the one on $Spatial\ Isolation * 2016$. In particular, in column (1) this coefficient is negative and very large. It suggests that the effect on locality i's ANC share of being closer to a smaller share of ANC supporters is negative. The probability of interacting with someone who is willing to discredit the ANC party is higher for larger SI and, in turn, this has a direct consequence on future political behavior. As expected, in columns (2-3) the coefficient is positive, indicating that social interaction makes individuals voting for other parties or, as column (4) indicates, increases political disaffection.

What is the effect of spatial isolation on the way mobile information affects political preferences? The triple-interaction coefficient on $Spatial\ Isolation * Coverage * 2016$ should address this question. In column (1) it is negative and significant. This indicates that Internet coverage is more effective in damaging the ANC reputation when its political support in the neighbors is lower. At the same time the converse is true. This finding provides some evidence on the presence of online information segregation: news and facts that reach locality i are "filtered" by the opinions of the neighboring places. Another way to look at the phenomenon is considering the Internet as a tool that facilitates convergence of preferences over space. Columns (2-3) suggest that the main opponent, the DA, benefits from this interaction, while smaller and newly formed parties do not. This fact may reflect the stronger presence of territorial organizations for the biggest parties (ANC and DA), which might be more effective and influential in using online channels for their propaganda. Moreover, column (5) indicates no spatial patterns for the number of parties. Finally, standalone spatial isolation is found to have no impact on the number of riots and protests, while its interaction with coverage seems to be associated with a reduction of them. To interpret this sign it useful to think the opposite way. That is, places with 3G coverage which are surrounded by neighbors where ANC support is larger (i.e. SI tends to -1) experience an increase in protests. Here, the Internet seems to serve a specific purpose, that is it makes individuals realize the divergency in opinions with their neighbors. Consequently, willingness to engage in public demonstrations increases.

Table 12: Spatial analysis

Diff-in-Diff-in-Diff, years 2006 to 2016, whole sample

	ANC share	DA share	Other parties	Turnout	(log) N. of parties	N. of protests
	(1)	(2)	(3)	(4)	(5)	(6)
Coverage*Year 2016	-0.067***	0.027***	0.041***	0.005	0.063**	0.023**
	(0.015)	(0.008)	(0.014)	(0.009)	(0.030)	(0.009)
Spatial Isolation*2016	-0.224***	0.090***	0.142***	-0.025**	0.049	-0.010
	(0.022)	(0.013)	(0.018)	(0.010)	(0.033)	(0.016)
Spatial Isolation*Coverage*2016	-0.088**	0.130***	-0.032	0.015	-0.039	-0.120**
	(0.035)	(0.031)	(0.025)	(0.018)	(0.043)	(0.053)
Voting District FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
All controls	✓	✓	✓	✓	✓	✓
Polynomial	✓	✓	✓	✓	✓	
Observations	103,597	98,748	103,046	103,620	103,620	103,764
Adj. R-squared	0.756	0.849	0.718	0.514	0.815	0.133

Notes - Standard errors in parentheses clustered at the smallest stable aggregation of voting districts. Spatial Isolation is an index described in equation (4). All other interactions are included but not reported for conciseness. Same controls as those included in the baseline specification are included here. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

7. Conclusions

In this paper I analyzed the causal impact of mobile Internet coverage on political outcomes looking at the last South African municipal election results between 2000 and 2016. I mitigated concerns on potential endogeneity exploting a newly constructed high-resolution dataset along with two alternative empirical approaches, a Diff-in-Diff and a 2SLS estimations. In addition, I conducted complementary exercises to validate the robustness of my estimates.

My findings demonstrated that the arrival of fast mobile Internet in South Africa explained the decline in the popularity of the incumbent party, and the simultaneous gains of its rivals. These results are not driven by changes in affection towards politics. Indeed, 3G coverage did not alter political participation. By contrast, mobile Internet lowered entry costs into politics: it promoted the proliferation of new parties and facilitated existing parties to run in new districts. In turn, this resulted in an overall increase in political competition, at the expenses of the incumbent party. Furthermore, empirical results showed that covered localities experienced a surge in the number of riots and protests against political institutions. This may be the consequence of better coordination mechanisms, or the result of increased discontent – amplified by the exposure to online content– towards the economic/political situation. All findings are robust to various model specifications and different estimators.

In the second part I enriched the previous results developing a more sophisticated study of the potential mechanisms. Firstly, I conducted an analysis of the heterogeneity across mutually exclusive subsamples. This procedure revealed the prominent role played by education on the way 3G impacted on political behavior. Localities with higher average years of schooling exhibited greater coefficients, suggesting that (1) educated people used the Internet to retrieve political information and (2) non-educated individuals may have used it exclusively to access entertainment content. Meanwhile, historical ICT and traditional media adoption rates matter as well. In fact, baseline results are driven by those localities where individuals were used to be exposed to news circulation through non-digital technologies. By contrast, technologically disadvantaged people are not affected by the Internet.

Secondly, I studied the role for mobile Internet to convey specific information that could harm the incumbent party and its leader. I exploited a triple difference estimation, interacting 3G coverage with either (1) irregular and unauthorized municipal expenditure, or (2) with the relevance of the mining sector in the locality. The methodologies take advantage of the spatial variation in the probability of exposure to (1) corruption scandals or (2) administrative scandals related to the mining strikes and the subsequent violent events, respectively. Results demonstrated that in localities where individuals had higher chances of facing these issues, Internet arrival was even more detrimental for the popularity of the incumbent party. Mobile technologies provided the voters with some additional information and this led to a change in their political behavior. Moreover, I took advantage of the heterogeneity across and within ethnic lines to speculate on the persuasive power of such information. In particular, I showed that results of 3G coverage on ANC share are mostly driven by one specific ethnic group, the Zulu people, that is the tribe Jabob Zuma belongs to. I argued that the persuasive power of online information was larger for these people, as they share common linguistic and ethnic traits with the former ANC leader. In other words, ethnic affinity made voters more responsive to the information about the scandals conveyed by the web.

The last part of the paper focused on the way political beliefs in the surrounding environment directly and indirectly impacted on the voting outcomes of a locality. Firstly, I documented the presence of heterogeneous effects of 3G coverage on ANC vote share across places with different past political preferences. I showed that the Internet did not play any role in localities were attachment to the incumbent party was high in the past. Secondly, I illustrated that this heterogeneity vanishes when the analysis is conducted on on two distinct groups of municipalities: those where ANC share in the past was overall above and below the median. This pointed out the importance of beliefs in the surrounding environment, and their influences in the way information affects a locality. Hence, I constructed an index of relative spatial divergence in preferences towards the incumbent and employed it in a triple difference estimation. The results provided evidence in favor of the existence of online information segregation over space: Internet coverage led to a larger drop in the vote for the incumbent in places with a smaller share of ANC supporters in their neighbors. This could potentially indicate that online information was partially filtered by the neighboring network, and this phenomenon fostered convergence of preferences over space: opinions of neighboring districts with ex-ante different beliefs became more aligned with Internet availability.

The existence of the above mentioned mechanisms does not exclude the presence of additional ones. For instance, one may argue that the final impact of 3G access on political outcomes can be explained by the availability of new monitoring technologies at the voting stations and their effect on vote buying. Although I cannot completely rule out this hypothesis, I might use self-reported voting preferences to shed some light on it. In particular, results from the descriptive evidence of section 3 showed that intentions to vote for the ANC where much smaller for Internet users. This fact should partially invalidate the proposed channel. At the same time, the whole research suggested that, in the context of South Africa, the Internet might be an effective tool to monitor politicians' performance and promote political accountability. Understanding how politicians react to the new technology and if, for instance, they become more attentive/reactive to the voters' demands is left for future research.

Appendix

Figure 11: A FAKE EFF POSTER

Figure 12: ISPs MARKET SHARES (BUSINESSTECH)

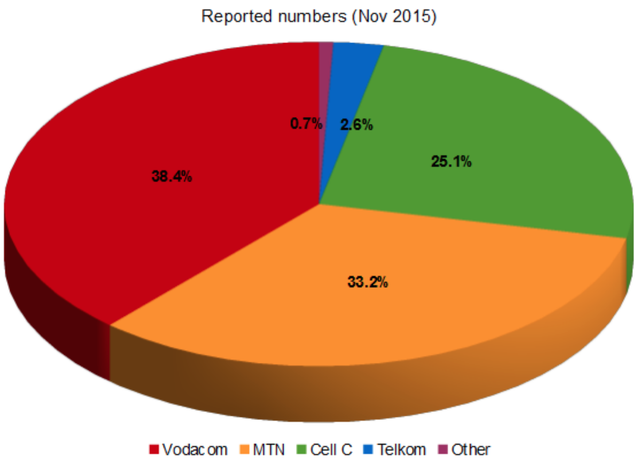
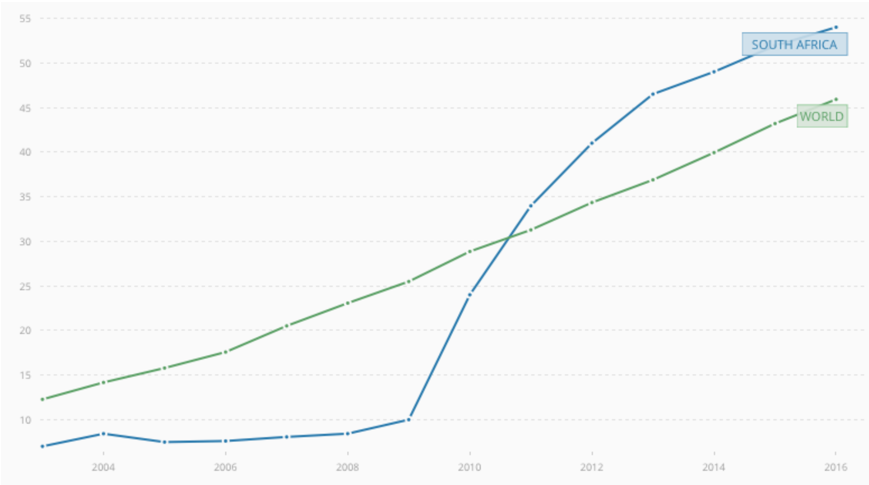
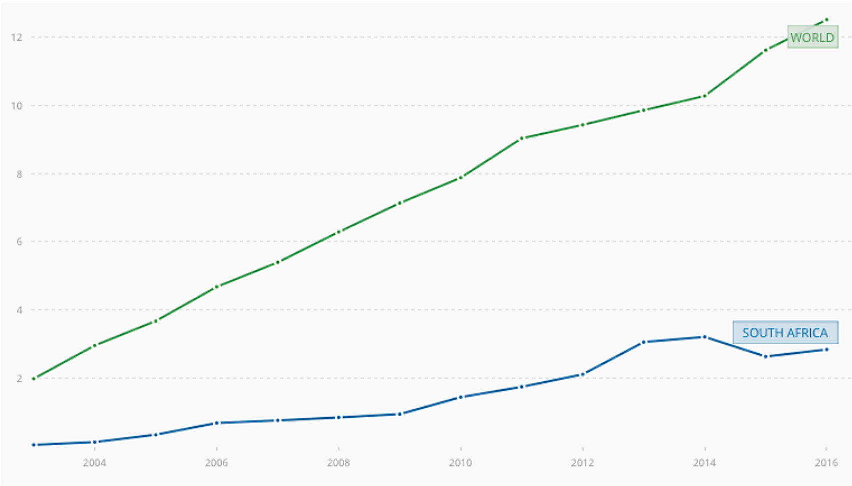


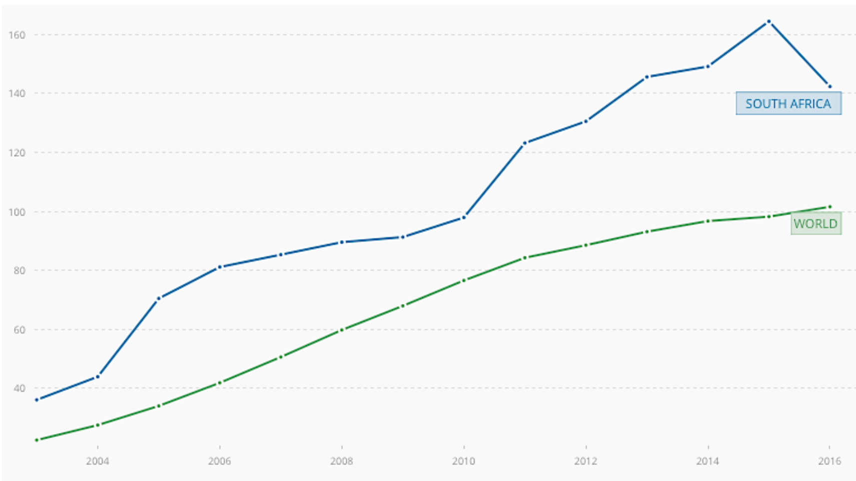
Figure 13: Trends over the last 15 years (World Bank)



(a) Internet users as percentage of population



(b) Fixed broadband internet subscribers



(c) Mobile cellular subscriptions per 100 people

Figure 14: Mobile internet coverage 2007-2015 (Collins Bartholomew)

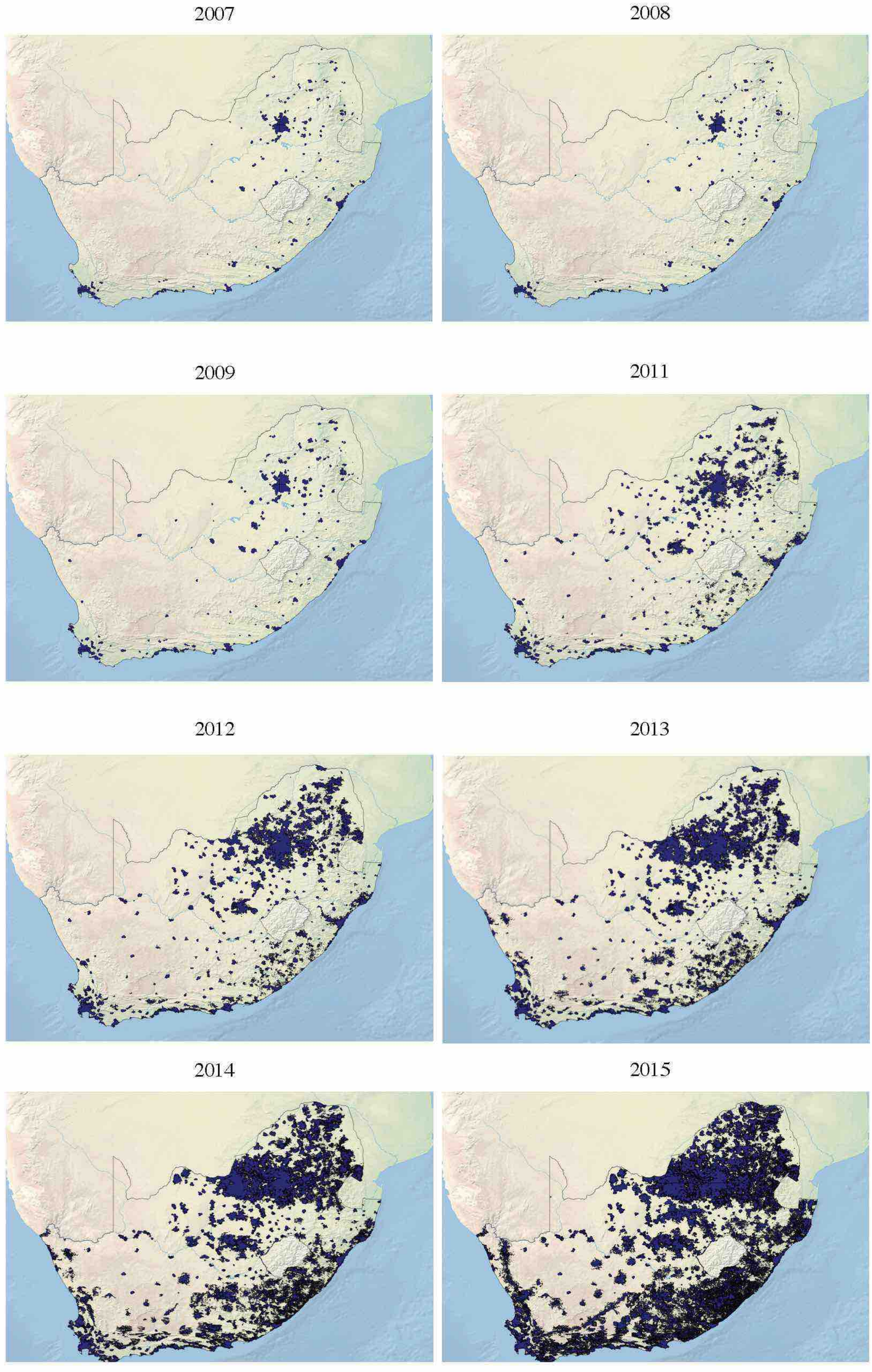
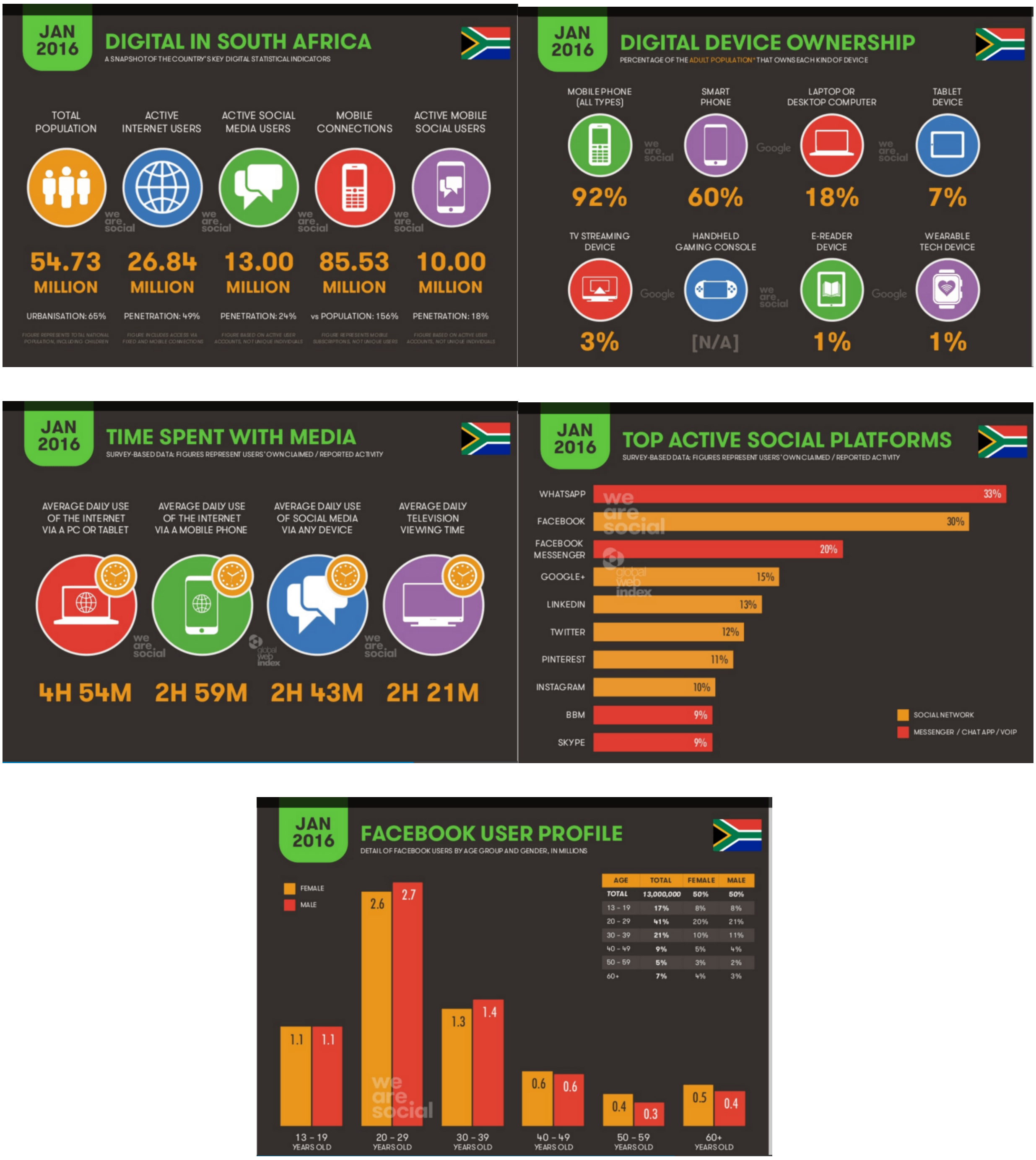


Figure 15: Media users in South Africa (We are social)



AGE	TOTAL	FEMALE	MALE
TOTAL	13,000,000	50%	50%
13 - 19	17%	8%	8%
20 - 29	41%	20%	21%
30 - 39	21%	10%	11%
40 - 49	9%	5%	4%
50 - 59	5%	3%	2%
60+	7%	4%	3%

Figure 16: Screenshot of municipal money website and Google trends for "corruption"

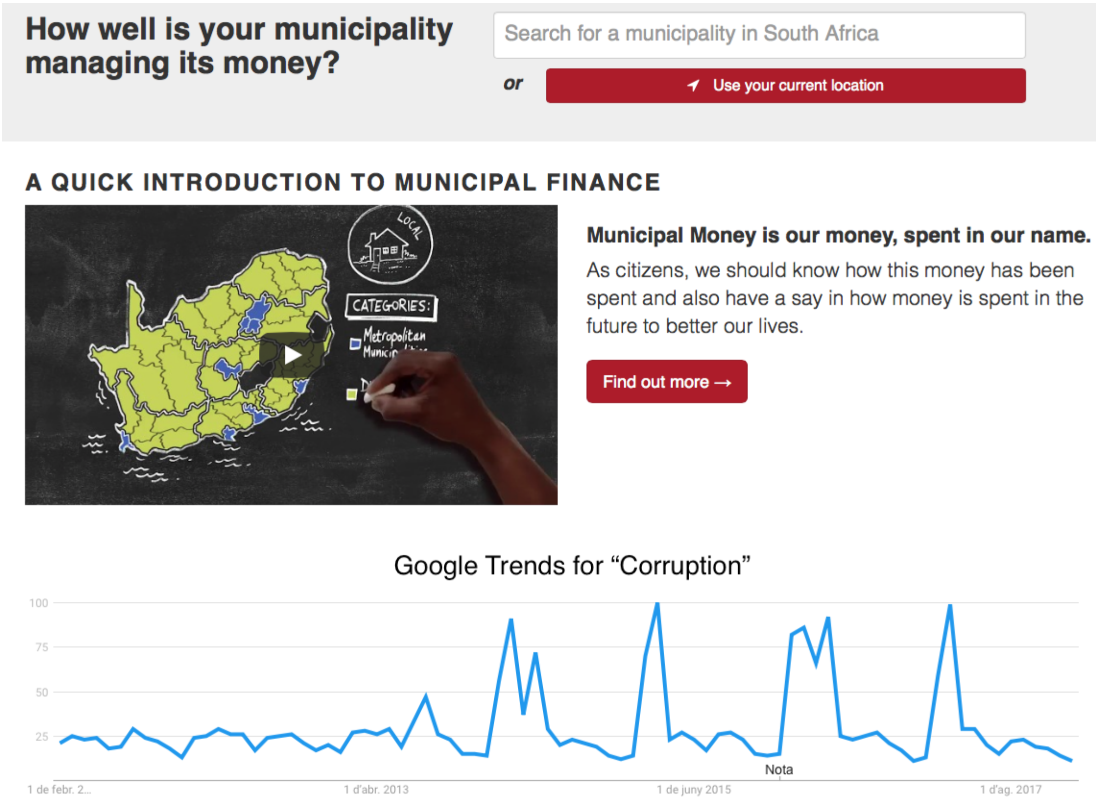


Figure 17: Construction of observational units

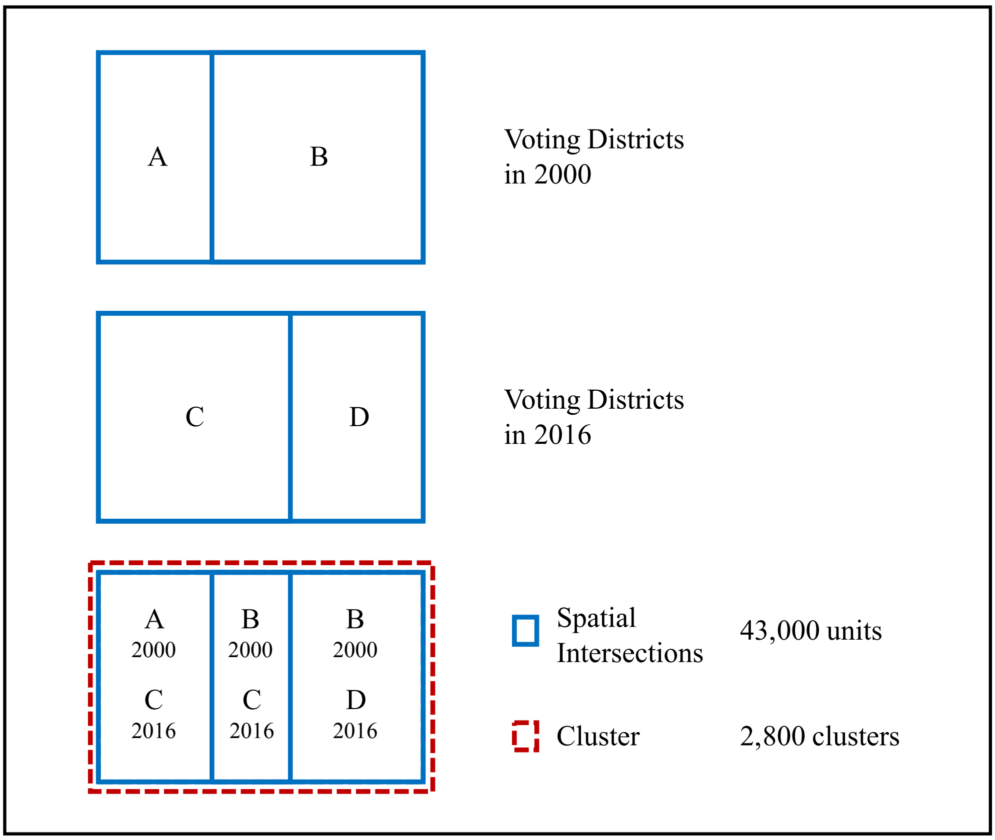


Table 13: DETERMINANTS OF 3G COVERAGE

OLS; years 2000 to 2016; whole sample

	Covered area (1)		Years of coverage (2)	
log(Pop. Density)	0.003	(0.002)	0.027*	(0.015)
log(Nightlight)	0.012**	(0.006)	0.161***	(0.029)
Urbanization	0.122***	(0.017)	1.521***	(0.188)
Schooling	0.012***	(0.004)	0.090***	(0.026)
Age	-0.004***	(0.001)	-0.018***	(0.006)
Young	-0.006	(0.060)	-0.494	(0.484)
Mining*2006	-0.004	(0.027)	-0.049**	(0.024)
Mining*2011	0.059**	(0.023)	-0.027	(0.149)
Mining*2016	-0.007	(0.018)	-0.006	(0.184)
Road*2006	0.025***	(0.009)	0.016	(0.010)
Road*2011	0.031***	(0.011)	0.103*	(0.053)
Road*2016	0.034***	(0.012)	0.285***	(0.085)
Waterway*2006	0.020*	(0.011)	0.036***	(0.012)
Waterway*2011	0.034***	(0.011)	0.129**	(0.060)
Waterway*2016	-0.003	(0.017)	0.067	(0.111)
log(Elevation)*2006	0.006	(0.006)	-0.002	(0.006)
log(Elevation)*2011	-0.002	(0.008)	0.014	(0.037)
log(Elevation)*2016	0.011	(0.008)	0.105*	(0.064)
log(Ruggedness)*2006	-0.004	(0.003)	0.001	(0.005)
log(Ruggedness)*2011	-0.011**	(0.005)	-0.024	(0.021)
log(Ruggedness)*2016	-0.026***	(0.005)	-0.157***	(0.034)
Slope*2006	0.001	(0.001)	0.001	(0.001)
Slope*2011	-0.003**	(0.001)	0.001	(0.006)
Slope*2016	-0.009***	(0.002)	-0.052***	(0.012)
log(Distance)*2006	-0.043***	(0.011)	-0.030***	(0.011)
log(Distance)*2011	-0.025*	(0.014)	-0.206***	(0.066)
log(Distance)*2016	0.020	(0.014)	-0.176	(0.111)
log(Area)*2006	0.004	(0.005)	0.014	(0.010)
log(Area)*2011	0.018***	(0.006)	0.029	(0.029)
log(Area)*2016	-0.000	(0.009)	0.069	(0.055)
Phone (in 2000)*2006	0.120**	(0.057)	0.077	(0.060)
Phone (in 2000)*2011	0.134***	(0.046)	0.530*	(0.304)
Phone (in 2000)*2016	-0.047	(0.060)	0.267	(0.462)
Cellphone (in 2000)*2006	0.139***	(0.036)	0.141***	(0.039)
Cellphone (in 2000)*2011	0.069*	(0.042)	0.610***	(0.204)
Cellphone (in 2000)*2016	0.175**	(0.069)	1.659***	(0.390)
ANC share (in 2000)*2006	-0.050***	(0.014)	-0.024	(0.019)
ANC share (in 2000)*2011	0.002	(0.017)	-0.200**	(0.086)
ANC share (in 2000)*2016	0.154***	(0.030)	0.492***	(0.160)
Voting District FE	✓		✓	
Year FE	✓		✓	
Demography:Linear	✓		✓	
Observations	138,360		138,360	
Adj. R-squared	0.670		0.752	

Notes - Standard errors in parentheses clustered at the smallest stable aggregation of voting districts. Demographic variables measured in 2000 and interacted with time dummies are included. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table 14: SENSITIVITY OF BASELINE RESULTS TO DIFFERENT SPECIFICATIONS

	Diff-in-Diff; years 2006 to 2016; whole sample					
	(1)	(2)	(3)	(4)	(5)	(6)
Coverage*Year 2016	-0.081***	-0.057***	-0.051***	-0.051***	-0.052***	-0.067***
	(0.015)	(0.014)	(0.014)	(0.014)	(0.013)	(0.015)
Coverage*Year 2011	-0.039***	-0.023**	-0.020**	-0.019**	-0.022**	-0.033***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Coverage	0.039***	0.021**	0.016*	0.016*	0.018**	0.032***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Voting District FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Demography		✓	✓	✓	✓	✓
Demography:Linear		✓	✓	✓	✓	✓
Politics:Linear			✓	✓	✓	✓
Geography:Linear	✓	✓	✓	✓	✓	✓
Phone Ownership				✓		
TV Ownership					✓	
Radio Ownership					✓	
Demography:Polynomial						✓
Geography:Polynomial						✓
Observations	104,571	104,571	103,728	103,728	103,728	103,728
Adj. R-squared	0.744	0.748	0.748	0.748	0.752	0.753

Notes - Standard errors in parentheses clustered at the smallest stable aggregation of voting districts. Demographic variables include information on (log) luminosity and (log) population density, urbanization rate, years of schooling, age and share of youth. Political variables include the (log) number of parties and turnout in 2000 interacted with time dummies. Geographical variables include presence of mine, road, river, slope index, (log) elevation, (log) ruggedness, (log) area and (log) distance from closest city interacted with time dummies. Phone ownership also includes cellphone ownership, and these are measured in 2000. TV and radio ownership are measured in 2011.* Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table 15: BASELINE RESULTS INCLUDING YEAR 2000

	Diff-in-Diff; years 2000 to 2016; whole sample					
	ANC share	DA share	Other parties	Turnout	(log) N. of parties	N. of protests
	(1)	(2)	(3)	(4)	(5)	(6)
Coverage*Year 2016	-0.048***	0.013***	0.034***	-0.010**	0.034*	0.005**
	(0.011)	(0.004)	(0.011)	(0.004)	(0.017)	(0.002)
Coverage*Year 2011	-0.012*	0.009**	0.002	-0.005	-0.032*	-0.006*
	(0.006)	(0.004)	(0.006)	(0.003)	(0.017)	(0.003)
Coverage*Year 2006	0.018**	-0.012*	-0.006	-0.009	-0.018	-0.016***
	(0.008)	(0.006)	(0.008)	(0.006)	(0.018)	(0.006)
Voting District FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
All controls	✓	✓	✓	✓	✓	✓
Polynomial	✓	✓	✓	✓	✓	
Mean in 2000	0.604	0.149	0.257	0.514	4.561	0.000
Observations	138318	126661	136259	138384	138384	138360
Adj. R-squared	0.719	0.809	0.724	0.406	0.845	0.096

Notes - Standard errors in parentheses clustered at the smallest stable aggregation of voting districts. Same controls as those included in the baseline specification are included here. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

References

[1] Acemoglu, D., & Ozdaglar, A. (2011). Opinion dynamics and learning in social networks. Dynamic Games and Applications, 1(1), 3-49.

[2] Adena, M., Enikolopov, R., Petrova, M., Santarosa, V., & Zhuravskaya, E. (2015). Radio and the Rise of the Nazis in Prewar Germany. The Quarterly Journal of Economics, 130(4), 1885-1939.

[3] Aker, J. C., & Mbiti, I. M. (2010). Mobile phones and economic development in Africa. Journal of Economic Perspectives, 24(3), 207-32.

[4] Allcott, H., & Gentzkow, M. (2017). Social media and fake news in the 2016 election. Journal of Economic Perspectives, 31(2), 211-36.

[5] Altonji, J. G., Elder, T. E., & Taber, C. R. (2005). Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools. Journal of political Economy, 113(1), 151-184.

[6] Angrist, J. D., & Pischke, J. S. (2008). Mostly harmless econometrics: An empiricist's companion. Princeton university press.

[7] Batzilis, D., Dinkelman, T., Oster, E., Thornton, R., & Zanera, D. (2010). New cellular networks in Malawi: Correlates of service rollout and network performance (No. w16616). National Bureau of Economic Research.

[8] Bond, R. M., Fariss, C. J., Jones, J. J., Kramer, A. D., Marlow, C., Settle, J. E., & Fowler, J. H. (2012). A 61-million-person experiment in social influence and political mobilization. Nature, 489(7415), 295.

[9] Buys, P., Dasgupta, S., Thomas, T. S., & Wheeler, D. (2009). Determinants of a digital divide in Sub-Saharan Africa: A spatial econometric analysis of cell phone coverage. World Development, 37(9), 1494-1505.

[10] Campante, F. R., Durante, R., & Sobbrio, F. (2013). Politics 2.0: The multifaceted effect of broadband internet on political participation (No. w19029). National Bureau of Economic Research.

[11] Cantoni, D., & Yuchtman, N. (2014). Medieval universities, legal institutions, and the commercial revolution. The Quarterly Journal of Economics, 129(2), 823-887.

[12] Chen, Y., & Yang, D. Y. (2017). 1984 or the Brave New World? Evidence from a Field Experiment on Media Censorship in China.

[13] Chiang, C. F., & Knight, B. (2011). Media bias and influence: Evidence from newspaper endorsements. The Review of Economic Studies, 78(3), 795-820.

[14] DellaVigna, S., Enikolopov, R., Mironova, V., Petrova, M., & Zhuravskaya, E. (2014). Cross-border effects of foreign media: Serbian radio and nationalism in Croatia. American Economic Journal: Applied Economics, 6(3), 103-132.

[15] DellaVigna, S., & Kaplan, E. (2007). The Fox News effect: Media bias and voting. The Quarterly Journal of Economics, 122(3), 1187-1234.

[16] DellaVigna, S., & La Ferrara, E. (2015). Economic and social impacts of the media. In Handbook of media economics (Vol. 1, pp. 723-768). North-Holland.

[17] Dittmar, J. E. (2011). Information technology and economic change: the impact of the printing press. The Quarterly Journal of Economics, 126(3), 1133-1172.

[18] Durante, R., Pinotti, P., & Tesei, A. (2017). The political legacy of entertainment TV.

[19] Elbers, C., & Lanjouw, P. (2001). Intersectoral transfer, growth, and inequality in rural Ecuador. World Development, 29(3), 481-496.

[20] Eisensee, T., & Strömberg, D. (2007). News droughts, news floods, and US disaster relief. The Quarterly Journal of Economics, 122(2), 693-728.

[21] Enikolopov, R., Makarin, A., & Petrova, M. (2016). Social media and protest participation: Evidence from Russia. Universitat Pompeu Fabra.

[22] Enikolopov, R., Petrova, M., & Sonin, K. (2018). Social media and corruption. American Economic Journal: Applied Economics, 10(1), 150-74.

[23] Enikolopov, R., Petrova, M., & Zhuravskaya, E. (2011). Media and political persuasion: Evidence from Russia. The American Economic Review, 101(7), 3253-3285.

[24] Falck, O., Gold, R., & Heblich, S. (2014). E-lections: Voting Behavior and the Internet. The American Economic Review, 104(7), 2238-2265.

[25] Ferraz, C., & Finan, F. (2008). Exposing corrupt politicians: the effects of Brazil's publicly released audits on electoral outcomes. The Quarterly Journal of Economics, 123(2), 703-745.

[26] Gavazza, A., Nardotto, M., & Valletti, T. M. (2015). Internet and politics: Evidence from UK local elections and local government policies.

[27] Gentzkow, M., Petek, N., Shapiro, J. M., & Sinkinson, M. (2015). Do newspapers serve the state? Incumbent party influence on the US press, 1869–1928. Journal of the European Economic Association, 13(1), 29-61.

[28] Gentzkow, M., & Shapiro, J. M. (2011). Ideological segregation online and offline. The Quarterly Journal of Economics, 126(4), 1799-1839.

[29] Gentzkow, M., Shapiro, J. M., & Sinkinson, M. (2011). The effect of newspaper entry and exit on electoral politics. American Economic Review, 101(7), 2980-3018.

[30] Gentzkow, M., Shapiro, J. M., & Taddy, M. (2016). Measuring polarization in high-dimensional data: Method and application to congressional speech (No. w22423). National Bureau of Economic Research.

[31] Grace, J., Kenny, C., Zhen-Wei Qiang, C. (2004). Information and communication technologies and broad-based development: A partial review of evidence. World Bank Working Paper No. 12, World Bank, Washington, DC.

[32] GSMA report. (2015). The Mobile Economy.

[33] Halberstam, Y., & Knight, B. (2016). Homophily, group size, and the diffusion of political information in social networks: Evidence from Twitter. Journal of Public Economics, 143, 73-88.

[34] Harris, M. (2011). How cell towers work. Unison Site Management.

[35] Jensen, R. (2007). The digital provide: Information (technology), market performance, and welfare in the South Indian fisheries sector. The quarterly journal of economics, 122(3), 879-924.

[36] La Ferrara, E., Chong, A., & Duryea, S. (2012). Soap operas and fertility: Evidence from Brazil. American Economic Journal: Applied Economics, 4(4), 1-31.

[37] Little, A. T. (2016). Communication technology and protest. The Journal of Politics, 78(1), 152-166.

[38] Manacorda, M., & Tesei, A. (2016). Liberation technology: mobile phones and political mobilization in Africa.

[39] McChesney, R. W. (2007): Communication revolution: Critical junctures and the future of media. New Press.

[40] Miner, L. (2015). The unintended consequences of Internet diffusion: Evidence from Malaysia. Journal of Public Economics, 132, 66-78.

[41] Odendaal, N. (2014). Space matters: the relational power of mobile technologies. urbe. Revista Brasileira de Gestão Urbana, 6(1), 31-45.

[42] Odendaal, N. (2011, June). The spaces between: ICT and marginalization in the South African city. In Proceedings of the 5th International Conference on Communities and Technologies (pp. 150-158). ACM.

[43] Olken, B. A. (2009). Do television and radio destroy social capital? Evidence from Indonesian villages. American Economic Journal: Applied Economics, 1(4), 1-33.

[44] Oster, E. (2016): "Unobservable Selection and Coefficient Stability: Theory and Evidence," Journal of Business & Economic Statistics.

[45] Petrova, M., Sen, A., & Yildirim, P. (2016). Social Media and Political Donations: New Technology and Incumbency Advantage in the United States.

[46] Snyder Jr, J. M., & Strömberg, D. (2010). Press coverage and political accountability. Journal of political Economy, 118(2), 355-408.

[47] Steinert-Threlkeld, Z. C., Mocanu, D., Vespignani, A., & Fowler, J. (2015). Online social networks and offline protest. EPJ Data Science, 4(1), 19.

[48] Strömberg, D. (2004). Radio's impact on public spending. The Quarterly Journal of Economics, 119(1), 189-221.

[49] World Bank (2006). Information and communications for development 2006: Global trends and policies. Washington, DC: World Bank.

[50] World Bank (2008). Africa infrastructure country diagnostic: Information and communications technology in sub-Saharan Africa – A sector review. Mimeo.

[51] Yanagizawa-Drott, D. (2014). Propaganda and conflict: Evidence from the Rwandan genocide. The Quarterly Journal of Economics, 129(4), 1947-1994.