Liberation Technology: Mobile Phones and Political Mobilization in Africa[*]

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Can digital information and communication technology foster mass political mobilization? We use a novel geo-referenced dataset for the entire African continent between 1998 and 2012 on the coverage of mobile phone signal together with geo-referenced data from multiple sources on the occurrence of protests and on individual participation in protests to bring this argument to empirical scrutiny. We find that mobile phones are instrumental to mass mobilization during economic downturns, when reasons for grievance emerge and the cost of participation falls. Estimated effects are if anything larger once we use an instrumental variable approach that relies on differential trends in coverage across areas with different incidence of lightning strikes. The results are in line with insights from a network model with imperfect information and strategic complementarities in protest provision. Mobile phones make individuals more responsive to both changes in economic conditions - a mechanism that we ascribe to *enhanced information* - and to their neighbors' participation - a mechanism that we ascribe to *enhanced coordination.* Empirically both effects are at play, highlighting the channels through which digital ICT can alleviate the collective action problem.

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1. Introduction

In this paper we use a variety of geo-referenced data for the whole of Africa over fifteen years to investigate whether mobile phone technology has the potential to foster mass political mobilization and explore the underlying behavioral channels of impact.

The recent spread of digital information and communication technology has fed a wave of optimism and a large amount of rhetoric about its use as a "liberation technology" capable of helping the oppressed and disenfranchised worldwide. According to this argument, popularized by political sociologists and media scholars (Castells 2011, Diamond 2010, Shirky 2011), mobile phones and Internet, thanks to the opportunity they offer for two-way, multi-way and mass communication, and their low cost, decentralized, open-access nature have the potential to foster citizens' political activism and even lead to mass political mobilization, especially when reasons for grievance emerge and traditional, civic forms of political participation are *de facto* or lawfully prevented.[1]

This argument appears particularly appealing for Africa. Although a certain degree of optimism surrounds Africa's recent development path (Miguel & Easterly 2009), reasons for grievance abound, with the continent, and in particular Sub-Saharan countries, performing at the bottom of the world rankings in terms of most indicators of economic, social and democratic development (World Bank 2012). The continent has also experienced the fastest rise in the spread of mobile phone technology worldwide: while in 1999 an estimated 80 million African citizens had access to mobile phones, in 2008 this number was estimated on the order of 477 million, around 60 percent of the entire continent population (Aker & Mbiti 2010). The spread of mobile technology across the continent has taken place against the backdrop of a practically non-existent fixed telephone line infrastructure, and because of this, it is claimed to have had unprecedented economic and social effects on the lives of its citizens, in particular the poor and very poor. The ubiquitous use of mobile phones in the continent has also led to the emergence of a number of creative applications and technological developments, such as SMS-based election monitoring, health and disaster prevention SMS-based information campaigns, disaster relief campaigns and mobile banking (Aker et al. 2015, Rheingold 2008). Due to the lack of a fixed phone line and high-speed Internet cabling, mobile phones are also the most used way to access the Internet and social media in the continent (Stork et al. 2013), greatly enhancing their information and communication potential.

Consistent with the liberation technology hypothesis, Africa has witnessed over the last decade some of the most spectacular episodes of mass mobilization. Food riots swept the continent between 2007 and 2008 (Berazneva & Lee 2013), while mass civil unrest (the Arab Spring) exploded in the northern countries between 2010 and 2012 (Campante & Chor 2012*b*).

[1] Already as of 2007 The Economist highlighted the role of mobile phone technology in fostering political activism worldwide, launching the term "mobile activism" (The Economist, 2007). Digital ICT and new media, including blogging and twitter, are also claimed to have been instrumental in what appears to be a recent surge of protests worldwide (Ortiz et al. 2013), from the Occupy Wall Street movement in the USA and the *indignados* in Spain to the "Arab Spring" in North Africa and the Middle-east (Howard et al. 2011).

Simple economic reasoning - which we formalize below - suggests that increased information and communication brought about by mobile phones have the potential to trigger collective action. This technology in particular can help individuals acquire and spread *infomation* on issues and reasons for grievance.[2] Due to its open-source and open-content nature, and hence by granting access to unadulterated information, digital ICT has also the potential to offset government propaganda, which curbs discontent via misinformation and persuasion, especially when traditional media are under the control of the government or in the hand of powerful interests groups (DellaVigna & Gentzkow 2010).

These arguments focus on the role of information provision on citizens' private incentives to participate, via its effect on the perceived individuals costs and returns. However, when strategic complementarities in the provision of protests exist, *i.e.* when the returns to political activism increase or the cost of participation decrease the larger the number of others participating, mobile phone technology can also foster mass mobilization through its ability to promote *coordination*. Knowledge, albeit imperfect, of others' likelihood of participating in particular can foster individuals' willingness to participate and lead to the emergence of protests in equilibrium, an outcome that would not result in a world where individuals act atomistically.

Despite the popularity of the liberation technology argument, there is no lack of reasons for skepticism and no lack of criticisms even outside economics. First, governments can use this technology as a control, surveillance or propaganda tool, hence making protests less rather than more likely (Morozov 2012). This effect is enhanced by the nature of the technology, that makes centralized control possible, an effect that is magnified by the circumstance that physical infrastructures as well as market regulation of ICT is, for obvious reasons, often directly in the hands of governments.

A second often heard counter-argument against the liberation technology hypothesis is that digital ICT can discourage social capital accumulation and the establishment of "strong ties" (in favor of "weak ties") that are thought to be instrumental to mass mobilization (Bond et al. 2012, Gladwell 2010), ultimately leading to political apathy rather than mobilization.

Perhaps a more subtle argument why digital ICT might not ultimately lead to the emergence of mass mobilization is that this technology has the potential to increase government accountability via information spread and greater transparency or to directly improve living standards, in turn detracting from the rationale for mass political mobilization, which is widespread discontent with the perceived state of the economy and politics.

In sum, and despite a great deal of enthusiasm and plenty of anecdotal evidence on the role played by digital ICT - and in particular mobile phones - in fostering mass political mobilization, there are good reasons to be skeptical about the role effectively played by this technology, and the evidence remains admittedly scant. The mechanisms of impact are also poorly understood. As far as we are aware there is no systematic study that establishes a convincing relationship between digital ICT and political mobilization and explores the underlying behavioral channels

[2] Mass SMS, political and information campaigns are indeed increasingly popular in Africa (Aker et al. 2015, Rheingold 2008).

of impact and this paper aims precisely at investigating these questions.

We bring the liberation technology argument to empirical scrutiny using several novel and by and large unexploited datasets for the whole of Africa, respectively on the spread of mobile phone technology and on protest activity. What makes these different datasets particularly appealing is their level of geographical detail, which allows us to examine the spread of protests and mobile phone technology over time across small areas within countries.

Data on local mobile phone coverage come from the Global System for Mobile Communications Association (GMSA) which collects this information for the purpose of creating roaming maps for use by customers and providers worldwide. These data provide information on the availability of signal for the whole of Africa (with the only exception of Somalia) between 1998 and 2012 at a level of geographical precision of between 1 and approximately 20 km^2 on the ground, depending on the country. GSM technology accounts for around 80 percent of mobile technology worldwide and almost 100 percent in Africa.

In order to measure the incidence of protests, we use two datasets on individual protest events, both coming largely from compilation of newswires. First, we use data from a very large, open-source dataset, which relies on automated textual analysis of news sources, the Global Database on Events, Location and Tone (GDELT, Leetaru & Schrodt 2013) (http://gdeltproject.org/). As this is a largely yet unutilized dataset and since we have no control on the algorithm used to collect the data or the news sources effectively utilized, we complement this information with another widely utilized, but much smaller, manually compiled dataset on unrest in Africa, the Armed Conflict Location Events Database (ACLED, Raleigh et al. 2010).

We combine these data with data from a variety of sources about, among others, population, nature and use of land, infant mortality, natural resources, distance to cities, to the border and to the coast, kilometers of road, average rain and temperature etc. for approximately 10,500 (55 X 55 km) cells which compose the continent, which are ultimately the units of observation in the analysis.

This very detailed level of geographical disaggregation allows us to compare changes in the incidence of protests in areas within the same country that experienced differential changes in the coverage of mobile technology. By focusing on within, rather than between, countries variation in the incidence of protests and the spread of ICT, we hope to alleviate the obvious concern - and the ensuing bias in the estimates of impact - that ICT adoption and the incidence of protests are correlated due to country-specific trends or shocks in unobservable variables, such as the state of the economic cycle.

In the empirical analysis we start by showing that the two datasets on protests convey similar information offering some reassurance on their information content. We also show that protests are strongly counter-cyclical, *i.e.* more likely to occur during recessions. Once we turn to our regression estimates we find that, on average, in our sample of countries and years, while mobile phones do not appear to affect the incidence of protests, they act in magnifying the effect of recessions. Our estimates suggest that a fall in GDP growth of 4 p.p. (approximately one standard deviation) leads to a differential increase in protests per capita between an area with full mobile phone coverage compared to an area with no coverage of around 10 percent. In order to control for the possibility that local economic shocks or other determinants of ICT adoption and protests might drive our results, we show that our estimates are robust to very flexible specifications that condition for differential linear time trends across areas with the same large array of baseline characteristics.

Although, by including in the regressions interactions of a large array of cross-sectional cell characteristics with linear time trends, we attempt to control at best for the joint determinants of protests and mobile phone technology across areas, a concern remains that even conditional on these variables, mobile technology adoption remains correlated with unobserved trends in protests. To address this concern, we use an instrumental variable strategy that exploits the slower adoption of mobile technology in areas subject to high incidence of lightning strikes. Frequent electrostatic discharges during storms damage mobile phone infrastructures and negatively affect connectivity, acting on both the demand (as the risk of intermittent communications discourages adoption) and the supply (as power surge protection is costly and poor connectivity makes the investment less profitable). Based on NASA satellite-generated data on the incidence of lightning for the entire Africa, we show that areas with higher average incidence of lightning display slower adoption of mobile phone technology. A one standard deviation increase in flash intensity leads to a lower penetration rate of mobile phone technology of approximately 0.43 p.p. per year. The IV estimates - although typically less significant than the OLS - confirm that mobile phones on average do not have an effect of protests, although they appear to be instrumental to mass mobilization during bad economic times, which act as a trigger for protests. 2SLS estimates show even larger effects of economic downturns on the incidence of protests in high coverage relative to low coverage areas, with effects as large as three times the ones found based on the OLS. As robustness checks, we show that our results hold true if we restrict to the pre-Internet period or if we exclude observations during the Arab Spring. In addition, we also show that the effects are particularly pronounced under authoritarian regimes or when traditional media are captured.

Using data on night lights (Henderson et al. 2012), we show that the instrument does not directly affect local economic development, which might itself affect the incidence of protests while being correlated with mobile phone penetration. This evidence reinforces our claim that the instrument is exogenous to the dependent variable. Possibly more importantly, we find no correlation between the instrument and the outcome variable in periods when mobile phone technology was unavailable, which acts as a test for the validity of the exclusion restriction.

A remaining empirical concern is that mobile phones also increase the probability that an event is reported in the news, and hence observed in our data. In this case our estimates would suffer from a margin of endogenous selection: at the extreme these might simply be capturing increased reporting rather than increased mobilization. To address this issue we use micro-data from the Afrobarometer (for 27 countries out of the 48 countries in the analysis) between 2005 and 2012 to show that self-reported individual participation in protests (as opposed to news-reported measures of protest occurrence) follows a similar pattern, with participation increasing more during periods of economic downturns in covered relative to uncovered areas.

A major advantage of using micro-data on protest participation is also that they allow us to identify the precise mechanisms through which mobile phones affect political mobilization. In order to investigate these mechanisms we borrow from and extend Jackson & Yariv (2007) network model with imperfect information. In its barest form, the model assumes that agents maximize the payoff from taking a certain action (in the present case, protesting), which depends positively on the number of connections taking that action through strategic complementarities, and negatively on the cost of participation. The latter in turn depends positively on economic conditions, as worse economic conditions reduce the opportunity cost of participating in a protest or increase reasons for grievance. Individuals in society differ in the number of connections and in their cost of protesting. Although individuals do not know what actions their connections will take, they can make educated guesses based on the distribution of connectedness in the population, which is publicly known. This is key for the determination of the (stable) equilibrium level of protests.

In equilibrium, the level of protests is higher the lower GDP growth. There are two mechanisms at work. For one, since worse economic conditions reduce the individual cost of participation then the provision of protests will mechanically increase. This is a first-round effect. If strategic complementarities are at work, though, this mechanism is enhanced, as individuals iterate over their neighbors' best responses knowing that, when the economy does poorly, their neighbors will be more likely to participate, leading to a second-round increase in protest provision in equilibrium.

These effects are true irrespective of the extent of connectedness in society. However, if individuals with more connections are more likely to participate when the economy deteriorates - an effect that we ascribe to *increased information* - or if they are more responsive to changes in their neighbors' propensity to participate - an effect that we ascribe to *enhanced coordination* - then worse economic conditions unambiguously lead to a greater increase in protest participation in areas with higher connectedness. This is true because the magnitude of either of the mechanical first-round effect or of the second-round spillover effect - or of both - are enhanced.

The model is particularly appealing in our setting. Access to mobile phones can be thought as of increasing connectedness. If mobile phones warrant access to unadulterated information, meaning that those with mobile phones are better informed about the true state of the economy, and hence are more likely to respond to changes in economic conditions (something for which we provide direct evidence below), or if mobile phones improve coordination through greater communication - or both - then the protest differential between areas with high mobile phone coverage relative to areas with low coverage is deemed to increase when the economy deteriorates.

Regressions estimates based on aggregate data from GDELT and ACLED subsume potentially both mechanisms: increased information as well as increased coordination. We show however that one can use micro-data from the Afrobarometer to separately identify these two effects. Importantly, we exploit the circumstance that the Afrobarometer also provides an individual measure of mobile phone use. Intuitively, one can tell these two effects apart by examining the differential response between individuals with and without mobile phones to changes in economic conditions and in the fraction of others participating, effectively a spillover effect. Although the fraction of others participating is clearly an endogenous variable, due to a classical reflexivity problem (Manski 1993), one can identify the spillover effect through variations in the fraction of others connected in society, *i.e.* mobile phone coverage. If conditional on one's mobile phone ownership and the state of the economy, an individual in an area with greater coverage is more likely to respond to changes in economic conditions, then this effect must work through strategic complementarities.

Consistent with this model, we find that individuals are more likely to participate during bad economic times. We also find that individuals are more likely to participate the higher is the fraction of others participating in society, even in areas with no coverage. Our estimates imply that a 10 percent increase in the fraction of fellow citizens participating increases each individual's probability of participation by around 8 percent. This is strong evidence of strategic complementarities in the provision of protests. Taken together, these findings imply that worse economic conditions lead to an increase in protest through both a direct compositional effect and a spillover effect.

Mobile phones, though, enhance both these effects. Those with mobile phones are more likely to respond to changes in both economic conditions and in the fraction of fellow citizens participating. Empirically, both effects are at work, implying that the mechanism through which mobile phones foster political mobilization during recessions is both through enhanced citizens' information and enhanced coordination in protests participation.

Our paper borrows from and contributes to different strands of the literature. A small but established body of evidence shows that individual participation in mass political movements is negatively correlated with economic conditions, as worse economic conditions are associated with lower private opportunity costs of participation and provide a rationale for widespread grievance (Campante & Chor 2012*a*,*b*, DiPasquale & Glaeser 1998, Ponticelli & Voth 2011).[3]

Our paper is also closely related to studies focusing on the role of both traditional and new media on political participation. A number of studies for the USA show that media and newspapers foster political participation, most likely through information provision (Gentzkow et al. 2011, Gerber et al. 2009). These studies focus on traditional media and on civic forms of participation in advanced democracies and it is unclear whether these findings extend to ICT

[3] This parallels findings that worse economic conditions are typically associated with greater incidence or risk of conflict and insurgency (see Blattman & Miguel 2010, Collier et al. 2000, Harari & La Ferrara 2013, Miguel et al. 2004), although there is also an argument that economic growth can foster rather than discourage unrest through a rapacity effect (Dube & Vargas 2013). A related literature also emphasizes the role of protests and revolution threats during bad economic times as triggers for political changes and democratization (Acemoglu & Robinson 2001, 2006, Aidt & Franck 2015, Brückner & Ciccone 2011).

and to spontaneous, less codified and perhaps less civic forms of political participation in low income countries and in less mature democracies or in autocracies. There is also evidence though that Internet and new media can lead to greater political disaffection (Falck et al. 2014).[4]

Alongside, a small but growing body of literature emphasizes the role of traditional media on voters' political alignment through propaganda and persuasion, especially when these are in the hands of government or are politically aligned (DellaVigna & Kaplan 2007, Durante et al. 2015, Yanagizawa-Drott 2014), although independent media can counteract these effects (Enikolopov et al. 2011). Free media can also discipline politicians and increase accountability (Besley & Burgess 2002, Reinikka & Svensson 2011, Snyder Jr & Strömberg 2010, Strömberg 2004) and social media have the potential to reduce corruption and favoritism towards firms connected to the political elite (Acemoglu et al. 2014).

A different stream of studies focuses on the role of strategic complementarities in affecting collective action. Particularly relevant in our setting is Yanagizawa-Drott (2014) who studies the role of government propaganda during the Rwandan genocide. Using a global games approach, the paper argues that greater local radio coverage fostered participation in mass killing not only through a direct information channel, that the government was unwilling to punish perpetrators, but also through the spread of common knowledge, *i.e.* the knowledge that others also knew (and knew that others knew), in turn solving the coordination problem that plagues collective action. Somewhat in a similar vein, recent work by Madestam et al. (2013) shows that participation in rallies during the Tax day in the USA was lower in rainy locations. Probably, this is not only because individuals have greater private costs of participating but also because rain knowingly makes others less likely to participate, hence reducing each individual's private incentive to participate. Consistent with this, DiPasquale & Glaeser (1998) show that riots in the USA are more likely to occur in cities than in rural areas, an effect that they ascribe precisely to enhanced coordination when communication costs are lower.

The rest of the paper is organized as follows. Section 2 presents the data. Section 3 presents descriptive statistics. Section 4 builds on the theoretical model, which is discussed in detail in Appendix B, to lay out the empirical strategy. Section 5 presents the empirical results. Section 6 finally concludes.

2. Data

In this section we present the main sources of data used in the rest of the analysis. We start by focusing on geo-referenced data on mobile phone coverage and we then document the available geo-referenced data on protests. Further details on the data are reported in Appendix A. Most of our data cover the entire continent (with the exception of Somalia for which we have no

[4] These results echo findings for the USA on the negative effect of television on voters' turnout (Gentzkow 2006) and results for Indonesia that radio leads to reduced levels of trust and social capital (Olken 2009).

information on mobile phone coverage) over 15 years, from 1998 to 2012.[5]

2.1. PRIO-GRID cells

Our primary geographical units of observation in the analysis are cells of 0.5° x 0.5° degree resolution, approximately corresponding to areas of 55 x 55 *km* at the equator, which are constructed by the Peace Research Institute Oslo (PRIO) (Tollefsen et al. 2012). The advantage of focusing on grid cells rather than, say, on administrative partitions within countries, is that for these cells we have data on a large array of socio-economic and other characteristics, including population. This allows us to examine the relationship between ICT adoption and the spread of protests across relatively fine geographical areas, while controlling for a large array of local characteristics. The data refer to 10,409 cells, an average of 217 cells per country. Since the contours of cells do not correspond typically to a country's political border, we assign cells spanning over more than one country to the country which occupies the largest area in any given cell. At continent population of around 885 million, each cell accounts for around 84,000 individuals. This is shown in row 5 of Table 1. For comparison, these cells are similar to USA counties both in terms of population and extension.

2.2. Mobile phone coverage: GSMA data

Data on mobile phone coverage are collected by the Global System for Mobile Association (GSMA), the association representing the interests of the mobile phone industry worldwide, in partnership with Collins Bartholomew, a digital mapping provider. The data come from submissions made directly from mobile operators.

The coverage refers to the GSM network, which is the dominant standard in Africa with around 96 percent of the market share (Foster & Briceno-Garmendia 2011).[6] The data that have been licensed to us provide, for all years between 1998 and 2012, yearly geo-located information on mobile phone coverage aggregated across all operators. This allows us to measure the adoption of mobile phone technology at a very disaggregated geographical level. The data we have access to collate submissions from all member operators. The extent of geographical precision of the original data submissions ranges between 1 km^2 on the ground (for high quality submissions based on GIS vector format) and 15-23 km^2 (for submissions based on the location of antennas and their corresponding radius of coverage) (GSMA 2012, Sauter 2006).[7] Our data improve considerably over similar data used in previous studies. Most cross-country studies typically use measures of mobile subscription or penetration, which vary only at the country level (Ahn & Lee 1999, Gruber & Verboven 2001). Studies at greater level of geographical

[5] The data refer to 48 countries. In order to keep the dataset balanced we do not account for the creation of South Sudan in 2011, treating Sudan as a single country throughout the entire sample period.

[6] Based on restricted-use data from Collins Bartholomew we estimate that the operators submitting their data represent 86 percent of the total market share of African mobile operators.

[7] Since data on coverage are not available for 2005 and 2010 we interpolate linearly across neighboring years to derive an estimate of coverage in these two years.

detail, on the contrary, typically focus only on one country (Aker 2010, Jensen 2007, Shapiro & Weidmann 2015). The only studies we are aware of that use detailed information on mobile phone availability at a fine level of geographical detail for more than one country are Buys et al. (2009) and Pierskalla & Hollenbach (2013), although these studies only cover a limited time span (respectively 1999-2006 and 2007-2009).

2.3. Political mobilization: GDELT and ACLED

Our first source of data on political mobilization is the Global Dataset on Events, Location and Tone (GDELT, Leetaru & Schrodt 2013), an open-access database that, through an automated coding of newswires, collects information on the occurrence and location of political events, including protests, worldwide. The dataset contains an average of 8.3 millions fully geo-coded records of daily events per year for the entire world, although the number of observations increases considerably over time. For each event the data report the exact day of occurrence and precise location (latitude and longitude of the centroid) at the level of city or landmark.

Out of the 20 primary event categories in the data, we focus on "*Protests*", defined as "civilian demonstrations and other collective actions carried out as a sign of protest against a target". Figure A.2 reports GDELT data on protests in Cairo in 2011 and shows the level of geographical detail allowed by our data. There are as many as 70 different landmarks, with the size of the circles indicating the number of days of protest in each precise location. Events in Tahrir Square and Cairo University are easily recognizable, but other episodes and locations that are probably less familiar to readers, such as the recurrent strikes in the industrial district of Helwan in the southern suburbs of the city, are also identified.

Since GDELT is a yet largely unutilized dataset and in order to probe the robustness of our analysis to the measures of protests used, we complement the analysis with a widely used manually compiled dataset, the Armed Conflict and Location Event Dataset (ACLED, Raleigh et al. 2010). We restrict to events that are classified as protests and riots in the data. As in GDELT, events are atomistic in that they are coded by day, and the data report their precise location.[8]

2.4. Political mobilization: Afrobarometer

Both GDELT and ACLED data are derived from news reports. A concern here is that the likelihood of a protest being reported in the data is itself a function of the availability of mobile phones. This could mechanically inflate our estimates of the effect of mobile phone coverage on protests. A related issue is that we have no information on the characteristics of individuals who engage in protest activity, or other correlates of protest activity, which can help us shed light on the mechanisms through which mobile phone technology possibly affects political participation.

For these reasons, we finally complement our analysis with information from the Afrobarometer, a public attitude survey on governance and economic conditions in Africa (Afrobarometer

[8] Data are available at acleddata.com/data/.

2011). These data have been widely used for research in economics and political science (*e.g.* Michalopoulos & Papaioannou 2012, Nunn & Wantchekon 2011, Rohner et al. 2013). Importantly, in addition to a large array of socioeconomic variables, rounds 3 to 5 of the Afrobarometer provide information on self-reported participation in protests over the previous year for 27 African countries, as well as information on mobile phone use. The data are available for the years 2005 to 2012.

The version of the Afrobarometer that has been made available to us contains in addition information on individuals' locality of residence. This also allows us - although with a certain degree of approximation - to assign individuals in the Afrobarometer to PRIO-GRID cells. We discuss this assignment procedure in Appendix A.

One caveat with the Afrobarometer compared to GDELT and ACLED is that, not only do the data cover 27 out the 48 countries in GSMA but also their time span is more limited, and only a limited number of cells per country are covered. Information on the available data and the number of individual and cell observations by country and round is reported in Table A.2.[9]

3. Descriptive statistics

In this section we provide preliminary evidence on the spread of mobile technology and mass political mobilization throughout Africa. We focus on the fifteen-years period between 1998 and 2012 for which we have data on both coverage and protests from both GDELT and ACLED.

Figure 1 shows a map of 2G mobile phone coverage over the entire continent at 5-years intervals. While, as of 1998, only 3 percent of the African territory was covered by the mobile phone signal, by 2012 this figure was 27 percent. Figure A.1 zooms onto Nigeria, superimposing the lattice of 0.5° x 0.5° grid cells. One can appreciate the level of geographical detail allowed by our data together with the very rapid expansion in mobile phone infrastructure over the period.

This figure clearly does not provide information on the fraction of population covered, as coverage is higher in more populated areas. We use information on the share of each cell's area that is covered by mobile phone technology and we assume that population is uniformly distributed within cells in order to compute the fraction of individuals reached by the mobile phone signal in each cell/year. In the rest of the paper we use this measure as our primary measure of mobile phone penetration. We aggregate across cells using population weights to obtain country-level or continent-level measures of mobile phone penetration.

Row 1 of Table 1 reports the average population-weighted 2G mobile phone coverage across the 1998-2012 period across the entire continent. Coverage starts from a value of 9.2 percent in 1998, reaching 63 percent in 2012. This very fast continental growth masks large differences across countries. Figure 2 shows that among early adopters, such as Morocco and South Africa,

[9] Observations span over 51 percent of the countries' cells and account for 83 percent of the countries' population, meaning that more populated cells are more likely to appear in Afrobarometer.

coverage was virtually ubiquitous by the end of the period. This is in contrast with countries like Ethiopia and Mali where, as of 2012, still less than 10 percent of the population was covered.

In order to combine information on protests with information on coverage of mobile phone technology, we compute the total number of events falling within each cell in each year and we standardize this number to each cell's population (in 100,000). On average, over the entire continent, GDELT records 1.24 yearly protests per 100,000 population.

Trends in protests across the continent can be appreciated in Figure 3 that reports the evolution of protests per capita over the entire continent. One can see a pronounced positive trend in the incidence of protests, with an overall increase of around 200 log points over the period. One can also notice a temporary increase in 2008-09, when the food riots exploded and a very pronounced increase in 2010-12 when the Arab Spring swept part of the continent.[10]

Alongside trends in log protests per capita, Figure 3 reports average GDP growth (the dotted line) across the continent over this period.[11] A remarkable feature of the data is that protests are strongly counter-cyclical, consistent with the literature cited in the introduction that protests are more likely to occur when reasons for grievance abound and when the opportunity cost of participation falls, both of which are more likely to occur during recessions.[12] We revert to the effect of economic conditions on the incidence of protests later on in the paper when we present our regression analysis.[13]

Data from ACLED provide an estimate of the incidence of protests per 100,000 individuals on the order of 0.08, *i.e.* around one fifteenth of what found in GDELT (see rows 2 and 3 of Table 1). One possible reason why the number of protests in GDELT is much larger than in ACLED is that GDELT data are less likely to suffer from type-1 error, whereby truly occurring protests fail to be reported or are misclassified. In particular small mobilization events might fail to be recorded in ACLED.[14] On the other hand, given the automated coding, it is possible that GDELT suffers from a higher rate of type-2 error compared to ACLED, whereby events that are not genuine protests are incorrectly classified as such. A related problem is that, although

[10] Figure A.3 reports the evolution in log protests per capita (plus one to account for zeros) measured in GDELT separately by country. As the range of variation of this variable is very different across countries, we standardize these series to their value in 1998. One can observe an increase in protests around 2008 in countries like Mauritania, Madagascar and Guinea that experienced food riots. The variation in the data is - in all cases - dwarfed by the very rapid surge in protests at the beginning of the current decade, with clear spikes in countries like Algeria, Egypt, Libya, Morocco and Tunisia, where the Arab Spring took place.

[11] This is a weighted average of countries' GDP growth using cell population as weights. GDP growth is from the World Development Indicators (World Bank 2012). It represents the annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2005 U.S. dollars.

[12] The same correlation is found using ACLED data (results not reported but available upon request).

[13] Figure A.4 reports the cross-sectional correlation between mobile phone coverage and protests per capita in GDELT (again expressed in logs of protests per capita plus one) across all countries. Data are averages across the period for each country weighted by population weights. The data illustrate a clear positive correlation between these two series, with countries with full coverage, such as South Africa, showing rates of protests per capita around 50 log points higher than countries with virtually no coverage, such as Ethiopia. Results, not reported, are similar when using ACLED.

[14] Indeed, compared to manually complied datasets, machine coded datasets have typically low rates of false negatives (Schrodt 2012) and an independent appraisal of GDELT suggests that this performs particularly well in this respect even compared to other automated coded datasets (Ward et al. 2013).

in GDELT every attempt is made to collapse multiple reports of a unique event into a single record, the algorithm might fail to do so if the variables that uniquely identify an event differ across articles and newswires. We revert to this issue below.

We have investigated at length the correlation between GDELT and ACLED. Despite the marked difference in the number of reported protests, we find evidence that the incidence of protests across countries and over time, as well as within countries, is very highly correlated across the two datasets. This is discussed in Appendix A.

Turning to the micro-data from Afrobarometer, on average 12 percent of individuals report having participated in at least one protest during the past year (Table A.3). Reassuringly, we find a positive and significant within-cell correlation between self-reported protest participation in Afrobarometer and the incidence of protests in both GDELT and ACLED. This is also discussed in Appendix A.

4. Econometric model

As said, protests respond to the state of the economic cycle, increasing during recessions and falling during booms. Worsening economic conditions can increase the incidence of protests because they provide reasons for grievance and because they reduce the opportunity cost of participating in mass mobilization. In this section we use regression analysis to investigate whether, alongside the state of the economic cycle, mobile phone diffusion has an effect on the incidence of protests and whether possibly this effect varies as a function of the economic cycle.

In the rest, we start by modeling how overall protest occurrence in cell varies as a function of local coverage and the state of the economy and the interaction of the two. Information on coverage and protest activity by cell is available consistently for the entire continent for fifteen years (based on data from GSMA and GDELT or ACLED respectively).

In section 4.3 we turn to the micro-founded model that underlies this aggregate model. We show how one can use data on protest participation and mobile phone use at the individual level which are both available from the Afrobarometer - although for a limited number of cells/years - not only to validate results based on aggregate data but also to disentangle and quantify the different mechanisms of impact.

4.1. Aggregate outcomes: OLS

In this section we start by modeling the occurrence of protests in a cell as a function of aggregate economic conditions and mobile phone availability. We also allow for the effect of changes in economic conditions to vary as a function of mobile phone coverage. With this latter term we intend to capture the potential complementarity between economic downturns and mobile phones in protest provision. While it seems unlikely that mobile phones will affect mass mobilization during good economic times, it seems plausible that their effect will manifest - if anything - when reasons for grievance emerge.

If we denote a generic cell by j, with $j \in c$, where c denotes a country and t denotes a generic year, and ignoring other controls, our regression model is:

$$\bar{y}_{jct} = \beta_0 + \beta_1\ \Delta GDP_{ct} + \beta_2\ Cov_{jct} + \beta_3\ \Delta GDP_{ct}\ Cov_{jct} + f_{jc} + f_t + u_{jct} \tag{4.1}$$

where $\bar{y}_{jct}$ denotes the incidence of protests (or the fraction of individuals protesting, depending on the data used) in a cell in a given year, ΔGDP_{ct} is a measure of the country's economic growth while Cov_{jct} is a measure of local mobile phone coverage. f_{jc} and f_t are respectively cell fixed effects and time effects common across countries while u_{jct} denotes the error term. The coefficient β_1 in (4.1) captures the effect of aggregate GDP growth on local protests, the coefficient β_2 captures the effect of mobile phone coverage on protests while β_3 measures how country-level economic booms and downturns translate into differential protest activity in areas with different mobile phone coverage. This coefficient is negative if mobile phones magnify the effect of economic downturns on protests. Below we also experiment with more saturated specifications that include country X year effects (in which case the coefficient β_1 cannot be identified) as well as a large array of time-varying cell controls. We also present more restrictive specifications where we constrain the coefficient β_3 to 0, implying that the effect of mobile phones on protests is the same at any level of economic growth.

Ignoring other covariates, identification of model (4.1) is based on a differences in differences strategy that compares changes in the incidence of protests across cells within the same country experiencing differential trends in the adoption of mobile phone technology. Consistency of the estimates relies on the assumption that, other than for differential trends in mobile phone coverage, trends in protests per capita would be similar across cells within the same country.

One first issue worth discussing is the measure of economic growth used. A potentially better specified model than model (4.1) would include among the regressors the cell's rather than the county's GDP growth, as protests are likely to respond to local rather than to aggregate economic shocks. The reason why we focus on aggregate economic shocks is that measures of GDP growth at the level of the cell are not available and the measures of local economic conditions we have (that we discuss below) are likely to be affected by considerable measurement error. Inclusion of these error-ridden variables will affect the consistency of the estimates of equation (4.1).

Obviously, though, local economic conditions might themselves affect mobile phone penetration which would require controlling for measures of local economic conditions in the regressions. This is a classical omitted variable problem, which leads to the second major issue underlying the identification of model (4.1), namely the potential non-random allocation of mobile phone coverage across cells. We start to deal with this issue by introducing in the model a very high number of cell-level time-varying controls. The OLS estimates of the parameter of interest will be consistent if these covariates control adequately for differential trends in local economic growth and other local determinants of protests that happen to be correlated with mobile phone coverage. As conditioning on observables does not necessarily adequately control for all sources of potential correlation between coverage and the error term, in the next section we propose an alternative strategy that relies on an instrumental variable approach.[15]

4.2. Aggregate outcomes: 2SLS

As a way to address the potential endogeneity of mobile phone coverage with respect to protest activity we exploit the differential adoption of mobile technology in areas subject to different incidence of lightning strikes.

Frequent electrostatic discharges during storms are known to damage mobile phone infrastructures and in particular antennas on the ground that transmit the signal in their vicinity and negatively affect connectivity, hence reducing both the supply of (as power surge protection is costly and poor connectivity makes the investment in technology less profitable) and the demand for (as the risk of intermittent communications discourages adoption) mobile phone services (Andersen et al. 2011, ITU 2003). Hence, one will expect to see a slower adoption of mobile phone technology in areas subject to higher lightning incidence. As we show below, there is substantial variation in lightning intensity across areas, suggesting that this instrument has the potential to generate useful variation in the rate of mobile phone adoption across cells.

In practice, we use as an instrument for mobile phone coverage the interaction between the average number of flashes in a cell over the period 1995-2010, denoted by $Flash_{jc}$ and a linear time (year) trend t that captures the generalized increase in mobile phone adoption across the continent. In formulas, our first stage equation is:

$$Cov_{jct} = \delta_0 + \delta_1\ \Delta GDP_{ct} + \delta_2\ Z_{jct} + f_{jc} + f_t + \eta_{jct} \tag{4.2}$$

where $Z_{jct} = Flash_{jc}\ X\ t$. One can use predicted Cov from this model interacted with ΔGDP as an instrument for $\Delta GDP\ Cov$ in equation (4.1).[16]

Our identification ultimately relies on the assumption, that - conditional on the included controls - protest activity does not vary differentially over time across cells depending on average flash intensity, other than because of differences in mobile phone coverage.

This assumption might fail to hold unconditionally, as flashes might be correlated with geographical variables (*i.e.* distance to the coast or longitude and latitude) or climatic variables (*e.g.* rain and temperature) or with the availability of other infrastructures or services (*i.e.*

[15] An additional source of correlation between coverage and the error term is given by the gradual spread of the Internet. This might be correlated with the availability of mobile phones and also affect protests directly. We try to deal with this below by showing that the estimates remain effectively unchanged when we restrict to a period prior to the spread of the Internet. Additional sources of bias might result from measurement error in the coverage variable and, although probably less serious of an issue, by reverse causality, whereby local protests might affect economic growth. Both these sources of bias should be addressed by the instrumental variable approach discussed below.

[16] Since we have two endogenous variables and two instruments, an alternative, more efficient approach, which we end up using in the empirical section, consists in instrumenting both endogenous variables with both instruments (Wooldridge 2010). In formulas our first stage equations are: $Cov = \delta_0 + \delta_1\ \Delta GDP + \delta_2\ Z + \delta_3\ \Delta GDP\ Z + \eta$ and $\Delta GDP\ Cov = \theta_0 + \theta_1\ \Delta GDP + \theta_2\ Z + \theta_3\ \Delta GDP\ Z + \mu$.

electricity) that are known to matter for economic development and that might have an independent effect on protests. As said, we temper these concerns by including a large number of cell-level controls (*e.g.*, rain and temperature, electricity grid, distance to the coast, latitude and longitude etc.). More importantly, later on in the paper we bring direct evidence in favor of our identification assumption using data on protests for a period previous to the availability of mobile phone technology. If lightning strikes and their interaction with GDP growth affect protests only through their effect on mobile phone coverage, then one will expect no correlation between the outcome variable and these variables in periods in which mobile phone technology was not available. We use data from the early 1990s to test this hypothesis.

As an additional check, we also present regressions of measures of local economic development on the instrument. For the exclusion restriction to hold, one will expect local economic conditions to be unaffected by the instrument and its interaction with GDP growth.

4.3. A micro-founded model: mechanisms of impact

In this section we introduce a micro-founded model of protest participation that is consistent with the aggregate model in section 4.1. Compared to the aggregate model, the advantage of this model is that it allows us to specify and empirically identify the behavioral channels through which mobile phones affect protest participation.

The theoretical model is described in detail in Appendix B. In the model, the private cost of participation in a protest falls when the economy deteriorates, and the individual utility from participation increases with the fraction of connected individuals participating. Individuals make educated guesses about the probability of participation of their connections given the degree of connectedness in society, which is publicly known. The best guess estimate of the probability of participation of each individual's connections is the same for all individuals, irrespective of their degree of connectedness, and this also turns out to be the fraction of individuals participating in equilibrium. Worse economic conditions increase participation through two channels. First, they increase everybody's willingness to participate, a mechanical or purely compositional effect that we attribute to individuals' information about the state of the economy; second, via a spillover effect that results from strategic complementarities in protest provision, an effect that we attribute to coordination among individuals.

We argue that mobile phones have the potential to affect both margins of response, namely make individuals more responsive to variations in economic conditions - an effect that we label *enhanced information* - and to changes in others' willingness to participate - an effect that we label *enhanced coordination.*

The micro-founded empirical model of behavior that underlies model (4.1), postulates in particular that individual i's protest participation y_{ijct} will depend on the state of the economy ΔGDP_{ct} and on the average protest participation in the economy $\bar{y}_{jct}$. Mobile phone use (denoted by d_i) can potentially affect both the intercept and the slope coefficients. In formulas:

$$y_{ijct} = \gamma_0 + \gamma_1\ \Delta GDP_{ct} + \gamma_2\ d_i + \gamma_3\ \Delta GDP_{ct}\ d_i + \gamma_4\ \bar{y}_{jct} + \gamma_5\ \bar{y}_{jct}\ d_i + f_{jc} + f_t + \epsilon_{ijct} \quad (4.3)$$

The parameter γ_1 provides a measure of the individual response to economic downturns, while γ_3 provides a measure of the differential response among those with mobile phones relative to those with no mobile phones. γ_2 provides an indication of the differential protest activity between those with and without mobile phones, irrespective of GDP growth and others' propensity to participate. γ_4 provides a measure of the spillover effect, while γ_5 measures the differential response among those connected.

Note that aggregating across individuals by cell, and assuming for simplicity that the fraction of people with mobile phones in a cell ($\bar{d}_{jct}$) equals the fraction of people covered by the signal (Cov_{jct}), this gives equation (4.1), where $\beta_3 \approx \frac{\gamma_3}{(1-\gamma_4-\gamma_5\ \bar{d})}$ and $\bar{d}$ is the fraction of individuals using a mobile phone in the economy. For the equilibrium to be stable we expect $(\gamma_4+\gamma_5\ \bar{d}) < 1$.

If mobile phones make individuals either more responsive to the state of the economic cycle ($\gamma_3 < 0$) or to their fellow citizens' propensity to participate ($\gamma_5 > 0$), or both, then greater mobile phone coverage has the potential to magnify the effect of recessions on protests (*i.e.* imply that $\beta_3 < 0$ in equation 4.1).

If one is able to identify the parameters in equation, then one will be able to separately estimate what effect mobile phone coverage has on protest activity in response to changes in economic conditions due to the mechanical effect and to the spillover effect.

Identification of model (4.3) involves some challenges though. Even ignoring the possibility of non-random allocation of mobile phones across areas and individuals, estimates of model (4.3) will still be potentially plagued by a classical reflexivity problem (Manski 1993). However, equation (4.1) suggests that one can obtain consistent estimates of the parameters in (4.3) by instrumenting average participation in the economy $\bar{y}_{jct}$ (and its interaction with mobile phone use d_i) with mobile phone coverage Cov_{jct} and its interaction with GDP growth (as well as their interaction with mobile phone use d_i). Effectively, one can use the aggregate equation (4.1) as a first stage equation for the 2SLS individual-level equation (4.3). Intuitively, conditional on d_i, the fraction of those covered in society will only matter for individual participation through a spillover effect.[17]

5. Empirical results

In this section we turn to the empirical analysis. We start by presenting OLS and 2SLS estimates of equation (4.1), which analyze the effect of GDP growth and mobile phone coverage on the incidence of protests by cell and area. Later on in the analysis we turn to the micro-data from the Afrobarometer and present estimates of equation (4.3).

[17] Similarly to section 4.2, in practice we have two endogenous variables and four instruments. We follow the approach outlined in footnote 16 to increase efficiency of the first stage estimates.

5.1. Aggregate outcomes: OLS

Table 2 presents estimates of equation (4.1), where the dependent variable is the number of protests per capita in each cell/year as measured in GDELT (top panel) and ACLED (bottom panel). All specifications include cell fixed effects plus year effects and in even-numbered columns we include additionally a very large number of cell-level characteristics. These include the few available time-varying cell characteristics (log local population and a dummy for civil conflict), as well as a large number of cross-sectional cell-characteristics interacted with a linear time trend.[18] All regressions are weighted by population size and standard errors are clustered by cell. In the regressions we exclude the few observations for which we have no information on population or GDP growth. This gives a total of 152,415 observations.[19]

The dependent variable in all regressions is the log number of protests (plus one to account for zeros) per 100,000 population. In columns (1) and (2) we present OLS estimates of model (4.1) where we only include GDP growth and mobile phone coverage, *i.e.* we constrain the coefficient β_3 to be zero. For consistency with the estimates in the subsequent columns where we allow for the interaction between GDP growth and coverage, we standardize coverage and GDP growth to their overall mean so that the coefficient β_1 in (4.1) captures the effect of GDP growth on protests evaluated at the average coverage across countries and time (43 percent), while the coefficient β_2 captures the effect of coverage on protests at the average GDP growth (4.9 percent).

Consistent with the evidence in Figure 3, results in column (1) of Table 2, top panel, which refers to GDELT, show that protests are counter-cyclical, and this holds true even when we include a large array of cell-level controls (column 2). Point estimates suggest that a 4 p.p. (approximately a one standard deviation) fall in a country's GDP growth leads to an increase in protests per capita in a cell during a given year of around 0.22 percent (-0.565 X 0.04), an overall modest effect. At average GDP growth, we find no statistically or economically significant effect of coverage on protests (coefficient -0.026). Effects remain virtually unchanged when we include the entire set of controls in column (2), although it appears that conditional on these set of controls higher coverage if anything reduces protests.

[18] Cell characteristics include: fraction of the cell's area covered by mountains, forests, oilfields and irrigated; dummies for the presence of mines, diamonds and oilfields in the cell; latitude and longitude of the cell centroid, cell area, distance of the centroid to the capital, the coast and the border plus dummies for cells crossed by the country border, cells on the coast and cells hosting the country capital; number of cities in the cell, dummies for level-2 administrative units (typically districts); travel time to the closest city with more than 50,000 inhabitants, *km* of primary and secondary roads, of paved primary roads and primary roads in good conditions; *km* of electrical grid; infant mortality rate; average temperature and precipitation; number of years of drought over the period; average distance to the closest cell incurring a drought over the period, plus dummies for missing values of all these variables. Summary statistics for these variables are reported in Table 1, while Table A.1 reports their definition and original source. Note that these variables, except population (which is available every five years and which we interpolate linearly across these five-years intervals using logs) and a variable measuring the occurrence of civil conflict, only vary cross-sectionally.

[19] In particular we have no information for GDP growth for Djibouti from 2008 to 2012 and for Libya from 1998 to 1999 and from 2010 to 2012. We also have no information on population for 41 cells (32 in Egypt, 2 in South Africa, 4 in Tanzania and 3 in Uganda).

In column (3) of Table 2 we additionally control for the interaction between mobile phone coverage and GDP growth. Once more, estimates show that at average coverage protests are counter-cyclical (coefficient -1.016). At average coverage, a 4 percent increase in GDP growth leads to a reduction in protests of around 4 percent. At average GDP growth, higher coverage does not appear to affect protests (coefficient -0.011 not statistically significant at conventional levels). Differences in protest activity between areas with different rates of coverage, though, increase during recessions. A one s.d. fall in GDP growth is associated for example to an increase in the protest activity differential between areas with full and with no coverage on the order of 10 percent (-2.380 X 0.04). Results are once more virtually unaffected by the inclusion of additional controls (column 4).

In columns (5) to (8) of Table 2 we focus on specifications with the inclusion of country X year effects. Although this comes at the cost of us not being able to identify the coefficient on GDP growth β_1 in (4.1), this specification allows us to compare changes in areas with different baseline characteristics within the same country allowing for unrestricted time varying country determinants in the incidence of protests. Results are very similar to those in columns (1) to (4). We find no effect of coverage on protests on average although we still find clear evidence of coverage magnifying the effect of recessions on protests. Estimates on the interaction term imply that a one s.d. fall in a country's GDP growth leads to an increase in protests per capita between covered and uncovered areas of around 7.5 p.p. (-1.873 X 0.04).

Estimates based on ACLED are reported in the bottom panel of Table 2. Patterns of estimates are very similar to those found in GDELT. If one focuses on the most saturated specifications in columns (4) and (8), results show once more that protests are counter-cyclical (coefficient on GDP growth -0.191 in column 4) and that the coefficient on the interaction term between GDP growth and coverage is negative (-0.566 in column 4 and -0.393 in column 8), implying that a 4 p.p. fall in GDP growth is associated to an increase in the differential in the yearly incidence of protests between an area with full coverage and an area without coverage of between 1.6 and 2.2 percent, around one fifth of the effect found in GDELT. Similarly to GDELT, once we condition on country X year fixed effects (column 8) we find no statistically significant effect of coverage on protests (coefficient -0.001, insignificant at conventional levels).

In sum, although point estimates based on ACLED are typically smaller in magnitude than those found based on GDELT, as well as typically less precise - which is reasonable given the much smaller number of observations - remarkably results based on the two datasets are qualitatively similar. In both cases we conclude that while greater coverage on average does not lead to greater protest incidence, this magnifies the positive effect of recessions on protest occurrence, with an effect that is both statistically and economically significant.

5.2. Aggregate outcomes: 2SLS

In order to deal with the potential endogeneity of coverage with respect to protests, in this section we turn to the 2SLS estimates which exploit the differential trends in mobile phone adoption across areas with different flash intensity as an instrument for coverage. Figure A.7 reports average number of flash ground strikes between 1995 and 2010 in each of the 0.5° x 0.5° cells for the whole of Africa.[20] The continent has the highest flash density on earth, with an average of 17.3 flashes per km^2 per year, compared to a world average of 2.9 (Cecil et al. 2014). One can also see that there is substantial variation in lightning intensity across areas, suggesting that this instrument has the potential to generate useful variation in the rate of mobile phone adoption across cells.[21]

Table 3 reports estimates of the first stage equations. We only present regression results with the entire set of controls as in even-numbered columns of Table 2. Similarly to the OLS, we start with specifications with additive country and time effects plus cell fixed effects (in which case we also include for consistency the growth rate of GDP as an additional regressor, coefficient not reported). Column (1) presents OLS estimates of equation (4.2) where the instrument is defined as the interaction of the cell's average lightning intensity times a linear trend ($Z_{jct} = Flash_{jc}\ X\ t$). If greater flash activity leads to a slower adoption of mobile phone technology, the coefficient δ_2 in (4.2) will be negative. Indeed the table shows that a 1 s.d. increase in the number of flashes per year (0.43) leads to a lower growth in coverage of around 0.43 p.p. a year (-0.43 X 0.010), *i.e.* a differential growth of around 6.5 p.p. over the entire fifteen years period.

As we have effectively two endogenous variables (Coverage and its interaction with GDP growth) and two exogenous variables (Z and its interaction with GDP growth), we can gain in efficiency by instrumenting each endogenous variable with the two instruments (see footnote 16). These estimates are reported in columns (2) and (3) of Table 3. The effect of Z on coverage in column (2) remains unchanged both in magnitude and significance relative to column (1) while there is no effect of the interaction between Z and ΔGDP. Column (3) reports regression estimates where the dependent variable is the interaction between Cov and ΔGDP. For the model to be well specified one will expect the coefficient of Z in column (2) to be similar to the coefficient of $Z\ \Delta GDP$ in column (3). Column (3), row 2, shows indeed that this coefficient is negative, although about three times as large as the effect of Z on coverage alone in column (2) (-0.038 compared to -0.011).

Results are very similar once we include the interaction between year and country effects in columns (4) to (6). Remarkably, once we do so, the effect of the instrument on coverage (-0.009) is very similar to the effect of the interaction between the instrument and GDP growth on the interaction of coverage with GDP growth (-0.016). The values of an F-test that the 2SLS

[20] Data come from the Global Hydrology and Climate Center (GHCC), which makes publicly available the data collected by the National Aeronautics and Space Administration (NASA) through space-based sensors (Cecil et al. 2014). Flashes are recorded along with their spatial location (latitude, longitude) with a level of resolution of at least 10 *km* on the ground. Data are available at thunder.msfc.nasa.gov. The data have been used before by Andersen et al. (2012), who also show that flash activity is very persistent across areas.

[21] The peak annual number of flashes is in the Democratic Republic of Congo, with almost half a million flashes per year in each cell, or about a flash every two days for each km^2. Cells in a broad region of central Africa exceed 100,000 flashes per year while those in most land regions in the tropics and subtropics - except for arid regions - exceed 70,000 flashes per year.

estimates are biased towards the OLS due to a weak instruments problem are reported at the bottom of the table and one can see that the null is systematically rejected.[22]

Before presenting the 2SLS estimates and in order to add transparency to the identification strategy, in the following we present graphical evidence on the raw correlation between protests and the instrument, *i.e.* on the reduced-form equation:

$$\bar{y}_{jct} = \rho_0 + \rho_1 \, \Delta GDP_{ct} + \rho_2 \, Z_{jct} + \rho_3 \, \Delta GDP_{ct} \, Z_{jct} + f_{jc} + f_t + \zeta_{jct} \tag{5.1}$$

where $\rho_k = \beta_k \delta_2$, $k = 2, 3$.

For protests to respond negatively to the state of the economic cycle when coverage increases ($\beta_3 < 0$ in equation 4.1) and given that coverage varies negatively with the instrument ($\delta_2 < 0$ in equation 4.2) one will expect the protests differential between areas with high and low flash intensity (hence with low and high coverage) to be positively correlated with GDP growth (*i.e.* $\rho_3 > 0$).[23] Figure A.4 reports the within-country change in the differential in log protests (measured in GDELT) between high (in the top quartile of the continent distribution) and low (in the bottom quartile) flash intensity areas in each year, alongside average growth in GDP.[24] Indeed, one can notice a very strong positive correlation between the two series: in particular, the temporary increase in GDP growth in the mid 2000s is associated to a sizeable temporary increase in the protest differential between high and low flash intensity areas.[25]

We now turn to the 2SLS estimates in Table 4. The first four columns of Table 4 refer to GDELT while the subsequent four columns refer to ACLED and in odd- and even- numbered columns we present respectively results without and with the inclusion of country X year effects. As for the first stage, we only report results with the entire set of controls. Results are qualitatively very similar to the OLS. We still find that, on average, protests are counter-cyclical, with a one s.d. fall in GDP growth (4 p.p.) leading to between 0.4 (-0.093 X 0.04) and 1.8 percent (-0.442 X 0.04) more protests per capita, depending on the dataset used, and that the effect is magnified by the availability of mobile phones. Point estimates suggest that a one s.d. fall in GDP growth leads to an increase in the per capita protest differential between areas with full and with no coverage of between 7 (-1.425 X 0.04) and 25 percent (-6.264 X 0.04), with the estimates being larger in GDELT compared to ACLED. Across both datasets, we find no effect of coverage on protests at average GDP growth. Results in even-numbered columns where we

[22] We report the value of the Angrist-Pischke test for the case of multiple endogenous variables (Angrist & Pischke 2008).

[23] Note that $\rho_2 = 0$, since, as shown below, the 2SLS estimates of β_2 are close to zero. For this reason we do not investigate the correlation between protest differentials and Z *per se*.

[24] These are weighted averages across countries with weights equal to the country's population. Note that GDP growth in this figure is slightly different from what reported in Figure 3 that refers to all countries in the sample, rather than only to those with sufficient within-country variation in flash intensity.

[25] A regression coefficient of the protest differential on GDP growth with weights equal to population delivers a coefficient of 2.518, (s.e. 1.056, significant at 10 percent level). More subtly, as the coefficient ρ_3 captures the interaction between flashes, a linear trend and GDP growth, one will expect this correlation to change over time and in particular to show an upward trend. Indeed three separate regressions by sub-periods (1998-2002, 2003-2007, 2008-2012) deliver the following three coefficients: -1.367 (s.e. 4.535), 3.927 (s.e. 4.198) and 4.711 (s.e. 7.414). Although not individually significant these coefficients follow precisely the expected pattern.

include the interaction of country X year effects are virtually unchanged.[26]

The bottom row of Table 4 reports the p-value for an endogeneity test for coverage and its interaction with GDP growth. We are able to reject the hypothesis that coverage and its interaction with GDP growth are simultaneously exogenous to the dependent variable in GDELT (p-value 0.055), but we cannot reject exogeneity based on ACLED data (p-value 0.223)

Although first stage estimates and the evidence in Figure A.4 show that the rank condition is satisfied, clearly this is not informative about the validity of the exclusion restriction. As discussed above, for this restriction to hold, one will expect, conditional on the included controls, the effect of the instrument and its interaction with GDP growth on protests to act only through the availability of mobile phone technology. As said, for the exclusion restriction to hold, one would expect the coefficient ρ_3, *i.e.* the protest differential between high and low flash intensity areas to be equal to zero in a period when there was no mobile phone technology. We test for this using data on protests from GDELT since 1990, *i.e.* before the spread of mobile phone technology in Africa (note instead that ACLED data are only available starting in 1997).

Figure 5, top panel reports average mobile phone coverage across the continent between 1990 and 2012.[27] Coverage is zero in 1990 and it grows starting from 1996. Growth after that is basically linear, with a slight slowdown starting in the mid 2000s. The bottom panel of Figure 5 presents OLS estimates of ρ_3 in (5.1), separately by sub-periods, using the most saturated specification as in column (8) of Table 2, *i.e.* with the inclusion of cell fixed effects, country X year effects and cell-level time-varying controls. One can see that there is no effect of the instrument interacted with GDP growth on protests in the early period, *i.e.* up to effectively the late 1990s. Point estimates are small and not statistically significant at conventional levels. Positive effects tend to manifest since the early 2000s, when coverage starts to increase, and similar to the spread of coverage these effects follow an upward trend, with the gradient once more flattening towards the end of the period.[28,29]

As an additional check for the exogeneity of the instrument we present OLS estimates of the reduced-form equation (5.1) and 2SLS estimates of equation (4.1) where now the dependent variable is a measure of local economic development. For this, we use light density measured by satellites at night, a widely used measure in the literature (Henderson et al. 2012, Michalopou-

[26] Results are also very similar if we use flash density per km^2 as instrument, although F-stats are marginally lower. We also use the interaction of the continent-wide trend in coverage (as opposed to a parametric linear trend) with flash rates (flashes per km^2) finding overall very similar results.

[27] To obtain this series we have used information on coverage from GSMA (available since 1998). We also exploit the circumstance the 2G technology was not introduced in Africa until 1995 and for each cell we derive a predicted measure of coverage by linear interpolation between 1995 and 1998. The series plots the population weighted average coverage across the continent in each year.

[28] In Figure A.8 we also report the reduced-form coefficient of protests on the instrument ρ_2. We do not find any evidence of the instrument affecting directly protests per capita throughout the period, consistent with the 2SLS estimates of coefficient β_2 in equation (4.1) not being different from zero.

[29] Note that in these regressions we allow the coefficients on the interaction between the cross-sectional characteristics and the linear time trend to vary between the pre-1998 and post-1998 period. We do so to make sure that this specification is consistent with the reduced-form specification associated to our main estimates for the 1998-2012 period.

los & Papaioannou 2012), which has been shown to proxy well for local economic activity.[30] Importantly we find that local economic activity seems not to vary with the instrument and its interaction with GDP growth (see Table A.4). Consistent with this, we find that the 2SLS estimates for nightlights are not statistically significant. These result suggest that the effect of flash rates on the speed of mobile phone adoption across areas is not attributable to differential patterns of local economic growth, lending further credibility to the exclusion restriction underlying the consistency of the 2SLS estimates.

We have also performed a number of robustness checks on equation (4.1). 2SLS estimates from these alternative regressions using the entire set of controls as in columns (4) and (8) of Table 4 are reported in Table A.5 and we briefly discuss them here. In particular, we have clustered standard errors at the country rather than the cell level: this should take into account any spatial correlation in the error term across cells within a country (column 1). We have also attempted to control more flexibly for unobserved determinants of protests that might be correlated with the instrument by interacting all cell-level cross-sectional characteristics with country-specific (as opposed to continent-wide) linear trends (column 2). As said, one concern is that GDELT might fail to successfully de-duplicate protests in the data when reported in different articles or outlets, hence increasing the rate of false positives. We address this issue by constructing an alternative measure of protests, *i.e.* a variable that takes a value one if at least one protest event is recorded in a certain location in a certain day, treating events in the same location but classified as different in the data as a single event (column 3). Finally we have run regressions where instead of using the logarithm of protests per capita plus a constant (one) in order to account for zeros, we use the square root of protests per capita (column 4). We do so because of the concern that our results in Table 4 are sensitive to the value of the constant used. Clearly point estimates from these last regressions need not to be the same as those from our main regressions, although their sign has to be the same.[31] All these checks make no substantial difference to our results.

As an additional check, we also report results where we interact coverage with a dummy for positive GDP growth rather than a continuous linear function of GDP growth. We do so to investigate more directly whether effects are different during booms and recessions. Estimates in column (5) show that greater coverage tends to lead to greater protests during recessions (*i.e.* for negative economic growth, coefficient 1.178, significant at 5 percent level). The differential effect in periods of positive growth is almost identical but of the opposite sign, meaning that greater coverage does not affect the incidence of protests other than in periods of recessions.

In Table A.6 we have investigated whether our 2SLS results are driven by specific samples or periods.[32] Estimates of the coefficient on the interaction term β_3 are consistently negative

[30] Following Lowe (2014) and Henderson et al. (2012), we calculate the mean luminosity for each cell/year excluding cells with persistent lighting due to gas flares. Results are similar if these observations are not removed from the sample.

[31] Note in fact that $\frac{dY^{0.5}}{dX} \approx \frac{1}{2}Y^{0.5}\frac{dlnY}{dX}$.

[32] In order to obtain more precise 2SLS estimates, we constrain the first stage estimates to be the ones from the pooled sample in Table 3. We compute standard errors manually, in the spirit of a split-sample IV technique

across samples, although not always individually significant. In most cases, it also appears hard to reject the hypothesis that the coefficients are the same across subsamples. If anything, it appears that the effects are larger in large relative to small cities and in Sub-Saharan Africa compared to northern Africa. We also restrict to the pre-2011 period out of a concern that our results are driven by the Arab spring, something for which we find no evidence (see columns 5 and 6). We also do not find evidence that our results are driven by either the availability of the Internet, or of 3G technology (columns 7 to 10).[33] It appears, however, that effects are larger under autocratic regimes and in particular when the media are captured (columns 11 to 14).[34]

In sum, we have exploited the differential penetration of mobile phone coverage across areas with different flash intensity to identify the causal effect of mobile phones on protests. A number of tests lend strong support to our hypothesis that the instrument is excludable. 2SLS estimates of model (4.1) confirm that at average growth, mobile phones have no independent effect on protests, although they tend to amplify the positive effect of recessions on the incidence of protests. Although 2SLS estimates are larger in absolute value compared to the OLS estimates, we also show that, once we control for a very large number of cell-level characteristics, it is hard to tell these estimates apart, at least in ACLED.

5.3. Individual participation in protests: channels of impact

In this section we turn to individual data from the Afrobarometer to further investigate the effect of coverage and its interaction with GDP growth on participation in protests. Micro-data from the Afrobarometer have two major advantages. First, they allow us to validate results from GDELT and ACLED, and in particular to rule out that these results are driven by systematic reporting error. Second and more important they allow us to investigate the potential mechanisms of impact.

In addition to information on individual participation in protests, Afrobarometer data also provide information on individual mobile phone use. This variable though is only available for round 5 of the survey. We use this piece of information and a regression model to predict, for each individual in the sample, the probability of using a mobile phone at least once a day as a function of individual characteristics and a measure of cell-level coverage from GSMA. The exact procedure is discussed in Appendix A.

In the rest of this section we ignore the non-random allocation of coverage across areas, *i.e.* we revert to the OLS estimates in section 4.1. The reason for this is that data from the

(Angrist & Krueger 1995). In particular estimates of the variance covariance matrix of the 2SLS estimates can be obtained using the following formula: $(Z'\Omega^{-1}X)^{-1}(\sum_c Z_c\Omega_c^{-1}\hat{u}_c\hat{u}_c'\Omega_c^{-1}Z_c')(X'\Omega^{-1}Z)^{-1}$, where Z denotes the matrix of the instruments (including a constant), X the matrix of the endogenous variables (also including a constant), Ω is the matrix of weights and $\hat{u}$ are the 2SLS residuals. Variables denoted by the subscript c refer to sub-matrices and sub-vectors for each cell c.

[33] Internet availability is defined for penetration greater or equal to 3 percent of the population, based on data from the World Development Indicators. 3G mobile phone technology is calculated for each cell, based on GMSA data.

[34] Autocracy is defined for a score of the Polity2 indicator less or equal to 0. Media are considered captured if their score falls below the world median in the Reporters Without Borders World Press Freedom Index.

Afrobarometer only span over a limited number of cells/years and in addition these are concentrated towards the end of the period, when one can show that the instrument has relatively little bite on the endogenous variable. Indeed, first stage estimates of equation (4.2) for the sample of cells/years covered by the Afrobarometer data are systematically insignificant. We are reassured though by our findings in the previous sections that 2SLS provide - if anything - conservative estimates of the effect of interest and by the observation above (that unsurprisingly also holds for the Afrobarometer) that one cannot typically reject exogeneity of coverage and its interaction with GDP with respect to protests.

As preliminary evidence, Table 5 reports regressions of a number of dependent variables that reflect individuals' knowledge and perception of economic and political conditions. The point of this table is to shed light on how individuals respond to changes in economic conditions depending on access to mobile phones. This paves the way to the subsequent analysis of the effect of mobile phones on protest activity. All specifications include a dummy for mobile phone ownership and its interaction with GDP growth. Regressions also include cell fixed effects, country X year fixed effects and all cell-level controls plus an array of individual level covariates.[35] The dependent variable in column (1) is a dummy for the respondent's self-reported economic status, as proxied by non-employment. Dependent variables in columns (2) and (3) are, respectively, dummies if the respondent's self-reported perceptions of his own and the country's economic conditions are worse or much worse compared to twelve months before. The dependent variable in column (4) is a dummy if the respondent reports not trusting the country's president while the dependent variable in column (5) is a dummy if the individual disapproves the actions of the president. As the model includes country X year effects, the coefficient on GDP growth is not identified and is not reported in the table. Regressions are weighted by sampling weights and standard errors are once more clustered by cell.

There are several findings that emerge from Table 5. We focus on the interaction between GDP growth and mobile phone use. First, there is no evidence that individuals with mobile phones are more vulnerable to economic conditions than those without mobile phones (see columns 1 and 2). However they appear to be more likely to report than the economy is doing poorly when this is in fact happening compared to those with no mobile phones (column 3). Consistent with plenty of evidence from elsewhere in the literature (*e.g.* Wolfers 2002) that voters blame the government for poor economic performance, those with mobile phones are also more likely to distrust and disapprove the president when the economy does poorly (columns 4 and 5). In sum, Table 5 provides suggestive evidence that mobile phones make individuals more informed about the state of the economy. It does not seem though that mobile phones directly affect the opportunity cost of participation.

With this preliminary evidence at hand, we now turn to the effect of mobile phones on protests. Table 6, columns (1) and (2), reports OLS estimates of aggregate equation (4.1) based on data from the Afrobarometer. Here the dependent variable is a dummy for protest

[35] These are: age and age squared, a gender dummy, educational dummies, a dummy for urban residence, number of adults in the household.

participation. We regress this variable on the fraction of individuals using a mobile phone (as opposed to coverage in Table 2) in each cell X year and its interaction with GDP growth.[36] We also experiment below with regressions where we use as regressor mobile phone coverage as opposed to the fraction of individuals using a mobile phone (as in Table 2). As in Tables 3 and 4 all specifications include cell fixed effects plus country X year effects. Column (2) additionally controls for the same cell-level covariates as in even-numbered columns of Tables 3 and 4, as well as for individual level covariates available in the Afrobarometer. Regressions are weighted by the sum of sampling weights in each cell. Standard errors are again clustered at the level of the cell.[37] Similar to the results in columns (4) and (8) of Table 2, we find that at average GDP growth self-reported protest participation is not significantly affected by the fraction of individuals using a mobile phone in society although, the larger this fraction, the larger the effect of recessions on protests. Point estimates in row 2 suggest that a one s.d. fall in GDP growth is associated to an increase of around 4 p.p. in the protest differential between areas with full and zero coverage (-0.931 X 0.04). At a baseline protest participation of around 12 p.p. this is equivalent to an increase or around 33 percent. This is a sizeable effect, not much different from the effect found on GDELT and ACLED for the same sample, or on Afrobarometer when using coverage instead of fraction of people using a mobile phone (see Table A.8). Importantly results form the Afrobarometer are qualitatively in line with those from GDELT and ACLED, suggesting that systematic misreporting is not driving our estimates in section 5.1.

With this evidence in mind we finally turn to the individual determinants of protest participation. Columns (3) and (4) of Table 6 report estimates of a regression of a dummy for individual protest participation on a dummy for mobile phone use, the fraction of individuals in society using a mobile phone, GDP growth and the interaction of these last two variables with the dummy for mobile phone use. This is equation (4.3) in the text. As explained, we use an instrumental variable approach in order to obtain consistent estimates of the model. First stage estimates, which are very similar to those reported in columns 1 and 2 of Table 6, are reported in Table A.9. There are several important findings that emerge. First, individuals with mobile phones are marginally less likely to protest conditional on others' participation and the state of the economy ($\gamma_2 < 0$).[38] Second, conditional on others' participation, individuals with mobile phones are more likely to respond to changes in economic conditions than those without mobile phones ($\gamma_3 < 0$). A one s.d. fall in GDP growth leads to a differential increase in protest participation among those with mobile phone compared to those without of around

[36] Note that because the right-hand side variables only vary by cell/year this is equivalent to a weighted regression where the dependent variable is the fraction of individuals participating in a protest (as opposed to log number of protests in Table 2).

[37] It is worth remarking that OLS estimates of model (4.1) based on GDELT and ACLED on the sample of cells/years available in the Afrobarometer are qualitatively similar to the ones based over the entire sample (compare Tables 2 and A.8). If anything, point estimates of the parameter of interest β_3 are, larger in this restricted sample than in the entire sample.

[38] Note that mobile phones use is obtained as a prediction from an ordered probit model that includes the same variables as in the model. Identification of this variable is simply based on functional form, so one should be cautious in attaching an interpretation to this variable

1 p.p. (this is -0.239 X 0.04). This is consistent with evidence in Table 5 that individuals with mobile phones are better informed about the state of the economy and hence more likely to react to changes in aggregate economic conditions. Third, there is very clear evidence of positive spillovers in the provision of protests ($\gamma_4 > 0$). We estimate that a 10 p.p. increase in average protest participation in society leads to an increase in protest participation among those with no mobile phones on the order of 8 p.p. (0.800 x 0.10). Fourth, there is evidence that those with mobile phones are more responsive to an increase in others' protest participation than those with no mobile phones ($\gamma_5 > 0$). This seems to suggest that mobile phones are complementary to others' participation in the decision to join a protest. We find an additional increase in the probability of participation among those with mobile phones of around 20 p.p.[39] In sum, results in Table 6 suggest that both enhanced coordination ($\gamma_5 > 0$) and enhanced information ($\gamma_3 < 0$) contribute to explain why mobile phones tend to amplify the effect of economic downturns on protests.

With the estimates of model (4.3) at hand, we can also attempt to quantify the contribution of these two different mechanisms, Our estimates suggest that between 46 and 79 percent of the overall effect is ascribable to increased coordination with the residual attributable to increased information. [40]

6. Conclusions

In this paper we provide novel systematic evidence on the impact of mobile phone technology on mass political mobilization. Using detailed geo-referenced data for Africa from three different sources on protest incidence and self-reported protest participation we find strong and robust evidence in support of a nuanced and qualified version of the "liberation technology" argument. Mobile phones are indeed instrumental to political mobilization but this happens during periods of economic downturn, when reasons for grievance emerge or the opportunity cost of participation falls.

Using a combination of theory and micro-data we are able shed light on the behavioral channels behind this empirical result. We show that mobile phones play two roles in fostering political participation during economic downturns: on the one hand, they appear to make individuals more informed about the state of the economy; on the other, they also appear to make people more responsive to changes in others' participation, which is key in determining the equilibrium level of protests via strategic complementarities. Empirically, we find that both effects are at play.

[39] Recall that for the equilibrium to be stable, we expect $(\gamma_4 + \gamma_5\ \bar{d}) < 1$. As the overall fraction of individuals using a mobile phone is 0.67, this condition holds in the data.

[40] See Appendix for details of the calculation. To operationalize this we use estimates of γ_3, γ_4 and γ_5 from Table 6, columns (3) and (4). We derive estimates of $gamma_1$ from an estimate of equation (B.15) equation where we do not include year X country dummies and we also include Δ_{GDP}. Estimates of γ_1 vary between -0.130 and -0.052 depending on whether we exclude or we include controls (respectively as in columns 3 and 4 of Table 6. The role of enhanced information varies between 46 and 79 percent depending on whether we use parameter estimates form the model without or with controls.

While our results refer largely a period when the only technology available was 2G, the increasingly ubiquitous availability of 3G and 4G technology and the associated advent of social media - both of which seem to further facilitate coordination among citizens - lead us to believe that the potential for digital ICT to foster mass political movements will - if anything- increase in the future. This argument squares well with evidence - discussed in the paper - that participation in social movements and mass political mobilization have been globally on the rise, and this has happened against the backdrop of impending economic slowdown or outright recessions.

Results in the paper also indicate that mobile phones seem to be particularly effective in fostering mobilization in autocratic regimes and where traditional media are captured, suggesting that these technologies may play a key role in fostering political freedom. Whether digital ICT can effectively promote democracy and even lead to regime changes remains a first order question and one that is worth investigating but clearly beyond the scope of this paper.

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A. Data appendix

A.1. GSMA

GSMA data are collected for the purpose of constructing a roaming coverage map service used by network operators and users. The data that have been licensed to us provide separate information on the availability of 2G, 3G and 4G technology. 2G technology improved over previous technology by digital encryption of the signal, which allows for SMS, picture sharing and basic Internet access. 3G and 4G technologies allow for broadband access. These technologies are incremental in the data - 3G (4G) coverage is available only if 2G (3G) coverage was previously available in a certain area. Only 2 percent of the continent population was in reach of the 3G signal over the period, with this figure reaching a maximum of 6.3 percent in 2012. There was virtually no 4G technology available in Africa over the period of observation. Our measure of coverage is the fraction of population that lives within range of a mobile network signal, regardless of whether they actually subscribe to the service or use it. In order to gauge an understanding of what this implies in terms of mobile subscriptions, we compare our measure of mobile phone penetration with data on the number of subscribers by country and year from ITU (2015). Average coverage rate for the sample of country/year observations for which ITU data are available is 49 percent versus 43 percent for the entire set of countries/years for which GSMA data are available. The fraction of subscribers over population for this sample is 30 percent. A regressions of the fraction of log subscribers over total population (plus one to allow for zeros) on the log fraction of individuals covered by the 2G signal (plus 0.0001 to allow for zeros), controlling for country and year fixed effects leads to an estimated coefficients of 0.30 (s.e. 0.02), implying that a 10 percent increase in coverage is associated with an increase in mobile phone subscriptions of 3 percent.

A.2. GDELT and ACLED

Data in GDELT refer broadly speaking to political events in the area of verbal and physical mediation and conflict (Make a public statement, Consult, Threaten, Disapprove, etc.), including protests but excluding events that make part of the routine political process, such as those pertaining to elections, the legislative debate and government actions that do not fall into the categories of mediation or conflict. The data are available at www.gdeltproject.org/data (data downloaded on 30/01/2014). Events in GDELT come from both digitalized newspapers and news agencies (Africa News, Agence France Presse, Associated Press Online, Xinhua, BBC Monitoring, The Washington Post, New York Times...) as well as from web-based news aggregators such as GoogleNews, which gathers around 4,000 media outlets (Leetaru & Schrodt 2013). The data are extracted using an open-source coding algorithm, TABARI, or Textual Analysis by Augmented Replacement Instructions, that sifts through news articles in search of actions and actors available in CAMEO, the Conflict and Mediation Event Observation, a widely used coding system in the field of political science that provides a list of around 15,000 actions and

60,000 political actors. A precise location at the level of city or landmark is assigned to the event using the GeoNames gazetteer, which includes over 10 million toponyms for 9 million places with 5.5 million alternate names in up to 200 languages (www.geonames.org). The data also report information on the number of sources and articles across sources that refer to the same event as well as on the actors involved - both the source and the target - although this last information is missing for a large fraction of events. Importantly, the data do not provide any information on the issue, the number of participants, the original news sources or the issue at stake. In a comprehensive study of protests worldwide Ortiz et al. (2013) list, in order, the following reasons for protests which occurred between 2006 and 2013: Economic justice and Anti-austerity, Failure of political representation, Global justice, People's rights. Most protests are against national governments.

Since GDELT is a largely yet unutilized dataset and since we have no control on the algorithm used to collect the data or the news sources effectively utilized, we compare information from GDELT with another widely utilized, but much smaller, manually compiled dataset on unrest in Africa, the ACLED. The dataset provides information on political violence during civil wars or episodes of instability and state failure between 1997 and 2013, and as such it has been used widely in the literature on civil conflict (*e.g.* Harari & La Ferrara 2013, Michalopoulos & Papaioannou 2015, Pierskalla & Hollenbach 2013). However, events that are potential precursors or critical junctures of conflict, like protests and riots during peaceful times, are also recorded. We focus on these events, which represent around 20 percent of the total number of records in ACLED. Events are manually compiled from local, regional, national and continental media and are supplemented by NGO reports. The number of different sources used in ACLED has increased from 72 in 1998 to 232 in 2012 (ACLED, 2012). Like in GDELT, no information is available on the issue and the number of participants (although the data report the original news source). Figure A.5 reports the evolution in protests per capita measured in GDELT and ACLED, separately by country. As the scale of the different series varies across countries, we report the residuals from regressions of log protests per capita (plus one, to account for zeros) on country dummies and year dummies. In practice these series report the evolution of protests within countries from different sources net of continent-wide trends and differences in country-levels protest incidence that might also capture differences in reporting probabilities and time-invariant differences in country-protest incidence. Despite the difference in scale (note that the ranges of variation on the left and right-hand axes are different), one can appreciate a very strong positive correlation between the two series in most countries. In countries like Burkina Faso, Cape Verde and the Central African Republic to name a few, one can see that the series line up remarkably well. This is less true in other countries such as Algeria, Benin or Lesotho. Note that the series in Figure A.5 refer to average protests per capita in each country/year. As ultimately our analysis focuses on cells within countries, we also explore the correlation between protests per capita from the different sources across these cells. Figure A.6 reports on the vertical axis the intensity of protests per capita measured in GDELT and on the horizontal axis the intensity of protests from ACLED. Both series are obtained as residuals of logs of the relevant variables (plus one to account for zeros) on cell and country fixed effects, separately for each country. Regressions are weighted by population size. We superimpose to the data an estimated regression line, separately for each country. The pooled regression coefficient across all countries alongside the associated standard error clustered at the level of cell is reported at the bottom of the figure. One can clearly see that, even within countries, there is a very clear positive correlation between the two series. This is true in almost all countries, and the pooled regression coefficient of protests from GDELT on protests from ACLED is 1.844 (s.e. 0.138). Taken together these figures suggest that, despite some unavoidable measurement error, the two series convey very similar information.

A.3. Afrobarometer

In the analysis we use data from Afrobarometer, rounds 3 to 5, spanning from 2005 to 2013 (information on available data by country and round is reported in Table A.2). As a first step, we have assigned individuals in Afrobarometer to the PRIO-GRID cells. The Afrobarometer provides information on individuals' country, district and town/village of residence. The quality of information varies across rounds and countries.

We match observations in the Afrobarometer to data from Geonames, which are available for public download at http://www.geonames.org. Geonames is a dataset of placenames around the world with information on the latitude and longitude of each place centroids. We restrict to populated places in Geonames (*i.e.* we exclude for example mountains or lakes), defined as towns, villages or other places where people live and work. Geonames also provides alternate names for each place, which are typically other names by which the place is known or the name in the local language. We assign each populated place in a country to a PRIO-GRID cell based on its coordinates. This gives a list of places with the associated PRIO-GRID cell.

Importantly, even within a country, the same placename in Geonames can be shared by more than one populated place, meaning that we cannot always uniquely assign a placename to a cell. When two places share the same name and hence potentially belong to more than one cell, we expand the dataset and we assign that place to each of these multiple cells. We construct an adjustment factor for each observation in this dataset so that a placename X PRIO-GRID cell has an associated weight equal to the relative population of a cell expressed as a fraction of the total population among all cells to which that given place can potentially belong to. Clearly, for cells that are univocally assigned to a cell this population weight is equal to one.

We start by matching observations in Afrobarometer based on their (country and) district of residence to those in this newly created dataset using the first placename in Geonames. If an observation does not match, we match sequentially on the first, second and third alternate placename in Geonames. For unmatched observations, we proceed sequentially replicating the same procedure but matching on town/village of residence in the Afrobarometer.

The resulting dataset has a number of observations larger than the original Afrobarometer, as individuals whose place of residence can potentially belong to different cells will have as many observations in the data as the potential cells of residence. Afrobarometer data include sampling weights. We rescale sampling weights by the population weights described above. This is equivalent to assuming that these individuals have been sampled at random among all those living in all the potential cells of residence and guarantees that the sum of weights in this new dataset is the same as in the original Afrobarometer dataset.

In total we are able to assign 78,167 individuals in Afrobarometer to at least one PRIO-GRID cell, or 81 percent of total respondents. Unmatched observations are those in the Afrobarometer for which the district, town or village of residence cannot be found among the (main and first, second and third alternate) list of populated placenames in Geonames. This can be either because that place is genuinely missing in Geonames or because of differences in spelling across datasets. In total 49 percent of matched individuals have a unique cell identifier, while the rest are assigned to at least two cells.

Column (1) of Table A.7 investigates the individual correlates of protest participation. Protest participation increases and then decreases with age, peaking at age 36, increases with education and is higher for males than for females.

We have also studied the within-cell correlation between self-reported protest participation in Afrobarometer and the incidence of protests in both GDELT and ACLED. In order to do so, we have computed the fraction of individuals reporting having participated in at least one protest in each cell and year. We regress this fraction on a dummy equal to one if at least one protest occurred in that cell/year plus the number of protests (separately from GDELT and ACLED). The coefficient on the first variable captures the increase in participation associated to the first protest occurring, while the coefficient on the second variable captures the marginal increase in participation for each additional protest. If everybody who participates in one protest also participates in all other protests, the coefficient on the second variable will be zero. Regressions include cell fixed effects plus the interaction between year and country dummies and are weighted by the sum of Afrobarometer sampling weights in each cell/year. Standard errors are clustered by cell. Point estimates on a dummy for positive number of protest are 0.012 (*i.e.* 0.008) and 0.015 (se. 0.008) when using GDELT and ACLED respectively. We find small and statistically insignificant effects on the variable "number of protests" in both datasets. Taken together, these results imply that indeed protest incidence as measured in both GDELT and ACLED is associated to an increase in protest participation in Afrobarometer (of between 1.2 and 1.5 p.p.) and that protest participation is concentered among a set of politically engaged citizens.

A further issue with the data is that we only have information on mobile phone use for rounds 4 and 5. In addition, the phrasing of the question across rounds is different. In order to characterize the determinants of mobile phone use in Afrobarometer we run an ordered probit model of frequency of mobile phone use (5 categories, ranging from never to several times a day) in round 5, based on a number of socio-economic characteristics, country plus year fixed effects, and the fraction of the population in reach of signal in their cell from GSMA. Marginal effects from these regressions are reported in column 2 of Table A.7. Mobile phone use increases and then decreases with age, peaking at age 38, increases with education and is higher for males compared to females. Importantly, it is also strongly positively correlated with mobile phone coverage from GSMA. We use estimates from this model to predict mobile phones usage for all individuals in the Afrobarometer, including in rounds 3 and 4. We assign to each individual a dummy equal to 1 if the estimated probability of using a mobile phone at least once a day exceeds 50 percent. Based on this procedure, 67 percent of the individuals are predicted to use a mobile phone.

B. Theory appendix

B.1. Setup

We consider a network of individuals characterized by the distribution $P(d)$ ($d = 0, 1, \ldots, D$) of the number d of neighbors, or degree, where $\sum_{d=0}^{D} P(d) = 1$. We think of mobile phones as increasing the number of neighbors and - as a result - increasing the density of the network. We revert to a more formal definition below.

Each agent i has the choice between taking action 0, which can be thought of as the *status quo* (in the present case, not protesting), or action 1 (in the present case, protesting).

We denote the utility of an agent of degree d_i from taking action 1 relative to action 0 when he expects his neighbors to choose action 1 with probability $\bar{y}_{-i}$ by $v_i = v(d_i, \bar{y}_{-i})$. We follow others in the literature (Chwe 1999, Granovetter 1978, Jackson & Yariv 2007) by assuming that agents' decisions are characterized by strategic complementarities, *i.e.* that the utility of agent i from taking action 1 is non decreasing in $\bar{y}_{-i}$:[41]

$$\frac{\partial v_i}{\partial \bar{y}_{-i}} \geq 0 \tag{B.1}$$

Each agent i has a cost of taking action 1, which we denote by c_i. We follow others in the literature by assuming that the opportunity cost of participating is higher when the economy improves.[42] With no loss of generality, we depart from Jackson & Yariv (2007) and assume that costs can also vary as a function of an individual's degree d_i. In formulas, we assume that $c_i = c(d_i, \Delta GDP) + \epsilon_i$, where ϵ_i is an error term that we assume independent of d_i and with

[41] Jackson & Yariv (2007) assume that at given probability of participation among neighbors, individuals with a greater number of connections draw no less utility from participating than individuals with fewer connections, *i.e.* in formulas $\frac{\partial v_i}{\partial d_i} \geq 0$. We ignore this assumption as this is not key to our results.

[42] An alternative interpretation for this assumption is that reasons for grievance increase during bad economic times.

c.d.f. $H(.)$ and:[43]

$$\frac{\partial c_i}{\partial \Delta GDP} \geq 0 \tag{B.2}$$

We follow Jackson & Yariv (2006) and assume for simplicity that ϵ is uniformly distributed. From the above, it follows that the probability y_i that an agent i of degree d_i decides to join a protest given that his neighbors protest with probability $\bar{y}_{-i}$ is:

$$y_i = H(v_i - c_i) \tag{B.3}$$

B.2. Equilibrium

We assume that each agent has limited information over the structure of the network: he only knows his own degree d_i and cost c_i and the overall distribution of degrees in the population $P(d)$. The play is symmetric, in the sense that every agent perceives the distribution of play of each of his neighbors to be independent and to correspond to the population distribution of plays.

Individuals iterate over neighbors' best responses given the probability distribution of the neighbors' degrees. Under the above hypotheses an equilibrium for the game exists. In particular, at the equilibrium the fraction of individuals participating, $\bar{y}$, is defined by the solution to the following equation:

$$\bar{y} = \phi(\bar{y}) := \sum_{d=0}^{D} \tilde{P}(d) H(v(d, \bar{y}) - c(d, \Delta GDP)) \tag{B.4}$$

where $\tilde{P}(d) = \frac{P(d)\, d}{E[d]}$ denotes the probability that a random neighbor is of degree d. The equilibrium condition effectively states that individuals' best responses are mutually consistent.

Although both stable and unstable equilibrium are possible in this game, we focus on the stable equilibrium. Again following Jackson & Yariv (2007), at the stable equilibrium it must be true that:

$$\frac{\partial \phi(.)}{\partial \bar{y}} < 1 \tag{B.5}$$

B.3. Participation and the state of the economy

We start by performing comparative statics on the equilibrium of the model in response to changes in the state of the economy ΔGDP.

From the definition of y_i, note that, conditional on the state of the economy and the agent's degree, around the equilibrium individuals will be more likely to participate the higher is the

[43] As in the case of v we remain agnostic of the sign of the partial derivative of c with respect to d as this is not key to our results.

fraction of other individuals participating:

$$\frac{\partial y_i}{\partial \bar{y}}_{|d_i,\Delta GDP} \geq 0 \tag{B.6}$$

In addition, each individual's probability of participation will increase (decrease) as the state of the economy deteriorates (improves):

$$\frac{\partial y_i}{\partial \Delta GDP}_{|d_i,\bar{y}} \leq 0 \tag{B.7}$$

Note that equation (B.7) refers to an individual's propensity to participate in response to changes in the state of the economy *conditional* on the individuals' degree and the overall fraction of individuals participating, where the latter is itself a variable affected by economic conditions. In particular one can show that this fraction increases (decreases) as the state of the economy deteriorates (improves). From (B.4):

$$\frac{d\bar{y}}{d\Delta GDP} = \frac{\frac{\partial \phi(.)}{\partial \Delta GDP}}{1 - \frac{\partial \phi(.)}{\partial \bar{y}}} = \frac{\sum_{d=1}^{D} \tilde{P}(d)\frac{\partial H(.)}{\partial \Delta GDP}}{1 - \sum_{d=1}^{D} \tilde{P}(d)\frac{\partial H(.)}{\partial \bar{y}}} \leq 0 \tag{B.8}$$

where the last inequality follows from the fact that at the equilibrium the numerator in (B.8) is negative (from equation B.7), while the denominator is positive (from equation B.5).

The intuition for this result is straightforward. Worse economic conditions mechanically raise each individual's propensity to protest (equation B.7). This raises protest participation and hence increases the fraction of those participating (this is the numerator of equation B.8). Strategic complementarities generate an additional effect as individuals iterate over their neighbors' best responses, knowing that everybody else will be more likely to participate and to know that everybody else will know, etc. (this is the denominator of equation B.8). This mechanism further enhances the positive effect of recessions on the incidence of protests.

B.4. Differential responses based on the density of the network

We extend our analysis to study how economic conditions have a different impact on the probability of protesting depending on individuals' degree and the "density" of the network, *i.e.* the distribution of degrees.

In order to examine how the response of the equilibrium level of protests to changes in ΔGDP differs between denser and less dense networks we make the following two additional assumptions:[44]

$$\frac{\partial^2 c_i}{\partial \Delta GDP \, \partial d_i} \geq 0 \tag{B.9}$$

$$\frac{\partial^2 v_i}{\partial \bar{y}_{-i} \, \partial d_i} \geq 0 \tag{B.10}$$

Equation (B.9) states that the opportunity cost of participating responds more to the state of the economic cycle the higher an agent's degree. We take this assumption to reflect the circumstance that, compared to individuals with no mobile phones, those with mobile phones (*i.e.*, those with higher degree) experience greater decreases (increases) in the cost of participation when the economy deteriorates (improves). One explanation for this is that individuals with mobile phones are more likely to correctly perceive the actual state of the economy due to the unadulterated nature of the information they are able to access. We label this mechanism "*enhanced information*". An alternative explanation is that mobile phones are complementary to aggregate economic growth in determining one's productivity so the opportunity cost of protests varies differentially for those with and without mobile phones along the cycle. We investigate empirically these different explanations in Table 5.

Equation (B.10) states that the increase in utility from participation in response to a given increase in the fraction of neighbors participating is higher for those with mobile phones compared to those with no mobile phones. One way to rationalize this assumption is that mobile phones can help better coordinate with other protesters, which results in a higher increase in utility in response to an increase in the fraction of neighbors participating. We label this mechanism "*enhanced coordination*".

The implications of these assumptions for individual behavior can be easily derived. Under (B.9) and (B.10):

$$\frac{\partial^2 y_i}{\partial \Delta GDP \, \partial d_i}_{|\bar{y}} \leq 0 \tag{B.11}$$

This means that individual i's probability of participation increases more in response to a deterioration in economic conditions the higher this individual's number of connections. And:

$$\frac{\partial^2 y_i}{\partial \bar{y} \, \partial d_i}_{|\Delta GPD} \geq 0 \tag{B.12}$$

Equation (B.12) states that the effect of changes in the fraction of individuals participating on each individual's probability of participation increases with his number of connections.[45]

[44] We ignore the effect of changes in density of the network on the emergence of protest at given GDP growth. This effect is discussed in Jackson & Yariv (2007) who show that, if $\frac{\partial v_i}{\partial d_i} \geq 0$ (and $\frac{\partial c_i}{\partial d_i} = 0$), an increase in density unequivocally raises protests. We remain agnostic on this effect not least because we find no support for this prediction in the data, although a way to rationalize our empirical result is that $\frac{\partial v_i}{\partial d_i} \geq 0$ and $\frac{\partial c_i}{\partial d_i} \geq 0$.

[45] If the assumption that ϵ is uniform does not hold, conditions (B.9) and (B.10) are replaced by the following conditions: $\frac{\partial y_i}{\partial \Delta GDP \, \partial d_i}_{|\bar{y}_{-i}} \leq 0$ and $\frac{\partial^2 y_i}{\partial \bar{y}_{-i} \, \partial d_i}_{|\Delta GPD} \geq 0$.

To understand how the density of the network affects the overall fraction of individuals participating, we define density in terms of first order stochastic dominance (FOSD).[46] Given two networks P and Q , we say that Q is *denser* than P if $\tilde{Q}(d)$ FOSD $\tilde{P}(d)$, *i.e.* if:

$$\sum_{d=0}^{D} \tilde{Q}(d) f(d) \geq \sum_{d=0}^{D} \tilde{P}(d) f(d) \quad \text{for any non-decreasing function } f \text{ of } d. \tag{B.13}$$

We think of increasing mobile phone coverage precisely as leading to a FOSD shift in $\tilde{P}$.

From (B.8), (B.9) and (B.10) it follows that a deterioration in economic conditions leads to a larger increase in the fraction of people protesting in denser (Q) compared to less dense (P) networks. In formulas:

$$-\frac{d\bar{y}^Q}{d\Delta GDP} \geq -\frac{d\bar{y}^P}{d\Delta GDP} \tag{B.14}$$

To see this note that from equation (B.8), $-\frac{d\bar{y}}{d\Delta GDP} = \frac{-\sum_{d=1}^{D} \tilde{P}(d) \dfrac{\partial H(.)}{\partial \Delta GDP}}{1-\sum_{d=1}^{D} \tilde{P}(d) \dfrac{\partial H(.)}{\partial \bar{y}}}$. Under assumptions (B.9) and (B.10), as the density of the network increases, the numerator increases, while the denominator decreases, so that (B.14) holds. Note that conditions (B.9) and (B.10) are sufficient although not necessary for equation (B.14) to hold.

The intuition for this result has to do with the larger share of more connected agents in denser networks. If individuals with more connections are more likely to increase their participation when the economy deteriorates (equation B.9), then worse economic conditions will directly lead to greater protest participation in denser networks. This is a compositional effect.

In this setting though every individual will know that each individual's propensity to participate has increased - and that others know that - and this effect is greater in denser networks. Once more, this effect works through strategic complementarities and further magnifies the effect of recessions on protest participation in denser networks. This second effect is at play provided that those with lower connections are not disproportionately more likely to respond to greater protest participation of their neighbors, compared to those with more connections (*i.e.* if equation B.10 holds).

B.5. From theory to the empirical model

The previous model provides testable implications that can be brought to the data. Let us denote by d_i a dummy equal to one if an individual uses a mobile phone and let $\bar{d}$ denote the fraction of individuals with mobile phones in the population.

Linearizing equations (B.6), (B.7), (B.11) and (B.12) one can derive the following expression

[46] The concept of FOSD captures the idea that one distribution is obtained by shifting mass from another one to place it to higher values, so that the new distribution reflects an unambiguous increase in connectivity compared to the old one.

for individual i participation:

$$y_i = \gamma_0 + \gamma_1 \ \Delta GDP + \gamma_2 \ d_i + \gamma_3 \ \Delta GDP \ d_i + \gamma_4 \ \bar{y} + \gamma_5 \ \bar{y} \ d_i + \epsilon_i \tag{B.15}$$

were y_i is a dummy for individual i participating in a protest and ϵ is an error term. If assumptions (B.1), (B.2), (B.9) and (B.10) hold, we expect $\gamma_1, \gamma_3 \leq 0$ and $\gamma_4, \gamma_5 \geq 0$.

Assuming for simplicity that the fraction of individuals using a mobile phone ($\bar{d}$) is identical to the fraction of people in reach of the signal (Cov), and solving for $\bar{y}$, it follows that:

$$\bar{y} = \beta_0 + \beta_1 \ \Delta GDP + \beta_2 \ Cov + \beta_3 \ \Delta GDP \ Cov + \epsilon \tag{B.16}$$

where $\beta_k \approx \frac{\gamma_k}{1-\gamma_4-\gamma_5\bar{d}}$, $k = 0, 1, 2, 3$ and for the equilibrium to be stable we expect $\gamma_4 + \gamma_5\bar{d} < 1$ (this is effectively equation (B.5)).
[47]

Model (B.16) refers to aggregate outcomes. It says that the fraction of individuals protesting in the economy is a negative function of GDP growth, a positive function of the share of mobile phone coverage and a negative function of the interaction between these two variables. This model can be estimated using GDELT and ACLED data on the occurrence of protests by cell, or using individual data (or cell means) on protest participation from the Afrobarometer.

Although an advantage of model (B.16) is that it can be estimated directly on aggregate data by cell, which are available consistently for the entire continent through a long period of time, estimates of this model are unable to provide guidance on the micro foundations of the phenomenon under study. As said, the role of greater connectivity in enhancing protests during bad economic times hinges on either greater responsiveness of those more connected to economic conditions, or on their greater responsiveness to their peers' participation compared to those less connected. These two effects though cannot be told apart in an aggregate equation like (B.16).

One however can make some progress using micro-data. If one is able to consistently estimate the parameters of equation (B.15), then one will be able to say whether and to what extent the differential effect of mobile phone coverage in response to a recession on protests is due to either higher sensitivity to changes in economic conditions ($\gamma_3 < 0$) or greater strategic complementarities ($\gamma_5 > 0$) among those connected, or both.

Identification of model (B.15) involves some challenges though. Even ignoring the possibility of non-random allocation of mobile phones across areas and individuals, estimates of model (B.15) will still be potentially plagued by a classical reflexivity problem (Manski 1993). However, equation (B.16) suggests that one can obtain consistent estimates of the parameters in (B.15) by instrumenting average participation in the economy $\bar{y}$ (and its interaction with mobile phone use d_i) with mobile phone coverage $\bar{d}$ and its interaction with GDP growth (as well as their interaction with mobile phone use d_i). Intuitively, and conditional on d_i, the fraction of those

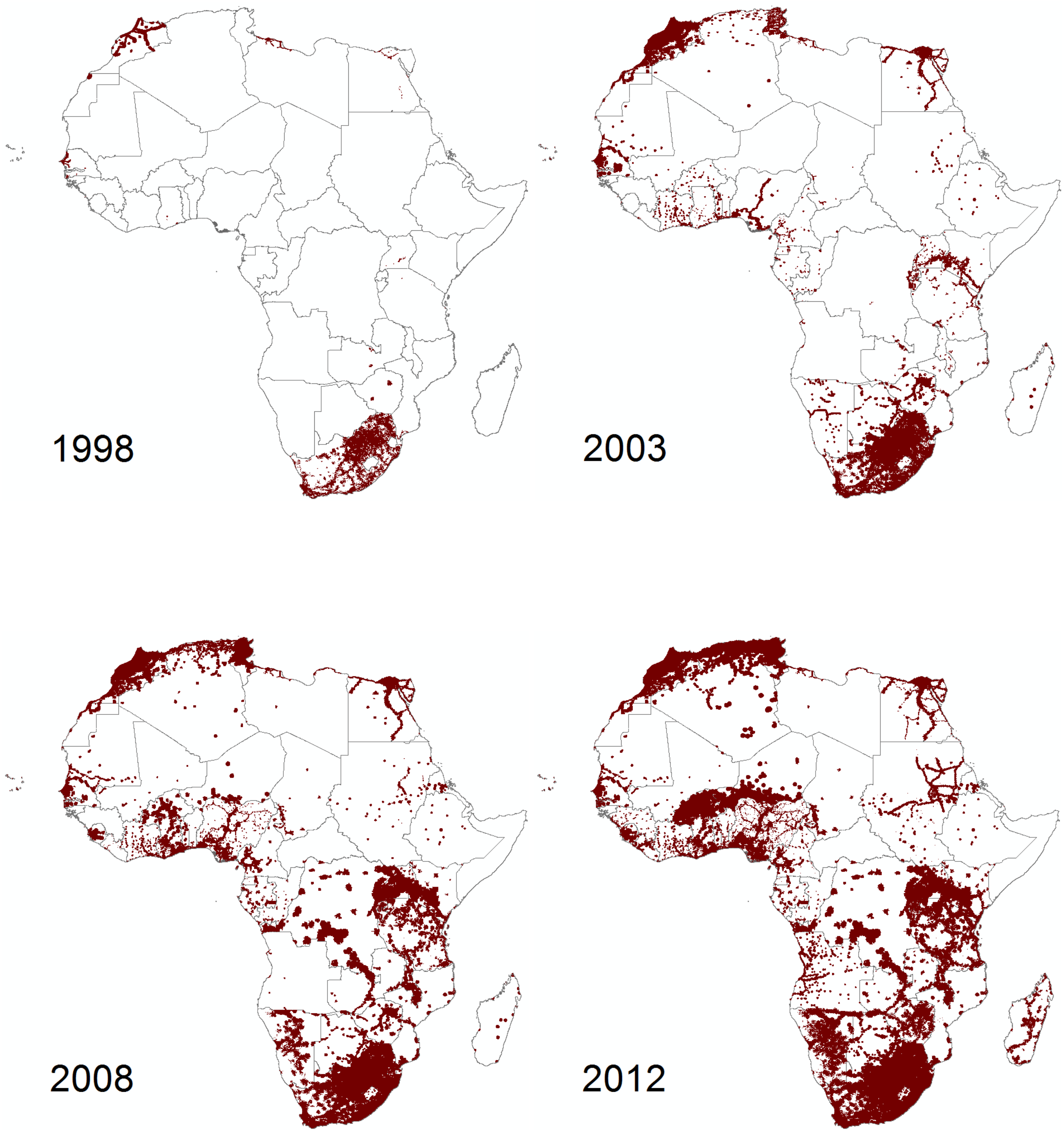
[47] Alternatively, let $\bar{d} = \kappa_0 + \kappa_1 \ Cov + \tau$. In this case, $\beta_1 \approx \frac{\gamma_1+\gamma_3\kappa_0}{1-\gamma_4-\gamma_5\bar{d}}$ and $\beta_k \approx \frac{\gamma_k\kappa_1}{1-\gamma_4-\gamma_5\bar{d}}$ for k=2, 3.

covered in society $\bar{d}$ will only matter for individual participation through a spillover effect.

B.6. The role of enhanced information and enhanced coordination

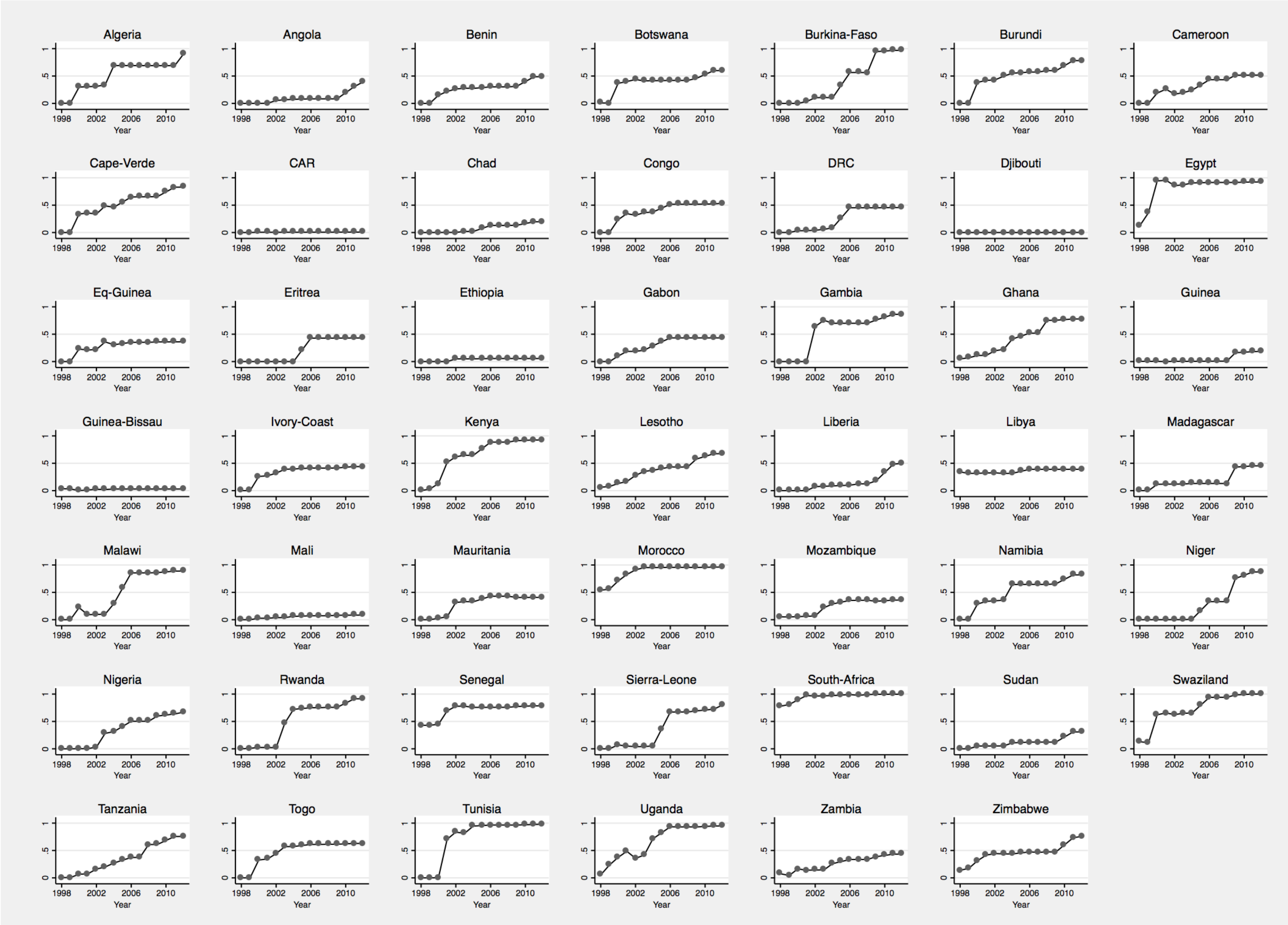
We separate the effect of enhanced information (through the term γ_3) from the effect due to enhanced coordination (through the term γ_5) as follows. Aggregating model (B.15) across individuals in each cell/year and linearizing, this delivers model (B.16), where $\beta_3 \approx \frac{\gamma_3(1-\gamma_4)+\gamma_1\,\gamma_5}{(1-\gamma_4-\gamma_5\bar{d})^2}$. The latter is a slightly more cumbersome expression for β_3 than the one in the previous section, although it is also more precise and it proves more useful for the decomposition at hand. The first term captures the effect of enhanced information while the second captures the effect of enhanced coordination. Their ratio is $\frac{\gamma_3(1-\gamma_4)}{\gamma_1\,\gamma_5}$. From this is straightforward to derive an expression for the fraction of β_3 attributable to the each of these different sources.

Figure 1 Mobile phone coverage diffusion, Africa 1998-2012



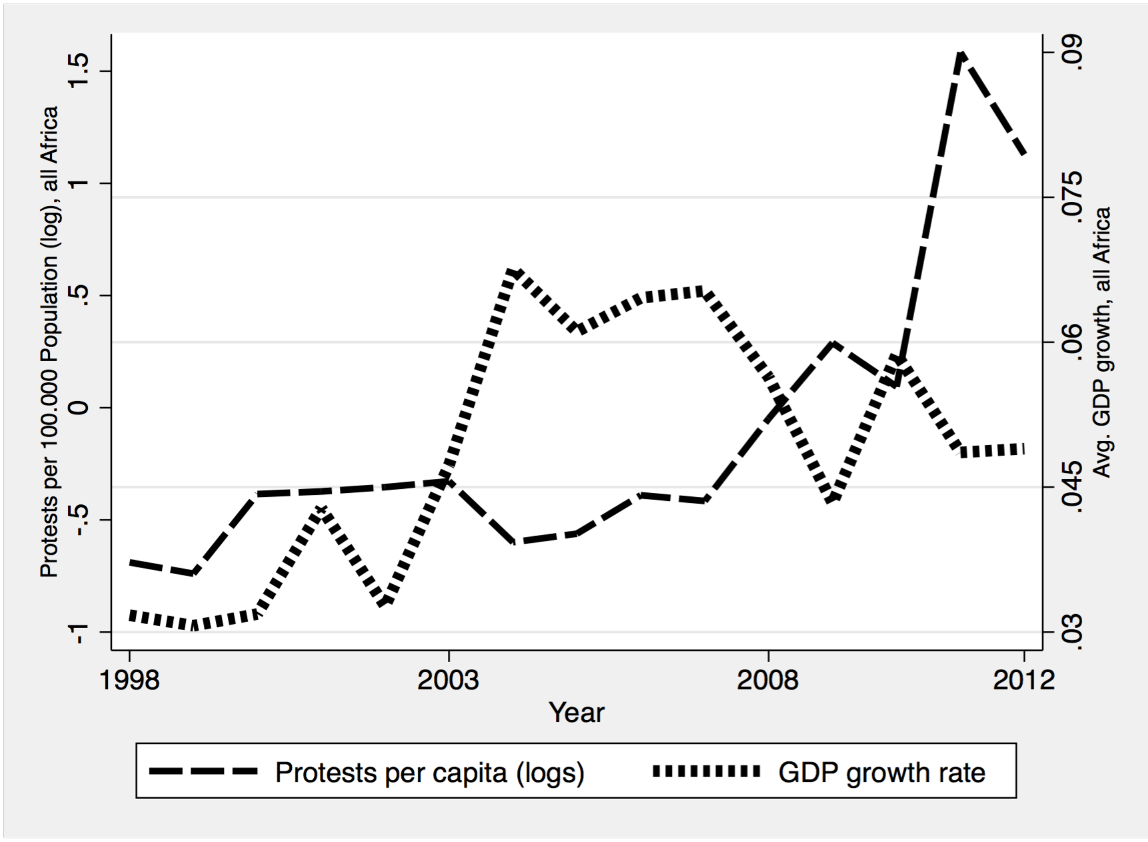
Notes. The figure reports geo-referenced data on 2G coverage for the entire of Africa at 5-year intervals between 1998 and 2012. Source: GSMA.

Figure 2 Trends in the fraction of population covered by mobile phone signal by country



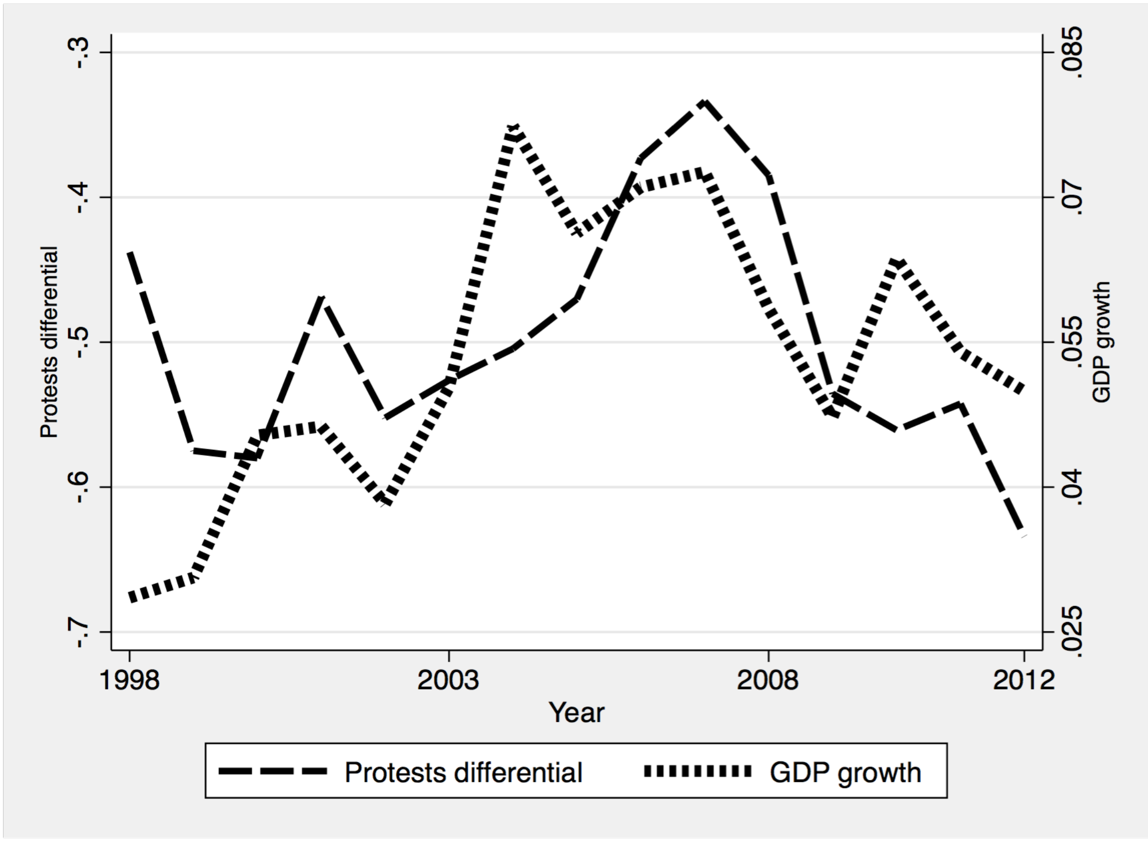
Notes. The figure reports the fraction of the population covered by 2G technology by country and time. Series are obtained as population-weighted averages of the fraction of each country's 0.5° x 0.5° degree cell that is covered by the signal in each year.

Figure 3 The evolution of GDP Growth and protests over time - Africa



Notes. The figure reports continent-wide log protests per 100,000 people (dashed line) and the rate of GDP growth (dotted line) as a function of time. Continent-wide GDP growth is obtained as a population-weighted average of GDP growth in each country.

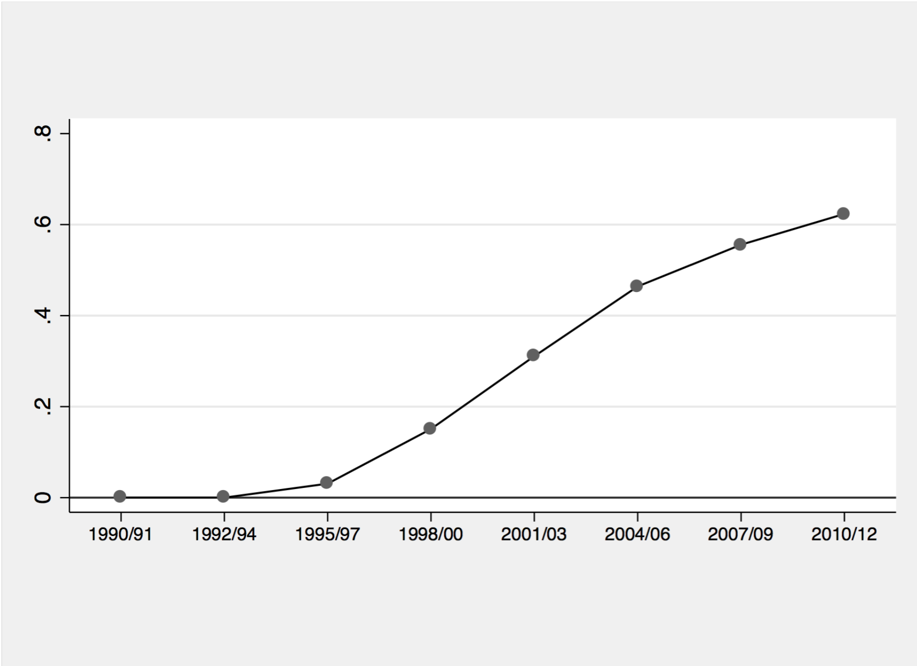
Figure 4 Protests differential between high and low flash intensity areas and GDP growth



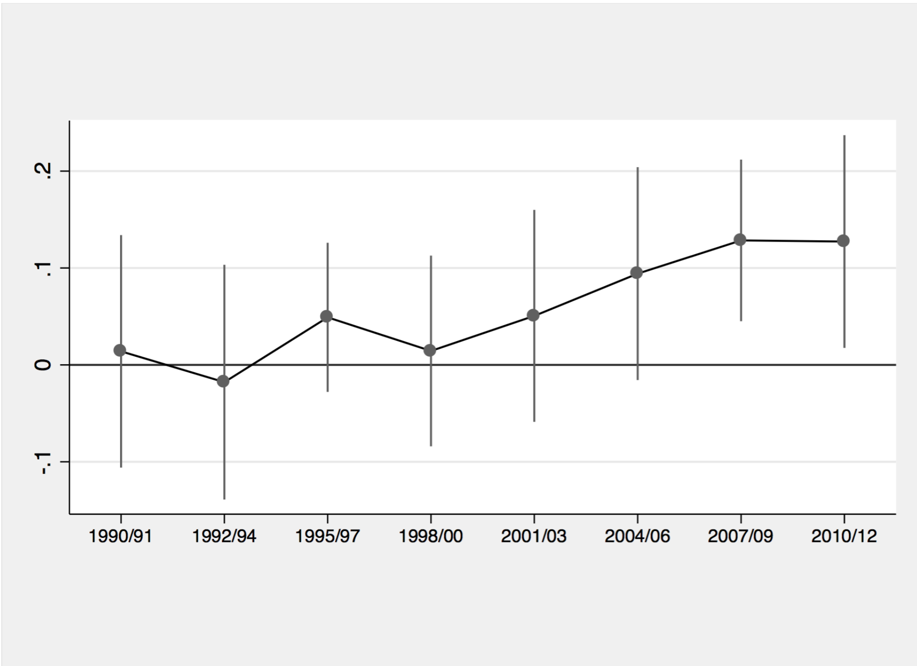
Notes. The figure reports the within-country trend in the log protest differential between high and low flash intensity areas (dashed line) and the continent-wide rate of GDP growth (dotted line). Series are population-weighted averages across countries. Observations only refer to countries-years for which there is sufficient variation in flash intensity across areas (see also text for details).

Figure 5 Placebo test

Panel A: Mobile phone coverage by sub-periods



Panel B: Reduced-form coefficients of $Z\,\Delta GDP$ by sub-periods



Notes. Panel A reports the continental trend in 2G mobile phone coverage by 3-years sub-periods. Coverage is set at 0 for all cells before 1995 (the year in which 2G technology was first introduced in Africa) and is linearly interpolated at the cell-level between 1995 and 1998 (the first year in our data). Panel B reports the estimated coefficients from the reduced-form regression of log protests per 100,000 people (plus one to account for zeros) on the variable Z X ΔGDP (parameter ρ_3 in equation 5.1) by 3-years sub-periods and the corresponding 90 percent confidence intervals.

Table 1 Descriptive statistics: cell characteristics

	Avg.	Std. Dev.	Min.	Max.
Mobile Phone Coverage (*percent*)	0.43	0.42	0	1
Protests per 100,000 *pop.* − *GDELT*	1.24	17.29	0	3,000,000
Protests per 100,000 *pop.* − *ACLED*	0.08	0.688	0	1,146.13
Country GDP growth	0.049	0.041	-0.33	0.63
Population (1000*s*)	84.32	266.78	0	12,860
Cities (*number*)	2.36	3.94	0	36
Border Distance (100 *km*)	1.73	1.47	0	10.54
Capital Distance (100 *km*)	3.57	3.35	0.04	19.48
Coast(*dummy*)	0.15	0.36	0	1
Primary Roads (100 *km*)	0.87	0.99	0	5.22
Primary Roads Paved (100 *km*)	0.49	0.72	0	4.66
Primary Roads Good Conditions (100 *km*)	0.26	0.49	0	3.80
Secondary Roads (100 *km*)	1.42	1.10	0	6.40
Electricity Network (100 *km*)	0.86	1.18	0	7.55
Travel Time nearest city pop. $\geq 50K$(*hours*)	4.21	3.69	0	102.2
Infant Mortality Rate (‰)	8.91	3.71	1	20.31
Mountain (*percent*)	0.23	0.32	0	1
Forest (*percent*)	0.23	0.25	0	1
Irrigated (*percent*)	0.08	0.17	0	0.87
Diamonds (*dummy*)	0.03	0.18	0	1
Minerals (*dummy*)	0.22	0.42	0	1
Oil (*percent*)	0.13	0.33	0	1
Conflict (*dummy*)	0.19	0.39	0	1
Temperature (*Celsius degrees*)	23.12	4.25	4.06	31.41
Precipitation (*mm.*)	876.2	487.5	69.39	3,296.4
Drought (*n. of years*)	1.44	1.25	0	11
Avg. distance from drought (100 *km*)	1.74	0.56	0	4.56
Flashrate (100,000 *per cell per year*)	0.513	0.426	0	5.046

Notes. The table reports descriptive statistics for each of the 10,409 cells of 0.5° x 0.5° degree resolution that compose Africa (excluding Somalia). All data, except population in row 5, are weighted by cell population. Row 1 reports the fraction of the population in reach of 2G mobile signal. Rows 2 and 3 report the average number of protests in a year per 100,000 people, from GDELT and ACLED respectively. Row 4 reports the country's yearly growth in GDP per capita. The residuals rows report cross-sectional physical, climatic, geographical and socio-economic characteristics of each cell. Table A.1 reports the definition as well as the source of each of these variables.

Table 2 Mobile phones and protests. Aggregate regressions: OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				GDELT				
ΔGDP	-0.565***	-0.394***	-1.016***	-0.909***				
	(0.159)	(0.107)	(0.267)	(0.197)				
Coverage	-0.026	-0.051***	-0.011	-0.041**	0.003	-0.004	0.008	0.001
	(0.035)	(0.019)	(0.032)	(0.018)	(0.022)	(0.018)	(0.022)	(0.018)
ΔGDP *X Coverage*			-2.380***	-2.849***			-1.627***	-1.873***
			(0.602)	(0.569)			(0.466)	(0.445)
				ACLED				
ΔGDP	-0.184***	-0.089*	-0.299***	-0.191**				
	(0.053)	(0.051)	(0.090)	(0.082)				
Coverage	-0.020***	-0.017**	-0.016**	-0.015**	-0.006	-0.002	-0.005	-0.001
	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)	(0.006)	(0.009)	(0.006)
ΔGDP *X Coverage*			-0.607***	-0.566***			-0.388*	-0.393*
			(0.213)	(0.210)			(0.234)	(0.230)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country X Year FE	No	No	No	No	Yes	Yes	Yes	Yes
Cell-level Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	152,415	152,415	152,415	152,415	152,415	152,415	152,415	152,415

Notes. The table reports separate OLS regressions of log protests per 100,000 people (plus one to account for zeros) by cell and year (equation 4.1). The upper panel refers to GDELT while the lower panel refers to ACLED. ΔGDP is the country yearly GDP growth rate in a given year. *Coverage* is the fraction of each cell area covered by mobile phone signal in a given year. Cell-level controls include log population and a dummy for civil conflict in that year/cell plus the interaction between a linear time trend with a large number of cross-sectional cell-characteristics (fraction of the cell's area covered by mountains, forests, oilfields and irrigated; dummies for the presence of mines, diamonds and oilfields in the cell; latitude and longitude of the cell centroid, cell area, distance of the centroid to the capital, the coast and the border plus dummies for cells crossed by the country border, cells on the coast and cells hosting the country capital; number of cities in the cell, dummies for level-2 administrative units (typically districts); travel time to the closest city with more than 50,000 inhabitants, *km* of primary and secondary roads, of paved primary roads and primary roads in good conditions; *km* of electrical grid; infant mortality rate; average temperature and precipitation; number of years of drought over the period; average distance to the closest cell incurring a drought over the period, plus dummies for missing values of all these variables). All regressions are weighted by cell population. Standard errors clustered at the level of cell reported in brackets. * Significantly different from zero at the 90 percent level, ** 95 percent level, *** 99 percent level.

Table 3 First stage estimates: mobile phone coverage and lightning strikes

	(1)	(2)	(3)	(4)	(4)	(6)
	Coverage	*Coverage*	ΔGDP X *Coverage*	*Coverage*	*Coverage*	ΔGDP X *Coverage*
Z	-0.010***	-0.010***	0.001***	-0.009***	-0.009***	0.000**
	(0.002)	(0.002)	(0.000)	(0.002)	(0.002)	(0.000)
$\Delta GDP\ X\ Z$		0.006	-0.038***		0.012	-0.016***
		(0.009)	(0.004)		(0.012)	(0.004)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country X Year FE	No	No	No	Yes	Yes	Yes
Cell-level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Angrist-Pischke F-stat	22.22	22.28	104.94	16.46	16.76	13.96
Observations	152,415	152,415	152,415	152,415	152,415	152,415

Notes. The table reports first stage regressions of *Coverage* and $\Delta GDP\ X\ Coverage$ on average flash intensity in a cell interacted with a linear time trend (Z), and the interaction of this variable with GDP growth. Regressions in columns (1) to (3) also include country GDP growth ($\Delta\, GDP$, coefficient not reported). All regressions include the entire set of controls. See also notes to Tables 2.

Table 4 Mobile phones and protests. Aggregate regressions: 2SLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GDELT				ACLED			
ΔGDP	-0.442***	-1.568***			-0.093	-0.349**		
	(0.125)	(0.393)			(0.057)	(0.143)		
Coverage	-0.233	-0.195	-0.094	-0.032	-0.030	-0.022	0.015	0.032
	(0.240)	(0.245)	(0.263)	(0.261)	(0.097)	(0.099)	(0.106)	(0.107)
$\Delta GDP\ X\ Coverage$		-6.264***		-6.325***		-1.425**		-1.713*
		(1.650)		(2.031)		(0.565)		(0.917)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country X Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Cell-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogeneity test	0.433	0.014	0.730	0.055	0.886	0.116	0.876	0.223
Observations	152,415	152,415	152,415	152,415	152,415	152,415	152,415	152,415

Notes. The table reports the same specifications as in columns (2), (4), (6) and (8) of Table 2, respectively for GDELT (columns 1 to 4) and ACLED (columns 5 to 8). Method of estimation: 2SLS, where the variables *Coverage* and $\Delta GDP\ X\ Coverage$ are instrumented for average flash intensity in a cell interacted with a linear time trend (Z) , and the interaction of this variable with GDP growth. See also notes to Table 2.

Table 5 Mobile phone use, economic conditions and political opinions

	(1)	(2)	(3)	(4)	(5)
	Worse Economic Conditions			*Opinion President*	
	Individual		*Country*		
	Actual	*Perceived*	*Perceived*	*Distrust*	*Disapprove*
Mobile	-0.020***	0.005	0.003	0.009*	0.007**
	(0.006)	(0.007)	(0.007)	(0.005)	(0.003)
$\Delta GDP\ X\ Mobile$	-0.117	-0.173	-0.349**	-0.624***	-0.350***
	(0.139)	(0.175)	(0.167)	(0.132)	(0.109)
Cell FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country X Year	Yes	Yes	Yes	Yes	Yes
Cell-level controls	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes
Observations	77,096	77,096	77,096	73,988	74,090

Notes. The table reports estimated coefficients based on individual-level OLS regressions using data from Afrobarometer, rounds 3 to 5. *Mobile* is a dummy for mobile phone use. See Appendix A for a definition and the method used to construct this variable. The dependent variable is a dummy equal to one if the respondent: is unemployed (column 1); thinks his own economic conditions have worsened during the previous year (2); thinks the country's economic conditions have worsened during the previous year (3); does not trust the President at all (4); strongly disapproves of the President's performance (5). All regressions are weighted by sampling weights. Standard errors are clustered at the cell level. All regressions include the entire set of cell-level controls described in notes to Table 2, plus the following individual controls: age and its square, gender, rural/urban status, dummies for education levels, number of adults in the household.

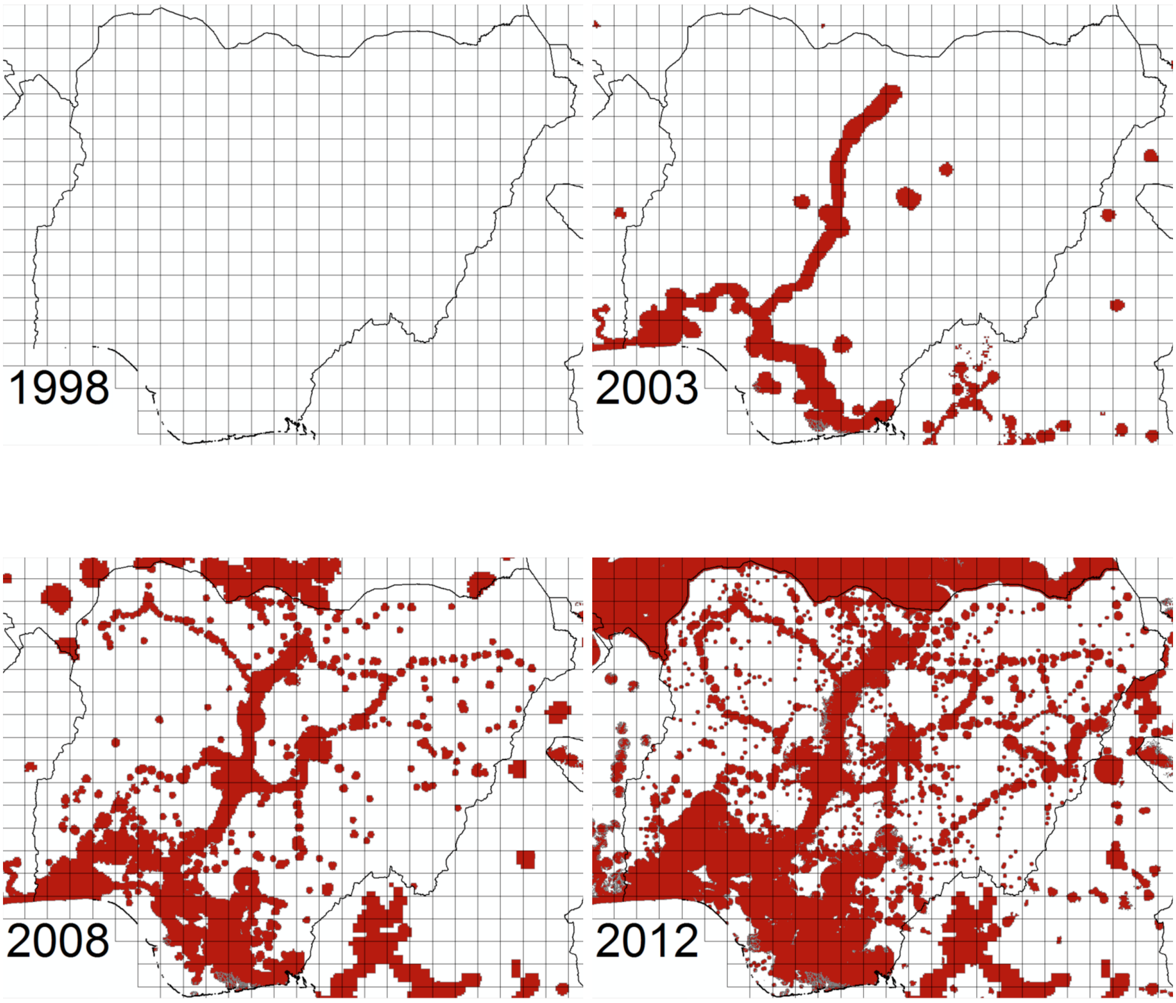
Table 6 Mobile phones and protests. Aggregate (OLS) and individual level regressions

	(1)	(2)	(3)	(4)
	% Participating		*Indiv. Participation (0/1)*	
% Mobile	-0.014	-0.007		
	(0.018)	(0.019)		
ΔGDP X % Mobile	-1.066***	-0.720*		
	(0.351)	(0.367)		
Mobile			-0.024	-0.030*
			(0.017)	(0.018)
ΔGDP X Mobile			-0.239**	-0.263**
			(0.105)	(0.104)
% Participating			0.904***	0.800***
			(0.161)	(0.198)
% Participating X Mobile			0.208	0.259*
			(0.149)	(0.153)
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country X Year	Yes	Yes	Yes	Yes
Cell-level Controls	No	Yes	No	Yes
Individual Controls	Yes	Yes	Yes	Yes
Observations	75,175	75,175	75,175	75,175

Notes. The table reports coefficients from regressions estimated using Afrobarometer data. Columns (1) and (2) report estimated coefficients from regressions of a dummy for participating in protests on the fraction of individuals using a mobile at least once a day in each cell and year and its interaction with GDP growth. Columns (3) and (4) report estimated coefficients from regressions of a dummy for participating in protests on a dummy for mobile phone use, the fraction of individuals participating in the cell and interactions of a dummy for mobile phone use with this latter variable and with GDP growth. Method of estimation is 2SLS. First stage estimates reported in Table A.9. All regressions weighted by sampling weights. Standard errors clustered by cell. See also footnotes to Table 2.

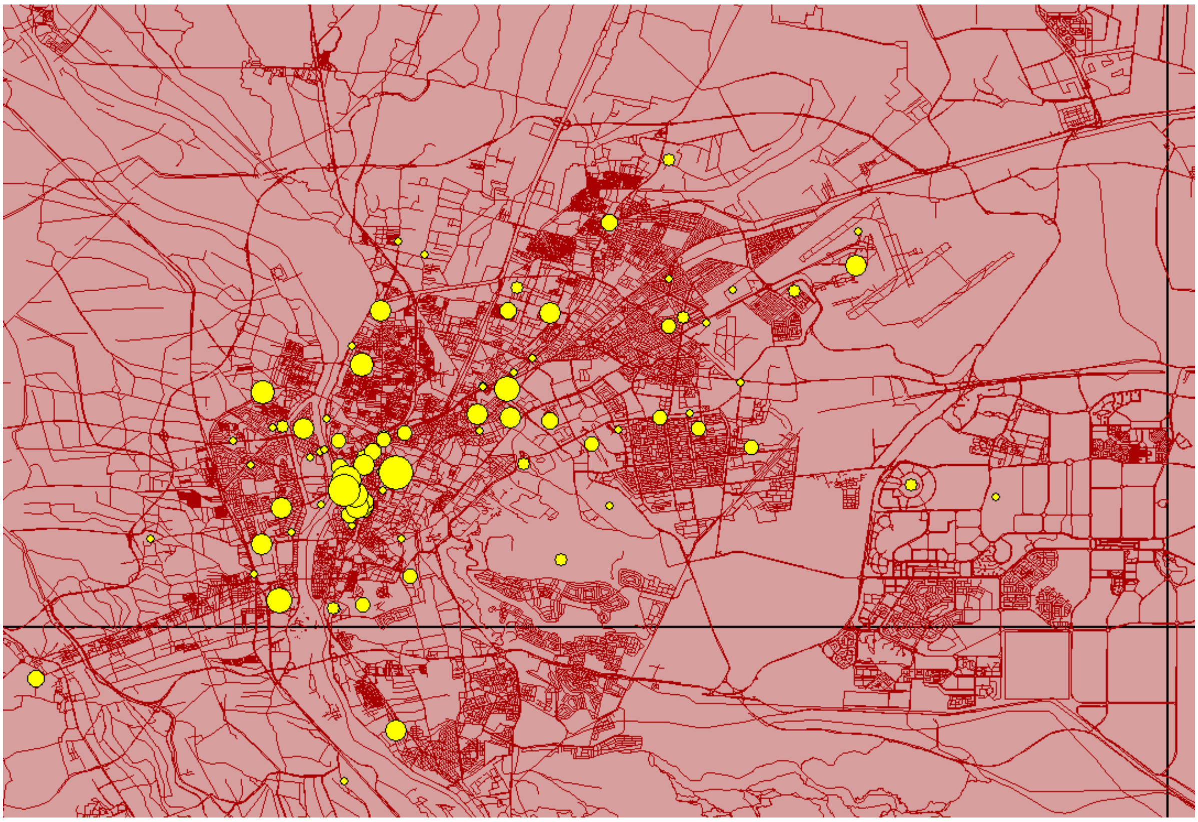
A. Appendix figures and tables

Figure A.1 Mobile phone diffusion, Nigeria 1998-2012



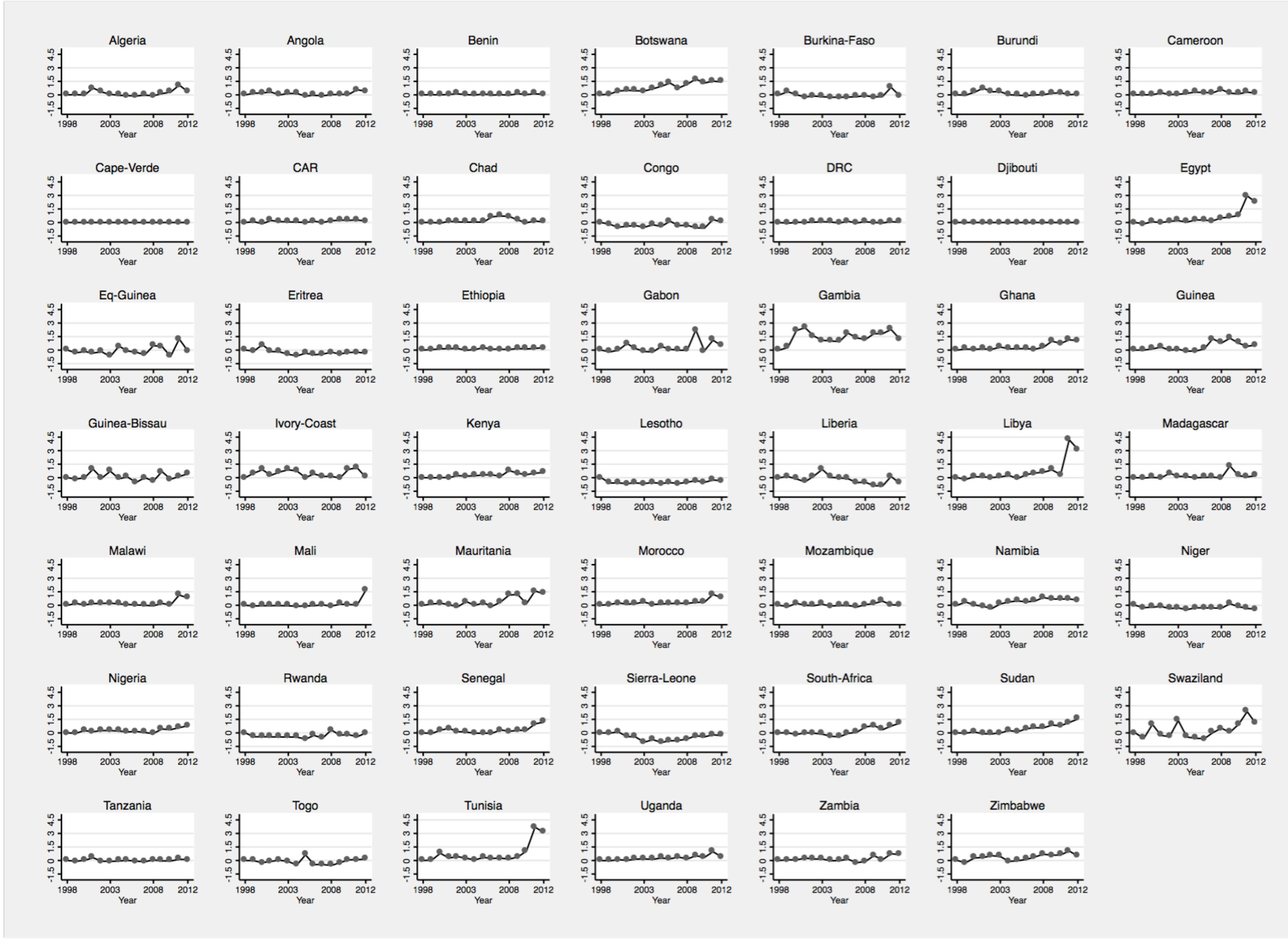
Notes. The figure reports the spread of 2G coverage in Nigeria between 1998 and 2012 at 5-years intervals. Source: GSMA.

Figure A.2 Geo-located protest events, Cairo 2011



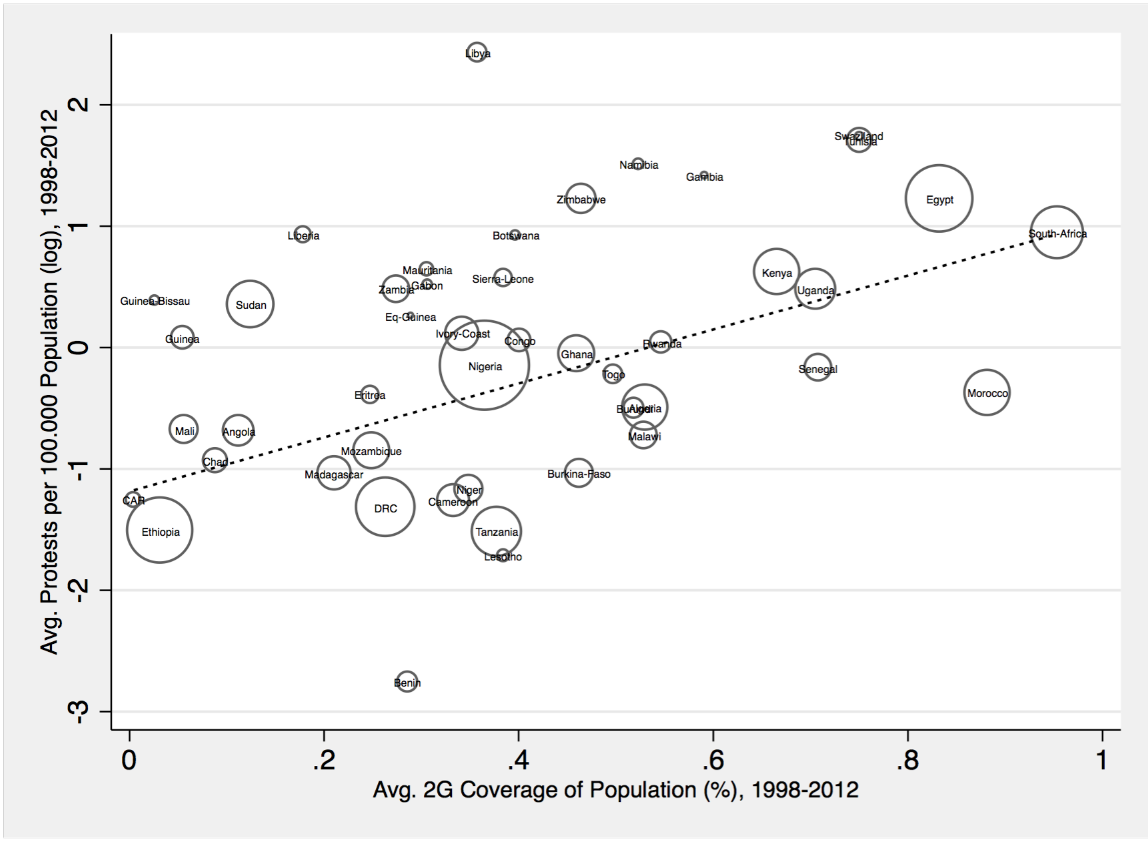
Notes. The figure reports the occurrence of protests in Cairo in 2011 by location. Larger dots correspond to more days of protests in a certain location. Source: GDELT.

Figure A.3 Trends in protests by country - GDELT



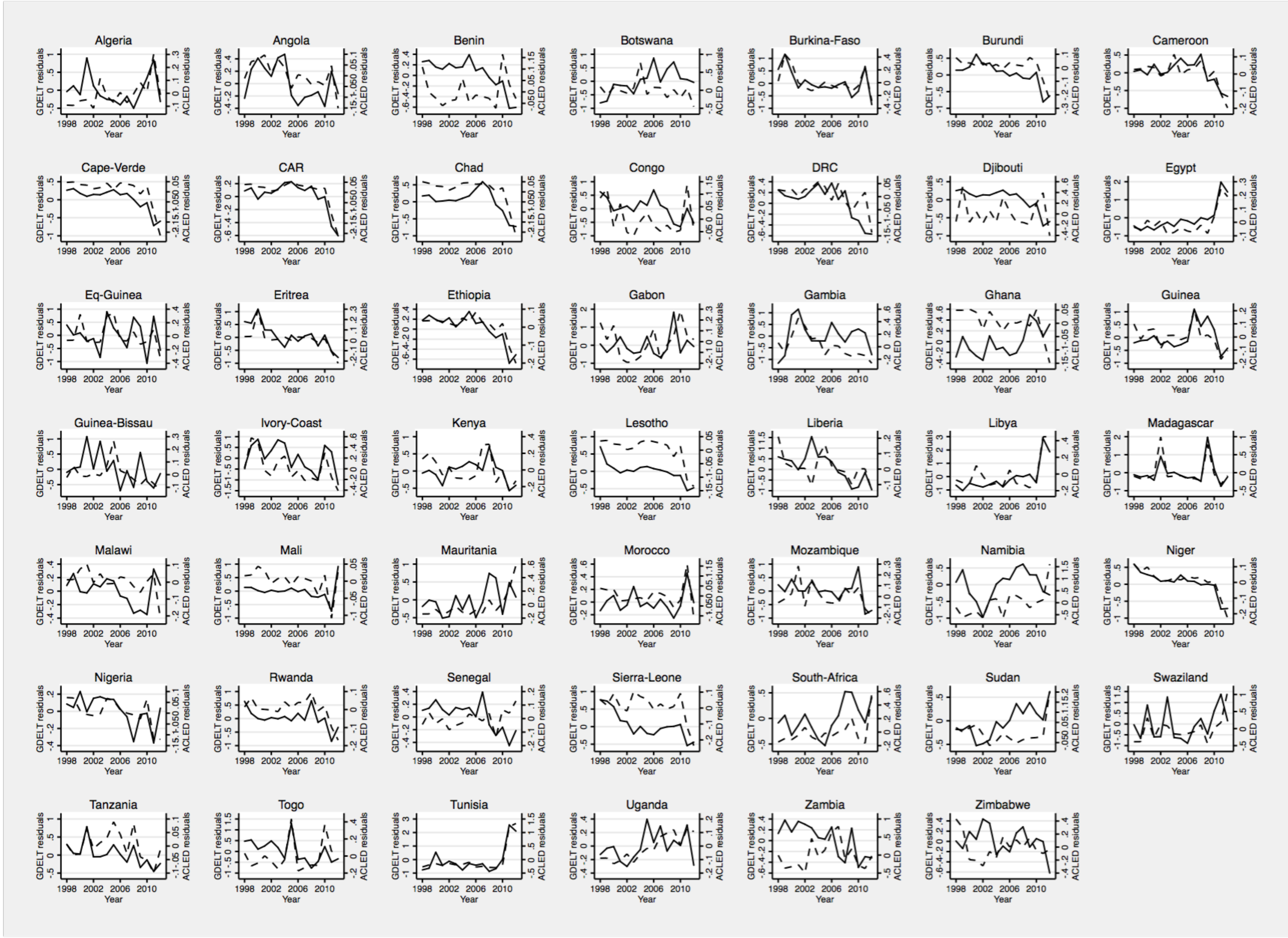
Notes. The figure reports the evolution of log protests per 100,000 individuals (plus one) by country based on GDELT. All series are standardized to their value in the first year.

Figure A.4 Cross-sectional relationship between coverage and protests



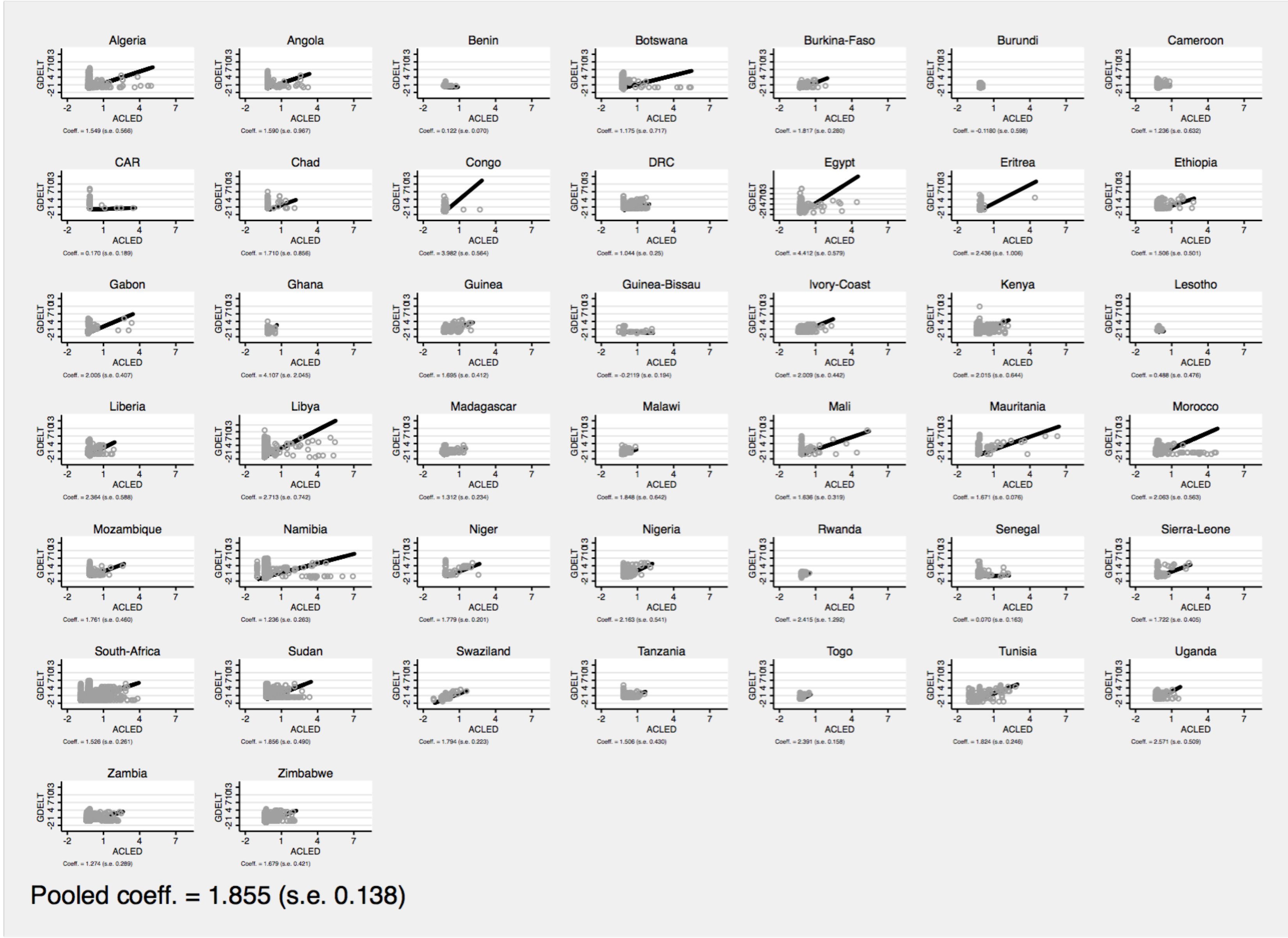
Notes. The figure reports log protests per 100,000 individuals based on GDELT on the vertical axis and the fraction of the population covered by 2G signal on the horizontal axis. Averages between 1998 and 2012 by country reported. The size of each circle is proportional to the country population.

Figure A.5 Correlation between reported protests in GDELT and ACLED across countries



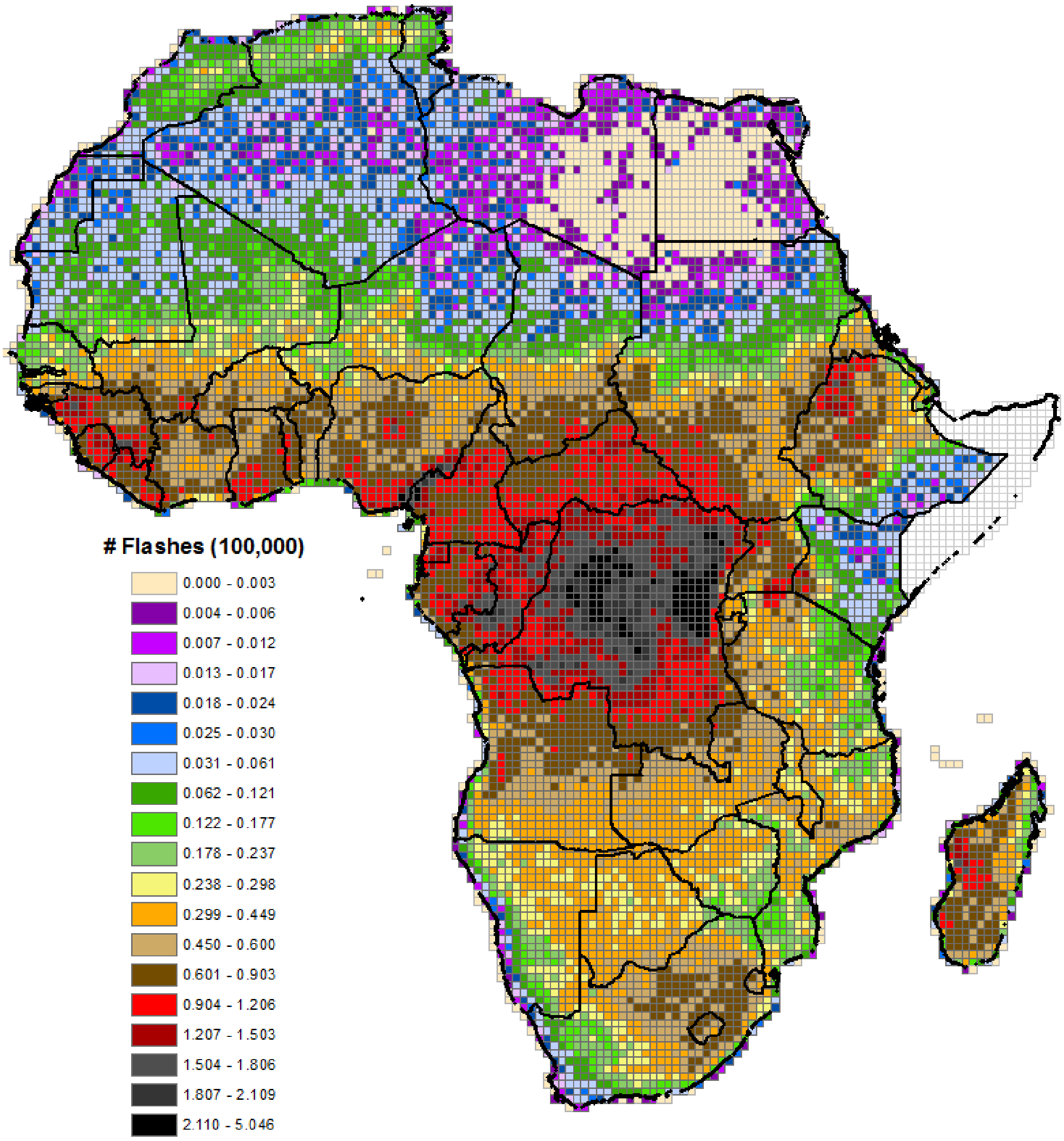
Notes. The figure reports log protests per 100,000 individuals in GDELT (solid line) and ACLED (short-dashed line) by country and year. Residuals from regressions on country and year fixed effects reported.

Figure A.6 Within-country correlation between reported protests in GDELT and ACLED



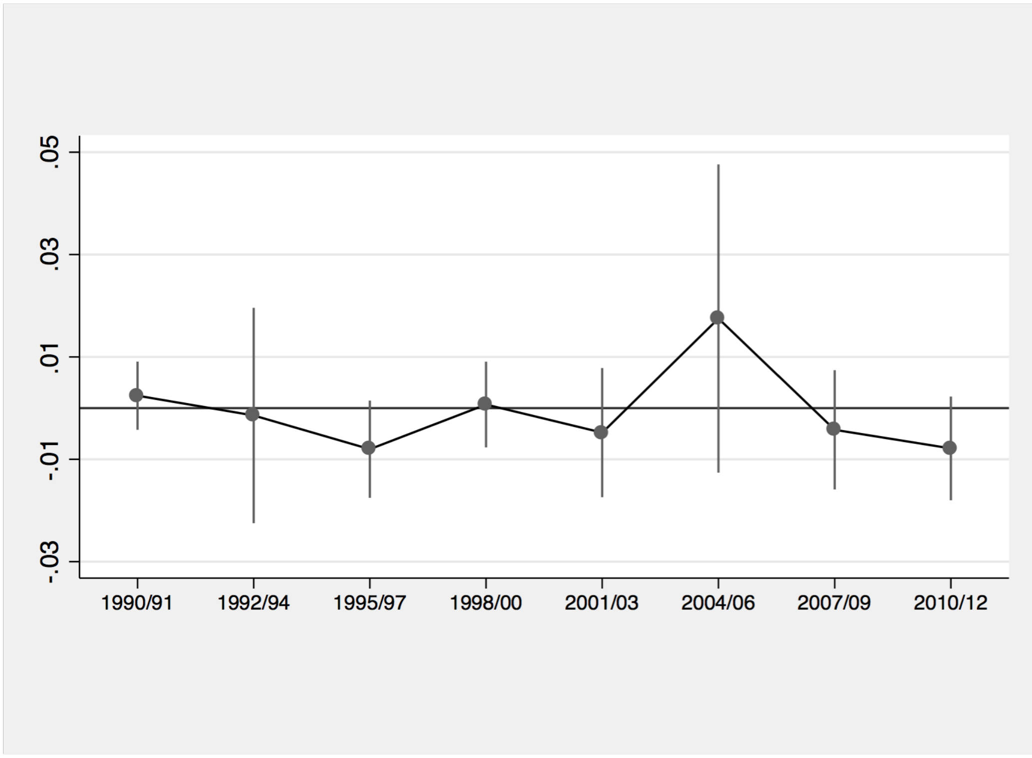
Notes. The figure reports the relationship between protests in GDELT (on the vertical axis) and ACLED (on the horizontal axis) within each country. Each point refers to a cell X year observation. All series are expressed in logs (plus one to account for zeros). Residuals from regressions on cell fixed effects and year X country fixed effects reported. A GLS best-fit regression line (and the associated slope coefficients and standard errors) of protests in GDELT on protests in ACLED with weights equal to the population in each cell in each year also reported.

Figure A.7 Lightning strikes in Africa



Notes. The figure reports the average number of lightning strikes between 1995 and 2010 in each 0.5° x 0.5° degree cell. Source: NASA.

Figure A.8 Reduced-form estimates of protests on Z by sub-periods



Notes. The figure reports the estimated reduced-form coefficients of the variable Z (parameter ρ_2 in equation 5.1) by 3-years sub-periods and the corresponding 90 percent confidence intervals.

Table A.1 Cell-level covariates

Variable	Source	Short Description
Population	PRIO-GRID	Population size for each cell, extracted from the Gridded Population of the World, v.3 (CIESIN 2005). Data are available for 1990, 1995, 2000, and 2005. We obtain the remaining years by linear interpolation.
Cities (*number*)	GRUMP	Number of cities in the cell at year 2000, calculated in GIS from the Global Rural-Urban Mapping Project, v.1
Border Distance (100 *km*) *Capital Distance* (100 *km*) *Coast* (*dummy*)	PRIO-GRID	Border distance calculated from the cell centroid to the border of the nearest neighboring country, regardless of whether this is located across international waters. Capital distance calculated from the cell centroid to the national capital city. Geographical coordinates for the capital cities capture changes over time wherever relevant. Coast is a dummy for the cell being coastal.
Primary Roads (100 *km*) − *Total* − *Paved* − *Good conditions* *Secondary Roads* (100 *km*)	Africa Infrastructure Country diagnostic (ADB)	Geo-referenced roads files are downloaded separately for each country. Data usually refer to network in 2007, and are discussed in Gwilliam et al. (2008). For each cell we calculate the road network in GIS. Country-specific files are not available for North-African countries. In this case, data are obtained from the Roads of Africa dataset, but lack information on roads conditions.
Electricity (100 *km*)	Africa Infrastructure Country diagnostic (ADB)	Geo-referenced electricity files are available from the ADB dataset for all countries, except Egypt, Libya and Morocco. For these countries, data are obtained from the Openstreetmap project. Data usually refer to the network in 2007. For each cell we calculate the electricity network in GIS.
Travel Time nearest city : *pop.* $\geq 50K$ (*hours*)	PRIO-GRID	Estimated cell-average travel time (in hours) by land transportation from the cell centroid to the nearest major city with more than 50,000 inhabitants. The values are extracted from a global high-resolution raster map of accessibility, where time reflects the average pixel value within each cell.
Infant Mortality Rate (‰)	PRIO-GRID	The cell-specific infant mortality rate is based on raster data from the SEDAC Global Poverty Mapping project. The variable is the average pixel value inside the grid cell. The unit is the number of children per 10,000 that die before reaching their first birthday. The indicator is available for the year 2000.
Mountain (%) *Forest* (%) *Irrigated* (%)	PRIO-GRID	Mountain is the share of mountainous terrain within each cell. This indicator is based on high-resolution mountain raster data from the UNEP's Mountain Watch Report 2002. Forest is the share of forest cover in a cell extracted from the Globcover 2009 dataset. Irrigation is the share of area equipped for irrigation within each cell from the FAO Aquastat irrigation raster.
Conflict (*dummy*)	PRIO-GRID	The dummy indicates whether the grid cell is located in a conflict zone in each given year, from the Conflict Site coding, v.3 (Dittrich Hallberg 2012). The indicator contains time-varying values for the period 1998-2008.
Diamonds (*dummy*)	Diamond dataset PRIO	The variable includes any site with known activity, meaning production or confirmed discovery. For each cell we calculate the presence of a diamond mine in GIS.
Oil (%)	Petroleum dataset PRIO	The petroleum dataset groups oil fields in polygons within a buffer distance of 30 *km* For each cell we calculate the percentage that is covered by an oil-field in GIS.
Mineral (*dummy*)	U.S. Geological Survey	For each site it is reported the exact location and type of mineral, as well as the magnitude of production. For each cell we calculate the presence of a mine in GIS.
Temperature (Celsius) *Precipitation* (*mm.*) *Drought* (*number of years*) *Avg. Distance from drought* (100 *km*)	PRIO-GRID	Temperature and precipitation are the yearly mean temperature and total amount of precipitation in the cell, from the University of Delaware (NOAA 2011). We calculate the average for the period 1946-2008. Drought is number of years during 1998-2012 in which the cell is subject to drought, measured as within-year deviations from average. The measure is coded 1 if at least three consecutive months were more than 1 standard deviation away from the average monthly values. Distance from drought is the average distance over the period 1998-2012 to the nearest cell incurring a drought.
Flashrate (*per* km^2 *per year*)	GHCC/NASA	Data refer to lightning activity calculated from the Optical Transient Detector (OTD) and the Lightning Imaging Sensor (LIS). Each flash is recorded along with its spatial location (latitude, longitude) with a level of resolution of 5-10 *km* on the ground. The GHCC calculates the average flash density in 0.5° x 0.5° grid cells over the period 1995-2010.

Table A.2 Afrobarometer country-rounds availability

	Round 3 (2005/06)	*Round* 4 (2008/09)	*Round* 5 (2011/13)
Benin	1,190 [37]	1,184 [33]	592 [33]
Botswana	1,182 [53]	920 [42]	880 [41]
Burkina-Faso	-	968 [53]	576 [40]
Burundi	-	-	1,200 [15]
Cameroon	-	-	656 [55]
Cape-Verde	765 [5]	656 [10]	719 [7]
Ghana	1,165 [71]	960 [60]	1,376 [66]
Guinea	-	-	1,136 [42]
Ivory-Coast	-	-	1,136 [57]
Kenya	1,246 [45]	960 [34]	2,135 [31]
Lesotho	1,161 [10]	1,192 [9]	1,197 [9]
Liberia	-	797 [28]	873 [25]
Madagascar	1,333 [191]	1,152 [183]	1,012 [216]
Malawi	1,199 [34]	1,152 [23]	1,523 [40]
Mali	1,187 [101]	960 [115]	986 [94]
Mozambique	1,198 [111]	1,088 [85]	1,936 [99]
Namibia	1,139 [82]	1,024 [49]	1,097 [52]
Nigeria	2,200 [193]	1,781 [197]	1,936 [182]
Senegal	1,200 [47]	1,030 [25]	1,176 [34]
Sierra-Leone	-	-	550 [28]
South-Africa	2,171 [212]	2,220 [188]	1,400 [130]
Swaziland	-	-	456 [7]
Tanzania	1,203 [102]	1,024 [68]	2,144 [94]
Togo	-	-	368 [14]
Uganda	2,400 [60]	2,431 [46]	1,444 [57]
Zambia	1,200 [103]	1,200 [68]	1,176 [71]
Zimbabwe	914 [44]	1,000 [42]	1,888 [48]

Notes. The table reports the number of individuals by country in rounds 3 to 5 of Afrobarometer. The number of cells identified for each country in each round is reported in parenthesis.

Table A.3 Descriptive statistics Afrobarometer

	Avg.	Std. Dev.	Min.	Max.
		Individuals (78,167)		
Protest participation	0.12	0.32	0	1
Mobile phone	0.67	0.47	0	1
Age	36.66	14.65	18	130
Primary education	0.61	0.49	0	1
Gender	0.5	0.5	0	1
Adults in household	3	2.29	0	40
Unemployed	0.66	0.47	0	1
Worse economic condition (personal)	0.35	0.48	0	1
Worse economic condition (country)	0.38	0.49	0	1
Distrust President	0.64	0.48	0	1
Disapprove President	0.70	0.46	0	1
		Cells (2,082)		
Population (1000*s*)	527.61	876.83	0	7,841
Mobile Phone 2*G Coverage (percent)*	0.82	0.28	0	1
Protests per 100,000 *pop.* − *GDELT*	2.86	8.54	0	540.41
Protests per 100,000 *pop.* − *ACLED*	0.27	0.87	0	217.63
Country GDP growth (percent)	0.06	0.02	-0.18	0.15

Notes. The table reports descriptive statistics for individuals in Afrobarometer (upper panel) as well as the corresponding cell characteristics (lower panel). Data in the upper panel are weighted by individual sampling weights. Data in the lower panel are weighted by cell population.

Table A.4 Nightlights

	(1)	(2)	(3)	(4)
	Reduced-form estimates		2SLS estimates	
Z	-0.012	-0.012		
	(0.019)	(0.019)		
$\Delta GDP\ X\ Z$	0.029	0.043		
	(0.080)	(0.067)		
Coverage			3.911	1.016
			(6.482)	(1.853)
$\Delta GDP\ X\ Coverage$			-2.183	-5.048
			(8.918)	(7.645)
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country X Year	Yes	Yes	Yes	Yes
Cell-level Controls	No	Yes	No	Yes
Observations	148,010	148,010	148,010	148,010

Notes. The table reports estimated coefficients from separate regressions of average night lights intensity in each cell/year, on a number of variables. Columns (1) and (2) report reduced from specifications (equation 5.1) while columns (3) and (4) report 2SLS estimates (equations 4.1 and 4.2). See also notes to Table 3.

Table A.5 Robustness checks: 2SLS

	(1)	(2)	(3)	(4)	(5)
	S.e. clustered at country level	Country trends	One protest per day	Square root protest	$I(\Delta GDP > 0)$
			GDELT		
Coverage	-0.032	-1.078	-0.065	-0.001	1.178**
	(0.284)	(1.315)	(0.204)	(0.001)	(0.478)
ΔGDP *X Coverage*	-6.325**	-8.963***	-5.317***	-0.040***	
	(2.850)	(3.216)	(1.600)	(0.012)	
$I(\Delta GDP > 0)$ *X Coverage*					-1.185***
					(0.346)
			ACLED		
Coverage	0.032	0.214	0.009	0.000	0.110
	(0.154)	(0.308)	(0.103)	(0.000)	(0.221)
ΔGDP *X Coverage*	-1.713**	-1.635	-1.782**	-0.007*	
	(0.760)	(1.029)	(0.855)	(0.004)	
$I(\Delta GDP > 0)$ *X Coverage*					-0.089
					(0.179)
Cell FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country X Year FE	Yes	Yes	Yes	Yes	Yes
Cell-level Controls	Yes	Yes	Yes	Yes	Yes
Observations	152,415	152,415	152,415	152,415	152,415

Notes. The table reports the same specification as in columns (4) and (8) of Table 4. The upper panel refers to GDELT while the lower panel refers to ACLED. Column (1) reports standard errors clustered at the country level. Column (2) controls for cell-specific cross-sectional characteristics interacted with country-specific linear trends. In column (3) the dependent variable is defined as number of days of protests in a given cell/year. In column (4) the dependent variable is the square root of the number of protests per capita. In column (5) *Coverage* is interacted with a dummy for positive GDP growth. See also notes to Table 4.

Table A.6 Aggregate outcomes. Heterogeneous effects: 2SLS

	City Size		Region		Arab Spring		Internet		3G Mobile		Institutions		Media	
	(1) Small	(2) Large	(3) North	(4) SSA	(5) Pre-2011	(6) 2011-12	(7) Pre	(8) Post	(9) No 3G	(10) 3G	(11) Democr.	(12) Autocr.	(13) Free	(14) Captured
Coverage	-0.099	0.053	-0.728	0.076	-0.192	0.290	0.139	-0.827	-0.034	-1.232	0.177	-0.294	1.062	-0.218
	(0.205)	(0.432)	(2.098)	(0.249)	(0.232)	(0.676)	(0.186)	(3.005)	(0.235)	(3.738)	(0.525)	(0.224)	(2.259)	(0.234)
ΔGDP *X Coverage*	-2.100	-9.745***	-2.488	-7.943***	-5.237***	-9.022**	-7.031***	-6.350	-5.695***	-28.157	-5.110	-7.497***	-1.960	-6.797***
	(2.655)	(3.025)	(3.274)	(2.800)	(1.994)	(4.132)	(2.684)	(3.928)	(2.025)	(24.627)	(8.207)	(2.070)	(13.345)	(2.080)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country X Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	119,020	33,395	42,415	110,000	132,921	19,494	98,334	54,081	150,191	2,224	69,288	82,633	53,760	98,655

Notes. The table reports the same specification as in column (4) of Table 4 using GDELT data. Columns (1) and (2) report separate regressions by city size. Small cities are those with population below the sample median. Columns (3) and (4) report separate regressions for Northern and Sub-Saharan African countries. Columns (5) and (6) report separate regression for the years 1998-2010 and 2011-2012. Columns (7) and (8) report separate regressions depending on Internet availability in the country, based on data from the World Development Indicators. Internet is defined available for penetration greater or equal to 3 percent of the population. Columns (9) and (10) report separate regressions for availability of 3G mobile phone technology in a cell, based on data from the GSMA. Columns (11) and (12) report separate regressions for democratic and autocratic regimes, based on the Polity Index. Autocracy is defined for Polity scores less or equal to zero. Columns (13) and (14) report separate regressions based on media freedom. Countries with captured media are those with a value of the Reporters Without Borders World Press Freedom Index below the worldwide median. See also notes to Tables 2.

Table A.7 Individual correlates of protest participation and mobile phone use

	(1)	(2)
	Protest Participation	*Mobile phone use*
Age/100	0.193***	2.580***
	(0.043)	(0.244)
Age/100 sq.	-0.270***	-3.410***
	(0.045)	(0.283)
Female	-0.035***	-0.221***
	(0.003)	(0.013)
City	0.005	0.433***
	(0.004)	(0.028)
Adults in household	0.004***	0.022***
	(0.001)	(0.003)
Informal ed.	-0.003	0.393***
	(0.007)	(0.046)
Incomplete primary	0.009*	0.432***
	(0.005)	(0.027)
Completed primary	0.017***	0.789***
	(0.005)	(0.029)
Incomplete sec.	0.041***	0.989***
	(0.006)	(0.030)
Completed sec.	0.033***	1.267***
	(0.006)	(0.033)
Some tertiary (not college)	0.048***	1.531***
	(0.007)	(0.051)
Some College	0.133***	1.525***
	(0.013)	(0.068)
Completed college	0.076***	1.682***
	(0.010)	(0.057)
$Post-graduate$	0.116***	1.813***
	(0.027)	(0.142)
Coverage		0.378***
		(0.060)
Cell FE	Yes	No
Country FE	Yes	Yes
Year FE	Yes	Yes
Country X Year FE	Yes	No
Cell-level Controls	Yes	No
Observations	75,175	30,465

Notes. The table reports individual-level regressions based on Afrobarometer data. The dependent variable in column (1) is a dummy variable equal to 1 if the respondent attended a demonstration or protest during the previous year; in column (2) is an ordered variable for frequency of mobile phone use (from 0 or "never" to 4 or "several times a day"). This latter variable is only available for Round 5. Method of estimation in column (1): OLS; in column (2): Ordered Probit (marginal coefficients reported). Regressions weighted by individual sampling weights. Standard errors clustered by cell.

Table A.8 Protests, GDP growth and mobile phone coverage in Afrobarometer cells: OLS

	(1)	(2)	(3)	(4)	(5)	(6)
	Afrobarometer		GDELT		ACLED	
Coverage	-0.035	-0.049**	-0.156	0.061	-0.101**	-0.089*
	(0.023)	(0.022)	(0.137)	(0.135)	(0.039)	(0.050)
$\Delta GDP\ X\ Coverage$	-0.931***	-0.761**	-6.573**	-8.874***	-3.569**	-4.307**
	(0.252)	(0.320)	(3.279)	(3.375)	(1.658)	(2.135)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell-level Controls	No	Yes	No	Yes	No	Yes
Observations	4,336	4,336	4,336	4,336	4,336	4,336

Notes. The table reports the same specifications as in columns (7) and (8) of Table 2 estimated for the sample of cells/years available in Afrobarometer, where the dependent variables are: fraction participating in a protest from Afrobarometer (columns 1 and 2), log protests per 100,000 people from GDELT (columns 3 and 4) and log protests per 100,000 people from ACLED (columns 5 and 6). See also notes to Table 2.

Table A.9 First stage estimates: Afrobarometer

	(1)	(2)	(3)	(4)
	% Participating		*% Participating X Mobile*	
% Mobile	-0.012	-0.004	-0.029**	-0.032**
	(0.018)	(0.019)	(0.013)	(0.014)
$\Delta GDP\ X\ \%\ Mobile$	-0.975***	-0.692*	-0.103	0.228
	(0.373)	(0.365)	(0.211)	(0.249)
$\%\ Mobile\ X\ Mobile$	-0.002	-0.003	0.062***	0.064***
	(0.007)	(0.005)	(0.011)	(0.010)
$\Delta GDP\ X\ \%\ Mobile\ X\ Mobile$	-0.145	0.004	-1.230***	-1.151***
	(0.233)	(0.186)	(0.330)	(0.330)
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country X Year	Yes	Yes	Yes	Yes
Cell-level Controls	No	Yes	No	Yes
Individual Controls	Yes	Yes	Yes	Yes
Observations	75,175	75,175	75,175	75,175

Notes. The table reports first stage estimates underlying the 2SLS estimates of equation (4.3) reported in columns (3) and (4) of Table 6.