Facebook Causes Protests*

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Abstract

Internet and social media have been considered crucial determinants of recent political turmoil and protests. To estimate the causal impact of Facebook on collective action for a large set of countries, we use Facebook's release in a given language as an exogenous source of variation in access to social media where those languages are spoken. Using country, subnational, and individual-level data we show that Facebook had a significant and sizable positive impact on citizen protests. Complementary findings show that these results are not driven by reverse causality or correlated changes in protest reporting. Also, the response to Facebook access is particularly important in countries with pre-existing underlying conditions that facilitate using the technology (more internet access), grievances (economic downturns), few other opportunities to coordinate action against authorities (no freedom of assembly and repression of the opposition), and factors making the country more conflict-prone (natural resource abundance and denser urban populations). It is also more present in countries with either very strong or very weak accountability. Finally, we find that the effect is present for individuals with very different characteristics and we detect no evidence of displacement in other forms of political participation or news consumption.

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1 Introduction

The political events unraveled in the Middle East in 2011 together with the development and adoption of information technologies have created a widespread perception that the Internet, and social media in particular, was a major precipitant factor in popular uprising against authoritarian regimes. However, much of this perception comes from journalistic accounts, not careful research. As highlighted in Farrell (2012), the Internet has been repeatedly described as a major precipitating factor in the Arab spring, yet "good quantitative and qualitative data on these events are still extremely sparse" (p. 44). Aday et al. (2010) conclude that journalistic accounts, based on anecdotes rather than rigorously designed research may exaggerate the impact of new media in episodes like the protests during the Iranian 2009 presidential elections. And just as social media platforms provide enormous possibilities for movement organizers, they also present the government with opportunities to detect and suppress collective action (Diamond & Plattner, 2012; Sanovich, Stukal, Penfold-Brown, & Tucker, 2015).

Besides, progress in understanding the net impact of these possible effects is hindered by the challenges in estimating the causal influence of the Internet and social media on political outcomes. Internet access is correlated with a variety of relevant socio-economic characteristics that influence politics. Reverse causality is also an issue: increased political mobilization may drive the growth in internet and social media participation and penetration, not the other way around.

This paper takes the challenge of more systematically examining the effect of social media on collective action across a broad sample of countries and regions in the world. Our identification strategy relies on the introduction of Facebook, the world's most common and widely used social media outlet, in different languages. Facebook's platform, launched worldwide in September of 2006 in English, was subsequently and gradually extended to versions in different languages. We exploit the release of Facebook in a given language as an exogenous source of variation in access to social media among countries, regions, and people speaking such language. Our strategy builds on the idea that the introduction of Facebook in French, for example, increases the number of Facebook users in French-speaking countries, regions, and among French-speaking people.

Collecting data from a variety of sources, we present results at the national, subnational, and individual levels. At the national and subnational levels, we test whether protests increase after Facebook is launched in a language commonly spoken in a given country or region within a country. Collecting information from various surveys worldwide (Afrobarometer, European Social Survey and World Values Survey), we run individual-level regressions where protest participation is a function of Facebook availability in the language spoken by the respondent.

Each one of these approaches offers advantages that complement each other. In the national-level regressions, we can more directly examine a key concern for our empirical strategy: that the timing of language-specific platforms responds to an increased demand for social media in protest-prone countries. Three findings suggest this source of reverse causality is unlikely a concern. First, there are no pre-existing differential trends between countries with more or less people speaking languages available on Facebook. Second, collective action in a given country does not predict increased efforts to translate the platform into languages spoken in the country. Third, the main results are not driven by any given region, country, language, or by significant countries in terms of their wealth, size, or level of political turmoil. The national-level regressions are also useful to explore potential mechanisms by studying the heterogeneous effects of Facebook availability as a function of national socio-economic and political characteristics. Finally, Facebook user data is scarce and estimates rely on either partial reports by the company or estimates from Internet users' access to the platform. But at the national level, we can validate that language-specific Facebook platforms increase access to Facebook using the available data on users and search interest for Facebook in Google Trends. Comparable data on Facebook use is more incomplete at the subnational level, and protest location may be measured with more error when studying smaller geographical regions. Despite these two drawbacks, the subnational analysis is useful to control for national and even regional trends in collective action, which relaxes the assumptions for identification.

Individual-level data from surveys complete the analysis on several dimensions. First, it allows us to examine *who* protests, and not simply *where* protests take place. Second, it also enriches the set of outcomes and likely mechanisms of influence that we can study by exploiting variation in individual circumstances. Finally, one disadvantage of the national and subnational analysis is that protests measures are based on media reports. Thus, results could reflect merely that Facebook increases *reported* protests because it makes them more visible, with no impact on *actual* protests. Several robustness exercises in our national and subnational level regressions suggest that this is unlikely. But the individual-level data is also crucial for this since it relies on direct reports rather than what gets covered by the media.[1]

Consistently across these approaches, we find a positive and robust effect of Facebook access on citizen protests. The increase in the total number of protests is also apparent for different types of protests, suggesting a very generalized impact not confined to a particular form of collective action. Effects are more pronounced in countries with pre-existing underlying conditions that facilitate using the technology (more internet access), grievances (economic downturns), few other opportunities to coordinate action against authorities (no freedom of assembly and repression of the opposition), and factors making the country more conflict-prone (natural resource abundance and denser urban populations). It is also more present in countries with either very strong or very weak accountability.

When examining individual protest participation, we find that the effect is present for individuals with very different characteristics in terms of age groups, gender, education or income. Only in the World Value Surveys and European Social Survey samples, we find a larger effect for women, and education and income seem to be a barrier to use the technology only in the African sample.

Also important, with the individual data we can test whether other forms of political participation and news consumption are crowded out by Facebook. We detect no evidence of such displacement, and in fact, there is a very precisely measured zero effect in political activities like voting, engagement and interest in political discussions, party identity and association membership and participation. The same occurs with Radio, TV and newspaper consumption.

The magnitudes of the effect we uncover are economically meaningful. Our estimations based on protest counts suggest a 22% to 38% increase in protests when the share of people who speak a language available on Facebook (a variable that we term "Facebook Speakers") increases from zero to one hundred percent. The lower bound of the effect corresponds to our national-level regressions and the upper bound to those exploiting subnational variation. This is consistent with the idea that national-level effects are attenuated by averaging regions that are heavily treated and others that are not when Facebook appears in one new local language. To get a better sense of the quantitative importance of these effects, we construct the counterfactual amount of protests implied by our estimates assuming no version of Facebook had ever been launched (that is, imposing zero Facebook Speakers throughout). We then estimate the cumulative difference since September of 2006 (when Facebook first appeared)

[1] With the survey data we also verify, where possible, that Facebook availability in a given language increases Facebook use.

and up to December of 2015 (when our sample ends) between protests with and without Facebook. The calculations imply that, had it not been for Facebook, the world would have observed close to 14%-22% fewer protests over our sample period. The magnitudes at the individual level are similar, where being a Facebook Speaker increases participation by 12% on average, and up to 25% relative to the base level in the Afrobarometer sample where we find the largest response.

We also provide direct evidence against several empirical concerns that might bias our estimates. Validating our identification assumption and addressing concerns about reverse causality, we show: parallel trends in aggregate protest counts and individual protest participation before the arrival of new Facebook platforms, robustness to the exclusion of countries that could influence Facebook's translation into a new language and the lack of any correlation between collective action events subsequent Facebook platforms translation activity. Omitted variables causing differential trends correlated with Facebook expansion is also not a likely confounder given the fine-grained variation we can use, allowing us to control for country and even regional trends in collective action, as well as for trends parametrized as a function of initial country characteristics. We also directly examine whether results are driven by major episodes likely changing the nature of collective action coinciding with Facebook's expansion into new languages (in particular, the Arab Spring or the global financial crisis of 2007-2008). Finally, we provide evidence that reporting biases do not contaminate our protest-count results and confirm those results with individual answers that are independent of media reports.

Our paper contributes to several strands of research. We add to the literature exploring the impact of the expansion of the Internet (e.g. increased access to broadband) on various political outcomes. These include, for instance, turnout and voting behavior (Campante, Durante, & Sobbrio, 2013; Larcinese & Miner, 2017), ideological polarization (Gentzkow & Shapiro, 2011; Barberá, 2014; Boxell, Gentzkow, & Shapiro, 2017), economic growth (Czernich, Falck, Kretschmer, & Woessmann, 2011), and policies (Gavazza, Nardotto, & Valletti, 2017). Like several of these papers, we emphasize devising a credible identification strategy to identify causal effects. However, these studies typically evaluate the overall role of Internet access, without discriminating which of the many tools brought about by the Internet determines the results.[2] We contribute by focusing on social media, one of the key innovations of the Internet era, and its impact on protests, a fundamental outcome

[2] An exception is Enikolopov, Petrova, and Sonin (2013), who study the impact of blog posts about state-controlled companies on the stock returns and management turnover.

emphasized extensively by academics and the media.

As noted, however, many previous studies fail to provide evidence of a causal effect of new media in general, or social media in particular, on protests. A key exception is Enikolopov, Makarin, and Petrova (2017), who take advantage of arguably exogenous variation in the expansion of VKontakte (VK), Russia's main social network, to identify the impact of network penetration on political protests. An important question that our study contributes to is whether their findings for the Russian context, naturally circumscribed to a particular institutional environment and in a specific juncture of citizen discontent following electoral corruption allegations, generalize to other areas and settings. Also related is the work of Manacorda and Tesei (2016) and Christensen and Garfias (2015), who evaluate the impact of mobile phones access on protests in Africa and a panel of countries, respectively, finding a positive effect as well.[3] Like social media, mobile phones give access to information and connect individuals (and smartphones connect to online social networks), but their impact can also reflect broader influences.

No previous study that we are aware of has offered convincing quantitative evidence on the causal effect of social media on a global scale. Our paper fills this gap, focusing on the role of Facebook, the largest social media platform worldwide. One key advantage is that we can examine not only how generalized these potential effects are, but also under which circumstances they appear more likely. Also, since we complement the protest count analysis with individual reports on protest participation, we look directly at who responds more to Facebook and whether the technology has significant crowding out of other activities.

Our results also complement a very large literature on online social networks' content and activity to evaluate the role that platforms like Twitter and Facebook play during protest events. Much of this literature focuses on explaining online behavior during protest events (Segerberg & Bennett, 2011; Munger, Bonneau, Jost, Nagler, & Tucker, 2016; González-Bailón, Borge-Holthoefer, Rivero, & Moreno, 2011). Others rely as well on surveys of participants to show that they learn about the protests and are encouraged to participate by information and friends in these networks. Evidence from Turkey, Ukraine, Occupy Wall Street, Chile, and Tahir Square (e.g., Jost et al., 2018; Tufekci & Wilson, 2012; J. Tucker et al., 2015; Valenzuela, Arriagada, & Scherman, 2012; Valenzuela, 2013) reveals that platforms like Twitter and Facebook are used to share information on key logistical issues (ranging from carpools to protest sites to measures to counteract the effects of tear gas), to spread motivational appeals emphasized in social psychological theories of protest participation (shared

[3] Pierskalla and Hollenbach (2013) looks at cell phone coverage and violence in Africa.

interests, a sense of injustice or grievance, and social identification), and to publicize visuals from the demonstrations.[4]. Steinert-Threlkeld, Mocanu, Vespignani, and Fowler (2015) also show, for 16 countries during the Arab Spring, that coordination via Twitter messages using specific hashtags correlates with increased protests the following day, Acemoglu, Hassan, and Tahoun (2014) find that Twitter activity predicts Tahrir Square protests, and Qin, Strömberg, and Wu (2017) find that penetration of China's microblogging platform Sina Weibo correlated with the incidence of collective action events.

While these are not necessarily causal correlations, they illuminate the potential channels of influence that might underlie our results; that is, this research sheds light on *how* social media influences collective action. However, these studies are not designed to tackle the question of how much additional protest activity might we owe to these tools. Indeed, in the extreme there could be full "substitution" between these and prior means of coordination and communication: had online social networks not been available, people might have found other ways.[5]

Our goal is more ambitious than the literature documenting social media use during protests in that we attempt to estimate this net effect of greater Facebook accessibility. This naturally has a cost: to tease out the underlying mechanisms there are limitations to how much we can do by relying on our specific source of variation and data for a large set of countries. Nevertheless, some of our findings suggest the importance of certain mechanisms and help inform theories of collective action and protest participation, as well as the related debate on whether the net average effect of social media on collective action is positive or negative. In a famous magazine article, Gladwell (2010) argues that online social networks, based on "weak ties" are not likely to promote, and can displace, offline costly action and commitment for successful protest movements. In contrast, recent research on information diffusion through online social networks highlights instead the potential *advantages* of the very decentralized and diffuse nature of organization (Bennett & Segerberg, 2012; Barberá

[4]One paper that goes beyond documenting the uses of social networks to evaluate the impact of the network is Larson, Nagler, Ronen, and Tucker (2016), who collect data on Twitter activity during the 2015 Charlie Hebdo protests in Paris, recording both real-world protest attendance and social network structure. The paper shows that, relative to comparable Twitter users, protesters are significantly more connected to one another. By shaping these connections, therefore, online social network structure influences offline protest participation

[5]Global Position System (GPS) devices and applications provide a useful analogy. Do people drive more since applications like Waze that track their location and suggest a route appeared? Probably. But surely many drives would have occurred in any case without the technology. So, while there is little doubt that people use Twitter and Facebook during protests, it is less clear that these technologies produce more protests and if so how important this effect is.

et al., 2015), as well as the complementaries that might exist between online and offline activities (Campante et al., 2013; Vaccari et al., 2015).[6] Several recent theories also argue that social media increase the probability of political protests by facilitating collective action (Edmond, 2013; Little, 2016; Barbera & Jackson, 2016; Enikolopov et al., 2017; Manacorda & Tesei, 2016), both because they increase information relevant for protesters to take action and because they facilitate coordination between them. Our findings suggest that these advantages, on average, dominate any possible negative impacts. Also, complementary findings suggest that both information (since we document larger effects in areas with lower freedom of the press) and coordination (since effects are stronger in places where people otherwise have few options to organize as opposition) likely play a role.

Of course, the positive average impact on collective action does not directly translate into positive social outcomes. Evaluating the normative consequences of the increase in collective action is beyond the scope of this paper, and we briefly return to this issue in the final discussion.

The rest of the paper proceeds by presenting, in Section 2, our data and empirical strategy. Results using protests counts are in Section 3 and with individual reports in Section 4. Section 5 concludes with a final discussion of our results and implications.

2 Data sources and empirical strategy

2.1 Data

To measure protests at the national and subnational levels, we use several variables from the *Global Database of Events, Language and Tone (GDELT)*, a global and daily database recording different types of collective action events.[7] The data are based on news reports from a variety of international news sources. Using this dataset, we aggregate the number of total protest events per month in each country or region. Protests include six different types of collective action episodes: demonstrations or rallies, hunger strikes, strikes or boycotts, obstructions or blockages, engagements in political dissent and violent protests.[8]

[6] The potential strength of weak ties has been long recognized; a key reference is Granovetter (1977).

[7] This section describes the main data and variables in our analysis. Description and sources for all the variables we use are in Appendix Table A-1.

[8] In 2008, demonstrations or rallies represented about 72.5% of total protests. The other two most important protest types were violent protests and engagement in political dissent representing roughly 9.8% and 7.8% of the total, respectively. Strikes or boycotts (5.8%), hunger strikes (2.2%) and blocks (1.8%) are

To construct our main independent variable, we coded the introduction dates of Facebook for the 81 languages available by March of 2016 (including beta versions).[9] Launch dates for each Facebook interface were coded by conducting Google searches for news announcing the release. Dates for relatively uncommon languages were found in specialized blogs. In the cases (24 in total) were both options failed, we relied on the first crawl from the Internet Archive (`https://archive.org/index.php`) to identify the initial date at which the corresponding webpage (e.g. `https://es.Facebook.com` for Facebook in Spanish) was created.

Information on the official languages spoken in every country comes from Ethnologue (version 16). This provides the number of people in each country speaking any given language as their mother tongue. To illustrate the type of variation we exploit, Figure 1 shows the fraction of people speaking Mandarin, English, Spanish, and German as their first language across the globe. The map illustrates, for instance, that when Facebook in Spanish is launched, most of Latin America, except Brazil, and Spain get a large increase in potential access to the platform. However, other countries like the US, UK, and others in Europe also gain access to some degree.

Also, Ethnologue reports polygons within countries where each language is spoken, a feature that we also exploit for our subnational analysis. Ethnologue reports the aggregate number of speakers by country and language, and not those speaking each language in each polygon. This is not an issue for 85% of the polygons, where only one language is reported as the main one. For the remaining areas, which we refer to as *overlapped zones*, we use the gridded global population data from the Socioeconomic Data and Applications Center (SEDAC) to infer shares by polygon (we also drop these zones in regressions to verify robustness finding identical resources, suggesting that measurement error in shares of speakers of each language per polygon does not affect our results).

Our sample includes 245 "countries" for the period January 2000 to December 2015.[10] The subnational-level regressions rely on political administration divisions within countries as

less frequent.

[9]Facebook reported, in March of 2016, 91 different platforms. However, some of them differ so insignificantly that Ethnologue does not treat them as separate languages. Examples are English spoken in the United States and the United Kingdom, or Spanish from Spain, from Latin America generically, or from specific countries in Latin America.

[10]Strictly, these are not just countries as some 'non-sovereign territories' have independent data for our main dependent and independent variables (Appendix A.2 lists the full set of countries and non-sovereign territories in the sample). We will continue to use the term 'countries' for simplicity. Our results are similar when we restrict the analysis to sovereign territories.

units of analysis (and robustness tests show similar results when using Ethnologue polygons).

For the individual-level estimations, we collect data from several surveys reporting protest participation and language spoken by the respondent. Specifically, we rely on several rounds of the World Values Survey, European Social Survey, and Afrobarometer. In this individual-level analysis, protest activity is thus not based on the media but on direct individual reports. Similarly, the language spoken is defined at the individual level.

Facebook does not publicly disclose its number of users at the country-month level. However, combining a variety of sources including Facebook's partial reports and figures from secondary sources we can construct an unbalanced country-month panel containing Facebook users' information for a subset of our sample. Also, we use search interest for Facebook in Google Trends as another measure for Facebook use. We show that, where data are available, Facebook users and Facebook searches are very strongly and significantly correlated.

Facebook searches offers two main advantages relative to Facebook users. First, this variable is available for a larger sample of countries. Second, since some Facebook users are subscribed to the platform but do not actively participate, search interest may more accurately capture interest and activity in the social network. The main disadvantage, in theory, is that some Facebook searches may have little to do with activity in the network. For instance, when people search for information on the stock price of the company, or are curious about its founder, or are looking for an employment opportunity in the company, etc. However, this is a negligible problem in practice.[11]

2.2 Identification strategy

The study of the effect of social media on various forms of collective action faces multiple empirical challenges. First, differences in the political landscape between countries with

[11] Information from Google Trends itself shows that the top-25 "related queries" have to do with access to the platform. Specifically, "facebook login" is the most commonly search query, followed by Spanish equivalents for facebook login ("facebook entrar", "iniciar facebook", and "iniciar sesion facebook", with 35%, 35% and 30% as many queries as "facebook login", respectively), and followed with the following terms that again indicate interest in logging in to Facebook or using its tools (all with 5% as many queries as "facebook login"): "facebook español", "facebook login in facebook", "facebook login in", "facebook download", "my facebook", "entrar no facebook", "facebook com", "facebook lite", "facebook en español", "facebook sign in", "www facebook", "free facebook", "mi facebook", "facebook messenger", "facebook log in". The final seven related queries in the top 25 still relate to Facebook access, and are consulted less than 1% as much as "facebook login": "facebook live","facebook app", "facebook mobile", "login to facebook", "iniciar sesion en facebook", "facebook belépés". These numbers are from a google search query conducted on September 26, 2017.

high and low social media consumption may capture the effect of other characteristics. For instance, social media outlets such as Facebook or Twitter are available globally and thus variation in access is largely driven by internet access, which confounds other country characteristics such as country wealth, education or infrastructure. The sign of the omitted variable bias is not simple to determine a priori: areas with more social media activity may be more prosperous and democratic and experience less citizen discontent and demonstrations, or people could be drawn to the internet and social networks where social capital and collective organizations are stronger, which in turn may correlate with more citizen demonstrations. Second, in some countries access to social media may be low due to state censorship (see for example King, Pan, and Roberts (2013)). In this case, a naive comparison of countries with high and low access to social media will confound the effect of state censorship on collective action with the effect of access to social media, leading to underestimating the potential impact of social media. Finally, as noted in the introduction we cannot rule out reverse causality causing a positive bias.

To address these concerns and estimate the causal effect of social media access on collective action, our identification strategy relies on the introduction of Facebook, the world's most common and widely used social media outlet, in different languages. Facebook was launched worldwide in September of 2006. However, its original platform was in English. This may have limited the adoption and use of Facebook in countries where English is not a native language. Subsequently, Facebook launched its Spanish platform in February of 2008 and soon after (in the next couple of months) the German and French versions. Facebook has continued launching versions of its platform in different languages and the most recent one in our data was the release of the Assamese version in December of 2015.

Thus, we propose using the release of Facebook in a given language as an exogenous source of variation in access to social media in countries where such language has been officially adopted. The strategy relies on the assumption that the timing of the introduction of Facebook in a given language is orthogonal to political developments, or in particular, collective action episodes in countries that speak that language. For example, our strategy relies on the assumption that the introduction of Facebook in French does not depend on political developments in French-speaking countries as diverse as France and Cote d'Ivoire.

We estimate the following regression for protests in a panel of countries using monthly observations:

$$\text{Protests}_{ct} = \beta \times \text{Facebook Speakers}_{ct} + \gamma_c + \delta_t + \gamma_c \times f(t) + \mathbf{Z}'_{ct}\psi + \varepsilon_{ct}, \tag{1}$$

where γ_c are country fixed effects and δ_t time (month) fixed effects that partial out any global trends in collective action. We also allow linear (or quadratic) country-specific time trends $\gamma_c \times f(t)$ to recognize that countries may be on differential protest trends that would have been observed even absent the new Facebook interfaces. $\mathbf{Z}'_{ct}$ is a vector of additional controls which always includes, to allow for scale effects, initial population interacted with time dummies. In robustness exercises we include additional baseline variables interacted with time dummies, permitting flexible differential trends based on country features.

Our main independent variable, Facebook Speakers$_{c,t}$, captures the share of each country's population that can access a Facebook interface in their language. To compute it, we interact Facebook$_{t,l}$, indicating if at time t a Facebook version in language l exists, and Speakers$_{c,l}$, the share of the population in country c speaking language l. More formally:

$$\text{Facebook Speakers}_{ct} \;=\; \left(\sum_{l} \text{Facebook}_{tl} \times \text{Speakers}_{cl} \right). \tag{2}$$

This variable equals zero if either Facebook has not been released or, if released, it has appeared only in languages l not spoken at country c.[12] Once Facebook appears in a language spoken at country c, the interaction equals the share of the population speaking this language. Moreover, we aggregate these interactions over all languages to recognize that there is an additional "treatment" at country c every time Facebook appears in a language that can be interpreted by at least a fraction of the population. Speakers$_{cl}$ refers to the share of people in country c speaking l as their first language. There may be individuals who also understand l as a second or third language, but data for second languages is very incomplete in Ethnologue. We thus focus on variation on access stemming from main language availability in our baseline regressions. Where available, we also examine the impact of platforms launched in a second language spoken by the population.

In short, Facebook Speakers measures the share of people who can potentially benefit from increased access to Facebook as the new language platforms are launched. For instance, in the United States this variable equals 81.7% when Facebook was first launched (in English). The percentage increases to 92.4% when Facebook was released in Spanish,

[12]Notice that direct effects in the interaction are absorbed by the time and country fixed effects.

given that 10.7% of the US population speaks Spanish as their mother tongue. Our identification assumption is that absent these language-specific versions of the platform, countries with a larger or smaller proportion of speakers of the corresponding languages would have observed similar collective action trends. This assumption seems plausible, especially since our regression framework takes into account any time-invariant country characteristics (absorbed by the country fixed effects), plus country-specific temporal trends. Only trends that would have differentially affected places with comparably more speakers of a given language *and* that are not well captured by this country-specific (linear or quadratic) trends could contaminate our results. As we show below, moreover, we perform a number of robustness exercises to test whether our findings reflect the influence of omitted variables (differential trends that would have been observed even absent the new Facebook interfaces) or reverse causality (targeting of Facebook interfaces to languages spoken in countries where demand for protests was on the rise).

GDLET locates protest events and Ethnologue reports polygons within countries where each language is spoken. We thus also exploit within-country variation in regressions where, unlike the national level regressions, in this case we can control for a full set of country times time fixed effects. This relaxes the identification assumption and examines whether Facebook platforms in a given language increase collective action in regions where people can interpret that language relative to other areas in the same country where they cannot. For region (language polygon) j in country c at time (month) t, we estimate:

$$\text{Protests}_{cjt} = \beta \times \text{Facebook Speakers}_{cjt} + \gamma_c \times \delta_t + \omega_j + \mathbf{Z}'_{cjt}\psi + \varepsilon_{cjt}, \tag{3}$$

where $\gamma_c \times \delta_t$ are fixed effects for each country and month, ω_j are region fixed effects. As in equation (1), $\mathbf{Z}_{cjt}$ includes initial population of region j interacted with month fixed effects and other controls. Similar to equation (2), our main independent variable is defined as:

$$\text{Facebook Speakers}_{cjt} = \left(\sum_l \text{Facebook}_{tl} \times \text{Speakers}_{cjl} \right),$$

where $Speakers_{cjl}$ is the share of the population in region j of country c speaking language l.

Finally, our individual-level regressions take the following form, for individual i in country

c responding the survey at time (year) t:

$$\text{Protests}_{cit} = \beta \times \text{Facebook Speaker}_{cit} + \gamma_c \times \delta_t + \gamma_c \times \ell_i + \mathbf{Z}'_{cit}\psi + \varepsilon_{cit} \tag{4}$$

where collective action is now a dummy variable that equals one if the individual reports recent participation in protests and Facebook Speaker$_{cit}$ is a dummy variable that equals one if individual's i main language has already been made available in Facebook. Also, in addition to country-specific flexible time trends, we include in this specification language fixed effects (ℓ_i) and their interaction with country fixed effects, to allow for potential differential participation in collective action activities by individuals with specific linguistic backgrounds within a polity. Finally, $\mathbf{Z}_{cit}$ now stands for individual controls.

Since standard errors may be underestimated by the temporal and spatial correlation (Bertrand, Duflo, & Mullainathan, 2004), we use two-way clustered standard errors at the country and month (year, in the case of individual data) level.

To illustrate the variation we use to estimate the impact of Facebook, Panel A of Figure 2 shows (on the left vertical axis) the number of Facebook language-specific platforms since the English version was made available in 2006. Starting in 2007 and for the next four years, Facebook had its largest language expansion, accumulating 62 additional versions. The number of versions remained relatively stable from 2012 to 2014, and 16 new platforms were launched from 2014 to 2015. The figure also measures, on the right vertical axis, the average country-level value of Facebook Speakers. Panel B then looks at the share of Facebook Speakers in our -individual-level data, by survey wave. The share of speakers increases as new versions are launched, and it is clear that languages launched earlier on tend to have, on average, a stronger impact on the number of speakers than those launched later on. Nevertheless, even the latter platforms create meaningful variation for our regressions because in some regions within countries, and some waves and places in the survey data, significant shares of the population observe the appearance of a Facebook platform in the language they speak.

2.3 Parallel trends and endogenous translation

Before discussing our main effects, we present exercises that help validate our identification assumption. First of all, if our assumptions hold we should not observe differential trends in collective action in countries with and without increased Facebook access in their languages *before* these language-specific platforms are launched. Panel A of Figure 3 confirms that this is indeed the case. This figure extends our baseline regression (1) to include anticipation effects (leads) of our treatment variable (Facebook Speakers$_{c,t+n}$, for n ranging from one to eighteen months). While the treatment effect (lead zero) is positive and significant, other leads are not significantly different from zero, are typically smaller than the treatment, and follow no discernible pattern. Moreover, the conclusions are similar when we use Facebook search intensity in google (Facebook Searches) as the dependent variable in Panel B: there is no increase in Facebook interest months before Facebook Speakers increase.[13] While we do not have sufficient variation to do this same exercise at a monthly frequency with our individual data, Panel C explores the same parallel trends exercise with yearly leads in the survey data. Again, years ahead a Facebook platform becomes available in a respondent's language, we see no difference in collective action. Placebo treatments for anticipation effects one, two, three and up to 6 years are consistently not statistically significant and smaller in magnitude. Only when it is available Facebook Speakers report protesting more.

These parallel trends in the media-based and survey data before Facebook versions become available support our identification assumption. However, Facebook platforms are not randomly assigned. Facebook translations are partly carried out by Facebook users who voluntarily contribute by translating phrases on the website. Others then vote on the preferred translations, and a platform is launched when sufficient phrases have been tested and approved. It could therefore be the case that users from certain "protest-prone" countries are more likely to contribute to the translations, hoping to have a local platform launched sooner (perhaps precisely to organize protests). If this were the case, it would invalidate our identification assumption.

Our parallel trends results suggest this is unlikely since in this case one would expect at least some anticipated action in protests (and certainly in Facebook search interest) before the actual translation. But we cannot fully rule out this possibility with parallel trends alone. For this reason, in Appendix Table A-2 we show that (previous) protest activity does not

[13]In Appendix Figure A-1 we follow a slightly different approach and include, in regression (1), quarter dummies for the periods leading to the adoption of the first available Facebook version in any of the country's languages. The coefficients of these quarterly dummies are marked with negative integers in the x-axis. We also include Facebook Speakers but, to gauge the timing of the effects, interact it with quarterly dummies for each quarter after this first adoption of a Facebook platform in a language spoken in the territory (and plot the coefficients in the positive integers in the horizontal axis). Again, there is no anticipated increase in protests (Panel A) or Facebook Searches (Panel B) before local languages are available. Point estimates are statistically insignificant and close to zero. Instead, as soon as a local language becomes available, we see a sizable increase in protests and searches, and though there is naturally noise when estimating this high-frequency effects, even the quarterly effects become individually significant after just a few quarters.

predict Facebook translations.[14] Finally, in robustness checks below we show that our results are not sensitive to removing countries that might have induced the arrival of Facebook's language-specific platforms. This set of results supports our identification assumption and the causal interpretation of our findings.

3 Results from protest counts

We first present the results using GDLET measures of collective action. The dependent variable is the natural logarithm of the number of protests (plus one, to allow for zero values). This transformation reduces the skewness when protests are measured in levels, which is 21.8 at the country level with a standard deviation around 6 times as large as the mean. Descriptive statistics for the main variables in the country-level analysis are in Table 1.[15] We focus on linear estimators because they are consistent under comparably weaker assumptions and more flexibly admit fixed effects and clustering of the standard errors (Cameron & Trivedi, 2013). There are protests in 68% of our country-months, and among the different types of protests, demonstrations are the most frequent ones on average and hunger strikes the least common.

3.1 The effect of Facebook Speakers on protests and Facebook use

Table 2 reports our baseline estimation of equation (1) for total protests at the country-month level. All panels in this table follow the same structure. Column 1 includes linear country-specific trends and column 2 uses a quadratic polynomial instead. Column 3 runs the same specification as in column 2 but restricts attention to the sample of countries for which we have complete data on a set of pre-determined covariates. This facilitates comparison

[14] To conduct this exercise, we created Facebook profiles in each of the languages in our sample to access information on top translators by language. We then coded each translator's location and counted the frequency of translations from each country and language. Details on the data construction and a discussion of these results are in Appendix A.3.

[15] It is now increasingly popular in applied work to apply the inverse hyperbolic sine (or arcsinh) transformation because it retains zero values and approximates the natural logarithm of the variable, facilitating the interpretation of coefficients as elasticities or semi-elasticities. However, this interpretation is only valid when the dependent y variable and/or independent x variable of interest are/is large enough. The same occurs when using $log(1+y)$. Bellemare and Wichman (2019) suggest directly deriving elasticities analytically for each regression specification and their standard errors (using the delta method) to calculate exact values. In our application, the coefficients we report imply very similar magnitudes to those using the exact formula, and regressions with $log(1+y)$ or $arcsinh(y)$ are very similar to each other, as we verify in Table A-6. Nevertheless, when presenting the main results we show the implied exact magnitudes as well for reference.

with column 4, where time fixed effects are interacted with these controls, allowing for fully flexible temporal patterns in collective action as a function of these characteristics.[16] The estimates in Panel A show that an increase in Facebook Speakers increases protests and this effect is very robust and stable across specifications. The coefficient for Facebook Speakers ranges from 0.22 to 0.27 and is significant at more than the 99% level. The stability of the effect across these specifications suggests that Facebook Speakers, not other omitted factors creating differential trends, increase protests.

Considering the size of the effect in column 2 (our benchmark specification for what follows since it is the most demanding one with the full available sample), the coefficient of 0.221 implies close to a 22% increase in protests when Facebook Speakers increase from zero to one hundred percent. This approximation is almost identical to the implied magnitude with the exact formula (see footnote 15) which is also reported in the lower row of the panel.

To further illustrate the magnitude of this impact, Panel A in Figure 4 plots the observed total number of protests together with the corresponding quantity implied by our estimates assuming no version of Facebook had ever been launched (that is, imposing zero Facebook Speakers throughout). The Figure also plots the cumulative difference since September of 2006 (when Facebook first appeared) between protests with and without Facebook (expressed as percent of total cumulative protests without Facebook up to each moment). This gives an estimate of how much Facebook increased protests since it was launched. The calculations imply that, had it not been for Facebook, the world would have observed close to 14% fewer protests over our sample period.

These estimates presume that Facebook availability in local languages increase collective action via an increase in Facebook use. Precisely establishing this key mediating channel is not simple given lack of consistent Facebook user data (especially for a large sample of countries and at high frequency). However, as discussed in the Data section, search interest for Facebook in Google is a good proxy for Facebook use and is available at the country-month level. Therefore, in Panel B of Table 2 we estimate the same specifications as in Panel A with Facebook Searches as the dependent variable. The results show a clear increase in Google searches for Facebook when Facebook Speakers increase. The coefficient for Facebook Speakers ranges from 0.07 to 0.09 and is precisely estimated, significant at more than the 99% level.[17] These estimations demonstrate the relevance of the proposed

[16] Covariates included are: initial GDP and share of GDP per capita in manufacturing, population, share of population between 15 and 24 years old, internet users and language polarization.

[17] In this case, the implied semi-elasticity using the exact formula indicates that a move from zero to 100% Facebook Speakers increases average Facebook Searches from 34 to 48% depending on the specification.

mechanism: Facebook availability in a local language strongly increases Facebook use. For further confirmation of this conclusion and validation of the Facebook Searches variable, Panels C and D use the yearly (unbalanced) panel of Facebook users that we put together using various sources (see Appendix Table A-1).[18] Panel C presents regressions of Facebook Searches on Facebook Users, confirming that Facebook search interest strongly correlates with the number of users. Panel D examines whether Facebook Speakers increase Facebook Users, again finding a robust positive and significant correlation in every specification (even if the magnitude of the coefficient of Facebook Speakers is somewhat more sensitive with this more limited sample than what we observed in Panel B).

Appendix Table A-3 presents two-stage least squares (2SLS) estimates of the effect of Facebook Searches on protests, instrumenting searches with Facebook Speakers (the first stage is column 2 of Panel B in Table 2, with an F-statistic of 15.52). The coefficient on Facebook Searches (2.65 with standard error 1.08) is positive and significant at the 95% confidence level. A one-standard-deviation increase in Facebook use as captured by searches implies close to one-third of a standard deviation increase in protests ($2.65 \times 0.24 = 0.33$).[19] For comparison, the Table also shows the corresponding ordinary least squares (OLS) relationship between protests and Facebook searches, which is also positive and statistically significant, but appreciably smaller (coefficient 0.54, standard error 0.14). This could reflect that the sources of negative bias in OLS estimations discussed above are empirically more important than those leading to a positive bias. Probably more important, despite Facebook Searches capturing Facebook interest and use, it measures with considerable error the amount of time and intensity of interactions by users in the platform. Thus, attenuation bias likely also explains part of the gap between the OLS and IV estimates.

[18] In these panels with a more limited sample, there is no difference between columns 2 and 3 since we have covariates for all countries with Facebook user data.

[19] For reference, comparing the magnitudes of our findings with those in Enikolopov et al. (2017) suggest smaller impacts on protests than in their settings, while our speakers variable is at least as relevant for Facebook use as their instrument is for VK use. Since treatment and outcome variables are measured differently, for comparison consider the implied standardized effects or "β-coefficients" (how many standard deviations each dependent variable changes per standard deviation increase in the treatment variable). Our estimate of 0.22 for Facebook Speakers in column 2 of Panel A in Table 2 implies an standardized effect of 0.04 ($(0.22 \times 0.34)/1.88$), smaller than the 0.096 standardized effect of Enikolopov et al's instrument on (log of one plus) protesters in Russia (coefficient 0.259, column 6, Table 2). Also, as noted our IV estimates in Appendix Table A-3 for the effect of Facebook Searches on protests is 0.33, while Enikolopov et al. (2017) find that a one-standard-deviation increase VK users increases (log of one plus) protesters in 1.2 standard deviations (coefficient 1.787 in column 2 of Table 3). The first stage relation between their instrument and VK has a standardized effect of 0.08, while a one-standard-deviation increase in Facebook Speakers increases Facebook Searches in 0.11 standard deviation (using column 2 of Panel B in Table 2, $(0.083 \times 0.34)/0.24$).

We focus on the "reduced form" relationship between protests and Facebook Speakers in what follows both for simplicity and, more importantly, because we can run comparable regressions at the subnational and individual level (where we have no good proxy for Facebook use).

Also, before presenting more substantive findings, we briefly mention one important robustness test. Even though the parallel trend analysis and the lack of association between collective action events and translation activity by Facebook users (reviewed in section 2.3) suggest reverse causality is not likely to drive our results, we further explore the concern that social changes, turmoil, modernization, increased openness, and other trends can drive a society "to demand" Facebook local platforms and simultaneously be more prone to protesting. In Panel A of Table 3, we show the baseline specification for subsamples that exclude territories that could plausibly influence the pace of adoption of Facebook in a particular language. Specifically, we drop countries with the largest number of people (Column 1), GDP (Column 2), internet users (Column 3) and protests (Column 4) per each given language, and similarly for the same variables measured in per capita terms in columns 5-7. In addition to excluding countries based on frequent protests as in columns 4 and 7, we also rely on the World Bank's governance indicators to drop those performing worst in the indicators rule of law and control of corruption in columns 8 and 9. Panel B in the Table presents the same exercise, just that the set of languages used to drop countries is restricted to those available in the platform (since these drive the variation in Facebook Speakers).[20]

The exercise is motivated by the idea that, for instance, Facebook may be launched in Portuguese to please Brazil's or Portugal's demands, but it is less likely to respond to the political and social situation in smaller Portuguese-speaking country (by population, income, and internet users) like Cape Verde. Also, that even small but very conflict-prone countries may drive the introduction of Facebook. Nevertheless, the results are not only maintained but if anything strengthened, suggesting that Facebook's arrival in new languages is not driven by a rise in demand for social networks in large countries and those with increasing protest activity or political turmoil.[21]

[20] In Appendix Table A-4 we found similar results when excluding countries with most Facebook Speakers (and Facebook Speakers per capita) by language, and those with worst performance using additional governance indicators (voice and accountability, political stability, government effectiveness, and regulatory quality).

[21] Appendix Figure A-3 shows that our results are not sensitive to excluding different clusters of countries, by sub-regions (Panel A), continents (Panel B), or former colonies of the main colonial powers (Panel C). Panel D addresses the concern that single-country languages drive our effects. Indeed, if a Facebook platform will benefit just one (or very few) countries, then it is more likely that circumstances in that country or groups

In short, the impact we document is a widespread phenomenon, relevant to the world as a whole. Also, that no single country, no relevant group of countries, or languages can explain the totality of our estimated impact is additional evidence against the possibility of a demand-driven increase in Facebook spuriously correlated but not causing protests.

3.2 Heterogenous effects with national characteristics

Overall, these results provide compelling evidence of a causal effect of Facebook on citizens' protests. Table 4 examines heterogeneous effects with some country characteristics to better understand both the mechanisms at play and the additional implications of our findings. We start with a simple reality check in column 1 of Panel A: Facebook's arrival in a language spoken by a significant share of people should have larger impacts where there are more internet users. As with other interactions with variables that Facebook might influence, we measure internet users before Facebook appeared to avoid a "bad control" bias (Angrist & Pischke, 2008). As expected, Facebook Speakers increases protests more in places with more initial internet users.[22] A one-standard-deviation increase in internet users increases the baseline effect by around 32%.

Columns 2 and 3 delve into the likely nature of the protests and relation with political accountability. In particular, Facebook Speakers increase protests more where there is no freedom of assembly or association (column 2) and where no oppositional activity is permitted (column 3). These findings suggest that part of the role that Facebook plays is coordination where opposition is otherwise curtailed and that this acts in the direction of empowering citizens in places with poor political accountability (a matter that we investigate in more detail below).

Poor economic conditions might also trigger discontent and reduce the opportunity cost

of countries drive the arrival of Facebook. On the x-axis, we exclude the set of languages "spoken" (as the main, most-spoken language) in 1, 2, 3, 4 countries and so on. Again, the effect of Facebook Speakers varies only slightly and is always statistically significant. Finally, Panel A in Appendix Figure A-4 reaches the same conclusion when excluding one country at a time and the set of Arab Spring countries. Similarly, Panel B in Figure A-4 shows that the effect survives when dropping one language at a time. Even the largest drop in the effect when removing one language (English) is modest. That English matters most is reasonable not just because the marginal impact of additional language-specific platforms is likely to be smaller than the original appearance of the network, but also because a large number of countries worldwide have non-negligible shares of the population speaking English as their first language (recall Figure 2).

[22] With the exception of categorical variables, other variables interacted with Facebook Speakers in this table are standardized to ease interpretation of the magnitudes. In column 1, initial population is also interacted with Facebook Speakers to account for mechanical effects due to a correlation between population and internet users (this does not make a difference, however, and population does not play a major role in creating a differential effect).

of protest participation. In line with this, in column 4 the effects are stronger in moments of weak economic performance, measured with GDP growth.[23] This coincides with the evidence for the effects of mobile phones in Manacorda and Tesei (2016), except that we find Facebook to matter not merely in economic downturns, but also during average "normal" times. In column 5 we search for differential effects during election months, when there is increased attention to political developments. While there are indeed more protests in election than in non-election months, Facebook access does not exacerbate this difference, and the interaction coefficient is negative.[24]

The rest of the table examines some common determinants of collective action and social strife. A vast literature has documented a positive relationship between education and various forms of political participation, including protests (see, e.g. Campante & Chor, 2012, 2014). Column 6 in Panel A interacts with average initial years of schooling (for population over 15), finding that increased Facebook access has a larger effect in more educated countries.

Diversity along ethnic, religious and linguistic dimensions has been linked both theoretically and empirically to collective action, social capital, and conflict (see, among others, J.-M. Esteban & Ray, 1994; Alesina, Baqir, & Easterly, 1999; Montalvo & Reynal-Querol, 2005b, 2005a; J. Esteban & Ray, 2008). In columns 1 and 2 of Panel B, we interact with linguistic diversity, examining both fragmentation and polarization given some dispute regarding which is the relevant measure of diversity for particular outcomes. We focus on linguistic diversity since we can measure it directly with Ethnologue for our full sample, and find no evidence that either index exacerbates the impact of Facebook Speakers.

Together with ethnic tensions, natural resources also stand out as a salient potential determinant of conflict (for a review, see M. L. Ross, 2004). In columns 3 to 5 of Panel B, we focus on diamond production per capita and oil reserves (from Humphreys, 2005) and oil and gas rents per capita (from M. Ross, 2006a).[25] In this case, we find consistent evidence that Facebook Speakers increase protests more in countries with more resource rents. The magnitude is also important. A one standard deviation increase in diamond production, oil reserves, and oil and gas rents per capita increase the baseline effect of Facebook Speakers

[23] Results are similar using GDP per capita growth instead.

[24] We also experimented with months preceding or immediately following elections, with similar results.

[25] Though the share of natural resource exports is commonly used as a measure of resource abundance, it is a poor measure of relevant rents when there is high local consumption, when extraction costs vary, and if countries that have endogenously low non-resource exports (see M. Ross, 2006b; Acemoglu, Fergusson, & Johnson, in press).

by 46%, 17%, and 68% respectively.

Finally, there is a long-standing debate on whether denser urban populations contribute to more social unrest, as mobilization is both easier to coordinate and potentially more effective to bring about change in urban areas (e.g. Weiner, 1967; Traugott, 1995; DiPasquale & Glaeser, 1998; Nash, 2009; Wallace, 2014; Glaeser & Steinberg, 2017; Campante, Do, & Guimaraes, 2019). In Column 6 of Panel B we observe that initial urban population increases the impact of Facebook Speakers (coefficient 0.16, standard error 0.08, significant at the 90% confidence level).

In short, Table 4 shows consistent evidence that Facebook Speakers matter more for collective mobilization in countries where we would expect this because there are more opportunities to take advantage of increased access to Facebook in a local language (more internet users that can use the technology, more politically involved educated citizenry), there are more grievances (economic downturns) and few opportunities to coordinate action to oppose authorities (no freedom of assembly and repression of the opposition), and there are other conditions that make the country more protest prone (in particular, natural resource abundance and urbanization).

The role of the quality of democratic institutions deserves a deeper look. In Figure 5, we explore differential effects using the more commonly used indicators of democratic accountability and governance. In particular, we use: the Freedom House indices for political rights (Panel A), civil liberties (Panel B), and the combined index (Panel C); the Freedom Press index combining press pluralism, media independence, censorship, legislative framework, transparency, infrastructure and abuses against journalists (Panel D); Polity IV's democracy index (Panel E); and the World Bank's governance indicators for voice and accountability (Panel F), regulatory quality (Panel G), rule of law (Panel H) and control of corruption (Panel I).[26] In the figure, we plot the effect of Facebook Speakers on protests at different levels of these indicators. Since the Freedom House indices are constructed on a 7-point scale, we interact dummy variables for each level with Facebook Speakers and plot the coefficients. For Freedom Press, we use the three categories "not free", "partially free" and "free". With the Polity IV and World Bank indices (ranging from -10 to 10 and from -5 to 5, respectively), we divide the scales into three equal parts (low, intermediate and high)

[26] We exclude the political stability and government effectiveness indices of the World Bank since these are mechanically correlated with citizen protests. In particular, government effectiveness considers citizen's satisfaction (or discontent) with several public goods and government services, as well as infrastructure disruption from strikes. Political stability also directly considers social unrest, and protest and riots.

and plot the coefficients for these interactions.[27]

The figure produces a very consistent U-pattern, with the sole exception of control of corruption where there is a negative monotonic relation. That is, Facebook has stronger impacts on places that are either very democratic, free and well-governed or very autocratic, authoritarian and poorly governed. One rationale for this is that very autocratic regimes have many grievances, so protests respond despite limited opportunities for collective action. In very democratic areas, there is instead plenty of freedom to protest, so protests respond despite presumably fewer grievances.

3.3 Examining the language barrier

Our findings indicating that Facebook Speakers in a given country increase Facebook use (as captured both by the number of users where data is available and by Facebook Searches) confirms that not having the platform in a local language is an important barrier to access the technology. However, there could be spillover effects on protests by people speaking languages that are close enough to a language already in a Facebook platform (for instance, the Facebook English platform is more likely to be interpreted by Welsh-speaking rather than Spanish-speaking people). If so, our baseline effects could underestimate Facebook's effects since some "non-treated" speakers could use this linguistically akin Facebook version and increase their protest participation.

To explore this hypothesis, we construct a similarity index for each pair of languages, using the Automated Similarity Judgment Program (ASJP). The index compares a list of 40 words and assesses their similarity across pairs of languages (Wichmann, Holman, & Brown, 2016).[28] In Figure 6 we redefine Facebook Speakers to be not simply those who observe a Facebook version in their language, but in any language that is at least $x\%$ as similar according to the index (measured in the horizontal axis). The vertical axis on the left measures the resulting coefficient for Facebook Speakers, and the vertical axis on the right the number of languages that are considered as "treated" under each threshold (which

[27] We use the levels of the indices (rather than dividing the sample by quantiles, for example) because they build on the conceptual framework used in each case to determine whether a country fares low or high in democracy and governance, irrespective of whether few or many countries are very democratic or functional.

[28] We follow Holman (2014), who points out that the best way to compute a similarity index for languages k and i involves three steps. First, computing the *Levenshtein Distance (LD)* for each word between both languages i and k (where LD is the minimum number of characters that must be replaced for one of them to be identical to the other). Second, normalizing LD for the maximum length of the word in both languages *(LDN)*. Finally, the pairwise similarity index is one minus the ratio between the average LDN between words with the same meaning and the average LDN between words with different meanings.

obviously decreases as we increase the similarity threshold). As expected, Facebook's impact is slightly larger when similar languages are considered treated, but the change is very small and the effect of Facebook Speakers is very stable regardless of the threshold used. Therefore, these potential spillovers don't appear to bias our baseline estimates significantly.[29]

3.4 Subnational variation and additional results

Table 5 presents the results for the subnational level regressions described in equation (3). In column 1 we look at total protests as the dependent variable. The coefficient for Facebook Speakers is, as with the national-level regressions, positive and precisely estimated (0.38 with standard error 0.06). This implies close to a 38% increase in protests when Facebook Speakers increase from zero to one hundred percent. This is larger than the magnitude in national regressions, where the effect is likely attenuated by averaging regions that are heavily treated and others that are not when Facebook appears in one new local language. To compare the implications, in Panel B of Figure 4 we replicate the counterfactual exercise we conducted using the national-level estimates. Again, we plot total observed of protests and protests assuming Facebook was never launched (i.e., imposing zero Facebook Speakers throughout), and the resulting cumulative difference since Facebook first appeared. These calculations imply that Facebook accounts for close to 22% additional protests over our sample period (recall the corresponding number using the national-level estimates is 14%).

In columns 2 to 7, we examine the impact on different types of protests. Protests are classified as demonstrations, hunger strikes, strikes or boycotts, blocks, violent protests and other political protests.[30] Facebook Speakers significantly increases all types of protests. [31] Thus, the subnational level analysis reaffirms the very robust, positive, and generalized effect of Facebook access on protests. Moreover, since we are including fully flexible country-level temporal trends, these specifications relax our identification assumption and rely on more

[29] Another idea is that if language is a barrier to access Facebook, the writing system might also keep some people away from the platform. To explore this idea, in Figure A-2 we decompose the total effect of Facebook Speakers taking into account whether the language in question is also the first one in the corresponding writing system. Thus, for instance, English was the first language in Latin, Arabic the first in Arabic and Russian the first in Cyrillic (Spanish, Panjabi and Serbian came second in each of the writing systems, respectively). Though the coefficients are measures with considerable noise, the pattern is clear that the impact of Facebook Speakers is larger for the first language in the writing system, followed by the second one, third and so on.

[30] See Schrodt (2012) for more information.

[31] In similar regressions at the country level Facebook Speakers also has a positive coefficient for all types of protests, and is statistically significant at conventional levels with the only exception of hunger strikes and violent protests.

fine-grained variation than country-level regressions.[32]

To explore the possibility that reporting errors may be driving our findings (an issue that we examine in more detail below and also probe with the individual-level regressions), we use the Armed Conflict Location & Event Data Project (ACLED). This is a public collection of political violence and protest data for Africa since 1997. As GDELT, this database is daily and georeferenced. But it has been more widely used and, while also media-based, information is complemented with reports from NGO's and "hand-checked". One limitation is that it is not available worldwide. Panel A in Figure A-5 shows the total number of protests reported on GDELT and ACLED for Africa since Facebook was originally released. The number in reported protests on GDELT is larger. There is, however, a strong correlation between both measures, with a correlation coefficient of 88.12%. It appears that, if anything, ACLED protests grow somewhat faster than GDELT since Facebook was launched. This suggests that the growth in GDELT protests is not likely to merely reflect a rise in reported but not actual protests after Facebook.

Also, consistent with our findings so far, column 8 in Table 5 shows that Facebook Speakers increase ACLED protests, and the magnitude (coefficient 0.36) is very similar to the baseline in column 1. For comparison, column 9 uses GDELT just for Africa, and the coefficient is smaller (0.23) than when we rely on ACLED. In Panel B of Figure A-5, we further compare the implied sizes by conducting once again the counterfactual analysis assuming no Facebook Speakers and plotting the cumulative difference with observed protests. While GDELT predicts Facebook accounts for a bit under 2% additional protests in our sample period, ACLED's estimates imply somewhat more than a 4% increase.

Finally, we focus on two important heterogeneous effects. First, in column 10 we take advantage of the subnational variation to interact with Facebook Speakers an indicator variable for whether the region is the ethnic homeland of a discriminated ethnic group. Presumably,

[32] In Appendix Table A-5 we present additional robustness checks. Column 2 shows that our results do not depend on our inferred population totals for polygons with more than one language reported in Ethnologue or "overlapped zones". Dropping these overlapped zones produces negligible changes in our baseline estimates. In columns 3 to 5, we check the choice of the relevant subnational areas is also not important for the findings, by using administrative divisions and not just language polygons. These divisions are also appealing since they may be a relevant unit of analysis for political collective action. In column 3 we use the intersection of administrative divisions (the first level of administrative division, equivalent to US states) with language polygons as the unit of analysis. In column 4, we exploit this specification by incorporating month times state fixed effects, thus flexibly controlling even for sub-national trends in collective action. In column 5, we use states as the level of analysis. In every specification we find a positive and significant impact of Facebook Speakers on protests. Also, the magnitude of the impacts, once we recognize the changing scales of our variables, are similar across most specifications (we report the beta-coefficients in the lower row of the Table).

such areas have more grievances and thus might be more enticed to protests when new tools facilitating mobilization arrive. On the other hand, historical discrimination against these groups may curtail their ability to mobilize collectively. The interaction coefficient (-0.23, standard error 0.13), suggests that areas with discriminated ethnic social groups react less (the magnitude of the effect falls close to 50%) than other regions when Facebook Speakers increase.

Second, we interact with Facebook Speakers a full set of year fixed effects, to explore whether its influence has decreased or increased over time. Figure A-6 plots the resulting coefficients and shows a clear pattern of increasingly important effects of Facebook on protests. This is relevant for several reasons. First, it suggests that Facebook continues to be important for collective mobilization until recently. Second, it shows that even though marginal languages entering late in the sample represent a small fraction of the population in the world, their appearance in Facebook is nonetheless important for collective mobilization in regions where these languages are spoken. Finally, one concern with our results thus far could be that they reflect the financial crisis of 2008 since this year marks both the crisis and Facebook's expansion. If Facebook's expansion correlated with the spread of the crisis around the globe, our effects might be spurious. Instead, we find that Facebook matters not just during the crisis' years but also, and even more, much later on.

Table 6 sheds some light on the nature of the protests that Facebook access promotes by looking at the different protest targets. Target data is however very incomplete (close to half the sample have missing values), so it is important to start by checking if missing data correlates with Facebook Speakers. In column 1 we run our baseline regression for an indicator variable on whether the protest target is known or not. Facebook Speakers have a negligible and not significant impact on reporting protest targets. In column 2, we restrict our sample to the 47.7% of protests with a known target and run our baseline specification, finding a coefficient very similar to our baseline number from Table **??**. In columns 3-10 we then run regressions where the dependent variable is protests against specific targets (in each column title under the protest target, we report how common each type is, expressed as a share of total protests with known targets).

Protests against the government are the single most common category (25.4%) followed by armed forces (15.2%). Other protests against actors of the institutional regime, like the legislature (3.4%), are less common. Protests against civilians and the opposition are also relatively rare (6.7 and 4.7% respectively). Nevertheless, notice that protests against all actors respond to Facebook Speakers. Thus, while results showing increased opposition to the government, the army or the legislature fall in line with the notion that Facebook is mostly promoting citizen empowerment against the government, the findings for protests against the political opposition suggest the government's own ability to call up rallies to attack the opposition can also increase with Facebook.[33]

3.5 Additional robustness

We relegate several additional robustness tests to the Appendix and briefly describe them here. Table A-6 verifies that our results are not driven by outliers (column 1), and explores alternative transformations of the dependent variable (columns 2-6). Our estimates are very similar when removing outliers (defined as observations with residuals in the upper or lower 2.5% of the distribution for our baseline specifications).[34] Column 2 shows, as expected given the average incidence of protests (see footnote 15), that the inverse hyperbolic sine transformation produces results that are close to our baseline choice of $log(1 + protests)$. Column 3 examines results for the extensive margin, running a simple linear probability model for the binary indicator of protests. The coefficient is positive in both the national-level and subnational-level specifications (Panels A and B respectively), though only statistically significant in the latter. Instead, examining indicators for an unusually large amount of protests (more than the median incidence, in column 4, or than the average, in column 5) reveals a positive and very significant relation with Facebook Speakers in both panels. Finally, column 6 ignores altogether the information on the number of protests in the month and finds that Facebook Speakers also increase a different measure of intensity that is less prone to errors in double-counting protests by the media: the number of days in the month with protests.

Table A-7 shows that our results are also robust to estimating nonlinear models, including quantile regressions for impacts at the median (column 1), a negative binomial regression (column 2), a zero-inflated negative binomial regression (column 3), and Logit and Probit models for the probability of having at least one protest (columns 4 and 5). We also estimated dynamic panel data models (Table A-8) which incorporate lagged protests at the

[33]Protests against business, labor, and the media (which is defined broadly to include journalists, newspapers, television stations, but also providers of internet services and other forms of mass information dissemination and therefore also akin to businesses or public sector providers) also react to Facebook Speakers, even though they are relatively infrequent (less than 4% of protests with known targets in each case).

[34]Also, if we use Cook's D criteria (Cook, 1977) for detection of influential observations, common rules of thumb as using $D > 0.5$ to identify outliers suggest that in our regressions we have no such unusually influential data points.

right-hand side of the equation and instrument these with longer lags as suggested by the generalized method of moments estimator originally proposed by Arellano and Bond (1991). The effect of Speakers remains robust to acknowledging persistence in the dependent variable.[35]. Also, while we prefer the continuous Facebook Speakers measure taking advantage of all the variation in potential access to Facebook, results are also similar with simple binary variables indicating whether there is a Facebook version in the most spoken language or in one language spoken for more than 50% (or 20%) of the inhabitants of country (Table A-9).

One final concern that deserves more attention is the possibility of reporting bias because Facebook makes protests more visible (e.g. creating spillovers on protest reporting), and therefore a fraction of the effect is explained because Facebook increases, not *actual* protests, but *reported* protests in GDELT (Weidmann, 2016). Crucially, recall that we found a generalized effect on very different types of protests. This is relevant substantively but also suggests effects cannot be fully accounted for by reporting spillovers when Facebook gains notoriety. Indeed, some types of protest events are likely relatively less visible and newsworthy, and these should be most influenced by increased reporting than others. Since Facebook Speakers increases all types of protests, pure reporting effects are not likely to explain our findings. Also, GDELT does not rely on Facebook as one of its sources, so any such effect would have to be indirect. Finally, ACLED incorporates more checks and produces similar effects as GDELT. But it still could be that smaller protests that went under the radar before the Facebook era are now detected, or that some protests that used to be ignored by the media for lack of interest or sources are now brought to their attention by Facebook.

Unfortunately, we do not have reliable information on the size of the protests from GDELT. But we can examine whether when there are more Facebook Speakers we observe more media outlets reporting a given protest. The motivation is that if certain media outlets with limited resources may now use Facebook as a primary source, we could now witness a change in the number of outlets reporting protests. In Panel A of Table A-10 we run our baseline specification using different features of the distribution of the number of outlets reporting protests as the dependent variable. Columns 1 to 4 report, respectively, the mean, median, 25th percentile, and 75th percentile of the number of news sources reporting each protest in each country-month. There is no evidence that Facebook Speakers change

[35] Also, we carried out several tests to check stationarity and reject the presence of unit root in the protest process. The null hypothesis in the Levin-Lin-Chu is strongly rejected (the adjusted $t-statistic$ is -90.8727). Since this test assumes that protest persistence is the same for all countries, we checked Dickey-Fuller tests for each country independently and always rejected the null hypothesis at 95% confidence

the distribution of the number of outlets presenting protests. This suggests that our effects are not simply capturing an increase in reported protests without any real impact on actual collective action episodes.

We also examine a related yet different source of reporting error in Panel B of Table A-10: that results are influenced by GDELT failing to successfully de-duplicate protests getting multiple reports. This would affect our estimates if Facebook directly affects this success rate (for instance by increasing the number of reports or the different stories around them). Following Manacorda and Tesei (2016), in Panel B-1 we construct an alternative measure of protests that treats events in the same location but classified as different in the data as a single event. Column 1 is the baseline, column 2 aggregates all columns within a day in a single location, column 3 takes a larger location grid with a resolution of 5km $\times$ 5km, and in column 4 one location represents an entire country. Even in the most conservative regression to avoid double-counting, we find similar qualitative results. Panel B-2 then combines geographic and temporal aggregation by counting as one all protests that occur in a week and landmark (column 1), week and 5km $\times$ 5km grid (column 2), month and landmark (column 3), month and 5km $\times$ 5km grid (column 4). Again, our results are not sensitive to these changes.

These checks all reinforce the idea that the Facebook Speakers variable matters because it increases Facebook access thus enabling collective action, not because it improves protest recording. However, we can further confirm this and explore additional implications, by relying on individual reports on protest participation which are completely independent of media reports. We turn to this approach in the next section.

4 Results from individual-level protest participation

We now turn to the individual-level analysis, relying on rounds of the European Social Survey, World Values Survey, and Afrobarometer. As shown in Table 1, protest participation is much higher in the World Values Survey and Afrobarometer (49 and 38% on average) than in the European Social Survey (7%). This may partly reflect the lower incidence of protests in European countries. However, this also reflects differences in the survey instruments. The European Social Survey asks whether respondents "have participated or not in a lawful public demonstration last 12 months?", and our protest indicator is one if the respondent answers yes and zero otherwise. In the case of the Afrobarometer and the World Values Survey, however, the response options include hypothetical participation, namely: "No, but would do if had the chance" in Afrobarometer and "Might do" in the World Values Survey.[36] In both surveys, we code the protest indicator as one if the respondent selects any of the straight *yes* categories ("Yes, once or twice", "Yes, several times", and "Yes, often" in Afrobarometer, or "Yes" in World Values Survey), or the hypothetical involvement options. The motivation is that these all signal a willingness to engage in protests, and it would not be reasonable to assume that those expressing willingness to participate fall into the "No" protest group. However, this obviously increases the incidence. Survey-wave fixed effects absorb any level effects that these different designs have on protest participation.[37] Not surprisingly, looking at the Facebook Speaker dummy, more people in our waves of the European Social Survey (39%) can interpret a Facebook platform in their first language than in the World Values Survey (19%) or Afrobarometer (14%) samples.

Table 7 shows the results from the individual-level regressions as in equation (4). In Panel A we pool all surveys, and regress the indicator variable for individual participation in protests on the Facebook Speaker dummy, with fixed effects controlling flexibly for heterogeneity at the country, time, and survey wave levels. Moreover, we allow each language in each survey to have differential patterns of protests, motivated by the idea that some groups may have more grievances and/or social capital than others. In case this varies by country, column 2 adds the full set of country times language and survey fixed effects. This specification is particularly flexible, allowing for potential differential participation in collective action activities by individuals who share specific linguistic backgrounds within a polity. Moreover, in columns 3 and 4 we also control for household and individual characteristics (age and sex in column 3, which are clearly predetermined) and education and wealth in column 4 (which probably do not react quickly to Facebook access but which we include separately since an argument could be made that these are "bad" controls). We also study each of the surveys separately, in Panels B-D.

The overall message of the table is again a very robust relationship between speaking a language already available in Facebook and protest participation. The average effect using the coefficients in Panel A implies that being a Facebook Speaker increases protest participation by a bit over 3 percentage points, from mean participation of 26%. Therefore,

[36]The questions read as follows. Afrobarometer: "Please tell me whether you, personally, have [participated in a demonstration or protest march] during the past year. If not, would you do this if you had the chance?". World Values Survey: "I'm going to read out some forms of political action that people can take, and I'd like you to tell me... whether you have ... attended peaceful demonstrations".

[37]Moreover, in Appendix Table A-11 we break down the effect on protest in these two surveys to the impact on expressing a mere intention to protest or to having effectively protested, and find that both indicators react to Facebook access.

close to a 12% increase. This masks some variation by survey, where the corresponding increases are: roughly 5 percentage points in the WVS with mean incidence of 0.49 (close to a 10% average increase), 1.5 percentage points in the ESS with mean incidence of 0.07 (a low absolute change but comparably larger 20% increase given the low base level) and about 10 percentage points in the Afrobarometer (the largest percent increase nearing 25% from a base average of 38%).

In Table 8 we examine who responds more to Facebook access. This table breaks down the reported average effects by age group, gender, level of education, and levels of income. The effect of speaking a language available on Facebook is very widespread. It is present and similar for most types of individuals, with some exceptions. In the European Social Survey and World Values Survey samples, the effect appears to be concentrated on women. Also, perhaps surprisingly since these tools might more likely be used by younger people, the coefficient for people over 55 in the World Value Survey (an to a lower extent in the European Social Survey) is larger than for the other age groups. Finally, in the Afrobarometer the relatively more educated exhibit a larger effect of Facebook accessibility, unlike in the other samples where the effect is relatively constant (point estimates, in fact, are higher for the less educated). This may reflect that in Africa education is a barrier to technological access more than it is in the other surveys' samples, where the impact of Facebook Speakers is very generalized. Along the same lines, though much less noticeably, the point estimates for Afrobarometer tend to increase with income and the opposite happens in the World Values Survey or European Social Survey.

Table 9 takes advantage of the wealth of information in the surveys to address two issues. First, whether Facebook access, while increasing protests, may decrease other forms of political participation or interest (Panel A). Second, whether it crowds out other sources of information (Panel B).

In the case of political participation and interest, we see no significant change in turnout, interest in politics or likelihood of signing a petition with estimated coefficients that are moreover small relative to the sample means. Membership in associations changes in the World Value Surveys, with a 7 percentage point drop (significant at the 90% confidence level) relative to a mean of 42%, a modest magnitude, and does not react in the other samples. Party identification does not change either, except for Afrobarometer (where the negative coefficient, of 0.03 for a mean identification of 2.87, is significant at the 90% level). Finally, attending meetings of an association, holding some sort of position of political leadership, and the likelihood to discuss politics (available for Afrobarometer only) again show modest, not significant effects of Facebook Speakers.

Since we look at multiple outcomes, we also explore the effect on a normalized average (rescaling all variables to be in the $[0, 1]$ interval) of all available measures of political interest and involvement. The conclusion is clear that being a Facebook Speaker in these surveys does not change political participation. Relative to the average index (0.38, 0.43 and 0.48 in WVS, EES and Afrobarometer respectively) the Speaker effect is in each case a precisely measured zero (effects are merely 0.006, 0.004, 0.006, respectively). In short, political participation and interest does not seem to be weakened (or strengthened) with Facebook access.

A similar conclusion emerges when looking at the use of other sources of information. The coefficient on Facebook Speaker in regressions for relying on Radio, TV, or newspapers as sources of information is not significant in any survey (in the European Social Survey, only the question on TV is available). Also, the magnitudes are small relative to the mean. As with political participation, in the bottom row we use the average for the set of political participation and information outcomes to reduce pote, and encounter again precisely measured non-effects.

These results contradict the fears that online social networks displace other forms of political engagement or sources of information voiced in the literature and discussed in the introduction.

Finally, with one wave of the Afrobarometer, we can check whether being a Facebook Speaker increases social media (Facebook or Twitter[38]) access. We find, consistent with the cross-country analysis, that having a Facebook version in one's language increase the likelihood of reporting using Facebook or Twitter in 11 percentage points, from a mean incidence of 17.5%. This strong effect further validates our proposed source of variation to study the impact of Facebook.

5 Conclusion

We study Facebook's effect on collective action on a global scale. Our empirical strategy overcomes the challenges in estimating the causal impact of social media on political outcomes. Social media is obviously correlated with a variety of relevant socio-economic characteristics that may influence politics through other channels. Reverse causality is also an issue. Even if we know that people use online social networks to prepare and during

[38]Unfortunately, a separate question for Facebook is not available, and the remaining surveys do not inquire about Facebook use.

protests, they might simply substitute other instruments for protests that would have taken place regardless. Hence, simple correlations between social media access and collective action or political participation have to be interpreted with caution before jumping to conclusions about causality.

To deal with these issues, we exploit the release of Facebook in a given language as an exogenous source of variation in access to social media in countries, regions, and among people speaking such language. Following this approach, we examine in a large panel of countries whether Facebook increases various forms of collective action and, relying on individual-level data, other forms of political engagement and interest as well as reliance on other sources of information. To the best of our knowledge, this is the first paper uncovering a causal effect of Facebook on protests at a global scale using a credible identification strategy, in spite of the abundant journalistic, academic, and case-study evidence suggesting the link. We find robust evidence that social media increases collective action. The effect appears when exploiting different sources of variation, including when we focus simply on within-country changes in Facebook access areas with different languages, as well as if we rely on media-based or individual reports of protest participation.

Our estimates imply a cumulative effect of 14 to 22% additional protests since Facebook originally launched depending on the specification. At the individual level, being a Facebook Speaker increases participation by 12% on average, with an effect ranging from 10% to 25% depending on the sample. We also show the types of countries and people who are more likely to respond to increased Facebook access with mobilization. While we find considerable heterogeneity as a function of country features, in contrast, our estimates suggest that very different types of people respond to Facebook access by increasing protest participation.

Finally, we fail to find important negative impacts on other forms of political participation or news consumption, contradicting fears that Facebook has displaced offline activity or other sources with more news content. The impact on protests, together with no signs of crowding out of other activities, is important beyond improving our understanding of the determinants of collective action. It is also relevant given the increasing evidence that protests matter for key political outcomes (e.g., Collins & Margo, 2007; Madestam, Shoag, Veuger, & Yanagizawa-Drott, 2013; Acemoglu et al., 2014; El-Mallakh, Maurel, & Speciale, 2016; El-Mallakh, 2017).

Of course, having established that Facebook does cause protests, many interesting questions emerge, including whether these protests have discernible additional effects, as in elections, policy, and regime change or regime repression. We leave this matter for future research as a key next step. This is of course also relevant to gauge the welfare consequences of our findings. We have documented that the average effect of Facebook on collective action is positive, but the final resulting impact on social welfare depends on the broader implications of these effects on society. A long tradition going back at least to Olson (1965) emphasizes the importance of collective action to bring about "good" social outcomes. Along these lines, theories and evidence on democratization give protests a key role (Acemoglu & Robinson, 2006; Aidt & Franck, 2015; Aidt & Leon, 2016).

Some of our results, like the stronger impacts on undemocratic areas and places with limited press freedom, on protests against the government, as well as the absence of any visible reduction in other forms of political activity, line up with this tradition by suggesting that Facebook is acting in the direction of empowering people and unsettling traditional elites in contexts of weak accountability (Farrell, 2012). Those results could dissipate fears that the Internet and social media in particular could facilitate control and propaganda by authoritarian regimes, empowering a small set of elites (Hindman, 2009), facilitating control of citizen collective action (Morozov, 2012, 2014; King et al., 2013), or spreading misinformation (Silverman, 2016; Silverman & Singer-Vine, 2016; Allcott & Gentzkow, 2017; Munger, Egan, Nagler, Ronen, & Tucker, 2017; Allcott, Gentzkow, & Yu, 2019). However, it would be adventurous to ascertain that social media is unambiguously a "liberation" technology. As any general-purpose technology, it can do much else, so the broader (and changing) implications as different players adapt are still up for debate (J. A. Tucker, Theocharis, Roberts, & Barberá, 2017). Our findings suggest that protests against the opposition also increase and that the additional mobilizations also include violent ones, results that may have negative welfare consequences.

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Table 1: Summary Statistics

	Descriptive Statistics					
	Observations	**Mean**	**Median**	**SD**	**Min**	**Max**
Panel A. Main variables country analysis, 2000.1-2015.12 (240 countries)						
Protests	46,080	63.36	5.00	364.06	0.00	16,951.00
log(1+Protests)	46,080	2.04	1.79	1.88	0.00	9.74
Facebook Speakers	46,080	0.18	0.00	0.34	0.00	1.00
Facebook Searches	45,120	0.19	0.01	0.24	0.00	0.69
Facebook Users	10,359	1.30	0.00	4.18	0.00	18.87
Panel B. Controls, Pre-2004						
Population (millions)	240	24.63	3.75	107.27	0.00	1,258.37
GDP per capita (thousands of dollars)	214	13.72	4.10	20.25	0.20	141.10
Internet users (millions)	214	3.15	0.11	13.65	0.00	169.01
Linguistic polarization	214	0.47	0.50	0.27	0.00	1.00
People aged between 15 and 24 (millions)	214	0.18	0.19	0.07	0.00	0.82
GDP per capita in manufacturing (% GDP)	214	0.23	0.12	1.54	0.00	22.60
Panels C: Main variables subnational analysis (4,777 jurisdictions)						
Protests	917,184	2.06	0.00	40.95	0.00	8,851.00
log(1+Protests)	917,184	0.16	0.00	0.65	0.00	9.09
Facebook Speakers	917,184	0.04	0.00	0.18	0.00	1.00
Only Africa...						
log(1+Protests), GDELT	131,904	0.24	0.00	0.71	0.00	8.55
log(1+Protests), ACLED	131,904	0.06	0.00	0.31	0.00	5.26
Facebook Speakers	131,904	0.00	0.00	0.06	0.00	1.00
Panel D. Main variables individual analysis						
Protest (All surveys)	704,122	0.26	0.00	0.44	0.00	1.00
Facebook Speaker (All surveys)	704,122	0.30	0.00	0.46	0.00	1.00
Protest (World Value Survey)	238,566	0.49	0.00	0.50	0.00	1.00
Facebook Speaker (World Value Survey)	238,566	0.19	0.00	0.40	0.00	1.00
Protest (European Social Survey)	341,115	0.07	0.00	0.25	0.00	1.00
Facebook Speaker (European Social Survey)	341,115	0.39	0.00	0.49	0.00	1.00
Protest (Afrobarometer)	143,526	0.38	0.00	0.48	0.00	1.00
Facebook Speaker (Afrobarometer)	143,526	0.14	0.00	0.35	0.00	1.00

Notes: In Panel A, the unit of observation is a month-country. In Panel B a country. In Panel C a region within a country and month. In Panel D an individual in a survey wave. Facebook Speakers is the proportion of people speaking (as first language) a language available in Facebook in each country and month, and Facebook Speaker an indicator variable for whether the respondent's main language is available in Facebook. Facebook Searches is the google trends index for intensity of searches for the word "Facebook" in each country-month. For all variable definitions and sources see Appendix Table A-1.

Table 2: Protests and Facebook
The Effect of Facebook Speakers

	(1)	(2)	(3)	(4)
Panel A. The effect of Facebook Speakers on protests				
Dependent variable is $log(1 + protests)$				
Facebook Speakers	0.2649***	0.2213***	0.2350***	0.2699***
	(0.0764)	(0.0788)	(0.0839)	(0.0868)
Semi-elasticity (exact formula)	0.2690***	0.2248***	0.2386***	0.2741***
	(0.0776)	(0.0800)	(0.0852)	(0.0881)
Panel B. Validating Facebook Speakers with google searches				
Dependent variable is Facebook Searches				
Facebook Speakers	0.0931***	0.0834***	0.0787***	0.0655***
	(0.0185)	(0.0212)	(0.0225)	(0.0229)
Semi-elasticity (exact formula)	0.4773***	0.4274***	0.4033***	0.3358***
	(0.0948)	(0.1085)	(0.1154)	(0.1176)
Observations (Panels A-B)	44,928	44,928	40,896	40,896
Countries (Panels A-B)	234	234	213	213
Panel C. Correlation of google searches and Facebook users				
Dependent variable is Facebook Searches				
Facebook Users	0.0563***	0.0603***	0.0603***	0.0552***
	(0.0060)	(0.0089)	(0.0089)	(0.0088)
Panel D. Validating Facebook Speakers with users data				
Dependent variable is Facebook Users				
Facebook Speakers	1.3326***	1.0552***	1.0552***	0.6736***
	(0.3455)	(0.2898)	(0.2898)	(0.2510)
Observations (Panels C-D)	10,357	10,357	10,357	10,357
Countries (Panels C-D)	115	115	115	115
Country fixed effects×linear trend	✓	✓	✓	✓
Country fixed effects×quadratic trend		✓	✓	✓
Controls×Time fixed effects				✓

Notes: Monthly data from January of 2000 to December of 2015 in Panels A and B, and yearly data from 2000 to 2015 in Panels C and D. All regressions include country and time (month in Panels A and B, year in Panels C and D) fixed effects as well as initial population interacted with time fixed effects. Facebook Speakers is the proportion of people speaking (as first language) a language available in Facebook in each country and month. Facebook Searches is an index of search interest for the term "Facebook" from Google Trends. Facebook Users, available for a subset of country-years, is the number of registered Facebook users. Controls, measured in the pre-treatment period, include initial GDP and share of GDP per capita in manufacturing, population, share of population between 15 and 24 years old, internet users and language polarization. Semi-elasticity (exact formula) is the percent increase in the dependent variable caused by a change from zero to one hundred percent Facebook Speakers. We compute this elasticity analytically and use the delta method for its standard error. Two-way clustering of standard errors at the month and country level.

Table 3: Protests and Facebook Speakers
Reverse Causality: Excluding Major Countries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable is $log(1 + protests)$									
	Excludes, per language...								
	...largest country by:							*...worst country by:*	
	Population	GDP	Internet	Protests	GDP per capita	Internet per capita	Protests per capita	Rule of law	Control of corruption
Panel A. Excluding any language									
Facebook Speakers	0.2692**	0.2809**	0.2749**	0.3148**	0.3517***	0.3975***	0.3781***	0.3704***	0.3854***
	(0.1112)	(0.1118)	(0.1071)	(0.1190)	(0.1129)	(0.1120)	(0.1197)	(0.1117)	(0.1070)
Observations	11,520	11,520	12,864	11,328	11,712	14,016	11,328	14,208	14,976
Countries	60	60	67	59	61	73	59	74	78
Panel B. Excluding only languages available in Facebook platforms									
Facebook Speakers	0.3647***	0.3650***	0.3522***	0.3736***	0.3611***	0.3425***	0.4030***	0.3371***	0.3521***
	(0.1074)	(0.1075)	(0.1031)	(0.1055)	(0.1021)	(0.0994)	(0.0984)	(0.1004)	(0.1016)
Observations	34,944	34,752	34,752	34,944	35,328	35,136	35,520	35,520	35,328
Countries	182	181	181	182	184	183	185	185	184

Notes: Monthly data from January of 2000 to December of 2015. All regressions include country fixed effects, month fixed effects, initial population interacted with time fixed effects and country-specific quadratic trends. Facebook Speakers is the proportion of people speaking (as first language) a language available in Facebook in each country and month. Two-way clustering of standard errors at the month and country level.

Table 4: Protests and Facebook Speakers
Heterogenous Effects with Country Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable is log(1 + protests)						
	Panel A. Facebook Speakers × ...					
	Internet users	No freedom of assembly or association	Repressed opposition	GDP Growth	Month of elections	Years of schooling
Facebook Speakers	0.2129***	0.1920**	0.1766*	0.1669*	0.2241***	0.1121
	(0.0813)	(0.0900)	(0.0913)	(0.0848)	(0.0777)	(0.0927)
Facebook Speakers × ...	0.0690***	0.2587***	0.2741**	-0.0827*	-0.1308*	0.1533**
	(0.0242)	(0.0944)	(0.1163)	(0.0424)	(0.0788)	(0.0758)
GDP growth				-0.0722***		
				(0.0177)		
Month of elections					0.2245***	
					(0.0435)	
Observations	42,048	37,056	32,064	38,424	46,080	36,672
Countries	219	193	167	209	240	191
	Panel B. Facebook Speakers × ...					
	Linguistic fragmentation	Linguistic polarization	Diamond production	Oil reserves	Oils and gas rents per cap.	Share urban population
Facebook Speakers	0.1649*	0.2035**	0.2355***	0.2284**	0.1859**	0.1570*
	(0.0945)	(0.0793)	(0.0894)	(0.0915)	(0.0872)	(0.0855)
Facebook Speakers × ...	-0.0955	-0.0631	0.1103***	0.0352*	0.1257**	0.1661*
	(0.0836)	(0.0597)	(0.0293)	(0.0181)	(0.0571)	(0.0884)
Observations	46,080	46,080	28,992	28,992	32,832	41,472
Countries	240	240	151	151	171	216

Notes: Country-level regression with monthly data from January of 2000 to December of 2015. All regressions include country fixed effects, month fixed effects, initial population interacted with time fixed effects, and country-specific quadratic trends. Facebook Speakers is the proportion of people speaking (as first language) a language available in Facebook in each country and month. Column 1 in Panel A includes the interaction of Facebook Speakers with population as an additional control. Repressed Opposition and Month of elections are dummies. All other variables used in interactions are standardized. Two-way clustering of standard errors at the month and country level.

Table 5: Protests and Facebook Speakers
Subnational Variation and Additional Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Dependent variable is $ln(1 + protests)$										
	Main	Political protests	Demons-trations	Hunger strikes	Strikes or boycotts	Blocks	Violent protests	ACLED (Africa)	GDELT (Africa)	Main
Facebook Speakers	0.3793***	0.1761***	0.3725***	0.0811***	0.1512***	0.0792***	0.1428***	0.3631**	0.2334**	0.4282***
	(0.0593)	(0.0309)	(0.0581)	(0.0206)	(0.0297)	(0.0198)	(0.0282)	(0.1573)	(0.0881)	(0.0679)
Facebook Speakers × Discriminated ethnic groups										-0.2307*
										(0.1301)
Observations	904,704	904,704	904,704	904,704	904,704	904,704	904,704	131,136	131,136	904,704
Polygons	4,712	4,712	4,712	4,712	4,712	4,712	4,712	683	683	4,712

Notes: Each observation is a language polygon (region) within a country, with data from January of 2000 to December of 2015. All regressions include fixed effects for each country and month, region fixed effects and initial regional population interacted with month fixed effects. Facebook Speakers is the share of the population in each region within a country speaking (as first language) a language already available in Facebook. Two-way clustering of standard errors at the month and country level.

Table 6: Protests and Facebook Speakers
Protest Targets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Protest share with known target	*Dependent variable is log of one plus the number of protests against each target... In parentheses under each title: share of total protests (col. 2) share of total protests with known target (cols. 3-10)*									
		Known target (47.7%)	Armed forces (15.2%)	Legislature (3.4%)	Government (25.4%)	Political opposition (6.7%)	Education (4.5%)	Media (3.6%)	Civilians (4.7%)	Business (3.6%)	Labor (2.4%)
Facebook Speakers	0.0088	0.3311***	0.1552***	0.0875***	0.1983***	0.1068***	0.0990***	0.0762***	0.0943***	0.0870***	0.0744***
	(0.0117)	(0.0528)	(0.0282)	(0.0202)	(0.0365)	(0.0222)	(0.0249)	(0.0158)	(0.0227)	(0.0193)	(0.0185)
Observations	64,062	904,704	904,704	904,704	904,704	904,704	904,704	904,704	904,704	904,704	904,704
Polygons	2,280	4,712	4,712	4,712	4,712	4,712	4,712	4,712	4,712	4,712	4,712
Beta coefficient	[0.004]	[0.116]	[0.111]	[0.123]	[0.115]	[0.111]	[0.125]	[0.101]	[0.111]	[0.121]	[0.120]

Notes: Each observation is a language polygon (region) within a country, with data from January of 2000 to December of 2015. All regressions include fixed effects for each country and month, region fixed effects and initial regional population interacted with month fixed effects. Facebook Speakers is the share of the population in each region within a country speaking (as first language) a language already available in Facebook. Protests are classified by target (when known) as follows. Armed forces: police forces, officers, criminal investigative units, protective agencies and troops, soldiers, all state-military personnel/equipment. Legislative: parliaments, assemblies, lawmakers, references to specific legislative entities or sub-entities such as committees. Government: the executive, governing parties, coalitions partners, executive divisions. Political opposition: opposition parties, individuals, anti-government activists. Education: educators, schools, students, or organizations dealing with education. Media: journalists, newspapers, television stations also includes providers of internet services and other forms of mass information dissemination. Civilians: Civilian individuals or groups sometimes used as catch-all for individuals or groups for whom no other role category is appropriate. Business: businessmen, companies, and enterprises. Labor: specifically individuals in or elements of organized labor, organizations concerned with labor issues. Two-way clustering of standard errors at the month and country level.

Table 7: Individual-level Protest Participation and Facebook
The Effect of Facebook Speakers

	(1)	(2)	(3)	(4)
Dependent variable is indicator variable for protest participation				
Panel A. All surveys				
Facebook Speaker	0.0310***	0.0328***	0.0312***	0.0334***
	(0.0084)	(0.0086)	(0.0086)	(0.0097)
Observations	704,034	703,644	703,644	703,644
Countries	123	123	123	123
Country × Year × Survey fixed effects	✓	✓	✓	✓
Language × Survey fixed effects	✓			
Country × Language fixed effects × Survey		✓	✓	✓
Age + Sex			✓	✓
Education + Wealth				✓
Panel B. World Value Survey				
Facebook Speaker	0.0529***	0.0573**	0.0539***	0.0692***
	(0.0186)	(0.0204)	(0.0188)	(0.0213)
Observations	238,536	238,456	238,456	238,456
Countries	90	90	90	90
Panel C. European Social Survey				
Facebook Speaker	0.0147**	0.0161***	0.0154***	0.0160**
	(0.0050)	(0.0047)	(0.0051)	(0.0055)
Observations	341,063	340,768	340,768	340,768
Countries	36	36	36	36
Panel D. Afrobarometer				
Facebook Speaker	0.0988***	0.0962***	0.0955***	0.0990***
	(0.0108)	(0.0150)	(0.0148)	(0.0168)
Observations	129,256	129,242	128,246	124,420
Countries	36	36	36	36
Panels B-D:				
Country × Year fixed effects	✓	✓	✓	✓
Language fixed effects	✓			
Country × Language fixed effects		✓	✓	✓
Age + Sex			✓	✓
Education + Wealth				✓

Notes: Individual data from several rounds of each survey. See list of rounds in Figure 2. In Panel B, Protest equals one if respondent answers "Yes" to the question "Have you ... taken part in lawful public demonstration last 12 months?". In Panel C, Protest equals one if respondent answers "Have done" or "Might do" to the question "I'm going to read out some forms of political action that people can take, and I'd like you to tell me ... whether you have ... attend peaceful demonstrations". In Panel D, Protest equals one if respondent answers "No, but would do if had the chance", "Yes, once or twice", "Yes, several times" or "Yes, often" to the question, "Please tell me whether you, personally, have done any of these things during the past year. If not, would you do this if you had the chance: Participated in a demonstration or protest march". In Panel A these definitions are used to define Protest when pooling all surveys. Facebook Speaker is a dummy that equals one if Facebook has been released in the language spoken by the respondent. Two-way clustering of standard errors at the year and country level.

Table 8: Individual-level Protest Participation and Facebook
The Effect of Facebook Speakers by Age, Gender, Education and Income

	(1)	(2)	(3)	(4)	(5)	(6)
	World Values Survey		*European Social Survey*		*Afrobarometer*	
Dependent variable is Protest						
Group	**Mean non speakers**	**Speakers effect**	**Mean non speakers**	**Speakers effect**	**Mean non speakers**	**Speakers effect**
Panel A: By Age Group						
Age $\in [18, 25]$	0.5187	0.0565**	0.1048	-0.0003	0.4218	0.1072***
	(0.0025)	(0.0270)	(0.0018)	(0.0070)	(0.0030)	(0.0153)
Age $\in (25, 40]$	0.5099	0.0372*	0.0761	0.0180**	0.3967	0.1035***
	(0.0019)	(0.0195)	(0.0012)	(0.0061)	(0.0023)	(0.0129)
Age $\in (41, 55]$	0.5034	0.0434**	0.0778	0.0110*	0.3711	0.0832***
	(0.0023)	(0.0176)	(0.0012)	(0.0060)	(0.0032)	(0.0184)
Age > 55	0.4027	0.1029***	0.0458	0.0237***	0.2996	0.0854*
	(0.0026)	(0.0186)	(0.0008)	(0.0058)	(0.0039)	(0.0419)
Panel B: By Gender						
Female	0.4402	0.0726***	0.0620	0.0201***	0.3649	0.0826***
	(0.0016)	(0.0162)	(0.0007)	(0.0043)	(0.0020)	(0.0220)
Male	0.5412	0.0365	0.0795	0.0098	0.4053	0.1073***
	(0.0016)	(0.0250)	(0.0009)	(0.0065)	(0.0021)	(0.0093)
Panel C: By Education Level						
Primary or less	0.3884	0.0784***	0.0557	0.0267**	0.3792	0.0833**
	(0.0019)	(0.0213)	(0.0011)	(0.0119)	(0.0017)	(0.0268)
Secondary	0.5065	0.0692***	0.0632	0.0285**	0.3923	0.0991***
	(0.0017)	(0.0222)	(0.0009)	(0.0112)	(0.0032)	(0.0090)
Tertiary	0.6235	0.0531***	0.1142	0.0166	0.4334	0.1435***
	(0.0024)	(0.0181)	(0.0015)	(0.0127)	(0.0061)	(0.0172)
Panel D: By Income						
Lowest income	0.4483	0.1083***	0.0520	0.0165***	0.3751	0.0776***
	(0.0019)	(0.0206)	(0.0010)	(0.0053)	(0.0024)	(0.0169)
Middle income	0.5063	0.0654**	0.0740	0.0159***	0.3851	0.0892***
	(0.0017)	(0.0263)	(0.0010)	(0.0050)	(0.0025)	(0.0137)
High income	0.5592	0.0357	0.0885	0.0170**	0.3946	0.1110***
	(0.0033)	(0.0285)	(0.0014)	(0.0072)	(0.0027)	(0.0219)

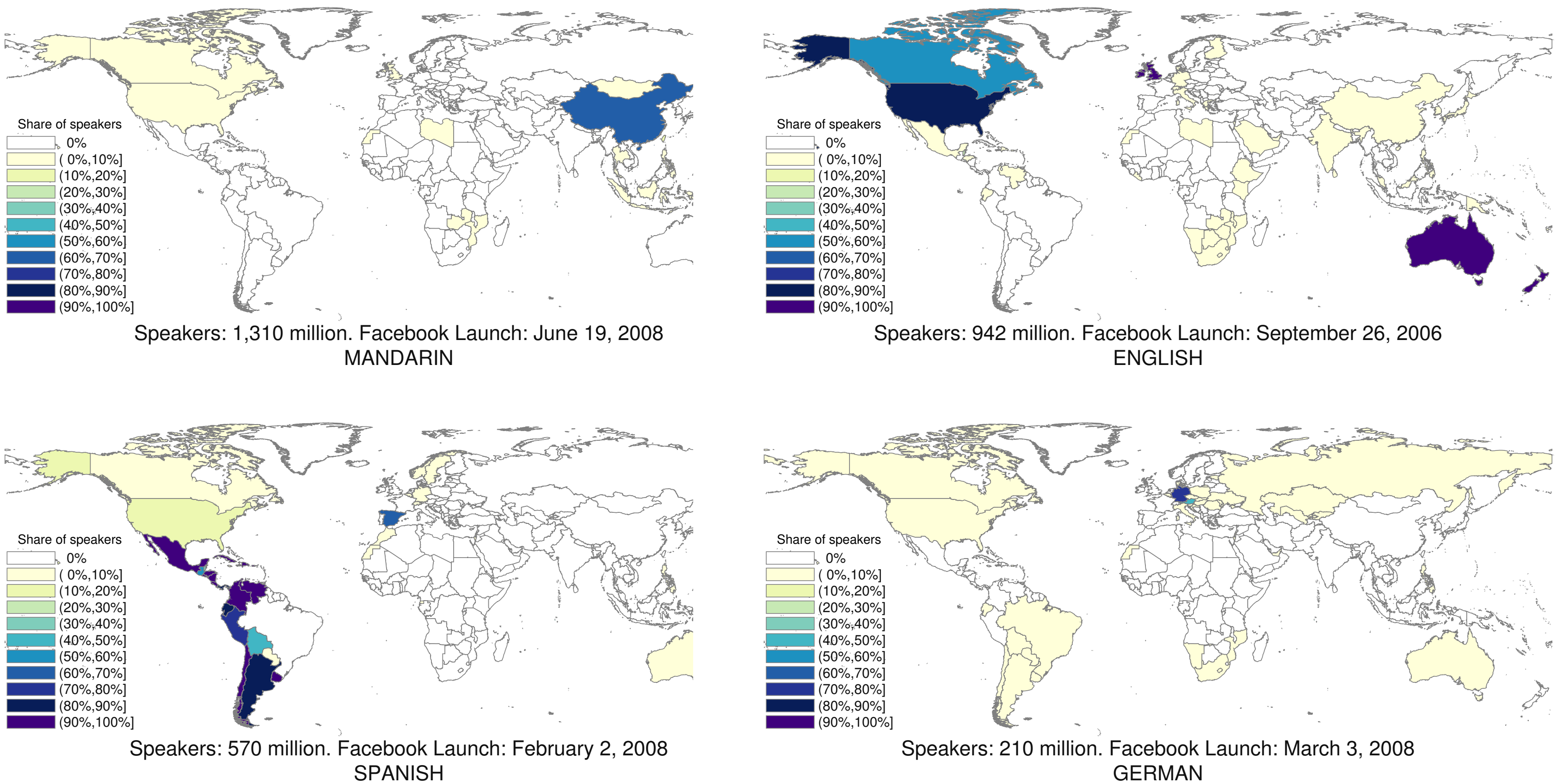
Notes: Individual data from several rounds of each survey. Odd columns report, for each sub-group, the average protest incidence (and its standard error) for non Facebook Speakers. Even columns report the coefficients of the interaction between Facebook Speaker and each sub-group in regressions with country × year fixed effects, country × language fixed effects, and sub-group fixed effects. The full set of sub-groups indicators are interacted with the Facebook Speaker dummy. Protest is defined as in footnote of Table 7. Facebook Speaker is a dummy that equals one if Facebook has been released in the language spoken by the respondent. Two-way clustering of standard errors at the month and country level.

Table 9: Political Participation, Information, and Facebook
The Effect of Facebook Speakers

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable indicated in each row						
	World Values Survey		*European Social Survey*		*Afrobarometer*	
Group	**Mean non speakers**	**Speakers effect**	**Mean non speakers**	**Speakers effect**	**Mean non speakers**	**Speakers effect**
Panel A. Other Political participation:						
Voted	0.7661	-0.0125	0.7802	-0.0025	0.7170	0.0119
	(0.0015)	(0.0219)	(0.0010)	(0.0101)	(0.0014)	(0.0135)
Interest in politics	2.3424	0.0418	2.4003	0.0162	0.2972	-0.0296
	(0.0022)	(0.0653)	(0.0020)	(0.0256)	(0.0014)	(0.0344)
Discusses politics					0.2118	-0.0152
					(0.0012)	(0.0216)
Political leader					0.0552	0.0011
					(0.0007)	(0.0056)
Member of association	0.4239	-0.0713*	0.2409	-0.0256	0.1914	-0.0022
	(0.0013)	(0.0403)	(0.0009)	(0.0287)	(0.0012)	(0.0054)
Attends assoc. meeting					0.8991	0.0550
					(0.0009)	(0.0425)
Signning a petition	0.3022	0.0096	0.2336	-0.0027	0.8639	0.0363
	(0.0020)	(0.0466)	(0.0009)	(0.0068)	(0.0010)	(0.0320)
Identity with party	0.0574	0.0078	2.8671	0.0280*	0.6165	-0.0132
	(0.0006)	(0.0174)	(0.0021)	(0.0150)	(0.0015)	(0.0170)
Normalized average	0.3878	0.0059	0.4311	-0.0044	0.4810	0.0062
	(0.0006)	(0.0108)	(0.0005)	(0.0098)	(0.0006)	(0.0125)
Panel B. Being informed by using the following sources:						
Radio	0.6408	-0.0659			0.7423	0.0422
	(0.0017)	(0.0577)			(0.0013)	(0.0228)
TV	0.6968	-0.0135	1.9544	0.0135	0.4323	0.0101
	(0.0016)	(0.0255)	(0.0031)	(0.0759)	(0.0015)	(0.0069)
Newspapers	0.5516	-0.0338			0.2013	0.0039
	(0.0017)	(0.0649)			(0.0012)	(0.0249)
Normalized average	0.6301	-0.0361	0.2792	0.0019	0.4593	0.0190
	(0.0013)	(0.0483)	(0.0004)	(0.0108)	(0.0010)	(0.0152)
Facebook or Twitter†					0.1754	0.1106***
					(0.0019)	(0.0007)

Notes: Individual data from several rounds of each survey. Odd columns report, for each sub-group, the average protest incidence (and its standard error) for non Facebook Speakers. Even columns report the coefficient for Facebook Speaker in regressions with country× year fixed effects, country × language fixed effects, and sub-group fixed effects. Protest is defined as in footnote of Table 7. Facebook Speaker is a dummy that equals one if Facebook has been released in the language spoken by the respondent. When computing averages, variables with a wider range are normalized to the [0,1] interval using $\frac{x-x_{min}}{x_{max}-x_{min}}$. Two-way clustering of standard errors at the month and country level.

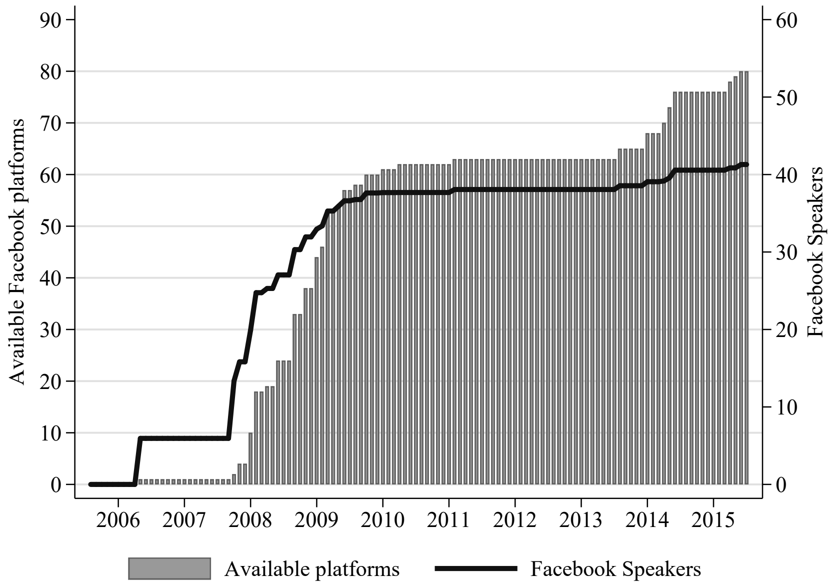
Figure 1: Distribution of some languages around the world



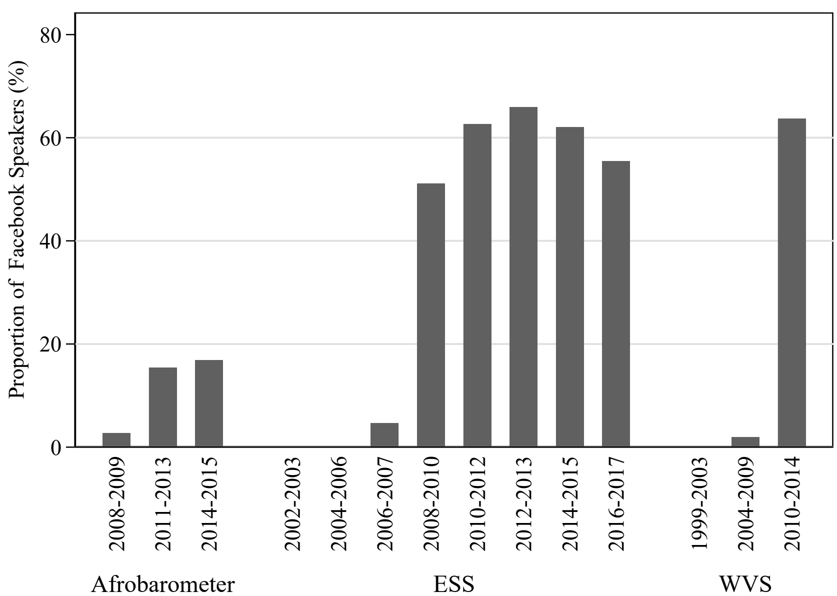
Notes: Share of country population speaking each language as their first language. Total speakers of the corresponding language and launch dates for the Facebook platforms indicated in each panel. Source: Ethnologue (version 16).

Figure 2: Facebook Language-Specific Versions and Facebook Speakers

Panel A. Number of Facebook versions (left axis) and Facebook Speakers (right axis)

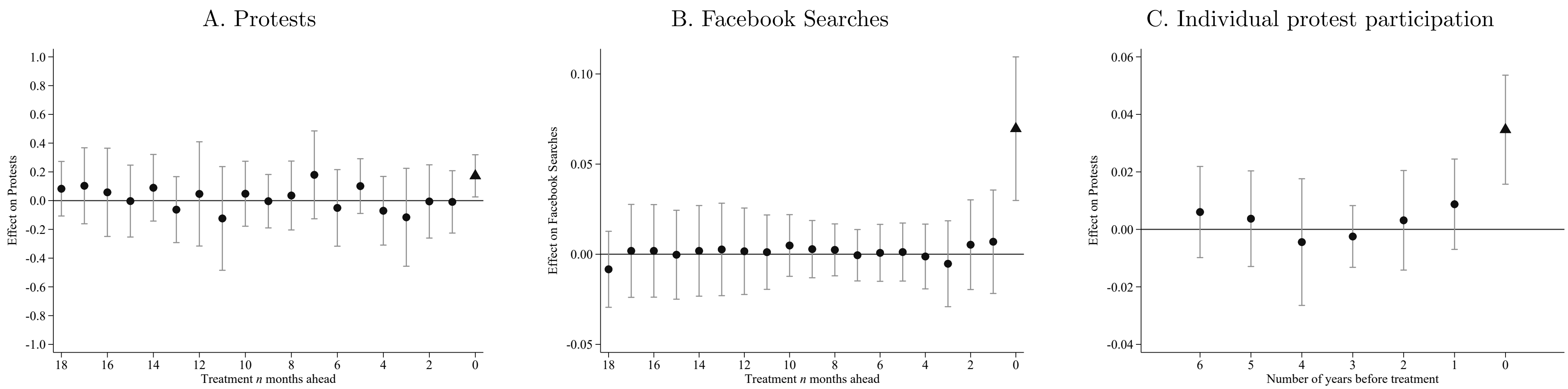


Panel B. Facebook Speakers in the survey data, by survey and wave



Notes: Facebook versions are language-specific platforms. Facebook Speakers is the average share of the population in each country (Panel A) or in each survey wave (Panel B) whose first language is available in a Facebook language-specific platform. ESS is European Social Survey and WVS is World Values Survey.

Figure 3: Parallel Trends in Protests Before Facebook
Exploring Anticipated Effects of Facebook Speakers

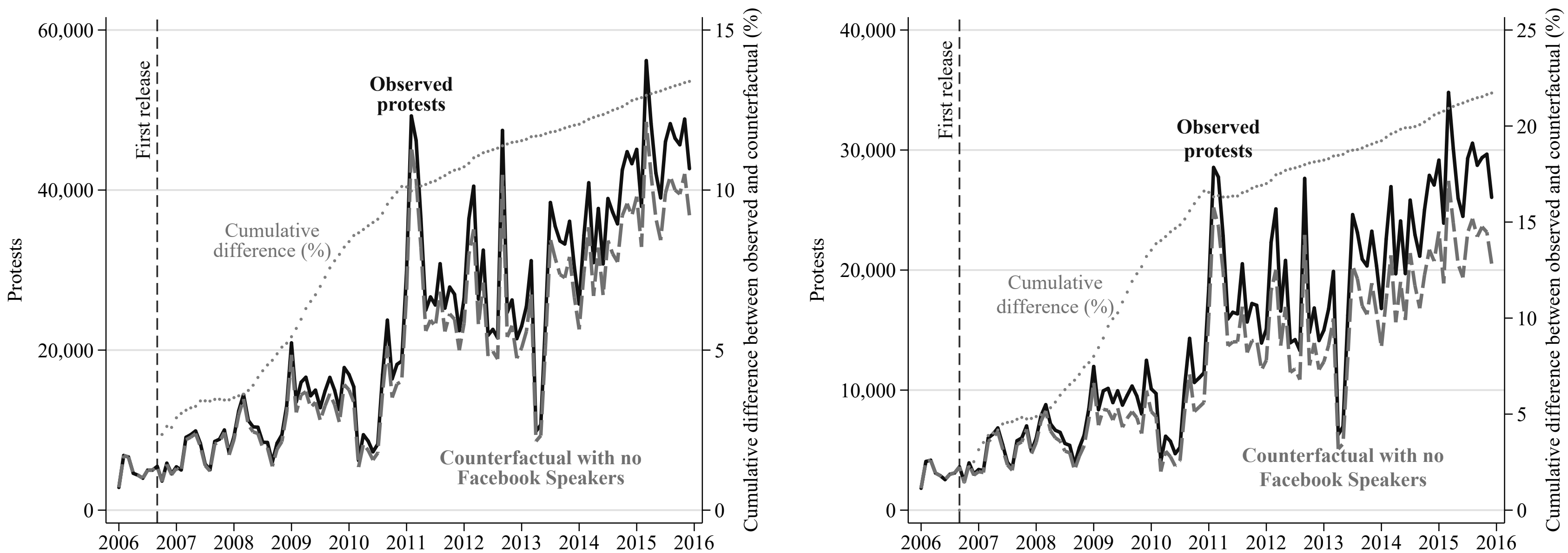


Notes: Panels A and B extend regression equation (1) to include anticipation effects (leads) of Facebook Speakers$_{ct+n}$, for n ranging from one to eighteen months, and Panel C extends equation 4 to include leads of Facebook Speaker$_{cit+n}$ for n ranging from one to 6 years. Each panel plots the coefficients and 95% confidence bands for each lead (as marked in the x-axis, and where lead zero is the treatment effect of Facebook Speaker(s)).

Figure 4: Implied Cumulative Effects of Facebook Speakers on Protests

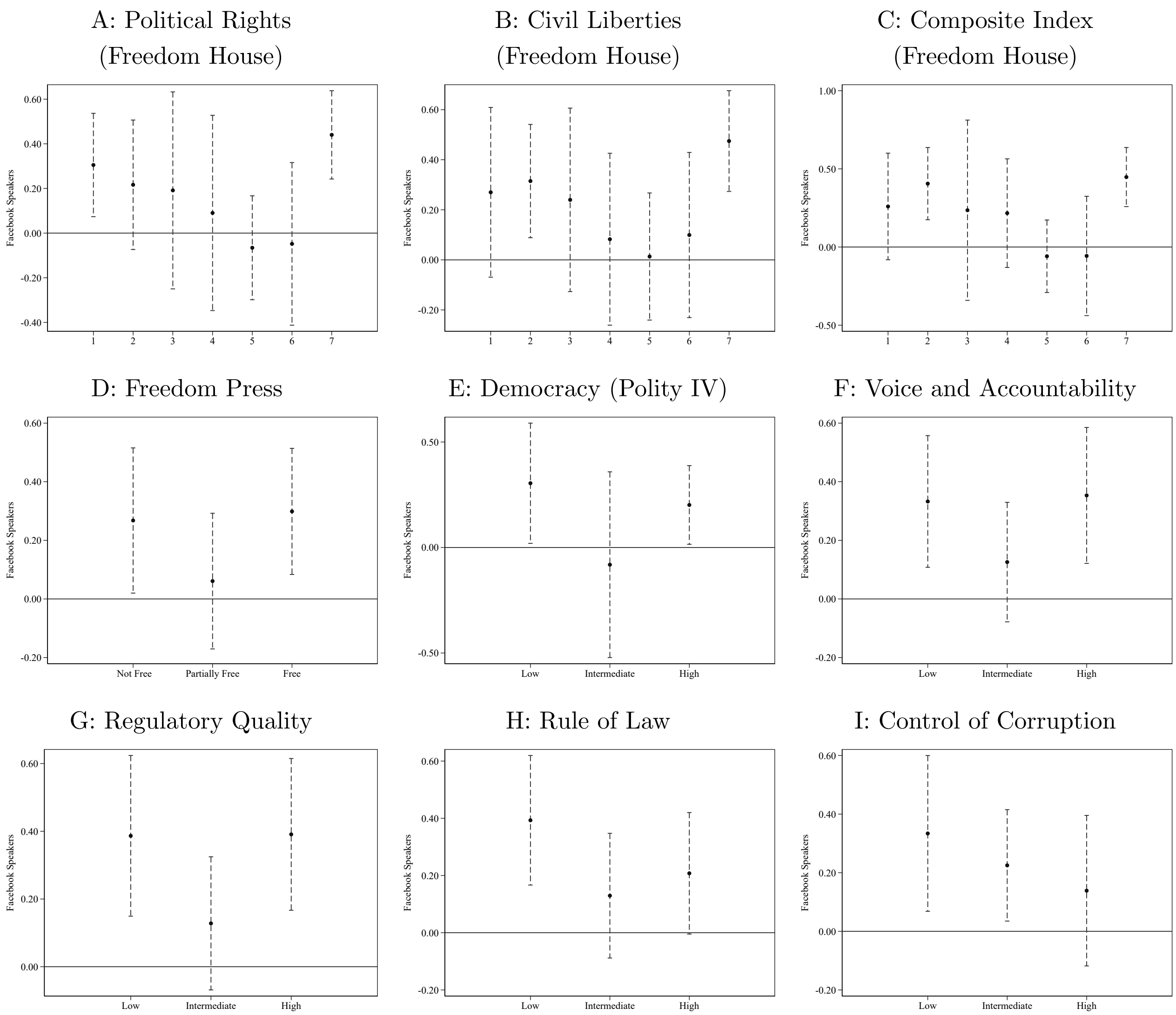
Panel A: National-level regressions

Panel B: Subnational-level regressions



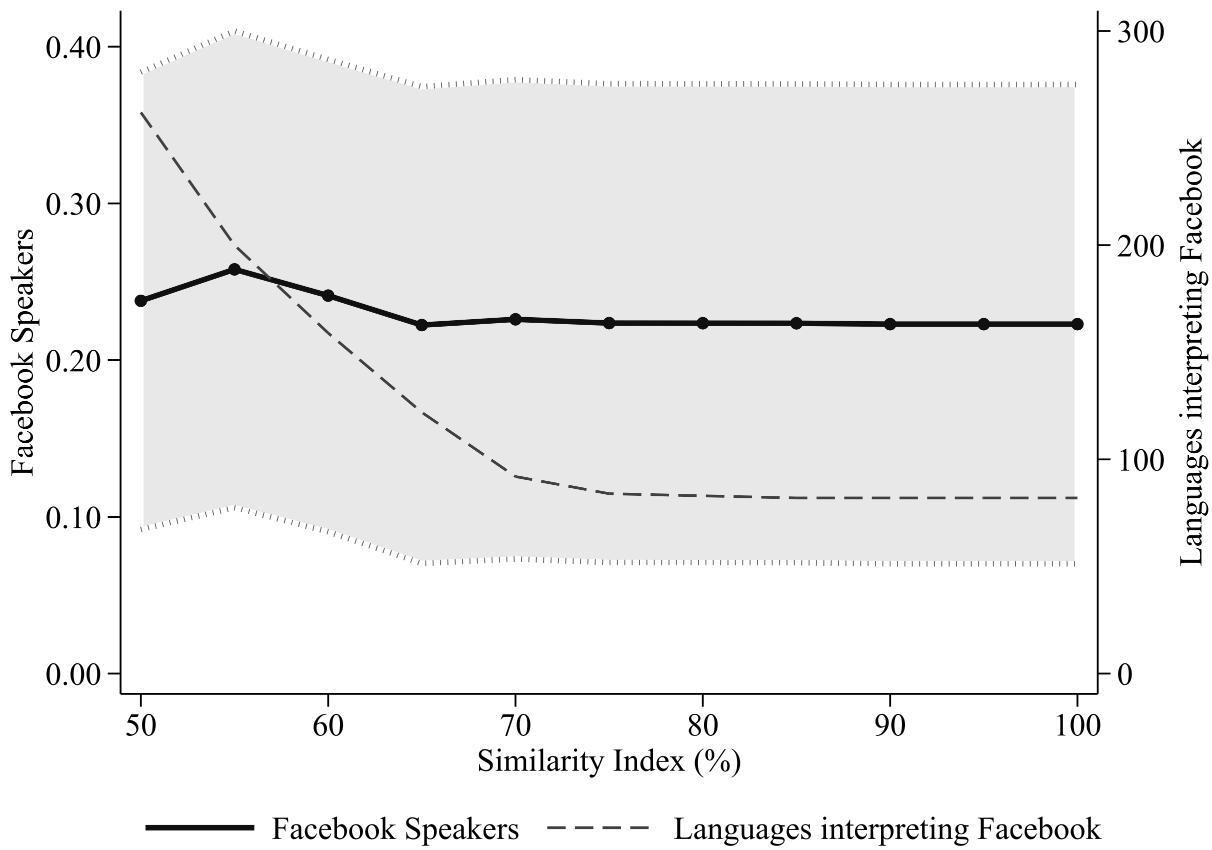
Notes: The solid line in each panel plots total observed protests in each month, from 2006 to 2015. The dashed line is the corresponding number of protests that would have been observed without Facebook (namely, if Facebook Speakers are held constant at zero throughout the period) as implied by our baseline national (Panel A) or subnational (Panel B) estimates. Finally, the dotted line is the cumulative difference since September of 2006 (when Facebook first appeared) between protests with and without Facebook (expressed as percent of total cumulative protests without Facebook up to each time period).

Figure 5: Facebook Speakers Impact by Features of the Political Regime



Notes: This figure is based on regression (1), extended to include the interaction of Facebook Speakers with indicator variables built with the measures of democracy and governance indicated in each Panel. We plot the effect (and 95% confidence bands) of Facebook Speakers on protests at different levels of the indicators. Since the Freedom House indices are constructed on a 7-point scale, we interact Facebook Speakers with dummy variables for each level and plot the coefficients. For Freedom Press we use the three categories “not free”, “partially free” and “free”. With the Polity IV and World Bank indices (ranging from -10 to 10 and from -5 to 5, respectively), we divide the scales in three equal parts (low, intermediate and high) and plot the coefficients for these interactions.

Figure 6: The Effect of Facebook Speakers on Protests Addressing Spillovers Between Similar Languages



Note: Estimates from regression in equation (1) with country and time fixed effects, quadratic country-specific trends, and initial population times time fixed effects. The figure plots the coefficient of Facebook Speakers, modified to assume that when a language version is launched people who speak similar languages (with a similarity index at least as large as indicated in the horizontal axis) can interpret this version. 95% confidence bands are shaded. Two-way clustering of standard errors at the month and country level.

A Appendix

A.1 Variables and sources

Table A-1: Variable Definition and Sources

Variable	**Description**	**Source**
	Panel A. National and subnational data	
Main variables		
Protests	Total protests by country and month. Main source is GDELT where protests include six different types of collective action episodes: demonstrations or rallies, hunger strikes, strikes or boycotts, obstructions or blockages, engagements in political dissent and violent protests. Information from ACLED only available for Africa.	GDELT and ACLED
Facebook Speakers	Proportion of people who, in each country-month, speak (as their first language) a language available in Facebook. We use Ethnologue to identify languages spoken in countries or regions, and use our own coding of launch dates for language-specific Facebook platforms from internet queries of news, official announcements, specialized blogs and (if no other source is available) the earliest date with a web crawl at the Internet Archive's Way Back Machine tool.	Ethnologue (version 16) and own coding from web searches and Internet Archive (`https://archive.org/`).
Facebook Searches	Index of Facebook use: log of (one plus) the total number of google searches of the word "Facebook" for country c during month m (as percentage of the highest number of searches in a month for the country c).	Google Trends
Other variables (in alphabetical order)		
Arab spring countries	Equals one if country is Algeria, Egypt, Gaza Strip, Iran, Iraq, Jordan, Kuwait, Mauritania, Morocco, Lebanon, Libya, Oman, Saudi Arabia, Sudan, Syria, Tunisia, West Bank, Western Sahara or Yemen.	Own coding

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Table A-1 – Variable Definition and Sources (Continues from Previous Page)

Control of Corruption	Part of the Worldwide Governance Indicators. Control of corruption captures "perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as 'capture' of the state by elites and private interests. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5." More details at `https://datacatalog.worldbank.org/control-corruption-estimate-0`	The Worldwide Governance Indicators (WGI).
Democracy (Polity IV)	Polity score which ranges from -10 to +10, where with -10 to -6 corresponding to autocracies, -5 to 5 corresponding to anocracies, and 6 to 10 to democracies. Available for all independent states with more than 500,000 total population. Based on an evaluation of elections for competitiveness and openness, the nature of political participation in general, and the extent of checks on executive authority.	Systemic Peace
Diamond production	Diamond Production per capita in 1960.	Humphreys (2005)
Election month	Equals one for observations where constituency-level elections were carried out in each country.	Constituency-Level Elections Archive (CLEA)
Facebook Most Spoken, 50% and 20%	Equals one if, in a country-month, a Facebook version had been released in: the most spoken language in the country (Facebook Most Spoken), a language spoken by more than 50% of the population (Facebook 50%) or one spoken by more than 20% of the population (Facebook 20%).	Own coding from Ethnologue and Facebook language-specific platforms launch dates.
Facebook Users	Number of Facebook users. Available for a subset of years and countries.	
Former colonies	Dummy variables that equal one if country is a former colony of: 1. England, 2. French, 3. Spain, 4. Another European country, 5. Another non-European country.	Own coding
Freedom House	Index measuring the degree of democratic freedoms in nations and significant disputed territories around the world. Based on two indices, each assessing the state of Civil Liberties and Political Rights on a scale from 1 (most free) to 7 (least free).	Freedom House (`https://freedomhouse.org/`)
GDP per capita growth	Annual gross domestic product (per capita) growth rate.	World Bank
GDP per capita	GDP per capita in thousands of constant (2011) dollars before Facebook was launched.	World Bank

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Table A-1 – Variable Definition and Sources (Continues from Previous Page)		
GDP per capita in manufacturing (% GDP)	GDP in manufacturing as percentage of total GDP before Facebook was launched.	World Bank
Internet users per capita	Per capita internet users before Facebook was launched.	International Telecommunication Union
Linguistic fragmentation	Fragmentation in country c is defined, following García-Montalvo and Reynal-Querol (2005), as $F_c = 1 - \sum_{i=1}^{N} \pi_{ic}^2$, where π_{ij} is the share of speakers of i language in country c before Facebook was launched. .	Own coding using Ethnologue
Linguistic polarization	Polarization for country c is defined, following Reynal-Querol (2002), as $P_c = 1 - \sum_{i=1}^{N} \pi_{ic} \left(\frac{1/2-\pi_{ic}}{1/2}\right)^2$, where π_{ic} is the share of speakers of the i language in country c before Facebook was launched.	Own coding using Ethnologue
News sources	Number of news sources reporting protests.	GDELT
Oil reserves	Oil reserves in 1960.	Humphreys (2005)
Oil and gas rents per capita	Oil and gas rents per capita in 1960.	Ross (2008)
People aged between 15 and 24	Millions of inhabitants aged between 15 and 25 before Facebook was launched.	World Bank
Population	Number of inhabitants by country and year. Population for 2000 (before Facebook was launched) is used when this variable is included as a control in the baseline regression.	United Nations and World Bank

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Table A-1 – Variable Definition and Sources (Continues from Previous Page)

Press Freedom	Index based on press pluralism (the degree to which opinions are represented in the media), media independence (degree to which the media are able to function independently of sources of political, governmental, business and religious power and influence), environment and self-censorship (the environment in which news and information providers operate), legislative framework (impact of the legislative framework governing news and information activities), transparency (transparency of the institutions and procedures that affect the production of news and information), infrastructure (quality of the infrastructure that supports the production of news and information) and abuses (abuses and acts of violence against journalists). Scores range from 0 to 100, with 0 being the best possible score and 100 the worst.	Freedom Press (`https://freedompress.org.uk/`)
Regulatory Quality	Part of the Worldwide Governance Indicators. Regulatory quality captures "perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5." More details at `https://datacatalog.worldbank.org/regulatory-quality-estimate-0`	The Worldwide Governance Indicators (WGI) project
Repressed opposition	Is a dummy variable equals one if no significant oppositional activity is permitted outside the ranks of the regime and ruling party. Totalitarian party systems, authoritarian military dictatorships, and despotic monarchies are typically coded here. Coded from *parcomp* in polity IV.	Systemic Peace
Rule of Law	Part of the Worldwide Governance Indicators. Rule of law captures "perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5." More details at `https://datacatalog.worldbank.org/rule-law-estimate-0`	The Worldwide Governance Indicators (WGI) project
Urban population share	Urban population as percentage of total population.	World Bank

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Table A-1 – Variable Definition and Sources (Continues from Previous Page)

Voice and Accountability	Part of the Worldwide Governance Indicators. Voice and accountability "captures perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5." More details at `https://datacatalog.worldbank.org/voice-and-accountability-estimate-0`	The Worldwide Governance Indicators (WGI) project
Years of schooling	Average schooling in inhabitants aged 15 and over.	World Bank

Panels B-D. Individual-level data from surveys (source is the corresponding survey)

Panel B. European Social Survey

Main variables	
Protest	Equals one if respondent answers "Yes" to the question, "There are different ways of trying to improve things in [country] or help prevent things from going wrong. During the last 12 months, have you done any of the following? Have you taken part in lawful public demonstration last 12 months?".
Facebook Speaker	Equals one if Facebook is available in the language most often spoken at home by the respondent, coded from the question "What language do you speak most often at home?"
Other variables (in alphabetical order)	
Age	Respondent's age in years.
Male	Equals one if respondent is male.
Member of association	Equals one if respondent answers "Yes" to any of the following questions 1. Are you or have you ever been a member of a trade union or similar organization? 2. Would you describe yourself as being a member of a group that is discriminated against in this country?
Party identity	Equals one if respondent answers "Yes" to "There are different ways of trying to improve things in [country] or help prevent things from going wrong. During the last 12 months, have you done any of the following? worked in a political party or action group?"
Sign petition	Equals one if respondent answers "Yes" to "There are different ways of trying to improve things in [country] or help prevent16 things from going wrong. During the last 12 months, have you done any of the following? Aigned a petition?"

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Table A-1 – Variable Definition and Sources (Continues from Previous Page)

TV	Based on the question "And again on an average weekday, how much of your time watching television is spent watching news or programmes about politics and current affairs?" Options are: 0=No time at all, 1=Less than 1/2 hour, 2=1/2 to 1hour, 3=More than 1 hour, up to 11?2 hours; 4=More than 11?2 hours, up to 2 hours; 5=More than 2 hours, up to 21?2 hours; 6=More than 21?2 hours, up to 3 hours; 7=More than 3 hours"
Voted	Equals one if respondent answers "Yes" to "Some people don't vote nowadays for one reason or another. Did you vote in the last [country] national15 election in [month/year]?"
income/wealth	Household's total net income.
Panel C. World Values Survey	
Main variables	
Protest	Equals one if respondent answers "Have done" or "Might do" to the question, "I'm going to read out some forms of political action that people can take, and I'd like you to tell me, for each one, whether you have done any of these things: Attending peaceful demonstrations"
Facebook Speaker	Equals one if Facebook is available in the language normally spoken at home by the respondent, coded from the question "What language do you normally speak at home?"
Other variables (in alphabetical order)	
Age	Respondent's age in years.
Interest in politics	Based on the question "How interested would you say you are in politics?" Options are 1=Not at all interested, 2=Not very interested, 3=Somewhat interested, 4=Very interested.
Male	Equals one if respondent is male.
Member of association	Equals one if respondent answers "Active member" to "Could you tell me whether you are an active member, an inactive member or not a member of any type of organization?"
Newspapers	Based on the question "People learn what is going on in this country and the world from various sources. For each of the following sources, please indicate whether you use it to obtain information daily, weekly, monthly, less than monthly or never (read out and code one answer for each): Newspapers." Variable equals one if response is daily or weekly, and zero if it is monthly, less than month, or never.

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Table A-1 – Variable Definition and Sources (Continues from Previous Page)

Party identity	Based on the question "Now I am going to read off a list of voluntary organizations. For each organization, could you tell me whether you are an active member, an inactive member or not a member of that type of organization?" We code 1 if active member of political party and zero if inactive member or don't belong
Radio	Based on the question "People learn what is going on in this country and the world from various sources. For each of the following sources, please indicate whether you use it to obtain information daily, weekly, monthly, less than monthly or never (read out and code one answer for each):" We code 1 if daily or weekly and zero if monthly, less than month, or never.
Sign petition	Equals one if respondent answers "Have done" or "Might do" to the question, "I'm going to read out some forms of political action that people can take, and I'd like you to tell me, for each one, whether you have done any of these things: Sign a petition"
TV	Based on the question "People learn what is going on in this country and the world from various sources. For each of the following sources, please indicate whether you use it to obtain information daily, weekly, monthly, less than monthly or never (read out and code one answer for each): TV." We code one if the answer is daily or weekly and zero if it is monthly, less than month, or never.
Voted	Based on the question "When elections take place, do you vote always, usually or never?" We code one if the answer is always and zero if usually or never.
Income	Based on the question "On this card is an income scale on which 1 indicates the lowest income group and 10 the highest income group in your country. We would like to know in what group your household is. Please, specify the appropriate number, counting all wages, salaries, pensions and other incomes that come in." We recode this variable by terciles.
	Panel D. Afrobarometer
Main variables	
Protest	Equals one if respondent answers "Yes, once or twice", "Yes, several times", "Yes, often" or "No, but would do if had the chance" to the question, "Here is a list of actions that people sometimes take as citizens. For each of these, please tell me whether you, personally, have done any of these things during the past year. If not, would you do this if you had the chance: Attended a demonstration or protest march?"
Facebook Speaker	Equals one if Facebook is available in the respondent's home language, coded from the question "Which language is your home language?"
Other variables (in alphabetical order)	

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Table A-1 – Variable Definition and Sources (Continues from Previous Page)

Attends assoc. meeting	“Here is a list of actions that people sometimes take as citizens. For each of these, please tell me whether you, personally, have done any of these things during the past year. If not, would you do this if you had the chance: Attended a community meeting?” We code one if“Yes, once or twice”, “Yes, several times” or “Yes, often” and zero if “No, would never do this”
Age	Respondent’s age in years.
Discusses politics	Equals one if respondent answers “Frequently” to the question “When you get together with your friends or family, would you say you discuss political matters:” Equals zero if “Not at all interested”, “Never” or “Occasionally” ,
Interested in politics	Equals one if respondent answers “very interested” to the question “How interested would you say you are in public affairs?”. Equals zero if “Not at all interested”, “Not very interested” or “Somewhat interested”.
Male	Equals one if respondent is male.
Member of association	Equals one if response is “active member” to the question: “Let’s turn to your role in the community. Now I am going to read out a list of groups that people join or attend. For each one, could you tell me whether you are an official leader, an active member, an inactive member, or not a member: Some other voluntary association or community group?”
Newspapers	Equals one if respondent answers “A few times a week” or “Every day” to the question “How often do you get news from the following sources: Newspapers?”. Variable equals zero if respondent answers “Less than once a month”, “A few times a month” or “Never”
Party identity	Equals one if response is yes to the question “Do you feel close to any particular political party?”
Political leader	“Let’s turn to your role in the community. Now I am going to read out a list of groups that people join or attend. For each one, could you tell me whether you are an official leader, an active member, an inactive member, or not a member: Some other voluntary association or community group?” We code one for “official leader” and zero otherwise.
Radio	Equals one if respondent answers “A few times a week” or “Every day” to the question “How often do you get news from the following sources: Radio?”. Variable equals zero if respondent answers “Less than once a month”, “A few times a month” or “Never”
Sign a petition	“Here is a list of actions that people sometimes take as citizens. For each of these, please tell me whether you, personally, have done any of these things during the past year. If not, would you do this if you had the chance: Got together with others to raise an issue?” We code one for “Yes, once or twice”, “Yes, several times” or “Yes, often” and zero for “No, would never do this”
TV	Equals one if respondent answers “A few times a week” or “Every day” to the question “How often do you get news from the following sources: Television?”. Equals zero if respondent answers “Less than once a month”, “A few times a month” or “Never”
Voted	“With regard to the most recent, national elections, which statement is true for you?”. We code one if response is voted in the elections and zero otherwise

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Table A-1 – Variable Definition and Sources (Continues from Previous Page)

Facebook or Twitter	Only available in round 6. Equals one if respondent answers “A few times a week” or “Every day” to the question “How often do you get news from the following sources: Social media such as Facebook or Twitter?”. Equals zero if respondent answers “Less than once a month”, “A few times a month” or “Never”
income/wealth	First principal component of amenities of the PSU (sampling unit/enumeration area).

A.2 Countries and non- sovereign territories

Countries included in the baseline regression are Afghanistan, Albania, Algeria, American Samoa, Andorra, Angola, Anguilla, Antigua And Barbuda, Argentina, Armenia, Aruba, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bermuda, Bhutan, Bolivia, Bosnia And Herzegovina, Botswana, Brazil, British Indian Ocean Territory, British Virgin Islands, Brunei, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Canada, Cape Verde, Cayman Islands, Central African Republic, Chad, Chile, China, Christmas Island, Colombia, Comoros, Congo (Republic), Congo Dr (Zaire), Cook Islands, Costa Rica, Croatia, Cuba, Cyprus, Czech Republic, Denmark, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Estonia, Ethiopia, Falkland Islands (Islas Malvinas), Faroe Islands, Fiji, Finland, France, French Guiana, French Polynesia, Gabon, Gaza Strip, Georgia, Germany, Ghana, Gibraltar, Greece, Greenland, Grenada, Guadeloupe, Guam, Guatemala, Guernsey, Guinea, Guinea-Bissau, Guyana, Haiti, Holy See (Vatican City), Honduras, Hong Kong (China), Hungary, Iceland, India, Indonesia, Iran, Iraq, Ireland, Isle Of Man, Israel, Italy, Ivory Coast, Jamaica, Jan Mayen, Japan, Jersey, Jordan, Kazakhstan, Kenya, Kiribati, Kosovo, Kuwait, Kyrgyzstan, Laos, Latvia, Lebanon, Lesotho, Liberia, Libya, Liechtenstein, Lithuania, Luxembourg, Macau (China), Macedonia, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Marshall Islands, Martinique, Mauritania, Mauritius, Mayotte, Mexico, Micronesia, Midway Islands, Moldova, Monaco, Mongolia, Montenegro, Montserrat, Morocco, Mozambique, Myanmar (Burma), Namibia, Nauru, Nepal, Netherlands, Netherlands Antilles, New Caledonia, New Zealand, Nicaragua, Niger, Nigeria, Niue, Norfolk Island, North Korea, Northern Mariana Islands, Norway, Oman, Pakistan, Palau, Palmyra Atoll, Panama, Papua New Guinea, Paracel Islands, Paraguay, Peru, Philippines, Pitcairn Islands, Poland, Portugal, Puerto Rico, Qatar, Reunion, Romania, Russia, Rwanda, Saint Helena, Saint Kitts And Nevis, Saint Lucia, Saint Martin, Saint Pierre And Miquelon, Saint Vincent And The Grenadines, San Marino, Sao Tome And Principe, Saudi Arabia, Senegal, Serbia, Seychelles, Sierra Leone, Singapore, Slovakia, Slovenia, Solomon Islands, Somalia, South Africa, South Korea, South Sudan, Spain, Sri Lanka, Sudan, Suriname, Svalbard, Swaziland, Sweden, Switzerland, Syria, Taiwan, Tajikistan, Tanzania, Thailand, The Gambia, Timor-Leste, Togo, Tokelau, Tonga, Trinidad And Tobago, Tunisia, Turkey, Turkmenistan, Turks And Caicos Islands, Tuvalu, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan, Vanuatu, Venezuela, Vietnam, Virgin Islands, Wake Island (US), Wallis And Futuna, West Bank, Western Sahara, Western Samoa, Yemen, Zambia and Zimbabwe.

Non sovereign territories included in the baseline regression are American Samoa, Anguilla, Aruba, Bermuda, British Indian Ocean Territory, British Virgin Islands, Cayman Islands, Christmas Island, Cook Islands, Falkland Islands, Faroe Islands, French Guiana, French Polynesia, Gaza Strip, Gibraltar, Greenland, Guadeloupe, Guam, Guernsey, Hong Kong, Isle Of Man, Jan Mayen, Jersey, Macau, Martinique, Mayotte, Midway Islands, Montserrat, Netherlands Antilles, New Caledonia, Niue, Norfolk Island, Northern Mariana Islands, Palmyra Atoll, Paracel Islands, Pitcairn Islands, Puerto Rico, Reunion, Saint Helena, Saint Martin, Saint Pierre And Miquelon, Svalbard, Tokelau, Turks And Caicos Islands, Virgin Islands, Wake Island (US), Wallis and Futuna, West Bank and Western Sahara.

A.3 Examining whether collective action predicts Facebook translations

Facebook publishes, for each language, a ranking of the top 100 users by number of published phrases and makes it available for users of that language. We use this feature to measure the frequency of translations by country and language.

More specifically, we created several user accounts for the 81 different languages in our sample. For the top 100 translators in each platform (8,100 users) we identify the name, profile link, ranking position and number of published phrases. We next identify each user's country of residence. In 75% of the cases, this is directly identifiable in the user profile, either because the country of residence is listed (35%) or because we can match the city of district to the country (30%) using the *Geonames* dataset. In an additional 30% of the cases, we manually review the profiles and posts of the user to infer the country from complementary information (e.g., the user attends a University or works in a firm that can be located). We are unable to match the country for only 5% of the users.

We use this information to examine whether preexisting trends in collective action predict translations in Table A-2. In Panel A, the unit of observation is a country and the dependent variable is the total number of phrases translated by users of each country (cols 1 to 3) or the total number of translators of the country (columns 4 to 6), regardless of the language. This test may be weak, however, because it puts together all language translations within a country. Thus, in Panel B, the unit of observation is a country and the dependent variable is the total number of phrases translated by users of each country in the country's main (most-spoken) language (columns 1 to 3) or the total number of translators of that language in the country (columns 4 to 6). We then measure preexisting trends in collective action in various ways. Bearing in mind that Facebook was launched in September of 2006, columns 1 and 4 use protests growth from August of 2005 to August of 2006 as the independent variable. Columns 2 and 5 compare instead protests in the 12-month period before Facebook's launch with the preceding 12 months. Finally, for a longer term trend, columns 3 and 6 compare protests in the 12-month period before Facebook's launch with the corresponding 12 months five years before. Whether we are looking at published phrases or at number of translators, and whether we look at short-run or longer term pre-trends in protests, it is clear that collective action trends before Facebook appears do not predict increased translation efforts. Coefficients are typically not significant (the sole exception is in Panel B and column 4, with a negative sign) are statistically insignificant. Moreover, in the lower row of each Panel to gauge the magnitude of the correlations we report the beta-coefficients, and these are generally smaller than 5%, with few exceptions.

Finally, since by restricting to each country's main language we may be ignoring some other important languages and social groups that get mobilized for collective action, in Panel C the unit of observation a country-language (for languages spoken by more than 10% of the population) and the dependent variable is the total number of phrases translated by users of each country in each language (columns 1 to 3) or the total number of translators of each country and language (columns 4 to 6). For protests we do an analogous exercise as in Panels A and B, but the pre-trends are with respect to the launch date of each particular language. In fact, in this exercise we find even more precisely measured zero coefficients for previous patterns of protests.

In short, we find no evidence that collective action events speed up translations to promote the Facebook language-specific platform that is relevant for groups mobilizing.

A.4 Additional Tables and Figures

Table A-2: Predicting Translations

	(1)	(2)	(3)	(4)	(5)	(6)
	Published phrases			Translators		
Panel A. Dependent variable is published phrases or number of translators						
Protests growth during (final period/base period)...						
Ago. 2006/Ago. 2005	0.2832			0.0016		
	(6.0271)			(0.0071)		
Sep. 2005-Ago. 2006/Sep. 2004-Ago. 2005		61.4364			0.0896	
		(41.6504)			(0.0692)	
Sep. 2005-Ago. 2006/Sep. 2001-Ago. 2002			2.8851			0.0311
			(44.4587)			(0.0377)
Observations	214	214	214	214	214	214
Beta coefficient	0.002	0.104	0.004	0.009	0.149	0.043
Panel B. Dependent variable is published phrases or number of translators in country's most spoken language						
Protests growth during (final period/base period)...						
Ago. 2006/Ago. 2005	-3.5178			-0.0040*		
	(2.9454)			(0.0021)		
Sep. 2005-Ago. 2006/Sep. 2004-Ago. 2005		19.5070			0.0228	
		(23.7313)			(0.0209)	
Sep. 2005-Ago. 2006/Sep. 2001-Ago. 2002			2.0877			0.0155
			(34.1061)			(0.0278)
Observations	214	214	214	214	214	214
Beta coefficient	-0.035	0.055	0.005	-0.055	0.087	0.049
Panel C. Dependent variable is published phrases or translators in each language and country						
Protests growth during...						
Month before launch	-0.7386			-0.0001		
	(1.7535)			(0.0015)		
12-month before launch		-1.0105			-0.0008	
		(1.2813)			(0.0011)	
Five years before launch			-0.3852			0.0004
			(0.7819)			(0.0006)
Observations	1,529	1,529	1,529	1,529	1,529	1,529
Countries	225	225	225	225	225	225
Beta coefficient	-0.012	-0.009	-0.008	-0.002	-0.009	0.012

Notes: In Panel A, the unit of observation is a country and the dependent variable is the total number of phrases translated by users of each country (cols 1 to 3) or the total number of translators of the country (columns 4 to 6), regardless of the language. In Panel B, the unit of observation is a country and the dependent variable is the total number of phrases translated by users of each country in the country's main (most-spoken) language (columns 1 to 3) or the total number of translators of that language in the country (columns 4 to 6). In Panel C, the unit of observation is a country-language (for languages spoken by more than 10% of the population) and the dependent variable is the total number of phrases translated by users of each country in each language (columns 1 to 3) or the total number of translators of each country and language (columns 4 to 6). The right hand side variable of interest is the increase in protests in the time period indicated in each row. Robust standard errors.

Table A-3: The effect of Facebook Searches on Protests
Instrumental Variable Estimates

	(1)	(2)
Dependent variable is $log(1 + protests)$		
Estimator:	OLS	IV
Facebook Searches	0.5346***	2.6541**
	(0.1370)	(1.0810)
First-stage F-statistic		15.52
Observations	44,928	44,928
Countries	234	234

Notes: Monthly data from January of 2000 to December of 2015. Country and month fixed effects, initial population times month fixed effects and country-specific quadratic trends included. Facebook Speakers is the proportion of people speaking (as first language) a language available in Facebook in each country and month. Facebook Searches is an index of search interest for the term "Facebook" from Google Trends. Column 1 is an OLS regression and column 2 an instrumental variable regression with the first stage given by column 2 of Panel B in Table 2. Two-way clustering of standard errors at the month and country level.

Table A-4: Protests and Facebook Speakers
Reverse Causality: Excluding Major Countries, Additional Categories

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable is log(1 + protests)						
	Excludes, per language...					
	...largest country by:		*...worst country by:*			
	Speakers	Speakers per capita	Voice and Accountability	Political Stability	Government Effectiveness	Regulatory Quality
A. Excluding any language						
Facebook Speakers	0.2242**	0.4021***	0.3233***	0.2950***	0.3508***	0.3932***
	(0.1074)	(0.1298)	(0.1080)	(0.1115)	(0.1057)	(0.1134)
Observations	9,984	9,408	13,824	14,400	14,976	14,400
Countries	52	49	72	75	78	75
B. Excluding only languages available in Facebook platforms						
Facebook Speakers	0.3755***	0.4180***	0.3434***	0.3154***	0.3584***	0.3546***
	(0.1145)	(0.1228)	(0.1003)	(0.1031)	(0.0994)	(0.1019)
Observations	33,984	33,600	35,136	35,136	35,712	35,712
Countries	177	175	183	183	186	186

Notes: Monthly data from January of 2000 to December of 2015. All regressions include country fixed effects, month fixed effects, initial population interacted with time fixed effects and country-specific quadratic trends. Facebook Speakers is the proportion of people speaking (as first language) a language available in Facebook in each country and month. Two-way clustering of standard errors at the month and country level.

Table A-5: Protests and Facebook Speakers
Subnational Variation Robustness

	(1)	(2)	(3)	(4)	(5)
Dependent variable is $log(1 + protests)$					
Unit of analysis:	*Language Polygons*	*Language Polygons*	*State-Lang*	*State-Lang*	*State*
Facebook Speakers	0.3793***	0.4850***	0.2183***	0.1941**	0.0707**
	(0.0593)	(0.0839)	(0.0832)	(0.0796)	(0.0346)
Observations	904,704	781,824	1,776,576	1,455,936	640,704
Polygons	4,712	4,072	9,253	7,583	3,337
Beta-coefficient	0.1058	0.1095	0.1242	0.1104	0.0335
Month × State fixed effect				✓	
Overlapped zones	*Yes*	*No*	*Yes*	*Yes*	*Yes*

Notes: Unit of observation indicated in each column title, with data from January of 2000 to December of 2015. All regressions include fixed effects for each country and month, region fixed effects and initial population interacted with month fixed effects. Facebook Speakers is the share of the population in each region within a country speaking (as first language) a language already available in Facebook. Beta-coefficient is the implied effect on the dependent variable, in standard-deviation units, of a one-standard deviation increase in Facebook Speakers. Overlapped zones refers to polygons in Ethnologue where more than one language is spoken by the population. Two-way clustering of standard errors at the month and country level.

Table A-6: Robustness to outliers and variable transformation

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable is...	log (1+ protests), without outliers	arcsinh (protests)	Protests>0	Protests>median	Protests>mean	days in month
A. National						
Facebook Speakers	0.2788***	0.2454***	0.0191	0.0448*	0.0537**	0.1726***
	(0.0618)	(0.0861)	(0.0179)	(0.0248)	(0.0251)	(0.0505)
Observations	44,006	46,080	46,080	46,080	46,080	46,080
Countries	240	240	240	240	240	240
B. Subnational						
Facebook Speakers	0.1634***	0.4266***	0.0460***	0.0460***	0.0748***	0.2556***
	(0.0247)	(0.0670)	(0.0132)	(0.0132)	(0.0150)	(0.0396)
Observations	863,396	904,704	904,704	904,704	904,704	904,704
Polygons	4,497	4,712	4,712	4,712	4,712	4,712

Notes: Monthly data from January of 2000 to December of 2015. In Panel A the unit of observation is a country, and in Panel B a language polygon (region) within a country. All regressions include country (Panel A) or region (Panel B) and month fixed effects as well as initial population interacted with time fixed effects. Facebook Speakers is the proportion of people speaking (as first language) a language available in Facebook. Outliers, removed in column 1, are observations with residuals in the upper or lower 2.5% of the distribution in the corresponding baseline regression. arcsinh (protests) is the inverse hyperbolic sine transformation on the number of protests. Two-way clustering of standard errors at the month and country level.

Table A-7: Protests and Facebook Speakers
Non-linear Estimators

	(1)	(2)	(3)	(4)	(5)
	Dependent variable is...				
	Number of protests			*Probability(Protests > 0)*	
Estimation	Quantile median	Negative binomial	Zero-inflated	Logit	Probit
Facebook Speakers	12.1162***	0.4451***	0.2637**	0.2071***	0.1074***
	(1.5070)	(0.0730)	(0.1051)	(0.0490)	(0.03045)
Observations	46,080	46,080	46,080	46,080	46,080
Countries	240	240	240	240	240

Notes: Monthly data from January of 2000 to December of 2015. Facebook Speakers is the proportion of people speaking (as first language) a language available in Facebook in each country and month. *Quantile regression* (at the median) includes country and month fixed effects and reports standard errors clustered at the country level. *Negative binomial regression* reports the fixed effect estimator and includes quadratic time trends. *Zero inflated negative binomial regression* includes country fixed effects and a quadratic time trend and reports standard errors clustered at the country level. *Logit regression* reports the fixed effects estimator while *Probit regression* the random effects estimator. *Negative binomial regression*, *Logit regression* and *Probit regression* include quadratic trends and report bootstrapped standard errors (500 repetitions) as suggested by Cameron and Trivedi (2009). Marginal effects are reported for the *Logit* and *Probit* regressions.

Table A-8: Protests and Facebook Speakers
Dynamic Panel Data Estimations (Arellano-Bond)

	(1)	(2)	(3)	(4)	(5)
Dependent variable is $log(1 + protests)$					
Estimation...	Baseline	Arellano & Bond			
Facebook Speakers	0.2212***	0.2598***	0.2651***	0.1888**	0.2011**
	(0.0777)	(2.72)	(3.12)	(2.34)	(2.27)
Lag 1		0.2392***	0.2361***	0.2505***	0.2396***
		(25.76)	(26.60)	(26.75)	(22.55)
Lag 2			0.0535***	0.0576***	0.0485***
			(8.72)	(9.33)	(6.38)
Lag 3				0.0286***	0.0202***
				(4.52)	(2.70)
Lag 4				0.0264***	0.0181**
				(4.58)	(2.46)
Lag 5				0.0068	-0.0015
				(1.12)	(0.20)
Observations	46,080	45,600	45,360	44,640	43,440
Countries	240	240	240	240	240
pvalue AR(2)		0.00	0.00	0.49	0.78
P-value lags 6-10					0.17

Notes: Monthly data from January of 2000 to December of 2015. All regressions include country fixed, month fixed effects, country-specific quadratic trends, and initial population interacted with time fixed effects. In the Arellano-Bond estimation, we restrict the maximum lags for use as instruments to ten. Two-way clustering of standard errors at the month and country level in column 1 and Arellano-Bond robust standard errors in columns 2-5. P-value AR(2) is the p-value for a test of serial correlation in the residuals of the log protests series. In column 5, ten lags of log protests are included (but not reported) as controls. P-value lags 6-10 is the p-value of a test for joint significance of these lags.

Table A-9: Protests and Facebook Speakers
Robustness to Speakers Definition

	(1) **Definition A** (Baseline)	(2) **Definition B** (Most spoken)	(3) **Definition C** (50%)	(4) **Definition D** (20%)
Dependent variable is $log(1 + protests)$				
Facebook Speakers*	0.2212***	0.1246**	0.1805***	0.1735***
	(0.0777)	(0.0625)	(0.0647)	(0.0625)
Observations	46,080	46,080	46,080	46,080
Countries	240	240	240	240

Notes: *In **Definition A** Facebook Speakers is defined as in the baseline: the share of people in each country-month whose main language is already available in a Facebook platform. For the next columns, Facebook Speakers indicates if, in a country-month, a Facebook version had been released in: the most spoken language (**Definition B**), a language spoken by more than 50% of the population (**Definition C**), or by more than 20% of population (**Definition D**). All regressions include country fixed effects, month fixed effects, country-specific quadratic trends and initial population interacted with time fixed effects. Two-way clustering of standard errors at the month and country level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table A-10: Facebook Speakers and Reporting Biases

	(1)	(2)	(3)	(4)
	Panel A. Number of media outlets reporting protests			
	Dependent variable is statistic in column for number of outlets reporting			
	Mean	Median	Percentile 25	Percentile 75
Facebook Speakers	0.0045	-0.0080	0.0004	-0.0179
	(0.0351)	(0.0112)	(0.0064)	(0.0331)
Observations	32,121	32,121	32,121	32,121
Countries	237	237	237	237
	Panel B: Treating events in the same location or period as single events			
	Dependent variable is log of one plus protests, aggregation by...			
Panel B-1 (location)	None (Baseline)	Day-landmark	Day-Grid	Day-Country
Facebook Speakers	0.2212***	0.2198***	0.2193***	0.1726***
	(0.0777)	(0.0622)	(0.0622)	(0.0505)
Panel B-2 (period)	Week-Landmark	Week-Grid	Month-Landmark	Month-Grid
Facebook Speakers	0.2069***	0.2071***	0.1861***	0.1873***
	(0.0520)	(0.0517)	(0.0441)	(0.0437)
Observations	46,080	46,080	46,080	46,080
Countries	240	240	240	240

Notes: Monthly data from January of 2000 to December of 2015. All regressions include country fixed effects, month fixed effects, initial population interacted with time fixed effects and country-specific quadratic trends. Facebook Speakers is the proportion of people speaking (as first language) a language available in Facebook in each country and month. Panel A runs the baseline specification using different features of the distribution of the number of outlets reporting protests as dependent variable, with the statistic used indicated in each column. In Panel B-1, instead of counting the total reported occurrences of protests by country-month as in the baseline (column 1), we construct alternative measures of protests treating protests occurring in the same location, but classified in GDELT as different protests, as a single event. In column 2, the location is the specific geographic coordinates provided in GDELT, in column 3 we use grids with a resolution of 5km $\times$ 5km, and in column 4 one location represents an entire country. Panel B-2 combines geographic and temporal aggregation by counting as one all protests that occur in a week and landmark (column 1), week and 5km $\times$ 5km grid (column 2), month and landmark (column 3), month and 5km $\times$ 5km grid (column 4). Two-way clustering of standard errors at the month and country level.

Table A-11: Individual-level Protest Participation and Facebook Robustness to Discriminating Participation and Intention to Participate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable is							
	Protest				*Intention to protest*			
Panel A. World Values Survey								
Facebook Speaker	0.0458**	0.0458**	0.0428**	0.0562***	0.0453**	0.0453**	0.0441**	0.0550**
	(0.0164)	(0.0164)	(0.0163)	(0.0178)	(0.0205)	(0.0205)	(0.0188)	(0.0212)
Observations	159,256	159,256	159,256	159,256	203,760	203,760	203,760	203,760
Countries	90	90	90	90	90	90	90	90
Panel B. Afrobarometer								
Facebook Speaker	0.0378	0.0378	0.0391	0.0367	0.1245**	0.1245**	0.1273**	0.1275**
	(0.0379)	(0.0379)	(0.0368)	(0.0381)	(0.0404)	(0.0404)	(0.0418)	(0.0416)
Observations	89,002	89,002	89,002	89,002	112,577	112,577	112,577	112,577
Countries	36	36	36	36	36	36	36	36
Country × Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Language fixed effects	✓				✓			
Country × Language fixed effects		✓	✓	✓		✓	✓	✓
Age+Sex			✓	✓			✓	✓
Education+Wealth				✓				✓

Notes: Individual data from several rounds of each survey. See list of rounds in Figure 2. In columns 1 to 4 Protest equals one if the respondent answers "2 (Yes, once or twice)", 3 "Yes, several times" or "4 (Yes, often)" to the question "Please tell me whether you, personally, have done any of these things during the past year. If not, would you do this if you had the chance: Participated in a demonstration or protest march". It is zero otherwise and the option "1 (No, but would do if had the chance)" is excluded. In columns 5 to 8, Intention to Protest equals one if responding to this question with "1 (No, but would do if had the chance)", and zero if the answer is "No". Facebook Speaker is a dummy that equals one if Facebook has been released in the language spoken by the respondent. Two-way clustering of standard errors at the month and country level.

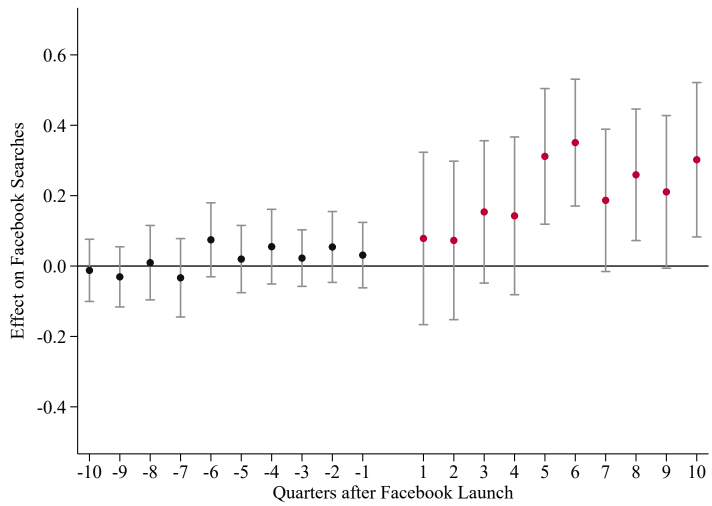
Table A-12: Individual-level Protest Participation and Facebook Approximating the Effect of the Second Language

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable is indicator variable for protest participation										
Survey:	ESS		WVS		Afrobarometer		WVS+Afrobarometer		All – pooled	
Facebook Speaker in...										
First language	0.0177**	0.0174**	0.0652***	0.0845***	0.1017***	0.1182***	0.0686***	0.0788***	0.0338***	0.0346***
	(0.0061)	(0.0060)	(0.0185)	(0.0202)	(0.0161)	(0.0189)	(0.0157)	(0.0168)	(0.0089)	(0.0088)
Second language	0.0253***	0.0230***	0.0507*	0.0702**	0.0083*	0.0096	0.0156*	0.0187**	0.0220***	0.0236***
	(0.0039)	(0.0075)	(0.0267)	(0.0279)	(0.0040)	(0.0051)	(0.0080)	(0.0081)	(0.0057)	(0.0070)
First $\times$ Second		0.0042		-0.0937*		-0.0405		-0.0428**		-0.0065
		(0.0081)		(0.0468)		(0.0328)		(0.0205)		(0.0088)
Observations	340,768	340,768	238,249	238,249	124,420	124,420	362,669	362,669	703,437	703,437
Countries	36	36	90	90	36	36	113	113	123	123

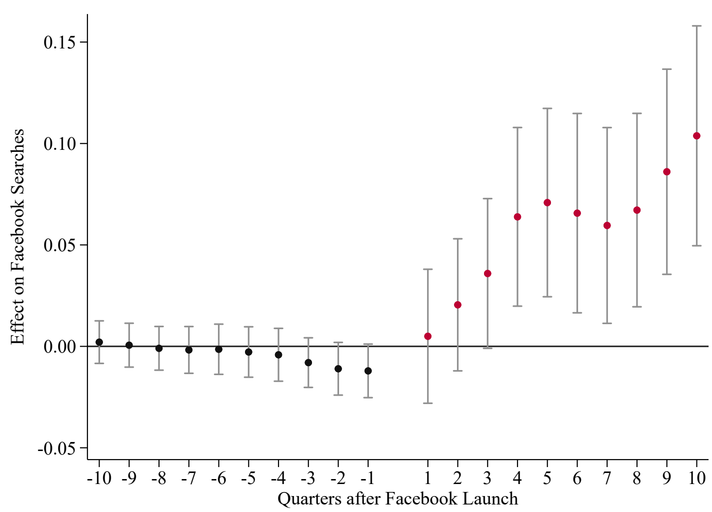
Notes: Facebook Speaker in first language is a dummy that equals one if Facebook has been released in the language spoken by the respondent. Protest is a dummy for protest participation as defined in Table 7. Facebook Speaker in second language is a dummy that equals one if Facebook has been released in a second language spoken by the respondent, proxied by the language of the interview when this does not coincide with the language declared as main by the respondent. Two-way clustering of standard errors at the year and country level.

Figure A-1: Parallel Trends in Protests Before Facebook
Alternative Approach to Exploring Anticipated Effects of Facebook Speakers

A. Protests

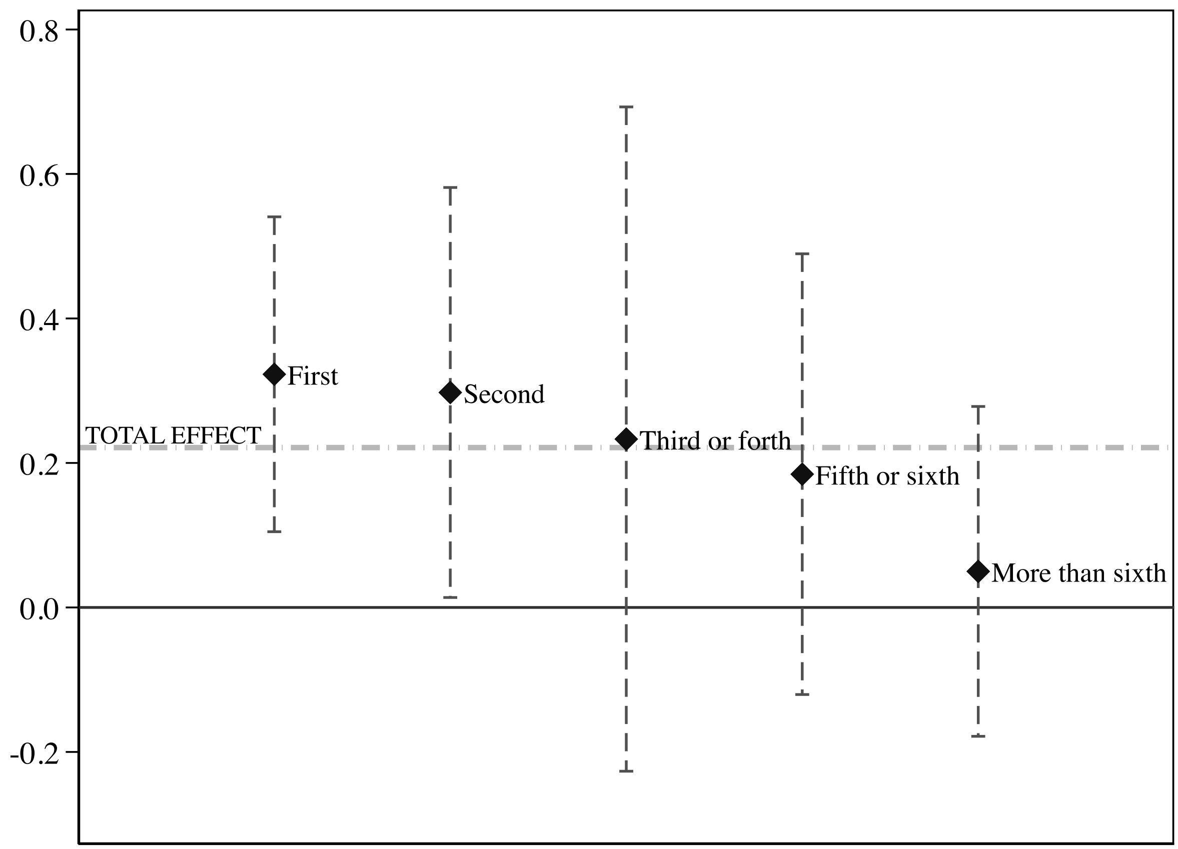


B. Facebook Searches



Notes: Each panel presents estimates from a modified version of the baseline regression in equation (1) with Protests (Panel A) or Facebook Searches (Panel B) as the dependent variable. In addition to country and time fixed effects, quadratic country-specific trends, and initial population times time fixed effects, we include and plot the coefficients for: (a) quarter dummies for the periods leading to the adoption of the country's language first available in Facebook (marked with negative integers in the horizontal axis) and (b) quarter dummies after this first adoption interacted with Facebook Speakers (positive integers in the horizontal axis). Coefficients are reported with 95% confidence bands, allowing for two-way clustered standard errors at the country and year level.

Figure A-2: Protests and Facebook Speakers
Differential Effects by Order of Appearance of Corresponding Writing System

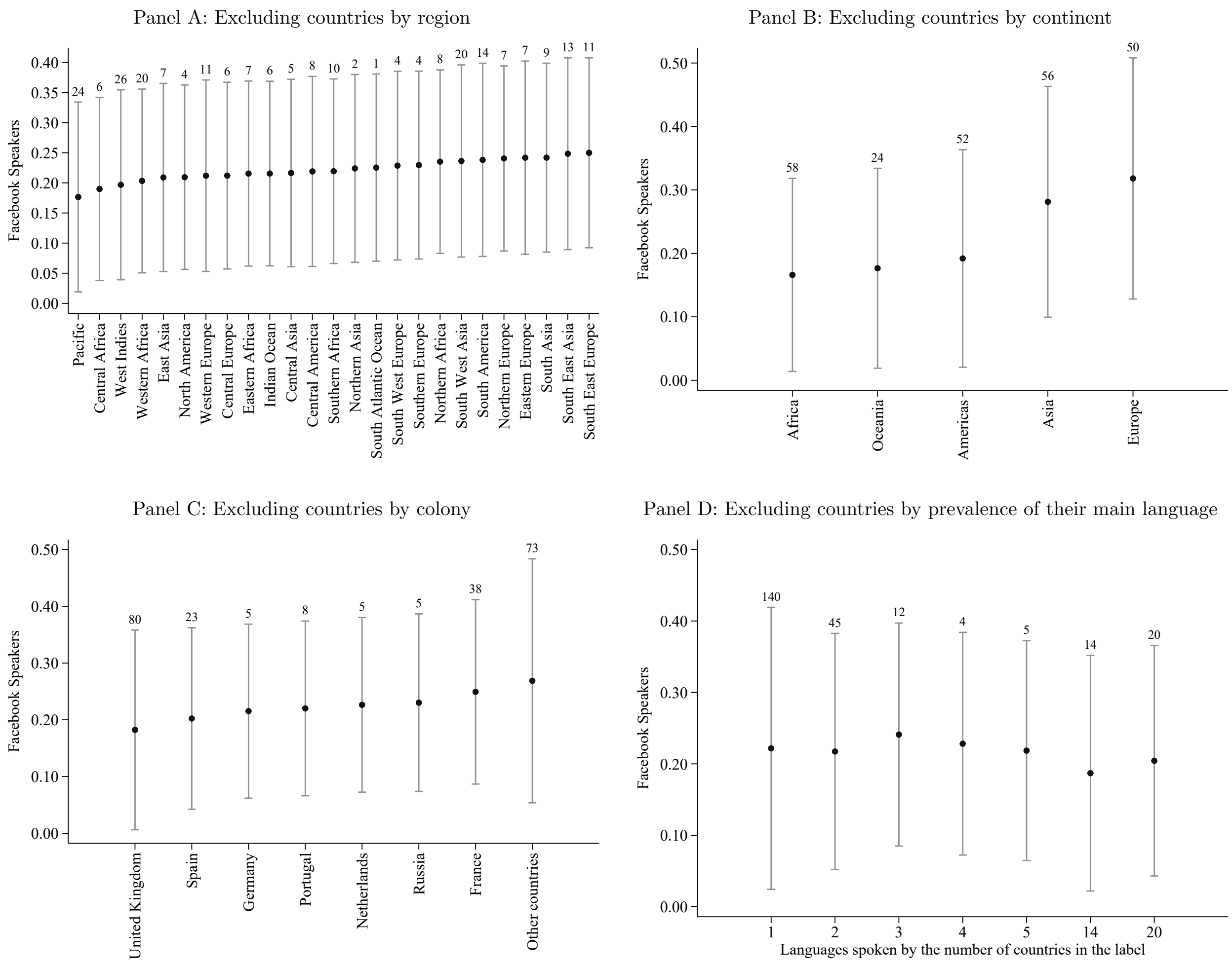


Notes: The figure breaks down the effect of Facebook Speakers according to the order in which the platforms were launched in each writing system. Let R_l be such order/rank. For example, $R_l = 2$ for platforms/languages such as Spanish, Panjabi or Serbian that were launched second in their corresponding writing system (Latin, Arabic and Cyrillic respectively). They were launched after English, Arabic and Russian for which $R_l = 1$. Then Facebook Speakers at writing system order "r" can be calculated as:

$$\text{Facebook Speakers}^r_{c,t} = \left(\sum_l \text{Facebook}_{t,l} \times \text{Speakers}_{c,l} \times \mathbb{1}\{R_l = r\} \right)$$

The figure reports the coefficient of five subgroups r (1 to 5 and greater than or equal to 6) in a regression for log of (one plus) protests at the country-level with monthly data from January of 2000 to December of 2015, including country fixed effects, month fixed effects, initial population interacted with time fixed effects, and country-specific quadratic trends. Since Facebook Speakers$_{c,t} = \sum_r$ Facebook Speakers$^r_{c,t}$, the total effect of Speakers is a weighted average of the subgroups.

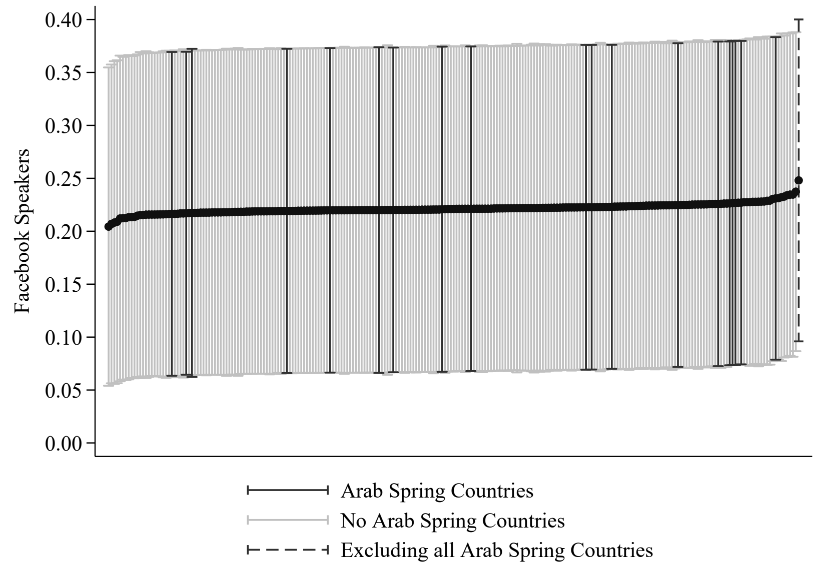
Figure A-3: The Effect of Facebook Speakers on Protests
Robustness to Excluding Country Clusters



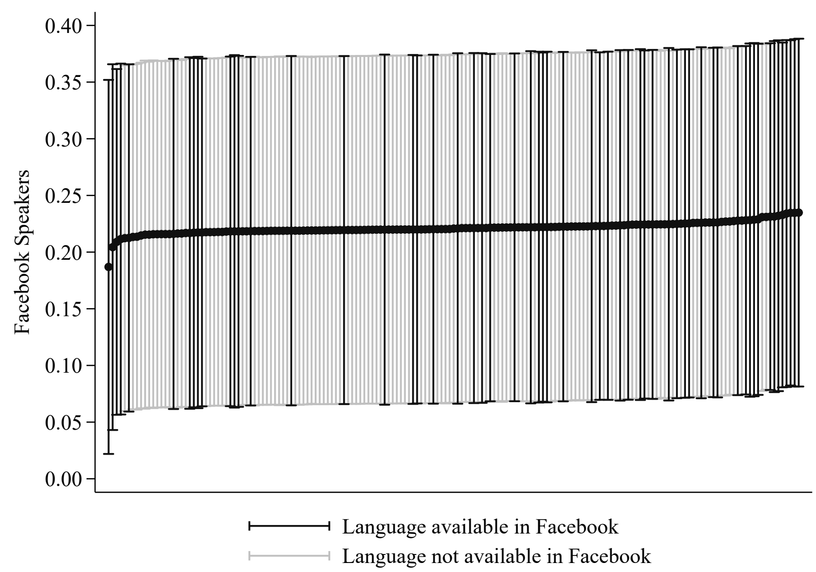
Notes: The figure reports the coefficients for Facebook Speakers (and 95% confidence interval) in a regression for log of (one plus) protests at the country-level with monthly data from January of 2000 to December of 2015, including country fixed effects, month fixed effects, initial population interacted with time fixed effects, and country-specific quadratic trends. Different groups of countries excluded in each case, with the number of excluded countries indicated over each bar. Excluded groups are: regions (Panel A), continents (Panel B), colonies by former colonizer (Panel C). Panel D excludes countries according to how widespread worldwide each language is: the first bar excludes all countries whose main language is only spoken (as the most popular language) in that country, the second removes all countries whose main language is the most popular language in two countries, and so on.

Figure A-4: The Effect of Facebook Speakers on Protests Robustness to Excluding Countries and Languages

Panel A: Excluding each country



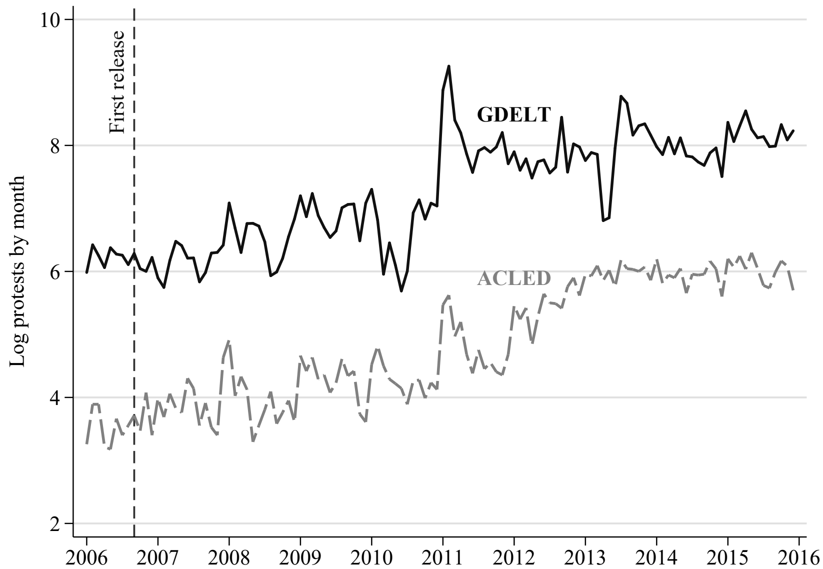
Panel B: Excluding each language available in Facebook



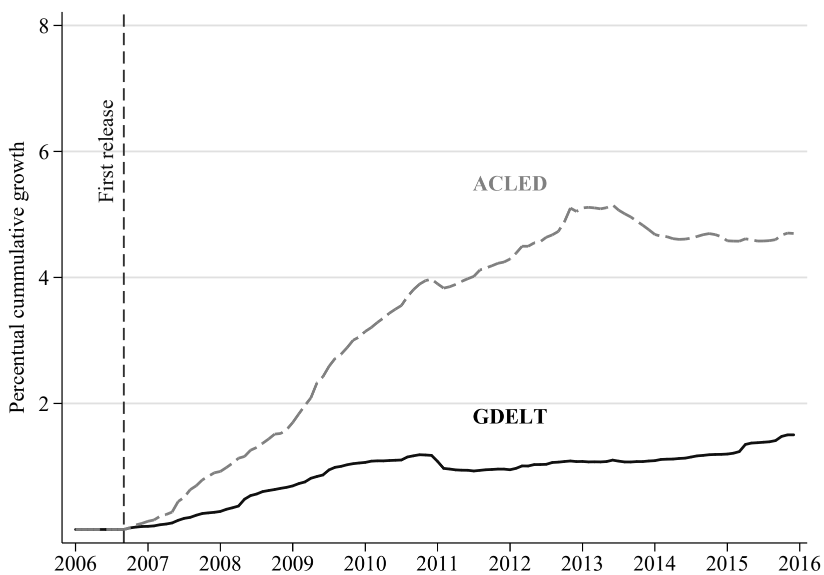
Notes: Country-level regression with monthly data from January of 2000 to December of 2015. All regressions include country fixed effects, month fixed effects, initial population interacted with time fixed effects, and country-specific quadratic trends. Panel A shows plots the coefficient and confidence interval for Facebook Speakers when excluding each country (or groups of countries, as noted in the label). Panel B instead excludes all countries where the most spoken language is the one indicated in the horizontal label.

Figure A-5: GDELT vs ACLED:
Differences in Protests and Cumulative Effects of Facebook Speakers

Panel A: Evolution of the number of protests in Africa

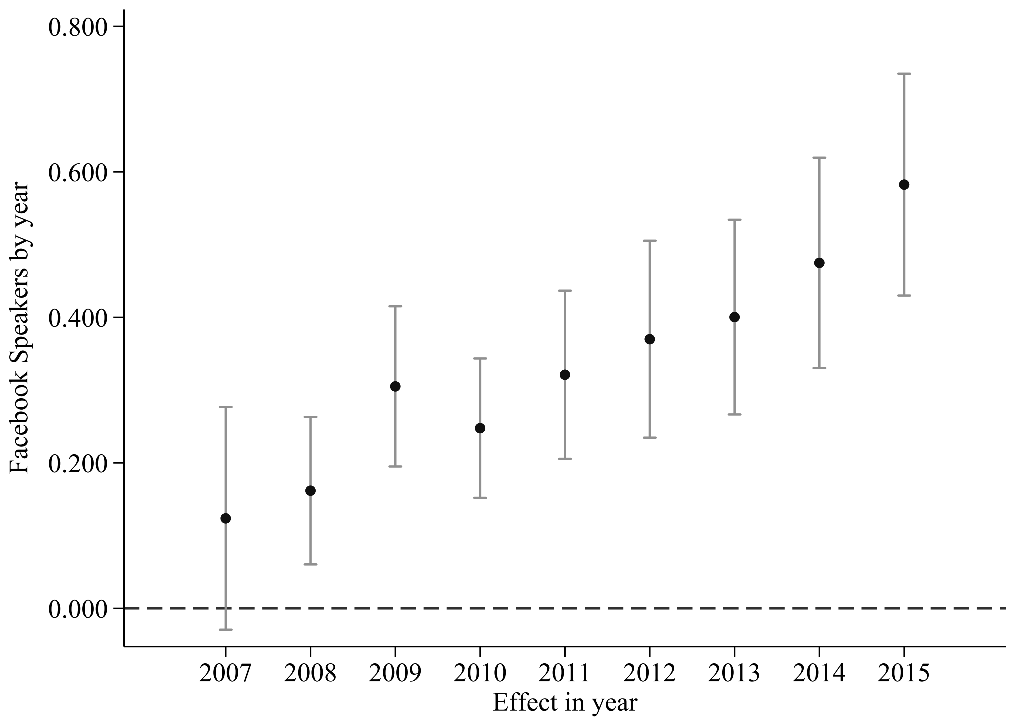


Panel B: Cumulative effect of Facebook Speakers in Africa, GDELT versus ACLED



Notes: To construct the counterfactual in Panel B, we estimate the number of protests that would have been observed without Facebook (namely, if Facebook Speakers are held constant at zero throughout the period) as implied by our baseline subnational estimates using each protest database (restricted to Africa where both sources are available). We then depict the cumulative difference since September of 2006 (when Facebook first appeared) between protests with and without Facebook (expressed as percent of total cumulative protests without Facebook up to each time period).

Figure A-6: The Effect of Facebook Speakers on Protests Heterogenous Effects by Year



Notes: Coefficients, and 95% confidence bands, for the interaction of Facebook Speakers with year dummies in our baseline subnational regression for log(1+ protests).