Bigger Cities Have More Intense Protests

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WORKING PAPER

Abstract

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1 Introduction

Protests scale superlinearly with city size: large cities contain more protesters per capita than small cities. For example, New York City contains three times as many residents as Log Angeles, but protests there, on average, will be more than three times as large. This behavior is surprising, as there is no clear reason larger cities' protests should not be larger than small cities in direct proportion to their population difference. Why do protests scale superlinearly?

This paper suggests that protests scale superlinearly because social networks densify as they grow. In other words, large social networks have a higher average number of connections per individual than smaller ones. These connections make it more likely that individuals in large social networks (large cities) learn about a protest, increasing the size of protests above and beyond what would be expected if that same network had the same density as smaller ones.

Three analyses support this claim. First, protests in the United States in 2017, **others, others, and others** scale superlinearly with city size. Second, a "forest fire" model of network formation, where new individuals randomly connect to existing individuals recursively, generates densification (Leskovec, Kleinberg and Faloutsos, 2008). Simulation protest mobilization with this network model generates protests that scale superlinearly with the size of the network on which they occur. Third, measurements of the average number of connections of city inhabitants, using geolocated Twitter accounts, shows that social networks in cities densify as a function of city size.

BELOW IS VESTIGIAL, FROM V1. Two new data sources, the Crowd Counting Consortium (CCC) and geolocated Twitter accounts present advances in the HCED and MCED domains, respectively. Both record multiples more protests than their predecessors as frequently and with more precise geographic precision. Using the January 21, 2017 Women's March protests in the United States, this paper shows that Twitter records 6.71 times (503 to 75) as many events as the Global Database of Events, Location, and Tone 2.0 (GDELT

2.0, the best MCED); CCC, 8.89 (667 protests). Across Twitter's 503 protests, it more accurately estimates crowd size than GDELT, *especially when* restricting analysis to the 69 in both. Twitter has location matches for 74.18% of the events recorded in the CCC data, but it records tweets in 11,635 cities on the day of the Women's March, compared to 667 from CCC. For 25 of these, CCC does not estimate protest attendance, meaning Twitter can estimate crowd size when estimates may otherwise not exist. GDELT, which does not record crowd size, only has estimates (number of protests in a city, number of articles about protests) for three of these 25.

This paper proceeds as follows. Section 2.2 explains how I gathered, processed, and matched data, and Section 2.3 presents the analysis supporting this paper's claims. Section **??** shows that Twitter can be used when CCC records a protest but not a crowd size. Section 4 concludes with discussions of when to prefer CCC, Twitter, or GDELT 2.0 and a general approach to using Twitter to identify large events.

2 Superlinear Scaling

2.1 Description

An outcome grows superlinearly if its rate of growth is faster than an input to it. It grows linearly if the rates are the same, and sublinearly if its grows less quickly than its input. Superlinear growth means that as the input grows, there is proportionally more an output. For example, economic output of cities grows superlinearly, meaning that large cities have higher per capita income than small ones (Bettencourt et al., 2010); on the other hand, urban infrastructure grows sublinearly, meaning larger cities have fewer roads, sewers, and gas stations per capita, for example, than smaller cities (West, Brown and Enquist, 1997). In other words, per capita income grows superlinearly with the number of inhabitants in a city, while infrastructure grows sublinearly.

If protests scale at the same rate as city size, a doubling of city size would correspond to twice as many protesters. If there are increasing returns to city size, however, protest size will scale with a slope greater than 1; decreasing returns, less than 1. For example, is protest size increases 109% for every increase in city size, then a city ten times the size of another city will have a protest $10^{.09}$ times as large as that city, e.g. if a city of 10,000 has 100 protesters, a city of 100,000 should have $10^{1.09*} * 100 = 1230.269$ protesters. Linear scaling would predict 1,000 protestors.

The distinction between superlinear, linear, and sublinear scaling provides suggestive evidence of causal processes. The logic, applied to protests, is as follows. If protests require joint production, i.e. if a protest cannot occur from the action of just one individual, then how its size grows as a function of the size of the city in which it occurs hints at how it is produced. If there are decreasing returns to scale for the production of protest, then the cost of organizing protests increases faster than the size of the people being organized. Decreasing returns to scale would suggest that protesting requires organized communication amongst all potential participants, and the combinatorial explosion of potential connections ($\frac{n(n-1)}{n}$, where n is number of people) means that communication costs rise more quickly than the size of city population. Constant returns to scale suggests that the growth of inefficiencies as a population grows is equally offset by a growth in efficiencies. For example, organizing in a larger city requires more people to organize, but if the marginal cost to organizing an additional person equals the benefit they provide to the protest, then protest size grows in lockstep with city size.

Increasing returns to scale, however, suggests that the cost of organizing each additional protester decreases as the number of potential protesters increases. The combinatorial explosion of communication costs must not matter in this case, or there is another factor in the costs not accounted for. The most likely explanation, in the context of social processes, is for a positive feedback loop. As a protest starts, the cost faced by additional protesters may decrease; these protesters further lower the cost to subsequent protesters, causing the costs to decline further. Since larger cities have more people, the feedback loop can run longer, generating more intense protests than in smaller cities operation under the same logic. Biggs (2003) has explored positive feedback loops in the context of strikes, and Cederman, Warren and Sornette (2011) demonstrates that war mobilization follows a positive feedback loop as well.

This distinction is especially important if there exists a relationship between protest size and the likelihood of policy change. If protesters jointly produce policy change (Tullock, 1971), linear scaling means that policy change becomes more likely at the same rate as city size increases. If protest size scales sublinearly, then policy change becomes more likely at a rate slower than the increase in city size. If protest scales superlinearly, then a doubling of city size will more than double the likelihood of policy change.

2.2 Data

2017 US Women's March. Crowd size estimates for the 2017 United States Women's March from the Crowd Counting Consortium (CCC) and two approaches using geolocated Twitter data (Chenoweth and Ulfelder, 2017) The Crowd Counting Consortium is an open-source hand-coded events dataset established to record protest size. Submissions should contain links to sources and crowd size estimates, but it is not a requirement. (In fact, of the 667 protests recorded on January 21, 2017 in the United States, only 447 contain links to sources. 383 have links to sources that are not Facebook or Twitter posts.) It then periodically releases the resulting datasets, with the first release relating to the Women's March protests and subsequent releases occurring monthly. This paper uses the `Best Guess` variable, usually an average of the low and high estimate, as the crowd size variable.

For the Women's March, two approaches approximate the number of protesters. First is a count of the number of unique accounts in a city per day using one of three common keywords, "womensmarch", "whyimarch", or "imarchfor" . Tweets are not resolved to intracity locations, for three reasons. First, for the majority of tweets, Twitter aggregates the specific location of a tweet to local polygons while reporting the actual location as the city that contains that polygon. The polygon, however, does not envelop the location of the actual tweet. For example, Rancho Palos Verdes and Monterrey, two cities near Los Angeles, recorded, based on GPS coordinates, the most number of tweets from January 21, but Twitter labels those tweets as coming from Los Angeles. Intracity location information is therefore unknown for almost all tweets. Second, the Crowd Counting Consortium rarely provides intracity geographic information. A protest they label as occurring in Seattle would require further research for obtaining the specific location; since Twitter does not provide intracity location information, matching both sets at the city level is natural. Third, most cities, even large ones, contain only one protest per day. Though not able to identify tweets for specific urban sites, I keep only tweets between 10 a.m. and 5 p.m. local standard time, the most likely protest hours.

The second approach to estimate the number of protesters at the Women's March is to count the number of faces in any protest photo from a city. A convolutional neural network (CNN) first identifies protest photos, then another CNN identifies faces in that photo. Faces in a protest photo are summed and added per city-day. For verification of this approach, see (Joo and Steinert-Threlkeld, 2018). The **Supplementary Materials** details location matching Twitter to city population estimates.

2013 Brazil Vinegar Protests. Bastos, Recuero and Zago (2014) analyzes the relationship between Twitter and protests during Brazil's 2013 Vinegar protests. They recorded the size of protests in Brazil from February 18th, 2013 through June 30th, 2013.[1] Covering 196 protests across 142 cities, these data are easily merged with population estimates from Wikipedia; 107 cities (158 protests) have population estimates from 2010.

Mass Mobilization in Autocracies Database. Weidmann and Rod (2018) introduces the Mass Mobilization in Autocracies Database, which codes pro- or anti- government protests of more than 25 people between 2003-2012 in 60 authoritarian regimes. Sources are English articles from the Associated Press, Agence France Presse, and BBC Monitoring.

[1] I am grateful to Marco Bastos for sharing protest size data.

The database contains 14,161 protests, of which 9,253 have precise estimates for protest size. Each protest is assigned a city code from the GeoNames database, facilitating the merger of population data using GeoNames' population data for cities with more than 1,000 people.[2] 7,628 protests match to a city with GeoNames population data.

German Democratic Mobilization. Extensive protest size data also exists for protests in the German Democratic Republic from September 1989 through March 1990, thanks to **?**. **?** is narrative and not structured for quantitative analysis, so **?** has digitized and structured it.[3] City population data come from `Wikipedia.de`, which in turn takes its data from the nearly decennial censuses; these data are for cities with over 30,000 inhabitants. The last census was in 1988, just before the start of protests. The full data contain 2,734 protests, of which 1,301 are matched to their respective city's 1988 population.

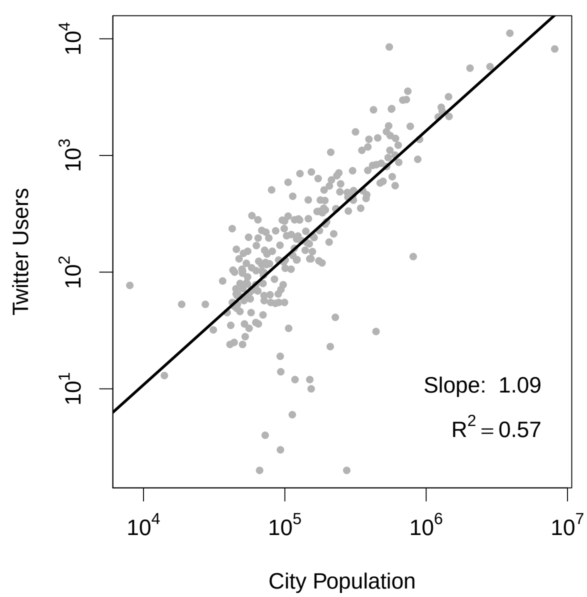
2.3 Results

Figure 1 shows that the 2017 United States' Women's March scaled with a slope greater than 1: an arbitrary percentage increase in city size leads to a greater percentage increase in protest size. (These results hold for cities with more than 40,000 inhabitants in 2006, the threshold for city inclusion in R's `maps` package.) According to Twitter's data, . 10^1 is the linear increase expected because the city is ten times as large, $10^{.09}$ is the increase unexplained by city size. Since CCC finds a slope of 1.14, it predicts 1,380.384 protesters. In other words, increasing a city size by 10 leads to $23.02\% - 38.04\%$ more protesters per capita; increasing by 100, $51.35\% - 90.55\%$, $(100^{.09} - 100^{.14})$ More concretely, Clinton, Michigan had just over 100,000 residents in 2006, Fremont, California double that, and Dallas, Texas was ten times as large. This simple scaling model predicts that Fremont should have 6.44% (Twitter, $2^{.09}$) to 10% (CCC, $2^{.14}$) more protesters per capita than Clinton, Dallas 51.36% (Twitter, $10^{.09}$) to 90.55% (CCC, $10^{.14}$).

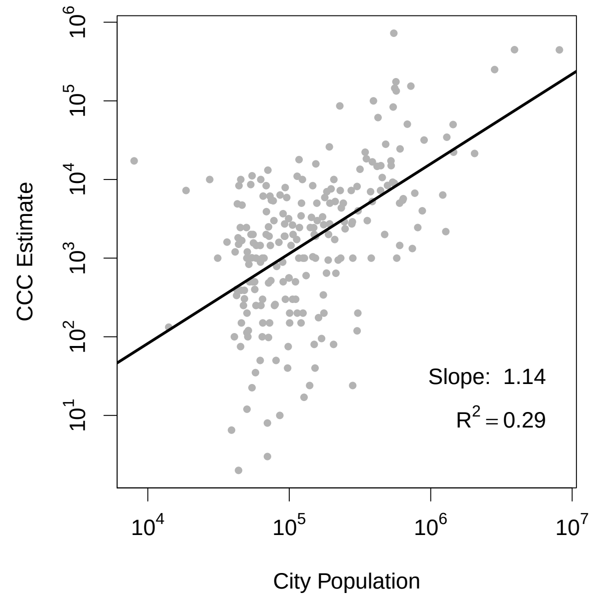
[2] GeoNames provides the date of the population estimate, but it does not provide a source for that estimate.

[3] Many thanks to Holger Kern for saving me hours of coding.

Figure 1: Superlinear Scaling, United States Women's March



(a) Twitter



(b) Crowd Counting Consortium

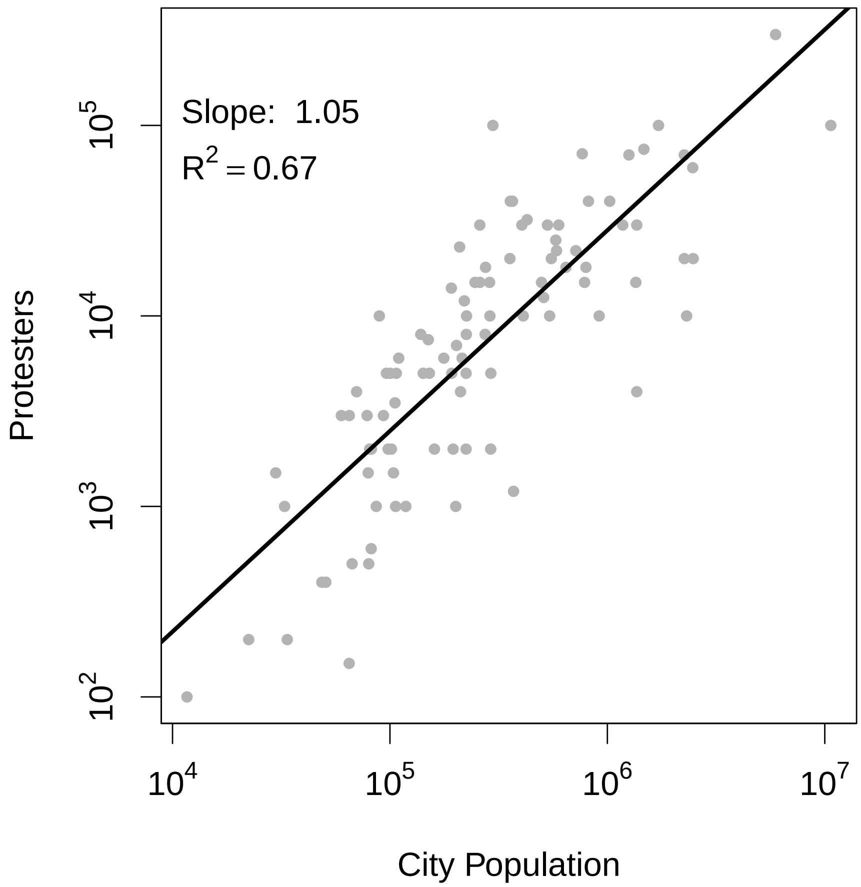
Figure 2 shows the 2013 Vinegar protests in Brazil scale superlinearly as well. The protests analyzed are from June 20th and June 21st, 2013, the two days with the most widespread protests.

Figure 3 shows that anti-Putin protests in 2011 also scale superlinearly. (Other dates - 2011.12.11, 2012.02.26, 2012.03.10, 2012.06.12, 2012.09.15, 2012.11.04 - associated with the movement also contain superlinear scaling.) The figure shows the dates of the largest protests, December 10th and December 24th.

Figure 4 shows superlinear scaling in the German Democratic Republic as the first wave of protests against the Communist party peaked (**?**). Many other dates between the end of 1989 and the first quarter of 1990, especially Mondays, have the same dynamics.

Some overall trends are clear from these examples. First, superlinear scaling does not characterize all protests. Instead, it appears to arise on days of nationwide mass protests. For example, Brazil's protest movement had built over the week of June 17, but the largest protests, both in numbers and cities, was the two shown in Figure 2. The same is true of

Figure 2: Superlinear Scaling, Brazil Vinegar Protests

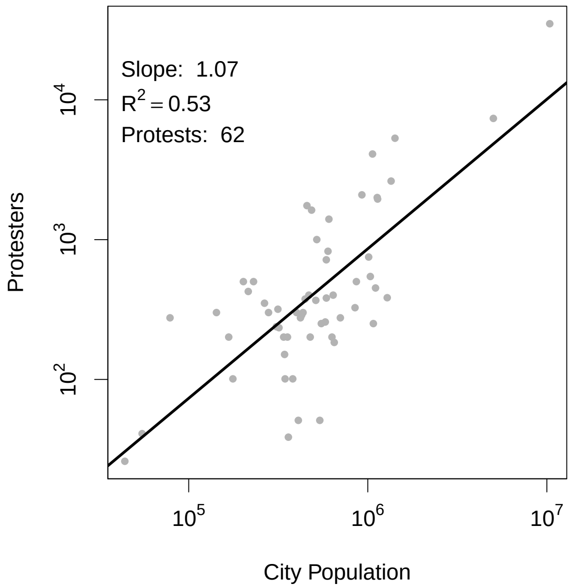


(a) Brazil, June 20th-21st

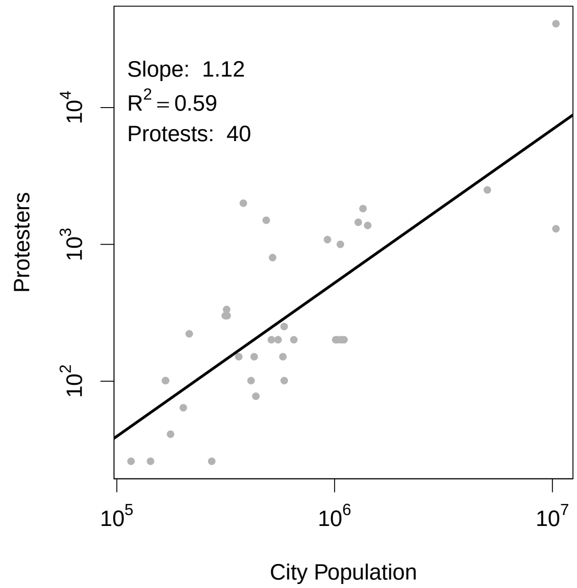
Russia: superlinear scaling only appears on the days of the largest protests. Second, the days without superlinear scaling, not shown here but available upon request, have many fewer protests. Superlinear scaling occurs during widespread protests, not during every protest wave. Third, the increase of protest size is not extraordinarily greater than linear. That is, scaling is not 200%, 100%, or even 50%. The effect of superlinear scaling, though consistent, is modest. Third, the percent of variation of the protest size that city size explains is large and similar across the events, ranging from .53-.67 (ignoring the Crowd Counting Consortium estimate, whose data generating process is the least standardized of the datasets here).

Notice as well, in Figure 1, that city population better predicts Twitter's crowd size

Figure 3: Superlinear Scaling, Russia Anti-Putin

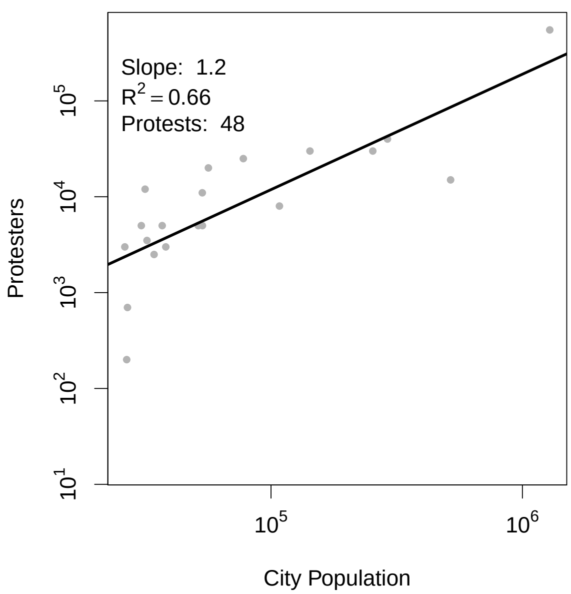


(a) Russia, December 10th, 2011

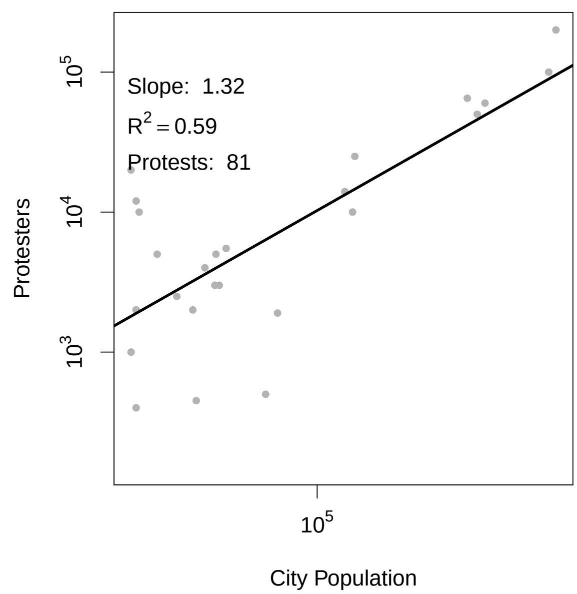


(b) Russia: December 24th, 2011

Figure 4: Superlinear Scaling, German Democratic Republic



(a) GDR, November 4th, 1989



(b) GDR: November 6th, 1989

estimate than it does that from the Crowd Counting Consortium ($R^2 = .57$ for Twitter versus .29 for CCC). The R^2 using protest size estimates from Twitter is closer to that of the other results, suggesting that using social media to generate protest event data is a valid research methodology. The relatively poor model fit deserves further investigation; one possibility is that relying on contributor-provided estimates, in addition to newspapers, introduces more noise than using either social media or a standardized coding procedure with a trained team of research assistants.

3 Networks

3.1 Network Densification

Larger social networks are denser: they have more connections per person than smaller ones (Leskovec, Kleinberg and Faloutsos, 2008).[4] Leskovec, Kleinberg and Faloutsos (2008) documents that **FINDFINDFIND**. This section provides further evidence that social networks densify.

A generative network model that generates a network with heavy-tailed degree distribution and increasing density is the Forest Fire model. In this model, a new node (v) attaches randomly to an existing node (w_i) in a graph. It then attaches to $\frac{p}{1-p}$ of w_i's neighbors, a fraction of these new connections' neighbors, and so on. (Leskovec, Kleinberg and Faloutsos (2008) use a directed graph, a detail ignored here.) Thus, a new node "burns" through connections on a network, explaining the network name. Anyone who has learned a literature by reading an article, reading some of the articles it cites, reading some of those articles' citations, and so on, has partook in this process.

Social networks also densify.

Geocoded tweets provide the data to document that social networks in large cities are denser than those in small ones. Each tweet contains information on its author, including their number of followers. Grouping tweets by city, deduplicating users, and analyzing within country shows how social networks scale as a function of city size.

[4] Many thanks to Albert-Lásaló Barabási for pointing me in this direction.

THIS IS WHERE THE NETWORK DATA WORK GOES.

One concern is that these results are driven by celebrities living in major cities. Celebrities, however, rarely geocode their tweets. The presence of celebrities therefore should not explain the superlinear scaling of social networks. If the effect was driven by celebrities, however, that would be okay. Densification has to derive from some source, and if it is the habitation decisions of celebrities, then it is the habitation decisions of celebrities.

3.2 Network Theory and Protests

The decision to protest is an example of a complex contagion (Centola and Macy, 2007; Steinert-Threlkeld, 2017). Instead of deciding to protest based on knowing one person already protesting, bystanders need to know multiple people protesting (Opp and Gern, 1993; Opp and Kittel, 2010). If this number surpasses an internal, individually-varying threshold, the bystander protests (Granovetter, 1978; Steinert-Threlkeld and Steinert-Threlkeld, 2018).[5]

3.3 Network Model of Protest

Figure 5 shows that superlinear scaling is not due simply to an increase in city size. Both panels show the result from a model of protest diffusion where the network varies in size from 1,000 to 40,000 nodes and a state engages in varying rates of repression. The model is run 1,000 times for each combination of network size and repression, and the average protest size of these 1,681 combinations is recorded. Figure 5a shows that protest size increases sublinearly if all protests are kept, while Figure 5b shows that mass protests, a more accurate representation of the events in this paper, increase only linearly with network size. Superlinear scaling is not simply a function of the size of the pool of potential participants. A feature of cities that is not their size must explain superlinear scaling.

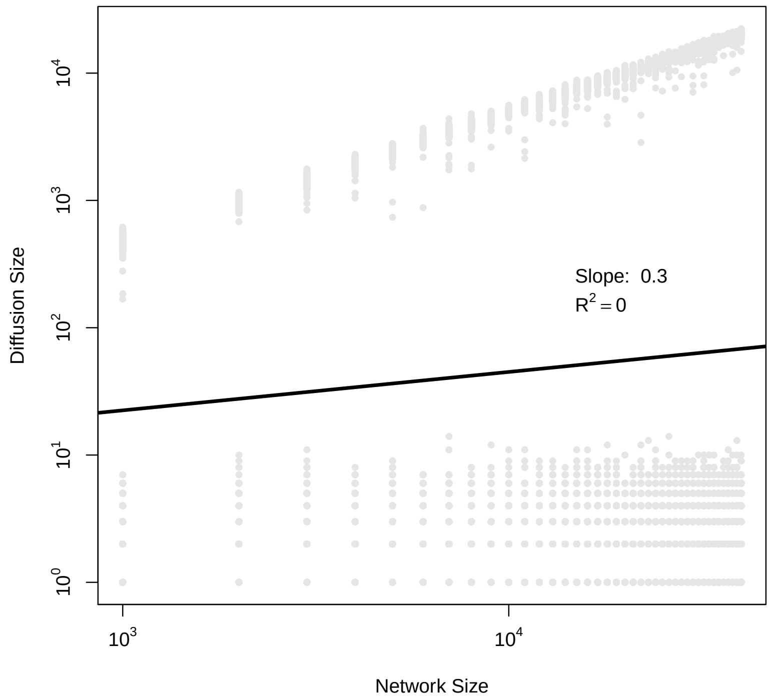
Figure 6 shows that protests do not scale superlinearly across all city sizes. It shows the

[5] Whether this threshold is absolute number of percentage is unknown.

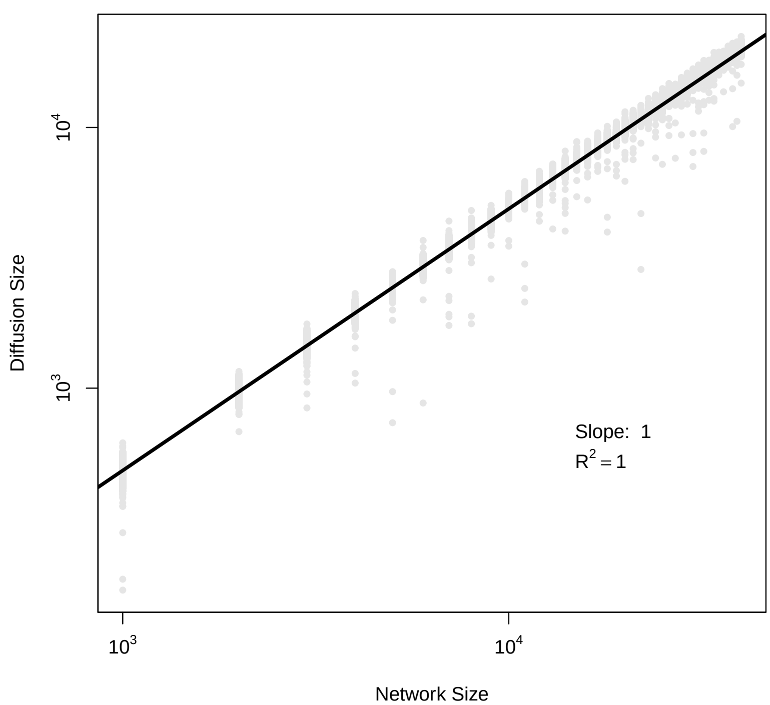
results from taking a moving window of varying size (indicated in each subfigure caption) modeling the relationship between protest size and city size using Twitter and CCC data for that subset, and moving the window across the dataset. Two results pop. First, fewer data produce noisier results. Second, protest does not appear to scale superlinearly until above a certain threshold, roughly 150,000 ($10^{5.2}$) people. Below that, they scale sublinearly. Given their size, medium to large cities have more protesters per capita than small ones, but the set of small cities have fewer per capita than expected as one goes from a small small city to a large small one.[6] This relationship holds when restricting accounts to only those that used protest hashtags, as documented in the Supplementary Materials.

[6]Narrower windows also suggest that small cities have a negative relationship with protest size: for some class of cities, it may be that larger cities in that class experience smaller protests, not just fewer protesters per capita.

Figure 5: Linear Scaling with Constant Density



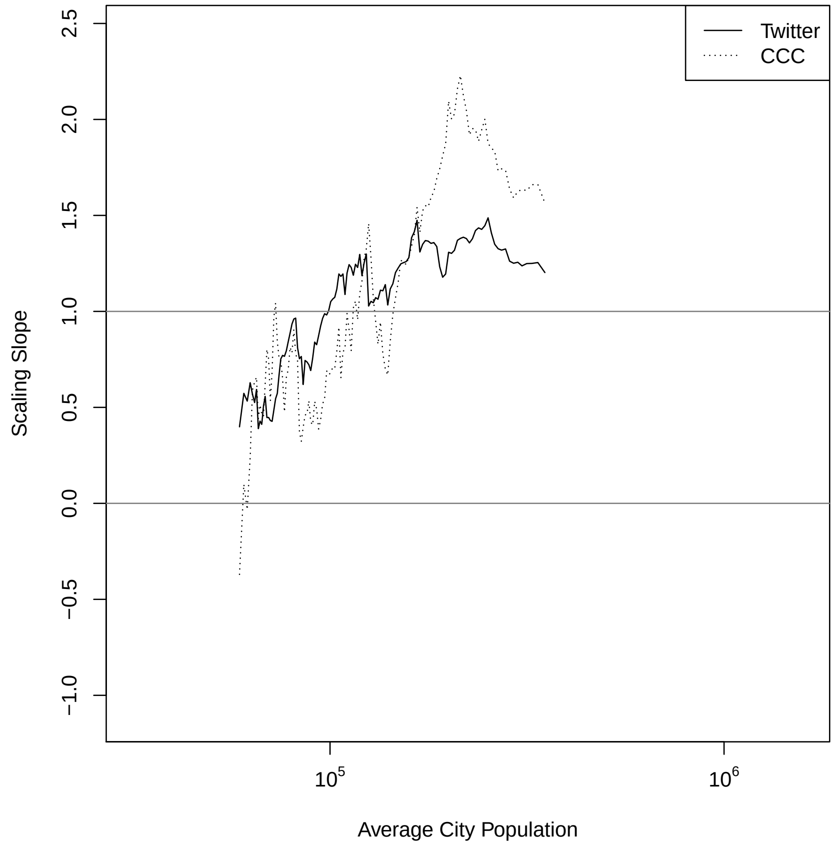
(a) All Protests



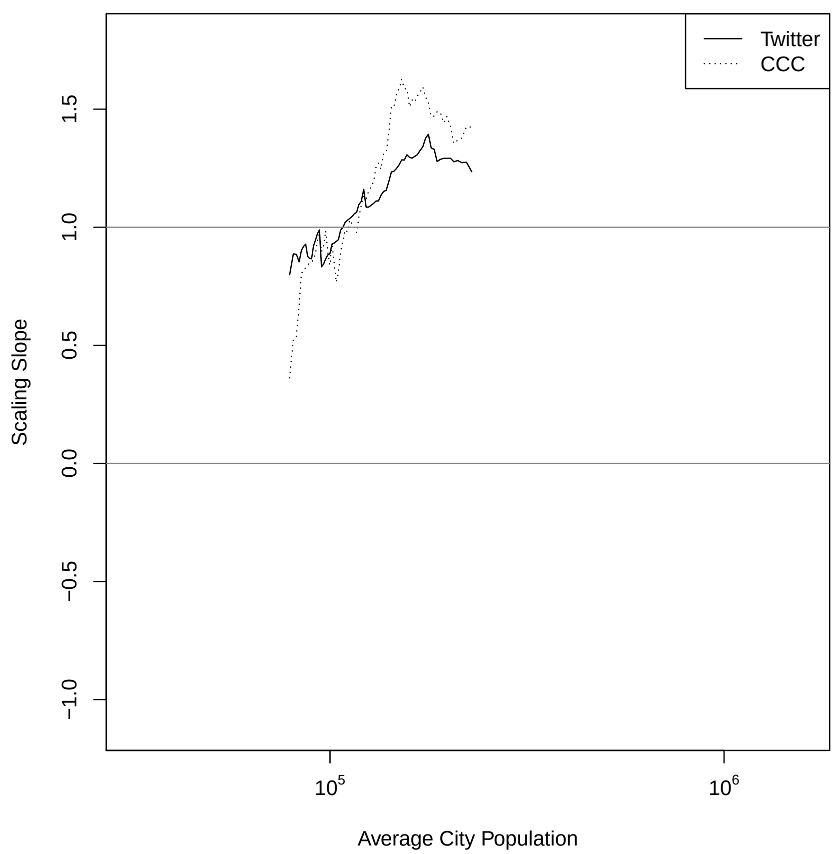
(b) Mass Protests

Figure 6: Scaling Relation with City Size

(a) Rolling Window, 100 Protests



(b) Rolling Window, 150 Protests



REMAINING TESTING

1. Regress protest size on city size, show slope is different than 1.

2. Regress protest size on city size, with dummies for autocracy.

3. Regress protest size on city size, with dummy for post-2009. That dummy is for "social network effect", so if that slope differs from pre-2009 slope, that would be cool.

4 Discussion

BEHAVIORS IT EXPLAINS

1. Moving capital city - makes it smaller.

2. Limiting who can live in the capital city - makes it smaller.

While Twitter is not a panacea, it still holds much potential for researchers in general and conflict scholars in particular. Because accounts on it generate the raw data, it can record events in many more locations than even crowd-sourced events datasets (van der Windt and Humphreys, 2014; D'Orazio et al., 2014). Because news media favor novel events (Masad, 2013), nearby ones (Myers and Caniglia, 2004), and locations of interest to their subscribers (Herkenrath and Knoll, 2011; Weidmann, 2015), they misreport persistent conflicts, especially ones from non-OECD countries. Because a social media events dataset would be automated, it would not suffer intercorder reliability issues (Ruggeri, Gizelis and Dorussen, 2011). Because social media production occurs in real time, it measures intraday dynamics, such as how shifts in public support affect conflict actors' subsequent behavior (Zeitzoff, 2016). It can also measure sentiment and conflict dynamics in locales too dangerous for academics or enumerators (Zhukov, 2015; Driscoll and Steinert-Threlkeld, 2018). In short, social media data, and Twitter specifically, are an exciting frontier worthy of greater exploitation.

While CCC represents an important advance in the measurement of protest events, its reliance on proactive individuals is a limitation. Because anyone can contribute a record, the dataset contains no uniform naming convention. For example, a protest was recorded as being in "Minneapolis/St. Paul" and "Washington, District of Columbia", both of which do not follow convention. While manageable for this paper, the number of quirks for which the researcher will have to account will only grow as a project does. Moreover, many of the events are sourced from social media (often without links to that platform) or do not provide documentation. While the exclusion of those events does not change results, Twitter's estimates may be more valid since each account at a protest is a verifiable source.

Regardless of the dataset chosen, the true crowd size, and therefore the most accurate data source, is currently not knowable. The use of geotagged tweets is biased towards cities and certain ethnic groups (Malik et al., 2015), but newspapers have biases as well (see above). Facebook data would be better, but they will not touch sensitive topics. Cell phone records may provide more accurate crowd size estimates, but no provider has made its data public, and I am aware of only one paper which uses them to measure protest size (Traag, Quax and Sloot, 2017).[7] It is currently not known whether CCC or Twitter provide the most accurate estimate of crowd size; that they agree on major contours of protest dynamics is reassuring. True protest size is probably a latent variable of the two.

Superlinear scaling characterizes many urban phenomena, not just protest Bettencourt et al. (2010). Bettencourt et al. (2010) find a scaling exponent of 1.082 to 1.284 and R^2 of .665 to .963 for social outcomes such as income, patents, and crime per capita. That protest scales at approximately the same rate despite being a complicated, contingent, and rare event measured imprecisely is astonishing. This unexpected concordance suggests a universal force may drive these seemingly disparate phenomena.

[7]Though the paper is public, no associated data, even crowd size, is. The country of the study is anonymous as well.

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