Means, Meters and Methods:

A study on the effect of nonviolent anti-government campaign diffusion on violent and nonviolent anti-government campaigns

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Abstract

Previous research has showcased how a violent anti-government campaign in one country increases the likelihood of violent anti-government campaigns in others. Similarly, a nonviolent anti-government campaign in one country increases the likelihood of nonviolent anti-government campaigns other countries. Furthermore, the lesser the distance between two countries, the greater this proposed diffusion effect gets, i.e. the likelihood of anti-government campaign diffusion increases as distance decreases. This research seeks to broaden the scope and not only look at violent to violent and nonviolent to nonviolent diffusion, but looks at the effect of nonviolent anti-government campaign diffusion on both violent and nonviolent anti-government campaign onset in other countries. The results we got suggest that nonviolent anti-government campaigns do indeed increase the likelihood of both violent and nonviolent anti-government campaigns in other countries, strengthening the case for the diffusion theory. Furthermore, we have taken a more detailed look at how the distance between two countries affects the nonviolent anti-government campaign diffusion effect. It was found that the closer two countries are to each other, the greater the diffusion effect gets. Lastly, we have looked at some of the mechanisms of conflict escalation, mainly repression. We found that anti-government campaigns are more likely to turn violent after a government increases repression.

1. Introduction

The wave of nonviolent protests and violent uprisings throughout the Middle East following the relatively peaceful Tunisian revolution of January 2011, commonly referred to as the Arab Spring, have once more renewed the interest of researchers and policymakers alike in the mechanisms of conflict diffusion. While the motivations, methods and outcomes of these protests varied across the Arab Spring uprisings, they all shared a somewhat similar target and goal (Anderson, 2011). They were all anti-government campaigns, i.e. organized efforts that pushed for institutional change, regime change or secession. In an effort to grasp what caused these sudden anti-government campaigns, country-level predictors like economic growth, inequality and regime type were quickly pointed out as the usual suspects. While these predictors do give us insight as to why these protests occurred, they cannot sufficiently explain why they happened in rapid succession and close proximity of each other, i.e. why they tend to cluster in space and time (Buhaug & Gleditsch, 2008).

Another explanation circulating the public discourse on the Arab Spring was the idea that the Tunisian revolution was in fact the prime catalyst of all other events in the Arab Spring. After the onset of nonviolent protests aimed at the regime in Tunisia, protests in other neighbouring countries ensued, seemingly emulating these protests. In a way, it seemed like Tunisia passed on the fever of rebellion to its neighbours. This contagion effect is referred to as conflict diffusion in scientific literature. According to conflict diffusion theory, the root causes for anti-government campaigns are not necessarily endogenous, but can also be fuelled by exogenous factors, such as conflicts in the vicinity of a state (Buhaug & Gleditsch, 2008). An anti-government campaign in one country could inspire disenfranchised citizen, but more importantly change the opportunity costs for those who already seek institutional change in one form or another (Alcorta et al., 2020; Buhaug & Gleditsch, 2008). In other words, diffusion can occur through two primary means, which we will now briefly discuss. First, a violent or nonviolent anti-government campaign in one country can help people in other countries define their goals and needs. Second, a violent or nonviolent anti-government campaign in one country can help learn people in other countries how to best mobilize, organize, use resources and find the right timing for their anti-government campaign. In the case of a violent anti-government campaign, the possible of influx of material goods such as weapons could also be a factor (Hegre & Sambanis, 2006). Furthermore, previous research on the diffusion of strikes across economic sectors suggests that the more similar and or economically intertwined two sectors are, the higher the likelihood of sector to sector strike diffusion is (Jansen et al., 2016). This research is preoccupied with anti-government campaigns and not strikes, yet similarity and economic interdependence are well recognized to play an important role in the diffusion of information and, as such, might well lower the opportunity costs for political action in the form of anti-government campaigns as well (Dorussen et al., 2016). Recent research has found quantitative proof that supports this conflict diffusion theory, where anti-government campaigns in one country can incite similar campaigns in other countries (Hegre & Sambanis, 2006).

Another assumption often made in diffusion literature, is that the likelihood of violent anti-government campaign diffusion from one country to another will increase the more proximate the two countries are relative to each other, which is why it is sometimes dubbed the “neighbourhood effect” (Buhaug & Gleditsch, 2008). First off, it is generally easier to keep track of developments closer to home rather than far away. Furthermore, countries that are more proximate are often, but not always, more similar in many ways, like culture, but they also have a higher interdependency which increases opportunities for exchanging and mimicking strategies and organization, or in some cases physical goods such as weapons and supplies (Hegre & Sambanis, 2006). All these help us understand why the distance between two countries is an appealing way to capture all these less tangible variables on a global scale.

However, proponents and opponents of this theory have primarily focussed on violent anti-government campaigns and had little to no attention for nonviolent anti-government campaigns such as protests, strikes and other forms of civil disobedience (Gleditsch & Rivera, 2017). As such, most research and data efforts have focussed on violent-to-violent diffusion. Using new data, Gleditsch and Rivera (2017) broadened the scope of campaign diffusion literature by also looking at nonviolent campaign diffusion. They found that, similar to violent-to-violent campaign diffusion, a nonviolent campaign in one country increases the likelihood of a nonviolent campaign in another country. They also found that this effect is effect is stronger when these countries are neighbouring, i.e. proximate to each other (Gleditsch & Rivera, 2017). Therefore, like violent anti-government campaigns, there is evidence for a nonviolent anti-government campaign "neighbourhood effect". What Gleditsch & Rivera (2017) consider as a neighbouring country remains rather arbitrary throughout their research. Therefore, this research will first and foremost give a more detailed analysis on the interaction between the effect of nonviolent campaign diffusion and the distance between two countries on the likelihood of nonviolent campaign diffusion from one country to another.

If we return to the examples given by the Arab Spring, qualitative research implicitly links the events that unfolded in Tunisia to the events that led up the chaotic civil war in Syria (Aras & Falk, 2015). The violent civil strife in Syria started as a series of nonviolent protests for democratization, not too different from those we have seen in Tunisia, but they were immediately met with strong repression by the Assad-regime. The dynamics between protesters and government have since drastically changed to a situation where both sides are now entrenched in a violent, sectarian civil war (Droz-Vincent, 2014). Violent and nonviolent campaigns are not isolated events, there is empirical evidence that they can be related to one another, as the previous example shows us. Furthermore, nonviolent anti-government campaigns may continue while other parts of a campaign organization opt for more violent means. Yet, in quantitative conflict diffusion theory, this link is often lost in an effort to make a clear distinction between violent and nonviolent anti-government campaigns. To get a more elucidated view on the link between violent and nonviolent campaigns across the world, we will therefore build on previous research on nonviolent-to-nonviolent campaign diffusion through Gleditsch and Rivera's (2017) research. Yet, in contrast to Gleditsch and Rivera (2017), we will not solely look at the diffusion of nonviolent to nonviolent, but will instead look at the diffusion of nonviolent anti-government campaigns to both violent and nonviolent anti-government campaigns in other countries, as these two concepts are often not as dichotomous as they are portrayed in other research. To summarize this all, the choice on what campaign methods will or will not work are not solely dictated by the campaign methods of other nonviolent campaigns, but are often a complex combination of both the strategies and other information protesters learn from these other nonviolent government campaigns as well as how the government in that particular country responds to the protests. For quantitative analysis, it therefore seems more suitable to first look at both violent and nonviolent anti-government campaigns when assessing the effect of anti-government campaign diffusion. When it comes to diffusion theory, especially, restricting ourselves to only halve the possible outcomes, be it violent or nonviolent, creates an incomplete picture. The first research question this research poses is therefore as follows:

To what extent can nonviolent anti-government campaigns in one country explain the onset of violent and nonviolent anti-government campaigns in another country?

Our first research question is focussed primarily on the diffusion of nonviolent anti-government campaigns, and less so in how nonviolent campaigns turn violent. Previously, we also made the assumption that anti-government campaigns that start nonviolent can potentially turn violent given the government's response. To substantiate this assumption , we will also investigate the effect of repression on campaign methods in countries already in conflict, in hopes of reinforcing the idea that violent and nonviolent anti-government campaigns are often part of a single campaign, levying between violent and nonviolent campaign methods. Lichbach (1987) proposed that the use of violence on both government and anti-government campaigner can be attributed to strategic, rational decisions. When a government opts to increase repression of nonviolent protests, nonviolent means of government opposition become less effective and chances of the campaign reaching its objective are diminished, as the opportunity cost of nonviolent campaigns rises. Violence therefore becomes a relatively more viable alternative to maintain campaign intensity and momentum (Lichbach, 1987). Therefore, this research also proposes that the likelihood of an anti-government campaign turning violent increases as governments ramp up repressive policies and behaviour. We will do so by looking to answer the second research question:

To what extent can government repression explain when nonviolent anti-government campaigns turn violent?

In answering these questions, we hope to contribute towards a model which furthers our understanding of conflict diffusion in general, and, more specific, the dynamic nature of violent or nonviolent anti-government campaigns. More well-rounded knowledge on the role of nonviolent anti-government campaign on violent and nonviolent anti-government campaign onset could furthermore help policymakers identify and prepare for regional instability, violence and humanitarian aid in an earlier stage.

To answer the research question this paper poses, we will conduct a two-staged analysis. First, we will conduct and analyse a multilevel logistic regression to determine whether the proposed nonviolent anti-government campaign diffusion effect exists. For this analysis, we will use a dataset with a dyadic data structure including data on 161 countries over a period of 32 years. Then, we will conduct an ordinary logistic regression to take a closer look at the dynamics of violent and nonviolent anti-government campaigns, and get a better understanding of how the two types of anti-government campaigns relate to each other. For this leg of our research, we will use a similar but non-dyadic dataset also containing data on 161 countries over a period of 32 years, including other variables relevant for answering our research question.

2. Theory

Theories of conflict diffusion gained traction in the early 1990s, after the collapse of the Soviet Union and the subsequent democratization of most of its former satellite states (Saideman, 2012). Until the end of the Cold War, the dominant paradigm on intrastate conflict and dispute was that these should be seen as something that resided within state borders and is isolated from the rest of the world (Kaldor, 2013). However, the age of globalization and the new world order after the Cold War have brought forth a paradigm-shift in conflict studies, with an increasing regional rather than state focus and more acknowledgement of the fluidity and transparency of state borders (Kaldor, 2013).

Before we dive into the campaign diffusion and escalation theories proposed by this paper, we must first briefly define what nonviolent and violent anti-government campaigns are. An anti-government campaign is an organized protest, strike, riot or other civil conflict with at least a 3000 participants, aimed directly at the government of a country over a prolonged time (Gleditsch & Rivera, 2017). The goals of what we consider an anti-government campaign can be institutional reform, state capture or secession, amongst other things. The one thing all anti-government campaigns have in common is that they strive to take back power from the state in one form or another. An anti-government campaign is generally considered violent when a 1000 or more people die in one year as a direct result of violence between protesters and government (Gleditsch & Rivera, 2017).

2.1 Campaign Diffusion Theory

In their 2017 article, Gleditsch and Rivera make their case for nonviolent anti-government campaign diffusion. While their initial conception of nonviolent anti-government campaign diffusion was drawn from the more prevalent research on violent anti-government campaign diffusion, they argue that nonviolent campaign diffusion has different underlying mechanisms. For us to understand the differences and similarities between violent and nonviolent anti-government campaign diffusion, we must first take a look at the mechanisms behind violent anti-government campaign diffusion. There are a wide variety of theories on how violent anti-government campaign diffusion works, but one common assumption is that violent anti-government campaign diffusion occurs when a country with a 'weak' border sees a sudden influx of weapons, strategic resources, militia refugees. This influx of goods and people from a violent anti-government campaign in one country to another country can alter the strategic behaviour of anti-government actors within the former country. These goods crossing the border can, when falling into the hands of these anti-government actors, make violence a more feasible and therefore rational alternative to other forms of opposition (Gleditsch & Rivera, 2017). Yet the opportunity costs for violent anti-government campaigns remain arguably higher due to the greater risks individuals will have to accept. Therefore, violence is more often than not an endpoint, not a beginning. Most anti-government campaigns start nonviolent and eventually turn violent in some cases (Sambanis, 2004).

Now that we have a better understanding of some of the underlying mechanisms of violent anti-government campaign diffusion, we will look what general comparisons we can and cannot draw between violent and nonviolent anti-government campaign diffusion. By extend, this will yield to us the differences between the two forms of anti-government campaigns. While the general idea of campaign diffusion theory nowadays has been widely accepted in social sciences and, to be more specific, regional conflict studies, its origins lay in the intrastate diffusion of riots and upheaval in cities and suburbs. Protests in one city or suburb would incite similar protests in other areas across a country where similar societal problems occur (Spilerman, 1970). Nonviolent anti-government diffusion is assumed to have similar diffusion mechanisms to other forms of protest, like the protests in these suburbs. Spillerman (1970) argues that the protests spread due to the spread of information through word of mouth on a local level and media reporting on a national level. Basically, the effect of this information can be divided into two categories: the first type of information raises awareness on a particular topic, the second type of information is more strategic in nature, altering the ways in which people engage in these protests.

The first type of information therefore lies more in defining what people want, need and expect. If you, for example, earn low wages and pay high taxes, you might not be immediately inclined to protest, as you and most around you perceive this as the normal, i.e. the status quo. A protest in another neighbourhood or country, however, might alter your view on what you perceive as normal and help you define new goals and you in turn might be more eager to mobilize in protest. If one is made aware of his or her circumstances and why these particular circumstances are a problem, the perceived opportunity costs for that individual joining a protest might be lower than they initially seemed, as that individual, and, by extend, group has less to lose and more to gain than one initially thought.

The second type of information one may gain from another nonviolent anti-government campaign is strategic information on how those needs that became apparent through the first type of information may be fulfilled in a more effective and efficient manner. In their research on the sit-in protests for racial equality that took the southern United States by storm in the spring of 1960, Andrews and Biggs (2006) observed that these protests mainly diffused through information carried by news media. The information on protests in one neighbourhood could change the political opportunity costs for protests elsewhere by learning and subsequently emulating strategies that work while simultaneously learning about possible hazards such as police responses to certain strategies used by protesters (Andrews & Biggs, 2006). This strategic information, just like information about wants and needs, in turn decreases the opportunity costs for anti-government campaigns, as a better understanding on how to organize, mobilize and allocate resources makes for a more efficient anti-government campaign.

Gleditsch and Rivera (2017) argue that nonviolent anti-government campaign diffusion between countries works in a similar fashion to the protest diffusion observed by Andrews and Biggs. An argument can be made though that for cross-country diffusion to be successful for the anti-government campaigners, they must overcome a few extra hurdles. Unlike violent anti-government campaign diffusion, nonviolent anti-government campaign diffusion does not rely on a physical, tangible influx of resources and people, and is instead set in motion by the new information and subsequent emulation of the knowledge gained from, amongst other sources, new media and word of mouth on another nonviolent anti-government campaign.

Information is a resource nonetheless, and this is where the similarities with violent anti-government campaigns surface again. Violent and nonviolent anti-government campaign diffusion works through an influx of resources decreasing the political opportunity costs for anti-government actors, therefore increasing the feasibility of anti-government campaigns (Gleditsch & Rivera, 2017). A nonviolent campaign in one country is therefore likely to increase the odds of anti-government protest in other countries. From campaign diffusion theory we now deduct our first hypothesis for this research.

Hypothesis 1: A nonviolent anti-government campaign in one country increases the likelihood of violent or nonviolent anti-government campaign onset in another country.

Although there is substantial evidence that a diffusion process exists, the process through which diffusion takes place is often harder to grasp, especially in quantitative research (Forsberg, 2014). This is because an exchange of information between individuals in itself is hard to quantify. Therefore, we are more inclined to look to structures through which information can be exchanged, like media, but also cultural or economic ties that can function as networks for the more efficient transfer of information (Forsberg, 2014). We can, however, logically and empirically deduct that a campaign in one country does not equally affect all the other countries, as we would otherwise expect the protests or uprisings to spread to all other countries. In practice, we rarely see nonviolent anti-government campaign diffusion in effect, as for the few countries in which we do perceive diffusion from nonviolent anti-government campaigns from one country to another, we have an overwhelming majority of countries that do not seem to be affected by the nonviolent anti-government campaigns in that country, while other countries do seem to be affected but have a different outcome, i.e. a violent instead of a nonviolent anti-government campaign. This leads to the assumption that something else must be moderating the effect of nonviolent anti-government campaign diffusion (Buhaug & Gleditsch, 2008). While there are many theories on the potential causes and mechanisms of nonviolent anti-government campaign diffusion, two different arguments can be identified. Firstly, protests in a country that is very similar to the 'receiving' country will likely increase the odds of conflict diffusion. Secondly, the reason why conflict does spread to one country but not to another could be because of circumstances specific to that country. Some countries with a certain socio-economic environment or regime type might be more likely to mitigate the effects of a nonviolent anti-government campaign in another country on nonviolent anti-government campaign onset within their own borders (Gleditsch & Rivera, 2017). Moreover, active repression by governments may change the opportunity costs of nonviolent anti-government campaigns and increase the likelihood of a transition to more violent means by protesters (Lichbach, 1987). The remainder of this chapter will explore both these arguments and their explanations of the diffusion process.

2.2 Campaign Diffusion Through Proximity

In the previous subchapter we discussed how nonviolent anti-government campaigns diffusion works and discussed why there must be other factors that boost or hinder the odds of nonviolent anti-government campaigns diffusing to other countries, as not all countries in the world seem to be affected equally by a nonviolent anti-government campaign in another country. Buhaug and Gleditsch (2008) investigated several different patterns of campaign diffusion. First and foremost, geographic proximity to a country with a nonviolent anti-government campaign increases the likelihood of conflict in that country. Conflict in a neighbouring country thus makes a country far more susceptible to the diffusion than conflict in a country on the other side of the globe. The closer a country is to an anti-government campaign in another country, the higher the salience of this campaign is to both the government and the people residing in said country, as people are often more aware of what is going on in their regionality and the protests and outcomes of protests close to home are more likely to, respectively, relate to and affect them (Buhaug & Gleditsch, 2008). Furthermore, the higher the proximity of two countries, the more likely they are to show signs of similarity, e.g. a similar culture, shared communal diaspora, and a shared political history. Communities within countries are often more homogeneous than communities between countries, although there are strong cases for communal ties that show a stronger homogeneity with communities in other countries than other communities in the same country (Tung, 2008). Diffusion is more likely to occur when two countries are similar to each other, as the information gained from nonviolent anti-government campaigns in one country is more effectively transmitted through these cultural and economic networks to people in the other country. This information can then raise awareness and increase strategic behavior in would-be protesters in the former country, decreasing the political opportunity costs for political action in the form of anti-government campaigns (Andrews & Biggs, 2006; Gleditsch & Rivera, 2017). The proximity between two countries could therefore be an important, albeit indirect, moderating variable that captures the moderating effect information networks have on the diffusion of nonviolent anti-government campaigns. This leads us to the following hypothesis:

Hypothesis 2: The positive relation between a nonviolent anti-government campaign in one country and the likelihood of violent or nonviolent anti-government campaign onset in another country is stronger the smaller the distance between those two countries is.

2.3 Repression and Nonviolent Anti-Government Campaign Escalation

So far, we sought for explanations for the diffusion of nonviolent campaigns and found two likely catalysts: close geographical proximity and country-specific indicators like socio-economic status and regime type. This, however, does not account for the complexity of conflict diffusion mechanisms and the discrepancies we find in previous results (Lichbach, 1987). First of all, we do not have a sufficient explanation on why nonviolent anti-government campaigns would turn violent in some cases and remain peaceful in others. Theories on campaign escalation state that nonviolent protests can escalate into violent conflicts when met with government repression. This does not necessarily mean that violent campaigns are always preceded by nonviolent ones, as actors anticipate the effect and success chance of their actions beforehand. Protesters who live in very repressive regimes are therefore more likely to immediately look for more violent and clandestine measures, as they anticipate that peaceful protests will not be successful and might only harm their cause and help the government to identify and repress them (Lacina, 2006). With the so-called 'action-reaction nexus', Lichbach (1987) explains how government repression initial anti-government campaigns can either deter or escalate subsequent nonviolent protests. Governments are in a constant strategic balancing act on how to maintain in power while trying to keep the anti-government campaigns to a minimum. In other words, state repression may cease protests altogether through effective deterrence or further escalate the scope of protests into violent campaigns if deterrence proves ineffective. Lichbach (1987) argues that protesters and campaign organizations are rational actors too, and rational actors will seek for other, means to achieve their goals if the target government does not respond to their demands and does not facilitate peaceful means of protest. When the stakes in a nonviolent anti-government campaign get higher, e.g. due to fear of government repercussions when the protests stop, and the nonviolent means of continuing the anti-government campaign cease to exist, protesters will sometimes look for other, more violent means to respond to government repression (Pierskalla, 2009). Of course, one could argue that a campaign is already violent as soon as a government decides to violently repress said campaign. For this research, however, we will focus on violence used by anti-government actors, as it is their actions that make the campaign itself violent. For example, a nonviolent anti-government campaign met with repression that either ceases the campaign altogether or maintains a nonviolent posture, will still be considered a nonviolent anti-government campaign for the purpose of this research.

Hypothesis 3: An increase in repression of a nonviolent anti-government campaign by the government increases the likelihood of the campaign turning violent.

3. Data & Measurements

In this chapter we discuss the data we collected for our research and how this data was combined into the datasets required to run our models and test our hypotheses.
We will then explain how the various variables used for this research were operationalized and also take a look at the descriptive statistics.

3.1 Data Structure

To test our hypotheses, this research will use longitudinal data from a total of 161 countries over a period of 32 years. The 161 countries include both major and minor economies from all over the world with a population of at least 500,000 inhabitants. For each country, the dataset includes yearly data for each of the variables necessary to test our hypotheses. This dataset comprises data on the years 1975 through 2006.
In order to test Hypotheses 1 and 2, which state that a nonviolent anti-government campaign in one country increases the likelihood of violent or nonviolent anti-government campaign onset in another country and that the positive relation between a nonviolent anti-government campaign in one country and the likelihood

of violent or nonviolent anti-government campaign onset in another country is stronger the smaller the distance between those two countries is, this research combines data from the Polity IV Annual Time Series (Polity IV), the World Development Indicators (WDI), as well as the Violent or nonviolent Campaigns and Outcomes (NAVCO) data project (Center for Systemic Peace, 2017; Chenoweth & Lewis, 2013a; World Bank 2018a; World Bank 2018b; World Bank 2018c). Polity IV is a long-running project started by Gurr and continued by Marshall which comprises data on countries' regime types, i.e. whether they are more democratic or authoritarian (Davenport et al., 2002). The WDI is an open access data project by the World Bank, compiling a broad array of cross-country socio-economic and other development related indicators. The NAVCO data project was initiated by Chenoweth & Lewis (2013b) and catalogues prior qualitative research on violent and nonviolent campaigns into data ready for quantitative analysis, with the explicit goal of facilitating more in depth analysis on the dynamics of anti-government campaigns.

The data used in this research from both WDI and NAVCO indicators is on a cross-country and annual basis, each variable providing one observation for each country and year. First, the data from both sources was combined using the corresponding Correlates of War (CoW) country-code and year. Then, the data was restructured into the previously discussed dyadic dataset.

For the first two hypotheses, a dyad was created between each of the 161 countries, resulting in observations for both country *A* and country *B* in each case. Through the thirty-two years this data encompasses, new countries have come and old countries have gone, e.g. the dissolution of the Soviet Union left many new countries in its wake. Therefore, not all countries have data over 32 years, as some of them dissolved or succeeded dissolved countries during the period this data encompasses. This results in an uneven number of country dyads for each year, as when a country ceased to exist, its dyads with all other countries also disappears. In total, this leads to 706,660 cases, each case including observations unique to a specific combination of country *A*, country *B*, and a year.

Furthermore, the dyad used to test Hypothesis 1 and 2 is directional in nature, as our hypothesis states that a nonviolent anti-government campaign in *country B* is to affect the odds of violent or nonviolent anti-government campaign onset in country *A*. For example, one dyad is composed of Egypt and Tunisia, where Egypt is country *A* and Tunisia is country *B*. We have country *A* level predictors such as gross domestic product and regime type, but also country *B* level predictors, namely whether there is a nonviolent or violent anti-government campaign in country *B*. Our dependent variable, on the other hand, is a country *A* level observation. We want to analyze whether a nonviolent anti-government campaign in Tunisia increases the likelihood of a violent or nonviolent anti-government campaign in Egypt. Thus, there is a supposed directional relation from country *B* independent variables to a country *A* dependent variable. For each combination of countries, there are therefore two dyads in a given year. In the example of Tunisia and Egypt, this means that there is one dyad in which Tunisia is country *A* and Egypt country *B*, and another in which Egypt is country *A* and Tunisia country *B*.

For Hypothesis 3, we will use a similar but non-dyadic dataset to test whether an increase in repression of a nonviolent anti-government campaign by the government increases the likelihood of the campaign turning violent. For this hypothesis, the same Polity IV and WDI indicators were used, whereas some NAVCO variables used for Hypotheses 1 and 2 have been replaced with other NAVCO variables required to test Hypothesis 3 (Center for Systemic Peace, 2017; Chenoweth & Lewis, 2013a; World Bank 2018a; World Bank 2018b; World Bank 2018c). This dataset was build using a number of the same variables used for Hypotheses 1 and 2, which we will discuss later in this chapter. The timespan and number of countries included in this dataset is the same as the data on which the previously discussed dyadic data was build, including 161 countries over a thirty-two year period, spanning from 1975 through 2006, i.e. a period of 32 years. However, in order to test Hypothesis 3, we are only interested in those cases in which a nonviolent anti-government campaign is already ongoing, so all cases with no violent or nonviolent anti-government campaign will be filtered out of the data. This significantly reduces the number of countries included in the data, bringing the remaining total down to 111 countries. Furthermore, we are only interested in violent anti-government campaigns when they transition from nonviolent to violent, so all cases with an ongoing violent anti-government campaign that do not follow up a nonviolent anti-government campaign in the previous year are also filtered out. This leaves us with a comparatively small subset of 1449 cases with observations spanning a thirty-two year period.

To avoid confusion about these similarly labeled variables, we have split the operationalization and descriptive statistics sections in two parts, first discussing the operationalization and descriptive statistics for Hypotheses 1 and 2, which use the dyadic dataset. Thereafter we will do the same for Hypothesis 3 and the variables in the nondyadic data used for this hypothesis.

3.2 Operationalization Hypothesis 1 and 2

We will now operationalize the dependent and independent variables required to test Hypothesis 1, which states that a nonviolent anti-government campaign in one country increases the likelihood of violent or nonviolent anti-government campaign onset in another country, and Hypothesis 2, which states that the positive relation between a nonviolent anti-government campaign in one country and the likelihood of violent or nonviolent anti-government campaign onset in another country is stronger the smaller the distance between those two countries is. As we only have yearly observations, to guarantee that no wrong conclusions are made as a result of errors in the temporality of our observations, all variables other than the dependent variable are lagged by one year. Furthermore, as we plan on doing a logistic regression, some data for some variables has been interpolated using previous and subsequent points in the data to remove missing values, as logistic regression cannot handle missing values on any of the independent variables and will otherwise remove the entire case from the equation.

The dependent variable, the onset of a violent or nonviolent campaign in country *A*, is subtracted from the NAVCO data project (Chenoweth & Lewis, 2013a). In the data used from the NAVCO data project for the purpose of this research, a violent or nonviolent campaign is an anti-government protest aimed at secession, state-capture or significant institutional reform with at least one-thousand participants. Whether a campaign was deemed violent or nonviolent was based on inter-coder reliability and a consensus list of mature, maximalist campaigns (Chenoweth & Lewis, 2013b). The onset of a violent or nonviolent campaign in country *A* is a binary dummy variable. A score of 0 indicates there is no violent or nonviolent campaign onset, and a score of 1 indicates violent or nonviolent campaign onset. When a violent or nonviolent campaign in country *A* continues past the year in which campaign onset occurred, the observation for onset of a violent or nonviolent campaign in country *A* will be counted as missing and is thus effectively filtered until the year the campaign subsides.

The first independent variable for Hypothesis 1 is an ongoing nonviolent anti-government campaign in country *B*. Just like the dependent variable, this is a dichotomous dummy variable with two values, 0 and 1. This variable was also attained using the NAVCO dataset (Chenoweth & Lewis, 2013a). A score of 0 indicates no nonviolent anti-government campaign is ongoing in country *B* during the year previous to the observation on our dependent variable. A score of 1 indicates that a nonviolent anti-government campaign is ongoing in country *B* during the year previous to the observation on our dependent variable.

For our second, third, fourth and fifth independent variables, we will make an independent variable combining each variable with the previously mentioned variable, an ongoing anti-government campaign in country *B*, to make four interaction variables. These four variables will all be a measure of the distance between country *A* and country *B,* each having a different measure or threshold for when a country dyad is labeled as being proximate. Four different measures are used to better understand what the effect of proximity is. This way, we hope to get a better understanding of whether there is a certain drop-off distance beyond which the effect of nonviolent anti-government campaign diffusion no longer has an effect or whether the assumed diffusion effect gradually degrades as the distance between two countries decreases. We will do so in the analysis chapter, but will first briefly discuss each of the four variables that will eventually help make up the interaction variable.

The first variable measures the distance in kilometers between country *A* and country *B*. This is a ratio variable which has a minimum value of 1 and an undefined maximum score which in practice would translate to approximately 20000 kilometers distance, as this is half the circumference of the earth (Sharp, 2017). However, we assume that the effect of distance grows stronger the closer two countries are to each other. Therefore, we will use the natural logarithm for this variable in our analysis. As we want to use this variable in our interaction effect, we want a countries in close proximity to each other to score high on this variable as the other independent variable used for the interaction effect, i.e. an ongoing nonviolent anti-government campaign in country *B*, is also positive in nature. We want a higher score on the interaction variable to represent a closer proximity to an ongoing nonviolent anti-government campaign in country *B*. Therefore, after the logarithmic transformation, we will conduct another transformation on this variable. We have subtracted the maximum value of this variable, 9.868, from all observations on this variable and then multiply those values by -1. For example, the maximum score, i.e. the highest distance measured, will now score (9.868 – 9.868) * - 1 = 0, whereas the lowest score, i.e. the lowest possible distance of 1 kilometer, will now score (0 – 9.868) * -1 = 9.868.

The second variable uses the data from the previous variable, but instead makes a dummy variable out of it with a score of either 0 or 1. A 0 indicates country *A* and country *B* are further than 100 kilometers apart, whereas a score of 1 indicates the countries 100 or less kilometers from each other. The same was done for 250 kilometers and 500 kilometers. In those variables, a score of 0 indicates country *A* and country *B* are more than 250 kilometers or 500 kilometers apart, respectively, and a score of 1 indicates country *A* and country *B* are 250 kilometers or less or 500 kilometers or less apart, respectively.

An argument can be made for new media, i.e. social media, as an information network that negates the effect of proximity entirely. New media have decreased the capabilities of states to contain information structures within its state borders, as demonstrated by the thousands of protesters who took to the streets and organized through social media in the protests in Egypt. Whereas the government had full control of conventional media, e.g. television broadcasts and printed press, the internet brought new media over which the government had far less control (Shirky, 2011). The lack of control over their own borders could also lead to ethnic rather than national identities becoming even more salient (Nordstrom, 2004). The scope of this research is restricted to from 1975 to 2006, however, so we expect the effect of social media to be marginal when compared to the traditional cultural and economic networks of information. Therefore, proximity can still be effectively used as a proxy for these traditional cross-country information networks.

Our first control variable is a violent anti-government campaign in country *B*. Just like nonviolent anti-government campaign diffusion, we expect that there is also a violent anti-government campaign diffusion to other countries. Previous research has found evidence for the existence of a violent-to-violent diffusion effect (Schutte & Weidmann, 2011). Furthermore, as mentioned earlier, the emulation that drives anti-government campaign diffusion is not solely based on an emulation of strategies, but also an emulation of goals. It is therefore not unlikely that a violent campaign in one country can also inspire nonviolent anti-government campaigns other countries, as these protesters are inspired by similar campaign goals yet face different opportunity costs in the country they live in. This is a dummy variable with two values, 0 and 1. A 0 indicates no violent anti-government campaign is observed in country *B*, whereas a 1 indicates that a violent anti-government campaign in country *B* is ongoing.

Our second control variable is a recent violent or nonviolent anti-government campaign in country *A*. First off, the success of a previous campaign may inspire protesters to push for new campaigns. Even when a campaign is not successful, however, the experiences and organizational structures set up during a previous violent or nonviolent anti-government campaign can lower the opportunity costs of future anti-government campaigns (Gleditsch & Rivera, 2017). Furthermore, grievances that still linger after a previous anti-government campaign can lower the bar for people to join future anti-government campaigns, regardless of the success of the previous campaign (Murshed & Tadjoeddin, 2009). This is also a dummy variable with a score of either 0 or 1. A 0 indicates no violent or nonviolent anti-government campaign has occurred in country *A* the past five years. A 1 indicates that a violent or nonviolent anti-government campaign did occur in country *A* somewhere in the past five years. Just like our independent and dependent variable, this variable was attained from the NAVCO dataset (Center for Systemic Peace, 2017).

Carey (2006) found that democracies have different opportunity structures than autocratic regimes. Democracies offer more openness and political means to settle conflict, therefore the necessity to campaign against a government in the first place is much lower, as there are democratic institutions through which one can reform the government (Carey, 2006). Therefore, it is likely to assume that the odds of both violent and nonviolent anti-government campaigns increase as countries become more autocratic. For our third control variable, we will therefore use a commonly used gauge to measure each country's regime type: the Polity score. The Polity score is retrieved from Polity IV (Center for Systemic Peace, 2017). Polity score indicates country *A*'s regime type. This is an ordinal variable with values ranging between -10 and 10, where a score of -10 signifies country *A* has a fully autocratic regime, and 10 signifies country *A* has a fully democratic regime. A 0 indicates a regime has neither an autocratic nor a democratic regime, i.e. a score of 0 would indicate that country *A* is an anocracy.

A large military can increase the risks involved in anti-government campaigns and therefore alter the opportunity costs of participating in these campaigns for individuals and organizations alike (Croissant et al., 2018; Gleditsch & Ruggeri, 2010). Furthermore, a study by Langton (1984) found that people who served in the military or knew someone close that served in the military are less likely to participate in anti-government campaigns and protests in general. A large military expenditure can therefore deter people from joining these protests, decreasing the likelihood of violent or nonviolent anti-government campaigns. Military expenditure as a percentage of the gross domestic product of country *A* is a ratio variable with a minimum score of 0 and no theoretical maximum, as spending can theoretically grow larger than the gross domestic product. In practice, however, this variable will likely range between 0 and 1, as it is unlikely that a country can afford to spend more than its total gross domestic product. It was lifted from the data provided by the World Bank (2018b).

The fifth control variable used to test hypotheses 1 & 2 is the urban population a country has as a share of the total population. An urban population tends to have a denser concentration of social networks and a higher amount of resources per capita, and, as such, a lower opportunity cost to organize an anti-government campaign when compared to a rural population (Gleditsch & Rivera, 2017). We therefore expect the opportunity cost for anti-government campaigns to be lower in countries with a smaller share of urban population, thus increasing the likelihood of violent or nonviolent anti-government campaigns in countries with a higher urban population proportional to their rural population. Urban population as a percentage of the total population of country *A* is a ratio variable with a minimum score of 0 and a maximum score of 1. A score of 0 means 0 percent of the total population of country *A* lives in an urban environment, i.e. cities and suburbia. A score of 1 means that 100 percent of the total population of country *A* lives in an urban environment. By multiplying the observed score of country *A* by 100, we thus get the percentage of the total population of country *A* living in an urban area. A score of 0.200, for example, means that 0.200 * 100 = 20.0 percent of the population of country *A* lives in an urban environment. The data for this variable was also attained from the World Bank (2018c).

Another variable we lend from the World Bank data, the gross domestic product per capita of country *A*, or GDP p.c., is the sum of the economic wealth accumulated in country *A* divided by its total population (World Bank 2018a). Previous research has discovered that a lack of economic development is an important indicator for rising anti-government sentiments and increasing dissatisfaction with the status quo, and could thus well help explain when both violent and nonviolent anti-government campaigns occur (Dalton et al., 2010). The gross domestic product per capita of country *A* is a ratio variable with a minimum score of 0 and no theoretical maximum score.

For the previous three variables, i.e. military expenditure, urban population and GDP p.c., we will use the natural logarithm of each variable. We do this because we are less interested in the absolute change, but rather the relative changes in these variables. For GDP p.c., for example, we expect an increase of 1000 US$ to have a more notable effect on countries with a GDP p.c. of 2000 US$ than a country with 20000 US$. Similarly, the effect of a 10 percent point change is expected to be larger on a country with an urban population of 10 percent, amounting to a 100 percent increase, than on a country with an urban population of 50 percent, amounting to a 20 percent increase.

The year is an interval variable that signifies the current year for the observation of violent or nonviolent anti-government campaign onset in country *A*. It has a minimum value of 1975, the year our observations for violent or nonviolent campaign onset in country *A* started, and a maximum score of 2006, signifying the year 2006, the last year in which we observed the onset of a violent or nonviolent anti-government campaign in country *A*. A score of 1975 indicates an observation for 1974 on all but our dependent variable however, as these measures were lagged by

Table 1. Descriptive statistics hypothesis 1 & 2

Variables	Mean/Odds	Std. Deviation	Min	Max
Onset violent or nonviolent campaign *A*	0.001		0	1
Nonviolent campaign *B*	0.047		0	1
Distance	6368.283	4212.165	1	19299.000
Ln distance	-4.281	1.983	0	9.868
100 km distance	0.031		0	1
250 km distance	0.041		0	1
500 km distance	0.052		0	1
Violent campaign *B*	0.179		0	1
Recent campaign	0.278		0	1
Polity Score	0.307	6.393	-10	10
Military expenditure	0.009	0.082	0.001	0.451
Ln military expenditure	-5.392	1.038	-6.550	-0.796
Urban population	0.244	0.177	0.011	0.903
Ln urban population	-1.557	.717	-4.510	-0.102
GDP p.c.	4906.260	6034.142	104.033	32068.868
Ln GDP p.c.	8.205	1.260	4.645	10.376
Year	1990.166	8.194	1975	2006

N countries = 161, N observations = 706660.

one year. If we look at the parameters for the first set of variables shown in Table 1, we can see that the dependent variable for our first two hypotheses, the onset of a violent or nonviolent anti-government campaign in country *A*, scored a minimum value of 0 and a maximum value of 1. This is not surprising, as this variable is binary and has only these two values to begin with. As such, the mean value of 0.001 can be interpreted as being a percentage, where a score of 0 indicates 0 percent of the observations in that variable scored a 1, or alternatively, 100 percent of the observations in that variable scored a 0. After all, if 0 percent of all observations in the variable scored a 1, all other non-missing observations must be 0, and the mean of 706,660 times 0 is still 0. The mean value in Table 1 can take on any value between 0 and 1. For example, if 25 out of 100 observations score 1 on this variable, the mean value of (75 * 0 + 25 * 1) / 100 would be 0.25, and, by multiplying this by 100 we can subtract that 25 percent of the observations included in this example scored a 1 on this variable. So, if multiplied by 100, the reported mean parameter of 0.001 on the onset of a violent or nonviolent anti-government campaign in country *A* therefore tells us that approximately 0.1 percent of all observations scored a 1 on this value. It is important to stress that this percentage only tells us the percentage of observations within the data, i.e. within the country dyads. Therefore, with the parameter shown in Table 1, we cannot make any conclusions about the precise percentage of observations that scored a 1 on this variable in all unique year-country *A* combinations, i.e. the non-dyadic data. The percentage in the dyadic data is skewed towards the observations in those countries that had more year observations in the initial data, prior to the dyadic conversion. This same restriction applies to all the parameters reported in Table 1: the parameters on display in Table 1 report the mean or, for binary variables, percentage of observations within the dyadic data. Nonetheless, 0.1 percent of the observations in the dyadic data still indicates that the number of observations in which violent or nonviolent anti-government campaign onset was observed is likely comparatively small to the number of observations in which no violent or nonviolent anti-government campaign onset was observed.

Our first independent variable, a nonviolent anti-government campaign in country *B*, scored a minimum value of 0 and a maximum value of 1. Just like the dependent variable, this variable is binary and can only score these two values. Because of the binary nature of this variable, the mean value in Table 1 again indicates the relative percentages of observations that scored a value of 1 on this variable. In 0.047 * 100 = 4.7 percent of all valid observations in the dyadic data, a score of 1 on this variable was observed, i.e. a nonviolent anti-government campaign was recorded in country *B*.

Our second independent variable, the distance in kilometers between country *A* and country *B*, scored a minimum of 1 kilometers, i.e. a country-dyad with two countries bordering each other, and a maximum of 19299 kilometers. The mean distance in all observations for this variable is 6368.283 kilometers distance between country *A* and country *B*. Assuming the observations are normally distributed, we can therefore assume that 68.2 percent of all observations lie within the 6368.283 – 4212.165 = 2155.668 and 6368.283 + 4212.165 = 10580.898 kilometers distance, i.e. within one standard deviation from the mean. However, as we discussed earlier, we will be using an inversed natural logarithm of this variable. As we can see in Table 1, the minimum value on the logged variable is 0, and the maximum value is 9.868. We must be careful to remember 9.868

represents the lowest distance and 0 the highest distance, as they were inversed for the sake of our interaction variable.

Our third, fourth and fifth independent variables are dummy variables that determine whether countries lie within 100, 250 or 500 kilometers apart, respectively. They each scored a minimum value of 0 and a maximum value of 1. This makes sense, as the values on these dummies were derived from the previously discussed variable for distance in kilometers. The range on distance between country *A* and country *B*, varied between 0 and 19299 kilometers. The minimum and maximum distance are therefore both within and without 100, 250 and 500 kilometers, hence the minimum and maximum scores for these three variables are 0 and 1. The mean again gives us the relative percentage of observations that scored 1 when multiplied by 100, as these variables are all binary with only scores of 0 and 1. Regarding the distance between country *A* and country *B*, we can therefore see in Table 1 that 0.031 * 100 = 3.1 percent of all observations in this variable showed a distance of less than 100 kilometers, 0.041 * 100 = 4.1 percent of all observations on this variable showed a distance a distance of less than 250 kilometers, and 0.052 * 100 = 5.2 percent of all observations on this variable showed a distance less than 500 kilometers.

Our first control variable, a violent anti-government campaign in country *B* again is a binary variable, scoring a minimum value of 0 and a maximum value of 1. When multiplied by 100, the mean value can again be transformed to the percentage of cases scoring 1. Of all valid observations, 0.179 * 100 = 17.9 percent observed a violent anti-government campaign in country *B*.

A recent violent or nonviolent anti-government campaign in country *A* is again a dummy variable, so we can interpret the mean in Table 1 as a percentage when multiplied by 100. In 0.278 * 100 = 27.8 percent of observations, country *A* has endured a violent or nonviolent anti-government campaign sometime during the five years previous to the year in which the observation for this variable was made.

The parameters for polity score of country *A* tell us this control variable has a minimum score of -10 and a maximum of 10. This indicates that both the most undemocratic, or most autocratic regimes with a score of -10 as well as the most democratic regimes with a score of 10 were observed within the data. The mean polity score is 0.307. As this mean is higher than 0, albeit with a small margin, we can see that the observations in this data are ever so slightly skewed towards the more democratic side of the scale.

Military expenditure as a percentage of the gross domestic product of country *A* has a minimum score of 0 and a maximum of score of 0.451. This indicates that there are countries within the data with a military expenditure of 0 percent of the gross domestic product at the lower bound, and 0.451 x 100 = 45.1 percent of the gross domestic product in the upper bound. The mean for this variable tells us that on average, the observed military expenditure as a percentage of the gross domestic product is 0.009 * 100 = 0.9 percent. The standard deviation is 0.82, or 0.82 * 100 = 8.2 percent point. The mean of 0.009 is much closer to the minimum of 0 than the maximum value of 0.451. This, combined with the relatively large standard deviation, indicates that the observations on this variable are likely skewed towards the upper bound observation, with a number of notable cases where countries spend vastly more than the average country. The natural logarithm for military expenditure has a minimum value of -6.550 and a maximum value of -0.769.

Urban population as a percentage of the total population in country *A* has a minimum score of 0.011 and a maximum score of 0.903. The least urbanized country observed in the data therefore has an urban population that amounts to 0.011 * 100 = 1.1 percent of the total population in that country. On the contrary, the country with the highest urban population as a share of its total population we observed had an urban population of 0.903 * 100 = 90.3 percent. On average, the observed urbanization per country is 0.244 * 100 = 24.4 percent. Again, the mean is not centered right between our minimum and maximum value, indicating that the data is skewed and not normally distributed, likely so because of outliers on the upper bound observations on the urban population as a percentage of the total population. The natural logarithm for urban population has a minimum value of -4.510 and a maximum value of -0.102.

Gross domestic product per capita of country *A* has a minimum score of 104.033 US$ and a maximum of 32068.868 US$. The average observed gross domestic product per capita is 4906.260 US$, with a standard deviation of 6043.142 US$. Once again, these values indicate that the data is probably skewed rightwards. The natural logarithm for GDP p.c. shows us a minimum value of 4.645 and a maximum value of 10.376.

For our final control variable, year, the minimum value is 1975 and the maximum is 2006. The first year observed for country *A* is 1975, the last year is 2006. The mean score is of 1990.166. Had all countries been included for the entirety of thirty-two years, the mean would have been (1975 + 2006) = 1990.5. Although the mean score of 1990.166 is close to this number, it is important to remember that some countries only had observations for the former or latter years, as they came into existence or ceased to exist during the years this data spans.

3.3 Operationalization Hypothesis 3

We now move on to the operationalization of Hypothesis 3, which states that an increase in repression of a nonviolent anti-government campaign by the government increases the likelihood of the campaign turning violent.

Our dependent variable, anti-government campaign method, is a dummy variable which can either be 0 or 1. A 0 indicates that an anti-government campaign in a country is nonviolent, whereas a 1 indicates that an anti-government campaign in a country has turned violent in the previous year. This variable was made using data from the NAVCO data project (Chenoweth & Lewis, 2013a).

The independent variable, change in government repression, captures the change in government repression compared to the government repression in the previous year. This variable is made using a variable from the NAVCO dataset recording the government repression for each year with an ordinary variable ranging from 0 to 3 (Chenoweth & Lewis, 2013a). A score of 0 on this variable means no repression, whereas a score of 3 means heavy or maximum repression. As our variable, a change in government repression, measures the change, it can take on a value between -3 and 3. A score of -3 would indicate that while there was heavy government repression the past year, i.e. a score of 3, government repression is now reduced to 0, bringing a change of -3. A score of 0 on the government repression change variable indicates no change. A positive number therefore signals an increase in repression and a negative number signals a decrease in repression.

The first independent variable for this dataset is the regime type of a country. Like we discussed earlier in this chapter, a more autocratic regime is more prone to anti-government campaigns in general because the institutions of more autocratic regimes generally offer less opportunities to push for change through legal means. Moreover, autocratic regimes are less likely to give in to protesters demands unless they are forced to do so, heightening the opportunity costs for nonviolent anti-government campaigns and lowering the opportunity costs of violent anti-government campaigns (Carey, 2006). In other words, not only are more autocratic regimes more likely to see anti-government campaigns in general, they are also relatively more likely to face violent anti-government campaigns. The Polity score is retrieved from Polity IV (Center for Systemic Peace, 2017). Polity score indicates country *A*'s regime type. This is an ordinal variable with values ranging between -10 and 10, where a score of -10 signifies country *A* has a fully autocratic regime, and 10 signifies country *A* has a fully democratic regime. A 0 indicates a regime has neither an autocratic nor a democratic regime, i.e. a score of 0 would indicate that country *A* is an anocracy.

As we have established, a large military with a large military expenditure can deter protesters to join an anti-government altogether (Gleditsch & Ruggeri, 2010). Yet, when a nonviolent anti-government campaign is already ongoing, we expect the presence of a large military itself to be a deterrent for further escalation on the side of the protesters, as the risk of direct confrontation with a large military will increase the opportunity costs of violent campaigns relative to nonviolent campaigns. Military expenditure as a percentage of the gross domestic product of country *A* is a ratio variable with a minimum score of 0 and no theoretical maximum, as spending can theoretically grow larger than the gross domestic product. In practice, however, this variable will likely range between 0 and 1, as it is unlikely that a country can afford to spend more than its total gross domestic product. It was lifted from the data provided by the World Bank (2018b).

As for the previous hypotheses, we again include urban population as a control variable to test the third hypothesis. Since the countries in the data used for our third hypothesis are already going through an anti-government campaign regardless of the value on our independent variable, the opportunity cost argument we used earlier makes less sense this time around as both violent and nonviolent anti-government campaigns should benefit from these reduced opportunity costs. Instead, the argument here is that a more urbanized population can make guerilla tactics by protesters less effective and government repression more effective, increasing the opportunity costs of violent anti-government campaigns when compared to nonviolent anti-government campaigns (Gleditsch & Rivera, 2017). Urban population as a percentage of the total population of country *A* is a ratio variable with a minimum score of 0 and a maximum score of 1. A score of 0 means 0 percent of the total population of country *A* lives in an urban environment, i.e. cities and suburbia. A score of 1 means that 100 percent of the total population of country *A* lives in an urban environment. By multiplying the observed score of country *A* by 100, we thus get the percentage of the total population of country *A* living in an urban area. A score of 0.200, for example, means that 0.200 * 100 = 20.0 percent of the population of country *A* lives in an urban environment. The data for this variable was also attained from the World Bank (2018c).

Another variable we lend from the World Bank data, the gross domestic product per capita, or GDP p.c., is the sum of the economic wealth accumulated in country *A* divided by its total population (World Bank 2018a). The gross domestic product is an important indicator of the economic development of a country. Economic development, in turn, is also an important indicator for violence and unrest breaking out in a country. A low or declining economy has a multitude of effects which each on their own could be predictors for violent anti-government campaign onset, like political decay, poverty and an increased perception of deprivation and injustice which could in turn be the straw that break the camel's back (Auvinen & Nafziger, 2002). Simply put, the opportunity costs for individuals to participate in violent rather than nonviolent anti-government campaigns is shrinks as the individual in question has less to lose him- or herself (Chassang & Miquel, 2009). Because of this, it is an ideal control variable for the sake of our research. The gross domestic product per capita is a ratio variable with a minimum score of 0 and no theoretical maximum score.

Just like in the previous dataset we discussed, we will be using the natural logarithm of military expenditure, urban population and GDP p.c. in our analysis.

As we have explained previously, this is because we are more interested in the relative change in these variables rather than the absolute change, as we expect the effect of these variables to be proportionate to the relative rather than the absolute change.

The year is an interval variable that signifies the current year for the observation of violent or nonviolent anti-government campaign onset. It has a minimum value of 1975, the year our observations for violent or nonviolent campaign onset started, and a maximum score of 2006, signifying the year 2006, the last year in which we observed a previously nonviolent anti-government campaign change to a violent anti-government campaign. Just like our data for Hypothesis 1 and 2, a score of 1975 indicates an observation for 1974 on all but our dependent variable however, as these measures were again lagged by one year.

In Table 2 we see the parameters for the observations on the variables and cases included in our analysis for Hypothesis 3. The dependent variable, the current campaign method, has a minimum of 0 and a maximum of 1, as it is a binary variable. As only those violent anti-government campaigns that scored a 0 in the previous year are included, i.e. those violent anti-government campaigns that turned violent this year, the mean tells us something about the odds of a nonviolent anti-government campaign turning violent. Just like the binary variables we discussed for Hypotheses 1 and 2, the mean can be transformed into a percentage of valid observations in which a nonviolent anti-government campaign turned violent relative to the percentage of nonviolent anti-government campaigns that have not turned violent yet if we multiply this number by 100. By doing so, we see that in 0.082 * 100 = 8.2 percent of all observations in this variable, a previously nonviolent anti-government campaign turned violent that year. This means that (0.081 / (1 - 0.081)) * 100 ≈ 8.9 percent of all nonviolent anti-government campaigns included in this data turned violent the subsequent year.

We now move on to discussing the control variables in Hypothesis 3. When interpreting these numbers, it is important to remember that while their labels are identical to some of the variables used for Hypothesis 1 and 2 and the parameters can look similar as well due to both Hypothesis 1, 2 and 3 variables deriving from the same data, the observations on these variables included in our analysis of Hypothesis 3 is much smaller. It is a subset of the overall data on these variables, only including those observations within a country-year combination in which a country had an ongoing nonviolent anti-government campaign or had a violent anti-government campaign that had just turned violent after a nonviolent anti-government campaign in that same country a year earlier. We will therefore still interpret these data, as the subset data might seem familiar but are skewed in one direction or another when compared to the overall data.

Now for our independent variable used to test Hypothesis 3, the change in government repression has a minimum score of -3 and a maximum score of 3. This means that government repression has both leapt from no repression to maximum repression and maximum repression to no repression at least once, as the change is the result from the repression in the previous year minus the repression in the current year and the score for no repression is 0 and the score for maximum repression is 3. Looking at the positive value on the mean, the data suggests that the average government response to nonviolent anti-government campaigns is to increase repression, as a net positive mean indicates that the sum used to calculate the mean of all government repression changes must be positive as well. This sum can only be positive if there is a higher increase in government repression relative to those cases in which government repression reduced.

Our first control variable used to test Hypothesis 3, a country's polity score, has lower and upper bound observations of -10 and 10. This confirms that both very undemocratic and very democratic countries experience nonviolent anti-government campaigns, i.e. nonviolent anti-government campaigns occur in a broad variety of regime types. Furthermore, the negative mean of -0.412 on polity score indicates that the average country with a nonviolent anti-government campaign leans slightly towards the less democratic part of the polity score spectrum.

Our second control variable, military expenditure, has a lower bound score of 0.002 and an upper bound score of 0.454. Multiplied by 100, these numbers signify that the lowest percentage a country between 1975 and 2006 spent on their military relative to the total gross domestic product while a nonviolent anti-government campaign was ongoing in that country, is 0.002 * 100 = 0.2 percent. On the contrary, the highest amount spent on this by a country between 1975 and 2006 while a nonviolent anti-government campaign was ongoing in that country is 0.545 *

100 = 54.5 percent. The natural logarithm of military expenditure shows a minimum value of -6.215 and a maximum value of -0.790.

The third control variable, urban population as a percentage of total population, has a lower bound score of 0.008 and an upper bound of 0.902. Multiplied by 100, the lowest observed proportion of people living in urban rather than rural areas is 0.008 * 100 = 0.8 percent, whereas the highest proportion of people living in urban rather than rural areas has 0.902 * 100 = 90.2 percent of its total population living in an urban environment. The average country embroiled in a nonviolent anti-government campaign has an urban population of 0.211 * 100 = 21.1 percent. If we look at the natural logarithm for this variable, we see a minimum value of -4.828 and a maximum value of -0.103.

The fourth control variable, the gross domestic product per capita of a country with an ongoing nonviolent anti-government campaign, has a lower bound score of 132.820 US$ and an upper bound score of 27629.866 US$. Countries with both low and high gross domestic products per capita thus seem susceptible to nonviolent anti-government campaigns. The average gross domestic product per capita of a country with an ongoing anti-government campaign is 4248.327 US$. The natural logarithm for this variable shows a minimum value of 4.889 and a maximum value of 10.227.

Finally, for our last independent variable in this research, the lowest score for year found in this data is 1975 and the highest score is 2006. This may seem obvious at first glance, as the scope of this research includes all years between 1975 and 2006, but this did not necessarily have to be the case as this part of our research only includes those country-year combinations in which a nonviolent anti-government campaign in ongoing. What this actually tells us, is that the earliest year we observed an ongoing nonviolent anti-government campaign in the data was 1975, and the latest year we observed an ongoing anti-government campaign was 2006. Not necessarily all years are included this subset, only those in which we observed an ongoing nonviolent anti-government campaign in country, and data on that year is only included in that specific country-year combination. The mean year of our observations is 1989.662.

Table 2. Descriptive statistics hypothesis 3

Variables	Mean/Odds	Std. Deviation	Min	Max
Campaign method	0.082		0	1
△ Repression	0.040	0.461	-3	3
Polity score	-0.412	6.263	-10	10
Military expenditure	0.056	0.302	0.002	0.454
Ln military expenditure	-5.448	1.608	-6.215	-0.790
Urban population	0.211	0.168	0.008	0.902
Ln urban population	-1.864	0.849	-4.828	-0.103
GDP p.c.	4248.327	5299.464	132.820	27629.866
Ln GDP p.c.	7.388	1.797	4.889	10.227
Year	1989.662	8.164	1975	2006

N countries = 111, N observations = 1449.

4. Results & Analysis

In this chapter we will present and analyze the results this research brought to light. First, we will present the models build for this research. Then, we will test if our models fit the various assumptions before we conduct our logistic regression. We will check for multicollinearity between the variables in each dataset. Thereafter, we will check the linearity and heteroscedasticity or our independent variables. Once we made sure none of these assumptions are violated, we will look at the results of our various models and analyze if they meet the expectations set out by our hypotheses.

4.1 Model Presentation

To test the first two hypotheses on diffusion and similarity, we will estimate the likelihood of violent or nonviolent anti-government campaign onset in country *A* with binomial logistic regressions. A multilevel model was chosen, to counter the clustering of observations due to the dyadic nature of our dataset. The dyads were nested within country *A*. Other nesting possibilities were considered, like nesting in years as well as countries, but nesting in country *A* was eventually considered ideal, as the model fit was significantly better than an unnested model, yet only had a slightly worse fit than a model nested in both country and year. Due to resource restrictions, we decided that nesting within country *A* was the best option for this research, as it was still a big improvement over an unnested model, yet was significantly less time consuming than a model nesting in both country and year. This model was first used to test the first hypothesis, and therefore included nonviolent anti-government campaign in country *B*. Furthermore, it includes the following control variables: violent anti-government campaign *B*, recent campaign, polity score, military expenditure, urban population, GDP and year. Together, these variables make up Model 1.

Model 1 was reiterated four times to test the second hypothesis, for each one of four interaction variables was added and subsequently removed for the next model. Model 2 adds an interaction between nonviolent anti-government campaign *B* and the natural logarithm of the kilometer distance in kilometers between country *A* and country *B*. Model 3 adds an interaction between nonviolent anti-government campaign *B* and a dummy variable indicating if country *A* is within 100 kilometers distance of country *B*. Model 4 adds an interaction between nonviolent anti-government campaign *B* and a dummy variable indicating if country *A* is within 250 kilometers distance of country *B*. Model 5 adds an interaction between nonviolent anti-government campaign *B* and a dummy variable indicating if country *A* is within 500 kilometers distance of country *B*.

For our third hypothesis on government repression, we will estimate the likelihood of a nonviolent anti-government campaign turning violent with a binomial logistic regression. Model 6 includes the independent variable change in repression, as this model will be used to test our third and final hypothesis. Polity score, military expenditure, urban population, GDP and year were added as control variables.

4.2 Model Assumptions

Multicollinearity occurs when two or more independent variables closely correlate with each other. Though multicollinearity has little effect on the logits in logistic regression, one possible effect of multicollinearity is an overestimation of standard errors. This in turn could lead to a false rejection of a hypothesis in favor of the null hypothesis, i.e. a type II error (Scott, 2002, p.p. 75-78).

To prevent this from happening in our models, we will have to check them for multicollinearity. In this research, we will do so using the variance inflation factor (VIF). VIFs are obtained by regressing every independent variable in a model against each other. The resulting R^2 is used to calculate the VIF for each independent variable as follows: VIF = 1 / (1 - R^2). A high R^2 indicates high correlation. From this formula we can distill that a higher R^2 results in a higher VIF, thus a higher VIF indicates more collinearity.

It is to this day contentious how high a VIF should be to be considered “too high”, yet there are some generally accepted thresholds one should keep an eye out

Table 3. Variance inflation factors Models 1 through 5

	Model 1	Model 2	Model 3	Model 4	Model 5
Nonviolent campaign *B*	1.010	1.009	1.009	1.009	1.009
Ln distance		1.005			
100 km distance			1.001		
250 km distance				1.001	
500 km distance					1.001
Violent campaign *B*	1.015	1.015	1.015	1.015	1.015
Recent campaign *A*	1.074	1.074	1.074	1.074	1.074
Polity score	1.503	1.546	1.546	1.546	1.545

Ln military expenditure	1.521	1.458	1.458	1.458	1.458
Ln urban population	1.591	1.543	1.542	1.542	1.543
Ln GDP p.c.	1.744	1.673	1.673	1.673	1.672
Year	1.191	1.215	1.215	1.216	1.216

N countries = 161, N observations = 706660.

for. A VIF below four is generally accepted as offering little concern for multicollinearity in a model, but some less strict approaches advice that a VIF value below ten is not necessarily a concern for serious multicollinearity either (O'Brien, 2007).

In Table 1 we see the VIFs for our models. Since the values for Model 1, 3, 4 and 5 showed very similar values when compared to those in Model 2, we will only show the VIFs for Model 2 and Model 6 in this section. As we see in Table 1, none of the VIFs for the variables in Models 1, 2, 3, 4 & 5 exceeds two, which remains safely even within the conservative threshold of four, so do the VIFs for the independent variables in Model 6. We can thus safely conclude that no serious concern over multicollinearity is warranted in our models. In Appendix A, the bivariate correlation matrices for all 6 models are displayed for those who want to get a more detailed look at how to different independent variables and control variables interact with each other.

Table 4. Variance inflation factors Model 6

	VIF
∆ Repression	1.007
Polity score	1.129
Ln military expenditure	1.863
Ln urban population	1.522
Ln GDP p.c.	1.504
Year	1.363

N countries = 111, N observations = 1449.

4.3 Spatial Diffusion of Nonviolent Anti-Government Campaign Onset

For hypotheses 1 and 2, we have conducted a multilevel logistical regression on the likelihood of anti-government campaign onset in country *A*. Hypothesis 1 states that a nonviolent anti-government campaign in one country increases the likelihood of violent or nonviolent anti-government campaign onset in another country. Hypothesis 2 states that the positive relation between a nonviolent anti-government campaign in one country and the likelihood of violent or nonviolent anti-government campaign onset in another country is stronger the smaller the distance between those two countries is. We used “no anti-government campaign onset” as our reference category. A positive coefficient therefore indicates an increase in the likelihood of anti-government campaign onset in country *A*, whereas a negative coefficient indicates a decrease. A total of 706,660 observations in 164 countries were included in this analysis. We will first analyze the first model in depth, after which we will look at the second, third, fourth and fifth model.

Upon first inspection of Model 1 in Table 2, we see that our dependent variable, a nonviolent anti-government campaign in country *B*, has a positive and significant effect on the likelihood of violent or nonviolent anti-government campaign onset in country *A*. Using the exponent of the ß-coefficients shown in Table 2, we can now calculate the odds ratio for a nonviolent anti-government campaign in country *B*. The exponent of 0.210, the ß-coefficient for a nonviolent anti-government campaign in country *B* in Model 1, is 1.233. This odds ratio tells us that the likelihood of violent or nonviolent anti-government campaign onset in country *A* is 1.233 times, or 23.3 percent more likely when there is a nonviolent conflict in country *B*.

Furthermore, again using the respective ß-coefficients we are able to interpret the effects of our control variables in Model 1. A violent anti-government campaign in country *B* has a positive and significant effect on the likelihood of violent or nonviolent anti-government campaign onset in country *A*. It increases the likelihood of violent or nonviolent anti-government campaign onset in country *A* by 1.099 times, i.e. violent or nonviolent anti-government campaign onset in country *A* Is 9.9 percent more likely in the event of a violent anti-government campaign in country *B*.

A recent anti-government campaign in country *A* has a negative and significant effect on the likelihood of violent or nonviolent anti-government campaign onset in country *A*. It increases the likelihood of violent or nonviolent anti-government campaign onset in country *A* by 0.201 times. In other words, it decreases the likelihood of violent or nonviolent anti-government campaign onset

in country *A* by 1.799 times, i.e. violent or nonviolent anti-government campaign onset in country *A*
is 79.9 percent less likely in the event of a violent or nonviolent anti-government campaign in country *A* the past five years.

A higher polity score has a negative and significant effect on the likelihood of violent or nonviolent anti-government campaign onset in country *A*. It decreases the likelihood of violent or nonviolent anti-government campaign onset in country *A* by 1.048 times, i.e. violent or nonviolent anti-government campaign onset in country *A* Is 4.8 percent less likely for each increment increase on the polity scale. Violent or nonviolent anti-government campaign onset in a very democratic country with a maximum polity score of 10 is therefore 96 percent less likely than in a very autocratic country with a polity score of -10.

Both military expenditure and urban population have a positive and significant effect on the likelihood of violent or nonviolent anti-government campaign onset in country *A*. A higher military expenditure and urban population increases the likelihood of violent or nonviolent anti-government campaign onset in country *A*. As both variables are both logged using the natural logarithm, we can tell that a country with 2.718 times the relative military expenditure of another country is 1.320 times, or 32.0 percent, more likely to experience violent or nonviolent anti-government campaign onset. As for urban population, a country with 2.718 times the proportionate urban population is 2.418 times, or 141.8 percent more likely to experience violent or nonviolent anti-government campaign onset. Gross domestic product per capita has a negative and significant effect on the likelihood of violent or nonviolent anti-government campaign onset in country *A*. A higher gross domestic product per capita decreases the likelihood of violent or nonviolent anti-government campaign onset in country *A*. A country with a 2.718 times higher GDP p.c. is 0.526 times more likely, or, in other words 47.4 percent less likely to experience violent or nonviolent anti-government campaign onset.

Table 5. Spatial diffusion of nonviolent campaign onset

	Model 1	Model 2	Model 3	Model 4	Model 5
Nonviolent campaign *B*	0.210***	0.169***	0.184***	0.184***	0.176***
	(0.241)	(0.263)	(0.247)	(0.245)	(0.248)
Ln distance		-0.002			
		(0.005)			
Nonviolent *B* * Ln distance		0.068**			
		(0.011)			
100 km			-0.084		
			(0.117)		
Nonviolent *B* * 100 km			0.547***		
			(0.055)		
250 km				-0.077	
				(0.098)	
Nonviolent *B* * 250 km				0.429***	
				(0.049)	
500 km					-0.078*
					(0.096)
Nonviolent *B* * 500 km					0.424***
					(0.049)
Violent campaign *B*	0.094***	0.091**	0.094***	0.090***	0.091***
	(0.141)	(0.142)	(0.142)	(0.143)	(0.142)
Recent campaign	-1.603***	-1.612***	-1.606***	-1.605***	-1.605***
	(0.038)	(0.040)	(0.041)	(0.041)	(0.041)
Polity score	-0.049***	-0.049***	-0.049***	-0.049***	-0.049***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
Ln military expenditure	0.278***	0.280***	0.278***	0.278***	0.278***
	(0.015)	(0.015)	(0.014)	(0.013)	(0.015)
Ln urban population	0.883***	0.883***	0.876***	0.876***	0.876***
	(0.028)	(0.031)	(0.031)	(0.029)	(0.029)
Ln GDP p.c.	-0.642***	-0.634***	-0.635***	-0.635***	-0.635***
	(0.025)	(0.024)	(0.024)	(0.025)	(0.025)
Year	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Intercept	19.984***	19.784***	19.700***	19.739***	19.723***
	(4.401)	(4.429)	(4.475)	(4.476)	(4.480)
Country *A*-level variance	6.727	6.708	6.707	6.708	6.708
Log likelihood	3071630.602	2918470.269	2969242.343	2971734.848	2967281.739

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. For all five models: N countries = 161, N observations = 706660.

Finally, the passage of time has a negative and significant effect on the likelihood of violent or nonviolent anti-government campaign onset in country *A*. It decreases the likelihood of violent or nonviolent anti-government campaign onset in country *A* by 1.011 times, i.e. violent or nonviolent anti-government campaign onset in country *A* Is 1.1 percent less likely for each year that passes. In 2006, violent or nonviolent anti-government campaign onset is 32 * 1.1 = 35.2 percent less likely than in 1975.

Now that we have studied Model 1 up close, it is time to assess what the added effect of our interaction variables is in Model 2 through 5. These Models will be used to assess the validity of hypothesis 2. As the change in effect of our control variables is negligible, we will refrain from repeating our findings from Model 1 and focus solely on the perceived changes of our main predictors.

In Model 2 we added an interaction between the occurrence of a nonviolent anti-government campaign in country *B* and the natural logarithm of the distance in kilometers between country *A* and country *B*. A nonviolent anti-government campaign in country *B* has a positive and significant effect on our dependent variable, increasing the likelihood of a violent or nonviolent anti-government campaign in country *A* by 1.184 times, i.e. 18.4 percent, when a 0 is scored on the interaction variable, i.e. for the two countries most distant from each other. The natural logarithm of the distance between country *A* and country *B* shows a negative but not significant effect. We had no prior expectations for this variable, and as the effect remains insignificant, we will refrain from examining it for the upcoming models. The interaction variable between the natural logarithm of the distance between country *A* and country *B* and the occurrence of a nonviolent anti-government campaign in country *B* is also significant and positive. As this is a natural logarithm, it is a bit more difficult but not impossible to interpret the results. As we have used the natural logarithm, we know that a country which is approximately 2.718 times closer to a country with an ongoing nonviolent anti-government campaign than another is Exp(-0.002 + 0.068) = 1.068, i.e. 6.8 percent, more likely to experience violent or nonviolent anti-government campaign onset. In a scenario where there is an ongoing nonviolent anti-government campaign in one country, a country with a minimum distance of 1 kilometer to this country, i.e. a maximum value of 9.868 on the distance variable, is Exp(-0.002 *

9.868 + 0.068 x 9.868) = 1.918 times, or 91.8 percent, more likely to experience violent or nonviolent campaign onset than a country with a minimum value is, i.e. the greatest distance measured in the data relative to the other country. Finally, a country with a minimum distance to another country with an ongoing nonviolent anti-government campaign is Exp(0.169 – 0.002 * 9.868 + 0.068) = 2.271 times, i.e. 127.1 percent more likely to undergo violent or nonviolent anti-government campaign onset than when there a no ongoing nonviolent anti-government campaigns in the other country. We can therefore conclude that the closer country *A* is relative to country *B*, the stronger the effect of a nonviolent anti-government campaign in country *B* on the onset of violent or nonviolent conflict in country *A* is. To better assess the our interaction effect, we will have to look at the third, fourth and fifth model, as these models use an interaction effect with a dummy variable for the distance between country *A* and country *B* instead of a natural logarithm of the kilometer distance.

Models 3, 4 and 5 replace the natural logarithm of distance in our interaction variable for a dummy variable of the distance between country *A* and country *B*. Because of this, the interaction variable now consists of two dummy variables. This means that it can either score a one or a zero. The dummy variable will only score a one in Model 3, 4 and 5 if there is a nonviolent anti-government campaign in country *B*, and country *B* is within respectively 100, 250 and 500 kilometers from country *A*.

In Model 3, a nonviolent anti-government campaign in country *B* has a positive and significant effect on the likelihood of violent or nonviolent anti-government campaign onset in country *A*. A nonviolent anti-government campaign in country *B* with a distance of over 100 kilometers between country *A* and *B* increases the likelihood of violent or nonviolent anti-government campaign onset in country *A* by 1.202 times, or 20.2 percent. Likewise, there is a positive and significant effect for our interaction variable. When we add the ß-coefficient of both a nonviolent anti-government campaign in country *B* and our interaction variable and then look at the exponent of the combined ß-coefficient, we can conclude that country *A* is Exp(0.184 – 0.084 + 0.547) = 1.910 times, or 91.0 percent more likely to experience anti-government campaign onset when it is within 100 kilometers of a nonviolent anti-government campaign in country *B* than when there is no nonviolent anti-government campaign in country *B*.

In Model 4, a nonviolent anti-government campaign in country *B* has a positive and significant effect on the likelihood of violent or nonviolent anti-government campaign onset in country *A*. A nonviolent anti-government campaign in country *B* with a distance between country *A* and country *B* exceeding 250 kilometers increases the likelihood of violent or nonviolent anti-government campaign onset in country *A* by 1.202 times, or 20.2 percent. Just like Model 2 and 3, there is a positive and significant effect for our interaction variable. When we add the ß-coefficient of both a nonviolent anti-government campaign in *B* and our interaction variable and then look at the exponent of the combined ß-coefficient, we can conclude that country *A* is Exp(0.184 – 0.077 + 0.429) = 1.709 times, or 70.9 percent, more likely to experience anti-government campaign onset when it is within 100 kilometers of a nonviolent anti-government campaign in country *B* than when there is no nonviolent anti-government campaign in country *B*.

In Model 5, a nonviolent anti-government campaign in country *B* has a positive and significant effect on the likelihood of violent or nonviolent anti-government campaign onset in country *A*. A nonviolent anti-government campaign in country *B* with a distance greater than 500 kilometers between country *A* and country *B* increases the likelihood of violent or nonviolent anti-government campaign onset in country A by 1.192 times, or 19.2 percent. There is a positive and significant effect for our interaction variable. When there is a nonviolent conflict in country *B* within 100 kilometers of country *A*, this further increases the likelihood of violent or nonviolent conflict in country *A* by 1.528 times, or 52.8 percent. When we add the ß-coefficient of both a nonviolent anti-government campaign in country *B* and our interaction variable and then look at the exponent of the combined ß-coefficient, we can conclude that country *A* is Exp(0.176 – 0.078 + 0.424) = 1.685 times, or 68.5 percent, more likely to experience anti-government campaign onset when it is within 100 kilometers of a nonviolent anti-government campaign in country *B* than when there is no nonviolent anti-government campaign in country *B*.

The results from Model 3, 4 and 5 seem to confirm the proximity-effect we already witnessed in the results for Model 2. The results from Model 3, 4 and 5 also confirm that the closer country *A* is relative to country *B*, the more likely it is to be affected by a nonviolent anti-government campaign in country *B*.

The positive and significant effect of a violent or nonviolent anti-government campaign in country *B* in Model 1 confirms our first hypothesis: a nonviolent anti-government campaign in one country increases the likelihood of violent or nonviolent anti-government campaign onset in another country. The positive and significant effect of the four interaction variables in Models 2 through 5 also confirm our second hypothesis, therefore concluding that the positive relation between a nonviolent anti-government campaign in one country and the likelihood of violent or nonviolent anti-government campaign onset in another country is indeed stronger the smaller the distance between those two countries is.

4.4 Repression Effect on Anti-Government Campaign Method

For hypothesis 3, we have conducted a binary logistic regression on the likelihood of a change in campaign method from nonviolent to violent conflict. Hypothesis 3 states that an increase in repression of a nonviolent anti-government campaign by the government increases the likelihood of the campaign turning violent. A positive coefficient indicates an increased likelihood of a nonviolent campaign turning violent, whereas a negative coefficient indicates a decreased likelihood of a nonviolent campaign turning violent. The number of observations included for this analysis is 1449, distributed over 111 countries.

Table 3 shows model 6, the multivariate logistic regression we performed to test our third hypothesis. An increase in repression has a positive and significant effect on the likelihood of a nonviolent campaign turning violent. An increase by one point increases the likelihood of a nonviolent campaign turning violent by 1.074 times, or 7.4 percent. An increase from no repression to maximum repression, i.e. a score of three on the change in repression variable, would therefore result in a 7.4 * 3 = 22.2 percent increased likelihood of a conflict turning violent.

Our first control variable, change in repression, has a positive relation with campaign method change, indicating that a country with a higher polity score, i.e. a nonviolent campaign is more likely to turn violent in a more democratic country.

The effect, however, is insignificant. This finding still is surprising, as we found previously that polity score decreased the likelihood of violent or nonviolent anti-government campaign onset. The other control variables have no significant effect on the likelihood of a nonviolent anti-government campaign turning violent. Nonetheless, we shall briefly analyze their effects. A higher military expenditure has a negative relation with the campaign method, which would indicate that a higher military expenditure would reduce the chance of a nonviolent anti-government campaign turning violent. Urban population has a negative relation with the campaign method, which would indicate that a higher urban population relative to its total population

would reduce the chance of a nonviolent anti-government campaign turning violent. Gross domestic product per capita has a negative relation with the campaign method, which would indicate that a higher GDP would reduce the chance of a nonviolent

Table 6. Repression effect on campaign method

	Model 6
△ Repression	0.071*
	(0.011)
Polity score	0.051
	(0.014)
Ln military expenditure	-0.163
	(0.053)
Ln urban population	-0.406
	(0.123)
Ln GDP p.c.	-0.028
	(0.013)
Year	-0.012
	(0.006
Intercept	25.543
	(11.521)

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. N countries = 111, N observations = 1449.

would reduce the chance of a nonviolent anti-government campaign turning violent. Gross domestic product per capita has a negative relation with the campaign method, which would indicate that a higher GDP would reduce the chance of a nonviolent anti-government campaign turning violent. Year, or passage of time, has a negative relation with the campaign method, which would indicate that the chance of a nonviolent anti-government campaign turning violent would decline as the years go by.

5. Conclusion & Reflection

5.1 Conclusion

In this research we set out to answer the following research questions: to what extent can nonviolent anti-government campaigns in one country explain the onset of violent and nonviolent anti-government campaigns in another country and to what extent can government repression explain when nonviolent anti-government campaigns turn violent?

To answer our first research question, we distilled two hypotheses from theories rooted in conflict diffusion literature. Violent anti-government campaign works by creating new opportunities for protesters when there is a violent anti-government campaign in another country, because the latter campaign can gather physical resources and information from the other campaign to organize their own campaign. We expect that nonviolent anti-government campaign diffusion works through a similar mechanism, yet opportunities that arrive from nonviolent anti-government campaigns in other countries are less physical and more informational. A nonviolent anti-government campaign in a country can firstly make a broad public in other countries more aware of problems that might occur in their own country as well, and secondly give people helpful information to more effectively and efficiently organize their own anti-government campaigns. Furthermore, the closer two countries are, the stronger this campaign diffusion effect is expected to be. Countries that are close to each other have more cultural and economic ties, which can function as information networks to help spread the information needed for nonviolent anti-government campaign diffusion to take place. Without these networks, information is much less likely to reach a broad public in another country.

For our second research question, we have distilled a third hypothesis. This hypothesis is distilled from conflict escalation theory. When a government increases repression of an already ongoing nonviolent anti-government campaign, the opportunity costs for nonviolent means of anti-government protest are increased. This makes violent means a more and more appealing alternative to nonviolent means, increasing the likelihood of a nonviolent anti-government campaign turning violent.

All hypotheses were tested using logistic regression. For the first two hypotheses, a large dataset with data for 164 country dyads over a 32 countries with nested observations within the country dyads. The third hypothesis uses another, dataset with data for 111 countries over a 32 year period. This dataset only includes observations for years in which a country experienced a violent or nonviolent campaign, which results in a comparatively small dataset as violent and nonviolent campaigns are relatively rare occurrences.

Our first hypothesis states that a nonviolent anti-government campaign in one country increases the likelihood of violent or nonviolent anti-government campaign onset in another country. A positive and significant relation was found between nonviolent anti-government campaign in one country and violent or nonviolent anti-government campaign onset in another country. The results match the predictions we made in our first hypothesis. We can therefore conclude that there is a nonviolent campaign diffusion of violent or nonviolent anti-government campaigns to other countries.

Our second hypothesis states that the positive relation between a nonviolent anti-government campaign in one country and the likelihood of violent or nonviolent anti-government campaign onset in another country is stronger the smaller the distance between those two countries is. A positive and significant relation was found between a nonviolent anti-government campaign in one country and violent or nonviolent anti-government campaign onset in another country, and the more proximate the two countries are to each other, the stronger this relation gets. Multiple iterations with a variety of differing proximity variables were used, all yielding a similar positive and significant effect. Therefore, we can conclude that the diffusion of violent or nonviolent anti-government campaigns we confirmed with our first hypothesis gets greater the more similar the countries are in terms of locality, relative to a country experiencing a nonviolent anti-government campaign at the time.

Our third and final hypothesis states that an increase in repression of a nonviolent anti-government campaign by the government increases the likelihood of the campaign turning violent. A positive and significant relation was found between an increase in government repression and the nonviolent anti-government campaigns turning violent. We can therefore conclude that there is evidence that increased government repression increases the likelihood of nonviolent anti-government campaigns turning violent.

With our three hypotheses concluded, we can answer our research questions. Nonviolent anti-government campaigns in one country can, in part, help explain the onset of violent and nonviolent anti-government campaigns in other countries. Diffusion of nonviolent anti-government campaigns increases the likelihood of violent or nonviolent anti-government campaigns in other countries, especially those when those countries are situated close to each other. The closer two countries are, the more likely they are to be affected by a nonviolent anti-government campaign in the other country through nonviolent anti-government campaign diffusion. This is an interesting finding, as most other literature on campaign diffusion uses a dichotomous distance variable, whereas our research indicates a continuous variable may be more suited as the effect of distance in the diffusion interaction variable seems to gradually degrade rather than stop outright at a certain distance. Furthermore, those countries that are affected by nonviolent anti-government campaign diffusion and experience nonviolent anti-government campaign onset, are in turn more likely to turn violent when their governments repress these campaigns, as we found that an increase in repression increases the likelihood of a nonviolent anti-government campaign changing its methods and turning violent.

5.2 Reflection

Although we are satisfied with the conclusion this research presents, there are a number of issues with this research that unfortunately remain unaddressed, most of which are due to data limitations in the operationalization of this research. We will briefly address the most glaring issues we came across.

First of all, while the distance between two countries can be used as an indirect measure of cultural and economic ties, and, by extent, the information networks that these ties represent, but there are some obvious flaws to this approach. From a face validity perspective, it is not hard to think about two or more countries with great distances between them that share strong cultural and economic ties nonetheless. One notable example is the strong ties many countries still have with their former colony and vice versa, both through formal institutions like, The Commonwealth of Nations countries, and through less formal institutions like language, e.g. the English and Spanish speaking America's. Furthermore, the internet has reduced the importance of distance as a factor in communications altogether, although some countries are, to different rates of success, trying to close their internet off, e.g. The Great Firewall of China. Nonetheless, all these examples show that there is a wealth of means through which people can network, and not all of them are equally restricted by distance. Therefore, future research efforts should focus on a more comprehensive approach, as most other studies have either focused on one of these aspects or used an imperfect proxy variable to try and catch all the different networks in one variable, like this research did.

Another contentious part of our operationalization of this change in methods to a violent anti-government campaign we used for the third hypothesis. In this research we defined a protest as violent when the protesters adopted violent methods, but one could argue that a campaign is already violent the moment a government starts using violence as well. This is a more general problem we ran into while researching the topic of nonviolent and violent campaigns: when is something coded as violent and when is something coded as nonviolent. The literature on this topic uses an array of different approaches to try and tackle this problem. More quantitative data on which side uses what kind of violence could increase our understanding of what really happens inside the black box of anti-government campaigns.

This brings us on to the final point of this discussion. As the time intervals used in the data are one year, we can only look at the diffusion effect on other countries of a nonviolent anti-government in one country a year after the fact.

Otherwise, we would risk making a temporality error due to a lack of data on which campaign started first when we have two campaigns in the same year. For a study on campaign diffusion, especially, more detailed information with smaller time intervals could give us a far better understanding of the effect nonviolent anti-government campaign diffusion has.

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Appendix

Appendix A. Correlation Matrices

Table A1. Correlation matrix models 1 through 5

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Nonviolent campaign *B*											
2. Ln distance	-.007***										
3. 100 km	.000	.789***									
4. 250 km	-.002	.668***	.865***								
5. 500 km	-.001	.601***	.765***	.885***							
6. Violent campaign *B*	-.103***	.040***	.034***	.041***	.032***						
7. Recent campaign	-.066***	-.009***	.004	.002	-.004	.006*					
8. Polity score	.001	-.027***	-.013***	-.021***	-.016***	-.013***	.079***				
9. Ln military expenditure	.017***	.061***	.019***	.027***	.037***	.004	-.067***	-.100***			
10. Ln urban population	.001	.020***	.009***	.017***	.026***	.003	.000	.262***	.345***		
11. Ln GDP p.c.	-.006***	.012***	-.009***	-.005	.005	-.014***	-.011***	.454***	.166***	.697***	
12. Year	.004	.017***	.003	.004	.010***	-.046***	.378***	.179***	.086***	.065***	.097***

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. For all five models: N countries = 164, N observations = 706660.

Appendix A2. Correlation matrix model 6

	1.	2.	3.	4.	5.
1. ∆ Repression					
2. Polity score	-.041				
3. Ln military expenditure	-.231***	-.100***			
4. Ln urban population	-.131***	.206***	.210***		
5. Ln GDP p.c.	-.079***	.324***	-.212***	.460***	
6. Year	-.020	.131***	.080***	.326***	.246***

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. N countries = 111, N observations = 1449.