State repression and violence: differences in actors

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Abstract

This article explores the relationship between repressive actors and the level of violence used during protests in the context of state repression. The leading question to examine this relationship is: *What is the effect of repressive actor types on their level of engagement during protests?* Existing literature focuses primarily on the concept of 'the state' or 'the incumbent' as the repressive actor without questioning all of the parties involved. Building on recent trends, I will explore these different actors and their impact on the level of violence they exert during protests. By using the principal-agent theory, I will connect the violence of repressive actors to the relationship they each have with the ruler. I argue that the relationship between the principal (the state) and the agents (the police or army) is filled with diverging interests. These differing objectives lead the military to be more violent towards protesters in comparison to the police forces. I perform a statistical analysis to examine this relationship and use the MMAD-RA dataset, the V-Dem database, and the Penn World Table (10.1) for the variables. The MMAD-RA dataset provides information on repressive actors and state repression in general, covering over 60 autocratic countries in Europe, Asia, Africa, and Latin America from 2003 until 2012. In contrast, the V-Dem is used for the electoral democracy index, and the Penn World Table (10.1) is used for the GDP per capita variable. Resulting from the empirical analysis, this study provides an answer to the research question and hypothesis. The army uses more violence than police forces do during a protest against the state.

Introduction

This article explores the relationship between the types of repressive actors and the level of violence and participation they use during protests. It aims to contribute to the general understanding of state repression and mobilization. The current literature explores who is involved in state repression or what the roles are, to a limited extent. Therefore, finding an answer to the question, '*What is the effect of repressive actor types on their level of engagement used during protests?*', is relevant in many different ways. Socially, it is relevant for civil society because it can potentially highlight certain patterns that could lead to policy recommendations or reports. Academically, it is established that a state's tactics to repress influence the strategies employed by the opposition (Arriola et al., 2021). Therefore, these strategies are important for human rights considerations that lack adequate discussion in the context of state repression (Davenport, 2007). The information gained from this research could improve and add to the current academic literature.

The theoretical argument used to connect these variables is the principal-agent theory. The principal is the head of state, which is the person with political power who is at risk of losing this power (Feaver, 1998). That is why the agent is employed by the principal. Consequently, the agent gains autonomy to act on behalf of the leader (Benson and Simpson, 2015). Specifically, this relationship highlights the conflicting interests, levels of risk, and diverging knowledge between the principal and the agent (Gottschalk, 2018). The agent is self-interested, which means that they become a liability for the ruler (Bosse and Phillips, 2016). In this particular case, there are two different agents: the police and the army. Following the principal-agent problem leads me to the hypothesis that the army uses more violence than the police forces.

I use statistical analysis to examine the relationship between the different repressive actors and their level of engagement. I utilize the MMAD-RA dataset, which presents information on repressive actors as well as details on protests and state repression. This database offers insight on 60 autocratic countries from Africa, Europe, Asia, and Latin America and ranges from 2003 to 2012. The results provide a valuable perspective on the different actors and their violence during protests. The article has the following structure: first, a literature review is done to examine the current literature and identify a gap. In addition, the theoretical argument will be presented thanks to the framework using the principal-agent problem. Lastly, I describe the methodology and conduct empirical analysis, followed by the discussion and, finally the conclusion, where I will present my results and findings.

Literature review

Most of the literature dedicated to state repression describes the state as the repressor. However, there is still some literature that is devoted to actors and the decision-making processes of state repression (DeMeritt, 2016). The existing literature on repressive actors can be divided into a few different categories.

The first subgroup operates under the assumption that state repression is executed by a single actor: the state. In this literature, there is no distinction made regarding the repressive authority or the decision-making processes. To illustrate, the authors Moore and Jaggers (1990) discuss state repression by using 'the state' or 'the government' as the only relevant player, however, it is not clear who the state is, who makes the decision, or who physically represses. Likewise, Davenport (2007) only discusses the concept of 'the state' without addressing the role or identity of the repressive entity either.

In contrast, the second subgroup within the literature differs because it acknowledges at least one repressive entity. Randle (1981) and deMeritt (2016) identify the military as the only relevant actor, thus making a distinction but completely ignoring other players. For instance, Randle (1981) describes the central role of the military during a repression; according to the author, the military is instrumentally and structurally related to repression. The army is employed directly to enforce suppression within the population; additionally, the maintenance of armed forces poses a threat to the liberties of the population (1981, p. 61). Consequently, the military influences economic, political, and social life to ensure coercion is unavoidable (1981, p. 61). To further elaborate, deMeritt (2016) explains that all governments have agents of repression. These agents are military forces, militias, or mercenaries, as long as they are seen as legitimate extensions of the government (2016). Nevertheless, these authors only discuss one actor and ignore the role of the police or other repressive agents.

Consequently, the third area of interest within the state repression literature incorporates the police forces as a relevant actor. Lefever (1970) discusses the importance of the police during state repression by asserting that the police are the first line of defense against subversion and insurgency (p. 202). Accordingly, they perform critical security services ranging from the collection of intelligence to the imprisonment of those that threaten public safety (1970, p. 202). In the same vein, police are the central force in maintaining stability and controlling crime, which highlights the importance of their role (Randle, 1981, p. 40). Similarly, Della Porta (1995) argues that protest violence tends to develop directly from interactions between social movements and the police (p. 189). This acknowledges the central role of the police in state repression.

Lastly, not many scholars recognize that it is worthwhile to focus on both simultaneously. However, according to a few authors, this focus on the police and subsequent lack of information on their position in this literature is worth investigating (Arriola et al., 2021; Eck, Conrad et al., 2021; Sullivan, 2018; DeMeritt, 2016). Arriola et al. (2021) recognize the importance of studying the role of the police, as there is a lack of insight in the current literature. Consequently, Eck, Conrad, et al. (2021) call for a better understanding of the division of labor between different security actors within a state. Additionally, DeMeritt (2016) describes that the focus on agency is another promising trend in emerging research. The aspect of agency focuses on the difference between repressive agents and those who order repression as agents who may be independently deterred from committing that violence (2016). Nonetheless, it still ignores the different types of repressive actors (2016).

Following the current literature, researchers need to examine the various types of repressive actors and differentiate between them. Therefore, the following research question will be investigated: *What is the effect of a type of repressive actor on their level of violence used during protests?*

Theoretical framework

A few theories could explain the differences between repressive actors and their differing levels of violence or participation employed during protests. However, the most appropriate theory is the principal-agent problem. In addition to presenting a theoretical argument, I discuss a few relevant concepts as well.

First, this study focuses on the military and the police as the primary repressive forces, considering only these two actors. However, it is important to note that distinguishing between the army and the military can be challenging. Generally, governments appoint police forces for domestic security and the military for external defense, even if that notion is changing nowadays as well (Friesendorf, 2010).

Second, it is essential to know what is understood as ‘the military’ or ‘the army’. The army encompasses the land military, whereas the ‘military’ encompasses all of the military branches (2010). Each state has a different interpretation of its military or its army; however, in general, these two concepts mean the same thing (Weidmann and Rød, 2019; Friesendorf, 2010). A recent trend across the globe illustrates that the military is providing law enforcement support within the territorial boundaries of the state as well as externally (2010). Consequently, in the context of this research, I use the army and the military interchangeably, as they are both relevant for this paper.

Third, the other repressive actor, the police, has a different position than the military as a security force. For instance, the police forces are the first line of defense against subversion and insurgency, according to Lefever (1970, p. 202). The training the police receive makes them more appropriate than the army to interact with citizens (Friesendorf, 2010). Therefore, the primary focus of the police is on domestic security tasks, and they are also the first security agency to be employed by the state when any protest happens (2010). On top of that, Smith (1981) emphasizes that the police are physically closest to centers where mass uprisings and rebellions occur, so their position is important to consider (p. 39).

Fourth, the context in which the repression happens is worth considering. Protests are the interactions between the public and the repressive actors that take place to indicate dissatisfaction with the current government (Carey, 2006). Consequently, Carey (2006) describes protests as ‘any confrontational activity by a domestic non-governmental actor that disrupts and challenges any government actor, agency, or policy’. On top of that, Weidmann and Rød (2019) add a numerical value to the concept of a protest. These authors conceptualize protests as a public gathering of at least 25 people with an expressed political motivation either opposing or supporting a central, regional, or local government or other non-governmental institutions (2019). For this research, it makes sense to use confrontational activity as a description; if the protests are supporting the state, there is no need for repressive behavior.

Fifth, the definition of state repression is still evolving; however, the definition given by Davenport (2007) is most appropriate. According to the author, state repression involves the threatened or actual use of physical sanctions against an individual or organization within the territorial jurisdiction of a state (2007, p. 2). The purpose of the repression is to impose a cost on the target as well as deter specific activities or beliefs that challenge state personnel, practices, or institutions (2007, p. 2). This follows the same logic as the description of a protest.

Lastly, I seek to understand exactly what the difference in violence is between these actors. Hence, I am using the terms ‘participation’ and ‘violence’ to understand exactly the position of these actors during a protest. Violence is not always used during protests; therefore, participation and, most importantly, the level of participation need to be considered as well.
To connect both the violence and the participation that these actors might exercise, the level of engagement will be the focal point and be used to mean both of these terms. To illustrate, participation can also be divided into two different categories: either there is participation or there is no participation, which would consequently mean there is no engagement (Weidmann and Rød, 2023). In addition, violence can be divided into two different categories: physical violence and lethal violence (2023). By combining the level of violence and the level of participation, the level of engagement is assessed. However, to be as clear as possible, I might utilize the level of violence or the level of participation, if that is precisely what is discussed.

Principal-agent theory

To understand how the type of repressive actor has a different effect on the level of engagement, I use the principal-agent theory to examine this relationship. According to Gottschalk (2018), this theory addresses management challenges in organizations. The problem arises when a principal employs an agent to create value for the principal’s goals (2018). This can be explained by the differing interests of the principal and the agent (2018). This is due to agents that are self-interested and actively seek to augment their private gains (Bosse and Phillips, 2016). Consequently, the exchanges between the agent and the principal encourage this increase in private gains because the agents have more freedom to act upon these interests (Pillay and Kluvers, 2014).

The main issues this theory presents are about preferences, knowledge, and risk (Gottschalk, 2018). Accordingly, agents have other preferences, oftentimes more knowledge and other types of risk than principals (2018). Therefore, principal-agent theory explains how the type of repressive actor is related to the level of engagement because it highlights the conflicting interests, levels of risks and diverging knowledge between the principal and the agent.

In this specific case, the agents are the military or the police, whereas the principal is either the head of government or the state. Davenport (2007) describes the decision-maker as the ‘political authorities’. These political authorities influence those within their territorial jurisdiction in different ways, for example, by using state-sponsored or state-affiliated help to stay in power (2007, p. 3). According to Dragu and Przeworski (2018), the principal in this relationship is the incumbent, the one that holds political power. The ruler can employ security agents to safeguard this political power (2018, p. 1). In addition, deMeritt (2016) discusses the principal-agent problem by describing the principal as ‘those who order repression and political violence’. Lastly, Feaver (1998) defines the principal as being ‘the civilian(s);’ these are the people who make military decisions but are not part of the military. In the relationship between the military (the agent) and the principal, the principal is dependent on who makes the military decisions and who is part of the military and can or cannot execute the consequent decisions (Feaver, 1998). Thus, the ruler or incumbent is the principal; this principal is also the one who holds political power and the person who orders repression (1998).

In consideration of a separate matter, Tyson (2018) discusses the relationship between the principal and agent in the context of autocratic regimes. According to Tyson (2018), the regime needs the support of members of the military and other bureaucrats. The agents (the military) are the ones who decide if repression happens; the level of engagement is up to them, not the principal (2018).

Consequently, DeMeritt (2016) argues that a repressing government does not consist of a single actor who decides to use violence and then implements these policies. Leaders issue orders to repress, and repressive agents are the ones that decide to ignore this or not (2016). These agents can commit abuse or engage in activities other than those explicitly ordered (2016). Butler et al. (2007) use principal-agent logic to understand sexual violence committed by security forces. They argue that while the leader is formally in charge, principal-agent logic holds that the agents’ superior information and selfish nature loosen control over these agents (2007). As a result, these agents will misuse their operational knowledge, their uniforms, and government resources for their own private benefit (2007, p. 670).

To be able to understand the exact relationship between these concepts, it is necessary to understand how the different types of repressive actors are connected to the principal.

In terms of the agent being the military, Feaver (1998) explains that civil-military relations are best understood as part of a game of strategic interaction. The civilian in question is the person who needs to make military decisions but is not part of the military (1998). Additionally, the military is increasingly becoming more independent from the state and desires even more decision-making abilities (Feaver, 1998). This creates an increasing gap between the interests of the central government and the military (1998). The military gaining more independence from the state means there could be more room for violence (Feaver, 1998).

In contrast, Dragu and Przeworski (2018) explain that there are two issues between the principal and the agent that arise when the police forces are the agents (2018, p. 1). These two moral hazards are ‘politics’ and ‘corruption’ (2018, p. 1). ‘Politics’ as a moral hazard is the way through which security agents can exert political influence to increase their payoff by decreasing the ruler’s rents from power (2018, p. 1). In addition, the issue of corruption describes how the agents, the police, can benefit by engaging in rent-seeking activities (2018, p. 1). This means that their interests differ from those of the principal, meaning that obeying the incumbent is not necessarily in their interest (2018). The specific issues that arise from corruption are mostly that police officers invest in private economic ventures, sell their services to private actors, and engage in graft and the shirking of their duties (2018, p. 2). This is problematic for the principal, as the police are close to the population (Smith, 1981, p. 39). Corruption often neglects the effectiveness of the work police forces are employed to do. In the context of this research, their job should be to use violence against protesters, as that is the order of the incumbent (Andvig and Fjeldstad, 2008). However, because of corruption, they are less likely to follow the instructions of the agent and use less violence as a result (2008).

In addition to the growing gap between the military and the principal, the military and the police are divided by the different strategies, techniques, and weapons they employ against protesters (Friesendorf, 2010). The military often utilizes more brutal and severe methods compared to the police, highlighting the distinct approaches each actor takes in handling the protests (2010).

By using this logic in the context of this research, it implies that not all agents are alike. The military and police forces differ in their accountability and control mechanisms. The police are more interested in monetary incentives such as corruption, which leads to less trust in the police (Yahagi, 2021; Cruz, 2015). Consequently, this leads to less accountability for the police because of the corruption (Yahagi, 2021; Cruz, 2015). The military, on the other hand, is gaining more independence from its principal, which can lead to more violence and force used against protesters because their strategies and techniques are not meant to be used against a large crowd but rather 'the enemy' (2015).

This means that the difference between the police and the army leads the army to use more violence. Therefore, the expectation is as follows:

H1: *Police have lower levels of engagement in reacting to protests during a repression.*

Research design

This research is a large-N observational study based on an existing dataset with a global focus of around 60 countries in Africa, Asia, Latin America, and Europe. The number of observations is around 3700. I will use the MMAD-RA (Mass Mobilization in Autocracies) database (Weidmann and Rød, 2023) for this research. This resource focuses on the different types of actors that repress during mass mobilizations (2023). This collection of data spans over a time period of 2003–2012 and has information on more than 60 autocracies (2023). The data included in the MMAD-RA originates from three different media sources: the Associated Press, Agence France Presse, and BBC Monitoring (2023). In addition to this database, I will make use of the V-Dem dataset as well as the Penn World Table (10.1) for the control variables.

The corresponding unit of analysis is the event-level report. The MMAD-RA database employs event-level analysis, which is why it makes sense for me to use this as well. An event-level unit of analysis means that every entry is therefore per location and day. There is a new entry if the protests move to a different city or place and if they span multiple days (2023). It is worth mentioning that an event or protest is used simultaneously and is described as 'a public gathering of at least 25 people with an expressed political motivation either opposing or supporting a) the central, regional, or local government, or b) other non-governmental institution' (2023).

The dependent variable, the level of engagement, is an ordinal variable. This variable originates from the MMAD-RA dataset. It has four different 'levels'. The first level is described as 'no presence or engagement', and the second level is 'presence' but no intervention (2023). These two levels are about presence and active engagement; the third level, on the other hand, describes the physical intervention of the actor, which ranges from crowd dispersal, arrest, and beatings but excludes lethal intervention (2023). That is what the fourth level is concerned with; there needs to be a report of lethal intervention, meaning at least one person died (2023). The variables will be coded as follows: 0 = no presence, 1 = presence, 2 = physical intervention, and 3 = lethal intervention. The mean of this variable is 1.87.

The independent variable is the type of repressive actor; this is a categorical variable. The MMAD dataset defines a repressive actor as follows: ‘organizations or groups with the capacity for violent repression of protest (police, militia, military)’ (Weidmann and Rød, 2023). For a protest event to be coded as one, a repressive actor needs to be involved (2023). In addition, there are multiple categories of repressive actors, but for this research, the only relevant ones are ‘police’ and ‘military’ (2023). This variable is turned into a dummy variable. Consequently, this means that in my model, there is a variable of ‘police’ where all else = ‘0’ and police = ‘1’. Similarly, the same applies to the variable ‘army’, all else = ‘0’, army = ‘1’. For both of the variables, the value of ‘all else’ consists of ‘militarized police, ambiguous security forces, others, militia’, and will not be taken into consideration.

To prevent the issue of the omitted variable from occurring, I am controlling for numerous issues that could otherwise affect the relationship between both of the variables. These control variables are found either in the existing dataset or merged into the database.

Participant violence

‘Participant violence’ is a variable that measures the level of violence that is being exerted by the participants in the protests (2023). By using this as a control variable, I am making sure that the level of engagement of a repressive actor is not a direct reaction to the violence dissidents employ (2023). This variable is ordinal and is categorized as: no report of violence from mass mobilization participants; explicit report of no violence; reports of property damage or clashes with civilians or security; reports of people injured or reports of people killed (2023). This variable is turned into dummy variables where the baseline category is ‘no reports of violence’ as this is the largest category (2023). The categories of this variable are coded as: 0 = no report of level of violence from mass mobilization participants. 1 = explicit report of no violence, 2 = reports of property damage or clashes with civilians or security forces, 3 = reports of people injured, 4 = reports of people killed (2023). I expect the results and effect on the dependent variable to be different for every category of this variable. On the one hand, when there is no violence from the participants, it makes sense that the violence from the security forces is less, making the relationship a negative one (Davenport, 2007). On the other hand, when there is violence from the side of the participants, the relationship might be positive, meaning we would see more violence from the repressive actor in question (2007).

Side participants

The second control ‘side’ is a binary variable. ‘Side’ describes whom the opposition is protesting against; either it is explicitly against a domestic public or private non-governmental institution (Weidmann and Rød, 2023). Or it is pro-government, showing support for the government and its actions (2023). As a control, it will take on the values: 0 = anti-government and 1 = pro-government (2023). In addition, this variable is divided as such because by far the largest number of protests were against the government, which is why the baseline category of 0 takes on the ‘anti-government’ value. For this research, the notion is that the protesters are against the government and its actions; otherwise, the violence perpetrated by the repressive actors will not be against the protesters (2023). Consequently, I expect this variable to have a negative effect on the level of engagement because the baseline category is anti-government protests, which means that if the protests are pro-government, the level of violence would decrease and not increase (Davenport, 2007).

Electoral democracy index

The other control variable that is going to be used in this research is the electoral democracy index, which is a part of the V-DEM dataset (Coppedge et al., 2019). This is an interval variable that ranges from 0 to 1 (2019). Zero is equal to low electoral democracy index, and one is equal to high electoral democracy index (2019). The mean of this variable is 0.26. This index is used to hold constant the democracy level of a specific state (2019). Using this control variable accounts for the level of autocracy or democracy within a state. In the dataset I use, the states are all autocratic, though most states vary from each other in their level of autocracy. Consequently, the level of autocracy matters in terms of the expected violence of the repressive actor. The authors Hill and Jones (2014) argue that it is necessary to look at democratic institutions when doing state repression research. In addition, Davenport (2007) adds that the level of democracy is expected to play a role in the level of repression against citizens. Therefore, I expect a negative relationship between the variables; the higher the level of democracy, the lower the level of violence (2007).

Real GDP

This variable comes from the Penn World Table and describes the GDP at the current purchasing power parity (PPP) rates. It reports expenditure-based real gross domestic product (GDP). Using this variable allows me to compare the relative living standards across countries and over time. This value was divided by the population at the time. I created a new variable of the real GDP expenditure-based per capita. I did this by computing this variable, which is all documented in Appendix B. This variable is presented divided by one million and in USD. This is a continuous variable ranging from $563.65 to $105,325.46. The mean of this variable is $10,195.93. Using the GDP in this model is found to be a helpful control variable within research on state repression (Hill and Jones, 2014). According to Davenport (2007), economic underdevelopment is a reason for an increase in repression. Following this logic, I expect that this variable has a negative effect on the level of violence employed. An increase in GDP would decrease the level of violence employed by repressive actors.

Population size in millions

In addition to the other control variables, the size of the population within a state is taken into account. The variable is continuous with a minimum value of 1.0228, which means the smallest state within the database has 1.022.800 inhabitants. The highest value is 1,384.20, which means the largest state has 1,384,200,000 inhabitants. The mean is 171,810,000 inhabitants. The research written by Hill and Jones (2014) discusses the necessity of including population size as a control variable. These authors discuss that the number of people, specifically a large population, contributes to more repression (2014). Therefore, there should be a positive relationship between the size of the population and the level of violence (2014).

Number of participants during the protests (mean)

In order to understand the level of violence perpetrated by a repressive actor, I need to take into consideration the size of the protest. By looking at the number of participants, I can control for the relationship between the actors and their level of violence by incorporating the value of the size of the protest. Having a high number of protesters means that the level of violence should increase because the perceived threat to the regime then increases (Chenoweth and Belgioioso, 2019). This variable is continuous, and the lowest number of participants is two, which is the mean. That is why it is possible, even if an event is supposed to have 25 participants or more.

The highest number of participants is 650,000 protesters, in addition, the mean is 5969.88 participants for an event.

Size of the protest per million inhabitants

To make sure the size of the protest is reflected well enough, I have computed the size of the protest and divided it by the population in millions. This creates a better understanding and makes it easier to interpret the results in each case. In addition to the actual size of the protests, the scale of the protests matters as well, which is why it is important to use this relative measure as well (Chenoweth and Belgioioso, 2019). With the increase in the number of participants, there should be an increase in the level of violence as well (2019). This is a continuous variable with the lowest value of 0.02 and the maximum value of 25,182.75, with a mean of 281.78 participants per million inhabitants.

Finally, I use an OLS regression analysis to estimate the relationship between the two variables (Field, 2018). OLS is a widely used tool for estimation, and in this context, it is appropriate because it is possible to use multiple independent variables as well as control variables (Field, 2018). Using OLS has multiple benefits, even if the dependent variable is ordinal. The researchers Angrist and Pischke (2009) found that OLS is the best method to estimate a relationship, regardless of the type of dependent variable.

Empirical analysis

To test my theoretical argument, I estimate the relationship between the independent variable and the dependent variable. I aim to demonstrate a difference between the two actors in their level of violence. To be able to achieve this, I have taken some steps to empirically estimate this relationship.

First, I have cleaned and organized the data that I have compiled from the MMAD-RA dataset. I am using multiple variables from this database, for instance: the independent variable, the dependent variable, and some of the control variables. However, I am using more than one dataset for this research, as some of the control variables are only accessible using other data. For this reason, I have merged multiple files to create a new database that I will use for this research. All of the variables were cleaned by coding the unnecessary data as 'system-missing' (Field, 2018). In addition to getting rid of the redundant cases, some of the variables are recoded as well. Namely, the control variable 'side' which expresses the side a participant protests against or for, needed to be recoded as 0 = anti-government, and 1 = pro-government because the largest number of cases are anti-government. For other variables, like participant violence, I created dummy variables. Some of the control variables are computed differently than the original variable. For instance, the GDP value is divided by the population so it is possible to know the GDP per capita. In addition, the control variable, ‘number of participants per million inhabitants’, was also computed to precisely determine the relative number of participants that joined an event.

Secondly, to be able to estimate a relationship, I use the OLS regression method in SPSS. I have chosen to perform two different models. The first model only looks at the independent variable to test the relationship, which means the variables ‘police’ and ‘military’ are included. In the second model, all of the relevant control variables are included as well as the independent variables: 'side of the protests’, ‘participant violence’, ‘GDP per capita’, ‘electoral democracy index’, ‘population size in millions’, ‘number of participants in protest’ and ‘number of participants per one million inhabitants’ are all included in this model.

	Model 1	Model 2
(Constant)	1.810*** (0.020)	2.017*** (0.034)
Military	0.218*** (0.036)	0.175*** (0.032)
Police	−0.067** (0.023)	−0.050* (0.021)
Electoral democracy index		−0.566*** (0.106)
Participant violence (No violence)		−0.564*** (0.029)
Participant violence (Property damage)		0.220*** (0.026)
Participant violence (People injured)		0.326*** (0.041)
Participant violence (People killed)		1.000*** (0.079)

Expenditure-side GDP PPP per capita		−0.00000372*** (0.000)
Population size in millions		0.000*** (0.000)
Pro-government protests		−0.412*** (0.045)
Number of participants (mean)		0.000001478** (0.000)
Number of participants per million inhabitants		−0.000017 (0.000)
R^2	0.014	0.216
Adj. R^2	0.014	0.213
N	3715	3715

Note: OLS regression coefficients with standard errors in brackets
***p < 0.001, **p < 0.01, *p < 0.05

Thirdly, to assess the model's fitness, the r-squared and adjusted r-squared values are outlined above. The r-squared value is relevant because it tells me what the proportional reduction in prediction error is when using the model compared to just using the mean of Y as the predictor (Field, 2018). For instance, the first model has an r-squared value of 0.014. In the second model, where the control variables are included, the variables explain 21.6% of the variance in Y. The adjusted r-squared value should be considered as well, because this is more accurate (Field, 2018). The first model still only explains 1.4% of the variance in Y, whereas the second model explains 21.3% of the variance in Y. This means the second model with the control variables explains a lot more of the variance in Y. All of the relevant control variables have been accounted for, and I am taking into consideration all of the different controlling mechanisms that most research on state repression uses in their analysis.

Results

First model

The first model only uses the independent variable and does not have any control variables. The number of coefficients in the first model is 1.810. The coefficient is statistically significant at a 99% confidence interval with a p-value of <0.001. When the military is the repressive actor, the value of the coefficient increases, on average, by 0.218 points, which means the military has a mean value of 2.03. The value of the independent variable is statistically significant at a 99% confidence interval with a p-value of <0.001. As this number is positive, it means the relationship between the variables is positive as well. On average, when the military is the repressive actor, the violence increases.

In comparison to the military, the police have a negative value in the model. This means the relationship between the level of violence and the police as the repressive actor is negative. The value of the coefficient decreases, on average, by 0.067 points, which means the police have a mean value of 1.74. This coefficient is statistically significant at a 99% confidence interval with a p-value of $p < 0.01$. Meaning that if the police is the repressive actor, the violence decreases on average.

According to the results in model 1, and in line with my theoretical argument, there is a difference of 0.29 between the two variables, and the military has a higher value than the police. This means the null hypothesis can be rejected in this model at a 99% confidence interval with a p-value of $p < 0.01$. On average, using no control variables, the military utilizes more violence during protests than the police. However, it makes more sense to look at the values obtained with the control variables.

Second model

In the second model, all of the control variables are included. This entails that all of the values in this model are held constant by the incorporation of these control variables. The mean value of the dependent variable coefficient here is 2.027. The coefficient is statistically significant at a 99% confidence interval with a p-value of <0.001. When the military is the repressive actor, the value of the coefficient increases, on average, by 0.181 points. This means the military has a predicted mean value of 2.014, holding the other variables constant. The value of the independent variable is statistically significant at a 99% confidence interval with a p-value of $p <0.001$. This number is positive, which means the relationship between the variables is positive as well. The military uses, on average, more violence during protests.

In comparison, the value for the police force is negative in the model, just like in the first model. This means the police have a negative effect on the mean level of violence. The value of the coefficient decreases, on average, by 0.052 points, which means the police have a mean value of 1.79, holding the other variables constant. This coefficient is statistically significant at a 95% confidence interval with a p-value of $p < 0.05$. Police forces use, on average, less violence.

According to the results in the second model, and in line with my theoretical argument, even with the control variables, there is a difference of 0.224 points between the two variables, and the military has a higher value than the police. This means the null hypothesis can be rejected in this model at a 99% confidence interval with a p-value of $p < 0.01$. This reveals the difference between both of the variables: the military uses more violence during protests than the police.

The values associated with the control variables can also give us an insight into the relationship between all of the variables in the model.

As the second model demonstrates, the coefficient for the democracy index is -0.566, indicating a negative relationship. The electoral democracy index has a negative effect on the level of violence employed by an actor. This means that the higher the democracy index on the electoral democracy scale, the less violence is employed by a repressive actor. This result is statistically significant at a 99% confidence interval with a p-value of $p < 0.001$. This type of relationship is expected and is in line with the theoretical understanding of this control variable.

In terms of the violence perpetrated by the participants in the protests, this variable has diverging effects on the level of violence of repressive actors. When there were reports of no violence from the dissidents, the value of the level of violence decreased by 0.564 points, therefore having a negative effect on the level of violence. Consequently, this means that when there were reports of no violence by the participants, there was less violence from the repressive actors. This result is statistically significant at a 99% confidence interval with a p-value of $p < 0.001$.

On the other hand, when there were reports of property damage as well as reports of clashes with civilians or security forces, the value for the dependent variable increased by 0.220 points, which means there is a positive relationship between these values. Therefore, if there were reports of property damage or clashes with civilians or security forces, the level of violence employed increased. This result is statistically significant at a 99% confidence interval with a p-value of $p < 0.001$.

Reports of people being injured also increase the level of violence by 0.326 points. This is also a positive relationship, which means that the level of violence was higher when there were reports of people being injured. This result is statistically significant at a 99% confidence interval with a p-value of $p < 0.001$.

In addition, if there were reports of people being killed, the level of violence by a repressive actor would also increase by 1 point, meaning there is a positive relationship between the variables. This result is statistically significant at a 99% confidence interval with a p-value of $p < 0.001$. These types of relationships between all of these variables were expected and are in line with the theoretical understanding of this control variable.

In contrast, the variable 'side of protests' has a negative relationship with the outcome variable. If the protests are pro-government instead of anti-government, the value of the level of violence by a repressive actor decreases by 0.412 points. This means that the side participants protest for has a negative relationship with the dependent variable. This result is statistically significant at a 99% confidence interval with a p-value of $p < 0.001$. This type of relationship is expected because when people are not against the state, the repressive forces are probably not violent.

When the GDP per capita increases, the level of violence perpetrated by a repressive actor decreases, which means this variable has a negative effect on the dependent variable. The coefficient associated with this relationship is -0.00000372 points. This means that in the states where the GDP is higher, the level of violence during protests decreases. This result is statistically significant at a 99% confidence interval with a p-value of $p < 0.001$. According to the literature, this type of relationship was expected.

For the population size, there is no way of saying if the relationship is positive or negative because the value obtained is 0.000. This result is statistically significant at a 99% confidence interval with a p-value of $p < 0.001$. This result was not expected because it is not possible to say anything about the relationship between the variables.

The size of the protest has a positive effect on the engagement level of a repressive actor. When the number of participants increases, the level of violence increases as well, by 0.000001478 points per participant. This result is statistically significant at a 99% confidence interval with a p-value of $p < 0.01$. The theoretical expectations are in line with these results.

Taking into consideration the number of participants per million inhabitants within a state, the model presents a negative relationship between this variable and the outcome variable. This means that when the number of participants per million inhabitants increases, the level of engagement decreases by 0.000017 points per one million inhabitants. This result is not statistically significant ($p = 0.18$). This is not the result I expected, but it is not statistically significant, which suggests that this variable does not play a significant role in explaining the dependent variable.

Additionally, multiple assumptions need to be met to make sure the empirical analysis is conducted properly and that the results are reliable (Field, 2018). Linearity, normally distributed errors, the equal variance of error (homoskedasticity), multicollinearity, outliers, and influential cases are all checked and can be found in Appendix A. Most of the assumptions were met; however, there were some issues with linearity as well as a few outliers.

Discussion

It is clear from the empirical research that the military is, on average, more engaged and more violent in protests than the police force, which is in line with the theoretical arguments presented. The coefficient is statistically significant at a 95% confidence intervals with a p-value of $p < 0.05$ in both models. This result supports my argument that the army is more violent during protests in comparison with the police forces. In addition, the null hypothesis can be rejected and the alternative hypothesis is therefore not rejected. Both of the models illustrate the difference in the level of violence for both of the actors. Therefore, the theoretical argument I present is in line with the empirical results.

This research aims at filling gaps in the current literature. As a result of the empirical findings, there are numerous ways this research has implications.

First, it shows that a repressive actor is not one entity but should be considered within a larger context where multiple players are involved. Simply acknowledging that multiple actors are worth considering is already an important step the literature should take.

Second, it highlights that the actor that is being considered in the research matters for the level of violence they employ. This suggests it may vary based on the specific actor under consideration; therefore, researchers should clarify the intended actor. By discussing the role of the military, it should be considered that their level of violence is higher than that of the police forces. That is why it is not possible to use ‘the state’ as the important actor but should take into consideration the specific repressive actor and how this has an effect on the level of violence employed.

Third, this research opens the dialogue and makes the area of research more focused on agency, actors, decision-making processes, etc. Given the current gap in knowledge, further research is warranted.

Fourth, it connects the principal-agent theory to the state repression literature, which is relevant and adds to the literature in many ways. The principal-agent theory is already used in many different types of themes within the realm of international relations; however, in the context of state repression, this is a rather new avenue.

Conclusion

This study highlights the utility of looking at the different actors that are involved in state repression. I argue that there is a difference in the level of violence and participation during protests of these types of actors. Specifically, I want to answer the following question: *What is the effect of a type of repressive actor on their level of violence used during protests?* This research finds an answer to this question, namely that the army as a repressive actor has a higher level of violence, on average, than the police force during protests. Therefore, my alternative hypothesis is not rejected either.

This article focuses on repressive actors because the current literature does not offer enough information on the actors involved in state repression. The biggest issue is that most of the literature does not discuss repressive actors as being different from one another but treats 'the state' as the only decision-making body.

The arguments presented are based on the principal-agent theory. By using this theoretical approach, I can argue that there is a difference between these actors, which leads to the hypothesis. The central argument is that the army has a higher level of violence and engagement than the police forces. This hypothesis is not rejected based on the empirical analysis I conducted.

This finding implies that policymakers should reconsider the employment of the military during a repression because the military uses more violence, which can become a human rights violation. In addition, there should be more policies surrounding protests, as I demonstrated that there is a difference in violence for each actor. This means that there should be more policies to keep the protesters safe because if one actor can use more violence, there is not enough accountability.

However, some limitations need to be mentioned as well. During the empirical analysis, not every assumption was met. The linearity assumption is not met, and other assumptions were just met. Therefore, future research might benefit from transforming some of the variables to meet this assumption. These can all be found under Appendix A for further discussion.

To make sure there is a broader analysis of the actors at play, this research could have benefited from using all of the repressive actors that are involved in the repression. I have decided to only look at the two most important actors, which are the military and the police, because that is what the literature mostly identifies as the most important actors. However, it can be beneficial to look at the militarized police as well, but in the literature, the concept of the militarized police is rather new, and there is not yet a consensus on their role. Because I looked at many different countries, it made sense to only focus on two actors because militarized police are different in each country, and therefore the results would not make a lot of sense. However, this article could open new avenues of research in the future by looking at more than these actors.

Another limitation is that it is not clear whether the state or incumbent would rather choose to employ an army over a police force, even if they are more powerful and violent. Using the military could also send a certain message to the international community that might not be perceived as a positive event. For future research, I would advise considering more aspects than just violence when looking at these actors.

Nonetheless, I present a strong theoretical argument for the hypothesis that the army has a stronger presence than the police.

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Appendix A: Assumptions

Independent error (Durbin-Watson)

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.119[a]	.014	.014	.609	.014	26.671	2	3712	<.001	
2	.465[b]	.216	.213	.543	.202	95.206	10	3702	<.001	1.559

a. Predictors: (Constant), Police as repressive actor, Military as repressive actor

b. Predictors: (Constant), Police as repressive actor, Military as repressive actor, No violence, Pro-government protests, People killed, Number of participants per million habitants, People injured, Expenditure-side GDP PPP per capita, Electoral democracy index, Property damage, Population size in millions, Number of participants (mean)

c. Dependent Variable: Engagement level of repressive actor

The assumption of independent error is calculated by looking at the Durbin-Watson test (Field, 2018). Residuals are prediction errors which is the difference between the observed value of Y and what our model predicts for that case (Field, 2018). The assumption here is that the residuals need to be uncorrelated with one another, the errors should be random and not systematic (Field, 2018). Ideally, the Durbin-Watson test should be around 2, but at least not lower than 1. This assumption is met because the value I obtained was 1.559 for the second model.

Multicollinearity (VIF)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1.810	.020		89.047	.000	1.770	1.849					
	Military as repressive actor	.218	.036	.101	6.100	<.001	.148	.287	.109	.100	.099	.971	1.030
	Police as repressive actor	-.067	.023	-.048	-2.923	.003	-.112	-.022	-.065	-.048	-.048	.971	1.030
2	(Constant)	2.017	.034		58.751	.000	1.950	2.085					
	Military as repressive actor	.175	.032	.081	5.434	<.001	.112	.238	.109	.089	.079	.950	1.053
	Police as repressive actor	-.050	.021	-.036	-2.376	.018	-.091	-.009	-.065	-.039	-.035	.928	1.077
	Electoral democracy index	-.566	.106	-.096	-5.364	<.001	-.773	-.359	-.101	-.088	-.078	.658	1.519
	No violence	-.564	.029	-.288	-19.310	<.001	-.622	-.507	-.339	-.303	-.281	.953	1.050
	Property damage	.220	.026	.132	8.533	<.001	.169	.270	.145	.139	.124	.891	1.123
	People injured	.326	.041	.121	8.016	<.001	.246	.405	.112	.131	.117	.933	1.072
	People killed	1.000	.079	.186	12.693	<.001	.845	1.154	.199	.204	.185	.985	1.015
	Expenditure-side GDP PPP per capita	-3.720E-6	.000	-.070	-4.746	<.001	.000	.000	-.127	-.078	-.069	.965	1.036
	Population size in millions	.000	.000	-.079	-4.208	<.001	.000	.000	.023	-.069	-.061	.606	1.649
	Pro-government protests	-.412	.045	-.135	-9.102	<.001	-.501	-.323	-.125	-.148	-.132	.969	1.032
	Number of participants (mean)	1.478E-6	.000	.081	3.102	.002	.000	.000	.059	.051	.045	.312	3.204
	Number of participants per million habitants	-1.700E-5	.000	-.041	-1.569	.117	.000	.000	.024	-.026	-.023	.311	3.212

a. Dependent Variable: Engagement level of repressive actor

Multicollinearity refers to how strongly the independent variables are correlated with one another (Field, 2018). If there is a high multicollinearity, it means that it is difficult to precisely estimate the relationship between the independent variables and the dependent variables (Field, 2018). The tool that is used to measure this strength is the VIF method, ideally it should be less than five (Field, 2018). The value of the number of participants and the number of participants per million inhabitants is higher than the other values for the VIF. However, this makes sense because they are the same variables but one is divided by the number of inhabitants within the country. Still, the value is lower than 5, which means there is no cause for concern. In this model, all of the variables are lower than five which means this assumption is met.

Outliers

Frequency Table

outlier_196

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	3495	57.3	94.1	94.1
	1.00	220	3.6	5.9	100.0
	Total	3715	60.9	100.0	
Missing	System	2386	39.1		
Total		6101	100.0		

outlier_258

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	3706	60.7	99.8	99.8
	1.00	9	.1	.2	100.0
	Total	3715	60.9	100.0	
Missing	System	2386	39.1		
Total		6101	100.0		

outlier_329

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	3715	60.9	100.0	100.0
Missing	System	2386	39.1		
Total		6101	100.0		

The observations should lie between 95% of all observations for the first table, which is not the case. I have an outlier problem; however, it is barely over the limit, so it is not a big concern for now. For the two other outlier tables, I have no issues with an outlier. Therefore, this assumption is not fully met but this is not a concern for now.

Influential cases

Residuals Statistics[a]

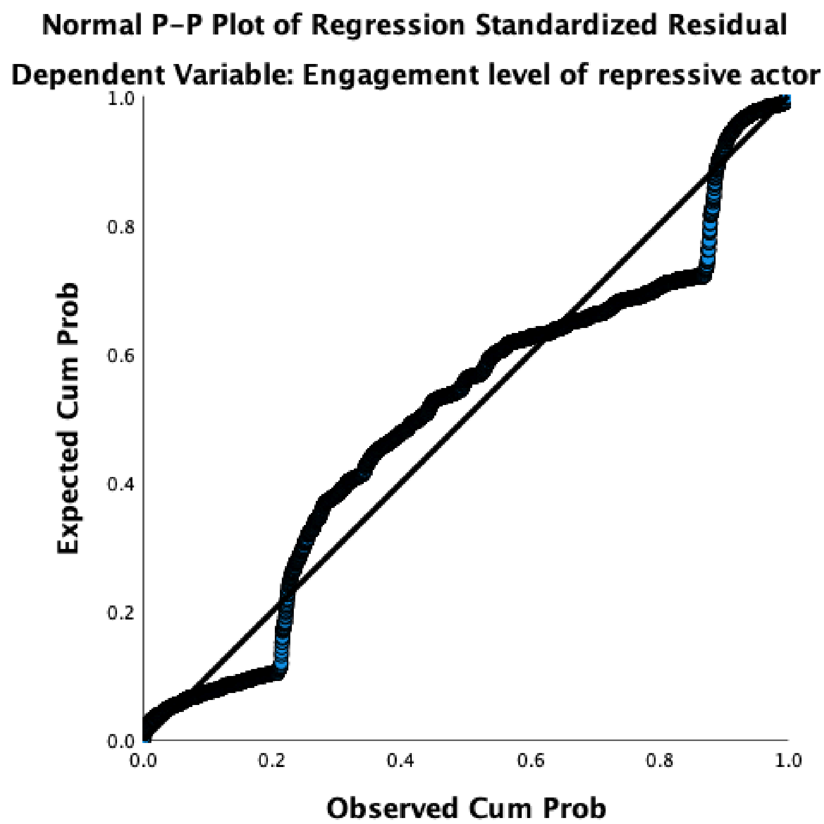
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.59	3.08	1.78	.285	3715
Std. Predicted Value	-4.162	4.561	.000	1.000	3715
Standard Error of Predicted Value	.013	.244	.028	.016	3715
Adjusted Predicted Value	.49	3.08	1.78	.285	3715
Residual	-1.569	1.645	.000	.543	3715
Std. Residual	-2.887	3.027	.000	.998	3715
Stud. Residual	-2.931	3.033	.000	1.000	3715
Deleted Residual	-1.617	1.652	.000	.545	3715
Stud. Deleted Residual	-2.934	3.036	.000	1.000	3715
Mahal. Distance	1.176	744.901	11.997	24.715	3715
Cook's Distance	.000	.029	.000	.001	3715
Centered Leverage Value	.000	.201	.003	.007	3715

a. Dependent Variable: Engagement level of repressive actor

Another assumption that needs to be met when doing an OLS regression is making sure there are no influential cases (Field, 2018). This assumption measures how much all of the fitted values of a model would change if a given observation were not to be included in the model (Field, 2018). Cook's distance should not exceed 1, which would be cause for concern (Field, 2018). However, in this model, this assumption is met because the maximum is 0.029 (Field, 2018).

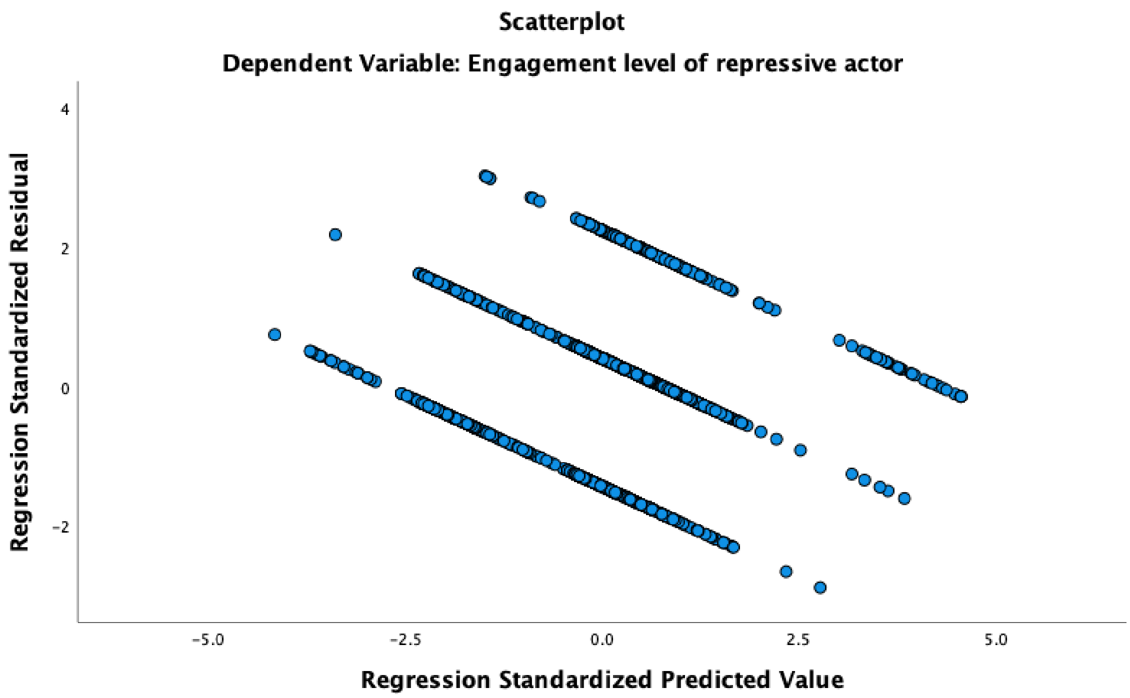
Normal probability

Charts



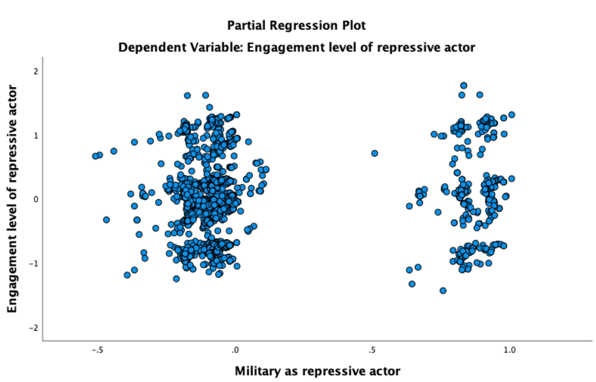
The assumption here is that the prediction errors in the population model are normally distributed and have a mean of 0 (Field, 2018). If this assumption is violated, the statistical significance cannot be fully trusted (Field, 2018). The errors are expected to be distributed normally (Field, 2018). If the dotted line follows the linear line, it means that the errors are normally distributed and have a mean of 0 (Field, 2018). However, this particular line is not exactly distributed normally (Field, 2018). Nevertheless, this is not cause for concern because the N is large in this research. It could be fixed by using bootstrapped standard errors, but this is not necessary in this particular case (Field, 2018). This assumption is met.

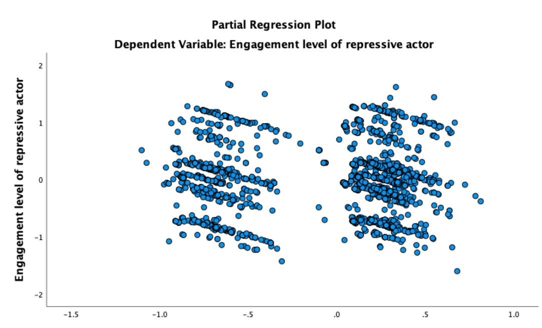
Homoskedasticity

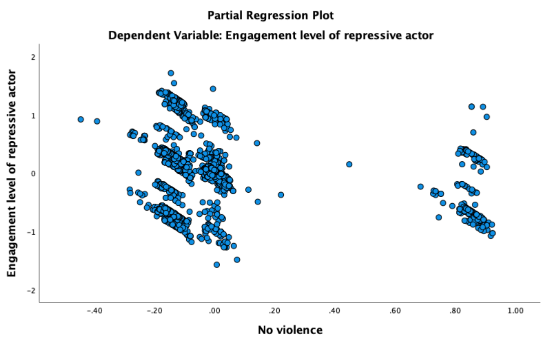


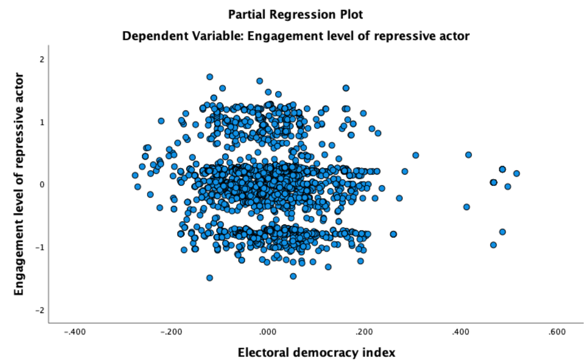
Homoskedasticity is the assumption that the predictions are going to be wrong, but they will be as wrong at low values of X as at high values (Field, 2018). In this scatterplot, it is clear that there is not a funnel pattern, which means there is no heteroskedasticity. Consequently, this entails that the assumption of homoskedasticity is met (Field, 2018).

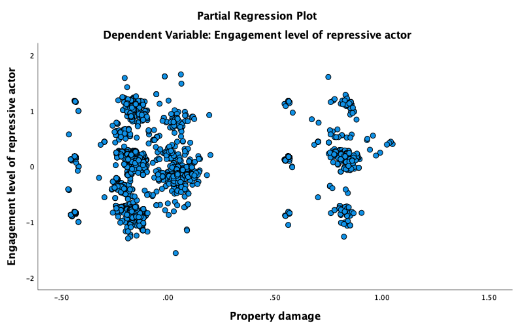
Linearity

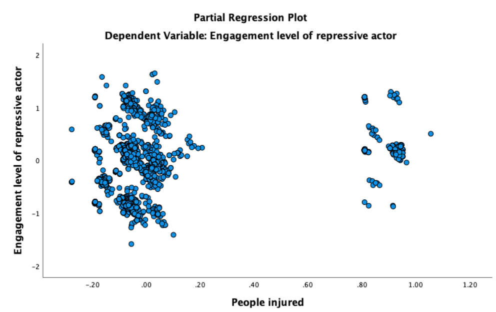


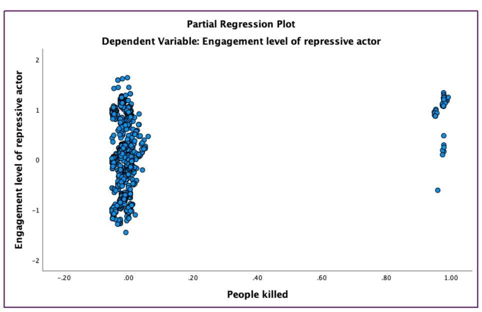


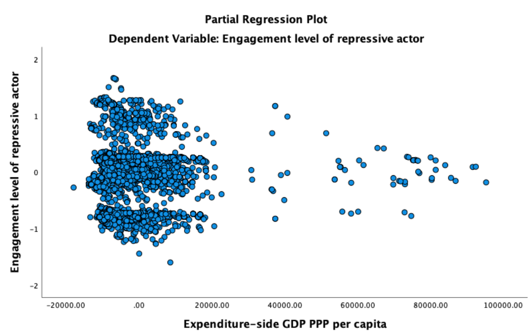

Partial Regression Plot
Dependent Variable: Engagement level of repressive actor
Engagement level of repressive actor
No violence

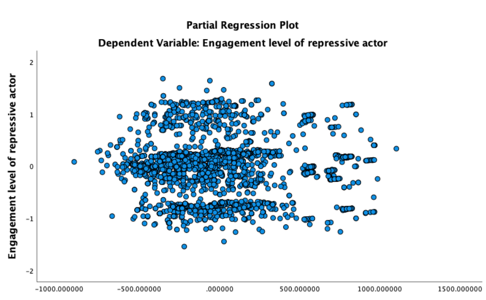

Partial Regression Plot
Dependent Variable: Engagement level of repressive actor
Engagement level of repressive actor
Electoral democracy index

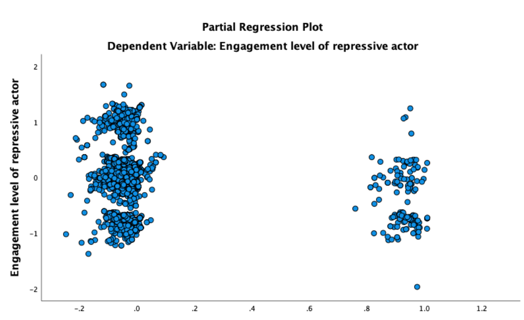

Partial Regression Plot
Dependent Variable: Engagement level of repressive actor
Engagement level of repressive actor
Property damage

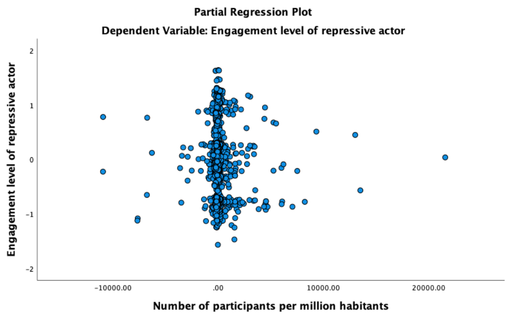

Partial Regression Plot
Dependent Variable: Engagement level of repressive actor
Engagement level of repressive actor
People injured

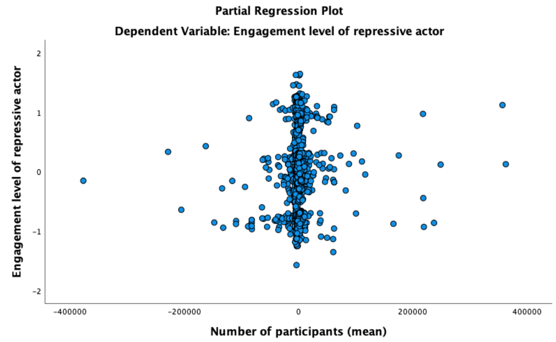

Partial Regression Plot
Dependent Variable: Engagement level of repressive actor
Engagement level of repressive actor
People killed


Partial Regression Plot
Dependent Variable: Engagement level of repressive actor
Engagement level of repressive actor
Expenditure-side GDP PPP per capita


Partial Regression Plot
Dependent Variable: Engagement level of repressive actor
Engagement level of repressive actor
Population size in millions


Partial Regression Plot
Dependent Variable: Engagement level of repressive actor
Engagement level of repressive actor
Pro-government protests





Most of these do not meet the assumptions of linearity which is an issue however, for now there is not a way to fix it because the solution would be to change the regression model to a logit model which is not relevant for now (Field, 2018).

Appendix B: Syntax

Computing and recoding of the variables:

```
COMPUTE RGDPE_PC=rgdpe / pop.
EXECUTE.
FREQUENCIES VARIABLES=RGDPE_PC
  /STATISTICS=RANGE MINIMUM MAXIMUM MEAN
  /ORDER=ANALYSIS.

COMPUTE Participants_mean_per_million_population=num_participants_num_mean / pop.
VARIABLE LABELS  Participants_mean_per_million_population 'Number of participants per
million '+
    'habitants'.
EXECUTE.

RECODE side_MMAD (0=1) (1=0) (SYSMIS=SYSMIS) (MISSING=SYSMIS)
(ELSE=SYSMIS) INTO side_MMAD_new.
EXECUTE.
FREQUENCIES VARIABLES=side_MMAD_new
  /STATISTICS=RANGE MINIMUM MAXIMUM
  /ORDER=ANALYSIS.

RECODE part_violence_MMAD ('0'=1) ('1'=2) ('2'=3) ('3'=4) (ELSE=0) INTO
part_violence_new.
EXECUTE.
FREQUENCIES VARIABLES=part_violence_new
  /STATISTICS=MINIMUM MAXIMUM
  /ORDER=ANALYSIS.
```

```
RECODE part_violence_new (0=1) (ELSE=0) INTO part_violence_0.
VARIABLE LABELS  part_violence_0 'No reports'.
EXECUTE.
RECODE part_violence_new (1=1) (ELSE=0) INTO part_violence_1.
VARIABLE LABELS  part_violence_1 'No violence'.
EXECUTE.
RECODE part_violence_new (2=1) (ELSE=0) INTO part_violence_2.
VARIABLE LABELS  part_violence_2 'Property damage'.
EXECUTE.
RECODE part_violence_new (3=1) (ELSE=0) INTO part_violence_3.
VARIABLE LABELS  part_violence_3 ' People injured'.
EXECUTE.
RECODE part_violence_new (4=1) (ELSE=0) INTO part_violence_4.
VARIABLE LABELS  part_violence_4 'People killed'.
EXECUTE.
```

Regression:

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE ZPP
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT sec_engagement_MMAD
  /METHOD=ENTER military police
  /METHOD=ENTER military police v2x_polyarchy part_violence_1 part_violence_2
part_violence_3
    part_violence_4 RGDPE_PC pop side_MMAD_new num_participants_num_mean
    Participants_mean_per_million_population
  /PARTIALPLOT ALL
  /SCATTERPLOT=(*ZRESID ,*ZPRED)
```

```
  /RESIDUALS DURBIN NORMPROB(ZRESID)
  /CASEWISE PLOT(ZRESID) OUTLIERS(2)
  /SAVE COOK ZRESID.
```

Outliers

```
RECODE ZRE_1 (SYSMIS=SYSMIS) (MISSING=SYSMIS) (Lowest thru -1.96=1) (1.96 thru Highest=1) (ELSE=0)
    INTO outlier_196.
EXECUTE.
RECODE ZRE_1 (SYSMIS=SYSMIS) (MISSING=SYSMIS) (Lowest thru -2.58=1) (2.58 thru Highest=1) (ELSE=0)
    INTO outlier_258.
EXECUTE.
RECODE ZRE_1 (SYSMIS=SYSMIS) (MISSING=SYSMIS) (Lowest thru -3.29=1) (3.29 thru Highest=1) (ELSE=0)
    INTO outlier_329.
EXECUTE.
FREQUENCIES VARIABLES=outlier_196 outlier_258 outlier_329
  /STATISTICS=RANGE MINIMUM MAXIMUM MEAN MEDIAN
  /ORDER=ANALYSIS.
```

part_violence_new

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	3763	61.7	61.7	61.7
	1.00	543	8.9	8.9	70.6
	2.00	1190	19.5	19.5	90.1
	3.00	416	6.8	6.8	96.9
	4.00	189	3.1	3.1	100.0
	Total	6101	100.0	100.0	

Descriptive Statistics

	Mean	Std. Deviation	N
Engagement level of repressive actor	1.78	.613	3715
Military as repressive actor	.09	.284	3715
Police as repressive actor	.74	.441	3715
Electoral democracy index	.25187	.104159	3715
No violence	.1098	.31271	3715
Property damage	.1604	.36705	3715
People injured	.0546	.22731	3715
People killed	.0132	.11410	3715
Expenditure-side GDP PPP per capita	10971.4722	11584.0237	3715
Population size in millions	220.405138	432.432922	3715
Pro-government protests	.042	.2000	3715
Number of participants (mean)	6191.31	33509.070	3715
Number of participants per million habitants	289.3606	1474.50714	3715

Model Summary[c]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.119[a]	.014	.014	.609	.014	26.671	2	3712	<.001	
2	.465[b]	.216	.213	.543	.202	95.206	10	3702	<.001	1.559

a. Predictors: (Constant), Police as repressive actor, Military as repressive actor

b. Predictors: (Constant), Police as repressive actor, Military as repressive actor, No violence, Pro-government protests, People killed, Number of participants per million habitants, People injured, Expenditure-side GDP PPP per capita, Electoral democracy index, Property damage, Population size in millions, Number of participants (mean)

c. Dependent Variable: Engagement level of repressive actor

Frequency Table

outlier_196

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	3495	57.3	94.1	94.1
	1.00	220	3.6	5.9	100.0
	Total	3715	60.9	100.0	
Missing	System	2386	39.1		
Total		6101	100.0		

outlier_258

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	3706	60.7	99.8	99.8
	1.00	9	.1	.2	100.0
	Total	3715	60.9	100.0	
Missing	System	2386	39.1		
Total		6101	100.0		

outlier_329

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	3715	60.9	100.0	100.0
Missing	System	2386	39.1		
Total		6101	100.0		