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# International backfiring

*When faced with state repression, are nonviolent resistance campaigns more likely to receive foreign support than their violent counterparts?*

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## Abstract

We are in the midst of the largest wave of nonviolent mass movements in world history; meanwhile, few researchers have examined movement features that improve the chances of resistance campaigns receiving international support. This thesis argues that nonviolent resistance campaigns are more likely to receive foreign support when faced with high levels of repression than violent resistance campaigns. The theoretical argument builds on backfiring in the civil resistance literature, which describes the strategic advantage of nonviolent methods under asymmetric conditions. This thesis offers a temporally disaggregated research design that analyzes the dynamics of 350 violent and nonviolent resistance campaigns from 1945-2013.

The aim of this thesis is to uncover if there is empirical evidence of international backfiring. Based on the results from the analysis, I cannot conclude with certainty that nonviolent resistance campaigns are more likely than their violent counterparts to receive foreign support when faced with extreme repression. However, an unexpected finding is that higher levels of state repression seemingly decrease the probability of resistance campaigns obtaining foreign support the subsequent year. This is a noteworthy finding as it goes against common expectations in the civil resistance field, and that calls for further analysis.

## Acknowledgements

The inspiration for this research project began with the Belarusian protests in 2020. At the time, every news outlet covered the political demonstrations against the government and President Alexander Lukashenko. The nonviolent activists expressed their dissatisfaction with the country's illegitimate election result and authoritarian status quo, and they were met with police brutality. However, months went by, and the international responses were close to silent, which made me curious about which protest movements receive foreign support and what factors are essential for this outcome. The past year was dedicated to analyzing protest movements from a statistical perspective, very far from activists' genuine grievances and experience of oppression. I have extremely high respect for those who sacrifice their safety in civil resistance movements in pursuit of making the world a better place.

First, I want to thank my supervisors, Professor Carl Henrik Knudsen (UiO) and Sirianne Dahlum (UiO), for helping me throughout this past year. Thank you for your valuable input and for believing in this project even when I thought it would never work out.

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Any mistakes are solely my own.
R scripts are available at request.

*Madeleine Schlyter Oppøyen*

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# 1. Introduction

Is the international community more willing to support nonviolent movements that face repression than their violent counterparts? The aim of this project is to determine if there is empirical evidence of nonviolent resistance campaigns receiving more ‘international sympathy’ than violent campaigns in the aftermath of violent crackdowns. This thesis offers a temporally disaggregated research design that analyzes the dynamics of 350 violent and nonviolent resistance campaigns from 1945-2013 from the Nonviolent and Violent Campaigns and Outcomes (NAVCO 2.1) dataset.

The civil resistance field has a long tradition and deals with issues concerning civil society, social movements, and other nonviolent opposition vis-à-vis the state that falls outside usual political channels. Nonviolent action has increasingly been used in the struggle against injustice and oppression, where in previous times, violent rebellion represented the only appropriate or viable response (Schock, 2013). Civil resistance campaigns have emerged as a consistently vital political force, from the early women’s rights and abolitionist movements until today’s mass movements such as the Black Lives Matter movement. Recent theoretical developments have revealed that nonviolent resistance campaigns are expected to have higher success rates, higher levels of participation, and better resilience in the face of repression than their violent counterparts (Chenoweth & Stephan, 2011). However, there has been less previous evidence of features that improve resistance campaigns’ chances of obtaining foreign support.

A whole range of different approaches to studying the motivations behind international support is available. This thesis sets out to examine the dynamics between resistance campaigns, the target regime, and foreign support in light of the literature on backfiring. Brian Martin (2007) defines backfiring as “a process that occurs when an action is counterproductive for the perpetrator” (3). In the civil resistance literature, backfiring describes situations where an illegitimate act by the regime vis-à-vis the opposition recoils against the regime, resulting in increased domestic and international support of the resistance campaign. Hess & Martin (2006) argue that two elements need to be present for a repressive event to generate backfiring. First, the event must be perceived as unjust by an audience. Second, information about the event must be communicated effectively to audiences substantial enough to force authorities to consider their outrage (Hess & Martin, 2006: 251). The term international backfire refers to the process where the regime's repressive actions towards activists' backlashes against the regime, resulting in increased direct or indirect foreign state support in favour of the opposition.

Signs of international backfiring have been present in various places, with the pro-democracy protests in Myanmar in 2021 being a recent example. Following Myanmar's general election on 1 February 2021, where Aung San Suu Kyi's NDP party won by a landslide, the military seized control of the country, detained political leaders, and declared a year-long state of emergency. The people answered with the largest protests since the Saffron Revolution in 2007, when thousands of monks rose against the military regime (Cuddy, 2021). The armed forces in Myanmar have used rubber bullets, water cannons, and live ammunition to disperse pro-democracy protesters. The worst days have had more than 100 people killed, leaving the whole country in mourning (Cuddy, 2021). In response to these horrible events, US President Joe Biden imposed sanctions on the leaders of Myanmar's coup in coordination with the European Union. Several countries have condemned the escalating violence against protesters and call on the military to immediately halt the use of force against peaceful protesters (Goldman, 2021). For autocratic leaders, it can be rational to direct repressive measures at mass movements because it imposes a cost on the opposition and can deter activists from engaging in activities perceived as threatening to government institutions, practices, or personnel (Davenport, 2007a; Goldstein, 1978). However, excessive use of force against civilians can backfire internationally against the regime, as it did in Myanmar.

The backfire mechanism builds on a process Gene Sharp (1973) calls 'political jiu-jitsu,' which describes the strategic advantage of nonviolent methods under asymmetric conditions. The argument is that state-inflicted violence is perceived as more illegitimate and disproportionate if the activists maintain a nonviolent discipline with solidarity and persistence in the struggle (Sharp, 1973). In turn, this can shift the public opinion and power relation in favour of the nonviolent resisters. However, if the protesters use violence themselves, it is easier for the regime to justify the violence against them. The aim of this thesis is to uncover if there is empirical evidence of 'political jiu-jitsu' or international backfiring, which leads me to the following research question:

*When faced with state repression, are nonviolent resistance campaigns more likely to receive foreign support than their violent counterparts?*

This thesis offers several findings and implications concerning the relationship between state repression, campaign strategy and foreign support. In contrast to the few empirical studies of backfiring that mainly focused on movement-level features such as participation and organizational structure (Kurtz & Smithey, 2018; Stephan & Chenoweth, 2011), this thesis set out to control structural factors as well such as regime type, press freedom, and GDP. The results of the empirical analysis find a weak correlation between the probability of receiving foreign support and the combination of a nonviolent campaign strategy and high levels of repression. Though, after robustness checks, these results seem to be driven by the operationalization of state repression. In sum, there is no substantial evidence to suggest that nonviolent campaigns are more likely to receive foreign support when faced with repression than their violent counterparts. However, an unexpected and interesting finding was the negative association between state repression and foreign support, implying that higher levels of state repression the previous year decrease the probability of receiving foreign support. I have not seen other findings in line with this before, which would be interesting to see future studies discuss.

## 1.1. Structure of the Thesis

I have started this thesis with a summary of the project. The remaining structure of the thesis is as follows:

**Chapter 2:** The thesis continues with an outline of previous research in the civil resistance field. First, critical findings on civil resistance and state repression are discussed. Second, the literature on the dynamics of backfiring is reviewed. Finally, the theoretical argument and hypotheses about international backfiring are presented.

**Chapter 3:** In this chapter, I present the data used in the analysis. First, I discuss the operationalization of the dependent variable foreign support. Second, I discuss the operationalization of the independent variables state repression and campaign strategy. The strengths and limitations with different repression indicators are contemplated. Third, the control variables used in the analysis are presented. Subsequently, descriptive statistics on the main variables are presented and discussed. Finally, I discuss the research design and statistical methods applied in order to test the various hypotheses.

**Chapter 4:** In the fourth chapter, I present and analyze the results from the logistic and event count models. In order to make sure these results are robust; I run several robustness tests and discuss whether the results can be driven by the operationalizations of foreign support or state repression. Moreover, the results are compared to previous findings on backfire effects.

**Chapter 5.** In the final chapter, I summarize the main findings and propose future research on the relationship between state repression and foreign support.

# 2. Theoretical framework

This chapter is devoted to the existing literature on civil resistance and the backfire mechanism. First, I review critical findings from civil resistance and state repression research. Second, the definition and origin of the backfire mechanism are discussed. Lastly, the chapter contains a presentation of the theoretical argument and hypotheses about international backfiring.

## 2.1. Civil resistance and state repression

*Civil resistance* is defined as the "sustained use of methods of nonviolent action by civilians engaged in asymmetric conflicts with opponents not averse to using violence to defend their interest" (Schock 2013: 279). Nonviolent action can take many forms, such as lobbying, boycotts, petitions, sit-ins, public speeches, picketing, or demonstrations. Gene Sharp (1973) catalogued 198 different methods of nonviolent action in his seminal work, The Politics of Nonviolent Action.

All over the world, nonviolent action has increasingly been used in the struggle against injustice and oppression, when in previous times, violent rebellion represented the only appropriate or viable response (Schock, 2013). Civil resistance campaigns have emerged as a consistently vital political force, such as the early women's rights and abolitionist movements (Schock, 2013). These movements relied heavily on protest and other attempts to influence their opponents. Another example is labor movements which have a strong tradition of using strikes to pursue their political objectives. From the 1950s and onward, incidents of nonviolent resistance are found across the globe representing various political issues. Famous examples include the student movement in France and across Europe in 1968, the civil rights movement that challenged discrimination and segregation in the American South, and the many pro-democracy movements from the 1980s into the 21st century, which challenged autocratic regimes all over the world (Schock, 2013). Today, researchers are debating whether we are in the midst of the largest wave of nonviolent mass movements in world history (Chenoweth et al., 2019).

The standard practice in research on violent and nonviolent conflict is to study *campaigns*, which are commonly defined along the lines of "observable, continuous, purposive mass tactics or events in pursuit of a political objective" (Chenoweth and Lewis 2013: 416). Campaigns fall outside of the routine political channels, such as voting or joining an interest group, but they are better organized than spontaneous large-scale demonstrations. A key reason for studying campaigns is that they often are more significant units of political importance than unorganized one-off events. As Chenoweth and Lewis (2013) put it: "protest events alone rarely threaten the stability of regimes, and social movements are not always interested in overturning the system within which they operate" (417). Campaigns with higher degrees of organization, specified political goals, and a combination of tactics have a higher likelihood of making significant changes in the political climate.

Typically, scholars distinguish between violent and nonviolent resistance campaigns based on their *primary* resistance method because the same campaign can use both violent and nonviolent tactics (Chenoweth & Stephan, 2011). An example of such mixed methods can be found in the yellow vest movement in France 2018. The protest movement for economic justice, emphasizing the increasing gas prices, began with an online petition that attracted nearly 1 million signatures. In November 2018, the campaign attracted more than 300,000 people, and the protesters constructed barricades and blocked roads and fuel depots. Initially, this took the form of nonviolent resistance. However, the following month some of the protests turned violent, with activists lighting fires in the streets and inciting riots that lead to property damage with an estimated cost of €1.5m. A spokesperson for the demonstrators insisted they were peaceful, telling the AFP news agency: "We are not here to pick a fight with cops. We just want the government to listen to us" ("France Fuel Unrest," 2018). In real life, the division between nonviolent and violent methods is not clear cut, such as in the yellow vests' movement. Still, yellow vest movements' *primary* resistance method was nonviolent, even though there were incidents of damage to property and rioting. In the civil resistance literature, there are various terms used to describe campaigns that use nonviolent methods. From this point on, I use the term nonviolent campaign strategy to describe resistance campaigns that use primarily nonviolent methods to pursue their goals. Likewise, insurgencies, rebellions, and other campaigns engaged primarily in violent action against the regime to achieve their goals will be referred to as having a violent campaign strategy.

A seminal contribution to the civil resistance field is Erica Chenoweth and Maria Stephan's (2011) book "Why Civil Resistance Works: The Strategic Logic of Nonviolent Conflict" Through a combination of statistical analysis and case studies, they conclude that nonviolent resistance campaigns historically have been more effective in achieving their goals than violent campaigns, even under harsh repression (Chenoweth & Stephan, 2011). The strategic logic of nonviolent resistance lies in the fact that the physical, moral, and informational barriers to participation are substantially lower in nonviolent campaigns than in violent campaigns (Chenoweth & Stephan, 2011). Lower barriers to participation in nonviolent campaigns give rise to a more diverse membership, resulting in higher levels of civic disruption through mass noncooperation, making regime supporters more prone to loyalty shifts (Chenoweth & Stephan, 2011). Moreover, nonviolent campaigns tend to be better at remaining resilient in the face of state repression. In comparison with violent campaigns, we can expect nonviolent resistance campaigns to have higher success rates, higher levels of participation, and better resilience in the face of repression.

Resistance campaigns do not operate in a political vacuum. In most cases, explicit demands are directed to the regime, which calls for some type of response from the regime to the ongoing protest activity. In many cases, the response is various levels of state repression. Christian Davenport (2007a) defines state repression as applications of state power that violate:

- **First amendment-type rights.** E.g., freedom of speech, assembly, travel, association, and religion. Furthermore, general freedom to protest, boycott without suffering criminal or civil penalties.
- **Due process in the enforcement and adjudication of law.** Violations of "generally accepted standards of police action and judicial and administrative behavior related to the political beliefs of the person involved" (Goldstein, 1978: xxxi).
- **Personal integrity or security.** Concerning individual security and survival, e.g., freedom from imprisonment, torture, extrajudicial execution, and mass killing.

This definition covers many different ways political authorities influence citizens within their territorial jurisdiction by using force. State repression can take many forms; violent or nonviolent; overt or covert; conducted by the state or state-sponsored militias (Davenport 2007a: 3). The conventional wisdom implies that repression reduces mobilization since it lowers the perceived opportunities of action, especially with nonviolent movements (Kurtz & Smithey, 2018). On the other hand, the absence of repression can open political opportunities and facilitate large protest waves (della Porta, 1995). Previous research has found support for a linear, negative association between repression and protest; in other words, higher levels of repression go together with lower levels of protest (Jenkins & Perrow, 1977; Oberschall, 1973; Tilly, 1978).

Conversely, others argue that state repression has a positive association with mobilization because outrage and a sense of injustice can override fears of further repression (Martin, 2007). Experimental evidence has also found support for the hypothesis that repression increases protest and mobilization (Dickson, 2007). State repression has the potential of successfully breaking down opposition, provoke a violent escalation of the conflict, or even end in regime collapse. Therefore, scholars such as Pierskalla (2010) argue that we should interpret government repression as a strategic interaction between multiple players rather than a simple action-reaction phenomenon.

Christian Davenport (2007a) discusses the state of the literature on state repression and presents two core insights. The first insight is the *Law of Coercive Responsiveness,* which states that "when challenges to the status quo take place, authorities generally employ some form of repressive action to counter or eliminate the behavioral threat" (Davenport 2007a: 7). This 'law' is especially relevant in scenarios where the challengers wish to remove the political leadership or the political system, making state authorities more likely to respond with repression (Davenport 2007a: 7). Challenges to the status quo include behavior perceived as a threat to the political system, the economy, beliefs, or the lives of those within their territorial jurisdiction. The nature of resistance campaigns is to challenge the status quo, and therefore, one can expect that most campaigns face some form of repression.

The second core insight on state repression is the *Domestic Democratic Peace* findings (Davenport, 2007b). The focus here is on factors that impede repression rather than compel it. These findings argue that (1) democratic institutions raise the costs of using repressive behavior since the political leadership is replaceable in the next election, (2) use of repression violates common democratic values such as toleration, communication, and deliberation; and (3) democracies use participation and contestation as an alternative mechanism for control (Davenport 2007a: 10-11). By facilitating the conveyance of grievances, the justification of repressive actions is weakened (Davenport 2007a: 10-11). There is a large consensus that democratic countries engage in repression more seldom and use different or less violent types of repression than autocracies (Davenport, 2007b; Davenport & Armstrong, 2004; Fein, 1995; Henderson, 1991).

Even though there is a large consensus regarding the domestic democratic peace findings, the functional form that links regime type and repression is still contested. Some scholars argue for a non-linear effect, e.g., “more murder in the middle” (Fein, 1995; Henderson, 1991). These studies find that hybrid and transitional regimes are the most coercive and that full democracies and autocracies apply relatively low amounts of repression (Davenport 2007a: 11). In intermediate regimes, with relatively new and untested institutional channels and an unstable balance of power, the general public and leaders are more prone to cycles of violence and protest (Pierskalla, 2010: 120). Others have argued for a threshold effect (Davenport & Armstrong, 2004), where state coercive behavior is not influenced by regime type before reaching the highest levels of democracy (Davenport, 2007a; Pierskalla, 2010). This research indicates that states above a certain threshold of democratic institutional consolidation are less likely to commit human rights abuses, use extralegal forms of repression or commit mass killings than authoritarian or hybrid regimes. The rising consensus seems to be that a set of *functioning* democratic institutions is associated with substantially reduced government repression. However, it is less clear which features determine violent repression and human rights violations in regimes ranging from semi-democratic to strictly autocratic regimes (Pierskalla, 2010: 120).

To sum up, we can expect nonviolent resistance campaigns to have higher success rates, higher levels of participation, and better resilience in the face of repression than violent campaigns. The nature of resistance campaigns is to challenge the status quo, and it is expected, building on *the law of coercive responsiveness* (Davenport, 2007a), that most resistance campaigns face some form of repression. An important distinction is that democracies engage in repression more rarely than autocracies. Lastly, prior research has found state repression to have the potential to both increase and decrease the level of mobilization. The following sections review prior research on the backfire mechanism and build the thesis's theoretical argument.

## 2.2. Backfiring

Brian Martin (2007) defines *backfiring* as “a process that occurs when an action is counterproductive for the perpetrator” (3). This general definition is helpful to explain scenarios in countless research fields. In the civil resistance literature, backfiring describes situations where an unlawful act by the regime vis-à-vis the opposition recoils against the regime, usually state repression of nonviolent opposition. The backfire mechanism builds on a process Gene Sharp (1973) calls ‘political jiu-jitsu,’ which describes the strategic advantage of nonviolent methods under asymmetric conditions. The core argument is that protesters can expose the violence incited by police or soldiers in the worst possible light if the campaign can maintain a nonviolent discipline with solidarity and persistence in struggle (Sharp, 1973). In turn, this can shift the public opinion and power relation in favour of the nonviolent resisters. However, if the protesters use violence themselves, it is easier for the regime to justify the violence against them.

In cases where extreme state repression backfires, it can take the form of increased mobilization against the regime, breakdown of compliance among regime supporters, or international condemnation of the regime in response to state repression (Stephan & Chenoweth, 2008: 11). Repressive events have the potential to produce massive public outrage, and the backfire mechanism can help to explain the conditions under which some repressive events can become transformative for social movements (Hess & Martin, 2006: 249). However, it is essential to note that repression of nonviolent resistance campaigns does not always end with backfiring as the outcome. Hess & Martin (2006) argue that two elements need to be present for a repressive event to generate backfiring. First, the event must be perceived as unjust by an audience. One can expect domestic and international audiences to perceive repression of peaceful mass demonstrations or sit-ins as more illegitimate than if it were to happen to a violent organization that harm civilians themselves. The use of state repression to demobilize violent campaigns can be justified on the grounds of public safety. Second, information about the event must be communicated effectively to audiences substantial enough to force authorities to consider their outrage (Hess & Martin, 2006: 251). Therefore, international media coverage is considered vital for raising awareness and pressuring regime allies to withdraw their support (Kurtz & Smithey, 2018: 48).

Some scholars call for a clear distinction between *ideological* and *strategic* nonviolence when discussing backfiring (Gross, 2018). On the one hand, ideological nonviolence avoids violence altogether because it is viewed as ineffective and morally wrong, for example, Mahatma Gandhi's Salt March in 1930. Strategic nonviolence, on the other hand, selectively refrain from violence only because it is ineffective. Michael Gross (2018) argues that violence plays a critical role in successful nonviolent resistance because their success can depend on the activists' ability to provoke violent, brutal, and often murderous reactions from the target regime (Gross 2018: 324). *Strategic* nonviolent resistance can be used to deliberately provoke backfiring in the hopes of strengthening solidarity among insurgents, sow problems in the opponents' camp, weakening international support for a repressive regime, or mobilize third parties in favor of the campaign (Gross 2018).

Binnendijk and Marovic (2006) exemplify strategic nonviolence in their analysis of the Serbian Otpor movement (2000) and the Ukrainian Orange Revolution (2004). Their decision to remain nonviolent was a fundamental strategic choice made by the campaign leaders (Binnendijk and Marovic 2006). The campaigns were aware that if they used violence, the regime would have resorted to force. Moreover, a violent crackdown against civilians in a peaceful movement would have more severe international ramifications for the regime than if the group was labeled as terrorists by state authorities (Binnendijk and Marovic 2006). The main factors that ensured legitimacy for the resistance campaigns were their composition (mostly mainstream youths), their maintenance of strict nonviolent discipline, and organizational structures focusing on local initiatives (Binnendijk and Marovic 2006).

The example above describes *strategic* nonviolent resistance; however, this is not necessarily a problem in itself. Gross (2018) uses the term 'backfire' to describe protesters engaging in strategic nonviolent tactics to *provoke* brutal responses from the regime in hopes of gaining domestic support, shift the international opinion to their side and encourage security force defections. In particular, he refers to violent movements that only use nonviolent tactics because violence is ineffective in realizing their goals. Gross (2018) point to groups such as Hamas, FALANTIL, and IRA that use nonviolence as a supplement for violence when they calculate that nonviolence "can get the job done" (Gross, 2018: 323). He brings forth two main dangers of the backfire mechanism. First, intentionally provoking violence to increase international sympathy undermines nonviolence's moral stature and efficacy. Second, the organizers of these campaigns can cause extreme harm to nonviolent resisters, which is difficult to justify morally

(Gross, 2018). Kurtz and Smithey (2018) refer to this phenomenon as a *moral hazard effect*, which is a situation in which an actor is willing to take higher risks because she knows that others will bear any potential costs. Their findings suggest that resistance campaigns with a violent radical flank have higher chances of achieving international media coverage (Kurtz & Smithey, 2018: 29). This finding coincides with similar arguments about the moral hazard of humanitarian intervention, namely that the international community tends to mobilize direct support for insurgents who use violence to accelerate humanitarian emergencies (Kuperman, 2008). Moreover, when international media capture nonviolent campaigns that experience high degrees of repression, it increases the likelihood of condemnation of the target regime (Kurtz & Smithey, 2018: 29). These findings underline the dark side of backfiring; opposition campaigns can capture international attention and gain foreign support against the regime by intentionally provoking higher repression levels against civilians and adopting violent flanks (Kurtz & Smithey, 2018: 29).

In their initial study of backfire effects, Kurtz and Smithey (2018) found sustained campaign participation essential in understanding domestic and international mobilization in favor of resistance campaigns that face repression. They argue that in order to have successful backfiring, continued participation is crucial regardless of campaign strategy (Kurtz & Smithey, 2018: 30). Moreover, higher levels of repression are found to reduce participation in the subsequent years, which paradoxically means that the campaigns that wish to benefit from backfiring might avoid the most extreme forms of repression (Kurtz & Smithey, 2018). It is essential to point out that nonviolent resistance achieves mass mobilization more often than violent resistance (Chenoweth & Stephan, 2011). In addition, nonviolent campaigns are more likely than their violent counterparts to succeed when faced with repression (Chenoweth & Stephan, 2011; Stephan & Chenoweth, 2008).

In sum, backfiring describes situations where state repression of resistance movements recoils against the regime, resulting in increased domestic and international support of the resistance campaign. The commonly discussed scenario is high levels of state repression directed at nonviolent resistance campaigns. Essential factors to generate backfire include that the event must be perceived as unjust and that information about the events must be communicated effectively. Activists and resistors can use this advantage strategically, which raises important concerns about moral hazard effects.

## 2.3. International backfiring

This section presents the theoretical argument and hypotheses of this thesis. The aim is to study the international components of backfiring to determine if there is empirical evidence of nonviolent resistance campaigns receiving more 'international sympathy' in the aftermath of violent crackdowns than violent campaigns.

Backfiring describes situations where state repression of resistance movements recoils against the regime, resulting in increased domestic and international support of the resistance campaign. Essential factors to generate backfire include

- the event must be perceived as unjust,
- the campaign should have continued participation, and
- information about the event needs to be communicated effectively.

This thesis applies the term *international backfire* for the process when state repression of resistance campaigns recoils against the regime, resulting in increased direct or indirect foreign state support in favor of resistance campaigns. Examples of this outcome include condemnation of the regime, former regime supporters withdrawing their support, international sanctions targeting the regime, and overt support of the campaign.

Following the logic of backfire effects, extreme state repression is the 'event' or 'catalyst' for foreign support because it is perceived as unjust by international audiences. Building on the *Law of Coercive Responsiveness* (Chenoweth et al., 2017; Davenport, 2007a; Kurtz & Smithey, 2018), one can expect most resistance campaigns to be met with some form of repression. The core argument in this "law" is that dissent always evokes state repression in some form due to states seeking order and leaders seek political survival (Chenoweth, Perkoski, and Kang 2017). This expectation is backed up in the NAVCO 2.1 dataset, where 2629 out of 2717 campaign years include some level of repression (Chenoweth & Lewis, 2013). Therefore, whether or not resistance campaigns are repressed is not essential in this thesis; the *degree* of state repression is in focus.

When backfiring occurs, the outcome is counterproductive for the regime. Therefore, scholars interested in backfiring make assumptions about the regime's *intentions* behind repressing civil resistance movements. The most common goal of state repression is to impose a cost on the target and deter specific activities or beliefs perceived as threatening to government institutions, practices, or personnel (Davenport, 2007a; Goldstein, 1978). Repression can be very effective in achieving these goals if it does not generate substantial domestic or international repercussions. Kurtz and Smithey (2018) argue that "any outcome that increases the costs to the regime of maintaining the status quo, reduces the regime's international or domestic political position, or threatens the regime's very survival should be viewed as an indicator of backfire" (34). The outcome is disadvantageous for the regime if it strengthens the opposition and weakens the regime.

A vital element for generating backfire is that the event must be perceived as illegitimate by an international audience (Hess & Martin, 2006). Regimes that suppress popular uprisings risk painful international consequences, such as powerful allies withdrawing their support or international organizations wielding sanctions against them – especially if international media outlets broadcast the abuse. In general, applying state violence in asymmetric conditions such as relatively small campaigns versus a regime with the backing of both military and police, excessive use of force is expected to make international actors shift their support in favor of many opposition movements. Followingly, this thesis argues that the likelihood of foreign support increases with the level of state repression because violent repression is more likely to be considered as illegitimate by international actors:

> **H1 (Naïve specification):** Higher levels of state repression increase the likelihood of resistance campaigns receiving foreign support.

The literature on backfire effects highlights the significance of having a nonviolent campaign strategy to generate backfire. Therefore, the Naïve specification (H1) acts as a premise for the following hypothesis about international backfire effects.

The risks the regime faces when repressing unarmed civilians involve loss of international and domestic legitimacy, in addition to possible renewed mobilization in favour of the opposition (Kurtz & Smithey, 2018: 33). Highly organized civil resistance campaigns are more resilient in the face of repression than their violent counterparts because of their ability to exploit repressive incidents to improve the odds of backfiring (Chenoweth et al., 2017). Moreover, violent state repression is more likely to generate international backfiring to benefit an unarmed opposition since the abuse is less justifiable (Dudouet 2013: 407). Campaigns can provoke backfiring by drawing attention to the abuse through social media, television, or other channels. As discussed concerning moral hazard effects, violent movements can also use nonviolent tactics to *provoke* brutal responses from the regime in hopes of gaining domestic support, shift the international opinion to their side and encourage security force defections (Gross, 2018; Kuperman, 2008). Even though this is not *ideological* nonviolence, a campaign like this can fall into the category of a primarily nonviolent campaign year in the analysis. This thesis argues that the choice of campaign strategy contributes to whether or not violent state repression leads to foreign support:

> **H2 (International backfire):** When faced with violent state repression, nonviolent resistance campaigns are more likely than their violent counterparts to receive foreign support.

One necessary condition for backfire to occur is that information about the event is communicated effectively to audiences substantial enough to force authorities to consider their outrage (Hess & Martin, 2006: 251). International media coverage has also been argued as vital for raising awareness and pressuring regime allies to withdraw their support (Kurtz & Smithey, 2018: 48). Therefore, international media coverage is expected to have a direct effect on foreign support of resistance campaigns. Moreover, building on *domestic democratic peace findings* (Davenport, 2007b; Davenport & Armstrong, 2004; Fein, 1995; Henderson, 1991), international backfiring is expected to be less likely for resistance campaigns in democracies than in autocracies. This expectation comes from the fact that democratic countries use repression more seldom and use different or less violent forms of repression than autocracies.

As mentioned, continued participation is crucial for achieving successful backfiring (Kurtz & Smithey, 2018). This thesis argues that the campaign strategy should be understood as an underlying cause of continued participation in resistance campaigns. The main argument for this is that nonviolent resistance campaigns have a strategic advantage over violent campaigns due to them having lower physical, moral, and informational barriers to participation (Chenoweth & Stephan, 2011). Followingly, nonviolent campaigns achieve mass mobilization more often than violent campaigns (Chenoweth & Stephan, 2011). Prior research has also found that state repression against large *nonviolent* campaigns is more likely to backfire against the regime than large *violent* campaigns (Chenoweth & Stephan, 2011). Consequently, a nonviolent campaign strategy should be crucial for achieving successful backfiring, underlined in the international backfire hypothesis (H2).

Other researchers have conducted empirical analyses of backfire effects with the NAVCO 2.0 dataset (Kurtz & Smithey, 2018). However, this study mainly focused on movement-level factors, such as participation, internal organization, media coverage, and nonviolent discipline. Their conclusion points out that future studies should examine how *contextual* factors such as demographic characteristics, regime features, and international system features affect their findings. Therefore, structural control variables are included in this study of international backfire effects, such as GDP, population, level of electoral democracy, press freedom and international media coverage (presented in the section on control variables, 3.5). Domestic forms of campaign support are significantly affected by domestic factors such as the participation size and security force defections (Chenoweth & Stephan, 2011). However, international backfiring involves state-to-state interactions, which I expect to be more prone to depend on structural factors. The next chapter presents the data and research methods that are applied in the analysis.

# 3. Data and research methods

The thesis aims to uncover if and to what extent state repression and campaign strategy affect the chances of resistance campaigns obtaining foreign support. The dynamics between resistance campaigns, the target regime, and foreign support are analyzed with data from NAVCO 2.1 with campaign-year as the unit of analysis. The chapter begins with a description of the data source and unit of analysis. After that, the operationalization of the dependent, independent, and control variables are discussed. Finally, the main explanatory variables' descriptive statistics and time trends are discussed, and the research design is presented.

## 3.1. Dataset and data structure

For this study, I have chosen the Nonviolent and Violent Campaigns and Outcomes (NAVCO) dataset version 2.1. to code the dependent and independent variables (Chenoweth and Shay 2019). NAVCO compiles annual data on 384 mass movements for regime change, anti-occupation, and secession from 1945 to 2013. It includes a total of 2717 campaign years.

As mentioned, campaigns as the unit of analysis have a precedent in violent and nonviolent conflict research. A key reason for studying campaigns is that they often are more significant units of political importance than unorganized one-off events (Chenoweth and Lewis 2013: 416). With higher degrees of organization, specified goals, and a combination of tactics, the possibility of changing politics is higher. In NAVCO, campaigns are operationalized as “a series of observable, continuous, purposive mass tactics or events in pursuit of a political objective” (Chenoweth and Lewis 2013: 416). To be included, campaigns must have at least 1,000 observed participants and a claimed ‘maximalist’ goal at some point during the campaign, respectively goals of regime change, secession, or the removal of a foreign occupier (Chenoweth and Lewis 2013: 417). In this way, campaigns are distinguished from unorganized one-off events, and the participation criteria secure that the campaigns are large enough to generate international attention and potential intervention. NAVCO 2.1. consist of panel data, which means that the same units (campaign-year) are measured several times on the same variables, e.g., the Anti-Milosevic campaign in Serbia is measured on the same variables for all five years of the campaign (1996-2000).

## 3.2. Dependent variable: Foreign support

First of all, to uncover trends that affect the likelihood of foreign support, there must be an appropriate foreign support measure. NAVCO 2.1. provide five relevant indicators that represent different types of foreign support (see Table 1). The combination of these indicators covers the most common ways foreign states show their support resistance campaigns, e.g., through economic measures and diplomatic support. For this thesis, foreign support is narrowed down to *state actors* and excludes support from international organizations. Before the operationalization of foreign support is presented, I need to address some concerns about the *a priori* relationship between foreign support and state repression.

*Table 1. Indicators of foreign support in the NAVCO 2.1. dataset*

| **Indicators of foreign support** | **Frequency (N = 2717)** |
|---|---|
| Condemnation by international actors (ab_internat) in response to state repression. | 902 |
| International material repercussions (ab_int_mat) in response to state repression. | 413 |
| Former state supporters withdraw support (wdrwl_support) in response to state repression. | 88 |
| The campaign has formal overt support from other states (camp_support) | 1273 |
| International sanctions in place on the regime (sdirect) for cracking down on opposition. | 349 |

### *A priori* relationship between foreign support and state repression

The five indicators listed in Table 1 show different forms of direct and indirect foreign support resistance campaigns receive. The implication is that four of them record foreign support *in response* to state repression. In a sense, this ensures an *a priori* relationship between the dependent (foreign support) and independent (state repression) variable. State repression is no longer independent since the dependent variable is coded in response to the independent variable. So how can I solve this?

One solution is only to use the indicator *camp_support* to measure foreign support since it measured independently from the state repression variable. The strength of the approach is that it is possible to conclude about the X – Y relationship. The drawback is that it does not cover the broad concept of “foreign support” since it only records if the campaign had formal overt support from other states. Moreover, by only using one indicator, there are fewer data to work with, making biased estimations more likely.

The other solution is to use all the indicators in Table 1 and assume repression has taken place. This alternative demands the removal of observations with no repression. The downside of this method is that the research design does not allow for any conclusion about the X – Y relationship: whether state repression increases the chances of foreign support. To evaluate the X-Y relationship, a measure of foreign support that does not presume that repression has taken place and a control group is needed (i.e., observations where resistance campaigns receive foreign support without facing extreme state repression). However, it is still possible to conclude how high levels of repression, compared to lower levels, affect the likelihood of foreign support. The advantage of this solution is that it provides more instances of foreign support, and the inclusion of several types of foreign support increases the validity of the foreign support concept. Moreover, the dependent variable can still be used to look at differential responses to violent and nonviolent campaigns and how these responses change with increasing levels of repression.

Building on the *Law of Coercive Responsiveness* (Chenoweth et al., 2017; Davenport, 2007a; Kurtz & Smithey, 2018), this thesis already expects most resistance campaigns to be met with some degree of repression. Therefore, both methodically and theoretically, the preferred solution is to use all indicators of foreign support and assume that repression has occurred. Followingly, the empirical analysis in this thesis focuses only on campaign years with some level of repression, which leads to the deletion of 86 observations with no state repression. The selection of observations with "no repression" is based on the *repression* variable (see Table 3) from NAVCO 2.1 (Chenoweth and Shay 2019). The assumption is that this repression variable coincides with the various foreign support variables, as it is the same team that coded this variable and the dependent variable – which hopefully means that the definition of repression does not differ between the variables.

Moreover, there are only two missing values on the *repression* variable in the dataset. More specifically, this pertains to the first years of the Sciri resistance campaign in Iraq (1989-1990), which also have missing data on the dependent variable. One solution is to replace these values, e.g., by comparing the level of repression with the latter campaign years (where it consistently is met with extreme repression). However, these two observations are removed rather than concluding the level of repression based on gut feeling. After removing the 88 observations and assuming repression has occurred, the problem with an *a priori* relationship between dependent and independent variables is reduced. However, it will still limit the conclusions I can draw from the analysis to questions pertaining to the intensity of repression.

**Operationalization**

The five variables from NAVCO 2.1 that measure different types of foreign support (Table 1) are used to operationalize the dependent variable. For the main part of the analysis, it is a need for a binary dependent variable, denoting whether foreign support occurred or not in a given campaign year. The binary dependent variable is used to analyze whether state repression and choice of campaign strategy increase the chance of *any* type of foreign support. The binary variable ***fsupport*** is assigned the value 1 if one or more types of foreign support are issued that campaign year and 0 if it is not.

Moreover, it is interesting to see if the empirical analysis results hold for increasing levels of foreign support. The indicator *fsupport* alone does not pick up all the annual variation in foreign support across campaigns. For example, the Anti-Milosevic campaign in Serbia in 1999 received all five types of foreign support, while the Afar Insurgency in Djibouti in 1991 only had international actors condemning the regime. If this data were only to be analyzed with logistic regression of *fsupport*, these two cases are treated as similar phenomena, which leads to loss of valuable information. Therefore, a count dependent variable ***fsupport2*** is made to run a separate count regression that reports the number of foreign support types a resistance campaign will likely experience in a given campaign year. The count variable ***fsupport2*** is based on *fsupport*: if *fsupport* has the value 1, *fsupport2* counts the number of different types of foreign support. The minimum value is 0, and the maximum is 5. Conversely, if *fsupport* has the value 0, *fsupport2* also has the value 0. The count dependent variable *fsupport2* is studied with a Poisson event count model to utilize the variation in the dependent variable. Combining these two models will hopefully give a more nuanced view of how state repression and campaign strategy affect the likelihood of foreign support and how it affects the *level* of foreign support.

## 3.3. Independent variable: State repression

A measure of the occurrence and degree of state repression is required to study the dynamics of international backfiring. As discussed in the previous section, this thesis assumes that repression has taken place. Therefore, the empirical analysis only concentrates on campaign years with some degree of repression. Followingly, the counterfactual response to violent state repression is *less violent forms* of state repression.

Several suggestions on how state repression can be measured are presented in this section. All are used for robustness checks to see which one best describes the data and determine if the results of the empirical analysis are robust. The core of the discussion about this operationalization is the vast number of campaign years with extreme repression in the *repression* variable from the NAVCO 2.1. dataset (see Table 2).

*Table 2. Repression variable in NAVCO 2.1.*

| **repression** | **Frequency (N = 2717)** |
|---|---|
| **None.** Few or no actions taken by the state, or the state is making concessions. It also includes expressions of intent to cooperate. | 86 |
| **Mild.** Verbal or threatening action short of physical action or economic measures, maintaining the status quo. | 45 |
| **Moderate.** Physical or violent action aimed at coercing opponent, harassments or arrests of campaign members. No intention to kill. | 124 |
| **Extreme.** Physical action demonstrating intent to kill and violently silence opponents. It also includes torture and mass violence | 2460 |

*Note:* 2629 campaign years with some form of repression, 86 with no repression (NA = 2).

### Operationalization

The *repression* variable from NAVCO 2.1. measures the most repressive episode enacted by the state in response to campaign activity that year (Chenoweth & Shay, 2019). All operationalizations of state repression are lagged one year since it is expected to take some time to generate international backfiring. The literature on backfiring emphasizes that *extreme* or *violent* repression against nonviolent campaigns can trigger foreign support (Martin, 2007; Sharp, 1973). Therefore, the empirical analysis employs a binary independent variable to capture whether extreme levels of state repression was directed at the resistance campaign that year. The independent variable “extreme state repression” lagged one year, is based on NAVCO’s *repression* variable, and given the value 1 if extreme repression occurred the previous year, and 0 otherwise.

The rest of this section is dedicated to the alternative operationalizations of state repression used for robustness checks of the results. In addition to the binary version presented above, I will run the same analysis on the lagged “state repression ordinal”-variable, which mirrors the original repression variable from NAVCO (Table 2). This variable then differentiates between mild, moderate, and extreme forms of repression.

One of the issues with the repression variable from NAVCO is the overrepresentation of observations with "extreme" levels of repression. A possible explanation for this is that it is a very inclusive category. Because of this, I want to cross-examine the results with other indicators of violent repression. Building on the literature on backfire effects (Martin, 2007), it is vital that the level of repression is extreme or violent to generate outrage and thereby backfire effects. An alternative indicator of *violent* state repression is the number of fatalities following protest activity. NAVCO 2.1 provides a variable that measures the estimated number of fatalities "directly inflicted by the state in its efforts to suppress the campaign during the year (fatalities among campaign participants and nonparticipants killed by state repression relating to an ongoing campaign)"(Chenoweth & Shay, 2019). Unfortunately, the number of fatalities is not consistently gathered for all campaign years, leaving 409 missing values. Nevertheless, the variable "fatalities_range" will be used in a robustness check following the empirical analysis, which is also lagged one year.

Another alternative measure from the Varieties of Democracy dataset version 11 (Coppedge et al. 2019) is an index that measures the level of state repression directed at civil society organizations in general (CSO) (v2csreprss). The CSO repression index differentiates between violent and nonviolent repression more precisely than the repression variable from NAVCO 2.1. It measures the degree to which the government attempts to repress civil society organizations on a country-year basis. Even though it does not specify direct repression of resistance campaigns, I believe it safe to say that at least more widespread campaigns will have some organizational structure that can be directly affected by the repression of CSOs in general. This variable is also available with an ordinal structure (as shown in Table 3). Both the CSO repression index and CSO repression ordinal are used for robustness checks, lagged one year.

*Table 3. Civil society organization repression variable (V-dem)*

| v2csreprss_ord (V-dem, v.11) | Frequency (N = 2629) |
|---|---|
| **No.** CSOs are free to organize, associate, strike, express themselves, and criticize the government without fear of government sanctions or harassment. | 253 |
| **Weakly.** The government uses material sanctions (fines, firings, denial of social services) to deter oppositional CSOs from acting or expressing themselves. | 681 |
| **Moderately.** Material sanctions, minor legal harassment (detentions, short-term incarceration). Restrictions on the association of CSOs, bar CSOs from taking certain actions or block international contacts. | 650 |
| **Substantially.** In addition to the harassment in the responses above, the government illegally arrests and imprison leaders and participants of oppositional CSOs. Violent sanctions of activists: beatings, threats to families. | 597 |
| **Severely.** The government violently and actively pursues members of CSOs, seeking to deter their activities and liquidate such groups. | 358 |

NA: 90

To sum up, there are several options for operationalizing state repression, and all are included as robustness tests. The operationalization I will apply in the analysis is the lagged binary independent variable "Extreme state repression". There are several reasons why this operationalization has an advantage. First, concerning the *a priori* relation between dependent and independent variables, this variable is best to assume that no repression has taken place, as the same team codes it as the dependent variable – which hopefully means that the definition of repression does not differ between the variables. Second, it has very little missing data, making it more acceptable to remove missing observations. Third, it describes state repression directed at resistance campaigns, so it is easier to conclude the research question than a variable recording the general level of repression for each country-year (as with the v2csreprss variableTo test if the results are consistent across the different measures of state repression, all the models are tested with alternative operationalizations of state repression, respectively "State repression ordinal (t-1)" (lstaterep_ord), “Fatalities range (t-1)” (lfatalities), "CSO repression index (t-1)" (lCSOrep_index) and "CSO repression ordinal (t-1)" (lCSOrep_ord).

## 3.4. Independent variable: Campaign strategy

Having a nonviolent campaign strategy is hypothesized to be vital in generating international backfiring; therefore, a measure of campaign strategy is needed. The choice of campaign strategy, either violent or nonviolent, can affect both the levels of state repression the possibility of receiving international support.

**Operationalization**

Typically, scholars characterize campaigns as violent or nonviolent based on the *primary* resistance method since they can include both elements from methods (Chenoweth & Stephan, 2011). Campaign strategy is operationalized using NAVCO 2.1. variable 'prim_meth', which denotes the primary type of resistance method used in a campaign year.

Nonviolent campaign years are required to have been prosecuted by unarmed civilians "who did not directly threaten or harm the physical well-being of their opponent" (Chenoweth and Lewis 2013: 418). When a campaign relies consistently on nonviolent resistance tactics -such as civil disobedience, boycotts, protests, strikes- instead of violent tactics, NAVCO characterizes the campaign as primarily nonviolent. Violent campaign years are classified as such if they are prosecuted by armed persons or "otherwise involving the regular and deliberate use of violence by civilian or guerrilla challengers are classified as armed or violent campaigns." (Chenoweth and Lewis 2013: 419). When a campaign relies consistently on violent tactics such as the use of force to harm, threaten or kill the opponent, NAVCO characterizes the campaign as primarily violent.

## 3.5. Control variables

In this section, the control variables for the analysis are discussed and operationalized.
While this thesis aims to uncover if and to what extent state repression and campaign strategy increase the chances of foreign support to resistance campaigns, it also recognizes that resistance campaigns occur within a political environment and context. Therefore, several control variables that have been proven to be robust in former studies of conflict are included: GDP and population. Moreover, additional controls are added based on the panel structure of the dataset and previous findings on state repression and backfire effects.

***Lagged foreign support (t-1).*** Substantially, we can expect that resistance campaigns that are already receiving foreign support of some kind have a higher likelihood of receiving continued support the following year. Therefore, the dependent variable lagged one year is included as a control variable. Apart from this practical interpretation, the inclusion of a lagged dependent variable also helps counteract autocorrelation, which is very likely in the data at hand as it has an unbalanced panel structure (Christophersen, 2013). The dependent variable is influenced by omitted factors I cannot control for. Therefore, the inclusion of a lagged dependent variable essentially acts as a control for these omitted factors. One issue that occurs when the dependent variable is lagged is that campaigns that only last one year and the first year of a new campaign are assigned a missing value – because the campaign did not exist the previous year. The lagged dependent variable is assigned the value 0 if it has missing cells, simply because if the campaign did not exist the previous year, it did not receive any form of foreign support either. This decision is made to counter the loss of observations because of this control variable.

***International media coverage.*** One necessary condition for backfire to occur is that information about the event is communicated effectively to audiences substantial enough to force authorities to consider their outrage (Hess & Martin, 2006: 251). International media coverage has also been argued as vital for raising awareness and pressuring regime allies to withdraw their support (Kurtz & Smithey, 2018: 48). Thereby, international media coverage has a direct effect on the dependent variable. Moreover, it is plausible that this coverage can change the repressive regime's behavior vis-à-vis the resistance campaign. For this control, I will use the variable 'in_media,' from NAVCO, which records the extent of international traditional media coverage of the campaign, differentiating between little to none, moderate, and high levels of international media coverage (Chenoweth & Lewis, 2013).

***Press freedom.*** Based on the same premise as international media coverage (Hess & Martin, 2006: 251), foreign support could depend on how elites control the media in the regime the resistance campaigns take place. Foreign support may be more effectively generated in regimes with relatively open and decentralized media. Therefore, I assume that press freedom has an independent effect on the probability of receiving foreign support that I want to control. I control press freedom by using the Freedom of Expression and Alternative Sources of Information index from the Varieties of Democracy (V-dem) dataset, version 11 (Coppedge et al. 2019). The index is measured on a country-year basis and ranges from 0 (low) to 1 (high).

***Electoral democracy index.*** As previously discussed, the domestic democratic peace findings suggest that the scope and intensity of repression are conditioned by regime type (Chenoweth et al., 2017; Davenport, 2007b; Kurtz & Smithey, 2018). More specifically, almost every study on the relationship between democracy and repression finds that "democratic political institutions and activities decrease repressive state behavior" (Davenport, 2007a). These findings indicate a positive association between regime type and state repression. Kurtz and Smithey (2018) point out that further research on backfire effects should examine contextual factors such as regime- and international system features. Therefore, to get the independent effect of state repression on foreign support, regime type is controlled by using the electoral democracy index from the Varieties of Democracy (V-dem) dataset, version 11 (Coppedge et al. 2019). The index is measured on a country-year basis, ranging from 0 (low) to 1 (high).

***GDP and population.*** Gross domestic product is included as a control variable to measure economic development. Previous research has consistently found that GDP has a negative influence on repression, meaning that poorer countries tend to repress more (Davenport 2007a). However, the exact reason for this is disputed. Since the effect of GDP has been consistently proven to have a negative relationship with state repression, I include it as a control in the analysis to make sure there is no confounding relationship. For operationalization of this control, I use the "GDP (PPP 2011) estimate" variable from the dataset used in the research article "Bread before guns or butter: Introducing Surplus Domestic Product (SDP)" (Anders et al., 2020). This thesis applies an estimate of GDP rather than real because there is a lot of missing data, especially in the earliest years of the dataset (1945). Anders, Fariss, Markowitz (2020) base their estimates on World Bank WDI, and the GDP variable is log-transformed. Since gross domestic product only acts as a control variable in my analysis, this measure is accurate. The population estimate is included as a control to measure the size of the population in the country the resistance campaign takes place. To operationalize the population number, I use the same dataset as GDP (Anders et al., 2020). This dataset provides a "Population estimate (based on World Bank WDI 2016)" similar to the GDP variable and log-transformed.

## 3.6. Descriptive statistics

This section presents descriptive statistics for each of the variables used in the analysis (Table 4). Moreover, time-series lines for essential variables are discussed.

*Table 4. Descriptive statistics of the variables.*

| Variable | n | Min | Max | Mean | St. dev. |
|---|---|---|---|---|---|
| Foreign Support | 2456 | 0.000 | 1.000 | 0.654 | 0.476 |
| Foreign Support 2 | 2456 | 0.000 | 5.000 | 1.146 | 1.172 |
| Campaign Strategy | 2456 | 0.000 | 1.000 | 0.166 | 0.372 |
| Extreme State Repression (t-1) | 2456 | 0.000 | 1.000 | 0.813 | 0.390 |
| International media coverage | 2456 | 0.000 | 2.000 | 1.079 | 0.806 |
| Foreign support (t-1) | 2456 | 0.000 | 1.000 | 0.563 | 0.496 |
| Foreign support 2 (t-1) | 2456 | 0.000 | 5.000 | 0.962 | 1.131 |
| Population (log) | 2456 | 8.817 | 20.916 | 17.036 | 1.959 |
| GDP (log) | 2456 | 15.466 | 29.613 | 25.097 | 2.149 |
| Electoral democracy index | 2456 | 0.009 | 0.916 | 0.332 | 0.239 |
| Press Freedom | 2456 | 0.013 | 0.965 | 0.483 | 0.307 |

After removing the 261 observations with no repressive state behavior vis-a-vis the resistance campaign and observations with missing data on the main explanatory variables, the sample used for the empirical analysis consists of 2456 campaign years. In this sample, there are 350 unique resistance campaigns across 127 countries.

Statistical models that ignore missingness can, in the worst case, result in biased estimates and standard errors that are highly inflated or deflated (Ward & Ahlquist, 2018). Part of the 'missingness' in this dataset can be due to ill-defined cells in the data matrices. For example, data on population or GDP is missing because the country was not an independent state when the resistance campaign took place. To analyze 2456 out of the entire NAVCO dataset of 2717 observations is an acceptable degree of missingness.

**Campaign strategy**

Figure 1 displays the count of active violent and nonviolent resistance campaigns in the period 1945-2013. The figure separates between campaigns that have a primarily violent or nonviolent campaign strategy. The majority of the observations in the NAVCO-dataset have a violent campaign strategy. Namely, the 2049 violent campaign years and 407 nonviolent campaign years. The total number of campaigns has increased over time, with peaks for both campaign strategies around 1990 and 2010.

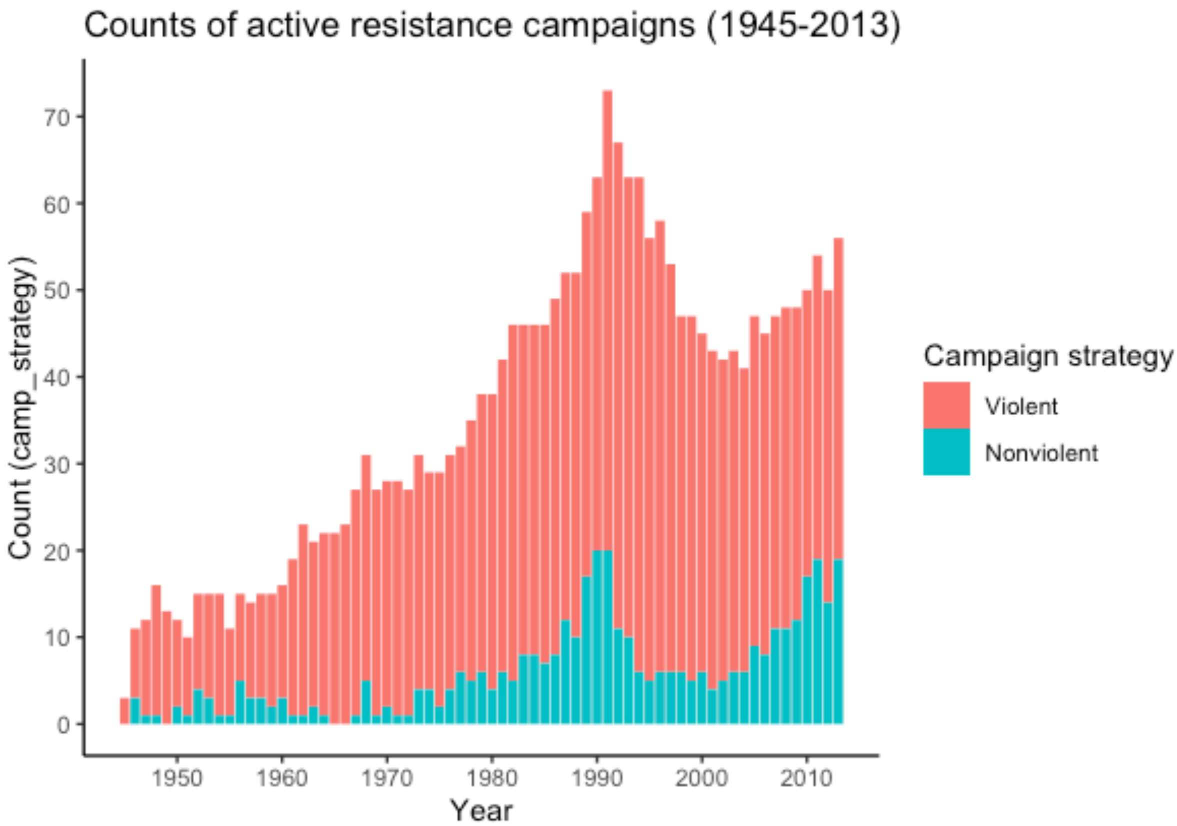


*Figure 1. Count of active resistance campaigns (1945-2013)*

**State repression**

Figure 2 displays the time trend in the number of resistance campaigns that met extreme and mild/moderate levels of state repression lagged one year in the period 1945-2013. As discussed previously, the NAVCO dataset has an overrepresentation of campaign years with extreme state repression. Moreover, some of the campaign years in the "mild/moderate" category are due to the recoding of the lagged state repression variable. More specifically, campaigns that only last one year and the first year of resistance campaigns are assigned the value 0 since there was no record of extreme repression the year prior. There is no single year with more than ten counts of mild to moderate repression in the original state repression variable, while this occurs in the lagged version. Consequently, the time trend is different between the lagged and not lagged state repression variable (see appendix). The distribution on lagged state repression is namely, 1997 campaign years with extreme state repression and 459 campaign years with mild to moderate levels of state repression the previous year.

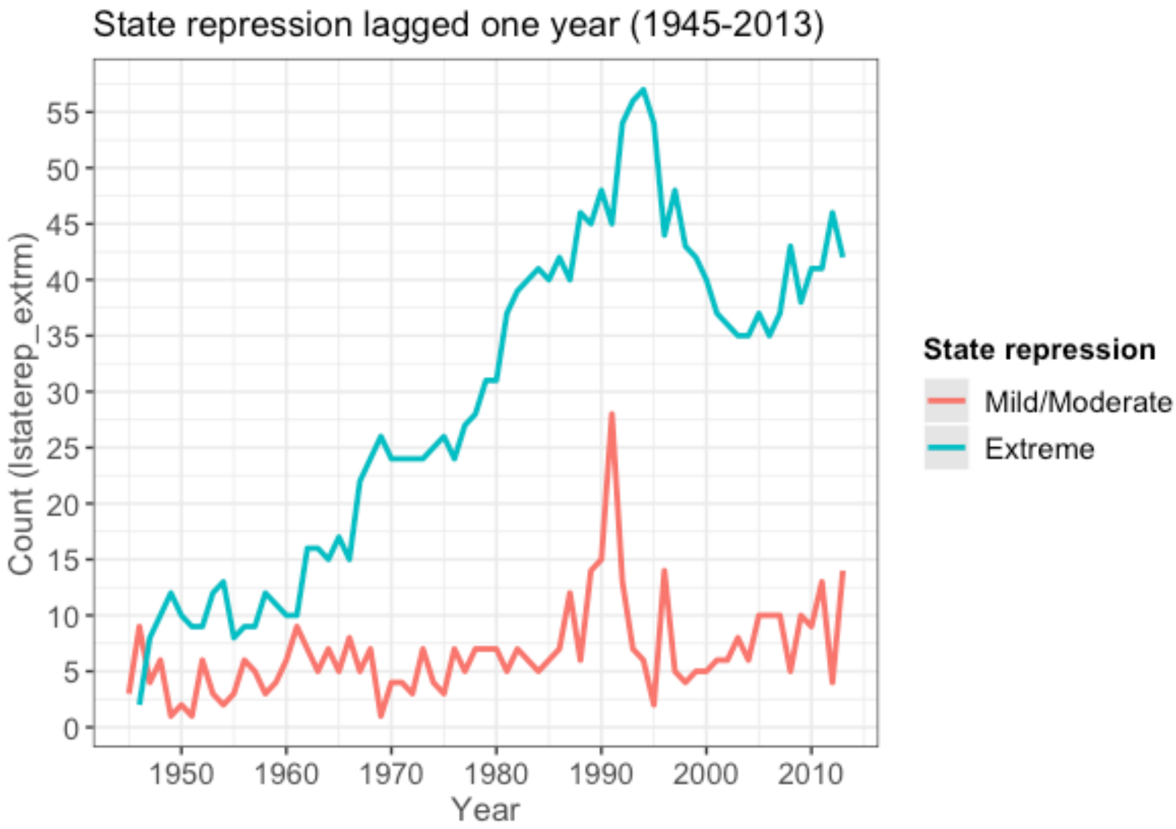


*Figure 2. Time trend of state repression (1945-2013).*

**Foreign support**

Figure 3 displays the count of instances foreign support was issued directly or indirectly in support of a resistance campaign in the period 1945-2013. The binary foreign support variable denotes whether a campaign receives *any* foreign support that year. By looking at the mean in Table 1, it is visible that the majority of campaign years have some type of foreign support. Namely, there are 1607 campaign years with at least one type of foreign support and 849 with no foreign support. The count dependent variable has good variation across the different values, except for the category with all five types of support with only eight observations (see the histogram in appendix). The majority of the resistance campaigns have either zero or one count of foreign support. Figure 3 displays the time trend of counts of foreign support issued directly or indirectly supporting a resistance campaign in 1945-2013. The time trend displays increased counts of foreign support over time, peaking in 1990 and 2010, similar to campaign strategy and state repression trends. This similarity is probably due to the increasing numbers of total resistance campaigns each year. Year dummies are included in the models to account for these time trends.

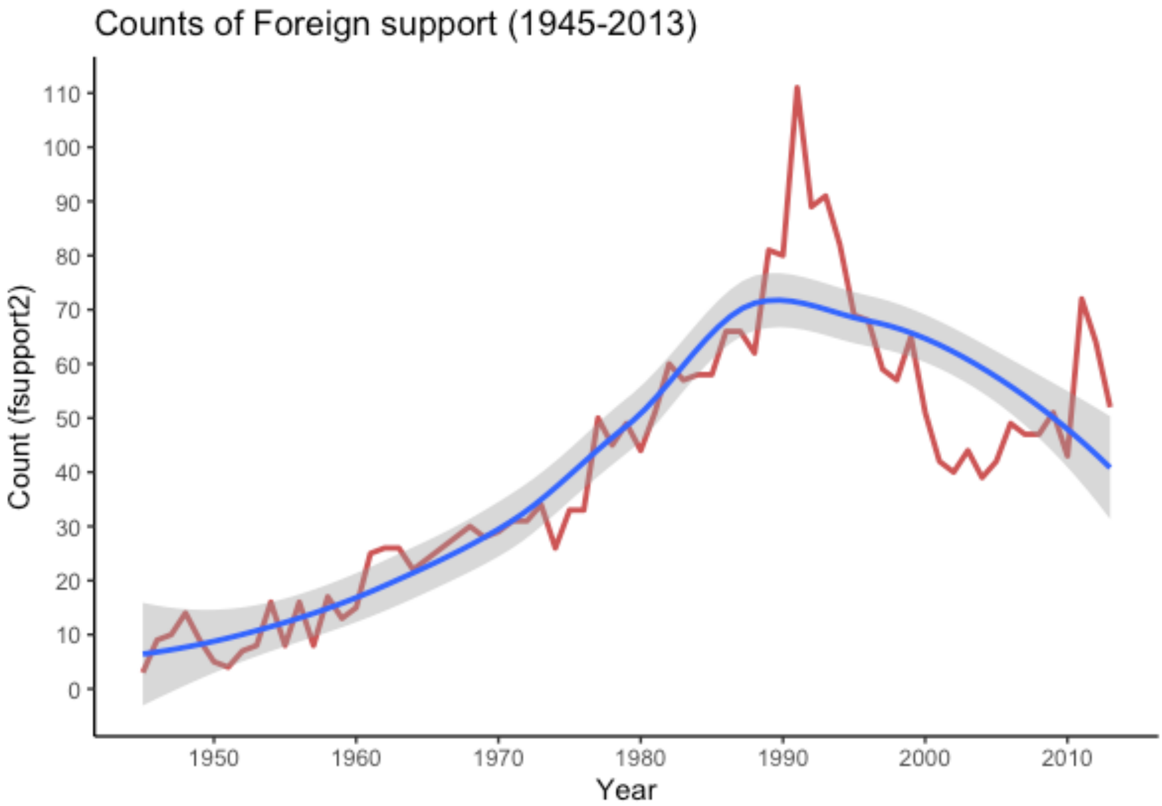


*Figure 3. Time trend of foreign support (1945-2013).*

## 3.7. Research design

In this section, the different model designs that are used in the analysis are presented. The designs and estimators used to analyze the different dependent variable specifications are discussed, namely logistic regression and Poisson regression for event count modelling.

The central part of the analysis focuses on the general probability of resistance campaigns receiving foreign support. For this part, the thesis applies several specifications of the logistic regression models with the binary dependent variable *fsupport*. The event count model with *fsupport2* is included to assess whether the results are dependent on the modelling strategy. Both of the models test the hypotheses presented in Chapter 2. The models have similar specifications, including year-dummies, lagged dependent variable, and standard errors clustered on ISO country-code.

Cultural, historical, and other factors in the country where the resistance campaign occurs are difficult to measure or even detect. Ideally, a model with country-fixed effects and cluster standard errors on country-id would be the preferred design. Including this could measure changes within countries across time that affect both the dependent and independent variables. Fixed effects models are a common way of solving omitted variable bias, but as a rule of thumb, it should be at least 20 observations per country (which I do not have). With insufficient data, this method can lead to underestimated residuals.

Since fixed effects modelling is not preferable with the data at hand, a middle solution is to only cluster standard errors on the *universal ISO* country-code (the country where the resistance campaign occurs). Clustering by country-id is a strategy to counteract autocorrelation, which is a common issue with a panel data structure. This strategy is applied throughout the empirical analysis. Moreover, the models include year dummies to control for time trends. In this way, the research design controls the country- and year-specific variation to get a clearer picture of how the independent variables affect the dependent variable.

I have chosen to estimate several logistic regression models for the binary dependent variable *fsupport*. I am building on a similar design from Chenoweth and Stephan (2011), who used logistic regression with robust standard errors clustered around the target country code. When the dependent variable is dichotomous, logistic regression is often preferred (Christoffersen, 2013). It is possible to use a Linear Probability Model (ordinary least squares estimator) for binary outcomes. However, the common problem is that such a model will often provide impossible values, such as probabilities below 0 or above 1. Therefore, the usual way of dealing with dependent variables of binary nature is logistic regression.

According to Ward and Alquist (2018), model comparison generally makes us prefer versions of logit and probit, where LPM models rarely provide a superior predictive model for binary data (Ward & Ahlquist, 2018: 50). The model fit is for the binary dependent variable is evaluated by comparing three alternative designs: Linear Probability Model (LPM), probit, and logistic regression models (see appendix). I evaluate the fit of the three models by comparing their predictive power using separation plots presented in Figure 4. Separation plots sort observations by the predicted probabilities and then compare this sorting to actual observed events (Ward & Ahlquist, 2018: 68). By using this method, I can visually compare the different models' ability to discriminate between cases. The red bars represent observed events, in this case, "Resistance campaign receives foreign support." The white bars are non-events. If the model perfectly discriminates between events and non-events, then the red bars (success) will cluster to the right side of the plot and the white bars (failures) to the left. The preferred model design after comparing the alternatives is the logistic regression model because it provides the best results in both the separation plots and the fit scores (Log-likelihood and AIC).

By looking at the separation plots, I immediately exclude the LPM model. The Linear Probability model does not show the probability of Y=1 as an S-shaped function of X. The probability of Y=1 should never go above 1 or below 0. Even though the LPM model has a better model fit, according to the Log-likelihood and AIC score, it struggles to describe the probability of Y=1 correctly. The probit and logistic regression models have very similar separation plots. Therefore, I choose to go forward with the logistic regression model only based on the marginally better Log-likelihood/AIC scores.

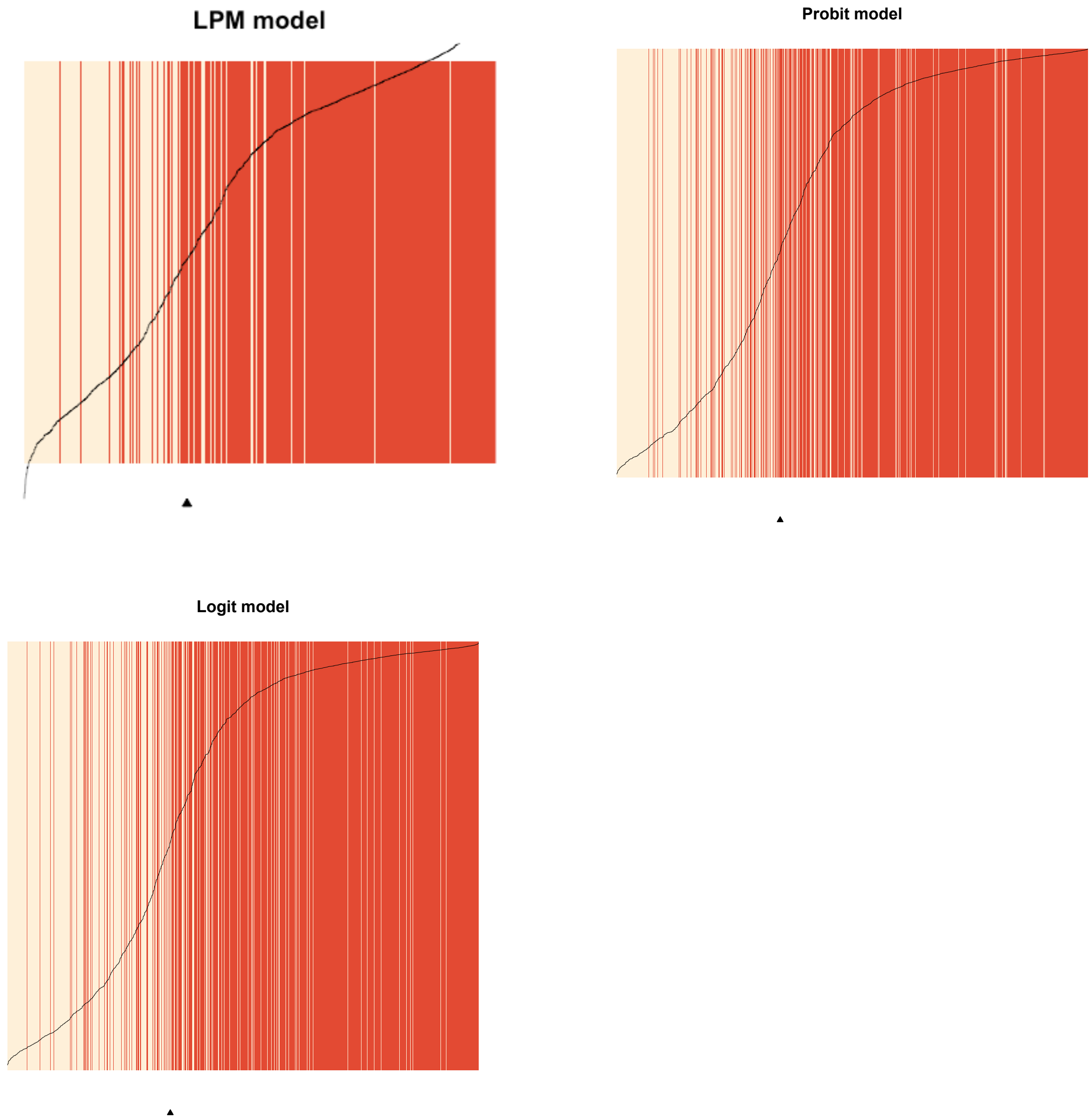


*Figure 4. Separation plots: LPM, probit and logit models.*

In models where the dependent variable is counts of events, like *fsupport2* "count of foreign support types," you can model it with event count models such as the Poisson regression (Ward & Ahlquist, 2018). Using ordinary least squares to model integer counts directly can lead to heteroskedasticity problems (Ward & Ahlquist, 2018). Alternatively, even worse, the model can produce predictions that are impossible to observe, such as negative counts. There are some benefits to test out different model designs on the same formula. First, it can provide more nuanced results than the logistic model. It can say something about the predicted probability for the number of foreign support types; given specific values on X. Second, and most important for this thesis, an additional model design acts as a robustness check on whether the modelling strategy drives the results.

The model fit is for the count dependent variable is evaluated by assessing overdispersion. One limitation of Poisson distribution is that it assumes that the variance is equal to the mean. A common problem is overdispersion. Overdispersion means that the variance is much greater than the mean. I use a rootogram of the Poisson regression to visually assess the degree of overdispersion, shown in Figure 5. The x-axis is "Number of Foreign Support Types," and the y-axis is the square root of the frequency. The hanging boxes represent the difference in expected and observed frequencies at different values of "Fsupport2". If the bar fails to meet 0, it means the model overpredicts counts, and if it crosses 0, it means that the model underpredicts counts (Ward & Ahlquist, 2018). Thereby, I can interpret that the Poisson model overpredicts counts of zero, two, and five types of foreign support. The model underpredicts counts of one and four types of foreign support.

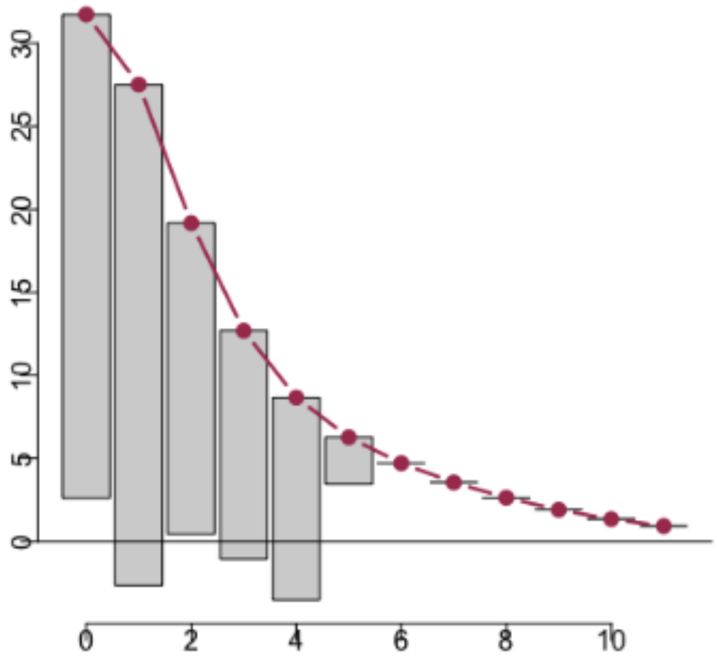


*Figure 5. Rootogram of Poisson regression model.*

Moreover, an additional test to assess the degree of overdispersion compares the residual deviance with the degrees of freedom in the Poisson model. The results show that the model is under dispersed; however, the under dispersion is not very sizable.[1] Therefore, this thesis argues that the Poisson regression is appropriate for the event count modelling.

[1] A score above 1 indicates overdispersion; below 1 indicates under-dispersion. The results for the Poisson regression are (1500/1888=) 0.794, indicating some under-dispersion.

# 4. Empirical analysis and discussion

This chapter presents the empirical analysis of the data. This thesis aims to test the hypotheses regarding associations between state repression, campaign strategy, and foreign support in favor of resistance campaigns.

The chapter begins with an inspection of the baseline models, which are several specifications of the logistic and Poisson models estimated without control variables and the interaction term. After that, the results section presents and discusses the results from the complete models with control variables and the interaction term. At the end of the chapter, the results of the empirical analysis are summarized. Finally, the validity of the results is discussed in light of robustness tests and previous research on backfire effects.

## 4.1. Baseline models

Table 4 shows the baseline models with only the covariates of state repression, campaign strategy and lagged foreign support. There are six baseline models for the logistic and Poisson regression models, including one baseline model for the main explanatory variables. Models 1-2 are logistic regression estimates on the associations between state repression and campaign strategy individually on the binary dependent variable foreign support (*fsupport),* and model 3 is the full baseline model for the logistic regression. Models 4-5 are Poisson regression estimates on the associations between state repression and campaign strategy individually with the count dependent variable foreign support (*fsupport2)*, and model 6 is the full baseline model for the Poisson regression.

*Interpretation of logistic regression coefficients.* A first step to interpret the logistic regression models is to determine the direction of the relationship between the dependent and independent variables. The coefficients are presented in logits for the logistic models, and positive coefficients indicate a positive covariation between the independent and dependent variables. For example, a negative state repression coefficient, such as in model 3, suggests that the chances that a given campaign year experiences foreign support (Yi =1) decrease with increasing levels of state repression, given that the other variables are held at constant.

*Table 5. Baseline models: State repression, campaign strategy, lagged foreign support.*

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Foreign Support (binary) | | | Foreign support (count) | | |
| | *logistic* | | | *Poisson* | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Extreme state repression (t-1) | $-1.85^{***}$ | | $-1.84^{***}$ | $-0.59^{***}$ | | $-0.58^{***}$ |
| | (0.14) | | (0.16) | (0.06) | | (0.06) |
| Campaign strategy | | $0.75^{***}$ | 0.01 | | $0.20^{***}$ | 0.02 |
| | | (0.14) | (0.16) | | (0.05) | (0.05) |
| Foreign support (t-1) | $4.16^{***}$ | $3.47^{***}$ | $4.16^{***}$ | | | |
| | (0.15) | (0.13) | (0.15) | | | |
| Foreign support 2 (t-1) | | | | $0.53^{***}$ | $0.47^{***}$ | $0.53^{***}$ |
| | | | | (0.01) | (0.01) | (0.01) |
| Constant | $0.18^{*}$ | $-1.01^{***}$ | 0.18 | $-0.10^{**}$ | $-0.53^{***}$ | $-0.11^{**}$ |
| | (0.10) | (0.08) | (0.12) | (0.05) | (0.03) | (0.05) |
| Observations | 2,456 | 2,456 | 2,456 | 2,456 | 2,456 | 2,456 |
| Log Likelihood | −933.75 | −1,010.25 | −933.75 | −2,869.33 | −2,911.65 | −2,869.27 |
| Akaike Inf. Crit. | 1,873.49 | 2,026.50 | 1,875.49 | 5,744.66 | 5,829.30 | 5,746.53 |
| *Note:* | | | | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

*Interpretation of Poisson regression coefficients.* The Poisson regression models the log of expected counts as a function of the independent variables. Therefore, the coefficients are interpreted as the change in expected counts of foreign support for one unit change in the independent variable, given that the other predictor variables are held constant. For example, the positive campaign strategy coefficient in model 5, suggests that observations with a primarily *nonviolent* campaign strategy (X = 1) is expected to have higher counts of foreign support than primarily violent campaign years, given that the other variables are held constant in the model.

The occurrence of foreign support in $\text{year}_{t-1}$ is held constant in all models because repression may have a different impact on campaigns already receiving foreign support and those that do not. Furthermore, it is conceivable that when foreign support is already issued to a resistance campaign, it is likely to continue the year after, especially if the campaign faces state repression. The lagged foreign support variables are statistically significant on a 1 % significance level, with a positive sign in all of the models. This finding indicates that resistance campaigns that received foreign support the previous year have a higher probability of receiving it the following year.

Regarding the state repression variable, the results across the models in Table 5 are mainly consistent. The Naïve specification, H1, speculated that higher levels of state repression increase the likelihood of resistance campaigns receiving foreign support. The initial results from the baseline models do not support this prediction. Conversely, resistance campaigns that met extreme repression the previous year are associated with a decrease in the probability of receiving foreign support. For the Poisson regression, this translates to a decrease in the expected counts of foreign support. The campaign strategy variable has a positive association with foreign support on its own. However, when controlling for state repression, the campaign strategy coefficient is no longer statistically significant.

Assessing the signs of the regression coefficients in baseline models is a good place to start as it sets a benchmark for the rest of the analysis. In the next section, I incorporate the control variables, add interaction terms in the models and present the final results.

## 4.2. Results

The following models include control variables that express structural attributes of the political environment in which the resistance campaigns occur. Kurtz and Smithey (2018) pointed out that further research on backfire effects should examine contextual factors such as regime- and international system features. The control variables are selected on this basis. In addition, two of the models include an interaction term between state repression and campaign strategy to test the international backfire hypothesis (H2). This hypothesis expects nonviolent resistance campaigns to be more likely than their violent counterparts to receive foreign support when faced with violent state repression.

Table 6 presents three logistic regression models with different specifications and the Poisson regression with and without the interaction term. Model 1 is identical to model 4 in Table 5 (baseline models) and is included as a benchmark for discussion. All the models include standard errors are clustered on ISO country code. In this sample, there are 350 unique resistance campaigns in 127 different countries. Models 2-5 include year-dummies (1946-2013) that are excluded from the table.

*Table 6. Nested logistic regression models and Poisson regression: state repression, campaign strategy and foreign support.*

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | Foreign Support (binary) | | | Foreign support (count) | |
| | *logistic* | | | *Poisson* | |
| | (1) | (2) | (3) | (4) | (5) |
| Extreme state repression (t-1) | −1.84*** | −1.67*** | −1.82*** | −0.53*** | −0.54*** |
| | (0.19) | (0.21) | (0.23) | (0.08) | (0.09) |
| Campaign strategy | 0.01 | −0.13 | −0.37 | 0.03 | 0.02 |
| | (0.20) | (0.21) | (0.28) | (0.06) | (0.12) |
| Foreign support (t-1) | 4.16*** | 4.17*** | 4.18*** | | |
| | (0.17) | (0.23) | (0.23) | | |
| Foreign support 2 (t-1) | | | | 0.46*** | 0.46*** |
| | | | | (0.04) | (0.04) |
| Electoral democracy index | | −0.85 | −0.78 | −0.44 | −0.44 |
| | | (0.90) | (0.91) | (0.34) | (0.34) |
| International media coverage | | 0.71*** | 0.71*** | 0.23*** | 0.23*** |
| | | (0.12) | (0.12) | (0.04) | (0.04) |
| Press freedom | | −0.80 | −0.84 | −0.07 | −0.07 |
| | | (0.65) | (0.65) | (0.16) | (0.16) |
| GDP (log) | | −0.15 | −0.16 | −0.07** | −0.07** |
| | | (0.13) | (0.13) | (0.03) | (0.03) |
| Population (log) | | 0.08 | 0.09 | 0.05 | 0.05 |
| | | (0.15) | (0.15) | (0.04) | (0.04) |
| Extreme repression X Campaign strategy | | | 0.59* | | 0.01 |
| | | | (0.33) | | (0.13) |
| Constant | 0.18 | 2.68 | 2.75 | 0.50 | 0.50 |
| | (0.20) | (1.73) | (1.73) | (0.50) | (0.50) |
| Observations | 2,456 | 2,456 | 2,456 | 2,456 | 2,456 |
| Log Likelihood | −933.75 | −828.53 | −827.13 | −2,785.05 | −2,785.04 |
| Akaike Inf. Crit. | 1,875.49 | 1,811.05 | 1,810.27 | 5,724.09 | 5,726.08 |
| *Note:* | | | | | *p<0.1; **p<0.05; ***p<0.01 |

In model 2, the explanatory variables of interest are included controlling for the structural variables: electoral democracy index, international media coverage, press freedom, GDP and population size. These are additional factors that are expected to have an impact on both dependent and independent variables. After including them in the model, the fit-values increase, e.g., the Log-likelihood increase from -903 in model 1 to -828 in model 2. This change to a fit score closer to 0 means that the second model is a better fit to describe the data.

The incorporation of control variables seems to have a moderating effect on the state repression coefficient, which changes from -1.84 to -1.67 on a 1 % significance level. This finding indicates that the chances that a given campaign year receives foreign support (Yi = 1) decrease with increasing levels of state repression when the other variables are held at constant. The same finding is apparent in the Poisson regression model 4 with similar model specifications, where the state repression coefficient is statistically significant at -0.53. The association between state repression and foreign support seems to be consistently negative, which is the opposite direction than predicted. Therefore, the Naïve specification does not hold.

What can explain that higher levels of state repression *decrease* the likelihood of resistance campaigns receiving international? A possible explanation can be that regimes only apply extreme coercion against activists in cases where it does not expect international backfiring. Moreover, suppose the levels of state repression have been consistently high over an extended period of time. In that case, extreme repression may not have the same triggering effect for backfiring as if it happened in an otherwise relatively calm political environment. On the other hand, international actors may be hesitant to intervene in cases with extreme violence because they interpret it as a signal that the regime would doubtfully back down in any case.

Another consistent finding across the models is that international media coverage has a positive coefficient significant on the 1 % significance level. In model 2, the coefficient is 0.71 when the control variables are added. The corresponding Poisson model 4 has a positive and statistically significant coefficient at 0.23. Substantially this means that higher levels of international media coverage increase the likelihood of campaigns receiving foreign support. For the Poisson regression, this translates to an increase in expected counts of foreign support. In the backfiring literature, it is argued that for backfiring to occur, information about the event is communicated effectively to audiences substantial enough to force authorities to consider their outrage (Hess & Martin, 2006). Therefore, the positive sign on this coefficient is not particularly surprising.

Similarly, the lagged dependent variable has significant and positive coefficients across all of the model designs. In the logistic regression estimates, the coefficients are consistently around 4.08, and in the Poisson estimates, it is 0.46. Substantially, this means that resistance campaigns that have already received foreign support the year prior are more likely to receive it the following year as well. Conversely, if the campaign did not receive support the prior year, it is less likely to receive foreign support the following year.

The international backfire hypothesis (H2) expects international responses in the aftermath of violent state repression to be conditioned by campaign strategy. More specifically, the expectation is that nonviolent resistance campaigns are more likely to receive foreign support when faced with extreme state repression than their violent counterparts. In order to test this proposition, I add an interaction term to the logistic and Poisson regression models 3 and 5, thereby assessing the conditional relationship between state repression, campaign strategy and foreign support.

In model 3, the estimation of the complete logistic model is presented. The coefficient for state repression decreases from -1.67 to -1.82 when the interaction term is added, and the coefficient of campaign strategy is consistently insignificant in all the models. Substantially, the interaction term is a separate coefficient that describes nonviolent campaigns (campaign strategy = 1) that faced extreme state repression the previous year (state repression = 1). The interaction term is positive (0.59) and statistically significant on a 10 % significance level, implying that it should be included in the model. This finding provides support for H2 and is visualized in Figure 6. Though I must address that this effect is marginal compared to, for example, the positive and significant lagged foreign support coefficient at 4.18.

Moreover, by inspecting the change in fit score between model 2 and 3, the inclusion of the interaction term gives the model only a slight increase in the fit to data. Figure 6 display the predicted probabilities of receiving foreign support for different values of state repression and differentiates between primarily violent and nonviolent campaign years. Figure 6 display the high uncertainties in the findings from the international backfiring hypothesis H2. This visualization can be a bit misleading as it shows generally very high probabilities of receiving foreign support across the different values of extreme state repression. Figure 7 displays the same association as Figure 6, only that it separates between the campaigns that received foreign support the year prior and those that did not. In Figure 7, it is visible that when a resistance campaign received foreign support the previous year (*lfsupport* = 0), the level of state repression has almost no impact on the probability of continued support. Regarding the main explanatory variables, the results from the previous logistic models also hold in model 3.

In model 5, the complete Poisson regression estimates are presented. The coefficients in this model are not considerably affected by including the interaction term. This finding indicates that the combination of a nonviolent campaign strategy and high levels of repression does not have a statistical association with the expected counts of foreign support. Therefore, the international backfire hypothesis (H2) does not hold in the Poisson regression. The empirical analysis has only focused on a mechanism thought to increase the possibility of nonviolent campaigns receiving foreign support, while violent campaigns might be affected by different mechanisms. The results would probably look quite different if these mechanisms were to be added in the models as well.

The empirical analysis studied the binary dependent variable (*fsupport*) and the count dependent variable (*fsupport2*). The event count model was included to assess whether the results were dependent on the modelling strategy. The results from the Poisson regression are pretty similar for the main explanatory variables concerning associations, direction, and significance level. The conclusions drawn about the Naïve specification (H1) are robust across all model designs. Specifically, that H1 does not hold because state repression has a negative association with foreign support on a 5 % significance level. Conversely, the international backfire hypothesis (H2) results are inconsistent between the logistic and Poisson regression models. The logistic regression model has a significant and positive coefficient for the interaction between state repression and campaign strategy, while the Poisson regression does not find a significant association. Moreover, this thesis sets a 5 % significance level. Therefore, I cannot conclude with certainty that nonviolent resistance campaigns are more likely to receive foreign support when faced with extreme repression than their violent counterparts.

The following section discusses the validity of the results more in-depth with robustness tests and prior research on backfiring.

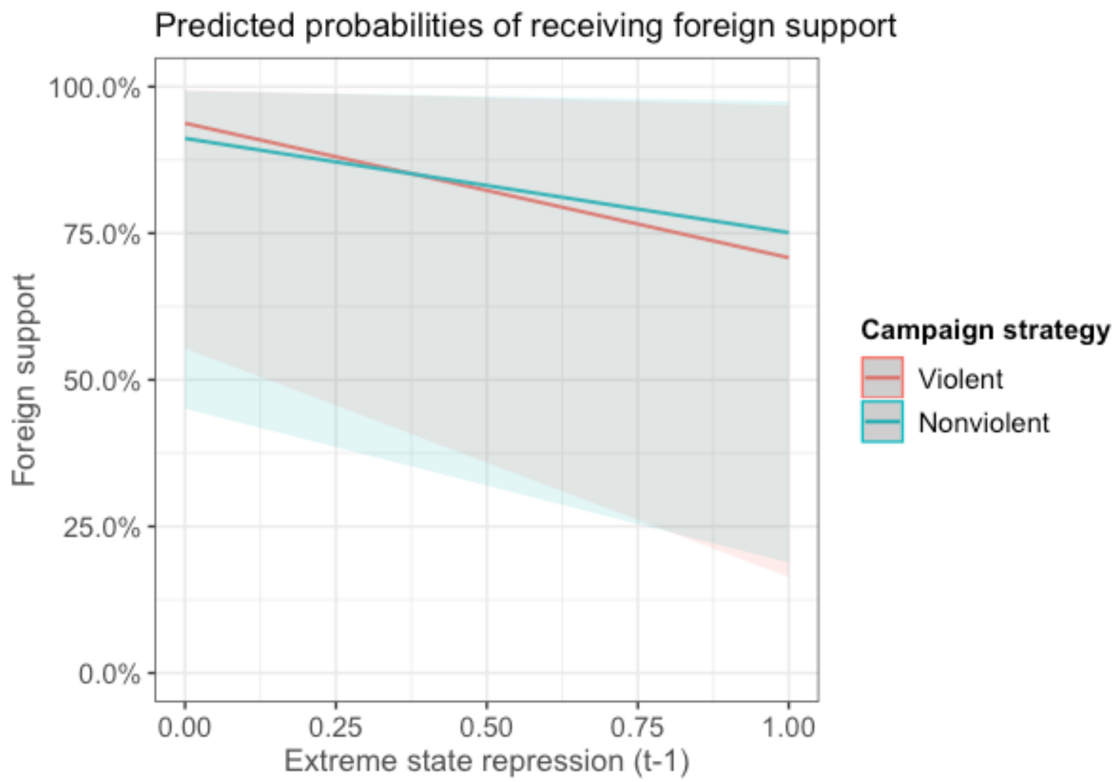


*Figure 6. Predicted probabilities plot. Model 3 in Table 5.*

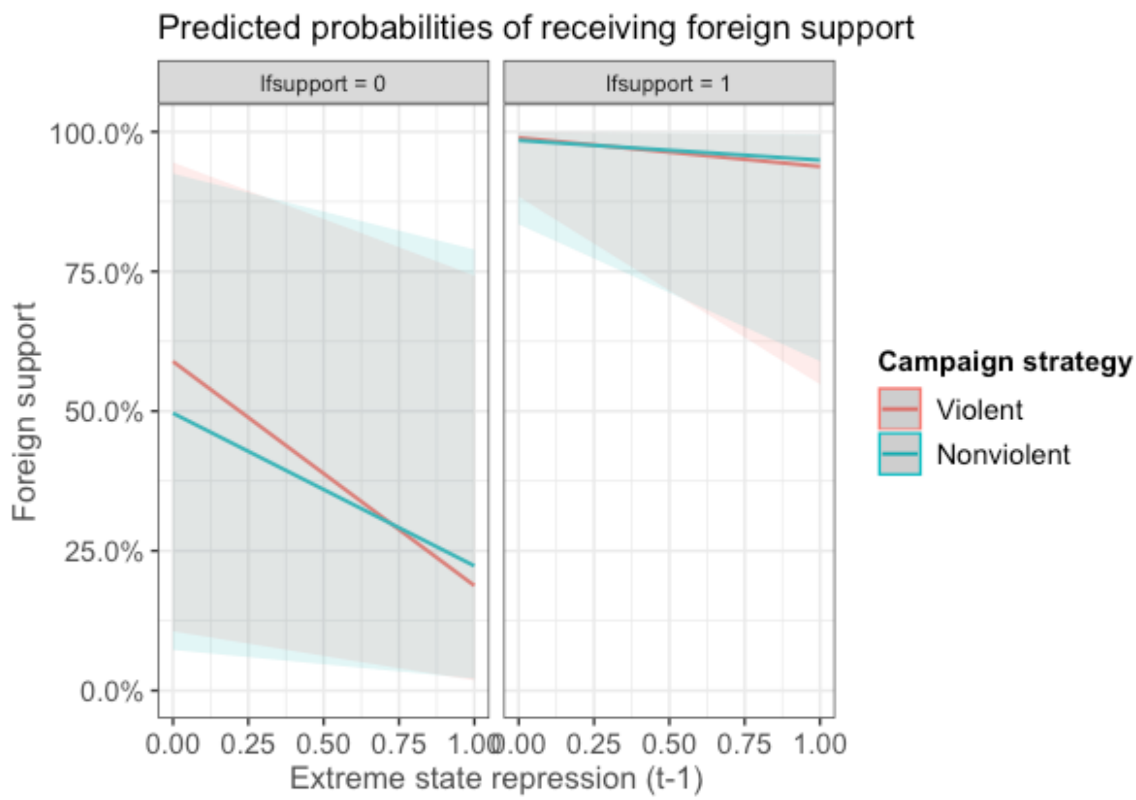


*Figure 7. Predicted probabilities plot, separating between campaigns that received foreign support the year prior.*

## 4.3. Validity of the results

The validity of the results in the empirical analysis depends partly on the strength of the associations and if the associations are statistically significant at standard levels of uncertainty (Lund, 2002). The uncertainty level describes the risk of making a Type-I error, in other words, to conclude that there is an association when it, in reality, is not (Stevens, 2012). This thesis adopts a level of statistical significance at the .05 level, meaning that I take a 5% chance of making type I errors. Significant coefficients indicate that the variable has an association with foreign support; however, one must still decide if the difference in the predicted probability of receiving foreign support is large enough to be of practical significance (Stevens, 2012). First, I discuss several robustness checks. Second, I compare the results of the empirical analysis with previous studies of backfire effects. Lastly, the validity of the results is summarized in relation to the hypotheses and research question.

**Robustness tests**

This section reviews several robustness checks on whether the operationalization of the independent and dependent variables drove the results in the empirical analysis. To do this, I estimated the models with various specifications of foreign support and state repression (see appendix).

First, I changed the dependent variable in the models with each of the indicators in the foreign support variable (see Table 1). The explanatory variables maintain quite similar results as in the empirical analysis. The international media coverage and lagged foreign support variables have positive and significant coefficients. The state repression coefficient is negatively associated with all of the foreign support indicators, ranging from -1.09 to -2.66 significant on a 5% level. The only exception was for the indicator "Former state supporters withdraw support," which is not significantly associated with the level of state repression. An interesting finding from this test is that the interaction term is only significant for the indicator "campaign has formal overt support from other states" (1.99***). This is the indicator I considered using as the dependent variable in the main analysis to avoid an *a priori* relationship with the independent variable, since the indicator is not coded in response to state repression. However, the concern I brought up in the method section seems accurate; with fewer data to work within the dependent variable, the estimations are more likely to be biased. The uncertainty is apparent when comparing the results. In the robustness test, most of the year dummy coefficients are significant and probably drive the results. In contrast, almost none of the year dummies in the models with the binary (*fsupport*) and count dependent variable (*fsupport2)* were significant in the main analysis. This test confirms the main results from the empirical analysis.

As discussed in the operationalization of state repression, it is more common with extreme repression than other forms of repression in the NAVCO 2.1. dataset. As a result, these observations are prone to drive the results. To check whether the operationalization of state repression is driving the results, I run the same models with different specifications of the NAVCO-repression variable (Table 2) and Varieties of democracy's CSO repression variable (Table 3). The main findings – covariation with extreme state repression, international media coverage, and lagged foreign support – are consistent across all the models. All operationalizations of state repression have negative and significant coefficients on a 5% significance level, except the lagged CSO Repression Index (*lCSOrep_index)* and the level of fatalities (*lfatalitites)* in connection to protest activity. This result is consistent with the empirical analysis. However, the interaction term between state repression and campaign strategy is only significant with the "Extreme state repression" operationalization. Therefore, the international backfire hypothesis (H2) results seem to be driven by the operationalization of state repression, implying that the finding is not robust.

The results of the empirical analysis only express the association between state repression in $year_{t-1}$ and foreign support in $year_t$ because the state repression variable is lagged one year. Followingly, one cannot draw conclusions about the long-term influence of repression based on this analysis. Ideally, there should be an additional variable in the analysis to account for time trends in the general level of state repression where the resistance campaigns occur. The current operationalization of state repression only captures repression directed at the specific resistance campaign in $year_t$. I would expect the results to be significantly impacted if the empirical analysis considered the general level of repression in the regime. It is reasonable to expect more international attention in cases where highly repressive measures were inflicted on protesters in a regime with otherwise low levels of repression, than in regimes with consistently high levels of repression.

**Structural versus movement-level control variables**

As previously discussed, Kurtz & Smithey (2018) have conducted an initial analysis of backfire effects mainly on movement-level factors such as participation, internal organization, campaign success, media coverage, and nonviolent discipline. They pointed out that future studies should examine how *contextual* factors such as demographic characteristics, regime features, and international system features affect their findings. One of their main findings was that large, hierarchical campaigns that obtain international media coverage are most likely to provoke sanctions or make foreign allies withdraw support for the regime (Kurtz & Smithey, 2018). Their main explanatory variables - hierarchical campaign structure, violent flank, and campaign size - are incorporated into my logistic regression models, and the results are presented in Table 7. Note that this is not meant as a replication. It is merely presented as a tool to discuss the different approaches to study backfiring.

In Table 7, the two first models are the baseline and full logistic regression models from the empirical analysis[2]. Model 3 includes the explanatory variables, the interaction term and the movement-level control variables: hierarchical campaign structure, campaign size and violent flank. Furthermore, model 4 includes the explanatory variables, the interaction term, and both movement-level and structural control variables. Due to missing data, the sample size decreases from 2456 to 2202 observations when including the protest-level variables. Therefore, it does not make sense to compare the fit scores. All models have standard errors clustered on ISO country code. In the sample for model 1 and 2, there are 350 unique resistance campaigns in 127 different countries. In the sample for model 3 and 4, there are 337 unique resistance campaigns in 125 different countries. Models 2-4 include year-dummies (1946-2013) that are excluded from the table.

The state repression coefficient remains consistently significant and negatively associated with foreign support across the models. This finding goes against the findings from the previous study, which found a positive association between higher levels of state repression, international condemnation, and sanctions (Kurtz & Smithey, 2018). Two critical differences between the previous study and my design are that I include a lagged foreign support variable, and I analyse 2202 observations compared to their 280 observations. By inspecting the models, the association between state repression, lagged foreign support, international media coverage,

[2] Respectively, Models 1 and 3 in Table 6.

and foreign support is robust when controlling for movement-level features. The interaction term in model 3 is positive and statistically significant at .077; however, not on a 5 % significance level.

*Table 7. Comparison of results with movement-level factors versus contextual factors.*

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Foreign Support | | | |
| | (1) | (2) | (3) | (4) |
| Extreme repression | −1.84*** | −1.82*** | −2.02*** | −1.78*** |
| | (0.19) | (0.23) | (0.27) | (0.24) |
| Campaign strategy | 0.01 | −0.37 | −1.22* | −0.78 |
| | (0.20) | (0.28) | (0.66) | (0.66) |
| Foreign support (t-1) | 4.16*** | 4.18*** | 4.33*** | 4.16*** |
| | (0.17) | (0.23) | (0.21) | (0.23) |
| Electoral democracy index | | −0.77 | | −0.91 |
| | | (0.91) | | (0.96) |
| International media coverage | | 0.71*** | | 0.67*** |
| | | (0.12) | | (0.12) |
| Press freedom | | −0.84 | | −0.87 |
| | | (0.64) | | (0.66) |
| GDP (log) | | −0.16 | | −0.14 |
| | | (0.13) | | (0.13) |
| Population (log) | | 0.09 | | 0.08 |
| | | (0.14) | | (0.16) |
| Hierarchical campaign structure | | | −0.03 | 0.15 |
| | | | (0.23) | (0.25) |
| Violent flank | | | 0.34 | 0.23 |
| | | | (0.35) | (0.36) |
| Campaign size | | | 0.31*** | 0.08 |
| | | | (0.09) | (0.09) |
| Extreme repression X Campaign strategy | | 0.59* | 0.77* | 0.63 |
| | | (0.33) | (0.40) | (0.40) |
| Constant | 0.18 | 3.08 | −0.91 | 1.30 |
| | (0.20) | (1.89) | (1.46) | (2.03) |
| Observations | 2,456 | 2,456 | 2,202 | 2,202 |
| Log Likelihood | −933.75 | −826.98 | −781.17 | −731.77 |
| Akaike Inf. Crit. | 1,875.49 | 1,809.95 | 1,714.34 | 1,625.54 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

**Assessing the evidence: When faced with state repression, are nonviolent resistance campaigns more likely to receive foreign support than their violent counterparts?**

Following the discussion of several robustness checks, is apparent that the scope of conclusions that can be drawn from the analysis is narrow. Moreover, the data structure only makes it possible to identify correlation, not causation.

The first hypothesis expected higher levels of state repression to increase the likelihood of resistance campaigns receiving foreign support. The results of the empirical analysis and several robustness checks find this association to be in the opposite direction. Resistance campaigns that experienced extreme levels of repression the previous year are associated with a decreased probability of receiving foreign support. A possible explanation is that violent groups use nonviolence strategically. As discussed, Michael Gross (2018) use the term 'backfire' to describe protesters engaging in strategic nonviolent tactics to *provoke* brutal responses from the regime in hopes of gaining domestic support, shift the international opinion to their side and encourage security force defections. His critique is directed explicitly at groups who use nonviolent tactics as a supplement for violence when it can "get the job done", which in turn undermines the moral stature and efficacy of nonviolence (Gross, 2018). The data that has been analyzed is primarily of violent campaign years; therefore, some of the nonviolent campaign years can represent violent groups that use nonviolence to achieve their goals. The international community may not sympathize or provide aid because it is perceived as a play to the gallery. Another explanation can be that in regimes where repression is a common remedy used to silence opposition, the regime might escalate the levels of repression knowing that it would not generate excessive international attention. In this way of seeing it, regimes may only apply extreme coercion against opposition campaigns in cases when it does not expect international backfiring.

Conversely, it can be that international actors are hesitant to intervene in cases with extreme violence because they interpret this as a signal that the regime would be hesitant to back down in any case. The dynamics between the regime, protesters and the international audience is more complex than the backfiring mechanism presented in this thesis. Alternative approaches are warranted, such as Pierskalla's (2010) suggestion that we should interpret government repression as a strategic interaction between multiple players rather than a simple action-reaction phenomenon.

The second hypothesis expected nonviolent resistance campaigns to be more likely to receive foreign support when met with violent repression than their violent counterparts. This thesis has applied the term *international backfire* for the process when state repression of resistance campaigns recoils against the regime, resulting in increased direct or indirect foreign state support in favor of resistance campaigns. The results of the empirical analysis find a weak correlation between the probability of receiving foreign support and the combination of a nonviolent campaign strategy and high levels of repression. However, the results seem to be driven by the operationalization of state repression. This is because the robustness checks showed that the alternative operationalizations lead to insignificant results. In sum, there is no substantial empirical evidence to suggest that nonviolent campaigns are more likely to receive foreign support when faced with repression than their violent counterparts.

# 5. Conclusion

This thesis has aimed to answer the research question: *When faced with state repression, are nonviolent resistance campaigns more likely to receive foreign support than their violent counterparts?*

Building on theories of backfiring and 'political jiu-jitsu' in the civil resistance literature, the theoretical expectation of this thesis was that nonviolent resistance campaigns would have a strategic advantage in obtaining foreign support when faced with state-inflicted violence. Prior studies have found state repression to be less effective against highly organized nonviolent campaigns because civilians can exploit repressive incidents to improve the odds of provoking domestic and international backfiring (Chenoweth et al., 2017; Dudouet, 2013). In contrast to the few empirical studies of backfiring that mainly focused on movement-level features such as participation and organizational structure (Kurtz & Smithey, 2018; Stephan & Chenoweth, 2011), this thesis set out to control structural factors as well such as regime type, press freedom, and GDP. The results of the empirical analysis find a weak correlation between the probability of receiving foreign support and the combination of a nonviolent campaign strategy and high levels of repression. Though, after robustness checks, these results seem to be driven by the operationalization of state repression. In sum, there is no substantial evidence to suggest that nonviolent campaigns are more likely to receive foreign support when faced with repression than their violent counterparts.

An unexpected finding in the empirical analysis was from the Naïve Specification, which expected higher levels of state repression to increase the likelihood of resistance campaigns receiving foreign support. The results of the empirical analysis and several robustness checks find this association to be consistently in the opposite direction. Higher levels of state repression the previous year decrease the probability of resistance campaigns receiving foreign support. I have not seen other findings in line with this before, which would be interesting to see future studies of. A possible reason for the negative association between state repression and foreign support is that violent groups use nonviolence strategically. As mentioned, Michael Gross (2018) use the term 'backfire' to describe protesters engaging in strategic nonviolent tactics to provoke brutal responses from the regime in hopes of gaining domestic support, shift the international opinion to their side and encourage security force defections. The use of nonviolent tactics as a supplement for violence when it can "get the job done" undermines nonviolence's moral stature and efficacy. If this is the case, the international community probably would not sympathize or provide aid as the nonviolent methods are perceived as a play to the gallery.

The dynamics between the regime, protesters and the international audience are more complex than the backfiring mechanism presented in this thesis, and alternative approaches are warranted. An interesting takeaway from this project was that violent state repression seemingly decreases the probability of foreign support, which is a finding that calls for further testing. Further research should dig deeper into the association between state repression and international support to resistance campaigns and assure that the measure of foreign support is gathered independently from the measure of state repression. If this is done, there is no issue with an *a priori* relation between the dependent and independent variables, meaning that one can conclude more explicitly on how state repression affects foreign support. Moreover, a more nuanced repression variable, along with controls for the general time trend of repression where the protest movements occur, could provide interesting results. Another interesting take on this topic would be to look at even more temporally disaggregated data and analyze the changes on a week-to-week basis rather than in years, because the strategies of protest movements can change rapidly as well as the size and influence they have domestically and internationally.

This research project contributes to the civil resistance field by examining features that can increase the chances of international support of nonviolent resistance. The possibility that violent crackdowns against opposition movements actually can *decrease* the chances of foreign aid warrants further investigations as this can have important political consequences. In line with the rising use of nonviolent methods in the fight against oppression and injustices, future studies should continue to explore the dynamics between civil resistance and foreign support.

# 6. Literature

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# Appendix

## 1. Method: Descriptive statistics and model evaluation

Figure 8 displays the counts of different levels of state repression in the period 1945-2013. This not lagged state repression variable was discussed in the descriptive statistics section, in contrast to the version used in the analysis which was lagged one year. The time trends look different because the lagged version recoded the missing cells to have the value 0, which means that those observations were put in the "mild/moderate" category of state repression.

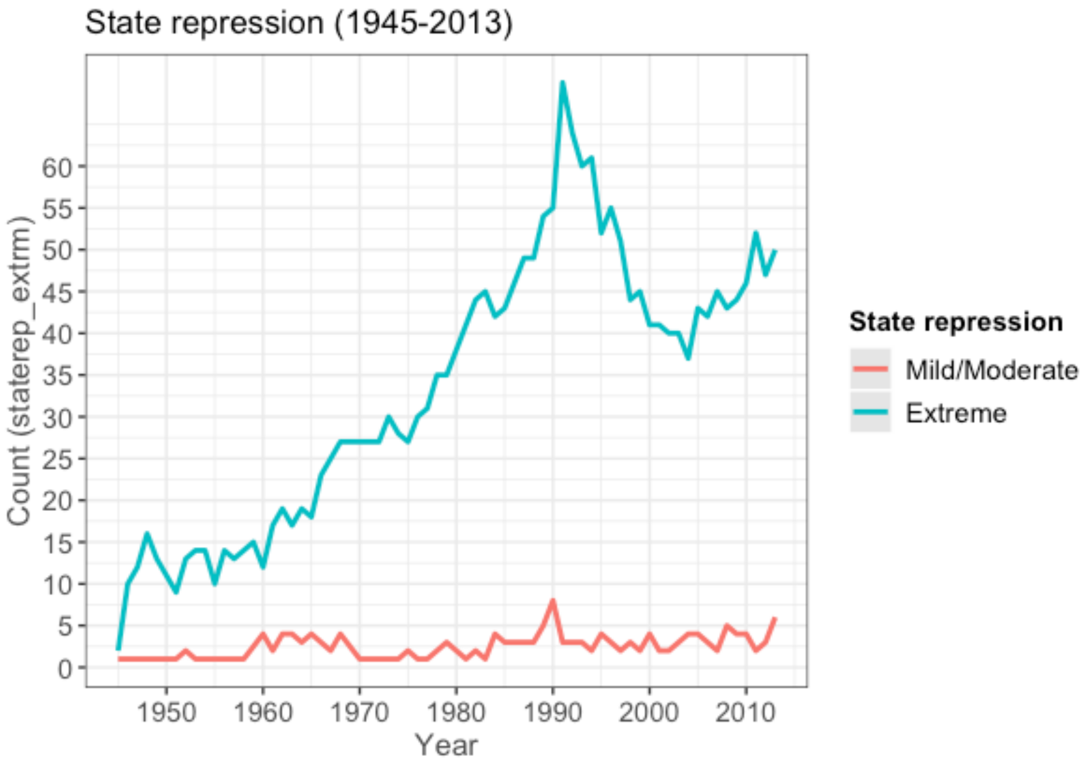


*Figure 8. Time trend original state repression variable (1945-2013).*

Counts of state repression in the period 1945-2013, separating between campaigns that receive mild/moderate and extreme state repression. In the analysis, this variable is used lagged one year.

Figure 9 displays a histogram of the count dependent variable foreign support 2. There is good variation across the different counts of foreign support in the dataset, except for five counts of foreign support, which only occurs in 8 of the observations.

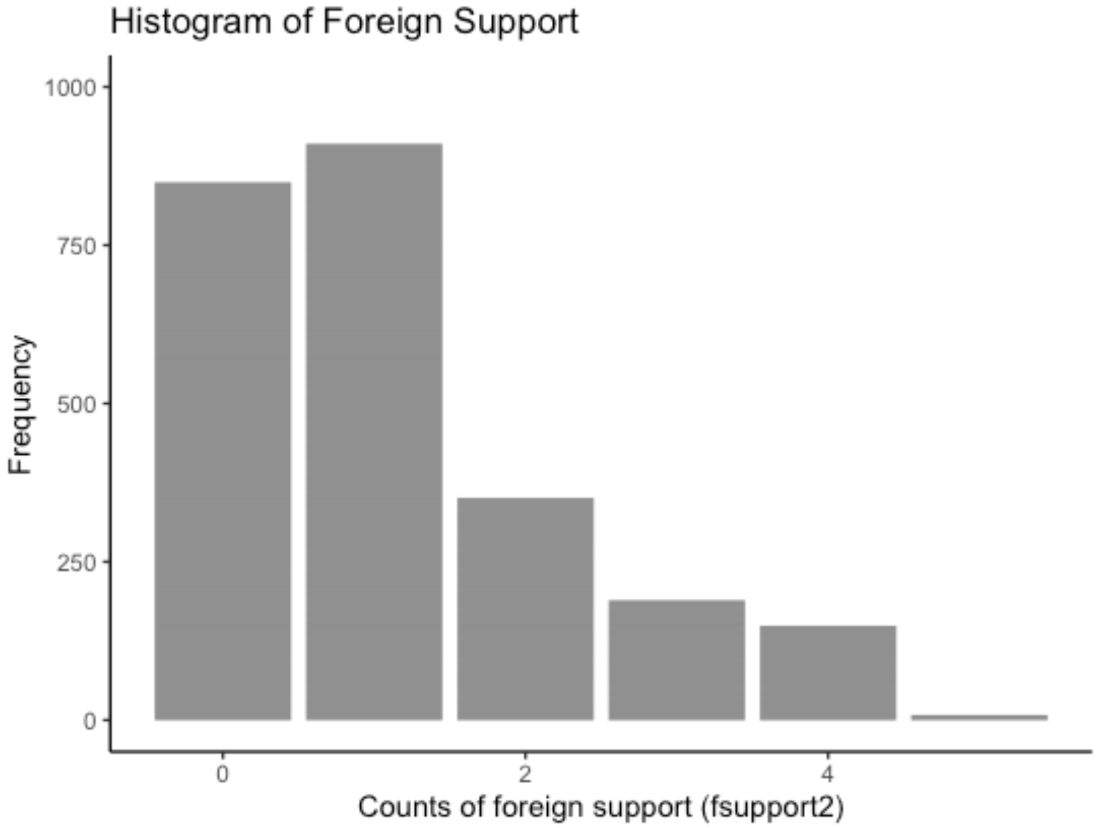


*Figure 9. Histogram showing the distribution on the count variable fsupport2*

Table 8 displays the Linear probability Model (LPM), probit and logit models, that were compared to evaluate which model strategy best describes the data. Additional tests were made to compare their predictive power and fit scores.

*Table 8. Binary dependent variable: Model evaluation. State repression, campaign strategy, interaction and foreign support.*

| | *Dependent variable:* | | |
|---|---|---|---|
| | Receive Foreign Support | | |
| | *normal* | *probit* | *logistic* |
| | (1) | (2) | (3) |
| Extreme state repression (t-1) | $-0.33^{***}$ | $-1.07^{***}$ | $-1.82^{***}$ |
| | (0.04) | (0.14) | (0.23) |
| Campaign strategy | $-0.08$ | $-0.25$ | $-0.38$ |
| | (0.05) | (0.16) | (0.28) |
| Electoral democracy index | $-0.12$ | $-0.44$ | $-0.81$ |
| | (0.11) | (0.50) | (0.90) |
| International media coverage | $0.08^{***}$ | $0.39^{***}$ | $0.70^{***}$ |
| | (0.01) | (0.06) | (0.12) |
| Press freedom | $-0.08$ | $-0.45$ | $-0.82$ |
| | (0.07) | (0.35) | (0.64) |
| GDP (log) | $-0.02$ | $-0.08$ | $-0.15$ |
| | (0.01) | (0.07) | (0.13) |
| Population (log) | 0.01 | 0.04 | 0.07 |
| | (0.01) | (0.08) | (0.14) |
| Foreign support (t-1) | $0.68^{***}$ | $2.37^{***}$ | $4.18^{***}$ |
| | (0.03) | (0.13) | (0.23) |
| Interaction (lstaterep_extrm:camp_strategy) | $0.09^{*}$ | $0.33^{*}$ | $0.59^{*}$ |
| | (0.05) | (0.20) | (0.33) |
| Constant | $0.89^{***}$ | 1.53 | 2.81 |
| | (0.27) | (1.01) | (1.76) |
| Observations | 2,456 | 2,456 | 2,456 |
| Log Likelihood | $-736.46$ | $-830.47$ | $-827.26$ |
| Akaike Inf. Crit. | 1,628.91 | 1,816.95 | 1,810.51 |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

## 2. Robustness tests

In the following section, the same models as in the analysis are presented, with all the operationalizations of state repression. Table 3 are the logistic regression models, and Table 4 are the Poisson regression models for testing the Naïve specification (H1).

*Table 9. Robustness check, logistic regression on all operationalizations of state repression (H1).*

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Foreign Support | | | |
| | (1) | (2) | (3) | (4) |
| Extreme state repression (t-1) | −1.67*** | | | |
| | (0.21) | | | |
| State repression ordinal (t-1) | | −0.67*** | | |
| | | (0.06) | | |
| CSO repression index (t-1) | | | 0.21* | |
| | | | (0.12) | |
| CSO repression ordinal (t-1) | | | | −0.51*** |
| | | | | (0.06) |
| Campaign strategy | −0.13 | −0.16 | 0.51*** | 0.16 |
| | (0.21) | (0.19) | (0.20) | (0.19) |
| Electoral democracy index | −0.85 | −0.57 | −1.09 | 0.08 |
| | (0.90) | (0.85) | (1.04) | (0.95) |
| International media coverage | 0.71*** | 0.70*** | 0.79*** | 0.70*** |
| | (0.12) | (0.12) | (0.12) | (0.11) |
| Press freedom | −0.80 | −0.87 | −1.22* | −0.07 |
| | (0.65) | (0.62) | (0.67) | (0.76) |
| GDP (log) | −0.15 | −0.11 | −0.15 | −0.09 |
| | (0.13) | (0.12) | (0.14) | (0.14) |
| Population (log) | 0.08 | 0.04 | 0.01 | −0.01 |
| | (0.15) | (0.13) | (0.16) | (0.16) |
| Foreign support (t-1) | 4.17*** | 4.26*** | 3.65*** | 3.91*** |
| | (0.23) | (0.22) | (0.23) | (0.23) |
| Constant | 2.68 | 2.38 | 3.85** | 2.43 |
| | (1.73) | (1.67) | (1.89) | (1.72) |
| Observations | 2,456 | 2,456 | 2,456 | 2,456 |
| Log Likelihood | −828.53 | −814.34 | −873.31 | −845.19 |
| Akaike Inf. Crit. | 1,811.05 | 1,782.68 | 1,900.62 | 1,844.39 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

The logistic regression models include standard errors are clustered on ISO country code. In this sample, there are 350 unique resistance campaigns from 127 different countries. Constant and year-dummies (1946-2013) are excluded from the table.

*Table 10. Robustness check, Poisson regression on all operationalizations of state repression (H1).*

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Foreign Support 2 (count) | | | |
| | (1) | (2) | (3) | (4) |
| Extreme state repression (t-1) | −0.53*** | | | |
| | (0.08) | | | |
| State repression ordinal (t-1) | | −0.24*** | | |
| | | (0.03) | | |
| CSO repression index (t-1) | | | 0.06** | |
| | | | (0.03) | |
| CSO repression ordinal (t-1) | | | | −0.14*** |
| | | | | (0.02) |
| Campaign strategy | 0.03 | 0.02 | 0.19*** | 0.13** |
| | (0.06) | (0.05) | (0.06) | (0.06) |
| Electoral democracy index | −0.44 | −0.36 | −0.48 | −0.26 |
| | (0.34) | (0.32) | (0.34) | (0.35) |
| International media coverage | 0.23*** | 0.21*** | 0.25*** | 0.22*** |
| | (0.04) | (0.04) | (0.04) | (0.04) |
| Press freedom | −0.07 | −0.08 | −0.25 | 0.22 |
| | (0.16) | (0.15) | (0.18) | (0.18) |
| GDP (log) | −0.07** | −0.06** | −0.07** | −0.05* |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| Population (log) | 0.05 | 0.04 | 0.05 | 0.04 |
| | (0.04) | (0.03) | (0.04) | (0.04) |
| Foreign support 2 (t-1) | 0.46*** | 0.49*** | 0.41*** | 0.43*** |
| | (0.04) | (0.04) | (0.04) | (0.04) |
| Constant | 0.50 | 0.46 | 0.69 | 0.36 |
| | (0.50) | (0.51) | (0.53) | (0.49) |
| Observations | 2,456 | 2,456 | 2,456 | 2,456 |
| Log Likelihood | −2,785.05 | −2,766.25 | −2,816.06 | −2,802.02 |
| Akaike Inf. Crit. | 5,724.09 | 5,686.50 | 5,786.13 | 5,758.05 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | | | |

The Poisson regression models include standard errors are clustered on ISO country code. In this sample, there are 350 unique resistance campaigns from 127 different countries. Constant and year-dummies (1946-2013) are excluded from the table.

*Table 11. Robustness check. Complete logistic regression model on all state repression operationalizations.*

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | Foreign Support | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| lstaterep_extrm | $-1.82^{***}$ | | | | |
| | (0.23) | | | | |
| lstaterep_ord | | $-0.71^{***}$ | | | |
| | | (0.07) | | | |
| lCSOrep_index | | | 0.18 | | |
| | | | (0.12) | | |
| lCSOrep_ord | | | | $-0.50^{***}$ | |
| | | | | (0.07) | |
| lfatalities | | | | | 0.01 |
| | | | | | (0.05) |
| camp_strategy | $-0.37$ | $-0.36$ | $0.52^{**}$ | 0.20 | 0.18 |
| | (0.28) | (0.26) | (0.20) | (0.24) | (0.41) |
| polyarchy | $-0.78$ | $-0.48$ | $-1.13$ | 0.07 | 0.09 |
| | (0.91) | (0.83) | (1.05) | (0.94) | (1.12) |
| inter_media | $0.71^{***}$ | $0.70^{***}$ | $0.79^{***}$ | $0.70^{***}$ | $0.61^{***}$ |
| | (0.12) | (0.12) | (0.12) | (0.11) | (0.15) |
| pressfreedom | $-0.84$ | $-0.92$ | $-1.17^{*}$ | $-0.08$ | $-0.82$ |
| | (0.65) | (0.61) | (0.67) | (0.76) | (0.83) |
| GDP.est | $-0.16$ | $-0.11$ | $-0.13$ | $-0.09$ | $-0.05$ |
| | (0.13) | (0.12) | (0.14) | (0.14) | (0.15) |
| population.est | 0.09 | 0.04 | 0.01 | $-0.01$ | $-0.02$ |
| | (0.15) | (0.13) | (0.17) | (0.16) | (0.17) |
| lfsupport | $4.18^{***}$ | $4.27^{***}$ | $3.65^{***}$ | $3.91^{***}$ | $4.27^{***}$ |
| | (0.23) | (0.22) | (0.23) | (0.23) | (0.25) |
| lstaterep_extrm:camp_strategy | $0.59^{*}$ | | | | |
| | (0.33) | | | | |
| lstaterep_ord:camp_strategy | | 0.14 | | | |
| | | (0.12) | | | |
| lCSOrep_index:camp_strategy | | | 0.18 | | |
| | | | (0.18) | | |
| lCSOrep_ord:camp_strategy | | | | $-0.03$ | |
| | | | | (0.13) | |
| lfatalities:camp_strategy | | | | | 0.01 |
| | | | | | (0.18) |
| Constant | 2.75 | 2.44 | $3.68^{*}$ | 2.45 | $-11.84^{***}$ |
| | (1.73) | (1.67) | (1.89) | (1.70) | (2.34) |
| Observations | 2,456 | 2,456 | 2,456 | 2,456 | 1,776 |
| Log Likelihood | $-827.13$ | $-813.66$ | $-872.80$ | $-845.16$ | $-530.94$ |
| Akaike Inf. Crit. | 1,810.27 | 1,783.31 | 1,901.61 | 1,846.32 | 1,215.89 |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | | |

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*Table 12. Robustness check. Each foreign support indicator as dependent variable.*

Table 6: H1: For each indicator

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | ab_internat2 | ab_int_mat2 | wdrwl_support2 | camp_support2 | sdirect2 |
| | (1) | (2) | (3) | (4) | (5) |
| lstaterep_extrm | $-1.09^{***}$ | $-1.34^{***}$ | 0.04 | $-2.66^{***}$ | $-1.39^{***}$ |
| | (0.22) | (0.35) | (0.45) | (0.25) | (0.28) |
| camp_strategy | $0.78^{***}$ | 0.51 | $0.93^{*}$ | $-1.30^{***}$ | 0.34 |
| | (0.25) | (0.40) | (0.52) | (0.31) | (0.36) |
| polyarchy | $-0.86$ | $-1.16$ | $-3.19^{*}$ | $-1.51$ | $-3.95^{***}$ |
| | (0.81) | (1.02) | (1.73) | (0.94) | (1.32) |
| inter_media | $0.72^{***}$ | $0.75^{***}$ | $0.33^{*}$ | $0.47^{***}$ | $0.98^{***}$ |
| | (0.09) | (0.14) | (0.17) | (0.11) | (0.18) |
| pressfreedom | $-0.33$ | 0.004 | 0.56 | 0.25 | $-0.65$ |
| | (0.63) | (0.75) | (1.04) | (0.53) | (0.71) |
| GDP.est | $-0.16$ | $-7.35^{***}$ | $-7.68^{***}$ | $-1.32$ | $-8.51^{***}$ |
| | (1.96) | (2.56) | (2.75) | (2.38) | (3.19) |
| population.est | $-0.52$ | $5.36^{***}$ | $4.10^{**}$ | $-0.31$ | $6.22^{**}$ |
| | (1.50) | (1.97) | (1.94) | (1.85) | (2.44) |
| lab_internat2 | $3.54^{***}$ | | | | |
| | (0.23) | | | | |
| lab_int_mat2 | | $5.70^{***}$ | | | |
| | | (0.39) | | | |
| lwdrwl_support2 | | | $1.96^{***}$ | | |
| | | | (0.45) | | |
| lcamp_support2 | | | | $5.75^{***}$ | |
| | | | | (0.31) | |
| lsdirect2 | | | | | $5.31^{***}$ |
| | | | | | (0.39) |
| lstaterep_extrm:camp_strategy | $-0.30$ | 0.16 | $-0.05$ | $1.99^{***}$ | 0.45 |
| | (0.29) | (0.58) | (0.58) | (0.45) | (0.50) |
| Constant | 2.16 | 7.42 | $-7.55$ | $-10.01^{**}$ | $-9.07^{**}$ |
| | (3.75) | (4.77) | (19.54) | (4.55) | (4.56) |
| Observations | 2,456 | 2,456 | 2,456 | 2,456 | 2,456 |
| Log Likelihood | $-923.48$ | $-436.83$ | $-276.56$ | $-674.87$ | $-364.94$ |
| Akaike Inf. Crit. | 2,002.96 | 1,029.66 | 709.11 | 1,505.73 | 885.88 |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | | |

In the table below, a sample of the year dummies is presented which was discussed as an indicator of biased results (since there is only one predictor used as the dependent variable):

| | | | | | |
|---|---|---|---|---|---|
| factor(year)1946 | $-3.44^{***}$ | $-3.62^{***}$ | 17.77 | $15.16^{***}$ | $-0.32$ |
| | (0.85) | (0.57) | (21.23) | (0.89) | (2.87) |
| factor(year)1947 | $-3.01^{***}$ | $-3.14^{***}$ | 17.53 | $14.57^{***}$ | 0.66 |
| | (0.83) | (0.56) | (25.53) | (1.30) | |
| factor(year)1948 | $-3.34^{***}$ | $-1.87$ | 17.20 | $14.21^{***}$ | 16.33 |
| | (1.16) | (1.29) | (20.81) | (0.98) | |
| factor(year)1949 | $-3.10^{***}$ | $-3.00^{***}$ | $-0.22$ | $14.11^{***}$ | 15.49 |
| | (0.86) | (0.59) | (22.57) | (0.46) | |
| factor(year)1950 | $-2.25^{**}$ | $-1.27$ | $-0.40$ | $13.13^{***}$ | 0.87 |
| | (1.13) | (1.64) | (20.23) | (1.49) | (3.92) |
| factor(year)1951 | $-14.35^{***}$ | $-18.98^{***}$ | $-0.30$ | $15.54^{***}$ | 1.16 |
| | (1.10) | (1.38) | (18.24) | (1.24) | |
| factor(year)1952 | $-2.47^{**}$ | $-16.93^{***}$ | $-0.39$ | $14.11^{***}$ | 0.18 |
| | (1.17) | (1.02) | (18.37) | (0.88) | (1.18) |
| factor(year)1953 | $-2.46^{**}$ | $-16.63^{***}$ | $-0.38$ | $14.25^{***}$ | 0.49 |
| | (1.22) | (0.97) | (15.41) | (0.87) | (3.27) |
| factor(year)1954 | $-1.17$ | $-1.35$ | 17.01 | $14.57^{***}$ | $-0.36$ |
| | (1.10) | (1.43) | (23.13) | (1.43) | (2.98) |
| factor(year)1955 | $-2.47^{**}$ | $-3.20^{***}$ | $-0.16$ | $12.99^{***}$ | 0.48 |
| | (1.05) | (1.11) | (29.95) | (1.47) | |
| factor(year)1956 | $-1.96^{*}$ | $-1.27$ | $-0.38$ | $15.75^{***}$ | 0.06 |
| | (1.11) | (1.12) | (15.06) | (0.93) | |
| factor(year)1957 | $-3.58^{***}$ | $-4.60^{***}$ | $-0.14$ | $14.35^{***}$ | 0.28 |
| | (1.16) | (1.51) | (25.03) | (0.73) | (1.91) |
| factor(year)1958 | $-1.54$ | $-0.63$ | 17.75 | $15.99^{***}$ | $16.77^{***}$ |
| | (1.22) | (1.30) | (22.18) | (1.11) | (3.79) |
| factor(year)1959 | $-2.93^{***}$ | $-2.94$ | $-0.59$ | $15.32^{***}$ | $-1.80$ |
| | (1.06) | (2.49) | (20.96) | (0.87) | (2.46) |
| factor(year)1960 | $-1.15$ | $-1.45$ | $-0.01$ | $15.23^{***}$ | 16.98 |
| | (1.11) | (1.41) | (9.60) | (0.82) | |
| factor(year)1961 | $-2.15^{**}$ | $-0.84$ | 0.09 | $16.34^{***}$ | 16.64 |
| | (1.00) | (1.15) | (21.35) | (0.94) | |
| factor(year)1962 | $-1.96^{**}$ | $-2.36$ | $-0.02$ | $14.28^{***}$ | 15.42 |
| | (0.99) | (1.84) | (14.05) | (0.91) | |
| factor(year)1963 | $-1.83^{*}$ | $-1.31$ | $-0.18$ | $15.56^{***}$ | $15.40^{***}$ |
| | (1.08) | (1.59) | (24.83) | (1.41) | (3.53) |
| factor(year)1964 | $-2.12^{**}$ | $-2.22^{**}$ | $-0.02$ | $14.48^{***}$ | $15.20^{***}$ |
| | (0.96) | (1.02) | (7.31) | (1.15) | (3.18) |
| factor(year)1965 | $-2.98^{**}$ | $-2.44^{**}$ | $-0.09$ | $15.33^{***}$ | $17.35^{***}$ |
| | (1.35) | (0.99) | (19.26) | (1.04) | (1.53) |
| factor(year)1966 | $-2.08^{*}$ | $-1.28$ | 17.46 | $15.12^{***}$ | 13.13 |
| | (1.11) | (1.14) | (17.61) | (0.90) | |
| factor(year)1967 | $-2.09^{**}$ | $-2.14^{**}$ | 17.15 | $14.56^{***}$ | 14.98 |
| | (1.00) | (0.96) | (23.75) | (0.70) | |
| factor(year)1968 | $-2.10^{**}$ | $-2.47^{**}$ | $-0.27$ | $15.03^{***}$ | $14.63^{***}$ |
| | (1.00) | (1.00) | | (0.80) | (2.24) |
| factor(year)1969 | $-2.26^{**}$ | $-2.00^{**}$ | 17.28 | $14.81^{***}$ | 15.09 |
| | (0.95) | (0.98) | | (1.07) | |
| factor(year)1970 | $-1.91^{*}$ | $-2.50^{**}$ | $-0.32$ | $15.94^{***}$ | 14.82 |
| | (0.99) | (0.98) | (17.42) | (0.77) | |
| Observations | 2,456 | 2,456 | 2,456 | 2,456 | 2,456 |
| Log Likelihood | $-923.48$ | $-436.83$ | $-276.56$ | $-674.87$ | $-364.94$ |
| Akaike Inf. Crit. | 2,002.96 | 1,029.66 | 709.11 | 1,505.73 | 885.88 |

*Note:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$