

Human Rights Violations in the Name of Countering Terrorism¹

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Under Peer Review: August 31 2022

Abstract

Why do some states abide by international law to counter terrorism, while others use broad definitions of terrorism to violate human rights? The lack of data differentiating human rights abuses in the name of counter-terrorism from other settings have impeded comparative investigations on this topic. I address this gap by creating the first annual global dataset of counter-terrorism human rights violations using a supervised machine learning method. I develop a new measure of counter-terrorism human rights abuses using a latent variable model to correct for bias in human rights reporting sources and use an instrumental variable analysis to control for endogeneity. I illustrate that countries are more likely to violate human rights in the context of counter-terrorism when there is greater political exclusion of ethnic groups. Framing out-groups as terrorists provides political cover for governments to stifle political dissent, provide legality for abuses, and avoid public backlash for violations.

¹This project receives funding from the Institute of Humane Studies 2021. The author thanks Luke Abbs, Margherita Belgiosio, Patrick Brandt, Grace Mueller, Robert U Nagel, Roman G. Olar, Clint Peinhardt, Marina G. Petrova and participants at the Faculty of Economics Research Seminar at the Universidad Externado de Colombia, the Texas Triangle International Relations Conference 2021, and the Political Science, Public Policy and Political Economy Seminar at the University of Texas at Dallas for their helpful comments and suggestions. I would also like to thank Kate Madufo and Kashmiri Medhi for their research assistance.

Introduction

Under what conditions are states more likely to violate human rights in the name of countering terrorism? Annual global data on counter-terrorism human rights abuses could help researchers and policy makers understand why some states abide by international law to counter terrorism, while others use broad definitions of terrorism to violate human rights. However, comparative data differentiating human rights abuses in the name of counter-terrorism from other settings does not exist. Although past studies have identified several factors that shape the relationship between counter-terrorism and human rights (e.g., terrorism threat and regime type), these findings are based on annual country human rights scores that capture many other types of abuses beyond those perpetrated in the name of countering terrorism (Daxecker and Hess 2013; Dreher, Gassebner, and Siemers 2010; Kurrild-Klitgaard, Justesen, and Klemmensen 2006; Piazza and Walsh 2009). Using a country's aggregate human rights score is unsuitable for studying this topic as counter-terrorism human rights abuses are just a subset of a country's repression portfolio. This can induce severe measurement error which bias results. While a few studies have used more direct measures of counter-terrorism repression to assess the influence of domestic factors on counter-terrorism repression (e.g., party orientation), the data is typically limited to just one country with a unique set of counter-terrorism policy choices. This is problematic as it casts doubt on whether these theories are generalizable across settings (Berrebi and Klor 2008; Getmansky and Zeitzoff 2014; Nanes 2017). This data gap has hindered empirical research on counter-terrorism and human rights and prevented the field from systematically answering comparative research questions on this topic.

I address this void by presenting the first global dataset of human rights violations perpetrated in the name of countering terrorism for 174 countries from 1999-2016 using a text as data approach. This original data is extracted from U.S. State Department, Amnesty International, and Human Rights Watch annual country human rights reports and coded using a supervised machine learning method. Results from a series of model performance evaluation metrics that compare the classes assigned by the machine to hu-

man coded data show that this method achieves high degrees of accuracy. This novel dataset enables me to test a new theory on the effect of ethnic political exclusion on counter-terrorism human rights violations and investigate whether previous findings hold up when we use a more accurate measure of counter-terrorism abuses with greater temporal and geographical coverage.

Yet, even with more precise data on counter-terrorism human rights violations it is still possible that estimates drawn from annual country human rights reports will be biased due to a changing standard of accountability (Fariss 2014). Specifically, abuses may appear worse during later years of the data and better during earlier years due to broad changes to international human rights standards and monitoring practices that have increased and improved the quality and quantity of information contained in reports over time. To correct for this temporal bias, I use a latent variable model to create a new measure of counter-terrorism human rights abuses using the machine coded data. This novel measure advances research on this subject by allowing for more accurate comparisons between and within countries over time.

I then move the field forward by developing and testing a new theoretical argument on the political cover of counter-terrorism human rights abuses. Human Rights Watch (2012) estimates that since 9/11, over 140 governments have passed counter-terrorism legislation that “reconfigure the balance between state powers and individual freedoms [...] at the expense of rights rather than to protect rights” (Amnesty International, 2018, p. 14). In addition to restricting the rights of terrorist suspects, governments are accused of using these laws to suppress political dissent and target ethnic, religious and social minorities (Human Rights Watch 2012). For example, in Turkey many Kurdish protesters, political party members and journalists have been arrested and prosecuted under counter-terrorism laws. Similarly, in Egypt counter-terrorism provisions have been used to convict and imprison government critics, lawyers and human rights activists (Amnesty International 2018). Additionally, democracies in western Europe (e.g., France, Spain, and the UK) have been accused of prosecuting civil society groups and activists using “vague laws punishing “glorification” or “apology” of terrorism” (Amnesty International, 2018, p. 49).

I argue that countries are more likely to violate human rights in the context of counter-terrorism when there is greater political exclusion of ethnic groups.² States are more likely to perceive excluded ethnic groups as threatening because of their mobilization capacity and political/territorial goals and are less likely to face public backlash for framing them as terrorists due to pre-existing negative perceptions of out-groups in society (Denny and Walter 2014; Kearns and Young 2020; Lee et al. 2004; Lupu and Wallace 2019). Framing politically excluded ethnic groups as terrorists provides political cover for governments to stifle dissent and prevent challenges to the distribution of power as anti-terrorism laws provide a legality for abuses that can reduce public backlash for violating human rights.

To test my hypothesis, I examine the effect of ethnic political exclusion on counter-terrorism human rights violations by calculating the size of politically excluded ethnic groups as a share of the total country population. To address endogeneity concerns, I use an instrumental variable approach that uses a spatial lag of ethnic political exclusion of nearby countries to instrument a country's local political exclusion. Results from the analysis indicate support for my theoretical argument and illustrate that countries with greater political exclusion of ethnic groups are more likely to violate human rights in the name of counter-terrorism. By highlighting the role of ethnic political exclusion in counter-terrorism human rights violations, this study sheds new light on debates on how terrorism can serve as an excuse for suppressing political dissent and the effectiveness of violent framing strategies for violating human rights.

This research contributes to the literature in several ways. First, this study provides a more accurate account of the causes of counter-terrorism human rights abuses at the cross-national level using data that disaggregates counter-terrorism abuses from a country's overall human rights practices—for the first time. Second, the article's theoretical argument moves beyond the relationship between regime type, terrorism threat, and hu-

²In line with Vogt et al. (2015), I define ethnicity as “a subjectively experienced sense of commonality based on a belief in common ancestry and shared culture” which includes “ethnolinguistic, ethnoreligious, and ethnosomatic (or “racial”) groups” (The Ethnic Power Relations (EPR) Core Dataset Codebook Version 1, p. 3). While ethnic political exclusion refers to groups who i) hold no political power in the national government (powerless) ii) are actively discriminated against by the state either formally or informally (discrimination) iii) have excluded themselves from central power by taking control of an independent sub-national territory (self-exclusion) (The Ethnic Power Relations (EPR) Core Dataset Codebook Version 1, p. 5-6).

man rights into other elements of domestic politics that reveal how counter-terrorism can provide political cover for using state violence to maintain the status quo. Third, this new theoretical contribution re-conceptualizes the public as having multi-dimensional preferences on human rights (rather than being viewed as a unitary actor) and suggests that government decisions to repress in the name of countering terrorism depend on expectations of how different coalitions/audiences will react to violations based on the identity of the target. Finally, the study's new measure will allow future researchers to test alternative explanations and develop new research agendas on the determinants of counter-terrorism human rights abuses. The findings from the article also have important implications for policy makers and civil society advocates that seek to prevent governments from violating human rights abuses in the name of national security and counter-terrorism.

Human Rights and Counter-terrorism

Terrorism Threat and Regime Type

Which countries are more likely to violate human rights in the name of countering terrorism? Prior research on this topic suggests that a states willingness to commit counter-terrorism human rights abuses depends on a security-civil liberties trade-off. On the one hand, countries must pursue a counter-terrorism strategy that pre-empts and deters future acts of terrorism (Rosendorff and Sandler 2004). On the other hand, states must ensure that the action adopted is measured in order to avoid public backlash for curtailing civil liberties (Cordell 2019). This trade-off produces complex challenges for governments as it requires them to consider multiple audiences when responding to terrorism (e.g., the terrorists and the public) (Davenport and Inman 2012).

The first implication from this research is that countries with high levels of terrorism should be more likely to trade-off civil liberties for national security than countries with low levels of terrorism. Following a terrorist attack, it is critical that governments demonstrate their competence in responding to terrorism and reassure the public that

their national security is more secure (Stohl 2006). In these situations, destroying a terrorist group and preventing future attacks becomes more important than respecting human rights as violations provide an opportunity for states to stop terrorist groups from recruiting supporters, punish perpetrators, and gather intelligence (Piazza and Walsh 2009). Indeed, public opinion research shows that the public is supportive of this trade-off and is often willing to “meet violence with more violence” and support government abuses that target terrorist suspects given the critical threat that terrorism poses to a country’s national interests (Davis and Silver, 2004; Kearns and Young, 2020, p. 4).

The second implication from this research is that democracies should be less likely to commit counter-terrorism human rights abuses than non-democracies. Restricting civil liberties at the expense of national security can create grievances that threaten a government’s support, increase sympathy for the group’s cause, and promote terrorist recruitment (Daxecker and Hess 2013; Rosendorff and Sandler 2004). Keeping citizen’s grievances to a minimum is of central importance in a democracy as democratic institutions increase the risk that governments will be held accountable for their repressive actions and punished by voters that question their legitimacy and disagree with their harsh counter-terrorism approach (Davenport and Inman 2012; Mesquita et al. 2005). Additionally, trading-off civil liberties in the name of national security is more likely to lead to public outcry in a democracy due to the presence of human rights norms and the perception that democratic actors are better at protecting human rights and respecting the rule of law (Kelley 2007). Alternatively, non-democracies do not need to be as concerned with balancing civil liberties and countering terrorist threats as human rights violations are more commonplace and individuals in non-democratic countries lack the ability to hold their governments account via free and fair elections (Cordell 2021; Daxecker and Hess 2013).

Although this research has improved our understanding of the incentives and political costs of violating human rights in response to terrorism, the empirical findings from existing studies are mixed. For example, Piazza and Walsh (2009) find that terrorism increases disappearances and extrajudicial killings but not torture, political imprisonment

or restrictions of freedom of speech. However, Dreher, Gassebner, and Siemers (2010) and Stone (2004) find opposite results for torture, political imprisonment and freedom of speech with terrorist attacks increasing these types of abuses. Similarly, while some studies find that democracies are less likely to violate civil liberties in the context of counter-terrorism (Choi 2010; Kurrild-Klitgaard, Justesen, and Klemmensen 2006), other studies find less consistent support for this core theoretical argument (Li 2005; Young and Findley 2011).

These inconsistencies are in part due to the lack of comparative data differentiating human rights abuses perpetrated in the name of counter-terrorism from other settings. For example, most of these studies base their findings on annual country physical integrity rights scores from the Political Terror Scale or CIRI Human Rights Data Project that capture many other types of abuses beyond those perpetrated in the name of counter-terrorism. Using a country's aggregate human rights score is unsuitable for studying this topic as counter-terrorism human rights abuses are just a subset of a country's repression portfolio. This can induce severe measurement error which bias results. The data developed in this study provides a solution to this problem by disaggregating counter-terrorism human rights abuses from a country's overall human rights record—for the first time. This new data allows me to unite the literature and shed light on existing debates by identifying which findings hold up when we use a more accurate measure of counter-terrorism human rights abuses.

Domestic Politics and Repressive Counter-terrorism

Another set of studies focus on how domestic politics influence the likelihood of violating human rights in the context of counter-terrorism. For example, Piazza and Walsh (2009) find that newer regimes that have experienced a recent ethnic-based civil conflict are more likely to engage in disappearances and extrajudicial killings in response to terrorism. The reason for this is two-fold. First, ethnic-based civil conflicts provide a firm basis for the “othering” of ethnic minority groups which increases the acceptability of targeted violence and reduces the likelihood of public backlash to government abuses. Second, newer

regimes with a recent ethnic-based civil conflict are more likely to have state agents that are accustomed to engaging in abuses and are less likely to have the institutional checks and balances established that prevent abusive behavior from occurring in the first place (Piazza and Walsh 2009).

Alternatively, Nanes (2017)'s analysis of Israeli counter-terrorism policies suggests that a country's choice of national security strategies depend on partisanship and election cycles. In the run up to elections, left governments are more likely to pursue defensive and moderate counter-terrorism policies, and right governments are more likely to adopt aggressive counter-terrorism policies in order to satisfy the security preferences of their core voters and win their support. Similarly, Berrebi and Klor (2008) and Getmansky and Zeitzoff (2014) find that the vote share for right-wing parties in Israel increases when an Israeli locality experiences a terrorist attack due to the perception that right-wing parties will respond more harshly to terrorism than left-wing parties. These findings are in line with public opinion research which suggests that left voters prefer human rights to be protected when countering terrorism while right voters value the protection of national security over the respect for human rights (Anderson and Richards 2018; Davis and Silver 2004).

Finally, recent case study research has focused on how governments use counter-terrorism laws to suppress political dissent and target ethnic, religious and social minorities. For example in Turkey and Ethiopia, anti-terrorism laws have been broadened far beyond preventing terrorist attacks to silence government critics including ethnic minorities, academics, journalists and activists to help the ruling party stay in power (Baser, Akgönül, and Öztürk 2017; Kibret 2017). Framing human rights victims as violent actors allows governments to violate human rights while avoiding public backlash for abuses as individuals are more likely to favor a harsh response to groups in society that they perceive as threatening (Conrad et al. 2018; Lupu and Wallace 2019; Workneh and Haridakis 2021).

Although this research has helped identify the factors directly linked to repressive forms of counter-terrorism, most studies are based on data for a single country and

have limited external validity. This is problematic as it is unclear whether previous findings for certain theories are generalizable across countries. The new cross-national measure presented in this article addresses this issue by providing a first account of counter-terrorism human rights across different political, social and economic contexts. Additionally, while some studies have begun to look at government misuse of counter-terrorism laws, no study has systematically evaluated why some countries use broad definitions of terrorism to suppress political dissent, while others do not. The theoretical argument presented in the next section fills this gap in the literature and builds a more solid foundation for future comparative research on this subject.

Ethnic Political Exclusion

Under what conditions are states more likely to violate human rights in the name of national security and counter-terrorism? I argue that countries with greater political exclusion of ethnic groups are more likely to engage in human rights abuses in the context of counter-terrorism than countries with less political exclusion of ethnic groups.³ Countries that deliberately discriminate against ethnic groups can use counter-terrorism discourse as political cover for preempting and deterring challenges from ethnic minorities and capitalize on pre-existing negative perceptions of out-groups to avoid public backlash for violating human rights (Davenport 2007; Ritter and Conrad 2016). Numerous contemporary examples illustrate this relationship. In China, the government continues to systematically violate the human rights of Uyghur and other Turkic Muslims in the Xinjiang region under the guise of counter-terrorism including mass arbitrary detention, torture, and surveillance (Kumar 2020; Wang 2020). Similarly, in India authorities have been accused of using anti-terrorism laws to imprison Muslim protesters and in Kenya anti-terror police have carried out extrajudicial killings and disappearances of Muslims (Human Rights Watch 2014, 2020). In the UK, the government has been accused of

³I follow Vogt et al. (2015)'s definition of ethnicity and ethnic political exclusion. Ethnicity refers to "a subjectively experienced sense of commonality based on a belief in common ancestry and shared culture" (The Ethnic Power Relations (EPR) Core Dataset Codebook Version 1, p. 3). Ethnic political exclusion includes groups who are politically powerless, discriminated against, or self-excluded from central power (The Ethnic Power Relations (EPR) Core Dataset Codebook Version 1, p. 5-6).

stopping and searching hundreds of thousands of people between 2007-2010 “without reasonable suspicion of wrongdoing” under a provision of a counter-terrorism law—most of whom were ethnic minorities (Human Rights Watch, 2012, p. 3).

Several scholars have pointed out that the lack of a single definition of terrorism has left a void for political actors to “define terrorism in ways that serve their own perceived political and strategic interests” (Crenshaw, 2014; Richards, 2014, p. 214). As a result, counter-terrorism laws have provided governments with political cover to legitimize broad definitions of terrorism far beyond preventing terrorist attacks to suppress groups that they perceive as threatening (Crenshaw 2004). However, I expect states to be selective in the groups that they target with anti-terrorism laws given the political costs of repression and a finite set of legal and repressive resources. Specifically, governments should be more likely to focus their repressive anti-terrorism efforts on those groups whose goals and capacity pose the greatest threat to maintaining the current distribution of power. Research on the link between ethnicity and conflict suggest that states are more likely to view ethnic groups as threatening than other groups as they have a unique mobilization advantage that allows them to organize more effectively and are more likely to be aggrieved and seek political representation that alters existing power structures (e.g., political or territorial change) (Denny and Walter 2014; Lee et al. 2004). In particular, large politically excluded ethnic groups pose a unique threat to governments as they have greater incentives to challenge the government, can capitalize on vast existing social networks to coordinate, and are more likely to enjoy legitimacy for their claims to power (Cederman, Buhaug, and Rød 2009; Cederman, Wimmer, and Min 2010).

The relationship between threat perception and repression is widely recognized in the literature. The higher the government’s perception of threat, the more likely they are to use repression to “prevent challenges that could alter the status quo policy or distribution of power” (Davenport, 2007; Lee et al., 2004; Ritter and Conrad, 2016, p. 86). However, repressing politically excluded groups has a downside by creating additional grievances that threaten a government’s support, increase sympathy for the group’s cause, and facilitate recruitment (Cordell 2021; Daxecker and Hess 2013; Rosendorff and Sandler 2004).

Anti-terrorism laws provide states with a solution to this problem by producing a narrative on the legality of abuses and a justified reciprocal response that has been shown to reduce public backlash for violating human rights. Legal arguments for restricting the rights of terrorist suspects increases the perceived legitimacy of violations and enable governments to re-frame abuses as necessary for promoting justice, protecting freedom and democracy, and defending public safety and national security (Tsoukala 2006). Indeed, survey research shows that portraying targets of human rights violations as violent actors increases public support for repression as individuals favor a harsh response to groups that they perceive as threatening (Conrad et al. 2018; Human Rights Watch 2012; Kearns and Young 2020; Lupu and Wallace 2019).

Labeling politically excluded ethnic groups as terrorists is likely to be a particularly effective tool for silencing dissent as governments can take advantage of pre-existing negative perceptions of out-groups in society to legitimize their violent framing strategies. In order for violent framing strategies to be successful, the public must believe the claims that the government is making (e.g., that members of an ethnic group are terrorists), with hostile stereotypes and existential threats from out-groups increasing the persuasiveness of propaganda messaging and reducing skepticism/public backlash to the claims being made (Frischlich et al. 2015; Horz 2021). Prior psychology studies on social identity theory show that individuals are more likely to endorse out-group stereotypes and perceive socially distant groups as threatening and inferior because of the perception that members of an out-group are more homogeneous than members of their own group (Brewer and Campbell 1976; Horowitz 2001). Governments routinely capitalize on the negative perceptions of out-groups to violate human rights as in-group bias and adverse perceptions of out-group members can alter the perceptions of victims as innocent and deserving of repression and change how individuals humanize and empathize with victims (Batson and Ahmad 2009; Cikara, Bruneau, and Saxe 2011).⁴

⁴The importance of the ethnic out-group framing mechanism can also be observed in the targeting of non-violent actors such as journalists, students, and human rights groups with anti-terrorism laws where countries such as Turkey and Israel emphasize their alleged connection to politically excluded ethnic groups in order to justify their actions and convincingly label them as terrorists (Bouscaren 2021; Mackey 2021).

Together, these mechanisms should lead governments to disproportionately target politically excluded ethnic groups with anti-terrorism laws as violating the human rights of out-groups is less politically costly than violating the human rights of in-groups, especially as incumbent governments are less likely to depend upon the support of out-groups for their survival in office (Mesquita 2005). This argument diverges from previous research which conceptualizes the public as a unitary actor with similar preferences on human rights and suggests that government decisions to repress in the name of counter-terrorism depend on expectations of how different coalitions/audiences will react to violations based on the identity of the target. Therefore, I hypothesize that:

***H1:** Countries with greater political exclusion of ethnic groups are more likely to violate human rights in the name of counter-terrorism than countries with less political exclusion of ethnic groups.*

Research Design

Data

Supervised Machine Learning Model

I present an original dataset of counter-terrorism human rights violations for 174 countries from 1999-2016 extracted from annual human rights reports and coded using a text as data supervised machine learning approach. Machine learning has become increasingly popular in political science as it allows scholars to overcome the huge resource costs of coding large amounts of data by hand without comprising classification accuracy (Bagozzi et al. 2018). Recent research on human rights use machine learning methods to explore potential biases in human rights reports and segment information from reporting sources to measure a country's human rights practices. Supervised learning models, which use human coded data to train machine learning algorithms, are particularly well suited for classifying textual data on human rights as researchers often have a set of predefined legal categories in mind that they wish to assign documents to (Grimmer and Stewart

2013). For example, Park, Greene, and Colaresi (2020) use human coded training data to train an aspect based sentiment model to identify different categories of rights and assess how judgments in annual country human rights reports have changed over time. Similarly, Cordell et al. (2022) use hand-labeled data and supervised machine learning algorithms to classify sentences and extract physical integrity rights violations from a corpus of annual country human rights reports.

To assess a country’s state of human rights on the topic of counter-terrorism, I use the Cordell et al. (2022) dataset of sentences which includes the text from annual country human rights reports produced by Amnesty International, Human Rights Watch and the U.S. State Department for all countries in the world between 1999 and 2016. Since the 1980s, researchers have used the information contained in these reports to produce popular measures of human rights including the Political Terror Scale and the CIRI Human Rights Data Project. The data from Cordell et al. (2022) contains 2,013,199 pre-processed sentences covering a range of human rights topics including physical integrity rights, civil liberties, political rights, womens rights, workers rights, and so on. The sentences include general statements summarizing the intensity of human rights violations for a country in a given year as well as detailed descriptions of human rights abuses at the event level. Researchers can use the information contained in these sentences to generate allegations of abuse for a range of different human rights categories.

I use a dictionary based approach and supervised machine learning model to classify which sentences in the Cordell et al. (2022) data describe a country’s human rights violations perpetrated in the name of countering terrorism. I begin by applying a dictionary to the pre-processed *stemmed.text* variable to extract sentences that contain the terms “counterterror”, “antiterror” and “terror” (13,375 sentences in total).⁵ Including the term “terror” in the dictionary is important as there are many sentences in the data that describe human rights violations targeting terrorist suspects without explicitly stating the counter-terrorism motive. A team of undergraduate and graduate research assistants

⁵This variable converts sentences from the human rights reports to lower case, removes punctuation, numbers and stopwords, and reduces words to their base-root form (e.g., “counterterror”, “counterterrorism” and “counter-terrorism” are all condensed to “counterterror”)

Table 1: Examples of counter-terrorism human rights sentences

Country	Year	Quote
Kyrgyzstan	2006	“In August opposition leader and member of the parliament Kadyrjan Batyrov accused security forces of violating the human rights of the Uzbek minority in the south by targeting them during antiterrorism and extremism operations.”
Uganda	2011	“There were numerous reports of torture and abuse in detention facilities operated by CMI, CMI’s Joint Antiterrorism Taskforce (JATT), and the RRU.”
Iraq	2013	“According to an April 11 AI report, government security officials severely tortured during interrogation Abdullah al-Qahtani, a Saudi national convicted under the antiterrorism law of robbery and murder to fund terrorist activities.”
Turkey	2014	“Authorities applied the broad antiterror law extensively with little transparency and continued to engage in arbitrary arrests, hold detainees for lengthy and indefinite periods, and conduct extended trials.”

Source: U.S. State Department Human Rights Reports (Cordell et al. 2022)

then coded the original text for a sample of these counter-terrorism sentences according to whether or not they described a human rights violation made in the name of countering terrorism (see Appendix 1 for the data collection instructions).⁶

The hand coded training data includes 6,136 counter-terrorism sentences in total, with 53% of sentences coded as a human rights violation (assigned the value 1) and 47% of sentences coded as a non-human rights violation (assigned the value of 0). For example, the following sentence was identified by coders as a violation: “Under the guise of counterterrorism and anti-separatism efforts, the government also maintains a pervasive system of ethnic discrimination against Uighurs and other ethnic minorities, along with sharp curbs on religious and cultural expression and politically motivated arrests”. Alternatively, coders classified the following sentence as a non-violation: “Shanghai Cooperation Organization Counter-terrorism was high on the agenda of the January Shanghai Cooperation Organization (SCO) meeting” (Cordell et al. 2022). Table 1 provides examples of sentences in the human coded data describing a human rights violation made in the name of countering terrorism.

To prepare the hand coded data for training, I create a Document-Term-Matrix

⁶Due to the multi-faceted nature of counter-terrorism human rights abuses, coders were asked to capture a broad array of human rights violations including physical integrity rights abuses (extrajudicial killings, disappearances, political imprisonment, and torture), allegations of harassment, and violations of freedom of speech, press, movement, assembly, association, and due process.

Table 2: Model accuracy with 5x repeated 5 k-fold cross validation

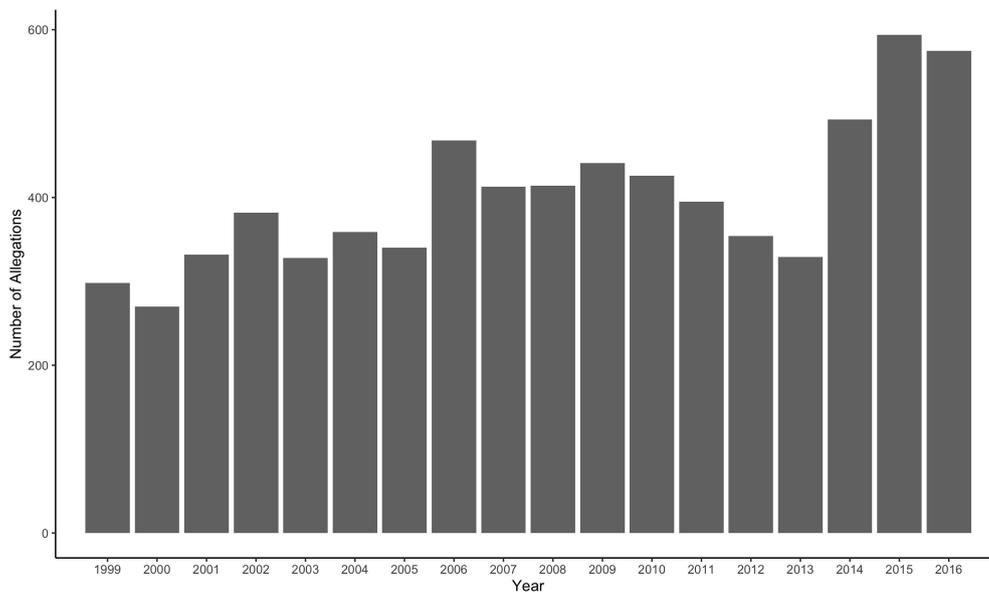
Model	Accuracy	Precision	Recall	F1 Score
NB	0.657	0.657	0.686	0.671
Logistic	0.719	0.731	0.74	0.736
RF	0.806	0.848	0.801	0.824
SVM	0.746	0.759	0.764	0.762

N = 6,136 sentences.

(DTM) that calculates the word count of terms for each sentence in the training data and add a dummy variable for whether or not human coders coded the sentence as a counter-terrorism human rights violation. To improve model efficiency, I reduce the DTM to the most common terms in the training data by removing less frequent terms that are more sparse than 99 percent. I then use repeated k-fold cross validation to train four different machine learning algorithms (Naive Bayes, Logistic Regression, Random Forest, and Support Vector Machine) on the labeled training data DTM.⁷ The models learn how to classify sentences by uncovering patterns between the word count of terms in the training data and their binary classification as a counter-terrorism human rights allegation by human coders. Just like the human coders, the model classifies sentences as containing information on human rights violations made in the name of countering terrorism by assigning a value of 1, and 0 otherwise.

To evaluate the quality of the supervised learning models, I conduct several performance metrics that compare the classes assigned to sentences from the unseen test data not used for training by the models and human coders. Table 2 displays the model performance statistics for each supervised machine learning model, measured as the mean value for each metric over each of the 5 k-sub-samples. The results in Table 2 show that this method achieves between 66%-81% accuracy. The Random Forest model is the best performing algorithm, achieving 81% accuracy (proportion of correct predictions to the total number of predictions), 85% precision (the proportion of true positives to the total number of true positives and false positives), 80% recall (the proportion of true positives

⁷This re-sampling process splits the training data into 5 k-subsets, removes a subset from the sample (test data), fits the model on all other subsets (training data), and evaluates the model using the test set-repeated 5 times.

Figure 1: Number of Counter-terrorism Human Rights Allegations, Over Time

Total number of counter-terrorism allegations for 174 countries from 1999-2016, coded using a Random Forest supervised machine learning model. $N = 7,211$ allegation sentences.

to the total number of true positives and false negatives), and 82% on the F1 score (the combined precision and recall scores using the harmonic mean). I use the Random Forest model to code the remainder of counter-terrorism sentences extracted from the Cordell et al. (2022) data. This method codes 7,211 sentences in the data as a counter-terrorism human rights violation (54% of sentences) and 6,164 sentences as non-allegations (46% of sentences).

Figure 1 displays the number of counter-terrorism human rights allegations identified by the model, over time. The greatest number of allegations are identified in 2015 (594 violations) and the lowest number of allegations are identified in 2000 (270 violations). Table 3 shows the top ten countries with the greatest number of allegations in the data: Turkey, Pakistan, Algeria, the United Kingdom, India, Peru, Morocco, Ethiopia, Iraq, and Egypt. The model identifies 546 allegations for the number one country—Turkey, who is well known for using broad definitions of terrorism to suppress political dissent. To give an indication of scale, this figure is almost three times as big as Egypt’s total number of allegations (the tenth highest country). The average number of allegations for countries in the data is 48 (e.g., Malaysia), while the minimum number of allegations is

Table 3: Top 10 Countries, Number of Counter-terrorism Human Rights Allegations

Country	Number of Allegations
Turkey	546
Pakistan	365
Algeria	290
United Kingdom	288
India	253
Peru	240
Morocco	214
Ethiopia	204
Iraq	201
Egypt	196

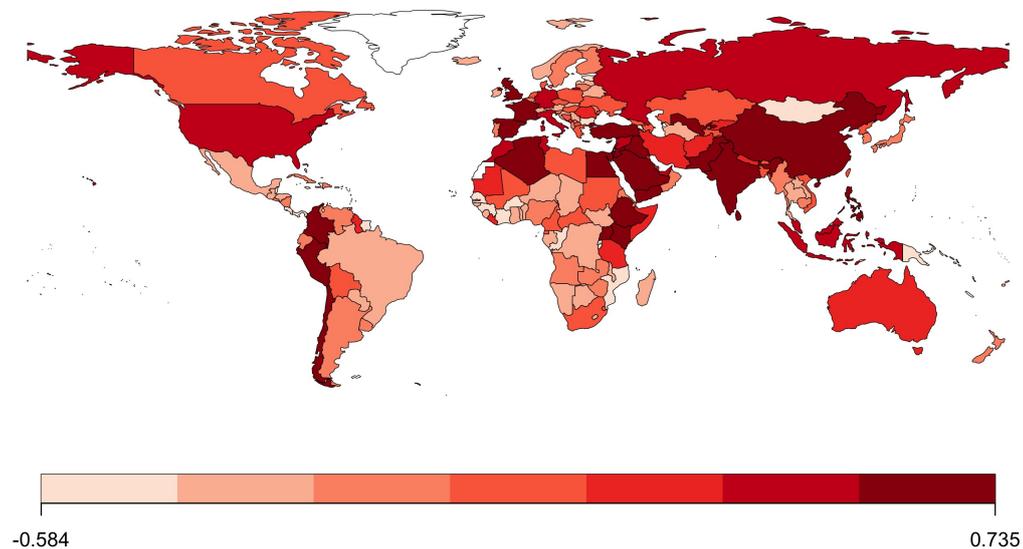
1 (e.g., Cyprus).

To examine the topical content of allegations, I report the top 10 terms in the allegation data. The term with the highest frequency is “terror” (mentioned 4,462 times), followed by “terrorist” (mentioned 2,630 times), “law” (mentioned 1,717 times), “govern” (mentioned 1,646 times), “suspect” (mentioned 1,585 times), “charg” (mentioned 1,567 times), “secur” (mentioned 1,242 times), “author (mentioned 1,081 times), “arrest” (mentioned 1,080 times), and “detent” (mentioned 1,077 times). One takeaway is that many violations seem to reference anti-terrorism laws (e.g., “law”); consistent with reports from human rights organizations that the proliferation of counter-terrorism legislation is associated with an increase in human rights abuses on this topic (Human Rights Watch 2012). Additionally, the high occurrence of the terms “arrest”, and “detent” (mentioned 2,157 times in total) indicate that the most common type of abuses include descriptions of suspects being arrested and held in detention (Cordell et al. 2022). These terms appear in sentences between three and six times more than other forms of physical integrity rights abuse, including torture (mentioned 621 times) and extrajudicial killing (mentioned 380 times).

Latent Variable Model

I use the machine coded data and a latent variable model to create a new global measure of human rights violations perpetrated in the name of countering terrorism. I start

Figure 2: Latent Measure of Counter-terrorism Human Rights Violations 1999-2016



The mean value for all countries on the latent measure of counter-terrorism human rights violations from 1999 to 2016. A higher value on the latent measure represents higher levels of counter-terrorism human rights violations and a lower value represents lower levels of counter-terrorism human rights violations.

by creating a variable that counts the total number of counter-terrorism human rights violations identified by the Random Forest supervised learning model for each country in a given year. I then use a dynamic Item Response Theory (IRT) model similar to Fariss (2014) to create unbiased country-year estimates that correct for a changing standard of human rights accountability.⁸ This method addresses temporal biases in the reports by using item difficulty parameters that vary over time to model the likelihood of a human rights violation being observed in a given year (Fariss 2014). This new measure is continuous and ranges from -1.428 (better respect for human rights in the name of counter-terrorism) to 0.9 (worse respect for human rights in the name of counter-terrorism). Figure 2 displays the mean value for all countries on this latent measure from 1999 to 2016. The country with the highest average violation score is Pakistan, the mean country is Cameroon, and the country with the lowest average violation score is the Solomon

Islands.

Independent Variable

To test my hypothesis that countries with greater political exclusion of ethnic groups are more likely to violate human rights in the name of counter-terrorism than countries with less political exclusion of ethnic groups, I create an independent variable that measures the size of politically excluded ethnic groups as a share of the total country population. I use Vogt et al. (2015)'s Ethnic Power Relations (EPR) Core Dataset which provides global annual data on the size and status of politically relevant ethnic groups. To calculate the relative size of politically excluded ethnic groups, I add together the size of all groups coded as powerless, discriminated, or self-excluded for a country in a given year. This *Ethnic Exclusion Size* variable is continuous and ranges from 0 where there are no politically excluded ethnic groups (e.g., United Arab Emirates) to 0.86 where there is greater political exclusion of ethnic groups (e.g., Syria).

Control Variables

To reduce the possibility that other factors affecting the likelihood of counter-terrorism human rights violations may be correlated with ethnic political exclusion, I control for a number of confounders. I control for terrorist attacks by taking the natural logarithm of the total number of attacks for a country in a given year using the START (National Consortium for the Study of Terrorism and Responses to Terrorism) (2021) Global Terrorism Database. Countries with a higher levels of terrorism should be more likely to abuse human rights in the name of countering terrorism in order to prevent future attacks (Piazza and Walsh 2009). To control for civil conflict, I take the natural logarithm of the total number of battle deaths a country experiences in a given year using the Pettersson et al. (2021) UCDP Battle-related Deaths Dataset. Countries experiencing internal armed

⁸Fariss (2014) describes how the quality and quantity of information contained in annual country human rights reports has increased and improved over time due to broad changes to international human right standards and monitoring practices. Therefore, introducing a reporting bias that makes human rights incorrectly appear worse today than in previous years.

conflict are expected to be more likely to experience terrorism and violate human rights (Davenport and Inman 2012). I control for a country’s overall level of human rights in a given year using the Fariss, Kenwick, and Reuning (2020) Human Rights Protection Scores. Countries with better human rights protections in general should be less willing to engage in violations in the name of counter-terrorism (Cordell 2019).

I control for a country’s level of democracy using the Coppedge et al. (2022) *polyarchy* variable from the Varieties of Democracy data. Democracies should be less likely to violate human rights as democratic institutions increase the risk that governments will be held accountable and punished by voters (Mesquita et al. 2005). To control for a country’s population size and GDP per capita, I take the natural logarithm of annual measures from the World Bank (2022) World Development Indicators dataset. Countries with large populations and lower levels of GDP are expected to be more likely to abuse human rights as they are more likely to have aggrieved populations that governments perceive as threatening (Davenport 2007). I control for the party orientation of a government by creating a dummy variable for whether or not the government is right-wing in a given year using the Cruz, Keefer, and Scartascini (2020) Database of Political Institutions. Right-wing governments should be more likely to abuse human rights in the name of countering terrorism as they are associated with being tougher on terrorism and more willing to trade-off civil liberties for national security (Nanes 2017). Appendix 2 displays summary statistics for the article’s independent and control variables.

Method

Instrumental Variable Analysis

I estimate the effect of ethnic political exclusion on counter-terrorism human rights violations using Ordinary Least-Squares (OLS) regression and Instrumental Variable regression. The instrumental variable approach addresses endogeneity concerns as endogeneity may exist in the OLS model due to reverse causation, omitted variable bias, and measurement error. It is possible that ethnic political exclusion not only effects counter-terrorism human rights violations but that counter-terrorism human rights violations influence ge-

ographical and temporal patterns of ethnic political exclusion. For example, the threat of politically excluded ethnic groups rebelling in response to counter-terrorism human rights grievances may lead governments to strengthen their exclusionary policies in order to maintain their position of power (Cederman, Wimmer, and Min 2010; Daxecker and Hess 2013; Rosendorff and Sandler 2004). Additionally, it is possible that the association between ethnic political exclusion and counter-terrorism human rights violations is a result of endogenous selection bias caused by the terrorist attacks and human rights variables. For example, ethnic political exclusion may lead a country to violate human rights in the name of countering terrorism because countries that politically exclude ethnic groups have more terrorism and have worse human rights (Choi and Piazza 2016). Similarly, countries that have a greater number of terror attacks and poor human rights protections may be both more willing to violate human rights in the context of counter-terrorism and politically exclude groups more generally (Piazza and Walsh 2009). Regarding measurement error, it is possible that Vogt et al. (2015)'s coding of the status and size of politically relevant ethnic groups in the EPR dataset is somewhat imprecise, especially due to the challenges of measuring ethnicity. Attenuation bias caused by measurement error in the independent variable is problematic as it will bias OLS estimates towards zero.

Spatial Lag of Ethnic Political Exclusion

To control for endogeneity, I create a spatial lag of the size of politically excluded ethnic groups of other countries around the world as my instrumental variable and run a Two-Stage Least-Squares (TSLS) Regression. I use a row-standardized approach to create the spatial lag which divides each neighbor weight by the sum of all neighbor weights; producing a weighted average of the ethnic political exclusion values of neighboring observations. In the first stage of the TSLS regression, I regress the spatial lag on the independent variable *Ethnic Exclusion Size*. In the second stage, I use the predicted values from the first stage to estimate the effect of ethnic political exclusion on counter-terrorism human rights violations.

A good instrumental variable should be related to the independent variable but unrelated to the dependent variable, except through its effect on the independent variable. Several related studies have used political conditions in nearby countries as an instrumental variable for a country's local political conditions as the "cross-border spread of political ideas and information" affect the norms, policies and institutions of states that are geographically close (Beiser-McGrath and Metternich, 2021; Berrebi and Ostwald, 2021; Meierrieks, Krieger, and Klotzbücher, 2021, p. 686). I expect states that are surrounded by countries who politically exclude ethnic groups are more likely politically exclude ethnic groups themselves through a process of diffusion and emulation. A state can use the experience of a close by state to learn which techniques and methods are most successful for maintaining their position of power and excluding ethnic groups. Similarly, excluded ethnic groups in one state may become inspired by the successes of ethnic groups in a nearby state and emulate their behavior in order to secure their own demands for inclusion (Cederman, Gleditsch, and Wucherpfennig 2018). However, the exclusionary policies of neighboring states should have no direct effect on a country's local counter-terrorism human rights violations, other than through its effect on local ethnic political exclusion.

Results

Table 4 displays the OLS estimates for the effect of *Ethnic Exclusion Size* on *Counter-terrorism Human Rights Violations*. Model 1 shows the baseline results for the independent variable only. Model 2 displays the results for the full model which includes the independent and control variables. The results in Table 4 provide empirical support for the article's main hypothesis: Countries with greater political exclusion of ethnic groups are more likely to violate human rights in the name of counter-terrorism than countries with less political exclusion of ethnic groups. As expected, the direction of the relationship between *Ethnic Exclusion Size* on *Counter-terrorism Human Rights Violations* is positive and statistically significant with a p-value of 0.04 in the full model (model 2).

Table 4: Ordinary Least-Squares Regression, Counter-terrorism Human Rights Violations

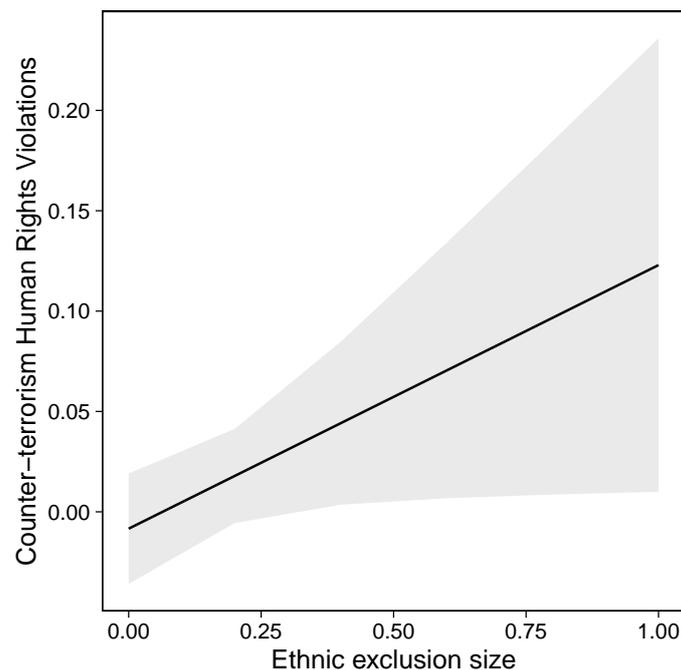
Variables	Independent Variable	Independent and Control Variables
	(1)	(2)
Ethnic exclusion size	0.288*** (0.065)	0.131** (0.065)
Democracy		-0.454*** (0.059)
Terrorist attacks (log)		0.085*** (0.009)
Civil conflict (log)		-0.0003 (0.007)
Human rights		-0.00003 (0.015)
Population (log)		0.076*** (0.009)
GDP per capita (log)		0.099*** (0.011)
Right orientation		-0.017 (0.031)
Constant	-0.035** (0.015)	-1.907*** (0.150)
Observations	3,094	2,986
R ²	0.006	0.155
Adjusted R ²	0.006	0.152
Residual Std. Error	0.657 (df = 3092)	0.607 (df = 2977)
F Statistic	19.643*** (df = 1; 3092)	68.048*** (df = 8; 2977)

Note: Significance codes *p<0.1; **p<0.05; ***p<0.01 with Standard Errors in parentheses

Framing politically excluded ethnic groups as terrorists can provide political cover for preventing challenges to the distribution of power as governments can capitalize on pre-existing negative perceptions of out-groups and use anti-terrorism laws provide a legality for abuses that can reduce public backlash for violating human rights. Figure 3 shows the predicted effects of ethnic exclusion size on counter-terrorism human rights violations with 95 percent confidence intervals from model 2. Moving from the minimum value of the size of politically excluded ethnic groups (0) to the maximum value (0.86) is associated with an increase of 0.13 points on the counter-terrorism human rights violation measure.

For the control variables, the results for the *Democracy*, *Terrorist attacks (log)*, and *Population (log)* variables are as expected: A higher rate of terrorist attacks and larger

Figure 3: Predicted Values of Counter-terrorism Human Rights Violations, by Ethnic Political Exclusion



Noted: Predicted values with 95% confidence intervals derived from Model 2 in Table 4.

population size is associated with higher levels of counter-terrorism human rights violations, while democratic states engage in less counter-terrorism abuses. For the *Civil conflict (log)* and *Human Rights* variables, the effect of civil conflict and human rights protections is negative but not statistically significant. The results for the *GDP per capita (log)* variable is surprising and suggest that countries with greater financial resources (and higher state capacity) may be better equipped to carry out repressive counter-terrorism operations (Hendrix and Young 2014). Interestingly, the results for the *Right orientation* variable indicate that partisanship does not influence a country's decision to engage in counter-terrorism human rights violations. This may be due to competing incentives for right-wing governments to pursue harsh counter-terrorism strategies to appeal to their traditional voter base and for left-wing governments to respond aggressively to terrorism to convince voters that they can be trusted with protecting national security (Lonardo 2019).

Table 5 displays the instrumental variable estimates for the effect of *Ethnic Exclusion Size* on *Counter-terrorism Human Rights Violations*. The results in Table 5 provide

Table 5: Instrumental Variable Analysis, Two-Stage Least-Squares Regression, Counter-terrorism Human Rights Violations

Variables	Independent Variable	Independent and Control Variables
	(1)	(2)
Ethnic exclusion size	0.981*** (0.208)	0.789** (0.306)
Democracy		-0.416*** (0.063)
Terrorist attacks (log)		0.089*** (0.010)
Civil conflict (log)		-0.012 (0.009)
Human rights		0.025 (0.019)
Population (log)		0.082*** (0.010)
GDP per capita (log)		0.096*** (0.011)
Right orientation		-0.022 (0.032)
Constant	-0.125*** (0.030)	-2.099*** (0.176)
Observations	3,094	2,986
<i>First Stage Regression</i>		
IV Spatial Lag	0.491***	0.345***
F statistic	236.25***	111.112***
Wu-Hausman	13.15***	4.995**
Anderson-Rubin CI	0.579-1.4	0.199-1.417

Note: Significance codes *p<0.1; **p<0.05; ***p<0.01 with Standard Errors in parentheses

further empirical support for the article's main hypothesis: Countries with larger politically excluded ethnic groups engage in a greater number of counter-terrorism human rights violations. Again, the effect of *Ethnic Exclusion Size* on *Counter-terrorism Human Rights Violations* is positive and statistically significant with a p-value of 0.04 in the full model (model 2). The size of the effect for the ethnic exclusion variable is much larger for the instrumental variable estimates than the OLS estimates. The diagnostic tests for the TSLS regression demonstrate that the *IV Spatial Lag* which computes the weighted average of the *Ethnic Exclusion Size* of neighboring observations is a valid instrument. In the first stage of the TSLS regression, the spatial lag has a positive and statistically significant effect on local ethnic political exclusion as anticipated with a p value below

.01. The F statistic indicates that the instrument is strong (well above the 10 threshold of instrument relevance) and the Wu-Hausman test for endogeneity suggests that *Ethnic Exclusion Size* is indeed an endogenous variable. The Anderson-Rubin confidence interval provides further evidence that the instrumental variable analysis is a robust approach.

Robustness Tests

I test the robustness of my results using a variety of different model specifications. To ensure that the results are not dependent on a particular measure of ethnic political exclusion, I use three alternative operationalizations for the independent variable. Table A.3.1-A.3.3 display the OLS estimates for a dummy variable of ethnic exclusion (whether the country in a given year politically excludes any ethnic groups), the size of the largest excluded ethnic group, and the total size of discriminated against ethnic groups (the most severe form of political exclusion). The results provide further empirical support for the article's hypothesis, with all three measures having a positive and statistically significant effect on the counter-terrorism human rights violation measure with a p value below .01.

To further exclude the possibility of reverse causality, I time-lag the independent and control variables by one period. Due to the complex relationship between ethnicity, terrorism and human rights, the concern here is that a country's exclusionary policies of ethnic groups is affected by the level of counter-terrorism human rights violations, terrorist attacks, and human rights protections. Table A.4.1 includes a time-lag of the independent variable, Table A.4.2 includes a time-lag of the terrorism and human rights variables, and Table A.4.3 includes a time-lag of all the independent and control variables. The results demonstrate that the effects of ethnic political exclusion on counter-terrorism human rights violations remain robust.

Conclusion

In this article, I examine the effect of ethnic political exclusion on human rights violations perpetrated in the name of countering terrorism using a new global dataset of

counter-terrorism human rights violations from 1999-2016 coded using a supervised machine learning approach. I argue that countries with greater political exclusion of ethnic groups are more likely to violate human rights in the context of counter-terrorism as states are more likely to perceive excluded ethnic groups as threatening because of their mobilization capacity and political/territorial goals and are less likely to face public backlash for framing them as terrorists due to pre-existing negative perceptions of out-groups in society. Framing politically excluded ethnic groups as terrorists can provide political cover to stifle dissent as anti-terrorism laws provide a legality for abuses that can reduce public backlash for violating human rights. Results from the analysis provide robust empirical support for the article's main hypothesis: Higher levels of ethnic political exclusion lead to higher levels of counter-terrorism human rights violations.

This research makes a novel contribution to the study of human rights and counter-terrorism in two major ways. First, this article provides a first account of the causes of counter-terrorism human rights violations using comparative data that differentiates human rights abuses in the name of counter-terrorism from other settings. Most existing studies base their findings on a country's aggregate human rights score or are limited to analyses on a single country. This is problematic as until now, it has been unclear whether prior findings hold using more accurate measures of counter-terrorism human rights abuses and if theories are generalizable across different political, economic, and social settings. Second, this study provides the first systematic evaluation of why some countries use broad definitions of terrorism to suppress political dissent but others do not. By highlighting the role of ethnic political exclusion in counter-terrorism human rights violations, this study contributes to debates on how counter-terrorism justifications can serve as political cover for suppressing political dissent and the effectiveness of violent framing strategies.

This study provides several avenues for future research. First, this new dataset will allow other researchers to test alternative explanations on the determinants of counter-terrorism human rights abuses at the cross-national level—for the first time. For example, researchers may wish to focus on how different terrorist threats (e.g., alternative group

ideologies and group tactics) influence the government’s willingness to violate human rights in the name of countering terrorism. Additionally, studies could examine how protests movements and the competitiveness of elections influence the propensity for violent framing strategies and anti-terrorism laws to be used against opposition groups to prevent challenges against the government. Second, the text from the counter-terrorism sentences extracted from the annual country reports provide an opportunity to examine the determinants of counter-terrorism human rights abuses by violation and victim type. It may be the case that countries reserve more severe types of violations (e.g., extrajudicial killings and torture) for certain victims (e.g., suspected terrorists and criminals) over other types of victims (e.g., political dissidents and journalists).

These results also have important policy implications for human rights advocates and policy makers that seek to prevent governments from violating human rights abuses in the name of counter-terrorism. Namely, they raise the alarm on how the proliferation of anti-terrorism laws during the post-9/11 period may have allowed governments to increase violations toward ethnic groups in order to strengthen their executive power and increase their chances of remaining in office. A re-examination of how democratic institutions can help to prevent governments from abusing human rights in the context of countering terrorism would be an important step.

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Appendix

Human Rights Violations in the Name of Countering Terrorism

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1 Data Collection Instructions

Human Rights and Counterterrorism Data Project

Your task is to code sentences in the excel spreadsheets according to whether or not the sentence contains information on a human rights violation made in the name of counterterrorism. These sentences are extracted from the annual country human rights reports produced by the US State Department, Amnesty International and Human Rights Watch. The end goal of the project is to create a dataset of human rights violations perpetrated by states in the name of counter-terrorism.

Coding Instructions

In the hr.violation column:

- Assign 1 to the sentence if it does contain information on a human rights violation made in the name of counterterrorism. Assign 1 to the sentence regardless of whether or not the human rights violation is being made “in principle” (such as a new counterterrorism law) or “practice” (such as torture).
- Assign 0 to the sentence if it does not contain information on a human rights violation made in the name of counterterrorism.
- Assign 999 to the sentence if you are unsure whether or not the sentence contains information on a human rights violation made in the name of counterterrorism. Enter a description of why it is unclear in the notes column.
- Assign 666 to the sentence if you need more information to classify the sentence. We will then go back into the dataset and find the sentence before and after. This should help us correctly classify the sentence as a 1 or 0.

Definitions of concepts being measured

Human Rights: “Human rights are universal values and legal guarantees that protect individuals and groups against actions and omissions primarily by State agents that interfere with fundamental freedoms, entitlements and human dignity. The full spectrum of human rights involves respect for, and protection and fulfilment of, civil, cultural, economic, political and social rights, as well as the right to development. Human rights are universal—in other words, they belong inherently to all human beings—and are interdependent and indivisible” (Office of the United Nations High Commissioner for Human Rights 2008).

Counterterrorism: “Measures designed to combat or prevent terrorism” (Merriam-Webster). “States must ensure that any measures taken to counter terrorism comply with all their obligations under international law, in particular international human rights, refugee, and international humanitarian law” (United Nations Security Council 2003).

2 Summary Statistics for the Independent and Control Variables

Table A.2.1 Summary Statistics, Independent and Control Variables

Variable	N	Mean	S.D.	Min	Max
Ethnic exclusion size	3094	0.13	0.18	0	0.86
Democracy	3040	0.52	0.27	0.02	0.93
Terrorist attacks (log)	3094	1.09	1.63	0	8.28
Civil conflict (log)	3094	0.68	1.89	0	11.18
Human rights	3094	0.52	1.46	-2.56	5.34
Population (log)	3076	16	1.65	12.38	21.05
GDP per capita (log)	3040	8.39	1.47	5.54	11.63
Right orientation	3094	0.19	0.39	0	1

3 Regression Results with Alternative Measures of Ethnic Exclusion

Table A.3.1 Ethnic Exclusion Dummy Variable, Ordinary Least-Squares Regression, Counter-terrorism Human Rights Violations

Variables	Independent Variable	Independent and Control Variables
	(1)	(2)
Ethnic exclusion dummy	0.215*** (0.026)	0.073*** (0.027)
Democracy		-0.471*** (0.059)
Terrorist attacks (log)		0.084*** (0.009)
Civil conflict (log)		0.002 (0.007)
Human rights		0.005 (0.015)
Population (log)		0.072*** (0.009)
GDP per capita (log)		0.096*** (0.011)
Right orientation		-0.015 (0.031)
Constant	-0.147*** (0.021)	-1.842*** (0.149)
Observations	3,094	2,986
R ²	0.022	0.156
Adjusted R ²	0.022	0.153
Residual Std. Error	0.651 (df = 3092)	0.607 (df = 2977)
F Statistic	71.067*** (df = 1; 3092)	68.579*** (df = 8; 2977)

Note: Significance codes *p<0.1; **p<0.05; ***p<0.01 with Standard Errors in parentheses

Table A.3.2 Size of Largest Excluded Ethnic Group, Ordinary Least-Squares Regression, Counter-terrorism Human Rights Violations

Variables	Independent Variable	Independent and Control Variables
	(1)	(2)
Ethnic exclusion size largest group	0.321*** (0.084)	0.215*** (0.082)
Democracy		-0.454*** (0.059)
Terrorist attacks (log)		0.085*** (0.009)
Civil conflict (log)		0.0003 (0.007)
Human rights		0.001 (0.015)
Population (log)		0.077*** (0.009)
GDP per capita (log)		0.099*** (0.011)
Right orientation		-0.017 (0.031)
Constant	-0.027* (0.014)	-1.925*** (0.150)
Observations	3,094	2,986
R ²	0.005	0.155
Adjusted R ²	0.004	0.153
Residual Std. Error	0.657 (df = 3092)	0.607 (df = 2977)
F Statistic	14.592*** (df = 1; 3092)	68.474*** (df = 8; 2977)

Note: Significance codes *p<0.1; **p<0.05; ***p<0.01 with Standard Errors in parentheses

Table A.3.3 Size of Discriminated Against Ethnic Groups, Ordinary Least-Squares Regression, Counter-terrorism Human Rights Violations

Variables	Independent Variable	Independent and Control Variables
	(1)	(2)
Ethnic discrimination size	1.145*** (0.149)	0.670*** (0.154)
Democracy		-0.415*** (0.060)
Terrorist attacks (log)		0.084*** (0.009)
Civil conflict (log)		0.0001 (0.007)
Human rights		0.007 (0.015)
Population (log)		0.079*** (0.009)
GDP per capita (log)		0.089*** (0.011)
Right orientation		-0.019 (0.031)
Constant	-0.026** (0.012)	-1.896*** (0.148)
Observations	3,094	2,986
R ²	0.019	0.159
Adjusted R ²	0.018	0.157
Residual Std. Error	0.653 (df = 3092)	0.606 (df = 2977)
F Statistic	58.722*** (df = 1; 3092)	70.256*** (df = 8; 2977)

Note: Significance codes *p<0.1; **p<0.05; ***p<0.01 with Standard Errors in parentheses

4 Regression Results with Lagged Variables

Table A.4.1 Time Lagged Independent Variable, Ordinary Least-Squares Regression, Counter-terrorism Human Rights Violations

Variables	Independent Variable	Independent and Control Variables
	(1)	(2)
Ethnic exclusion size (t-1)	0.299*** (0.067)	0.152** (0.066)
Democracy		-0.476*** (0.061)
Terrorist attacks (log)		0.083*** (0.010)
Civil conflict (log)		-0.001 (0.008)
Human rights		-0.00001 (0.016)
Population (log)		0.080*** (0.009)
GDP per capita (log)		0.107*** (0.011)
Right orientation		-0.029 (0.032)
Constant	-0.028* (0.015)	-2.010*** (0.154)
Observations	2,920	2,818
R ²	0.007	0.163
Adjusted R ²	0.007	0.161
Residual Std. Error	0.656 (df = 2918)	0.604 (df = 2809)
F Statistic	20.164*** (df = 1; 2918)	68.382*** (df = 8; 2809)

Note: Significance codes *p<0.1; **p<0.05; ***p<0.01 with Standard Errors in parentheses

Table A.4.2 Time Lagged Terrorism and Human Rights Variables, Ordinary Least-Squares Regression, Counter-terrorism Human Rights Violations

Variables	Independent Variable (1)	Independent and Control Variables (2)
Ethnic exclusion size	0.288*** (0.065)	0.137** (0.067)
Democracy		-0.493*** (0.060)
Terrorist attacks (log) (t-1)		0.089*** (0.010)
Civil conflict (log)		0.0002 (0.008)
Human rights (t-1)		0.005 (0.016)
Population (log)		0.080*** (0.009)
GDP per capita (log)		0.104*** (0.011)
Right orientation		-0.026 (0.032)
Constant	-0.035** (0.015)	-1.992*** (0.153)
Observations	3,094	2,818
R ²	0.006	0.165
Adjusted R ²	0.006	0.162
Residual Std. Error	0.657 (df = 3092)	0.603 (df = 2809)
F Statistic	19.643*** (df = 1; 3092)	69.289*** (df = 8; 2809)

Note: Significance codes *p<0.1; **p<0.05; ***p<0.01 with Standard Errors in parentheses

Table A.4.3 Time Lagged Independent and Control Variables, Ordinary Least-Squares Regression, Counter-terrorism Human Rights Violations

Variables	Independent Variable (1)	Independent and Control Variables (2)
Ethnic exclusion size (t-1)	0.299*** (0.067)	0.153** (0.066)
Democracy (t-1)		-0.495*** (0.061)
Terrorist attacks (log) (t-1)		0.091*** (0.010)
Civil conflict (log) (t-1)		-0.004 (0.008)
Human rights (t-1)		0.005 (0.016)
Population (log) (t-1)		0.080*** (0.009)
GDP per capita (log) (t-1)		0.103*** (0.011)
Right orientation (t-1)		-0.004 (0.032)
Constant	-0.028* (0.015)	-1.984*** (0.153)
Observations	2,920	2,818
R ²	0.007	0.164
Adjusted R ²	0.007	0.161
Residual Std. Error	0.656 (df = 2918)	0.603 (df = 2809)
F Statistic	20.164*** (df = 1; 2918)	68.777*** (df = 8; 2809)

Note: Significance codes *p<0.1; **p<0.05; ***p<0.01 with Standard Errors in parentheses

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