Terrorism and Political Violence

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Predicting Novel Terrorism: Media Coverage as Early-Warning System of Novelty in Terror Attacks

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ABSTRACT

In this article, we argue that the process of predicting terrorist attacks needs to integrate the evolving dynamic of terrorism and we make a case for novelty as crucial feature to encompass terrorism's changing nature. To predict when and how terrorist organizations will conduct their next attack, and whether it will have a novel approach, we base our analysis on media coverage. As media continuously covers political, economic, and societal analyses on a national and international scale, it provides rich information that can fuel early-warning systems for terror attacks. We analyze the content of 2,173,544 newspaper articles, reporting on 42,252 terror attacks by 1,121 organizations. Our analyses show that content of media coverage relates to the interval until the following attack from the same terror organization as well as whether they will conduct a novel and even more devastating terror attack. Hence, our approach and findings can contribute to building early-warning systems.

KEYWORDS

Media attention; terrorism; novel terror attacks; early warning

Introduction

Terrorists are often considered to be conservative in character and aversive to novelty and new techniques.[1] However, this stands in stark contrast to the changing and transformative nature of terrorism. Since the advent of what has been labelled "international terrorism" in the early 1970s, and despite the never-ending debate on how to define the phenomenon,[2] terrorism has been dynamic and evolving. From hijacking planes and placing bombs in warehouses to advancing its 'digital innovation'[3] and using improvised explosive devices (IED) or individuals as suicide attackers, terrorism has continuously introduced novel ways to foster its aims and wreak havoc on societies. These evolving dynamics made terrorism one of the main contemporary global threats to societies as terrorism is not only changing and transforming itself but also those it targets, the effects of the Global War on Terror (GWOT) being a case in point.

In order to get a clear analytical and quantifiable grasp of the societal impact of terrorism's transformative potential, we develop and operationalize the concept of terrorism novelty. For that purpose, we integrate the literature on terrorism innovation and creativity with the seminal notion of novelty from Schumpeter (1939),[4] and we define terrorism novelty as a new (re-)combination of tangible and intangible resources in terror attacks. Hence, our focus is not on the limited perspective of new types of resources (e.g. new types of weapons that have never been used before), but on new applications of (combinations of) particular resources in a particular place. Concretely, novelty in terror attacks is quantified in our analysis

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by detecting the first possible recombination—over more than three decades—of four vital aspects of terror attacks: (1) the weapon used, (2) the type of attack, (3) the target type, and (4) the country where the attack happened. This is further elaborated in our literature and method sections.

This focus on quantifying novelty is in particular relevant from the standpoint of counter-terrorism. First, we argue that novel attacks are not only more impactful in a direct way in terms of damage and human victims (which we show in the first part of our analysis) but they are also more impactful in how security is maintained and safeguarded in local contexts, for example by governments and their administrations in a particular region or country. In other words, while existing countermeasures might be appropriate for dealing with known and expected terror approaches, novelty might be applied by terror organizations in particular to circumvent these existing measures and/or because of shortcomings in these existing measures.[5] As a result, terrorism novelty shows potential weak spots in existing counterterrorism systems, which in turn can negatively influence public trust in countermeasure systems, as well as in the governments responsible for them. In the second part of our analysis, we explore these dynamics by documenting different types of media coverage following novel terror attacks, compared to non-novel terror attacks.

Second, the novelty of terrorism, fueled by its transformative potential, has presented counter-terrorism analysts and policymakers with many difficulties. These hurdles stand out in particular when it comes to predicting such novel attacks. While forecasting in terrorism has been notoriously difficult above all due to the clandestine and secretive character of the phenomenon,[6] novel attacks make it particularly hard to pinpoint the trajectory, predict where and when terrorists will strike, and to protect from and immediately deal with the ramifications of novel attacks.[7] "We know that groups that innovate have the potential to be more dangerous and thus more difficult to counter"[8] (Singh 2017, 626). Hence, reliable and accurate predictions of novel terrorist attacks are key for policymakers to develop effective preventive measures—even more so because "[p]olicy is about prediction since the effect of policy is always in the future."[9] Against this background, the third part of our analysis focusses on testing whether terror attacks can be predicted, including novel terror attacks, based on media coverage about known terror organizations.

Hence, while terrorist attacks have devastating effects on societies, we argue novel terrorism is particularly distressing and potentially destabilizing. For one, preparedness to novel terrorist attacks is near to impossible to achieve; second, due to the novelty of an act, there is no immediate answer to how to react and recover from it; and, third, novelty in terrorism most pertinently exposes the weak and vulnerable spots in current counter-terrorism and prevention measures. In light of this, our aim is to predict novel terrorism by gauging the potential of media coverage. We scrutinize the impact of novel terror attacks, with the first part of our analysis focusing on the immediate impact, i.e. on the casualties, and in the second part on the broader impact on society, approximated in the way newspapers report on these novel attacks and their casualties. The third part of our analysis tackles the crucial problem of novelty by aiming at predicting novel attacks, i.e., testing how preceding media coverage can function as an early-warning systems for subsequent terror attacks. This objective is achieved with leading variables from earlier media coverage that can help to address all three of the above in our argument: to prepare, to recover, and to identify weak and/or vulnerable aspects of counter-terrorism and prevention measures.

Concretely, we have identified media coverage as a quantifiable setting for predicting novel terrorism, given (1) the 24/7 news cycle, (2) high online and international access, and (3) the broadness of its content with respect to political, societal, and economic analyses.[10] Concretely, we focus on media coverage about known terror organization, and we quantify media coverage about these terror organizations in two ways. First, we use the number of newspaper articles following earlier attacks from these organizations as a measure for the amount of media coverage. Second, we use metrics that quantify the content in those newspaper articles. Concretely, we use the approach of Linguistic Inquiry and Word Count (LIWC),[11] which quantifies the relative use of different types of language components. These quantified measures are then in turn used, along with other metrics on the amount of media coverage, to predict (novel) terror attacks. In the context of this article, we focused on three major language dimensions of media content: (1) affective language, (2) cognitive process (reasoning), and (3) drivers. This is further explained in our method section.

Despite the fact that there is probably no or only a very limited causal association between media coverage on specific terror organizations and future terror attacks from those organizations, the coverage does contain analytic descriptions that summarize key elements about the terror organizations, their political goals and impact, the context in which they operate, and how other actors inter- and counteract with them.[12] In other words, media coverage does not or only to a limited extent provide a detailed insight into the concrete causal factors and decision processes of terrorists that lead to the actual planning and execution of (novel) terror attacks. Nevertheless, it provides an alternative source of information that is much more accessible and less risky to obtain, while at the same time it might still be supportive to increase precision for predicting (novel) terror attacks. Therefore, the descriptions from various world-view perspectives and with different purposes are a rich and accessible source of information that can assist in the prediction of future, novel terror attacks.[13] Media coverage has various characteristics of a wisdom-of-the-crowd system where singled-out individual opinions might not be good predictors for future events, but various aggregated and balanced measures of these opinions can be highly valuable in assessing the likelihood of future events.[14] Specifically, media coverage includes descriptions of (other) relevant (counter-)actors, comparisons with other events and organizations, clarifications about dependencies on other factors, and prospects about future risks and consequences.

Concretely, we study the association between media coverage and novel terror attacks using the LexisNexis database and Global Terrorism Database (GTD).[15] The GTD proves particularly apt for our purposes as it is one of the main sources for media-generated terrorism databases. We use the GTD as the best available open-access means to ascertain the extent to which the content analysis of media coverage on terror organizations helps to predict when and how these organizations will conduct their next attack. In this respect, we aim to further the ongoing discussion on how the GTD offers a viable source for research on early-warning systems and novelty in terrorism. Studies using the GTD for prediction are not numerous, with the edited volume by LaFree, Dugan, and Miller (2015; in particular Chapter 9 on tactical innovation)[16] being a notable exception. As such, we equally intend to fuel the debate on novelty and prediction using quantitative predictive modeling, which still remains scarce in the field of terrorism research.[17]

Related literature

Predicting political violence, and terrorism in particular

Although, predictions of political violence made great progress in general in recent years, there is still much scope for improvement.[18] In particular, when it comes to forecasting terrorism—as a type of political violence—those predictors with the highest explanatory power for political violence in general are mostly structural variables such as infant mortality or mountain terrain. These are predictors that, if at all, change very slowly. Yet, in light of the dynamic character of terrorism, operational short-term indicators are critical for momentary hazard mitigation, with predicting the timing of violence next to the location of occurrence being critical.[19]

Recently, methodological and statistical advancements have made their way into the study of terrorism and in the area of early-warning systems for terrorism in particular[20] (and for an overview on the period from 2000 to 2012, see Bakker 2012).[21] For example, there is a burgeoning interest in the prediction of terrorist attacks with the help of various methodological options.[22] Concretely, different predictive models have been informed by theories of terrorism research and, for instance, aimed at (1) predicting the future lethality of terrorist groups by focusing on their emerging period,[23] at (2) forecasting annual, national counts of terror attacks,[24] at (3) predicting terrorist acts at a fine temporal[25] and/or spatial scale,[26] while (4) for instance using deep neural networks to gauge future acts of terrorism.[27]

Within this literature on predicting political violence, we follow a recent avenue in which forecasting is done by establishing large databases that rely on news resources.[28] Media coverage is considered a very appropriate database because it provides fast reporting of events, and for forecasting models, it allows more timely predictions.[29] Examples of these event databases generated via media texts and with the help of automated algorithms and coding rules are, for example, the Conflict and Mediation Event Observations (CAMEO) event-coding database, the Global Data on Events, Location, and Tone (GDELT) or the Integrated Conflict Early Warning System (ICEWS). CAMEO identify events and the involved parties in conflict events based on glossaries of verbs, which Brandt, Freeman, and Schrodt[30] use to propose a framework for predicting violence based on actors and actions via dictionaries to investigate the conflict between the Israelis and Palestinians. Finally, Ward et al.[31] use the ICEWS event database to show the utility of creating forecasting models with a high degree of accuracy in predicting civil wars. All in all, this research often offers a better predicting power than models using only structural, and stable indicators. Therefore, and despite the skepticism against news as a data source, using media coverage is argued to be much more beneficial with respect to the timing of political violence.[32]

However, in this literature, media coverage is above all used for predicting special forms of political violence, such as domestic and international conflicts. Fewer studies turn to forecasting terrorism; yet, similar to the political violence research in general, more often than not, they rely on predicting terrorism with the help of structural and procedural variables instead of making full use of news reporting for predicting terrorism events.[33] So far, research in this context investigates mainly how media coverage in general invokes further terrorism attacks. For example, Jetter[34] analyzed and interpret the causal connection between media coverage and subsequent terror attacks on the country level. In a follow-up study, Jetter[35] investigated how suicide attacks draw more media attention than non-suicide terrorist attacks, Beckmann, Dewenter, and Thomas,[36] as another example, investigate how TV news broadcasts influence terrorism events and demonstrate that a higher number of terrorist incidents influence overall media coverage. In turn, they argue with their empirical analysis that a higher media coverage of terrorism causes a growth in terrorism incidents, as well as in the losses of life due to terror attacks in the third to the tenth month after a broadcast.

In sum, media coverage is a relevant source that can serve as an accessible basis to build and complement early-warning systems for (novel) terror attacks. Thus, there is not necessarily a causal relationship between media coverage and the future actions of terrorists. However, due to the accessibility, permanent availability, and analytic purpose of media coverage of terror organizations and their potential strategies, it provides a valuable alternative for the much more expensive, cumbersome, and risky data gathering and analysis of actual terror organization mechanisms. In particular because terror organizations operate clandestinely, relevant information is seldom available, very expensive, and/or risky to obtain.

Terrorism novelty, innovation, and creativity

For the context of this study, we define novelty, based on a Schumpeterian approach,[37] as the (re-) combination of (often known) tangible and intangible resources in a way not used before. While this concept is closely related to creativity and innovation, it also has some distinct features. While innovation, and to some extent also creativity, focusses on the identification—or even development —of new types of resources (e.g. new tactics or weapons that have never been used before), novelty can be understood as a concept that is broader, because it also includes instances of known or non-innovative resources, but these resources are applied (and mainly combined) in a new and unseen way. A well-known example to illustrate our operationalization of a novel terror attack, is the 9/11 attack on the World Trade Center in New York, U.S. In this attack, terrorists used a hijacked plane (Weapon type is “Vehicle (not to include vehicle-borne explosives, i.e. car or truck bombs)”; type of attack is “Hijacking”) to attack private citizens and property (Target type 1 is “Private Citizens & Property”; Target type 2 is “Business”). Each of these types were in themselves not new in the U.S. nor globally, but this particular combination was unseen and disruptive in the U.S., resulting in unforeseen countermeasures in the U.S., and eventually internationally too.[38]

From a theoretical standpoint, novelty is thus not only about the type of resources themselves but about combinations that have a disruptive effect in the concrete context where these recombined resources are applied. Therefore, novelty can range from an international perspective on the recombination of resources and practices, in turn having a global impact,[39] to first-time recombinations in a particular country or region, referred to as regional novelty.[40] For example, Uzzi et al.[41] use from an international perspective the recombination of knowledge, in terms of journal references of scientific articles, in order to document novelty in global research streams. In contrast, local and country-specific eco-systems are changed as a result of novel recombinations of resources for a given region in a given year.[42] For example, terrorist history has shown that some groups "built upon existing weapons and tactics, modifying them to such an extent that most dispassionate observers would apply the label of novelty."[43] Novelty, therefore, is inherently recombinant and recursive. As a result, for the context of terror attacks, the regional approach is in particular relevant, as attacks and countermeasures against those attacks are (most often) associated with local political, economic, or socio-cultural dynamics and conflicts.[44] In addition, countermeasures and the need for terrorism predictions are also largely the responsibility of national governments.[45]

Hence, with a novelty approach, our study builds on and expands seminal studies that have focused on terrorist innovation, and on potential reasons for terrorists to innovate.[46] For instance, Crenshaw's remarks on strategic innovations as "significant points of novelty"[47] for groups in that they "change the fundamental pattern of terrorist challenges to political authority."[48] Similarly, Dolnik's definition of innovation relates to the notion that novelty contains unseen elements: "the adoption of a tactic or technology that the *given organization* has not used or considered using in the past. This can take the form of the introduction of a weapon or tactic that is entirely new, or that has already been used by other organizations in the past."[49] Logan and colleagues consider novelty to be one of the three dimensions of innovation (the other two being relevance and elegance) and argue that novel attacks are characterized by their "high degree planning and used weapons or attack methods that were unique at the time of the incident."[50] They find that "novelty is largely related to weapon characteristics, and that novel attacks had more to do with how the attack was carried out as opposed to who was targeted. Attacks rated high in novelty were more likely to use explosives compared to other weapons for two reasons: most explosives require expertise and coordination to construct and successfully deploy (...)."[51]

In sum, novelty is a strongly related concept to innovation in general, in particular from the perspective of counterterrorism. This is also summarized in Logan et al.'s policy implications: "counter-terrorism efforts might allocate more resources to VEOs [violent extremist organizations, authors remark] whose attacks score higher on tactical innovation—especially the novelty (...) dimension."[52]

Data

We matched data on terror attacks from the GTD with newspaper articles from LexisNexis, consisting of 93,110 terror attacks from 2005 to 2016, of which 42,252 had a known perpetrator (terror organization). Of 1,121 organizations, 464 conducted one attack only. The mean amount of attacks per organization is 37.69, with a maximum of 6,490 and a skewness of 16.36. Based on identified perpetrators' names, 1,121 such terror organizations were listed. Nine additional organizations were mere variations of other names, and thus were manually merged; for instance, the Taliban and Taliban (Pakistan) were detected. Searching these terror organizations' names in the LexisNexis database for 2005 to 2017. This was done in combination with a list of terror-associated terms. Selection words were (not case-sensitive) as follows: terror, attack, violence, violent, bandit, rebel, criminal, fighter, subversive, extremist, revolution, threat, fear, bomb, war, killing, explosives, suicide, fire, sniper, radicalized, assassination, armed, assault, bombing, explosion, kidnapping, shooting, and strike. In doing so, 2,173,544 English-language newspaper articles were identified and used for the analyses. Figure 1 shows the yearly distribution of the newspaper articles and the novel terror attacks, with a distinction made between attacks by known and

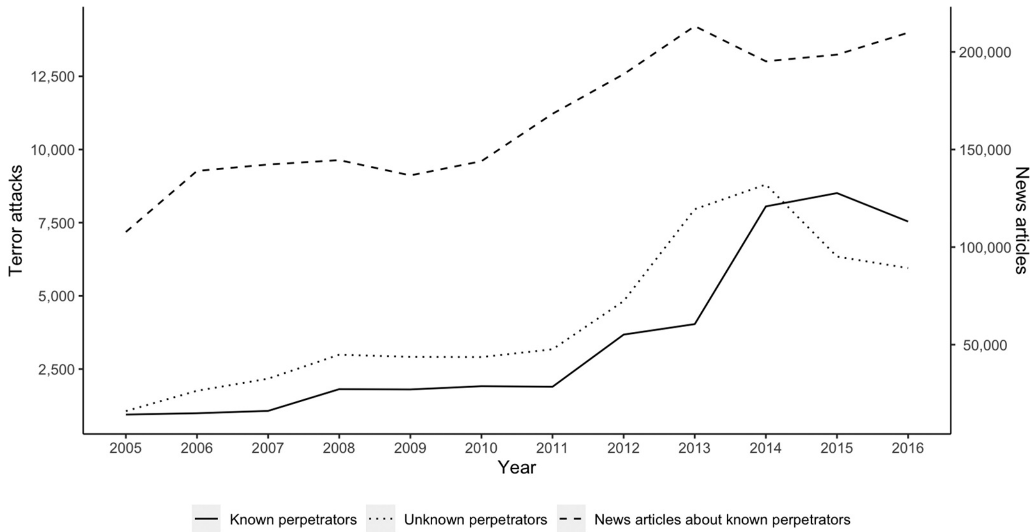

Figure 1. Overview of terror attacks and newspaper articles.

unknown perpetrators. Overall, an increase in terror attacks (from known and unknown perpetrators) as well as newspaper articles about known perpetrators is observed.

Novelty in terror attacks is quantified by detecting the first possible recombination of four vital aspects of terror attacks: (1) the weapon used, (2) the type of attack, (3) the target type, and (4) the country where the attack happened. Hence, an attack was considered as novel for the period analyzed in our study (2005–2016) if a similar combination had not been documented before that attack between 1970 and 2016. In other words, this variable was built considering all previous terror attacks (starting in 1970), meaning that an attack was considered novel when the exact same combination did not take place from 1970 until the attack. Against this background, we acknowledge that a combination that we classify as "novel" could have been used in a terror attack even before 1970. However, one could argue that because of the many societal, political, and/or economic changes over a timespan of at least 35 years, such an attack is still likely to be seen as "uncommon," and decision makers and/or governance systems in a particular country have thus no concrete experience with that particular type of attack. Therefore, country is also an important element of operationalizing concrete instances of novelty, in particular from a counterterrorism perspective. While counterterrorism strategies hugely benefit from international collaboration and coordination, novel terror attacks disturb local societies and need countermeasures that are mainly situated at national levels (e.g. national police or military organizations). Within the time span of this study (2005–2016), 3,111 of the 93,110 attacks were novel.

Figure 2 demonstrates the yearly distribution of novel terror attacks with regard to size of the perpetrator organizations. For this figure, we made a distinction between organizations based on their size, defined in terms of the number of attributed attacks. Due to the large range of attacks per organization, we have set a cutoff for two attacks and for 1000 attacks per organization, to categorize small, medium, and large terror organizations. The overall trend—with a steep increase in novel attacks since 2013—is mainly the result of novel approaches applied by medium and large terror organizations. This supports our approach to analyze terror novelty and predict future terror attacks with a focus on the organizational level.

Method and results

The analysis in this study contains three main parts: (1) characteristics of novel terror attacks, (2) media coverage following novel terror attacks and (3) early-warning signals of (novel) terror attacks.

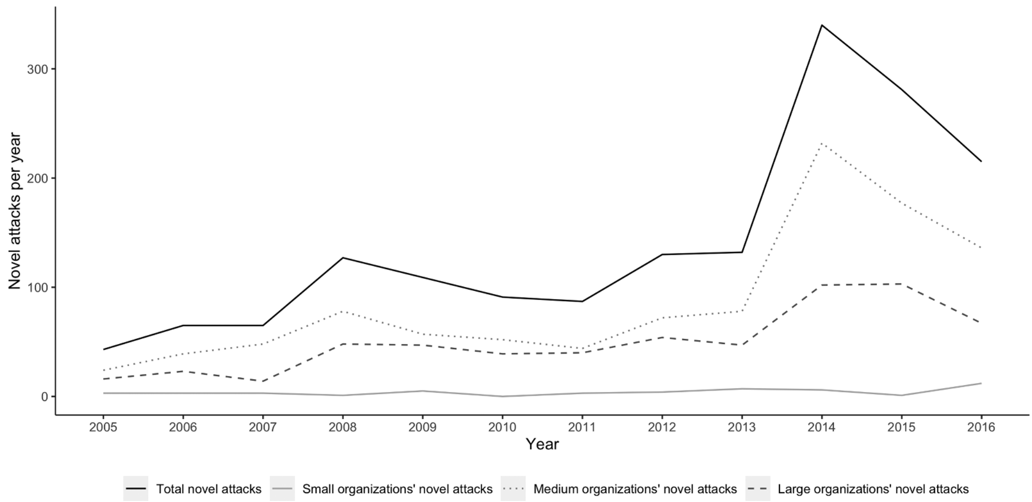

Figure 2. Novel terror attacks according to organization size.

For readability, we discuss in three separate subsections the method as well as the concrete results of each empirical part in these three respective steps. To further improve the readability, we provide a structured overview of the regressions (including the model number, the dependent variable, the model type, the independent variable, and the controls) in Table A1 (Online appendix).

Characteristics of novel terror attacks

In this part, we test the impact of novel terror attacks on attack *success, kills*, and *wounded*, compared to non-novel attacks, using data on all terror attacks from the GTD with known perpetrators from 2005 to 2016. Descriptive statistics and correlations for this first set of regressions are stated in Table 1. Success, reported as a dichotomous variable in the GTD database, was predicted with a logit regression. Kills and the wounded are count variables. Following previous research,[53] an overdispersion test led us to use a negative binomial regression. All model specifications include dummies for the region where an attack took place, the year, the attack type, and the target type. Hence, the first part of our analysis focuses on documenting the direct and particularly devastating effects of novel terror attacks.

Table 2 shows that novel terror attacks are, on average, more impactful with respect to those killed (incidence rate ratio = 1.55; $p = .004$) and wounded victims (incidence rate ratio = 1.78; $p < .001$). This means that novel terror attacks involve—all else being equal—an average of 55 percent more kills and 78 percent more wounded compared to non-novel attacks. An attack's success, however—which is operationalized as a direct measure from the GTD—was not found to be significantly affected by the novel nature of a terror attack.

Several tests were conducted to challenge the robustness of our analyses. First, we included all terror attacks from 2005 to 2016, even adding those where no terror organization could be identified (Results reported in the Online appendix, Table A2). The effects were in the same direction and significant. Novel terror attacks have killed (incidence rate ratio = 1.45; $p = .002$) and wounded (incidence rate

Table 1. Descriptive statistics for the first set of analysis

	Variable	Mean	S.D.	1	2	3
1	Success	0.90	0.30			
2	Kills	3.69	14.47	0.06		
3	Wounded	4.26	18.99	0.06	0.47	
4	Novel terror attacks	0.04	0.20	0.02	0.00	0.00

Table 2. Novel terror attacks' impact on success, kills and wounded (known perpetrators, 2005–2016)

Model type		Logit			Negative binomial			Negative binomial	
Dependent variable		*Success*			*Kills*			*Wounded*	
Model		*1.1*			*1.2*			*1.3*	
Predictors	*Odds Ratios*	*Conf. Int (95 percent)*	*P-value*	*Incidence Rate Ratios*	*Conf. Int (95 percent)*	*P-value*	*Incidence Rate Ratios*	*Conf. Int (95 percent)*	*P-value*
Intercept	2.06	0.81–5.24	.129	1.13	0.36–3.55	.837	8.17	2.39–27.92	**.001**
Novel terror attack	1.00	0.74–1.36	.986	1.55	1.15–2.07	**.004**	1.78	1.30–2.46	**< .001**
Included dummies:									
Region (12)		YES			YES			YES	
Year (12)		YES			YES			YES	
Attack type (9)		YES			YES			YES	
Target type (22)		YES			YES			YES	
Observations		42,252			39,812			37,636	
Tjur's R^2		0.158			0.269			0.255	

Two-tailed tests with clustered standard errors on the organization level. Only attacks with a known perpetrator from 2005 to 2016 are included, with an overall inclusion of 1,685 novel terror attacks. All model specifications include control variables for region, attack type, and target type (Jetter 2017).

ratio = 1.90; p < .001) more people than non-novel terror attacks. We further took all attacks from 1970 to 2016 with known perpetrators into account (Online appendix, Table A3). Again, we found that the impact of novel terror was stronger in terms of those killed (incidence rate ratio = 1.50; p < .001) and wounded (2.04; p < .001). Additionally, the results from Table 2 are replicated using alternative novelty specifications (Online appendix, Table A4), first using novel combinations of weapon type, target type and country, and then by attack type, target type, and country. Again, the results show the same significant direction and were robust, regardless of the different variables and model specifications.

Media coverage and novel terror attacks

The second part of our analysis elaborates on media coverage following novel terror attacks. In line with our argumentation above, we again used a negative binomial regression model, controlling for the region and the year an attack occurred. Further, we included variables considering prior years' news coverage of the focal organization as well as attack attributes: success, kills, wounded, and whether the attack was part of multiple attacks. The second part of our analysis thus focuses on documenting the broader societal effects—as reported in newspapers—of novel terror attacks.

The descriptive statistics and correlations are reported in Table 3 and the results are given in Table 4. Novel terror attacks receive significantly more media coverage, but this significant difference is only visible 5 days after the attack and later. Across several periods (5, 7, 10, 30, and 90 days), the significant incidence rate ratios are close to each other and range from 1.29 to 1.43. Thus, novel terror attacks receive, on average, 36 percent more media coverage and over a longer period as compared to regular terror attacks. The control variables show that the media coverage in the prior year as well as the number of wounded positively influence the media coverage of terror attacks (for all timespans).

Early warning signals of (novel) terror attacks

The third part of our analysis investigates the role of media coverage and its content as an early-warning system of (novel) terror attacks in the future. Taking the longitudinal nature of the data into account, we look at media coverage in terms of volume and content after every attack by a terror

Table 3. Descriptive statistics and correlations for the second set of regressions (known perpetrators, 2005–2016)

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12
Media coverage–day of attack	1.84	7.26												
Media coverage–3 days after attack	6.36	20.26	0.75											
Media coverage–5 days after attack	10.24	30.78	0.69	0.95										
Media coverage–7 days after attack	13.80	40.39	0.65	0.90	0.97									
Media coverage–10 days after attack	18.95	53.20	0.62	0.86	0.93	0.97								
Media coverage–30 days after attack	51.41	126.51	0.55	0.72	0.78	0.82	0.87							
Media coverage–90 days after attack	144.07	320.28	0.48	0.61	0.66	0.69	0.74	0.89						
Novel terror attack	0.04	0.20	0.01	0.01	0.01	0.01	0.02	0.01	0.01					
Prior year media coverage	581.70	1067.51	0.36	0.43	0.46	0.48	0.51	0.60	0.66	0.00				
Success	0.90	0.30	0.01	0.02	0.02	0.02	0.02	0.01	0.01	0.02	0.01			
Kills	3.69	14.47	−0.01	0.01	0.01	0.01	0.00	−0.01	−0.02	0.00	−0.02	0.06		
Wounded	4.26	18.99	0.00	0.03	0.03	0.03	0.02	0.01	0.00	0.00	−0.01	0.06	0.47	
Multiple attacks	0.22	0.42	0.03	0.06	0.06	0.06	0.05	0.03	0.02	−0.03	0.01	0.01	0.00	0.03

organization. We based our predictions on two different media dimensions. First, we analyzed the potential effects of media coverage (measured as the amount of related newspaper articles), and second, we analyzed different content-dimensions of media coverage of terror attacks. We, therefore, made use of one of the most widespread text analysis tools available, Linguistic Inquiry and Word Count (LIWC)[54]. Here, we focused on three major dimensions, tapping psychological constructs that can enable predicting (novel) terror attacks based on media content: (1) affective language, (2) cognitive process (reasoning), and (3) drivers. Affective language—as the first content dimension—covers both pleasant and unpleasant connotations (e.g., happy, ugly, bitter).[55] The second content dimension is language associated with cognitive processes, which includes language that focuses on reasoning-related causality, dependency, differentiation, and certainty. This dimension has, for example, been identified as an important component and mechanism in expressive writing.[56] Drivers—as the third content dimension—focus on the concrete elements in a discourse (e.g., ally, danger, success, and benefit). This overarching dimension is further broken down, capturing elements like needs, motives, affiliation, achievement, power, reward, and risk.[57] Subsequently, these dimensions were quantified with a score between 0 and 100, according to the percentage of a text that corresponds to each dimension (e.g., cognitive language ranges in our database from 0 to 14.89).

In a two-step procedure,[58] we first predict (1) the probability of a future attack from a terror organization. In the second step, we further break down the dependent variable to predict (2) the days until the next attack from that organization and (3) the likelihood of a novel attack in the future from that terror organization.

This two-step procedure helps to first assess the likeliness of a future attack based on the media coverage that follows in the days after a focal attack. Additionally, we can predict whether that future attack will be novel, as well as the days until that next attack. Moreover, this procedure is also instrumental in overcoming a potential sample selection bias, because the decision to conduct a future attack is unlikely to be random, with several selection and self-selection processes at work.[59] Thus, our first step in this analysis—predicting a dichotomous variable indicating if the focal attack will be followed by another attack by the same terror organization—accomplishes two roles. First, it estimates the probability of a follow-up attack, based on measures of media coverage. Second, it is the first-step regression of the two-step Heckman selection estimation. This regression was conducted using a probit regression, while the region and year in which an attack was carried out

Table 4. Regression results of novel terror attacks' media coverage (known perpetrators, 2005–2016)

Dependent variable: Media coverage in X days after attack	Day of attack		3 days after attack		5 days after attack		7 days after attack		10 days after attack		30 days after attack		90 days after attack	
Model	*2.1*		*2.2*		*2.3*		*2.4*		*2.5*		*2.6*		*2.7*	
Predictors	*Incidence Rate Ratios*	*p-Value*	*Incidence Rate Ratios*	*P-value*	*Incidence Rate Ratios*	*P-value*	*Incidence Rate Ratios*	*P-value*	*Incidence Rate Ratios*	*P-value*	*Incidence Rate Ratios*	*P-value*	*Incidence Rate Ratios*	*P-value*
	(Conf. Int −95 percent)		*(Conf. Int −95 percent)*		*(Conf. Int −95 percent)*		*(Conf. Int −95 percent)*		*(Conf. Int −95 percent)*		*(Conf. Int −95 percent)*		*(Conf. Int −95 percent)*	
Intercept	0.36 (0.16–0.80)	**.013**	4.59 (1.94–10.90)	**.001**	10.18 (4.19–24.68)	**< .001**	13.67 (5.50–33.97)	**< .001**	18.83 (7.61–46.60)	**< .001**	42.25 (17.44–102.36)	**< .001**	104.77 (42.26–259.75)	**<.001**
Novel terror attack	1.14 (0.83–1.55)	.420	1.29 (0.98–1.70)	.073	1.43 (1.09–1.88)	**.011**	1.43 (1.08–1.90)	**.014**	1.41 (1.06–1.88)	**.018**	1.38 (1.06–1.81)	**.018**	1.29 (1.01–1.64)	**.042**
Prior year media coverage	1.00 (1.00–1.00)	**< .001**	1.00 (1.00–1.00)	**< .001**	1.00 (1.00–1.00)	**< .001**	1.00 (1.00–1.00)	**< .001**	1.00 (1.00–1.00)	**< .001**	1.00 (1.00–1.00)	**< .001**	1.00 (1.00–1.00)	**< .001**
Success	1.17 (0.95–1.44)	.139	1.20 (0.98–1.47)	.080	1.21 (0.98–1.49)	.074	1.22 (0.99–1.51)	.060	1.21 (0.99–1.49)	.068	1.16 (0.95–1.43)	.148	1.18 (0.97–1.43)	.099
Kills	0.99 (0.98–1.00)	.290	1.00 (0.99–1.01)	.953	1.00 (0.99–1.01)	.934	1.00 (0.99–1.01)	.804	1.00 (0.99–1.01)	.599	1.00 (0.99–1.00)	.299	0.99 (0.98–1.00)	.090
Wounded	1.01 (1.00–1.01)	**< .001**	1.01 (1.01–1.01)	**< .001**	1.01 (1.01–1.01)	**< .001**	1.01 (1.01–1.01)	**< .001**	1.01 (1.01–1.01)	**< .001**	1.01 (1.00–1.01)	**< .001**	1.00 (1.00–1.01)	**< .001**
Multiple attacks	1.27 (0.94–1.70)	.115	1.77 (1.25–2.50)	**.001**	1.73 (1.22–2.45)	**.002**	1.67 (1.19–2.33)	**.003**	1.64 (1.20–2.24)	**.002**	1.31 (0.99–1.73)	.059	1.16 (0.88–1.53)	.293
Included dummies:														
Region (12)	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Year (12)	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Observations	37,483		37,483		37,483		37,483		37,483		37,483		37,483	
Nagelkerke's R^2	0.501		0.434		0.421		0.422		0.425		0.422		0.418	

Negative binomial regressions. Two-tailed tests with clustered standard errors on the organization level. Only attacks with known perpetrator from 2005 to 2016 are included. Overall, 1,685 novel terror attacks are included. All model specifications control for (i) media coverage of a terror organization in the prior year, (ii) if the focal attack was a success, (iii) how many killed and wounded, and (iv) if the attack was part of a multiple attack strategy. Additionally, we include in all models dummies for the region and year to control for time trends and regional differences. Clustered standard errors are used to control for heteroscedasticity and serial autocorrelation, treating each terror organization as a cluster.

were controlled. Additionally, we included variables taking an organization's age and the previous year's attacks into account.

The second step used this information by including the inverse Mills ratio from the first step to correct for potential sample selection bias for two different predictions: (i) the days until the next attack from an organization, and (ii) the likelihood of a future attack from a terror organization being novel. All of these variables start counting 3 days after the focal attack to ensure that the next attack is not part of a coordinated multiple attack action by the focal terror organization.[60] These two sets of regressions, in line with all other estimates, use clustered standard errors on the organizational level and further control for news coverage (within 3 days after an attack) and the number of previous attacks by the focal organization (1 year).

Table 5 provides the descriptive statistics and the correlations of the variables used. As expected, the correlation between an organization's amount of attacks and a follow on attack is positive (0.15). Furthermore, these results indicate that with an increasing amount of attacks, the amount of news coverage following attacks will decline (−0.18).

Table 6 displays the results of this first step in the analysis, predicting the chances of the focal organization's next attack. The results show that neither the number of attacks by an organization in the prior year (p = .119) nor the amount of media coverage (p = .211) within 3 days of the focal attack significantly explains the probability of an additional attack by the same organization. This last finding is especially of interest. While previous studies have shown significant correlations for these relationships, for example, by aggregating terror and media data on the country level and/or focusing on a limited set of known organizational characteristics,[61] we do not replicate these findings when analyzing these relationships at the more fine-grained level of terror organizations. Hence, by focusing on the level of terror organizations—which are the actual actors in conducting terror attacks—we can elaborate and adjust our understanding of the factors that can help predict future (novel) terror attacks.

Table 7 reports the descriptive statistics and correlations for the second step of the Heckman selection estimation, predicting the number of days until the next attack (Table 8) and the likelihood that the organization will conduct a novel attack in the future (Table 9). All analyses use the inverse Mills ratio, which is calculated to correct for sample selection bias.

Table 5. Descriptive statistics and correlations for the first regression of the third set of regressions (known perpetrators, 2005–2016)

Variable	Mean	S.D.	1	2	3
Follow on attack (dummy)	0.96	0.19			
News coverage (3 days after attack)	6.36	20.26	0.01		
Organization's amount of attacks (prior year)	337.00	409.30	0.15	−0.18	
Organization's age	16.12	12.76	0.10	0.11	−0.18

Table 6. Regression results of first step of Heckman selection model analyzing predicting factors for novel terror attacks

Dependent variable	Follow on attack (dummy)		
Model	*3.1*		
Predictors	*Risk Ratios*	*Conf. Int −95 percent*	*p-Value*
News coverage (3 days after attack)	1.00	(1.00–1.01)	.211
Organization's amount of attacks (prior year)	1.00	(1.00–1.01)	.119
Organization's age	1.03	(1.02–1.04)	**< .001**
Year dummies (12)	YES		
Region dummies (12)	YES		
Observations	42,252		
Nagelkerke's R^2	0.903		

Probit regressions; two-tailed tests with clustered standard errors on the organization level. Only attacks with known perpetrator from 2005 to 2016 are included, with an overall of 1,685 novel terror attacks. Year and region dummies are included in the analysis to omit region or year specific effects.

Table 7. Descriptive statistics and correlations for second step of Heckman selection model regressions—(known perpetrators, 2005–2016, only observations with a next attack)

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Days to next attack	25.32	129.76																					
Future novel attack (dummy)	0.84	0.37	−0.19																				
Inverse Mills ratio	0.07	0.09	0.14	−0.31																			
News coverage (3 days after attack)	6.40	20.33	−0.02	0.03	−0.18																		
Organization's amount of attacks (prior year)	349.11	411.18	−0.17	0.25	−0.43	0.07																	
Affective language	5.18	1.21	−0.05	0.03	−0.10	0.09	0.06																
Cognitive process	6.53	1.48	−0.03	0.06	−0.07	0.01	0.01	0.18															
Drivers	10.32	1.81	−0.07	0.10	−0.11	0.04	0.08	0.45	0.06														
Anxiety	0.53	0.42	−0.03	0.01	0.06	0.03	0.02	0.30	0.19	0.12													
Anger	2.04	1.04	−0.02	0.01	−0.04	0.07	0.00	0.67	−0.13	0.32	−0.05												
Sadness	0.22	0.18	0.01	0.00	−0.01	0.02	−0.04	0.15	0.09	0.02	−0.01	−0.02											
Insights	1.56	0.62	−0.04	0.13	−0.15	0.01	0.06	0.17	0.52	0.19	0.01	0.11	0.00										
Cause	1.48	0.54	−0.02	−0.02	0.04	−0.02	−0.07	0.11	0.45	0.11	0.08	0.03	0.03	0.02									
Discrepancy	0.56	0.36	−0.02	0.07	−0.07	0.07	0.02	0.09	0.62	0.03	0.19	−0.28	0.10	0.15	0.12								
Tentative	1.26	0.54	−0.01	−0.01	−0.01	−0.01	0.04	0.01	0.62	−0.08	0.15	−0.20	−0.01	0.11	0.03	0.35							
Certainty	0.52	0.31	−0.01	0.03	−0.04	0.05	0.00	0.09	0.57	−0.05	0.17	−0.28	0.11	0.15	0.11	0.52	0.29						
Differentiation	1.69	0.57	0.00	0.01	−0.02	−0.01	0.00	0.08	0.70	−0.08	0.15	−0.13	0.12	0.11	0.09	0.45	0.51	0.36					
Affiliation	1.97	0.74	−0.03	0.07	0.01	0.01	0.06	0.09	0.11	0.43	0.07	−0.04	0.00	0.13	0.00	0.13	0.00	0.14	0.07				
Achievement	1.24	0.54	−0.02	0.05	−0.09	0.01	0.10	0.10	0.24	0.27	0.14	−0.25	0.11	0.09	0.11	0.33	0.10	0.28	0.09	0.16			
Power	6.41	1.52	−0.03	0.06	−0.10	0.03	0.02	0.38	−0.10	0.81	0.00	0.47	0.00	0.16	0.03	−0.17	−0.16	−0.26	−0.18	−0.01	0.01		
Reward	0.59	0.30	−0.05	0.05	−0.07	0.01	0.01	0.01	0.22	0.16	0.05	−0.20	0.06	0.05	0.11	0.27	0.09	0.25	0.12	0.08	0.33	−0.10	
Risk	0.92	0.50	−0.06	0.03	−0.02	0.04	0.10	0.35	0.12	0.36	0.32	0.04	0.05	−0.06	0.15	0.16	0.09	0.10	0.04	0.00	0.13	0.09	0.07

Table 8. Regression results predicting the days to the next attack for second stage of Heckman selection model

Dependent variable	Days to next attack									
Model	*4.1*		*4.2*		*4.3*		*4.4*		*4.5*	
Predictors	*Estimates*	*p*	*Estimates*	*p*	*Estimates*	*p*	*Estimates*	*p*	*Estimates*	*p*
Inverse Mills ratio	291.30 (240.46–342.15)	**< .001**	174.45 (103.02–245.87)	**< .001**	225.11 (162.27–287.96)	**< .001**	183.54 (116.05–251.04)	**< .001**	185.89 (115.10–256.69)	**< .001**
News coverage (3 days after attack)	0.20 (0.06–0.34)	**.006**	0.08 (−0.07–0.23)	.308	0.13 (−0.02–0.29)	.080	0.11 (−0.05–0.26)	.172	0.10 (−0.06–0.25)	.220
Organization's amount of attacks (prior year)	−0.00 (−0.01–0.00)	.172	−0.16 (−0.23–0.09)	**< .001**	−0.12 (−0.17–−0.06)	**< .001**	−0.15 (−0.22–−0.08)	**< .001**	−0.15 (−0.22–0.09)	**< .001**
Content variables of news articles (3 days):										
Affective language			0.19 (−3.76–4.15)	.923						
Cognitive process			2.94 (0.21–5.67)	**.035**						
Drivers			1.22 (−1.05–3.49)	.292						
Anxiety					−0.57 (−8.29–7.15)	.885				
Anger					6.28 (2.51–10.05)	**.001**				
Sadness					37.16 (14.71–59.60)	**.001**				
Insights							4.68 (−1.30–10.66)	.125		
Cause							1.51 (−5.87–8.90)	.688		
Discrepancy							−10.42 (−27.60–6.77)	.235		
Tentative							4.97 (−4.67–14.61)	.312		
Certainty							6.72 (−11.72–25.17)	.475		
Differentiation							9.92 (1.66–18.18)	**.019**		
Affiliation									1.67 (−3.34–6.69)	.513
Achievement									11.71 (2.64–20.78)	**.011**
Power									3.93 (1.54–6.32)	**.001**

(*Continued*)

Table 8. (Continued).

Dependent variable	Days to next attack									
Model	*4.1*		*4.2*		*4.3*		*4.4*		*4.5*	
Predictors	*Estimates*	*p*	*Estimates*	*p*	*Estimates*	*p*	*Estimates*	*p*	*Estimates*	*p*
Reward									−9.50 (−21.61–2.61)	.124
Risk									−7.43 (−14.11–-0.74)	**.029**
Observations	40,614		12,937		12,937		12,937		12,937	
R^2/R^2 adjusted	0.069/0.069		0.083/0.082		0.079/0.079		0.083/0.082		0.084/0.084	

Ordinary Least Squares regressions. Two-tailed tests with clustered standard errors on the organization level. Only attacks with known perpetrators from 2005 to 2016 are included, with an overall of 1,685 novel terror attacks. The drop in observations between Model 4.1 and Models 4.2–4.5 is due to the focus of the latter on news content allowing only observations garnering news attention.

Table 9. Regression results predicting novel follow-on attack—second-stage Heckman selection model

	Dummy: future novel attack		Dummy: future novel attack		Dummy: future novel attack		Dummy: future novel attack		Dummy: future novel attack	
Model	*5.1*		*5.2*		*5.3*		*5.4*		*5.5*	
Predictors	*Risk Ratios*	*P-value*	*Risk Ratios*	*P-value*	*Risk Ratios*	*P-value*	*Risk Ratios*	*P-value*	*Risk Ratios*	*P-value*
Inverse Mills ratio	1.79 (0.71–4.51)	.220	0.05 (0.01–0.26)	**< .001**	0.15 (0.04–0.59)	**.007**	0.09 (0.02–0.38)	**.001**	0.05 (0.01–0.25)	**< .001**
News coverage (3 days after attack)	1.01 (1.00–1.02)	.117	1.00 (1.00–1.00)	.380	1.00 (1.00–1.00)	.893	1.00 (1.00–1.00)	.619	1.00 (1.00–1.00)	.343
Organization's amount of attacks (prior year)	1.00 (1.00–1.00)	**< .001**	1.00 (1.00–1.01)	.206	1.00 (1.00–1.01)	.113	1.00 (1.00–1.01)	.179	1.00 (1.00–1.01)	.215
Content variables of news articles:										
Affective language			0.95 (0.83–1.08)	.401						
Cognitive process			1.05 (0.99–1.11)	.135						
Drivers			1.08 (1.00–1.16)	**.043**						
Anxiety					1.26 (0.97–1.63)	.078				
Anger					1.13 (1.03–1.23)	**.009**				
Sadness					1.80 (1.07–3.01)	**.027**				
Insights							1.37 (1.04–1.81)	**.025**		
Cause							1.08 (0.94–1.24)	.277		
Discrepancy							1.24 (0.99–1.55)	.059		
Tentative							0.91 (0.78–1.08)	.281		
Certainty							0.97 (0.76–1.23)	.786		
Differentiation							1.05 (0.89–1.23)	.591		
Affiliation									1.18 (1.05–1.32)	**.007**
Achievement									0.99 (0.80–1.22)	.936
Power									1.06 (1.00–1.12)	.057

(*Continued*)

Table 9. (Continued).

	Dummy: future novel attack		Dummy: future novel attack		Dummy: future novel attack		Dummy: future novel attack		Dummy: future novel attack	
Model	*5.1*		*5.2*		*5.3*		*5.4*		*5.5*	
Predictors	*Risk Ratios*	*P-value*	*Risk Ratios*	*P-value*	*Risk Ratios*	*P-value*	*Risk Ratios*	*P-value*	*Risk Ratios*	*P-value*
Reward									1.18 (0.86–1.62)	.310
Risk									1.02 (0.86–1.22)	.798
Observations	40,614		12,937		12,937		12,937		12,937	
Nagelkerke's R^2	0.560		0.461		0.432		0.461		0.461	

Probit regressions. Two-tailed tests with clustered standard errors on the organization level. Only attacks with known perpetrator from 2005 to 2016 are included, with an overall 1,685 novel terror attacks. The drop of observations between Model 5.1 and Models 5.2–5.5 is due to the focus of the latter on news content allowing only observations garnering news attention. Nagelkerke's R^2 estimate how well a dependent variable is explained. With values between 0.3 and 0.5, the models have a moderate explanatory power.

Our analyses that predict the time until the next attack of a terror organization, based on media coverage about the terror organization (Table 8), show that media coverage that applies more effective language does not predict the time period until the next attack. However, media coverage focusing more on anger (Δdays = 6.28; p = .001) or sadness (Δdays = 37.16; p = .001) does predict a longer time until the next attack, of about six and 37 days, respectively, per one percentage point change in the language measure. Moreover, the results show that language depicting more cognitive processes (Δdays = 2.94; p = .035), especially with a stronger focus on differences (e.g., comparative analyses) (Δdays = 9.92; p = .019), predicts a longer time to the next attack from the same organization with about 10 days per percentage point change. A relatively greater proportion of media content referring to achievements (Δdays = 11.71; p = .011) or power (Δdays = 3.93; p = .001) were related to a longer time until the next attack of that organization, about 12 and 4 days, respectively, per percentage point change in the language measure. In contrast, more risk-related wording (Δdays = −7.43; p = .029) predicts a shorter period until the next attack by about seven days per one percentage point increase. In line with previous research (Jetter 2017), the amount of news coverage affects the days until the next attack (Model 4.1, Δdays = 0.20; p = .006). However, this effect loses significance when content variables from those newspapers are included, hinting at the further importance of not only analyzing the amount of media coverage, but rather the content, for predicting future terror attacks.

The final set of analyses predicts the likelihood of a terror organization's future attack being novel, as reported in Table 9. The results show that media's use of emotional language in the form of anger (risk ratio = 1.13; p = .009) and sadness (risk ratio = 1.80; p = .027) with regard to a terror organization predicts a higher likelihood for a future novel terror attack from that organization. Also, using more cognitive, explanatory language predicts a higher probability of a novel future attack (risk ratio = 1.37; p = .025). Media content using language relating to the drivers of attacks (risk ratio = 1.08; p = .043), especially an organization's affiliation (risk ratio = 1.18; p = .007), predicts a higher likelihood of a future terror attack being novel. Hence, the contextual settings of terror organizations and how they are viewed and described in the media encapsulate elements that can inform counter-terrorism measures.

Discussion and further research

Our results show that novel terror attacks have a more devastating and direct impact in terms of victims/lethality (killed and wounded), and that the societal resonance—in terms of media coverage—is significantly prolonged. In turn, the content of media coverage after terror attacks does relate to the time and novel nature of future attacks from the same terror organization. In contrast, we did not confirm our expectation that media coverage (amount and content) predicts whether an attack from the same organization will take place. This is likely the consequence of the observation that novel attacks are mainly committed by medium-sized and large terror organizations (see Figure 2). Yet, a next attack from them is anyway highly likely, in particular, *because* they are medium and large terror organizations. Despite this, our analysis does show the value of relying on fine-grained, but accessible media-related measures to increase precision in predicting next terror attacks.

Our analysis focusses on a straightforward and unidimensional operationalization of novelty, and our estimation procedures are—at least compared to the vast amount of advanced analytical techniques available—relatively uncomplicated. In doing so, we have shown that novelty in terror attacks deserves more scientific attention and that predicting them might potentially help in making authorities better prepared for them. However, it seems more than warranted to operationalize more and new fine-grained dimensions of novelty in future research. One very important method for collecting sufficient ideas on how novelty can be dimensioned would be to bring in the literature on terrorist innovation, a research strand still in its infancy,[62] as it is neither systematic and geared towards theory-building nor comparative in design.[63] Of course, one might object bringing the general idea of innovation to terrorism by arguing that terrorist innovation is —at minimum!—normatively different as terrorist innovation is not a cornerstone of growth in welfare and wellbeing but rather pursued for destructive purposes. However, as Ackerman[64] has aptly observed, "terrorists are human beings and terrorist groups are social organizations." By shedding some light on the "dark side of innovation," i.e. novel terrorism, innovation appears very much as a "double-edged."[65] Even more, in this study, we approached and conceptualized novelty from the perspective of counterterrorism. That means that we looked at differences between effects of novel attacks and non-novel attacks effect in terms of direct and indirect consequences for society, and how to predict them. Against this background, we have mentioned that we have no insight into whether novelty in itself is a deliberate consideration in the actual decision processes of terrorists planning. While access to such information is costly and risky, it would be a substantial source to better understand novelty and how to deal with it. Potentially other research methods can be valuable here, for example by relying on interviews, historical data and/or by thought experiments.[66]

Moreover, now that we have highlighted the potential value of media coverage as a source for early-warning signals at the level of specific terror organizations, substantially more advanced and precise—but also opaquer—prediction methods can be applied and evaluated. The recent developments with respect to machine learning can provide the next set of insights into which estimation methods and variables are most relevant to increase precision in terrorism predictions.[67]

Further, it has to be noted that we did not look into the actual process of innovation or how terrorists learn. We also did not analyze how and why terrorist groups might innovate or whether they seem to learn from successes and failures of other groups. Hence, future efforts may be accomplished by taking a closer look at the antecedents or the overall contextual setting within which an innovation takes place, as well as the kind of impact it has on society and other terrorist groups.[68] This development will not only lead to a more fine-grained operationalization of novelty, it can also open up avenues for other methods of research such as qualitative studies on novel terrorism.

The data used in this study's analyses is based on the GTD, which has been used in a broad range of scientific studies.[69] For our concrete research purpose, such open-access database has the advantage that it can be used to showcase how media coverage on terror attacks is a relevant source to predict in subsequent terror attacks. However, as any database, GTD likely includes errors. Consequently, our results might be dependent on these errors. We call on the one hand for further research that applies our predictive approach on other databases. This can contribute to the verification of our findings. On the other hand, we call upon researchers and public administrators to share relevant data—at high data quality—in order to make data availability better for projects that can contribute to the verification and elaboration of our findings herein. While one part of our analysis was based on GTD, the other part was based on English-language newspaper articles. The integration of additional languages in future studies would make the analysis more complex, but it might potentially also lead to (even) more precision in predicting (novel) terror attacks.

Finally, while our approach might be valuable to make some terror attacks more predictable, two additions have to be made about the future practical value. First, the approach we take builds on the key role of identifiable terror organizations. By identifying the responsible terror organization, media coverage is attributable to an actual actor whose behavior we want to predict. However, a substantial part of the attacks reported do not have a known perpetrator. As a result, higher accuracy might be reached to predict some terror attacks from known organizations, the method remains untested and would need substantial further elaboration for terror attacks where perpetrators have not been identified. Second, terror attacks are increasingly reported that are committed by for example unaffiliated, self-radicalized individuals that have now or no direct connection with known terror organizations.[70] In such case, predictions might not only be hard or impossible due to the inability of identifying well-organized perpetrators, but predictions might also need other types of information that are not covered by media. As we argued that a benefit of our approach is the massive and relatively cheap availability of media-related information, other sources might thus be more relevant to predict behavior of such unrelated individuals. Potentially, social media might be a good data source to explore in this context.[71]

Conclusion

We focused on novelty in terrorism, given its devastating impact in particular, because public governance systems in many countries are not prepared for or resilient against it. The first two parts of our analysis confirm this with respect to the larger direct impact of novel terror attacks in terms of victims as well as longer media resonance. Subsequently, in the third part of our analysis, we build on seminal insights of early-warning and wisdom-of-the-crowd systems to test whether media coverage about terror attacks entails early-warning signals about next terror attacks from the same terror organizations. The linkage of terror attack data and media coverage on the level of terror organizations is pivotal in our analysis as it is the level where future terror actions are planned and decided. While we can assume that subsequent terror attacks do not causally follow the content of media coverage about earlier attacks, media still provides access to relevant information. Our results confirm that content of media coverage relates to the duration until the next attack as well as its novel nature. This finding opens opportunities to further research and elaborate upon measures of novelty as well as evaluate the predictive power of more advanced estimation methods.

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No potential conflict of interest was reported by the author(s).

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