TERRORISM INCIDENTS AND CHARACTERISTICS, A MULTILEVEL LATENT CLASS MODEL

Luciano Nieddu, Roberta Varriale

Abstract. The aim of this study is to explore the impact of the 2001 attacks on the World Trade Center on the characteristics of terrorism worldwide and in individual countries using information from the Global Terrorism Database (GTD), a longitudinal dataset that provides detailed data on terrorist events worldwide. We focus on terrorist activity within a country, organizing the data by attacks and countries to detect latent patterns. We restrict our attention on a limited period of time, namely 7 years, and apply a multilevel latent class model that enables for simultaneous clustering of attacks and events into groups exhibiting distinctive profiles based on observed terrorism-related variables.

1. Introduction

The apparent increase in terrorist activity over time is particularly relevant to longitudinal studies and may partially reflect improvements in data collection rather than actual growth in attacks. Careful interpretation of trends, especially when comparing periods before and after major geopolitical events such as the 11 September 2001 attacks should be employed. The 9/11 attack changed the nature of terrorism, prompting a rapid response from security forces worldwide and modifying the way governments track threats, resulting in tighter surveillance and counterterrorism efforts everywhere (Magnani, 2021; Viney, 2021).

Our analysis aims to explore the impact of the 9/11 attacks on the World Trade Center on the characteristics of terrorism worldwide and in individual countries. To this end, we considered a seven-year window around September 11 2001, from 1988 to 2004, and we applied a Multilevel Latent Class (MLC) analysis introduced by Vermunt (2003) to the GTD data. The hierarchical structure considers terrorist attacks (events) at the lower level nested within countries at the upper level. MLC is typically used for simultaneously clustering or constructing both higher- and lower-level units in latent classes (unobserved populations) with observed variables. However, unlike traditional clustering analyses such as principal component or cluster analysis for single level data, the MLC is a model-based solution. In our analysis, we applied separate and independent MLCs to the data before and after

September 11, 2001. By comparing the classification results, we were able to describe the changes that had occurred in the phenomenon of terrorism.

The remainder of this paper is organized as follows: Section 2 describes the data analyzed in this work, and Section 3 describes the MLC. Results of the empirical applications are reported and commented in Section 4. Finally, Section 5 draws some conclusions.

2. The data

The Global Terrorism Database (GTD) is a comprehensive, event-level database that documents more than 200000 terrorist attacks worldwide since 1970. It is managed by the National Consortium for the Study of Terrorism and Responses to Terrorism (START) at the University of Maryland. Data have been collected from a wide range of media sources and subjected to a systematic coding and validation process to ensure consistency (START, 2022). The GTD dataset is freely available from the University of Maryland and allows users to filter incidents based on varying thresholds of ideological motivation, intent, and target type. Additionally, the GTD contains a rich set of variables - over 45 for most incidents, and more than 120 for recent years - enabling detailed temporal, geographic, and typological analyses. GTD is the most widely used in academic research and accessible source for empirical analyses of terrorism patterns. It is widely used in academic research, policy analysis, and risk assessment, and its event-level structure makes it particularly well suited to the statistical modelling of terrorism over time and across space. The GTD has become an empirical resource for the quantitative study of terrorism. It has been employed across a range of methodological approaches including machine learning, survival analysis and time series approach (see, for instance, Python *et al*., 2021; Guo, 2019; Singer and Golan, 2019).

In order to evaluate the possible effect of the World Trade Center attacks in New York on the characteristics of terrorism, we selected a period of seven complete years and divided it into two: before (pre in the following) and after (post in the following) September 11, 2001. This resulted in the two groups having different lengths of time and numbers of cases.

The variables were selected according to the following two criteria: absence of missing values and low sparsity. To avoid sparsity, the considered variables were dichotomized. The 13 variables used for the analysis are as follows:

- *Extended*: 1 if the duration of an incident extended more than 24 hours
- *Doubt*: 1 if there is doubt as to whether the incident is an act of terrorism
- *Multiple*: 1 if the attack is part of a multiple incident
- *Success*: 1 if the incident was successful

- *Suicide*: 1 if the incident was a suicide attack
- *Bomb*: 1 if bombs and assaults were used during the attack
- *Firearms*: 1 if explosives and firearms were used during the attack
- *Claimed*: 1 if a group or person claimed responsibility for the attack
- *Killed*: 1 if victims or attackers died as a direct result of the incident
- *Wounded*: 1 if victims or attackers wounded as a direct result of the incident
- *Property*: 1 if the incident resulted in property damage
- *Hostages*: 1 if presence of hostages or kidnapped in the incident
- *International*: 1 if a perpetrator group attacked a target of a different nationality.

Only countries that experienced at least fifty terrorist attacks in either periods (before and after 9/11) were selected. This approach avoids convergence problems when fitting the model (see Section 3) while ensuring that all countries most affected by terrorist attacks are considered. Twenty-seven countries from all over the world were selected. Tables 4 and 5 show the number of attacks in all the selected countries before and after 9/11, together with some results of the analysis.

3. The Multilevel Latent Class Analysis

Latent class (LC) analysis (Goodman, 1974) is usually applied in social sciences for clustering or constructing typologies with observed variables. When data have a multilevel structure, with level 1 (or individual or lower-level) units nested in level 2 (or group or higher-level) units, the multilevel approach is useful to correct inferences since the usual assumption of independent observations is violated (Snijders and Bosker, 2012). In this situation, a multilevel LC model (MLC) approach allows model parameters to differ across level 2 units (Vermunt, 2003). The application of MLC models simultaneously clusters individuals and groups into unobserved clusters (latent classes or mixtures). Lower-level units are classified into one of *L* latent classes based on differences in the distribution of observed responses, while higher-level units are assigned to one of *H* higher-level latent classes, which vary in the distribution of the lower-level latent classes.

In our data, y_{kji} is the observed value on the *i-th* variable ($i = 1, \dots, I$), on *j-th* lower-level unit ($j = 1, \dots, n_k$) in the *k-th* ($k = 1, \dots K$) higher-level unit. According to the hierarchical nature of the data, *i-th* variables are the attack characteristics, terrorist attacks are lower-lever units *j*, and countries are higher-level units *k*. The total number of countries is *K=27*, while the number of attacks, n_k, differs for each country; $N = \sum_{k=1}^{K} n_k$ is the total number of lower-level units. The variables of each attack are described in Section 2 (*I=13*). The vectors $\boldsymbol{y}_{kj} = (y_{kj1}, \dots, y_{kji}, \dots y_{kjI})$

and $\boldsymbol{y}_k = (\boldsymbol{y}_{k1}, .., \boldsymbol{y}_{kj}, ..., \boldsymbol{y}_{k\boldsymbol{n}_k})$ contain the *I*-variate responses of attack *j* in country *k*. The unobservable variables representing the lower- and higher-level latent classes membership are denoted by $x_{kj} = l \ \ (l = 1, ..., L)$ and $w_k = h \ (h = 1, ..., H)$.

The MLC model can be expressed in two basic equations (Vermut 2003). The first equation defines the mixtures model for $f(\boldsymbol{y}_k)$, the marginal density for the full response vector of group *k*; that is:

$$P(\boldsymbol{y}_k) = \sum_{h=1}^{H} P(w_k = h) \prod_{j=1}^{n_k} P(\boldsymbol{y}_{kj} \, | w_k = h) \tag{1}$$

where $P(w_k = h)$ is the probability that group *k* belongs to higher-level LC *h*, and $P(\boldsymbol{y}_{kj}|w_k = h)$ is the conditional density for the response vector of level 1 unit *j* in level 2 unit *k*. The second equation is:

$$P\big(\boldsymbol{y}_{kj}\big|w_k = h\big) = \sum_{l=1}^{L} P\big(x_{kj} = l|w_k = h\big) \prod_{i=1}^{I} P(y_{kji} = 1|x_{kj} = l \, , w_k = h) \tag{2}$$

where $P\big(x_{kj} = l|w_k = h\big)$, is the probability that the level 1 unit *j* of level 2 unit *k* belongs to LC *l* given that group *k* belongs to LC *h*, and $P(y_{kji} = 1|x_{kj} = l, w_k = h)$ is the conditional density for response variable *i* of level 1 unit *j* in level 2 unit *k* given the membership to lower-level LC *l* and to higher-level LC *h*.

In our analysis, we use the specification $P\big(y_{kji} = 1\big|x_{kj} = l \, , w_k = h\big) = P\big(y_{kji} = 1\big|x_{kj} = l \,\big)$ (Vermunt 2003, 2008). In this case, $P\big(y_{kji} = 1\big|x_{kj} = l \,\big)$ is estimated freely, but the parameters defining the conditional distributions are assumed to be independent of the higher-level class membership. This structure is the one used in almost all the applications aiming at the simultaneous clustering of higher- and lower-level units (Lukociene *et al.*, 2010), and the clustering of higher-level units is performed by “pushing up” the information contained in the multiple lower-level responses via the lower-level class memberships.

In equation (1) conditional independence between units is assumed inside each higher-level class, and in equation (2) conditional independence is assumed between the variables measured on the first-level units. The probability of observing a particular response pattern for a country, $P(\boldsymbol{y}_k)$, is expressed by three components: (i) the probability that country *k* belongs to higher-level LC, (ii) the probability that event *j* belongs to first-level LC, given the country latent class membership, (iii) the probability that the attack characteristic *i* of terrorist attack *j* in country *k* is equal to 1, given the terrorist attack latent class membership. Components (i) and (ii) are modelled through multinomial logit equations, while the third component (iii) is modelled through a logit equation.

For parameter estimation, we used the syntax module of the Latent GOLD v. 6.0 software (Vermunt and Magidson, 2021), using the EM algorithm adapted to the multilevel framework by Vermunt (2003).

4. Terrorist attacks and MLC analysis

As introduced, we applied two separate MLC models for terrorist attacks before and after September 11, 2001. The two analyses were carried out independently on the same variables and share the higher-level units. The two classifications of countries resulting from the two MLCs, which are based on different datasets, highlight the proximity and distance of second-level units determined under different conditions.

In the application of the MLC, the choice of the number of LCs at both levels is an important issue. In our analysis, the sample size is quite large ($N_{pre}=4712$, $N_{post}=3759$) which systematically favors more complex models when using standard comparison methods like likelihood-ratio tests. Additionally, when the null hypothesis lies at the boundary of the parameter space - as is the case when comparing models with varying numbers of latent classes - conventional asymptotic theory does not apply (Agresti, 2013). Consequently, we relied on penalized information criteria, such as the Bayesian information criterion (BIC). Following Lukociene *et al.* (2010), we used BIC with number of level-1 units as the sample size, BIC(N), to choose the number of lower-level classes, and BIC with number of groups as the sample size, BIC(Nk), to choose the number of higher-level classes. To contrast the tendency of information criteria to suggest a very high number of LCs, we compared the percentage difference between the information criteria of two successive models. In addition, we used substantive considerations related to the size and interpretation of the latent classes to choose the number of higher- and lower-level classes. Finally, we also used the geometric mean likelihood index $exp(LL/N)$ proposed by Agresti and Caffo (2002), where LL represents the logarithm of the maximized likelihood function for a model. This index removes the dependence of LL on the overall sample size N, and the closer to 1, the better the fit. As for the information criteria BICs, we also compared the percentage difference between the exp(LL/N) index of two successive models. Table 1 shows the results of goodness of fit for MLC models before 9/11. Both in lower- and higher-level, we observe an edge point for h=3 and l=3, that we chose as our final model. Similar results are obtained for MLC models after the September 11, 2001 attack.

Table 1 – *Information criteria and geometric mean likelihood index. MLC model before 9/11.*

h – l	BIC(N)	BIC(Nk)	BIC(N) % diff	BIC(Nk) % diff	exp(LL/N)	exp(LL/N) %diff
1 – 1	55776.1				0.0027	
1 – 2	52987.6		-5.00		0.0037	36.13
1 – 3	51871.5		-2.11		0.0042	14.00
1 – 4	50783.3		-2.10		0.0048	13.66
2 – 3		50348.3		-2.51	0.0049	14.89
3 – 3		*49976.5*		*-0.74*	*0.0051*	*4.12*
4 – 3		49851.6		-0.25	0.0051	1.43

The comparative reading of the results before and after 9/11 will focus on the aggregations (second-level latent classes) of the second-level units (countries) obtained through the MLCs, and whether these are preserved or not in the two periods. It is important to note that the MLCs results take into account also the transformation of the phenomenon as a whole.

For the interpretation of our results at the second-level of analysis, important elements come from the description of the first-level latent classes. Table 2 shows the estimated conditional probabilities (in percent) of each characteristic conditional on unit *k* belonging to the lower-latent class. For example, 2.04% is the probability of the attack being extended, conditional on unit *k* belonging to the lower-level latent class 2.

Table 2 – *Lower-level latent classes. MLC models before and after September 11, 2001 attacks.*

	pre			*post*		
i	*l=1*	*l=2*	*l=3*	*l=1*	*l=2*	*l=3*
Extended	0.19	2.04	**78.48**	0.09	0.16	**38.95**
Doubtterr	20.86	17.02	16.67	16.46	12.14	14.58
Multiple	15.5	28.68	16.13	9.34	32.27	8.91
Success	93.6	**82.07**	**99.75**	94.22	**80.96**	**99.24**
Suicide	4.07	**0.00**	1.21	12.02	**0.00**	0.53
Bomb	**88.67**	72.71	17.44	**94.48**	80.26	14.71
Firearms	**91.26**	70.89	62.44	**98.39**	78.99	54.41
Claimed	8.46	20.73	16.89	15.96	21.7	19.09
Killed	**68.05**	13.55	38.32	**75.6**	2.62	66.01
Wounded	**55.54**	20.01	14.96	**63.82**	17.33	15.22
Property	46.97	**62.26**	19.19	41.07	**66.91**	13.62
Hostages	0.01	0.00	**98.97**	0.00	0.00	**52.29**
International	1.85	**38.21**	23.59	10.7	**18.39**	18.71

As for the PRE data, latent class 1 (*l=1, pre*) is characterized by assaults with bombs and explosives, wounded and killed, latent class 2 (*l=2, pre*) is characterized by multiple attacks and property damage, and latent class 3 (*l=3*, *pre*) is characterized by events that last longer than 24 hours, are successful, and involve hostages. The proportions of lower-level units in the three latent classes are: 46%, 44%, and 10%. The results of MLC using POST data show important similarities in the structure of the lower-level latent classes. The proportions of lower-level units in the three latent classes are: 47%, 37%, and 16%.

As for the higher-level latent classes, we chose the solution with three classes in both *pre* and *post* analyses. The proportions of countries in the three latent classes are 37%, 37%, 26%, and 31%, 40%, 30% in the *pre* and *post* data, respectively. Table 3 shows the composition of the higher-level latent classes relative to the first-level latent classes.

Table 3 – *Higher-level latent classes. MLC models before and after September 11, 2001 attacks.*

	pre			*post*		
	h=1	*h=2*	*h=3*	*h=1*	*h=2*	*h=3*
l= 1	**44.6**	**89.9**	0.7	**50.4**	**78.7**	5.9
l= 2	**38.0**	4.0	**97.8**	**27.0**	10.3	**91.0**
l= 3	**17.4**	6.0	1.4	**22.7**	11.1	3.1

In both analyses, the higher-level latent class 1 (*h=1*) is composed of all three lower-level latent classes, although with a slight predominance of the lower-level latent class 1, the higher-level latent class 2 (*h=2*) is predominantly composed of lower-level latent class 1 (bombs, dead and wounded explosives), while higher-level latent class 3 (*h=3*) is characterized by the predominance of lower-level latent class 2 (multiple attacks, property damage, and a complete absence of suicide).

In the following we combine the results of the two MLCs, using the classification of the countries based on the empirical Bayesian posterior distribution. In particular, we analyze which countries classified in the same higher-level latent class in the *pre* analysis are still, or not, classified together in the *post* analysis. The fact that there is a correspondence between lower-level classes in the two periods allows us to evaluate not only how countries aggregate, but also if their profiles modify in time with respect to the observed variable. Just to give an example, countries A and B are classified in *h=1* by the MLC using *pre* data. It may happen that A and B are still classified together by the MLC using *post* data, but not in *h=1*.This means that the two countries are still similar, but they share a different profile with respect to observed variable.

Table 4 – *Combinations of higher-level latent classes in MLC models before and after September 11, 2001 attacks.*

h=1, pre – h=1, post			*h=2, pre – h=2, post*			*h=3, pre – h=3, post*		
Country	*n, pre*	*n, post*	Country	*n, pre*	*n, post*	Country	*n, pre*	*n, post*
Afghanistan	36	228	Algeria	482	300	France	99	85
Colombia	495	344	India	542	533	Greece	103	28
Lebanon	82	14	Israel	84	142	Kosovo	116	15
Turkey	184	53	Pakistan	171	149	Spain	247	101
Uganda	77	68	Russia	324	237	United King	280	63
			Sri Lanka	165	64	United Stat	152	99
			WB&Gaza	153	205	Yugoslavia	103	3

Out of the nine possible combinations of higher-level latent classes in the *pre* and *post* analyses (with each country associated with one of the three second-level clusters in both analyses), we observe only six because the countries classified as *h=3* in the *pre* analysis belong to the same group in both analyses. Macedonia is the only country that moves from *h=1* in *pre* MLC to *h=3* in *post* MLC. Tables 4 and 5 show the countries belonging to each higher-level combination, together with the number of events in both *pre* and *post* period.

Table 5 – *Combinations of higher-level latent classes in MLC models before and after September 11, 2001 attacks.*

h=1, pre – h=2, post			*h=2, pre – h=1, post*		
Country	*n, pre*	*n, post*	Country	*n, pre*	*n, post*
Angola	109	13	Burundi	72	45
Indonesia	248	100	Nepal	48	151
Iraq	32	431	Philippines	218	199
Thailand	21	67			

Figures 1-4 show the *pre* and *post* profiles of the identified combinations of countries, describing the evolution of the phenomenon over time. The profiles of the group of countries belonging to *h=1* in *pre* MLC and those belonging to *h=1* in *post* MLC remained nearly unchanged in the two analyses, and the same happen for *h=2* (see Figures 1 and 2).

A country that moves from one higher-level latent class to another, not only belongs to a different aggregation but also shows a different profile in the two analyses. As an example: Angola (together with Indonesia, Iraq and Thailand, Table 5) is in *h=1* in *pre* MLC, and moves to *h=2* in *post* MLC (and aggregates with India, Pakistan, Israel, etc. that were already in *h=2* in *pre* MLC and still are in *h=2 post* MLC, Table 4, second column). The countries moving from *h=1* in *pre* to *h=2* in *post* show an increase in killed and wounded (Figure 3), while we observe a softening of these characteristics for countries such as Burundi, Nepal and Philippines migrating from *h=2* in *pre* MLC to *h=1* in *post* MLC.

Figure 1 – *Profiles of higher-level latent classes. MLC models before and after September 11, 2001 attacks.*

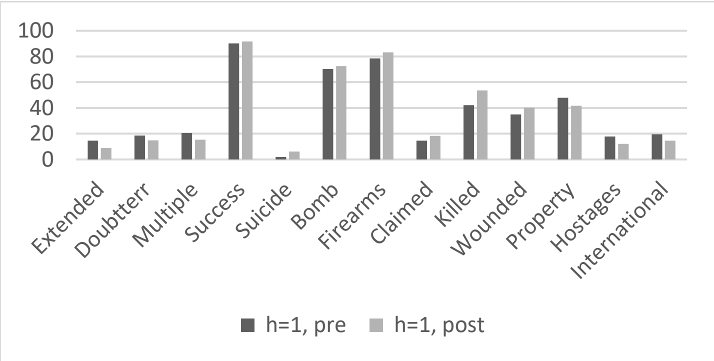

Figure notes. Authors' elaboration. MLC models on GDT data.

Figure 2 – *Profiles of higher-level latent classes. MLC models before and after September 11, 2001 attacks.*

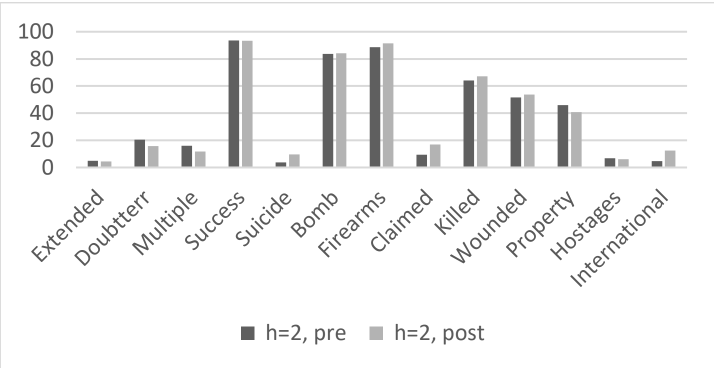

Figure notes. Authors' elaboration. MLC models on GDT data.

The group of countries belonging to *h=3* in *pre* MLC (composed by France, Greece, Kosovo, Spain, the United Kingdom, the United States, and Yugoslavia) still aggregate together in *post* MLC (Macedonia joins in the post analysis but with a small number of events, and therefore does not influence the class profile), as shown in Table 4. This group is the one that shows the most pronounced changes in its profile with respect to the observed variables. Indeed, while there is a substantial reduction in the number of events (in the post period, the number of events is reduced to just over one-third, except for France), their profile shows a different distribution among the different types of terrorist attacks: bomb and explosives attacks proportionally increase while hostage involvement decreases. Furthermore, as this group of countries is mainly characterized by *l=2* in *pre* and *post* analyses (Table 3), we observe in Table 2 a reduction of the probably of international attacks, from 38.21 to 18.39, and a reduction of the probability of victims killed from 13.55 to 2.62. All of these countries, seem to be the ones that have seen the most relevant changes following the attack on the World Trade Center on September 11, 2001.

Figure 3 – *Profiles of higher-level latent classes. MLC models before and after 9/11.*

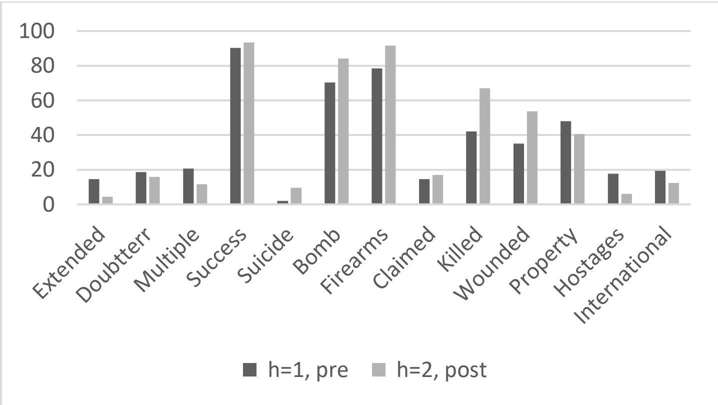

Figure notes. Authors' elaboration. MLC models on GDT data.

Figure 4 – *Profiles of higher-level latent classes. MLC models before and after 9/11.*

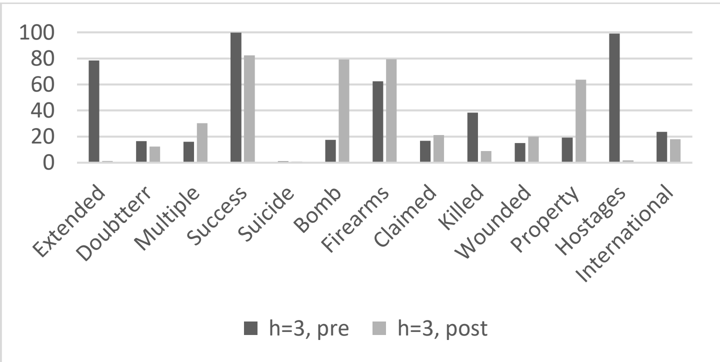

Figure notes. Authors' elaboration. MLC models on GDT data.

5. Results and conclusions

In this study, we analyzed a subset of the GTD dataset using a multilevel latent class analysis restricting our attention on a period of seven years from 1988 to 2004. This enabled us to evaluate the impact of the attack of September 11, 2001 on the characteristics of terrorism worldwide. The multilevel approach enabled us to describe changes in single countries by a classification based not only on their marginal profile but also on their composition with respect to different kinds of attacks. The drawbacks of this type of analysis is that it has requirements regarding data structure. We selected second-level statistical units with a ‘sufficient’ number of events and dichotomised the variables describing the attacks to avoid sparseness in the data. This clearly results in a loss of information. Furthermore, this analysis does not take into account the effect of the geographical proximity of countries, which will be an element of interest for future analyses.

The event of 9/11 appear to have had an impact on terrorism in various countries. The multilevel latent class model classifies countries into three (latent) groups *h*, both in the analysis of data before and after September 11, 2001. The comparison of these results suggested the presence of five subgroups (“*h=1, pre* - *h=1, post*”, “*h=2, pre* - *h=2, post*”, “*h=1, pre* - *h=2, post*”, “*h=2, pre* - *h=1, post*” and “*h=3, pre* - *h=3, post*”). In fact, with the exception of Macedonia, there are no shifts affecting group “*h=3, pre”*. The subgroups of countries in “*h=1, pre* - *h=1, post*” and “*h=2, pre* - *h=2, post*” show a similar profile of terrorist attacks before and after 9/11. The subgroups of countries in “*h=1, pre* - *h=2, post*” and “*h=2, pre* - *h=1, post*” change their profile, but the most significant change is observed for the subgroup of countries in “*h=3, pre* - *h=3, post*”. This is the group of Western countries (European countries and the United States), that remain together in the pre- and post-analysis and show the most significant changes in the characteristics of the terrorist attacks.

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Luciano NIEDDU, UNINT University, l.nieddu@unint.eu
Roberta VARRIALE, Sapienza University of Rome, roberta.varriale@uniroma1.it