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Journal of Economic Analysis

Homepage: https://www.anserpress.org/journal/jea

Determinants of terrorism in the MENA region: a Bayesian Model Averaging based approach

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ABSTRACT

In this work we aim to identify potential determinants and seek to predict terrorism attack. Thus, to eliminate uncertainty linked to explanatory variables we used the BMA method. We show that, contrary to expectations terrorism in MENA region is no longer purely of economic origin but mainly due to political problems, education, financial development and countries' demographic characteristics. Likewise, we find that national, international and global terrorism are not of same origins even they present many common roots. In the end, we show that it is possible to predict majority of attacks based on a small number of indicators measuring political risk, financial development and income inequalities.

KEYWORDS

Terrorism; MENA; Bayesian Model Averaging; Logit; Early warning system

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ISSN 2811-0943
doi: 10.58567/jea03030001

Received 3 July 2023, Accepted 10 August 2023, Available online 13 September 2023, Version of Record 15 September 2024

1. Introduction

In recent decades terrorism has drawn attention of both policy makers and academic research. It is considered as all acts of violence or attacks organized by an individual or a group to create insecurity and satisfy hatred towards the system. It is "*the commission of criminal acts, usually violent, that target civilians or violate war conventions when targeting military personnel; and who are engaged at least partially for social, political or religious purposes*" (Agnew, 2010). It corresponds to *"any harmful action intended to cause death and serious damage to the human body or to non-combatants, when the object of such an act, by its nature or context, is to intimidate a population or to force a government or an organization to do or refrain from doing any act"*.

Some works stated that is motivated by political factors others supported economic and social origins. However, none of these studies provide convincing explanations for the attacks occurred in politically stable and rich countries while poor and non-democratic ones were able to prevent violence. This means that the decision to carry out a terrorist attack is complex in such a way that neither economic conditions nor political factors alone can explain this multifaceted phenomenon. This is not to say that these factors are not important but are not sufficient to indicate the potential timing of the attack. Otherwise, in this work we seek to know the causes of an attack in a rich and politically stable country contrary to expectation. In addition, our contribution is to find the best combination of factors that can best indicate a potential attack that will come in the next two years to be able to take preventive actions. These facts pushed researchers and policy makers to dig into the deep origins of terrorism and works became diversified and frequent during the last decades, especially after the events of September 11. So, it is always important to deal with this subject. Our objective in this work is to know whether it is possible to predict and so to prevent or reduce terrorism attack. We try to response to these questions: What explain terrorism in the MENA countries and are terrorist attacks predictable in this region? To do this, we maintain that it is necessary to combine economic and political indicators in a single model which we add means of communication facilitating coordination between agents. Our contribution therefore consists firstly in using the BMA technique when choosing the potential determinants of terrorism. In addition to giving an idea about the relative importance of each factor, this technique has the advantage of giving the best combination between the potential determinants of the attack. We are based on a probabilistic approach contrarily to previous work usually using frequentist methodology where the choice of variables to be introduced is difficult and can be based on an iterative approach or statistical test depending on analyst's ability and experience. Secondly, we develop an early warning system for terrorist attacks, which did not attract any interest from previous works. We show that it was possible to predict most terrorist attacks occurred in the MENA region in 2018 based on macroeconomic data. Thirdly, we distinguish between domestic and international attacks in addition to the adoption of a composite global terrorism index. This approach enrich literature assessing country's exposure to terrorism taking into account the material damage in addition to the number of victims and woods which was not previously raised in a clear way.

We organize the rest of this paper as follow: in section 2, we present a literature review. Section 3 contains empirical evidence containing data description, methodology, and results discussions. We carry out two types of analysis; explanatory and predictive. In section 4, we conclude and provide some implications of the results.

2. Literature review

In this section we try to cite main works focusing on the determinants of terrorism.For example,Urdal (2006) explained violence by population structure such as when the ratio of young people increases the likelihood of terrorist attack rises also. Feldmann and Perala (2004) considered unemployment as a possible determinant of terrorism because of low cost opportunity. Similarly, Piazza (2006) asserts that "… the average national unemployment rate for each country should have a significant positive relationship with terrorism, as unemployment precipitates stress on inactive workers who might suffer from unfulfilled economic expectations and therefore turn to political violence". These results are confirmed by Schomaker (2013) in the Middle East especially with lack of political participation and migration opportunities of young people.

Similarly, Cincotta et al. (2003) supported that bad quality of education makes difficult to find meaningful employment and may motivate civil war. The poor job prospects make it is difficult to find accommodation which fuel resentment and push towards terrorism. Oyefusi (2010) finds that education combined with unemployment motivates young people to participate in political violence. However, Berrebi (2007) rejected this conclusion for Hamas organization, the Palestinian Islamic Jihad and the Palestinian National Authority.

Other works highlighted the role of poverty establishing a strong link between poverty and conflict. Blomberg and Hess (2002) find that economic recessions play an important role in triggering internal conflicts. In addition, Bruckner and Ciccone (2007) found that in African countries a 5% drop in income increases, in average, by 30% the risk of civil conflict the following year. In particular, Enders and Hoover (2012) suggest that the middle income class is more inclined to support or engage in terrorism. The rationale suggested is that the poor focus more on survival and the rich have fewer grievances leaving the environment as fertile ground for grievances and opportunities to fuel terrorist activity. The gap between the expected and actual well-being of an individual due to the lack of employment opportunities generates collective discontent and ultimately terrorism.

Further, Basuchoudhary and Shughart (2010) find that the lack of economic opportunity significantly engenders terror. Thus, it seems fair to say that the influence of economic conditions on the "production of terror" remains a moot point. In this context, Seven and Coskun (2016) postulated that financial development as a potential economic growth stimulator benefits for the rich more than the poor which increases income inequality and subsequently the risk of violence and sometimes terrorism. However, According to Daisaka et al. (2014) when the capital market and credit allocation become more perfect and efficient, the poor can easily access financial resources.Thus, financial development could have a remarkable effect on the distribution of income between different groups. According to Shahbaz et al. (2015) at the early stage of financial development, the rich can gain more benefits than the poor which worsens income inequality leading to violence. After reaching a certain level, the poor can access more easily to investible capital resulting to more equal distribution of income.Similarly**,** Von Ehrlich and Seidel (2015) suggest that financial development can make it easier for the poor to access external finance allowing them earn more by investing and thus income inequality could be reduced.Indeed, if financial development is accompanied by better protection of property rights, it could then prevent income losses for the poor leading to more equitable distribution (Gradstein, 2007). However, in unstable political environments, the traditionally channels of investor protection do not work well and therefore political instability hampers financial development (Roe and Siegle, 2011).

Tim and Daniel (2019) argue that high levels of income inequality may be associated with more domestic violence and terrorism. Empirical evidence for this relationship is scarce and inconclusive but major works supported substantial economic and social costs of terror. Piazza (2011) finds that greater income inequality is associated with increased national terrorism, while Enders et al. (2016) believe that income inequality leads to more national and transnational terrorism. In contrast, Gassebner and Luechinger (2011) suggest that there is no effect of inequalities on terrorism.

Additionally, the social network as a whole can be an active vector of violent radicalization which facilitates the proliferation of violent extremist ideologies. Since 2012, in part due to the 'Arab Spring', some research highlighted the similarity of social networks to terrorist groups as networks in that they are decentralized, ubiquitous and mobile (Weimann, 2016). The social media offers for extremist group’s information in greater volume and speed, as well as in various formats, including videos for visual and emotion-based communication, two-way communication of interactivity, horizontal links and more. It offers the ability to search or publish information with relative anonymity and away from government surveillance or control, especially when countries with high levels of protection of free speech have little censorship of content. In addition, information can be displayed on local networks while targeting a global audience across time and space, achieving its purpose anywhere and anytime (Tsfati and Weimann, 2002). Social media platforms offer significant benefits to extremist groups who otherwise might have remained marginal in terms of communications media.

In addition to these works emphasizing the economic and demographic framework others support the importance of the political and institutional situation. For example, Krueger and Malečkova (2003) consider political repression to be the main cause of terrorism. Kurrild-Klitgaard et al. (2006) find that democracy reduces the production of terrorists contrary to Lai (2007). Basuchoudhary and Shughart (2010) neglect effect of political and civil freedoms on terrorism decision. Kazeem et al. (2020) supported a relationship between political regime and terrorist attacks.According to Windsor (2003), the role of the political system has also been the subject of much debate. Although democracies are better able to alleviate grievances and enable the pursuit of goals by non-violent means, thus effectively reducing terrorism.He concludes that strong transitions to democracy increase terror more sharply, while smooth democratic transitions are characterized by a smaller increase in terror. Internal terror reacts a little more strongly to transitions and conflicts than international terror. Higher sustainability of autocratic reduces terror.In the last decades, the impact of political stability in addition to national and international conflicts on terrorism has gained prominence. For example, Drakos and Gofas (2006) show that international conflicts increase terrorist incidents. Campos and Gassebner (2009) come to the same conclusion for civil war and riots, while the sustainability of the regime reduces terrorist incidents. Li and Schaub (2004) find no impact of interstate military conflicts on terror. Piazza (2008) shows that majority of terror comes from failed and warring states. Aniruddha and Jomon (2018) show that there is a negative relationship between transnational terror and the quality of regulationand political stability; it is easy for terrorist groups to operate or recruit in failed or fragile states.

From an empirical point of view, the literature on terrorism that uses large transnational datasets can be categorized as whether the focus is on the origin or on the target of terrorists. This differentiation is important because most studies focus only on international terrorism. Kis-Katos et al. (2011) used a panel set of 159 countries during the period 1970-2007 and show that the probability that terror originate from a particular country increases with GDP per capita and higher political score meaning more open and competitive political system. In addition, they supported that in countries experiencing internal conflict anarchy and regime transition likelihood of terrorist originating from these countries is more important. This evidence contradicts the ideas that terrorism is rooted in economic deprivation or that strongly autocratic regimes breed more terrorists.

Rather, they show that weak or failing states are incubators for terrorism and that the causes of national and international terrorism are similar. Empirical research on the economics of terrorism has focused on two questions: "Where are the terrorists hitting?" and "What breeds terrorism? » Three groups of characteristics have been identified as determining the choice of targets and the likelihood of attack in a particular country: (1) Economic conditions measured by GDP per capita level and growth rate, economic freedom, quality of institutions and infrastructure, human development index and level of education, (2) political freedom and civil liberties, measured among other things by composite indices (Polity IV or Freedom House index) and the rate of participation in elections, And (3) political stability, which is influenced by the occurrence of civil wars, riots, military conflicts and also captured by the sustainability of the regime and periods of transition or anarchy. Other control variables include the openness of the economy and the size of the population, among others.

Empirical studies yielded conflicting evidence: Krueger and Malečkova (2003) provide evidence, from a cross-national sample of 143 countries that GDP per capita is not related to terror but that civil liberties reduce terror. Basuchoudhary and Shughart (2010) find no influence of civil liberties, political freedom only increases terror. Piazza (2008) uses Human Development Index to measure state's development and finds that is positively related to terrorism. Likewise, analyzing data on 315 suicide campaigns (from 1980s to 2003) and 462 individual suicide bombers, Pape (2005) concludes that the "economic explanation" for terrorism is weak.

In fact, several studies such as those by Blomberg et al. (2004) found that economic hardship is positively correlated with terrorism and that the poorest people are more likely being recruited by terrorist organizations and are more likely to engage in terrorism. In others words, those likely to engage in terrorist activity are poor and uneducated individuals with a pessimistic outlook on life.More recent evidences based on various measures of poverty / economic development - including (whether terrorism is rooted in poverty / economic factors) are conducted. For example, some used GDP and GDP per capita (Abadie, 2006); human development index (Piazza, 2006); Poverty indices (Kurrild et al. 2006) and Education and schooling rate (Krueger and Malecova, 2003). Several articles reject the role of economic variables as determinants of terrorism. For example, Krueger and Laitin (2008) find that GDP per capita and the rate of GDP growth are not reliable predictors of transnational terrorism. Instead, they find that politically free countries are vulnerable to being targeted by terrorists from politically oppressed countries. Krueger and Malečková (2003) examine the case of Palestinian terrorism and find that richer and more educated individuals are more likely to be terrorists than poorer individuals. Abadie (2006) finds that GDP per capita has little to do with terrorism and this lack of political rights is the main determinant of these acts. Piazza (2006) suggests that unemployment is not a strong indicator of terrorism. In fact, he finds no relationship between economic development variables such as economic growth, inflation, unemployment, inequality and terrorism. Krueger and Laitin (2008) suggest that political repression and not economic status is a better determinant of the national origins of terrorism. Burgoon (2006) finds that social well-being, measured by social spending as a percentage of GDP, reduces terrorism.

Despite a growing number of empirical studies, no consensus has emerged on the determinants of terror; on the contrary, the estimates differ considerably in terms of sign, size and significance. In addition, many works emphasized the importance of socio-economic factors others considered institutional and political indicators without unanimous findings. In this context, we seek to identify the optimal set of potential determinants of each type of attacks combining results of previous works. In addition, we develop an early warning system of terrorism attacks and test out–of-sample predictive ability of our model.

3. Empirical evidence

3.1. Data

Dependent variable: Our main dependent variable is Global Terrorism Index (GTI) which indicate terrorist activity taking into account at the same time the number of terrorist attacks, kills, woods and material damage in a country per year of observation.

Similarly, we use the number of incidents (Incid), kills (Kills) and woods (Woods) as alternatives measures of terrorist activity. In addition, we use a binary variable as a proxy for terrorism indicating the occurrence or not of a terrorist attack during a given year.

We adopt this approach in order to know if the different measures of terrorism lead to the same conclusions. In addition we chose a binary variable to carry out logit regressions allowing to asses robustness of our results and develop a forecasting framework.

Therefore, we distinguish between domestic and international terrorism and try to understand whether they have the same origins or they differ widely based on the classifications of "GLOBAL TERRORISM DATABASE CODEBOOK" published by the University of Maryland in 2018 distinguishing between logistical, ideological and miscellaneous dimensions.

International- Logistical: If the nationality of the group of perpetrators differs from the location of the attack, terrorism event is considered as international. If the perpetrator's group is multinational, the attack is international if all the nationalities of the group differ from the scene of the attack. However, when the nationality of perpetrators is the same as the attack place the latter is considered as domestic. If the perpetrator's group is multinational, the attack is national if one of the group's nationalities is the same as the location of the attack.

International- Ideological: The attack is ideologically international if the nationality of the group of attackers differs from the nationality of the target. If the group or target of terrorists is multinational, the attack is ideologically international. The attack is ideologically domestic if all the nationalities of the terrorist group are the same as the nationalities of the target.

International- Miscellaneous: Contrary to logistically and ideologically international variables, it does not require information on the nationality of the group of perpetrators. If an attack is miscellaneously international, it is by obligation international in terms of logistics or ideology, but we do not know which one. If an attack is domestic on this dimension, it can also be logistically international or ideologically international, or domestic in all dimensions. The attack was diverse international if the place of the attack differs from the nationality of the victim (s). The attack is domestic diversified if the place of the attack is the same as the nationalities of the target." So, our variable of interest "the attack" is considered international if it is international in all dimensions. The attack is domestic if it is domestic in all the dimensions described above (logistically, ideologically, Miscellaneous).

Explanatory variables: We use the GDP growth variable (GDPG) as an economic indicator measuring domestic economic production to quantify wealth production achieved over a given period, thanks to economic resident agents. It is therefore an indicator reflecting economic activity where change indicates about country's economic growth and poverty and so can impact terrorism (Blomberg et al. 2004; Piazza, 2006; Caruso and Schneider 2011).

In the same logic, we introduce the variables poverty (PAUV) such as Krueger and Malečková (2003) and GDP by habitant (GDPC) like Abadie (2006) to measure the purchasing power of citizens and institutional efficiency. These indicators should help untangle effects of poverty and inequality on terrorism. Indeed, Freytag et al. (2011) argue that lower income levels imply lower opportunity costs of violence, which makes challenging terrorism more attractive. In addition, the unemployment rate (Ut) is a statistic that can be used to reflect the country's economic situation (Piazza, 2006). Unemployment may cause poverty leading to the lack of insufficient materials and resources. Bad social and economic conditions can give rise to grievances and terrorism.

Consistent with the evidence from the existing literature on terrorism and according to Gassebner and Luechinger (2011), population size is proposed to be a positive predictor of terrorism. For example, the positive association between population size and terrorism may be due to a scale effect, where larger countries are expected to present more terrorist targets, victims and potential terrorists. Thus, in order to test whether terrorism depends on demographic indicators or on the spatial dispersion of citizens, we used the total number of people (POP) and population density (Popd) to determine effect of concentration on attack decision.

Likewise, given the effect of government spending in infrastructure, health, research and development on agents' feelings and therefore on violent behavior, we found it important to study the impact of general government final consumption expenditure (GGFCE) as done by Burgoon (2006).

Moreover, literature review shows that financial development can play an important role in explaining terrorism (Chiu and Lee, 2019). For this reason, we used capital inflows presented but Foreign Direct Investment (FDI) as an indicator of financial development via capital account liberalization. Then we used domestic credit to the private sector (DCPS) indicating financial resources provided to the private sector. These indicators are used as measures of financial development playing as conduit for investment.

In the same sense, the previous literature emphasized the feeling of privation and non-belonging as worsening with unequal opportunity especially in the distribution of wealth. So, we choose the GINI index (GINI) as the measure of income distribution inequalities to measure the effect of justice and social equity on the decision of terrorism like Piazza (2006).

Likewise, to measure the importance of social media and telephone network to facilitate communications and organization on the probability of terrorist attacks, we used the variable Mobile cellular subscriptions (MOBCS) where importance is highlighted by Weimann (2016). We also use three variables to measure the effect of agent's instruction on terrorism (Krueger and Malečková, 2003) namely: Primary School enrollment (schp); Secondary school enrollment (schs) and Tertiary school enrollment (scht).

Finally, we are based on political regime indicators (Preg) that allow assessing the effect of the democratic framework, civil liberties and participation in elections and political life on terrorism. We used the variable elaborated by Anckar and Fredriksson (2019) which corresponds to a score indicating about autocracy, anocracy and democratic situation where the high value implies more liberty and democracy. The last set of variables relates to governance quality and political risk indicators (Pr) as supported by Krueger and Laitin (2008) that political situation may be a potential determinant of terrorism (the list of sub-indicators is explained in Table A1 in the appendix).

3.2. Methodology

As we can see there are many potential determinants of terrorism attacks which pose a trade-off between keeping global jointly significance of indicators and reducing terrorist monitoring costs. On the one hand the introduction of a large number of non-important variables can inflate the standard error and on the other hand the sequential introduction of the variables can lead to the loss of important information by the excluding relevant variables based only on statistical results (Koop, 2003). To resolve this uncertainty, some works use the Bayesian model Averaging (BMA) such as Sala-i-Martin et al., 2004; Hamdaoui, 2016). This technique makes it possible to provide the optimal combination by examining all the possibilities that may arise for a set of indicators and weighting them according to their fit. In other words, the Bayesian approach can be used to detect potential indicators from a large number of variables. It is based on the key "Posterior Inclusion Probability" (PIP) statistic to measure the importance of each variable. The importance of a variable to explain the dependent variable can be expressed by the probability of inclusion of this variable in the regression. This statistic makes it possible to judge at which level a potential variable is associated with the dependent variable. Variables with high levels of PIP are considered robust indicators for the explanation of the dependent variable while variables with low PIP are not relevant indicators of the dependent variable. According to Kass and Raftery (1995): "the significance of each repressor is weak, positive, strong or decisive if the PIP lies between 0.5 and 0.75; 0.75and 0.95; 0.95 and 0.99 or 0.99 and 1, respectively ". Therefore, there is another important statistic giving an idea about the quality of the model "Model Probability" (PMP). This statistic permits to select the most performing model containing the best combinations of variables to be included. So, in this work we refer to this technique to choose the potential indicators of terrorism and the best possible combinations. Our idea is instead of monitoring several indicators it is possible to control a limited number of most important potential early warning system based on the BMA.

In the second part of this work our objective is therefore not to predict the exact timing of a crisis, but to predict whether a crisis occurs within a specific time horizon. Our approach consists in transforming the variable attack into a forward-looking variable $y_{i,t}$ defined as:

$$Y_{i,t} = \begin{cases} 1\ if\ \exists\ k = 1, \dots, h\ if\ attack_{i,t+k} = 1 \\ 0\ otherwise \end{cases} \tag{1}$$

In this case we attempt to predict the occurrence of an attack in the coming *h* years. The specification of the used binary logit model is as follow:

$$Y_{i,t} = \begin{cases} 1 \; with\; the\; probabilty\; pr(y=1) = p \\ 0 \; with\; the\; probabilty\; pr(y=0) = 1 - P \end{cases} \quad (2)$$

The probability of an attack for each country i at a given date t is given by:

$$pr(y_{it} = 1/X, \beta, \alpha) = \frac{e^{\alpha + \sum_{j=1}^{J} \beta_j X_{j,it}}}{1 + e^{\alpha + \sum_{j=1}^{J} \beta_j X_{j,it}}} \quad (3)$$

Where β_j corresponds to the estimated coefficient associated with the j^{th} indicator through the maximum likelihood method. $X_{j,it}$ is the jth expalnatory variable used to explain attack in country i during the t^{th} year.

3.3. Results and interpretations

As a preliminary analysis we start with the correlation matrix in order to study the link between the different variables to be included in our model. This approach allows us to exclude the variables strongly correlated with each other and avoid the problem of multicollinearity as indicated by the previous literature on panel data. The correlation matrix (Table 1) shows that some variables are strongly correlated such that the correlation coefficient exceeds 0.5 in many cases. In addition, for the global model there is a VIF statistic greater than 10 (39.35) and the average of the VIFS is greater than 2 (4.65) which imply that the introduction of all the variables in the same model may lead to wrong conclusions. For example, the « schs » variable is correlated with the variable (scht) indicating that the majority of children who attend secondary school finish their university studies such that the correlation rate is 0.64. So, given that the second variable is more correlated with the variable (mobs) we chose to keep the first. Likewise, the variable measuring political risk (pr) is a composite index of 12 risk indicators strongly correlated with different determinants that are themselves correlated with each other. Hence, we have chosen to carry out an iterative approach by introducing each time one of these sub-indices end of measurement their contribution to explain the likelihood of terrorism[1]. This approach leads to 13 specifications where only Mean VIFS are presented confirming that our various specifications are valid and no longer suffer from serious collinearity problems that influence credibility and robustness of our conclusions and implications[2].

3.3.1. Determinants of terrorism

3.3.1.1. Total terrorism

Global Terrorism Index (GTI): Results of the Bayesian inference method are presented in Table 2 (Line 2). We indicate that the nature of the relationship between explanatory and dependent variable is determined by the sign of the “post mean” indicator and importance of each variable can be assessed by the comparison of the corresponding PIP to the unit[3]. In this way, our results show that the variables "mobs" and "preg" positively and significantly affect the dependent variable since the corresponding post mean are positive and the PIP is 1.0. This means that more people are subscribed to the telephone line and the country is democratic, more it is exposed to terrorism risk when we used the GTI. However, the coefficients associated with the variables "dcps"; "schs" and "pr" are negative (post mean are negative) and statistically significant with corresponding PIP of 1.0; 0.98 and 0.97, respectively. According to the criteria of Kass and Raftery (1995) the significance of these indicators is strong and even decisive since corresponding PIPs are greater than 0.95. Therefore, more credit to the private sector, more secondary schooling and less political risk significantly reduce the likelihood of terrorist attacks and material damage.

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1 For paper length reasons, we present only the first model which contains the aggregate indicator of political risk. Results concerning sub-indicators of political risks are not provided.

2For the models from 1 to 13 and no longer for the initial model all the VIFS statistics are less than 10 and the mean VIFS are less than 2.

3 To avoid redundancy we presented with details the Principe of the BMA in the case of total terrorism index and total attacks and note that the same thing remains for the other cases. For this, we go sometimes directly to results discussions and results are provided in different tables.

Table 1. Correlation matrix.

	pauv	pop	gdpg	gdpc	gini	ggfce	dcps	mobcs	fdi	popd	schp	schs	sch_t	ut	preg	pr	gs	sc	ip	ic	ec	cor	mp	rt	lo	et	da	bq
pauv	1.0																											
pop	.36	1.0																										
gdpg	-.13	-.02	1.0																									
gdpc	-.67	-.37	.16	1.0																								
gini	-.49	-.30	.17	.61	1.0																							
ggfce	-.29	-.34	.01	.09	.05	1.0																						
dcps	-.21	-.15	-.07	.27	.16	-.07	1.0																					
mobcs	-.27	.09	-.02	.12	.04	-.16	.30	1.0																				
fdi	.03	-.08	.05	-.03	-.05	-.01	.24	.25	1.0																			
popd	-.26	-.22	-.08	.05	.05	-.03	.24	.29	.21	1.0																		
schp	-.13	-.09	-.21	.06	-.01	.08	.02	.21	.02	.11	1.0																	
schs	-.43	-.08	-.01	.26	.10	.17	.19	.57	.24	.30	.44	1.0																
sch_t	-.15	.12	-.11	-.08	-.21	.04	.18	.59	.27	.23	.26	.64	1.0															
ut	.47	.24	-.11	-.60	-.60	-.14	-.08	-.12	.01	-.33	.01	-.25	.07	1.0														
preg	.13	.25	-.17	-.25	-.22	-.06	.10	.14	.11	.05	.19	.14	.34	.20	1.0													
pr	-.19	.01	.16	.22	.17	-.11	.33	.40	.28	.13	.06	.48	.24	-.15	-.06	1.0												
gs	-.01	.14	.17	.10	.02	-.20	.16	.28	.31	.01	.09	.33	.18	-.01	-.02	.74	1.0											
sc	-.48	-.21	.16	.49	.47	.10	.30	.22	.08	.12	.05	.31	-.05	-.37	-.24	.56	.33	1.0										
ip	-.37	-.08	.16	.34	.28	-.10	.36	.55	.28	.24	.08	.45	.27	-.22	-.06	.70	.66	.57	1.0									
ic	-.06	.04	.17	.10	.06	-.11	.15	.24	.22	.02	.02	.35	.18	-.06	-.07	.86	.65	.40	.46	1.0								
ec	.07	.15	.11	.01	-.05	-.23	.17	.36	.22	.12	-.01	.35	.22	.06	.05	.82	.62	.23	.49	.78	1.0							
cor	-.20	-.21	-.03	.10	.09	.25	.18	-.16	-.11	.04	.05	.05	-.09	.01	.12	.13	-.10	.24	.004	.009	-0.6	1.0						
mp	-.32	-.11	.06	.41	.43	.002	.39	.19	.06	.04	.06	.35	.06	-.32	-.16	.63	.30	.52	.43	.45	.36	.25	1.0					
rt	.04	-.04	.07	-.02	.03	-.18	.14	.30	.16	.06	.08	.20	.17	-.01	-.03	.62	.47	.18	.30	.68	.61	-.04	.27	1.0				
lo	-.27	.03	.07	.24	.21	-.10	.29	.43	.24	.27	.13	.56	.39	-.25	.05	.82	.59	.43	.58	.72	.66	.04	.57	.52	1.0			
et	.06	.06	.13	.004	-.02	-.09	.12	.27	.26	.01	.02	.22	.06	.01	-.24	.65	.51	.27	.36	.71	.63	-.14	.32	.46	.52	1.0		
da	.03	.18	-.02	-.15	-.16	.02	.22	.19	.17	.20	.02	.14	.26	.02	.69	.22	.008	.01	.14	.11	.19	.22	.03	.01	.13	-.04	1.0	
bq	-.33	-.03	.06	.25	.20	-.02	.44	.25	.07	.22	-.07	.39	.21	-.19	.22	.53	.20	.41	.42	.28	.34	.39	.47	.04	.52	.04	.41	1.0
VIF0	3.39	1.96	1.24	4.01	2.55	1.80	1.89	3.13	1.42	2.34	1.70	4.21	3.21	3.15	3.29	39.35	4.52	2.96	4.66	7.37	7.55	1.90	3.17	3.41	5.15	3.69	3.41	3.68
Mean VIF0																4.65												
																1.92	1.89	1.89	1.92	1.88	1.92	1.87	1.92	1.87	1.92	1.89	1.99	1.93

Table 2. Total terrorism.

Variables			pauv	pop	gdpg	gdpc	gini	ggfce	dcps	mobcs	fdi	popd	schp	schs	ut	preg	pr
GTI	PIP		.04	.02	.06	.16	.03	.10	1.0	1.0	.19	.01	.14	.98	.01	1.0	.97
	Post Mean		-	+	+	+	+	+	-	+	-	-	+	-	+	+	-
	Topmodels	.39	.00	.00	.00	.00	.00	.00	1.0	1.0	.00	.00	.00	1.0	.00	1.0	1.0
	PMP	.11	.00	.00	.00	.00	.00	.00	1.0	1.0	1.0	.00	.00	1.0	.00	1.0	1.0
	(Exact)	.06	.00	.00	.00	.00	.00	.00	1.0	1.0	.00	.00	1.0	1.0	.00	1.0	1.0
Woods	PIP		.06	.03	.08	.19	.15	.26	1.0	1.0	.08	.01	.27	.97	.07	1.0	.96
	Post Mean		+	+	+	+	+	+	-	+	-	-	+	-	-	+	-
	Top	.31	.00	.00	.00	.00	.00	.00	1.0	1.0	.00	.00	.00	1.0	.00	1.0	1.0
	models	.10	.00	.00	.00	.00	.00	.00	1.0	1.0	.00	.00	1.0	1.0	.00	1.0	1.0
	PMP (Exact)	.06	.00	.00	.00	1.0	.00	.00	1.0	1.0	.00	.00	.00	1.0	.00	1.0	1.0
Kills	PIP		.01	.02	.04	.14	.07	.08	1.0	1.0	.16	.05	.09	.96	.01	1.0	.92
	Post Mean		+	+	+	+	+	+	-	+	-	-	+	-	-	+	-
	Top	.42	.00	.00	.00	.00	.00	.00	1.0	1.0	.00	.00	.00	1.0	.00	1.0	1.0
	models	.11	.00	.00	.00	.00	.00	.00	1.0	1.0	1.0	.00	.00	1.0	.00	1.0	1.0
	PMP (Exact)	.05	.00	.00	.00	1.0	.00	.00	1.0	1.0	.00	.00	.00	1.0	.00	1.0	1.0
Incidents	PIP		.01	.04	.03	.10	.09	.07	1.0	1.0	.58	.03	.21	.98	.02	1.0	.96
	Post Mean	-	+	+	+	+	+	-	+	-	-	+	-	-	+	-	
	Top	.28	.00	.00	.00	.00	.00	.00	1.0	1.0	1.0	.00	.00	1.0	.00	1.0	1.0
	models	.17	.00	.00	.00	.00	.00	.00	1.0	1.0	.00	.00	.00	1.0	.00	1.0	1.0
	PMP (Exact)	.05	.00	.00	.00	.00	.00	.00	1.0	1.0	1.0	.00	1.0	1.0	.00	1.0	1.0
Attacks	PIP		.08	1.0	.07	.04	.48	.04	.30	.10	.18	.98	.12	.96	.04	1.0	1.0
	Post Mean		+	+	+	-	+	-	-	+	+	+	-	+	-	+	-
	Top	.21	.00	1.0	.00	.00	.00	.00	.00	.00	.00	1.0	.00	1.0	.00	1.0	1.0
	models	.14	.00	1.0	.00	.00	1.0	.00	.00	.00	.00	1.0	.00	1.0	.00	1.0	1.0
	PMP (Exact)	.06	.00	1.0	.00	.00	1.0	.00	1.0	.00	.00	1.0	.00	1.0	.00	1.0	1.0

Total woods: If we use the variable number of woods or kills as a proxy for terrorism the results do not vary with respect to the use of the GTI composite indicator (Table 2, Line 3).

Total Kills: When measuring multinational terrorism by the number of victims, the results no longer differ from the two other previous measures, namely the number of injured and the global terrorism index (Table 2, Line 4).

Total incidents: When using the number of incidents as proxy for terrorism (Table 2, Line 5), we notice that the FDI variable becomes a potential indicator in the sense that it reduces the number of attacks in the MENA region in a significant way. We also note political risk is still relevant to explain multinational terrorism. In particular, the strengthening of socioeconomic conditions, the fight against corruption, low military participation in politics, the reduction of religious tensions and the strengthening of the legal and judicial system contribute to the reduction of terrorist attacks. So, our results show that terrorism is mainly due to technological innovation and the development of means of communication in addition to civil and ideological freedom in the democratic regimes. These terrorist triggers can be attuned by financial development, more schooling and more political risk reduction. Contrary to some previous work we find that the economic and demographic indicators are no longer statistically significant to explain terrorism except for income inequality which appears from time to time significant according to the specifications of the model.

Total attack: Unlike the various continuous measures of terrorism, taking a binary indicator that indicates whether or not the terror is unfolding changes the importance and significance of the variables (Table 2, Line 6). In one hand, we can see that the PIPs associated to the variables population growth (popg), population density (popd) and democratic political regimes are greater than 0.95 with positive sign of Post mean. This implies that there is at least a strong positive links between these indicators and the terrorism attack probability. Therefore, the decision of attacks depends on demographic conditions such as total and density of population dispersion. In other words, countries that are more popular and where people are more congregated form an important target for terrorists, and democratic political regimes promote this behavior. In the other hand, financial development once again remains a factor reducing the incentives to carry out terrorist attacks even not strongly since post mean is negative and can be chosen among the indicators in the best combinations of the three most optimal models. In addition, the understanding of telecommunication networks and the level of secondary schooling remain influential but are losing importance since post mean are positive but PIP associated to the variable (mobcs) is less than 0.5 corresponding to the low bound of PIP to consider a variable as important in explaining the endogenous variable. Similarly, the variable measuring inequality of opportunity is positively and at least weakly affecting terrorism attack decision with PIP of 0.48 too close to the lower limit of the Kass and Raftery (1995) criteria of factor's significance. Thus, our results indicate that essentially attacks are consequences of political risks since all political indicators are significant except for democratic accountability[4]. The Post Mean of the variable political risk is negative and corresponding PIP is 1.0 implying a decisive influence of this indicator on terrorism attack. Our results therefore imply that strengthening the political framework and reducing ethnic and religious tensions in addition to strengthening socio-economic and legal conditions significantly mitigate terrorist attacks in MENA region.

3.3.1.2. International terrorism

Global terrorism index: Table 3 (Line 2), which contains the results of potential indicators of international terrorism, taking the GTI as a measure, shows that the democratic environment and the development of telephone networks favor terrorism. Thus, the financial development measured by the level of credit granted to the private sector and secondary schooling significantly allow the slowing down of terrorist attacks in addition to foreign direct investment but less significantly. However, most governance indicators are no longer effective in explaining international terrorism, unlike terrorism of all kinds that we have already studied previously. Only socioeconomic conditions; the fight against corruption; reducing military participation in politics and religion tensions are important in determining the likelihood of attacks.

International woods: Similarly, when we use the number of woods as a proxy for international terrorism (Table 3, Line 3), we found that club effect is an important determinant of terrorism meaning that technological innovation and more adherence to communication means facilitates the planning and organization of international terrorism. In addition, democratic situation and more infrastructure development through more public spending favorite international terrorism, increasing the number of woods.

International kills: Our results show that determinants of terrorism do not differ significantly when using the number of injured instead of the number of deaths (Table 3, Line 4). In addition, when using one of these measures the results are similar to the case of using GTI as a proxy for terrorism except for the public expenditure variable which becomes a little more important in the latter cases.

International Incidents: The results differ slightly relative to other measures of terrorism as the Composite Political Risk Index becomes important in explaining the annual frequency of international terrorist attacks (Table 3, Line 5).

International attacks: Based on a binary indicator to specify the occurrence of an international terrorist attack the results differ widely from the conclusions previously found (Table 3, Line 6). Indeed, economic indicators such as the GINI index and poverty are gaining ground in explaining the occurrence of the attack while the number of telephone network subscribers no longer matters. The total population and population density became significant determinant of terrorism. Thus, the level of secondary schooling is no longer a relevant indicator, but the level of financial development and the quality of the political regime retain their major contribution to explain the attack. Likewise, political risk becomes a very determining factor of terrorism such that all of the sub-indicators are statistically significant to explain the international attack.

[4] For the length of the paper we present only results corresponding to the composite index.

Table 3. International terrorism.

Variables			pauv	pop	gdpg	gdpc	gini	ggfce	dcps	mobcs	fdi	popd	schp	schs	ut	preg	pr
GTI	PIP		.04	.01	.03	.06	.05	.32	.98	1.0	.72	.03	.07	.94	.04	1.0	.33
	Post Mean		-	+	+	+	+	+	-	+	-	+	+	-	-	+	-
	Top	.20	.00	.00	.00	.00	.00	.00	1.0	1.0	1.0	.00	.00	1.0	.00	1.0	.00
	models	.16	.00	.00	.00	.00	.00	1.0	1.0	1.0	1.0	.00	.00	1.0	.00	1.0	.00
	PMP (Exact)	.07	.00	.00	.00	.00	.00	.00	1.0	1.0	1.0	.00	.00	1.0	.00	1.0	1.0
Woods	PIP		.05	.02	.07	.11	.03	.77	.99	1.0	.81	.04	.05	.98	.07	1.0	.21
	Post Mean		-	+	+	+	+	+	-	+	-	+	+	-	-	+	-
	Top	.35	.00	.00	.00	.00	.00	1.0	1.0	1.0	1.0	.00	.00	1.0	.00	1.0	.00
	models	.08	.00	.00	.00	.00	.00	.00	1.0	1.0	1.0	.00	.00	1.0	.00	1.0	.00
	PMP (Exact)	.05	.00	.00	.00	.00	.00	1.0	1.0	1.0	1.0	.00	.00	1.0	.00	1.0	1.0
Kills	PIP		.03	.06	.01	.12	.07	.25	.97	1.0	.62	.03	.05	.95	.05	.98	.33
	Post Mean		-	-	+	+	+	+	-	+	-	+	+	-	-	+	-
	Top	.22	.00	.00	.00	.00	.00	.00	1.0	1.0	1.0	.00	.00	1.0	.00	1.0	.00
	models	.13	.00	.00	.00	.00	.00	1.0	1.0	1.0	1.0	.00	.00	1.0	.00	1.0	.00
	PMP (Exact)	.09	.00	.00	.00	.00	.00	.00	1.0	1.0	.00	.00	.00	1.0	.00	1.0	.00
Incidents	PIP		.01	.02	.01	.04	.06	.22	.94	1.0	.81	.02	.03	.63	.01	1.0	.94
	Post Mean	-	-	-	+	+	+	-	+	-	-	+	-	-	+	-	
	Top	.21	.00	.00	.00	.00	.00	.00	1.0	1.0	1.0	.00	.00	.00	.00	1.0	1.0
	models	.21	.00	.00	.00	.00	.00	.00	1.0	1.0	1.0	.00	.00	1.0	.00	1.0	1.0
	PMP (Exact)	.07	.00	.00	.00	.00	.00	1.0	1.0	1.0	1.0	.00	.00	1.0	.00	1.0	1.0
Attacks	PIP		.34	.74	.08	.05	.95	.07	.91	.30	.39	.86	.18	.47	.07	1.0	1.0
	Post Mean		+	+	+	-	+	-	-	+	+	+	-	+	-	+	-
	Top models	.09	.00	1.0	.00	.00	1.0	.00	1.0	.00	.00	1.0	.00	.00	.00	1.0	1.0
	PMP (Exact)	.08	.00	1.0	.00	.00	1.0	.00	1.0	.00	1.0	1.0	.00	.00	.00	1.0	1.0
		.07	.00	1.0	.00	.00	1.0	.00	1.0	1.0	.00	1.0	.00	.00	.00	1.0	1.0

3.3.1.3. National terrorism

Global Terrorism index: By using the GTI index as a measure of terrorism, we once again note that financial development, level of education as well as political risk management increase certainty and reduce the risk of attacks. The coefficients associated with these variables are negative and the corresponding PIPs approach unity (Table 4, Line 2). Likewise, our results show that the extent of the means of communication and the democratic atmosphere form a favorable ground for triggering terrorist attacks. Improved socioeconomic conditions reduced internal conflict, corruption, intervention of military on politics, reducing religious tensions and reinforcing law and order decrease domestic terrorism. Our results show that indicators did not differ in a remarkable way between domestic and international terrorism when we used the GTI indicator. With the exception of the FDI which was a potential determinant of international terrorism, it is not important for domestic terrorism and several governance indicators are more influential for domestic terrorism.

National woods: Using the number of injured as an indicator of national terrorism, we reiterate that the results do not differ significantly from the first case which relies on the GTI as a proxy for terrorism. Only the variable measuring the level of primary schooling increases the number of injured (Table 4, Line 3). In other words, agents with low levels of education seem to be easier to integrate with domestic terrorism.

National kills: To avoid redundancy we indicate that the determinants of terrorism when we use the number of deaths, victims or GTI are similar with more importance of education indicators relative to multinational and international terrorism (Table 4, Line 4).

National Incidents: Contrary to other continuous measures of domestic terrorism we note that capital flows (FDI) dramatically reduce the number of indents (Table 4, Line 5).

National attacks: Like other types of terrorism, global and international, when we use a binary measure to characterize national terrorism, several economic indicators become crucial, in particular the unemployment rate which was no longer significant (Table 4, Line 6). So, we found that the decision of a national attack is taken because of unequal opportunity and unemployment which are structural in most of MENA's countries. In this difficult economic situation, our results show that the level of education no longer matter and does not have an influence on the behavior of extreme violence.

Table 4. National.

Variables			pauv	pop	gdpg	gdpc	gini	ggfce	dcps	mobcs	fdi	popd	schp	schs	ut	preg	pr
	PIP		.10	.06	.04	.17	.10	.03	1.0	1.0	.05	.06	.26	.94	.03	1.0	.98
	Post Mean		+	+	+	+	+	+	-	+	-	-	+	-	+	+	-
GTI	Top models	.43	.00	.00	.00	.00	.00	.00	1.0	1.0	.00	.00	.00	1.0	.00	1.0	1.0
	PMP	.14	.00	.00	.00	.00	.00	.00	1.0	1.0	.00	.00	1.0	1.0	.00	1.0	1.0
	(Exact)	.05	.00	.00	.00	1.0	.00	.00	1.0	1.0	.00	.00	.00	1.0	.00	1.0	1.0
	PIP		.05	.03	.10	.08	.10	.05	1.0	1.0	.08	.05	.27	.86	.04	1.0	.96
	Post Mean		+	+	+	+	+	+	-	+	-	-	+	-	-	+	-
Woods	Top models	.34	.00	.00	.00	.00	.00	.00	1.0	1.0	.00	.00	.00	1.0	.00	1.0	1.0
	PMP	.17	.00	.00	.00	.00	.00	.00	1.0	1.0	.00	.00	1.0	1.0	.00	1.0	1.0
	(Exact)	.05	.00	.00	.00	1.0	.00	.00	1.0	1.0	.00	.00	.00	1.0	.00	1.0	1.0
	PIP		.10	.04	.06	.11	.05	.02	1.0	1.0	.03	.02	.17	.86	.10	1.0	.97
	Post Mean		+	+	+	+	+	+	-	+	-	-	+	-	+	+	-
Kills	Top models	.47	.00	.00	.00	.00	.00	.00	1.0	1.0	.00	.00	.00	1.0	.00	1.0	1.0
	PMP	.10	.00	.00	.00	.00	.00	.00	1.0	1.0	.00	.00	1.0	1.0	.00	1.0	1.0
	(Exact)	.05	.00	.00	.00	.00	.00	.00	1.0	1.0	.00	.00	.00	.00	.00	1.0	1.0
	PIP		.03	.05	.06	.17	.14	.03	1.0	1.0	.35	.07	.26	.95	.06	1.0	.92
	Post Mean	+	+	+	+	+	+	-	+	-	-	+	-	+	+	-	
Incidents	Top models	.21	.00	.00	.00	.00	.00	.00	1.0	1.0	.00	.00	.00	1.0	.00	1.0	1.0
	PMP	.15	.00	.00	.00	.00	.00	.00	1.0	1.0	1.0	.00	.00	1.0	.00	1.0	1.0
	(Exact)	.10	.00	.00	.00	.00	.00	.00	1.0	1.0	.00	.00	1.0	1.0	.00	1.0	1.0
	PIP		.04	1.0	.03	.04	.89	.02	1.0	.97	.26	1.0	.52	.95	.84	1.0	1.0
	Post Mean		+	+	+	+	+	+	-	+	+	+	-	+	+	+	-
Attacks	Top models	.38	.00	1.0	.00	.00	1.0	.02	1.0	1.0	.00	1.0	1.0	1.0	1.0	1.0	1.0
	PMP	.17	.00	1.0	.00	.00	1.0	.02	1.0	1.0	.00	1.0	.00	1.0	1.0	1.0	1.0
	(Exact)	.08	.00	1.0	.00	.00	1.0	.02	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

3.4. Prediction of terrorism attacks

3.4.1. Total attacks

Given the strong correlation between different governance measures, it is not possible to introduce all variables in the same model. So, as we indicated previously we used the Bayesian model averaging methodology. Based on this approach, we note that the majority of governance indicators are important in determining the likelihood of terrorist attacks. However, we argue that it is more interesting to choose a composite index taking into account all the indicators which explains our choice for the first model to study performance of our approach in predicting terrorist attacks. We compare an unrestricted model based on all traditional variables besides political risk with a BMA-based restricted model. The latter contains only variables highly significant to explain terrorism, namely the total population, the population density, the political regime which are significant for the 13 specifications in addition to the variable domestic credit granted to the private sector which is important for 12 specifications to which we add indicators of inequality and level of education important in many situations to explain endogenous variable and which are chosen by one of the three best combinations (Table 2, Line 6).

Our results through the logit model confirm those found by the BMA such that the variables chosen are significant in explaining the dependent variable (Table 5). However, variables with associated low values of PIP are no longer significant using the standard frequentist method, the logit model. For example, pip associated to the variable POPG was 1.0 with positive sign in the BMA case and the coefficient associated to this indicator is also positive (.001) and significant at the 1% threshold since the corresponding P-value is .001<0.01.

Table 5. Logit estimation.

Variables	Non restraint model		Restraint model	
	Coef	P-value	Coef	P-value
pauv	.184	0.199		
pop	.045***	0.000	.048***	0.000
gdpg	.0025	0.753		
gdpc	2.e^{-06}	0.682		
gini	7.67***	0.000	6.48***	0.000
ggfce	-.008	0.953		
dcps	-.008**	0.017	-.006***	0.030
mobcs	.002	0.186		
fdi	.034	0.197		
popd	.001***	0.001	.001***	0.000
schp	-.002	0.715		
schs	.013**	0.022	.013***	0.002
ut	.011	0.619		
preg	.231***	0.000	.240***	0.000
pr	-.063***	0.000	-.058***	0.000
cons	-1.49	0.345	-.649	0.423
Number of obs	882		882	
Prob > chi2	.000		.000	
Pseudo R2	.295		.290	

*Note: *; **; and *** indicate statistical significance at 10%; 5% and 1% respectively.*

Table 6 shows that our model is generally efficient in the sense that it manages to predict three quarters of the attacks that occur in the MENA region. Additionally, the probability of an attack given an alert is over 86% for both specifications. Thus, almost 80% of the observations are correctly classified. However, the restricted model seems to be more effective since it announces fewer false alarms (13.15%) versus (13.47%) and it is cheaper to follow 7 indicators instead of 15.

Table 6. Predictive ability.

	No restraint model			Restraint model		
	Attack	No attack	Total	Attack	No attack	Total
Alert	379	59	438	370	56	426
No alert	130	314	444	139	317	456
Total	509	373	882	509	373	882
% of observations correctly classified		78.57%			77.89%	
% of attacks correctly called (sensitivity)		74.46%			72.69%	
% of false alarms to total alarms		13.47%			13.15%	
% of attack given an alarm		86.53%			86.85%	
% of attacks given no alarm		29.28%			30.48%	

3.4.2. International attacks

Table (3) containing the determinants of international terrorist attacks via the BMA method shows that the probability of an international attack depends essentially on the political regime, political risk, income inequality, credit to the private sector, the density of the population, total population, level of secondary education attendance, less remarkably on the level of FDI and the country's level of poverty. These results are quite robust in the sense that they are confirmed by the logistic regression, the results of which are presented according to an unrestricted model (second column of Table 7). Otherwise, all the variables selected by the BMA method are statistically significant at the conventional threshold in the standard frequentist regression. So, we are trying to understand if it is possible to predict the occurrence of this type of attack by reducing the indicators to be followed by decision-makers by referring to the potential indicators chosen by the BMA.

Table 7. Logit results.

Variables	Non restraint model		Restraint model	
	Coef	P-value	Coef	P-value
pauv	.313**	0.042	.294**	0.021
pop	.011**	0.017	.013***	0.002
gdpg	.0004	0.954		
gdpc	7e-07	0.916		
gini	7.74***	0.000	8.04***	0.000
ggfce	-.006	0.647		
dcps	-.010***	0.003	-.010***	0.002
mobcs	.002	0.231		
fdi	.045*	0.093	.047*	0.075
popd	.001***	0.008	.001***	0.000
schp	-.008	0.214		
schs	.012**	0.043	.010**	0.029
ut	-.001	0.962		
preg	.236***	0.000	.238***	0.000
pr	-.063***	0.000	-.060***	0.000
cons	-.711	0.639	-1.88*	0.087
Number of obs	882		882	
Prob > chi2	0.0000		0.0000	
Pseudo R2	0.2647		0.2616	

*Note: *; **; and *** indicate statistical significance at 10%; 5% and 1% respectively.*

The contingency matrix presented in Table 8 shows that our model is globally efficient in the sense that more than 77% of the observations are correctly classified and almost 80% of the alerts are correct with a slight superiority in favor of the restricted model. In other words, our model based on a lower number of variables is more important given that the percentage of attacks given an alert (78.99%) is higher than that associated with the general model (78.33%) in addition to the other indicators which globally resemble each other. So, we argue that it is possible first to reduce terrorist behavior by predicting the occurrence of attacks and secondly it is possible to act on the cost of prevention.

Table 8. Predictive ability.

	No restraint model			Restraint model		
	Attack	No attack	Total	Attack	No attack	Total
Alert	318	88	406	312	83	395
No alert	109	367	476	115	372	487
Total	427	455	882	427	455	882
% of observations correctly classified		77.66%			77.55%	
% of attacks correctly called (sensitivity)		74.47%			73.07%	
% of false alarms to total alarms		21.67%			21.01%	
% of attack given an alarm		78.33%			78.99%	
% of attacks given no alarm		22.90%			23.61%	

3.4.3. National attacks

Our results presented in table (4) show that the probability of a national terrorist attack strongly depends on the total population, financial development, political regime, and political risk. It thus depends to a lesser extent on telephone networks, secondary education, gini index, unemployment and primary schooling. The inflow of foreign capital followed by the degree of poverty affects less significantly the decision of terrorist attack on the scale of the countries of the MENA region while the rate of economic growth, level of GDP per head and public expenditure are no longer interesting for terrorists. So, in order to predict this type of attack we try to study the predictive capacity of our reduced model on the basis of the results of BMA relative to the general model containing all control variables. Our idea is to identify the most decisive indicators to reduce the preventive costs of attacks. Our results show that the logit model is less demanding than the BMA technique in the sense that the indicator of poverty and FDI which were not chosen by the inferential method became significant at least weakly in the case of frequentist econometrics (Table 9). With the exception of this observation, the outputs of the two techniques are regularly in conformity with regard to the significance of the other variables.

Table 9. Logit results.

Variables	Non restraint model		Restraint model	
	Coef	P-value	Coef	P-value
pauv	.320**	0.027		
pop	.055***	0.000	.052***	0.000
gdpg	.006	0.430		
gdpc	.0001	0.124		
gini	9.36***	0.000	8.46***	0.000
ggfce	.018	0.256		
dcps	-.019***	0.000	-.017***	0.000
mobcs	.008***	0.000	.007***	0.001
fdi	.052*	0.081		
popd	.002***	0.000	.002***	0.000
schp	-.020**	0.013	-.020**	0.010
schs	.021***	0.002	.021***	0.001
ut	.102***	0.000	.084***	0.000
preg	.224***	0.000	.219***	0.000
pr	-.064***	0.000	-.057***	0.000
cons	-3.86	0.020	-2.10	0.120
Number of obs	882		882	
Prob > chi2	.000		.000	
Pseudo R2	.379		.372	

*Note: *; **; and *** indicate statistical significance at 10%; 5% and 1% respectively.*

Our results (Table 10) show that it is easier to predict the occurrence of national attacks than international attacks, as the percentage of correctly classified observations stands at over 83% for national terrorism compared to only 77% for the international case. Our results also show that the explanatory factors of national terrorism are more numerous and the prediction results are also more precise in the sense that the percentage of attacks given an alert exceeds 82% with a small advantage in favor of the restricted model. Additionally, the model fails to predict only 16% of attacks that correspond to situations where the model does not announce a signal while the attack is taking place. Thus, the model announces false alerts in 17% of cases, that is to say that the model rarely announces alerts while the attack does not occur in the two types of models.

Our results essentially show that it is easier to predict domestic attacks and that the political environment is a potential early warning indicator of different types of attacks. Financial development, capital flows, secondary enrollment, reduction of inequalities is factors that lower the probability of terrorist attacks. While the high population density and the high number of citizens, especially in democratic countries characterized by high mobility of agents and freedom of organization and expression, represent a valuable target for terrorists.

Table 10. Predictive ability of the model.

	No restraint model			Restraint model		
	Attack	No attack	Total	Attack	No attack	Total
Alert	320	69	389	316	68	384
No alert	79	414	493	83	415	498
Total	399	483	882	399	483	882
% of observations correctly classified		83.22%			82.88%	
% of attacks correctly called (sensitivity)		80.20%			79.20%	
% of false alarms to total alarms		17.74%			17.71%	
% of attack given an alarm		82.26%			82.29%	
% of attacks given no alarm		16.02%			16.67%	

3.4.4. Robustness tests: Out-of-sample performance of the logit model

Out-of-sample forecasts have become the cornerstone of testing the goodness-of-fit of EWS models since the contribution of Berg and Pattillo (1999a) supporting the failure of modes to predict financial crises in subsequent periods. In our case, to check whether our model is able to predict terrorism attacks out-of-sample, we estimate the model on restricted periods and compute the probability of a terrorist attack in the following 24 months. In other words, the evolution of the explanatory variables in this period allows assessing whether the country is exposed to a terrorist attack at a time horizon of two years. A high computed probability assumes a significant fragility of the country; the supervisor is able to transmit an alert if the probability exceeds a critical threshold (cut-off). Thus, the predictive power of the model can be assessed using simple predictive quality indicators related to error types. Therefore, this specification suggests that the terror could be anticipated two years before. Given the values of our independent variables and the corresponding estimated coefficients, we seek to know whether regulators could detect sign of social agitation in the two years T and T + 1 in order to anticipate possible attacks at T + 2.

After getting the expected probabilities as described above, the decision maker must choose if the probability is quite sufficient to issue an alert. Issuing an alert leads to a kind of preventive actions; for example, the decision maker may invest more in information gathering such as data acquisition on the potential terrorist groups. Alternatively, institutional framework can be used to decide whether to take preventive measures such as restricting movement of agents. For an alert system to be used, it is required that preventive measures are able to substantially reduce the costs of an attack. Assuming that this is the case, preventive measures are generally expensive especially in terms of human rights in addition to economic costs related to barriers on the movement of production factors such as labor. A useful warning system must minimize false alerts, especially when the preventive measures are taken but there is no attack. To illustrate how the logit model can be used us a predictive tool, we carry out the out-of-sample test for the episode of 2018. We estimated the model over the period ending in 2016 and 2017, respectively emphasizing the importance of using the Bayesian Model Averaging method to choose potential leading indicators. To do this we need to choose the critical threshold; the probability beyond which the attack becomes highly probable and the model must issue a warning signal. In the literature of early warning models, there is no consensus on the choice of the cutoff. In the case of banking crises, Demirguc-Kunt and Detragiache (1998a, 2000) suggest taking the unconditional probability measured by crisis frequency in the sample. In our study, we rely on this criterion to retain a cutoff of .577 for global attacks, .485 for international attacks and .452 for national attacks. The out-of-sample probabilities and the goodness-of-fit of the non restraint and logit-BMA based models are presented in Tables 11 and 12.

Table 11. Predicted probabilities.

			Global attack			International attack			National attack		
			End point 2017 (Cut -off =.577)		Attack in 2018	End point 2017 (Cut-off=.485)		Attack in 2018	End point 2017 (Cut-off =.452)		Attack in 2018
Id	Country name	Models	2016	2017		2016	2017		2016	2017	
1	Algeria	Non restraint	.929	.930	Yes	.744	.742	Yes	.900	.911	Yes
		Restraint	.938	.940		.726	.721		.909	.921	
2	Bahrain	Non restraint	.825	.823	Yes	.583	.576	Yes	.910	.885	Yes
		Restraint	.780	.799		.522	.559		.909	.887	
3	Egypt	Non restraint	.988	.990	Yes	.788	.811	Yes	.992	.993	Yes
		Restraint	.987	.989		.777	.799		.989	.991	
4	Iran	Non restraint	.913	.916	Yes	.354	.363	no	.889	.893	Yes
		Restraint	.922	.925		.358	.364		.897	.904	
5	Iraq	Non restraint	.991	.992	Yes	.968	.970	Yes	.988	.990	Yes
		Restraint	.992	.992		.968	.970		.988	.990	
6	Israel	Non restraint	.933	.935	Yes	.871	.876	Yes	.893	.893	Yes
		Restraint	.936	.937		.858	.865		.886	.881	
7	Jordan	Non restraint	.508	.440	no	.457	.358	no	.484	.349	no
		Restraint	.421	.396		.371	.294		.441	.375	
8	Kuwait	Non restraint	.498	.496	no	.349	.364	no	.344	.329	no
		Restraint	.444	.458		.284	.298		.356	.371	
9	Lebanon	Non restraint	.966	.966	Yes	.946	.945	Yes	.881	.878	Yes
		Restraint	.965	.965		.947	.946		.887	.886	
10	Libya	Non restraint	.764	.784	Yes	.690	.707	Yes	.748	.785	Yes
		Restraint	.747	.765		.630	.660		.797	.800	
11	Morocco	Non restraint	.652	.694	no	.345	.379	no	.416	.484	no
		Restraint	.624	.661		.341	.371		.396	.453	
12	Quatar	Non restraint	.238	.249	no	.154	.164	no	.136	.146	no
		Restraint	.217	.222		.129	.133		.125	.139	
13	Saoudia	Non restraint	.644	.621	yes	.300	.287	no	.607	.565	yes
		Restraint	.622	.622		.268	.259		.636	.622	
14	Syria	Non restraint	.637	.682	Yes	.573	.654	Yes	.557	.653	Yes
		Restraint	.533	.528		.486	.557		.516	.533	
15	Tunisia	Non restraint	.888	.886	Yes	.820	.814	Yes	.814	.801	Yes
		Restraint	.879	.876		.807	.804		.788	.769	
16	Turkey	Non restraint	.983	.985	Yes	.760	.780	Yes	.983	.987	Yes
		Restraint	.984	.985		.750	.755		.981	.986	
17	United Arab	Non restraint	.312	.354	no	.187	.214	no	.171	.236	no
		Restraint	.256	.291		.139	.160		.193	.257	
18	Yemen	Non restraint	.955	.964	Yes	.916	.939	Yes	.942	.959	Yes
		Restraint	.949	.951		.901	.928		.944	.944	

Overall, both models act well, even out-of-sample, predicting most attacks of different types in the Mena region during 2018. Table 12 provides an idea about the predictive quality of our two models. Our model allows us to predict the occurrence of global attacks in 13 times out of 13 possible cases (100%) in the case of non restraint logit model and 12 out of 13 possible (92.30%) in the case of B-logit based on BMA. Yet, our restraint model failed completely to predict only one attack in Syria and emits bad signals in 7.69% of cases similar to non restraint one but percentage of attacks given an alarm and of attacks correctly called are important exceeding 92%. Similarly, our models perfectly predict international attacks and act very well in predicting national attacks with 92.85% of attacks given an alarm and 100% of attacks correctly classified. In summary, we can see that there is no great difference in terms of predictive ability between restricted and no restricted models and that is possible to predict most of terrorist attacks in a window of 24 months giving opportunity for policy maker to react effectively.

Table 12. Performance out–of-sample.

Global attacks	No restraint model			Restraint model		
	Attack	No attack	Total	Attack	No attack	Total
Alert	13	1	14	12	1	13
No alert	0	4	4	1	4	5
Total	13	5	18	13	5	18
% of observations correctly classified	94.44%			88.88%		
% of attacks correctly called (sensitivity)	100%			92.30%		
% of false alarms to total alarms	7.14%			7.69%		
% of attack given an alarm	92.85%			92.30%		
% of attacks given no alarm	0%			20%		
International attacks	No restraint model			Restraint model		
	Attack	No attack	Total	Attack	No attack	Total
Alert	11	0	11	11	0	11
No alert	0	7	7	0	7	7
Total	11	7	18	11	7	18
% of observations correctly classified	100%			100%		
% of attacks correctly called (sensitivity)	100%			100%		
% of false alarms to total alarms	0%			0%		
% of attack given an alarm	100%			100%		
% of attacks given no alarm	0%			0%		
National attacks	No restraint model			Restraint model		
	Attack	No attack	Total	Attack	No attack	Total
Alert	13	1	14	13	1	14
No alert	0	4	4	0	4	4
Total	13	5	18	13	5	18
% of observations correctly classified	94.44%			94.44%		
% of attacks correctly called (sensitivity)	100%			100%		
% of false alarms to total alarms	7.14%			7.14%		
% of attack given an alarm	92.85%			92.85%		
% of attacks given no alarm	0%			0%		

4. Conclusion and recommendations

In this work we have tried to identify origins of terrorism and answer the following questions: what are the potential determinants of terrorism? Is there a difference between causes of local and international terrorism? Is it possible to predict terrorist attacks?

To address these concerns, we are based on a Bayesian inference approach that was never applied in this context. This methodology has the advantage of overcoming the uncertainty associated with the choice of explanatory variables. In this way, we were able to identify the determinants of each category of terrorism: in one hand, terrorism measured by a continuous variable, regardless of its location, depends essentially on political risk, political regime, financial development, level of education and foreign direct investments which seem more significant in the case of international terrorism. On the other hand, for terrorism characterized by binary variable, demographic indicators such as the number and density of the population become statistically significant. Thus, economic conditions such as the GINI index and the unemployment rate affect domestic terrorism and poverty influence international terrorism decisions. Education indicators are losing significance. Otherwise, our results show that the poor are more likely to be involved in international terrorism, especially when there is income inequality and unemployment encourages agents to participate in national terrorism.

At this level of research we conclude that divergence from previous results concerning potential origins of attacks is mainly due to the measurement of "terrorism" itself and the econometric approaches. We hold this remark given that there are not great differences between the national and international causes of terrorism but divergence becomes remarkable when using binary instead of continuous measure.

Finally, our contribution is to present an attempt to develop an early warning system for terrorist attacks in a macro prudential framework. Our idea is to extract through BMA the most important variables in order to reduce prevention cost. Then, by applying binary Logit we estimate different parameters. This methodology allowed us to assess the in-sample predictive ability of our model which is globally relevant in the sense that we can predict more than 80% of attacks in the three specifications studied[5]. The estimated parameters can be used to calculate the future probabilities of an attack based on the actual variables chosen by the BMA method and in this way we can assess the predictive capacity out-of-sample.

As implications for our results, decision makers must first reduce political risk by strengthening the quality of the rules and the legal system, socioeconomic conditions, fight corruption, do not allow military intervention in politics, and reduce political and ethnic tensions. Then, the state must ensure financial development, improve the attractiveness of foreign direct investment and provide a secondary level of education for the majority of the population. Thus, governments must control social networks in democratic countries. Finally, our results show that in order to reduce or try to cancel terrorist risks; countries must act on unemployment and poverty by reducing income gaps and try to support the category of the poor who are considered with high risk and vulnerable to attraction by terrorist groups.

Funding Statement

This research received no external funding.

Acknowledgments

The authors would like to thank the Journal editors and two anonymous referees for their helpful and very constructive comments that improve the paper.

Conflict of interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

Appendix

Table A1. Data description.

Variables	Définition	Sources
Dependent variables		
Attack	A binary variable taking the value 1 when a country experienced an attack and 0 otherwise.	GTD: Global terrorism data.
Incid	The number of incidents during a given year	
Kills	The number of kills in a given year. It corresponds to all victims and attackers who died as a direct result of the incident.	
Woods	The number of woods during the covered year. It records the number of non-fatal injuries to both perpetrators and victims.	
GTI	Global Terrorism Index, it contains: incid (number of attacks), Kills (number of	

[5] The critical threshold used is the in-sample unconditional probability of the attack as we have already indicated before.

	deaths), woods (number of injured) and dam (material damage). GTI=1*incid+3*Kills+0.5*woods+2 *dam.	
Explanatory variables		
1. Economic, social and financial indicators		
PAUV	It is a categorical variable used as a proxy for poverty to give an idea about financial situation of terrorists and indicating economic situation of a target country during a fiscal year. It is constructed as follow: 4 for low income (L); 3 for Lower middle income (LM); 2 for Upper middle income (UM) and 1 for High income (H). The highest value of this variable implies more poverty.	World Bank Analytical Classifications GNI per capita
POP	pop (millions)	WDI
GDPG	Real GDP growth; annual %	
GDPC	GDP per capita (constant 2010 US$)	
GINI	It is a measure of statistical dispersion with a coefficient of zero expresses perfect equality between individuals and a coefficient of one expresses maximal inequality meaning that only one person owns all the income or wealth of the economy. It is used as a proxy for income inequality distribution.	
GGFCE	General Government final consumption expenditure (% of GDP)	
DCPS	Domestic credit to the private sector (%GDP)	
MOBCS	Mobile cellular subscriptions (per 100 people)	
FDI	Foreign direct investment, net inflows (% of GDP)	
Popd	Population density (people per sq. km of land area)	
Schp	School enrollment, primary (% gross): It refers to the ratio of total schooling whatever the age by the population of age group officially corresponding to this type of education. Primary education provides children with elementary training in reading, writing and math skills in addition to preliminary understanding of certain subjects such as geography, natural sciences, social sciences, art and music.	
Schs	School enrollment, secondary (% gross): It corresponds to the total number of secondary school students regardless of their age divided by the total number of the population belonging to that age group officially concerned by this type of education. It complements basic education that started at primary level and aims to lay the foundations for lifelong learning and human development, offering more subject-oriented or skill-oriented education.	
Sch t	School enrollment, tertiary (% gross): It corresponds to the total number of students independently of the age reported to the total population officially interested by the level of education indicated. As a condition of admission, it requires successful secondary education.	
Ut	Unemployment, total (% of total labor force) (modeled ILO estimate)	
2. Political Indicators		
Preg	Political regime quality it corresponds to a score ranging between -10 and 10 indicating political regimes natures as follow: a score between -10 and -6 implies autocracy; from -5 to 5 indicates anocracy and a score ranging between 5 and 10 corresponds to a democratic situation.	Anckar and Fredriksson (2019)
3. Governance indicators		
PR[6]	A synthetic index measuring country's political risk as a proxy for governance quality. It contains 12 subcomponents and ranges between 0 and 100 where the higher score points equates to Very Low Risk (high quality of governance and a score of 0 points to Very High Risk (or bad governance quality).	ICRG
GS	Government Stability (12)	
SC	Socioeconomic Conditions (12)	
IP	Investment Profile (12)	
IC	Internal Conflict (12)	
EC	External Conflict (12)	
Cor	Corruption (6)	

[6] The highest level of risk points corresponds to the lowest risk for all components.

MP	Military in Politics (6): Lower value indicates greater degree of participation and higher level of risk.
RT	Religious Tensions (6): Higher ratings are given to countries where tensions are minimal.
LO	Law and Order (6): a high value implies an effective judicial system.
ET	Ethnic Tensions (6); Higher ratings implies minimal tensions.
DA	Democratic Accountability (6);
BQ	Bureaucracy Quality (4)”.

Table A2. List of countries.

North African countries	Middle East countries
Algeria; Egypt; Libya; Morocco; Tunisia	Bahrain; Iran; Iraq; Israel; Jordan; Kuwait; Lebanon; Qatar; Saoudi Arabia; Syria; Turkey; United Arab Emirates; Yemen.

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