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ARTICLE

The Socioeconomic Determinants of Terrorism: A Bayesian Model Averaging Approach

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ABSTRACT
This paper introduces model uncertainty into the empirical study of the determinants of terrorism at country level. This is done by adopting a Bayesian model averaging approach and accounting for the over-dispersed count data nature of terrorist attacks. Both a broad measure of terrorism and incidents per capita have been analyzed. Our results suggest that, among the set of regressors considered, those reflecting labor market conditions and economic prospects tend to receive high posterior inclusion probabilities. These findings are robust to changes in the model specification and sample composition and are not meaningfully affected by the generalized linear regression model applied. Evidence of a geographically heterogeneous relationship between terrorism and its determinants is also provided.

Abbreviation: BMA- Bayesian Model Averaging; GLM- Generalized Linear Models

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Terrorism determinants; model uncertainty; Bayesian model averaging; generalized linear models

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Motivation

There has been an upsurge in the empirical analysis of the socioeconomic determinants of terrorism at country level after the 9/11 attacks. Related studies explore alternative information sources and dimensions of terrorist activity, consider different potential determinants of terrorism and sample periods, and apply a wide array of estimation methods. This implies that, although it is important to unveil the main causes of terrorism to deal with this scourge and mitigate its substantial and multidimensional costs, there is no clear consensus on the origins of terror in the literature. As an example, Krieger and Meierrieks (2011) provide an overview and critical discussion of the early evidence about the sources and targets of transnational terrorism, reaching no conclusive results.

A theoretical foundation for the hypothesis that economic grievances generate terrorism, based on the rational-choice theory and without dismissing noneconomic factors, can be found in Meierrieks (2014). This author suggests that the lack of empirical consensus on the causes of terrorism has to do with its heterogeneity and that its link with the economy needs to be further investigated. Morris and LaFree (2016) also review the quantitative studies about country-level correlates of terrorism, with an emphasis on economic, political and demographic variables. These authors highlight the significant influence exerted by economic development and inequality, democracy, failed states and physical integrity rights. In a related work, Kis-Katos, Liebert, and Schulze (2011) find that the roots of domestic and transnational terrorism are similar. In particular,

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they show that failed and weak states[1] are a breeding ground for terrorism, but do not support the hypothesis that economic deprivation promotes terrorism. These results are relatively stable to changes in the sample period analyzed. Freytag et al. (2011) develop a theoretical framework to show that poor socioeconomic conditions may result in terrorism through opportunity costs, providing empirical evidence of this relationship in both domestic and international incidents.

Gassebner and Luechinger (2011) implement an extreme bounds analysis (EBA, see Leamer 1983; Leamer and Leonard 1983) to identify the variables with a robust relationship with the number of incidents in a given country. These authors find that, among the possible determinants of terrorism included, those with a negative influence are economic freedom, physical integrity rights, law and order and infant mortality rates. The variables positively related to terrorism are population, urbanization, religious and ethnic tensions, military expenditure and personnel, wars, strikes, government fractionalization, foreign portfolio investments, OECD membership and political proximity to the United States. The main conclusion that can be drawn from this study is that, although there are some robust correlates of terrorism, the majority of the variables suggested in the literature are not supported by the EBA.

Motivated by the lack of consensus on the determinants of terrorism at country level, we contribute to this literature by introducing model uncertainty into this context through a Bayesian model averaging[2] (BMA) approach (Raftery 1995; Raftery, Madigan, and Hoeting 1997). By proceeding in this way, we are able to simultaneously deal with model selection, estimation and inference. In a nutshell, BMA assigns a prior probability to a set of models and updates it according to the data. The posterior model probabilities are later averaged and used to construct posterior inclusion probabilities (PIP) for the candidate regressors. Our empirical analysis controls for the over-dispersed count data nature of the information about terrorist incidents by implementing the BMA in a generalized linear model (GLM) framework (McCullagh and Nelder 1989; Nelder, Robert, and Wedderburn 1972). A broad terror measure (Freytag et al. 2011) is being used, together with the common distinction between domestic and transnational attacks. By abstracting from this widely applied dichotomy, we try to capture the phenomenon of terrorism in a country as a whole. Nonetheless, as Mueller (2016) points out, the study of absolute counts referring to countries with very different sizes may be problematic. In addition, individual welfare is more likely to be affected by terrorism measured in per capita terms (Jetter and Stadelmann 2017). For these reasons, terrorist incidents have also been considered in relative terms to population in the present study.

The rest of the paper is structured as follows. Section 2 describes the data sources and the variables included in the analysis. Section 3 presents the empirical strategy adopted, explaining the GLMs that deal with over-dispersed count data and BMA techniques. Section 4 shows the main results and checks of their robustness. Finally, Section 5 concludes, establishes policy recommendations and proposes avenues for future research.

Data Sources and Variables

The information about terrorist attacks has been extracted from the Global Terrorism Database (GTD), maintained by the National Consortium for the Study of Terrorism and Responses to Terrorism (START,[3] see LaFree and Dugan 2007), which includes data regarding incidents worldwide since 1970 (except 1993, due to issues with that year). The GTD defines terrorism as '*the threatened or actual use of illegal force and violence by non-state actors to attain a political, economic, religious, or social goal through fear, coercion, or intimidation*'. Using the available information about the date and the location of each terrorist event, the number of attacks has been aggregated at the country level on a yearly basis. Apart from this general measure of terror, the incidents have also been distinguished by their domestic or international character.

In the present paper, we are following Krieger and Meierrieks (2011), who identified broad theoretical families linking terrorism with socioeconomic, political and demographic factors. The source for these potential determinants of terrorism, included with a temporal lag to mitigate

Table 1. Potential socioeconomic determinants of terrorism: Description of variables.

Variable	Description
lngdppc	GDP per capita; constant 2011 international $; PPP; in natural logarithms
Growth	GDP growth; market prices; constant local currency; annual; per cent
Unempl	Unemployment; national/ILO estimates; as percentage of labor force
Inflation	GDP implicit deflator growth rate; annual; per cent
Consumhh	Household final consumption expenditure; as percentage of GDP
gfcf	Gross fixed capital formation; as percentage of GDP
Govexp	General government final consumption expenditure; as percentage of GDP
Openness	Trade (exports plus imports); as percentage of GDP
Primaryx	Exports of agricultural raw materials, food, ores and metals; as percentage of merchandise exports
Fuelx	Fuel exports; as percentage of merchandise exports
fdi	Foreign direct investment; net inflows; as percentage of GDP
Transfers	Net current transfers from abroad; current US$; as percentage of GDP
Aid	Net official development assistance and official aid received; current US$; as percentage of GDP
Lnpopul	Total population; in natural logarithms
Popdens	Population density; people per square kilometer of land area
Urban	Urban population; as percentage of total population
Lifexp	Life expectancy at birth; in years
Female	Female labor force participation rate; modeled ILO estimate; as percentage of female population aged over 15
Primary	Primary school enrollment rate; gross; in per cent
Secondary	Secondary school enrollment rate; gross; in per cent
Armedf	Armed forces personnel; as percentage of total labor force
Milexp	Military expenditure; as percentage of GDP

Note: Data source is the World Development Indicators (The World Bank 2017). The sample period covers the years from 1990 to 2014.

possible reverse causality concerns, is the World Development Indicators (The World Bank 2017). Due to the lack of data on some variables, our sample is made up of 130 countries and covers the period 1990–2014 (see Appendix A for more details). A description of the whole set of regressors considered in the empirical analysis can be found in Table 1.

A first group of variables reflecting economic conditions and development is made up of real GDP per capita, the annual rate of real GDP growth, the unemployment and inflation rates, household and government final consumption expenditure and gross fixed capital formation. Further, there is a preconceived idea that globalization alters existing structures and provides new opportunities for alienated people. This hypothesis would imply that other things being equal, open countries will be less prone to terrorist attacks. For this reason, the sum of exports and imports as a percentage of GDP has been included as an explanatory variable. Exports of primary goods and fuel try to capture that, as in other forms of violence, terrorism may be related to the abundance of natural resources. Inflows of foreign direct investment, transfers from abroad and official development assistance and aid received have also been considered as potential determinants of terrorism.

A greater number of targets, victims and perpetrators can be found in large countries. Therefore, total population[4] and population density have been introduced into our set of candidates to explain terrorism. Urban population has been included because there is a consensus in the related literature that urbanization is conducive to terrorism. Other variables studied are life expectancy, female labor force participation and primary and secondary school enrollment rates. It has also been taken into account that terrorism is commonly used by the weaker contender in an asymmetric armed conflict. This has been proxied by the personnel in the armed forces and military expenditure. In this regard, it is worth noting that defence spending may also reflect counter-terrorism efforts and their effectiveness.

Empirical Strategy

GLMs for Count Data

As has already been well established in the related literature, the number of terrorist attacks is a count variable with a variance larger than its mean. The reason is that, while there are a non-negligible number of countries which have not experienced a terrorist incident in a given year, there are others that have suffered a large number of attacks. In order to obtain correct inferences, this data feature needs to be controlled for by the estimation technique applied to study the socioeconomic determinants of terrorism. Over-dispersed count data have traditionally been analyzed using quasi-Poisson and negative binomial regressions, which belong to the family of GLMs.

Broadly speaking, GLMs consider that a variable y depends on a vector of regressors x in such a way that the conditional distribution of y, given x, is a linear exponential family with probability density function (PDF):

$$f(y;\lambda,\phi) = exp\left[\frac{y\lambda - b(\lambda)}{\phi} + c(y,\phi)\right] \tag{1}$$

where λ is a canonical parameter that depends on the regressors and ϕ denotes the dispersion parameter. The functions $b(\cdot)$ and $c(\cdot)$ are determined by the member of the GLM family being used. The conditional mean and variance of y_i are:

$$E(y_i|x_i) = \mu_i = b'(\lambda_i) \tag{2}$$

$$Var(y_i|x_i) = \phi b''(\lambda_i) \tag{3}$$

with $i = 1, ..., n$, where n denotes the number of observations. $b'(\cdot)$ and $b''(\cdot)$ are, respectively, the first and second derivatives of $b(\cdot)$. Therefore, up to the dispersion parameter, the distribution of y_i is determined by its mean, its variance being proportional to $Var(\mu) = b''[\lambda(\mu)]$.

The dependence of the conditional mean (2) on the regressors is established through a link function $g(\cdot)$ and a set of parameters β, usually estimated through maximum likelihood and the iterative weighted least squares algorithm:

$$g(\mu_i) = x_i{}'\beta \tag{4}$$

For estimation purposes, and rather than focusing on the likelihood (1), it is more suitable to consider the regression model for the mean (4), where the functions used to fit the model are family-dependent (Zeileis, Kleiber, and Jackman 2008). The Poisson distribution is the benchmark for count data in the same way as the normal distribution is for continuous data (McCullagh and Nelder 1989). Its PDF is given by:

$$f(y;\mu) = \frac{exp(-\mu)\mu^y}{y!} \tag{5}$$

The Poisson regression model assumes a logarithmic link function ($g(\mu) = log(\mu)$), implying a log-linear relationship between the mean and the linear predictor. The dispersion parameter is set to one, the variance being equal to the mean ($Var(\mu) = \mu$). This is equivalent to saying that this model is not adequate for over-dispersed data. However, the quasi-Poisson regression model, which leaves the dispersion parameter unrestricted and estimates it from the data, is suitable. Although its coefficients coincide with those obtained by the Poisson model, inferences are adjusted for over-dispersion.

An alternative manner for dealing with over-dispersed count data is the negative binomial regression model. In this case, the conditional distribution of y is a gamma mixture of Poisson distributions, whose PDF can be parametrized as:

$$f(y;\mu,\theta) = \frac{\Gamma(y+\theta)}{\Gamma(\theta)y!}\frac{\mu^y\theta^\theta}{(\mu+\theta)^{(y+\theta)}} \tag{6}$$

where $\Gamma(\cdot)$ is the gamma function and θ denotes the shape parameter. The dispersion parameter has been set to one and the variance function is given by $Var(\mu) = \mu + \frac{\mu^2}{\theta}$. For a fixed value of the shape parameter, expression (6) is a special case of the GLM framework.[5] If θ has to be estimated, this is done jointly with β through an iterative procedure.

BMA

In a closely related paper to the present one, Gassebner and Luechinger (2011) implement an EBA to country-level data starting in 1980 to identify robust determinants of terrorism among a set of 65 regressors. These authors extract information about terrorist activity from three databases (ITERATE, GTD and MIPT) and focus on three dimensions of terrorism: location of the attack, target and perpetrator. The most surprising conclusion drawn from this study is that the majority of the variables previously suggested in the literature as terrorism determinants were not supported by their results.

This finding may be related to the main idea behind EBA, which explores whether the significance of a given variable is not altered by using alternative combinations of a large set of regressors. This is done by obtaining both a lower and an upper bound for the estimated coefficients and checking whether zero lies within them. Although Brock and Durlauf (2001) consider EBA to be useful in indicating the uncertainty regarding model specification, they acknowledge that this methodology might not be efficient in searching for the correct model specification due to collinearity problems. Rockey and Temple (2016) also point out that EBA may assess the significance of the regressors on the basis of flawed specifications or models with low explanatory power. Moreover, a policy-maker should be more interested in a probability distribution for the parameters associated with the variables under scrutiny than on their statistical significance.

Model averaging techniques – available both in frequentist and Bayesian contexts – consist of estimating all candidate models and then computing a weighted average of their estimates, taking into account the implicit uncertainty conditional on a given model and across different models. Following the initial work of Raftery (1995) and Raftery, Madigan, and Hoeting (1997), we adopt a Bayesian approach to model averaging. In general, BMA assigns a prior probability to a set of models and updates it according to the data at hand. The posterior model probabilities are averaged later and used to construct PIP for the candidate regressors. Therefore, BMA is able to deal simultaneously with model selection, estimation and inference.

Uncertainty in a GLM regression framework is related to the choice of the regressors to include in x (Moral-Benito 2015). More specifically, there are 2^q models (sets of regressors) to be estimated M_j, $j = 1, \ldots, 2^q$; each of them depending on a set of parameters β^j with a conditional posterior probability given by:

$$g(\beta^j|y, M_j) = \frac{f(y|\beta^j, M_j)g(\beta^j|M_j)}{f(y|M_j)} \tag{7}$$

where $f(y|\beta^j, M_j)$ and $g(\beta^j|M_j)$ denote the likelihood function and the prior, respectively.

For a given prior model probability $P(M_j)$, its posterior probability can be calculated applying Bayes' rule:

$$P(M_j|y) = \frac{f(y|M_j)P(M_j)}{f(y)} \tag{8}$$

Expressions (7) and (8) show that it is necessary to specify priors for both model parameters and probabilities. Leamer (1978) proposed assuming that β is a function of β^j to obtain the posterior density function of the parameters for all the possible models using the law of total probability:

$$g(\beta|y) = \sum_{j=1}^{2^q} P(M_j|y) g(\beta|y, M_j) \tag{9}$$

A common approach to further analyze point estimates and their variances is to take expectations in (9) to obtain their posterior mean and variance:

$$E(\beta|y) = \sum_{j=1}^{2^q} P(M_j|y) E(\beta|M_j) \tag{10}$$

$$Var(\beta|y) = \sum_{j=1}^{2^q} P(M_j|y) Var(\beta|y, M_j) + \sum_{j=1}^{2^q} P(M_j|y) [E(\beta|y, M_j) - E(\beta|y)]^2 \tag{11}$$

It is also possible to calculate PIP for the q regressors by adding the posterior model probabilities including them. In fact, Steel (2017) considers these posterior inclusion and model probabilities as virtues of the BMA methodology. It is worth noting that the estimation of the whole set of 2^q models can be avoided by excluding from (9) those that are much less likely than the best model. This search strategy has been carried out through the leaps and bounds algorithm (Furnival and Wilson 1974; Raftery 1995), which assumes a uniform distribution of model priors and uses a simple Bayesian information criterion approximation – which corresponds fairly closely to the unit information prior – to construct the prior probabilities of the regression coefficients.[6]

Socioeconomic Determinants of Terrorism

Main Results

Our empirical analysis begins with a preliminary estimation of the GLMs that deal with count data, described in subsection 3.1. The first three columns of results in Table 2 report estimated coefficients from a Poisson regression model fitted to the total number of attacks, domestic incidents and transnational incidents, respectively. The economic variables with a significant and positive relationship with the general measure of terrorism are real GDP per capita and growth. Household final consumption expenditure, fuel exports, total population, population density and military expenditure also have positive and statistically significant estimated coefficients. On the contrary, net FDI inflows, transfers from abroad, the rate of participation of women in the labor force and development assistance and aid have a negative relationship with terrorist attacks.

The lower panel of Table 2 reflects that a Poisson model sets the dispersion parameter to one and, hence, that the variance of the endogenous variable is equal to the mean. This assumption makes this model unsuitable for drawing inferences with over-dispersed count data. The results from fitting a quasi-Poisson model – which estimates the shape parameter from the data – are reported in the next three columns. The shape parameters are much greater than one in the three categories of incidents. Although the coefficients are equal to those estimated using a Poisson model, this is not the case of the standard errors. This implies that only household consumption expenditure, exports of fuel, population and military expenditure (transfers from abroad and female labor force participation) have a significant positive (negative) influence on terrorist attacks. As shown in the last three columns, these findings are corroborated by the negative binomial regression model, which assumes a quadratic relationship between the mean and the variance, determined by the shape parameter. These estimations also suggest that the unemployment rate

Table 2. Preliminary estimation results: Generalized linear models.

	Poisson			Quasi-Poisson			Negative binomial		
	All attacks	Domestic	Transnational	All attacks	Domestic	Transnational	All attacks	Domestic	Transnational
lngdppc	0.429***	0.487***	0.273***	0.429***	0.487*	0.273	0.164	−0.190	0.601**
	(0.016)	(0.030)	(0.047)	(0.166)	(0.265)	(0.213)	(0.194)	(0.376)	(0.251)
Growth	0.024***	0.033***	0.021***	0.024**	0.033	0.021**	0.002	0.061*	0.028
	(0.001)	(0.002)	(0.002)	(0.010)	(0.020)	(0.010)	(0.015)	(0.034)	(0.019)
Unempl	−0.003**	0.073***	0.018***	−0.003	0.073***	0.018	0.043***	0.115***	0.046***
	(0.001)	(0.002)	(0.003)	(0.014)	(0.019)	(0.014)	(0.011)	(0.021)	(0.015)
Inflation	0.001***	0.001***	0.000	0.001***	0.001**	0.000	0.002	0.004*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Consumhh	0.038***	0.031***	0.044***	0.038***	0.031**	0.044***	0.024**	0.046***	0.026**
	(0.001)	(0.001)	(0.002)	(0.009)	(0.013)	(0.011)	(0.009)	(0.017)	(0.011)
gfcf	−0.058***	0.012***	−0.076***	−0.058***	0.012	−0.076***	−0.069***	−0.080***	−0.040***
	(0.001)	(0.003)	(0.004)	(0.014)	(0.022)	(0.018)	(0.013)	(0.028)	(0.015)
Govexp	0.008***	−0.132***	0.044***	0.008	−0.132***	0.044*	−0.031*	−0.031	−0.004
	(0.002)	(0.004)	(0.005)	(0.020)	(0.034)	(0.024)	(0.018)	(0.036)	(0.023)
Openness	0.011***	−0.007***	−0.006***	0.011***	−0.007	−0.006	0.006***	−0.000	−0.009***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.006)	(0.004)	(0.002)	(0.004)	(0.003)
Primaryx	0.016***	0.012***	−0.001	0.016***	0.012*	−0.001	0.008**	0.020***	0.009*
	(0.000)	(0.001)	(0.001)	(0.004)	(0.007)	(0.006)	(0.004)	(0.007)	(0.005)
Fuelx	0.008***	0.008***	0.009***	0.008***	0.008**	0.009***	0.011***	0.020***	0.008*
	(0.000)	(0.000)	(0.001)	(0.003)	(0.004)	(0.003)	(0.003)	(0.006)	(0.004)
fdi	−0.047***	−0.056***	−0.026***	−0.047*	−0.056	−0.026	0.008	−0.007	−0.006
	(0.002)	(0.005)	(0.005)	(0.025)	(0.047)	(0.025)	(0.014)	(0.027)	(0.019)
Transfers	−5.202***	−4.099***	−3.479***	−5.202***	−4.099**	−3.479**	−4.433***	−3.253	−5.306***
	(0.157)	(0.214)	(0.366)	(1.593)	(1.860)	(1.675)	(1.315)	(2.302)	(1.441)
Aid	−10.258***	−7.444***	−0.828	−10.258***	−7.444*	−0.828	−3.042	−6.275	−0.130
	(0.312)	(0.514)	(0.682)	(3.174)	(4.467)	(3.122)	(1.971)	(4.248)	(2.300)
Lnpopul	0.852***	0.672***	0.487***	0.852***	0.672***	0.487***	1.125***	1.631***	0.740***
	(0.007)	(0.013)	(0.018)	(0.067)	(0.114)	(0.081)	(0.062)	(0.158)	(0.083)
Popdens	0.001***	0.000***	0.002***	0.001	0.000	0.002***	0.000	0.001	0.002**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Urban	−0.017***	0.002	−0.000	−0.017***	0.002	−0.000	−0.032***	−0.033***	−0.016**
	(0.001)	(0.001)	(0.001)	(0.006)	(0.011)	(0.007)	(0.006)	(0.012)	(0.008)
Lifexp	0.017***	−0.061***	0.014***	0.017	−0.061***	0.014	0.095***	0.162***	0.027
	(0.001)	(0.002)	(0.005)	(0.015)	(0.019)	(0.021)	(0.017)	(0.032)	(0.023)
Female	−0.035***	−0.036***	−0.037***	−0.035***	−0.036***	−0.037***	−0.011**	−0.017	−0.019***
	(0.001)	(0.001)	(0.002)	(0.005)	(0.008)	(0.007)	(0.005)	(0.011)	(0.007)
Primary	0.025***	0.059***	−0.000	0.025***	0.059***	−0.000	−0.001	−0.002	−0.004
	(0.001)	(0.001)	(0.002)	(0.006)	(0.008)	(0.007)	(0.005)	(0.011)	(0.007)

(*Continued*)

Table 2. (Continued).

	Poisson			Quasi-Poisson			Negative binomial		
	All attacks	Domestic	Transnational	All attacks	Domestic	Transnational	All attacks	Domestic	Transnational
Secondary	−0.016***	−0.015***	0.006***	−0.016***	−0.015**	0.006	−0.013***	−0.034***	−0.010*
	(0.000)	(0.001)	(0.001)	(0.005)	(0.008)	(0.006)	(0.004)	(0.009)	(0.005)
Armedf	0.066***	−0.023*	−0.117***	0.066	−0.023*	−0.117	0.141*	0.057	0.041
	(0.006)	(0.012)	(0.016)	(0.065)	(0.105)	(0.073)	(0.077)	(0.160)	(0.098)
Milexp	0.237***	0.403***	0.332***	0.237***	0.403***	0.332***	0.478***	0.858***	0.380***
	(0.005)	(0.009)	(0.011)	(0.050)	(0.077)	(0.050)	(0.076)	(0.154)	(0.090)
Constant	−18.584***	−15.420***	−12.094***	−18.584***	−15.420***	−12.094***	−23.070***	−35.784***	−18.361***
	(0.223)	(0.448)	(0.567)	(2.263)	(3.897)	(2.595)	(2.581)	(5.509)	(3.171)
ϕ	1	1	1	103.373	75.488	20.950	1	1	1
θ							4.348	9.656	5.941
Pseudo R2	0.577	0.524	0.468	0.577	0.524	0.468	0.082	0.100	0.082
Log likelihood	−43,199.694	−17,897.138	−7,546.236	−43,199.694	−17,897.138	−7,546.236	−4,322.774	−2,120.974	−2,340.015

Note: The number of observations is 1,644. Standard errors in parentheses. ϕ and θ denote the dispersion and shape parameters, respectively. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3. Bayesian model averaging: Quasi-Poisson regression, absolute values.

	All attacks			Domestic			Transnational		
	PIP	Mean	SD	PIP	Mean	SD	PIP	Mean	SD
lngdppc	13.6	0.036	0.108	11.5	0.036	0.110	67.5	0.338	0.251
Growth	0	0.000	0.000	0	0.000	0.000	1.8	0.000	0.002
Unempl	0	0.000	0.000	100	0.071	0.016	27.3	0.009	0.016
Inflation	0	0.000	0.000	2.9	0.000	0.000	0	0.000	0.000
Consumhh	100	0.031	0.007	9.2	0.001	0.006	70.9	0.021	0.017
gfcf	100	−0.060	0.010	22.3	−0.009	0.018	100	−0.011	0.025
Govexp	3.1	−0.001	0.004	100	−0.182	0.029	21.1	0.011	0.023
Openness	100	0.010	0.002	74.8	−0.011	0.001	7.6	−0.000	0.002
Primaryx	0	0.000	0.000	0	0.000	0.000	0	0.000	0.000
Fuelx	9.1	0.000	0.001	1.7	0.000	0.001	74.1	0.007	0.005
fdi	11.5	−0.005	0.017	0	0.000	0.000	1.9	−0.001	0.005
Transfers	100	−6.086	1.450	70.3	−3.009	2.402	37.2	1.539	2.242
Aid	7.7	−0.304	1.230	0	0.000	0.000	0	0.000	0.000
Lnpopul	100	0.827	0.047	100	0.583	0.110	100	0.574	0.061
Popdens	0	0.000	0.000	1.6	−0.000	0.000	97.6	0.002	0.000
Urban	4.6	−0.001	0.003	17.2	0.003	0.006	0	0.000	0.000
Lifexp	0	0.000	0.000	96.5	−0.062	0.022	34.1	0.019	0.028
Female	100	−0.045	0.004	100	−0.038	0.007	100	−0.035	0.005
Primary	100	0.026	0.005	100	0.052	0.007	0	0.000	0.000
Secondary	100	−0.011	0.003	0	0.000	0.000	0	0.000	0.000
Armedf	0	0.000	0.000	0	0.000	0.000	3.5	−0.004	0.025
Milexp	100	0.228	0.037	100	0.400	0.067	100	0.291	0.025
Constant	100	−13.041	1.589	100	−6.339	3.150	100	−11.954	2.561
Models		7			21			44	
BIC1		−11,256.14			−11,620.53			−11,438.87	
PP1		0.550			0.301			0.099	
CPP5		0.923			0.558			0.377	

Note: PIP denotes the posterior inclusion probability of each variable. Mean and SD are the posterior mean and standard deviation of each coefficient from model averaging, respectively. The lower panel reports the number of models selected, the values of the Schwarz information criterion (BIC1), the posterior probability (PP1) of the best model and the cumulative posterior probability of the five best models (CPP5).

and exports of primary goods are positively related to terrorist attacks, while the converse is true for gross fixed capital formation, urban population and secondary schooling.

More in line with the main aim of this study, Table 3 shows the results obtained from applying the BMA approach in a quasi-Poisson regression framework. The first three columns report, for each variable, the PIP (in percentage terms) and the mean and standard deviation of estimated coefficients when all types of attacks are jointly considered. These latter figures can be interpreted, respectively, as a BMA point estimation and standard error. It can be observed that household consumption, gross fixed capital formation, openness, transfers from abroad, population, female labor market participation, school enrollment rates and military expenditure are included in the seven models selected. The sign of the mean coefficients coincides with that obtained using a GLM regression. The high inclusion probabilities of population, female labor force participation, primary schooling and military expenditure do not change when we focus on domestic incidents. In this case, unemployment has a robust positive relationship with the number of attacks. Government expenditure and life expectancy are regressors with high PIPs and a negative influence on terrorism. Population density also displays a high inclusion probability when transnational incidents are considered. The number of models selected is much higher than in the two previous analyses. As a consequence, the posterior probability of the best model and the cumulative posterior probability of the best five models are lower.

As pointed out by Mueller (2016), it may be troublesome to work with absolute counts referring to countries with very different sizes. For this reason, the same BMA analysis presented before has

Table 4. Bayesian model averaging: Quasi-Poisson regression, in per capita terms.

	All attacks			Domestic			Transnational		
	PIP	Mean	SD	PIP	Mean	SD	PIP	Mean	SD
lngdppc	2.6	0.010	0.066	0.9	−0.003	0.036	2.5	0.007	0.058
Growth	19.1	0.004	0.009	0	0.000	0.000	0	0.000	0.000
Unempl	100	0.046	0.011	1.4	0.001	0.008	100	0.051	0.013
Inflation	1.3	0.000	0.000	0	0.000	0.000	0	0.000	0.000
Consumhh	59.7	0.018	0.016	11.7	0.006	0.018	5.9	0.001	0.005
gfcf	100	−0.090	0.021	24.4	−0.031	0.060	100	−0.139	0.017
Govexp	47.4	−0.024	0.029	15.2	−0.025	0.068	2.7	−0.001	0.005
Openness	0	0.000	0.000	9.1	−0.002	0.007	2.8	−0.000	0.001
Primaryx	25.5	0.002	0.004	0	0.000	0.000	0	0.000	0.000
Fuelx	0	0.000	0.000	0	0.000	0.000	0	0.000	0.000
fdi	0	0.000	0.000	5.1	−0.010	0.051	0	0.000	0.000
Transfers	56.3	−2.498	2.425	0	0.000	0.000	30.2	−1.083	1.854
Aid	0.9	0.022	0.261	0	0.000	0.000	0	0.000	0.000
lnpopul	0.7	−0.001	0.008	0	0.000	0.000	23.1	−0.038	0.078
Popdens	62.9	0.001	0.001	0	0.000	0.000	100	−0.002	0.000
Urban	0	0.000	0.000	0	0.000	0.000	7.5	0.001	0.004
Lifexp	100	0.107	0.019	0	0.000	0.000	100	0.125	0.029
Female	100	−0.022	0.005	29.9	−0.013	0.022	100	−0.029	0.006
Primary	25.4	0.003	0.006	0	0.000	0.000	0	0.000	0.000
Secondary	100	−0.027	0.006	5.7	−0.011	0.005	94.7	−0.020	0.008
Armedf	0	0.000	0.000	3.2	0.008	0.048	0	0.000	0.000
Milexp	100	0.281	0.033	12.5	0.044	0.130	100	0.339	0.026
Constant	100	−19.308	1.870	100	−13.955	2.210	100	−20.182	2.307
Models		34			26			10	
BIC1		−11,444.20			−12,084.59			−11,653.29	
PP1		0.124			0.178			0.408	
CPP5		0.504			0.540			0.807	

Note: PIP denotes the posterior inclusion probability of each variable. Mean and SD are the posterior mean and standard deviation of each coefficient from model averaging, respectively. The lower panel reports the number of models selected, the values of the Schwarz information criterion (BIC1), the posterior probability (PP1) of the best model and the cumulative posterior probability of the five best models (CPP5).

been applied to terrorist attacks expressed in relative terms with respect to population. The corresponding results are reported in Table 4. Similarly to Jetter and Stadelmann (2017), previous results change substantially once the focus is put on the number of terrorist attacks per capita. There are meaningful and relevant changes in terms of sign, magnitude and inclusion probabilities for several potential determinants of terrorism. As expected, population presents much lower PIPs than those obtained in the BMA exercise with attacks in absolute terms. The number of variables that, for each specification, are included in all selected models also tends to be lower. It is worth noting that there is no clear robust determinant of domestic terrorism when attacks are expressed per inhabitant. Further, controlling for country population does not alter the high PIPs attributed to female labor force participation and military expenditure and reveals the relevance of gross fixed capital formation, unemployment and secondary schooling.

A visual summary of the results described above is shown in Figure 1. Each graph ranks, vertically, the potential determinants of terrorism according to their PIPs. Likewise, selected models are ordered, horizontally, taking into account their posterior probability, which is proportional to the column width. A colored rectangle reflects that the variable is included in the model and indicates the sign of its estimated influence (red when positive, blue when negative). The number of models selected depends on whether terror is expressed in absolute or in relative terms. Due to the lower number of models chosen and the resulting higher PIPs, it seems more appropriate to use absolute values to draw conclusions about the robust determinants of domestic terrorism. This may be reflecting that national socioeconomic conditions are more important in this context. For each specification, military expenditure is consistently included in all selected models. Other

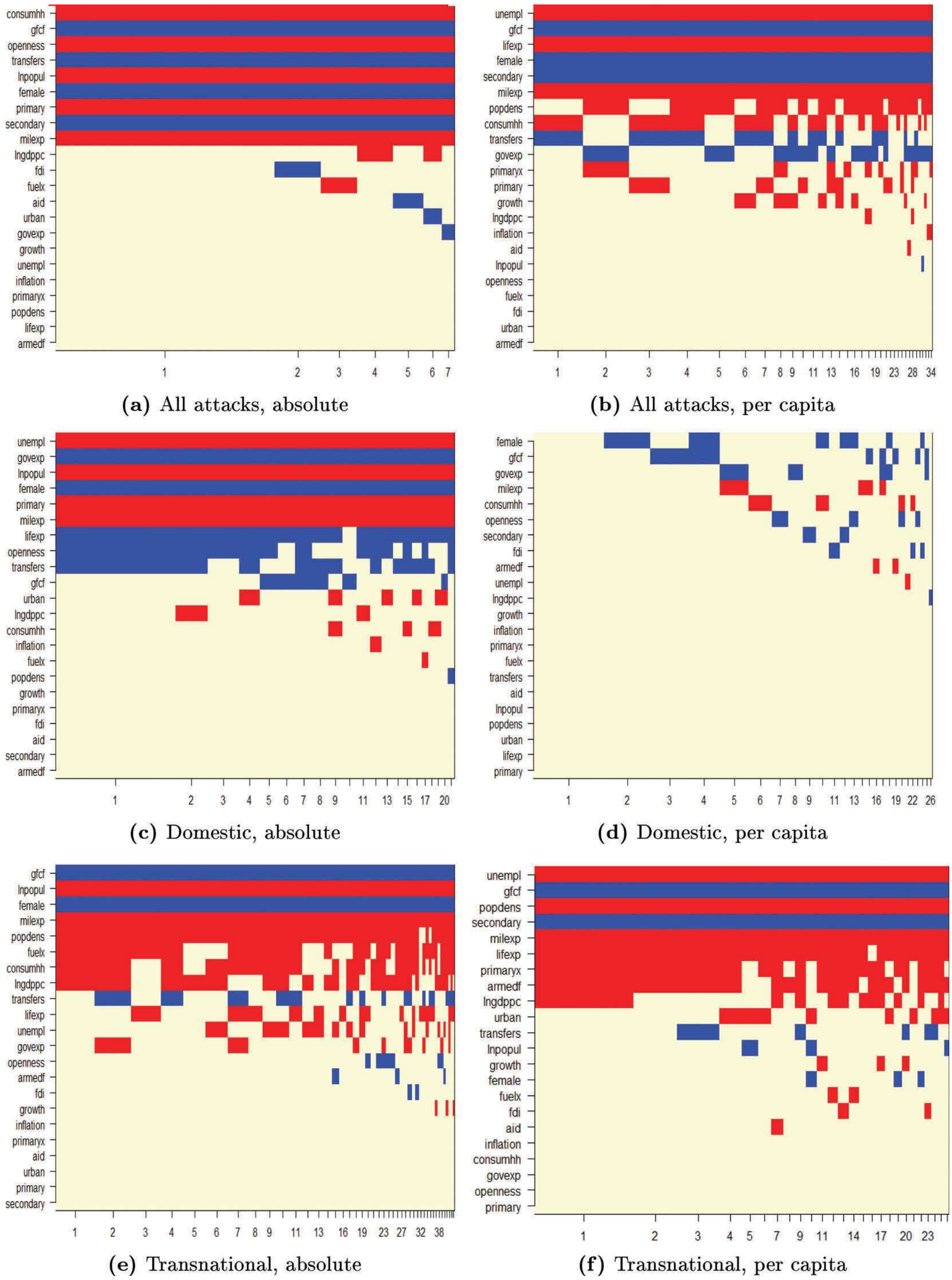

Figure 1. Selected models: Quasi-Poisson regression. Colored areas reflect the inclusion of variables in the model and whether their estimated coefficients are positive (red) or negative (blue).

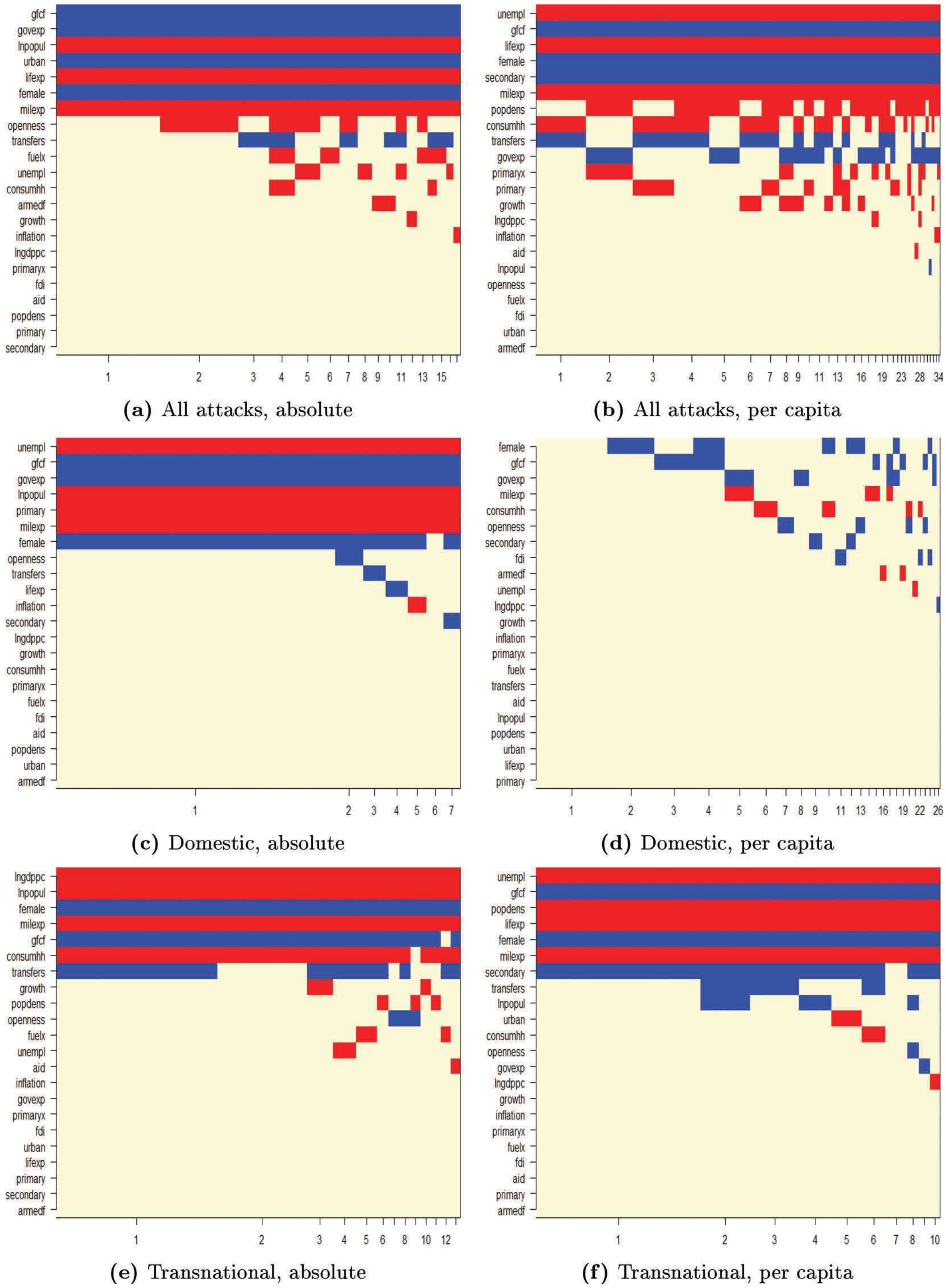

Figure 2. Selected models: Negative binomial regression. Colored areas reflect the inclusion of variables in the model and whether their estimated coefficients are positive (red) or negative (blue).

variables that display high PIPs are gross fixed capital formation, unemployment, female labor force participation and secondary schooling.

Robustness Checks

As a robustness check of previous findings, Figure 2 shows the selected models and the corresponding variables they include, together with the sign of their estimated influence on terrorism, when the BMA is implemented within a negative binomial regression framework. Before describing these results, it should be acknowledged that the computational methods available do not permit the estimation of the shape parameter. For this reason, the values obtained in the preliminary analysis, reported in the lower panel of Table 2, have been used to fit this regression model. The main difference with respect to previous results is that, with the exception of the general measure of terrorism, the number of models chosen is lower when the number of incidents is considered in absolute terms. Again, this specification is found to be more suitable to establish a robust relationship between the socioeconomic determinants of terrorism and domestic incidents. These results corroborate the conclusions drawn about the variables with a robust relationship with terrorism as well as their sign. Therefore, it can be stated that our findings are not determined by the GLM applied.

Up to now, neither the cross-sectional nor the temporal dimensions of the data have been taken into account. Time fixed effects (FEs) may be useful to control for common shocks, the cyclical behavior of terrorism and changes in data encoding procedures. Country and regional dummies will allow us to proxy for the possible presence of unobserved heterogeneity at these levels. Table 5 reports, for the quasi-Poisson regression framework, the inclusion probabilities obtained when time, country and regional FEs are introduced into the estimations. The use of country dummies leads to the selection of a small number of high-dimensional models. This finding corroborates the concerns about country FEs raised by, among others, Freytag et al. (2011) and Rockey and Temple (2016). Following their suggestion, we will focus on the results obtained when time and/or regional dummies are included in the estimations.

The introduction of time and regional FEs does not alter the main overall conclusions drawn about the regressors with a more robust relationship with terrorism. When the number of incidents is considered in absolute values, regional dummies increase the inclusion probabilities of GDP per capita, fuel exports, household consumption and urban population in the specifications for the broad measure of terrorism and transnational attacks. In the latter case, regional FEs also lead to higher (lower) inclusion probabilities for transfers from abroad and armed forces personnel (unemployment). These findings are in line with the widely-held belief that transnational terrorism is more likely to be driven by international factors than by national socioeconomic conditions. Time and regional dummies increase the PIPs of unemployment and female labor force participation rates when domestic incidents are considered in terms per capita.

As pointed out in Section 2, the composition of the sample analyzed in the present study has been determined by the availability of data of some variables, which may be inducing sample selection biases. In addition, results from BMA can be affected by measurement errors and outliers, two issues present in terrorism data. For these reasons, a sensitivity analysis similar to that in Ciccone and Jarocinski (2010) and Moral-Benito (2012) has been implemented. The PIPs obtained for each variable when individual countries are dropped from the sample one by one have been compared to that obtained using all observations by calculating the absolute value of their difference. Therefore, lower figures reflect a smaller sensitivity of the results to changes in the composition of the sample. The second and third columns of Table 6 report, respectively and for different specifications, average and median values of the absolute differences in PIPs for all variables. Regardless of the type of incidents and their consideration in absolute or relative terms, the average and, especially, the median of the differences are close to zero. These results allow us to state that the conclusions drawn about the socioeconomic variables that display a

Table 5. Robustness check: Time, country and regional fixed effects.

	Absolute values														
	All attacks					Domestic					Transnational				
lngdppc	0	0	100	100	100	2.2	100	0	100	0	58.2	100	13.7	3.8	0
Growth	91.3	0	0	0	18.7	4.7	21.2	0	100	0	7.3	12.1	100	0	96.8
Unempl	0	0	73.3	100	100	100	94.5	0	100	100	11.2	4.7	3.4	14.0	5.0
Inflation	19.7	12.9	0	100	0	3.9	100	0	100	0	0	100	0	100	0
Consumhh	14.6	21.8	100	100	100	7.6	0	3.6	0	4.0	100	53.7	100	100	100
gfcf	100	78.2	61.7	100	100	79.5	0	5.2	0	5.2	100	46.3	66.9	100	100
Govexp	71.1	0	0	0	0	100	94.5	14.5	0	16.1	100	24.2	3.0	0	4.7
Openness	100	0	100	0	100	19.8	100	2.8	100	13.3	0	100	100	0	12.4
Primaryx	0	100	100	100	41.1	0	100	0	100	0	0	100	0	0	0
Fuelx	0	21.4	100	4.0	100	0	100	5.6	100	87.7	100	100	95.7	3.8	100
fdi	0	0	74.0	0	0	0	72.8	0	100	0	0	9.8	55.3	84.6	10.2
Transfers	95.6	0	92.6	100	100	58.8	0	0	4.2	3.0	97.6	5.9	58.2	100	71.7
Aid	46.6	0	0	100	0	0	15.9	0	9.7	0	0	93.5	0	100	0
lnpopul	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Popdens	0	100	0	100	0	0	100	0	100	0	100	100	6.7	100	0
Urban	5.6	100	19.0	100	39.7	97.8	100	0	100	0	0	100	100	100	100
Lifexp	12.6	100	2.3	100	98.3	100	100	6.0	100	100	46.0	100	42.8	96.2	100
Female	100	92.2	100	100	100	100	100	82.8	100	100	100	100	47.5	100	34.6
Primary	100	0	100	100	100	100	100	3.0	4.6	100	0	100	0	27.8	6.2
Secondary	76.2	0	100	0	95.9	0	0	3.3	0	0	0	94.4	1.6	100	10.0
Armedf	47.9	0	19.8	11.1	100	0	20.1	0	100	71.3	0	100	100	100	100
Milexp	100	0	100	6.0	100	100	79.9	2.9	0	16.0	100	100	100	100	100
Time FEs	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes
Country FEs	No	Yes	No	Yes	No	No	Yes	No	Yes	No	No	Yes	No	Yes	No
Regional FEs	No	No	Yes	No	Yes	No	No	Yes	No	Yes	No	No	Yes	No	Yes
Models	34	5	20	4	10	13	8	13	4	12	8	12	36	6	21
CCP5	0.4	1	0.6	1	0.8	0.8	0.9	0.7	1	0.8	0.9	0.7	0.4	1	0.6

	Per capita terms														
	All attacks				Domestic					Transnational					
lngdppc	2.6	100	100	100	91.2	4.5	9.5	0	100	0	15.0	100	13.6	100	6.5
Growth	80.2	4.8	9.3	0	77.3	0	90.5	0.7	4.6	2.8	5.9	100	1.5	0	3.2
Unempl	100	0	100	0	100	100	86.4	100	100	100	100	53.6	88.6	100	100
Inflation	0	100	0	100	0	0	100	0	100	0	0	100	0	100	0
Consumhh	100	100	100	100	100	100	25.0	0	14.5	18.1	78.6	2.0	38.2	0	96.4
gfcf	100	100	100	100	100	17.9	75.0	3.3	92.6	16.0	100	100	100	100	100
Govexp	14.1	0	0	0	1.6	50.1	100	26.2	92.6	6.1	1.2	76.2	40.3	6.6	3.6
Openness	0	0	0	15.9	0	100	13.6	40.0	7.4	100	1.1	80.5	4.1	0	0

(*Continued*)

Table 5. (Continued).

	Per capita terms														
	All attacks				Domestic					Transnational					
Primaryx	0	100	33.1	100	28.6	15.7	100	0.5	100	0	1.0	100	2.8	100	0
Fuelx	41.8	100	22.1	100	47.0	32.2	100	0	100	4.4	74.6	100	0	100	86.7
fdi	1.0	0	0	89.3	0	0	100	25.4	100	0	0	0	0	0	0
Transfers	83.8	0	100	100	92.9	0	0	0	100	0	39.4	0	51.7	100	73.2
Aid	0	100	0	100	0	0	100	0	100	0	0	74.3	0	100	0
lnpopul	0	100	0	100	1.0	0	100	0	100	0	18.6	100	0	100	0
Popdens	65.3	100	100	100	100	15.2	100	43.8	100	100	100	100	79.5	0	94.7
Urban	0	100	0	100	0	3.8	100	0	100	2.1	6.3	100	0	100	0
Lifexp	100	100	0	100	0	0	100	78.4	100	100	100	4.1	89.6	100	100
Female	100	100	10.2	100	28.8	100	100	47.6	100	100	100	100	11.6	100	0
Primary	68.0	0	6.0	0	56.7	100	100	3.8	100	100	0	0	0	5.9	0
Secondary	100	0	100	100	100	93.4	100	28.5	100	16.0	84.9	100	100	0	100
Armedf	0	0	0	0	0.8	0	0	27.1	0	0	0	0	0	0	8.8
Milexp	100	100	100	100	100	100	100	73.5	100	100	100	100	100	4.5	100
Time FEs	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes
Country FEs	No	Yes	No	Yes	No	No	Yes	No	Yes	No	No	Yes	No	Yes	No
Regional FEs	No	No	Yes	No	Yes	No	No	Yes	No	Yes	No	No	Yes	No	Yes
Models	29	2	9	3	23	15	5	57	4	9	30	8	24	4	10
CCP5	0.5	1	0.9	1	0.5	0.7	1	0.3	1	0.9	0.51	0.9	0.6	1	0.8

Note: This table reports the posterior inclusion probabilities of a given variable under different specifications in a quasi-Poisson regression framework. Regional fixed effects have been defined according to the World Bank's list of economies (as of June 2018, see Appendix A). The lower panel reports the number of models selected and the cumulative posterior probability of the best five models.

Table 6. Sensitivity analysis: Sample composition.

	Countries		Regions	
	Average	Median	Average	Median
Absolute values				
All attacks	1.499	0.000	21.264	3.100
Domestic	1.904	0.000	21.727	5.850
Transnational	2.420	0.100	16.718	2.600
Per capita terms				
All attacks	2.142	0.000	14.256	1.450
Domestic	1.693	0.000	11.989	0.900
Transnational	1.228	0.000	11.188	1.550

Note: This table reports average and median absolute values of the difference between posterior inclusion probabilities for all variables when individual countries or regions are dropped consecutively from the sample.

robust relationship with terrorism are not determined by the countries included in the sample or by outlying observations.

The last two columns of Table 6 show average and median absolute differences between inclusion probabilities, obtained when geographical regions are subsequently removed from the sample. As expected, these differences are greater than those calculated in the previous sensitivity analysis based on individual countries, particularly when attacks are not expressed in relative terms. This finding suggests that a heterogeneous relationship may exist between terrorism and its determinants at the geographical level. To further explore this possibility, in the estimations, we have included the interaction of regional dummies with the variables for which a robust relationship with terrorism has been established. In doing so, and trying to take into account the concerns regarding the use of interaction terms in BMA within a growth regression framework (Crespo 2011; Papageorgiou 2011), the specification for all attacks per capita has been used.

The results for the interaction terms are reported[7] in Table 7. These figures show that there is no particular relationship between the selected variables and the general measure of terrorism per capita in Europe and Central Asia and in the Middle East and North Africa regions. However, the

Table 7. Regional heterogeneity: Interaction terms.

	East Asia & Pacific			Europe & Central Asia			Latin America & Caribbean		
	PIP	Mean	SD	PIP	Mean	SD	PIP	Mean	SD
Unempl	100	−0.626	0.224	1.9	0.001	0.005	0	0.000	0.000
gfcf	1.0	0.001	0.009	1.5	0.000	0.002	0.8	0.000	0.004
Female	39.8	0.016	0.021	0	0.000	0.000	44.1	−0.003	0.006
Secondary	30.9	0.011	0.017	0	0.000	0.000	100	−0.037	0.006
Milexp	0.5	−0.004	0.066	0	0.000	0.000	100	1.117	0.148
Models		60			39			52	
CCP5		0.344			0.488			0.341	
	Middle East & North Africa			**South Asia**			**Sub-Saharan Africa**		
	PIP	Mean	SD	PIP	Mean	SD	PIP	Mean	SD
Unempl	0	0.000	0.000	0	0.000	0.000	1.0	−0.000	0.004
gfcf	0.8	−0.000	0.005	100	−0.227	0.064	0	0.000	0.000
Female	3.8	0.001	0.006	78.8	0.043	0.026	87.5	−0.033	0.014
Secondary	0	0.000	0.000	89.9	0.055	0.024	0	0.000	0.000
Milexp	0	0.000	0.000	0	0.000	0.000	47.0	−0.092	0.119
Models		37			38			24	
CCP5		0.492			0.465			0.548	

Note: This table reports the results for interaction terms between regional dummies and selected variables. All types of attacks in per capita terms have been considered. PIP denotes the posterior inclusion probability of each variable. Mean and SD are the posterior mean and standard deviation of each coefficient from model averaging, respectively. Lower panels report the number of models selected and the cumulative posterior probability of the five best models.

influence of unemployment on terrorism seems to be smaller in the countries located in East Asia and the Pacific. Gross fixed capital formation plays an important role in attenuating terrorism in South Asia, where its relationship with secondary schooling becomes positive. On the contrary, the mitigating role of human capital is relevant in Latin America and the Caribbean. In this region, the mean coefficient of military expenditure is greater than in the others. Finally, it is worth noting that the only evidence of a weak relationship between military spending and terrorism is found in Sub-Saharan African countries.

Concluding Remarks

This paper contributes to the empirical literature on the socioeconomic determinants of terrorism at country level by introducing model uncertainty. With this aim, a BMA approach has been implemented within a generalized linear regression model framework. In this way, we have been able to take into account the over-dispersed count data nature of terrorist incidents. Together with the traditional distinction between domestic and international attacks, a general measure of terrorism has also been considered. Furthermore, terrorist incidents have also been expressed in per capita terms to control for country size.

When incidents are introduced in absolute values, the variables with a clear robust relationship with terrorism are female labor force participation, military expenditure and total population. Understandably, the PIP of population tends to zero when terrorist attacks are expressed per inhabitant. The use of a relative measure of terror also allows us to uncover the influence of gross fixed capital formation and the rates of secondary school enrollment and unemployment. These results do not depend on the generalized linear regression model applied, are robust to the inclusion of time and regional FEs, and do not seem to be determined by the countries included in the sample or by outliers.

It is worth noting that we are not establishing any causal relationship due to potential endogeneity concerns between terrorism and its determinants (Coggins 2015; Jetter and Stadelmann 2017). Although all explanatory variables have been included lagged one year trying to mitigate the possible presence of reverse causation, this might not be a completely satisfactory solution if terror persists over time. The reason is that past levels of terrorist activity might have also affected lagged socioeconomic variables (Kis-Katos, Liebert, and Schulze 2011). Indeed, the robust positive relationship between military expenditure and terror may be a consequence of their joint determination because terrorism is expected to be associated with other forms of political violence, conflicts and wars (Gassebner and Luechinger 2011).

Having said that, it can be observed that the regressors with high inclusion probabilities display estimated mean coefficients with the correct sign. More importantly, these variables reflect labor market conditions (unemployment and female labor force participation) and economic prospects (gross fixed capital formation and secondary schooling). This implies that a suitable strategy against terrorism may consist of improving economic conditions to reduce frustration and make violence less attractive to both perpetrators and their supporters (Freytag et al. 2011; Krieger and Meierrieks 2011). Hence, policies should be aimed at increasing the opportunity costs of terrorism by making labor markets efficient and inclusive and supporting education and entrepreneurship (see Okafor and Piesse (2017) for similar recommendations).

In contrast to previous studies, our results suggest that the roots of domestic and transnational terrorism are different. Nonetheless, it is difficult to find robust determinants of the number of domestic incidents using relative values. This implies that adopting a country-level perspective seems to be more appropriate to analyze transnational terrorism. In addition, we have provided some tentative evidence of a geographically heterogeneous relationship between terrorism and its determinants. Therefore, a promising research avenue would be to embrace a subnational standpoint (Abadie and Javier 2003) and explore within-country drivers of terrorism. By proceeding in this way, the over-dispersed nature of the data will be mitigated, increasing the ability to control for other relevant issues in the present context such as the severity of the attacks (Gassebner and Luechinger 2011), spatial dependence (Crespo Cuaresma and Feldkircher 2013; Sandler 2014) or reverse causality (Moral-Benito 2016).

Notes

1. A recent empirical study of the determinants of terrorism in fragile states can be found in Okafor and Piesse (2017).
2. A literature review on model averaging, with an emphasis on its application to economic issues, can be found in Moral-Benito (2015) and Steel (2017).
3. Retrieved from http://www.start.umd.edu/gtd.
4. GDP per capita and total population have been introduced in natural logarithms to control for skewness.
5. As an example, the case of $\theta = 1$ corresponds to the geometric model, which implies a quadratic relationship between the mean and the variance.
6. The methods described in this section have been implemented using the BMA R package (The R Core Team 2018; Raftery et al. 2017). Other available packages to perform BMA have been developed by Zeugner and Feldkircher (2015) and Clyde (2018). A comparison of their performance can be found in Amini and Parmeter (2011) and Forte, Garcia-Donato, and Steel (2018).
7. The North-American region has not been displayed as it only includes two countries: Canada and the United States. Inclusion probabilities for the interaction terms using this regional dummy tend to zero. Unreported results, available from the authors upon request.

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Appendix A. List of countries

The countries that have been included in the empirical analysis carried out in the present study are Albania [ECA] (18), Algeria [MENA] (14), Angola [SSA] (3), Argentina [LAC] (20), Armenia [ECA] (9), Australia [EAP] (21), Austria [ECA] (23), Azerbaijan [ECA] (2), Bangladesh [SOA] (8), Belarus [ECA] (7), Belgium [ECA] (12), Belize [LAC] (14), Benin [SSA] (8), Bolivia [LAC] (16), Botswana [SSA] (9), Brazil [LAC] (12), Bulgaria [ECA] (9), Burkina Faso [SSA] (15), Burundi [SSA] (8), Cabo Verde [SSA] (7), Cambodia [EAP] (7), Cameroon [SSA] (17), Canada [NOA] (19), Central African Republic [SSA] (1), Chile [LAC] (19), China [EAP] (18), Colombia [LAC] (23), Republic of the Congo [SSA] (1), Croatia [ECA] (16), Czech Republic [ECA] (12), Denmark [ECA] (23), Djibouti [MENA] (1), Dominican Republic [LAC] (15), Ecuador [LAC] (19), Egypt [MENA] (18), El Salvador [LAC] (19), Eritrea [SSA] (3), Estonia [ECA] (5), Ethiopia [SSA] (2), Fiji [EAP] (11), Finland [ECA] (23), France [ECA] (23), Gabon [SSA] (3), Gambia [SSA] (4), Georgia [ECA] (14), Germany [ECA] (21), Ghana [SSA] (15), Greece [ECA] (16), Guatemala [LAC] (22), Guinea [SSA] (6), Guyana [LAC] (13), Honduras [LAC] (10), Hungary [ECA] (10), Iceland [ECA] (4), India [SOA] (18), Indonesia [EAP] (4), Iran [MENA] (10), Iraq [MENA] (1), Ireland [ECA] (19), Israel [MENA] (11), Italy [ECA] (23), Jamaica [LAC] (7), Japan [EAP] (23), Jordan [MENA] (16), Kazakhstan [ECA] (9), Kenya [SSA] (11), South Korea [EAP] (9), Kyrgyzstan [ECA] (17), Latvia [ECA] (9), Lebanon [MENA] (14), Lesotho [SSA] (5), Lithuania [ECA] (1), Luxembourg [ECA] (1), Republic of Macedonia [ECA] (18), Madagascar [SSA] (9), Malawi [SSA] (21), Malaysia [EAP] (23), Mali [SSA] (15), Mauritania [SSA] (7), Mauritius [SSA] (12), Mexico [LAC] (22), Moldova [ECA] (16), Mongolia [EAP] (11), Morocco [MENA] (22), Mozambique [SSA] (17), Namibia [SSA] (8), Nepal [SOA] (7), Netherlands [ECA] (23), New Zealand [EAP] (16), Nicaragua [LAC] (6), Nigeria [SSA] (12), Norway [ECA] (19), Oman [MENA] (1), Pakistan [SOA] (13), Panama [LAC] (6), Papua New Guinea [EAP] (4), Paraguay [LAC] (18), Peru [LAC] (22), Philippines [EAP] (12), Poland [ECA] (9), Portugal [ECA] (23), Romania [ECA] (13), Russia [ECA] (6), Rwanda [SSA] (15), Senegal [SSA] (17), Serbia [ECA] (8), Slovak Republic [ECA] (10), Slovenia [ECA] (9), South Africa [SSA] (16), Spain [ECA] (23), Sri Lanka [SOA] (8), Sudan [SSA] (8), Sweden [ECA] (23), Switzerland [ECA] (23), Tajikistan [ECA] (1), Tanzania [SSA] (4), Thailand [EAP] (21), Timor-Leste [EAP] (1), Togo [SSA] (4), Trinidad and Tobago [LAC] (2), Tunisia [MENA] (21), Turkey [ECA] (23), Uganda [SSA] (6), Ukraine [ECA] (15), United Kingdom [ECA] (15), United States [NOA] (22), Uruguay [LAC] (20), Venezuela [LAC] (18), Yemen [MENA] (11), Zimbabwe [SSA] (13).

These countries have been grouped according to their geographic region following the World Bank's list of economies (as of June 2018) [EAP: East Asia & Pacific; ECA: Europe & Central Asia; LAC: Latin America & Caribbean; MENA: Middle East & North Africa; NOA: North America; SOA: South Asia; SSA: Sub-Saharan Africa]. The number of observations per country is reported in parentheses.