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This paper studies the determinants of terrorism at the sub-national level in Colombia during 2001-2014. In order to establish robust relationships, a Bayesian model averaging framework has been implemented using departmental data. We find that the violence suffered by this country is linked to economic factors, especially labor market outcomes. The results obtained are not significantly altered by the use of relative measures of terror, the specification of alternative parameters and model priors or the presence of spatial dependence. The main conclusion drawn from our analysis is that an appropriate strategy to fight against terrorism in similar contexts is to increase its opportunity cost. This might be achieved through the promotion of inclusive socioeconomic development, primarily in rural areas.

Palabras Clave: *(máximo 6 palabras)*

Colombia, terrorism determinants, model uncertainty, Bayesian model averaging, spatial dependence.

Clasificación JEL: C11, C23, D74, O18, O54.

Terrorism determinants, model uncertainty and space in Colombia*

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Abstract

This paper studies the determinants of terrorism at the sub-national level in Colombia during 2001-2014. In order to establish robust relationships, a Bayesian model averaging framework has been implemented using departmental data. We find that the violence suffered by this country is linked to economic factors, especially labor market outcomes. The results obtained are not significantly altered by the use of relative measures of terror, the specification of alternative parameters and model priors or the presence of spatial dependence. The main conclusion drawn from our analysis is that an appropriate strategy to fight against terrorism in similar contexts is to increase its opportunity cost. This might be achieved through the promotion of inclusive socioeconomic development, primarily in rural areas.

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1 Introduction

Unveiling the main causes of terrorism is a necessary, but not sufficient, condition to deal with this scourge and mitigate its substantial and multidimensional costs. This explains the recent upsurge in the empirical analysis of the socioeconomic determinants of terror (Meierrieks 2014; Morris and LaFree 2016), together with the increase in the number of attacks across the globe during the last two decades. Even so, there are no conclusive results in the literature about the roots of this type of violence, especially regarding the roles played by development, poverty and democracy (Krieger and Meierrieks 2011; Sandler 2014). This lack of consensus on the origins of terror might be related to the fact that studies have usually been carried out at the country level, hence comparing units with very different sizes (Mueller 2016). In addition, terrorism is too heterogeneous a phenomenon for an international average assessment to be an accurate approximation that can lead to appropriate policy conclusions, see Kis-Katos, Liebert, and Schulze (2014) and the references therein.

As an example, and at risk of being too simplistic, terror in the Middle East has principally been triggered by religion. Therefore, violence in this region has a clear ethnic dimension because terrorist groups act against alternative religious beliefs. Moreover, Islamist terror fights both a secular organization of the state and the introduction of Western values into traditional Muslim societies. By contrast, terrorism in Latin America was originally motivated by ideology, as it has mainly been driven by the campaigns of left-wing organizations. Violence in this region during the last two decades was mostly confined to Colombia, where the National Liberation Army (ELN) and the Revolutionary Armed Forces of Colombia (FARC) were operative. In fact, as reported by Kis-Katos, Liebert, and Schulze (2011), these two organizations were among the five most active terrorist groups worldwide, in terms of event counts[1], during the 2000s. If these two motivations of terror - religion and political doctrine - are compared, a stronger connection between socioeconomic variables and ideological terrorism should be expected than between the economy and religious terrorism (Meierrieks 2014).

[1]See Table A2, page 534.

Taking the previous arguments into consideration, it would seem more appealing to study the determinants of terrorism at the sub-national level. By proceeding in this way, the focus is put on domestic terrorism, much more frequent and homogeneous than international terrorism and with a higher sensitivity to local economic conditions. Consequently, terrorism in Colombian departments and the capital district will be analyzed in the present paper. There are several aspects that make the study of the driving factors of violence in this country interesting. Together with Brazil and Mexico, Colombia is one of the largest economies in Latin America. More importantly, this country has suffered the highest level of terrorist activity worldwide during 1970-2004, see Feldmann and Hinojosa (2009). The reason is that Colombia has been immersed in a multi-faceted conflict since the mid-1900s, characterized by its complexity, intractability and severity. This may explain why, according to data from the Security Assistance Monitor program of the Center for International Policy[2], this country has been among those receiving the highest quotas of military financing from the United States (US) and why it is the third largest recipient of funds from the Combating Terrorism Fellowship Program of the US Defense Department.

In line with Sanso-Navarro and Vera-Cabello (2018), and trying to identify robust correlates of terrorism, we introduce model uncertainty into the study of its determinants by adopting a Bayesian model averaging (BMA) approach (Raftery 1995; Raftery, Madigan, and Hoeting 1997). In doing so, model selection, estimation and inference are simultaneously dealt with. Following Gassebner and Luechinger (2011), several measures of terror have been considered in order to capture both the number and the severity of the attacks. Furthermore, terrorist incidents have been expressed in relative terms to population (Jetter and Stadelmann 2017; Mueller 2016) and differentiated by perpetrator group (Kis-Katos, Liebert, and Schulze 2014). The sensitivity of our results to the choice of the model-specific parameters and model priors, which is a critical aspect in the implementation of BMA (Forte, Garcia-Donato, and Steel 2018; Steel 2019), and to the possible presence of spatial dependence (Crespo Cuaresma and Feldkircher 2013; Sandler 2014) has also been assessed.

The rest of the paper is structured as follows. Section 2 briefly summarizes the Colombian conflict and reviews some of the related literature. Section 3 presents BMA techniques

[2] https://www.securityassistance.org

and Section 4 describes the data sources and the variables included in the empirical analysis. Section 5 shows the results obtained and checks of their robustness. The main findings are discussed in Section 6 and, finally, Section 7 concludes.

2 The Colombian conflict

Colombia can be considered to be a country of contrasts. On the one hand, it is the third largest economy of Latin America and has strong commercial and military links with the US. Colombia is well endowed with natural resources and, in comparison with its neighbors, has a long-lasting and solid democracy (Grassi 2014). On the other hand, this country has the second most unequal distribution of wealth in America (Holmes, Mendizábal, De La Fuente, Mets, Cárdenas, Armenteras, and Dávalos 2018) and - according to data from the United Nations Office on Drugs and Crime[3] - produced more than half of the world's coca in 2018. It is also well known that Colombia has suffered a severe, complex and multidimensional conflict during six decades, see Fernández and Pazzona (2017) and Depetris-Chauvin and Santos (2018) for some recent figures on its magnitude and implications.

There is a certain degree of consensus that the origin of the Colombian conflict dates back to the period referred to as *La Violencia* (1948-1958), characterized by a strong rivalry between the Liberal and the Conservative political parties. During these years, self-defence and guerrilla groups fought for the liberal cause against the police and other organizations controlled by the conservatives. These two opposing parties signed an agreement in 1957 (*Pacto de Sitges*) and, under the so-called National Front, alternated the presidential office arbitrarily during 16 years. In the meantime, left-wing guerrilla groups - like the ELN, the FARC and the People's Liberation Army (EPL) - emerged in rural areas, exerting a negligible influence on national politics due to the low intensity of their operations. However, this intensity increased in the 1980s and, especially, the 1990s for two reasons. First, the guerrillas became involved in drug trafficking. Second, rural landowners and dealers created paramilitary groups to defend themselves against the extortion of guerrillas. As pointed out by Feldmann and Hinojosa (2009), this wide range of contenders with a changing dynamic behavior - together with the activity of governmental forces, the

[3] https://www.unodc.org/.

intervention of the US, and ordinary crime - led this country to exhibit the highest level of terrorism worldwide between 1970 and 2004.

The length and magnitude of the Colombian confict has made it a testing ground to study the social and economic consequences of violence. Lemus (2014) shows that it increased poverty in rural areas. Further, Moya and Carter (2019) conclude that violence significantly lessens beliefs about socioeconomic mobility and increases the expected likelihood of extreme poverty. Castañeda and Vargas (2012) and Moya (2018) analyze the effects of incidents on the perception of economic and financial risks. In this line, Kutan and Yaya (2016) study the impact of large-scale terrorist attacks on the stock market and industrial production. Camacho and Rodríguez (2013) find a positive influence of the number of guerrilla and paramilitary attacks on the probability of plant exit at municipality level. Rozo (2018) shows that firms more exposed to conflict display lower levels of output and input prices. Angrist and Kugler (2008) and Dube and Vargas (2013) establish a link between shocks to commodity prices and violence.

There has also been interest in the influence of the Colombian conflict on labor market outcomes, especially through internal forced migration. Bozzoli, Brück, and Wald (2013) conclude that there is a positive relationship between net displacement rates and self-employment rates in the services sector. Similarly, Calderón-Mejía and Ibáñez (2016), Morales (2018) and Giménez-Nadal, Molina, and Silva-Quintero (2019) show that forced migration reduces wages. Depetris-Chauvin and Santos (2018) conclude that internally displaced people not only affect real wages in the construction sector of recipient cities, but also alter the housing market and increase homicide rates. Fernández and Pazzona (2017) analyze violence spillovers from Colombia to Ecuador, without finding any influence of the arrival of asylum seekers and of the presence of armed groups in bordering provinces on, respectively, violent crime and homicide rates. In a related study, Martínez (2017) documents that the intensity of FARC operations increased in municipalities at the border with Venezuela after Hugo Chávez was appointed as its president.

Despite the foregoing, and as a motivation of the present paper, less is known about the socioeconomic factors driving terrorist activity in Colombia. In a related work, Poveda (2012) analyzes the determinants of violence in the seven largest cities between 1984 and 2006, concluding that economic growth, human capital, inequality and poverty exert a significant influence. Population density and deprivation are also found to be positively related to homicide rates. Rodríguez and Daza (2012) study all Colombian municipalities during a similar sample period, acknowledging that, to a great extent, their results are determined by data availability, the measure of conflict considered and the estimation methods applied. That being said, these authors conclude that the socioeconomic variable that displays the most robust relationship with violence is the concentration of land ownership. Vargas (2012) suggests that the duration of the conflict at municipality level decreases (increases) with institutional quality and military operations (illegal rents from coca cultivation).

Holmes, Mendizábal, De La Fuente, Mets, Cárdenas, Armenteras, and Dávalos (2018) implement a multilevel analysis with data for Colombian municipalities and departments during 2000-2010. They claim that reducing unemployment, promoting the energy and mining sector, and incorporating the deprived into public services will reduce violence. Holmes, Amin Gutiérrez de Piñeres, and Curtin (2006) study the relationship between departmental coca production and FARC activities during the 1990s. These authors conclude that political intervention - through crop eradication or improving economic prospects - is more important to explain violence than coca cultivation. Further, Holmes, Amin Gutiérrez de Piñeres, and Curtin (2007) find that the intensity of FARC terrorism is inversely related to trade and GDP per capita levels and the presence of the state. In this paper, we try to contribute to this literature by analyzing the determinants of terrorism in Colombia at the sub-national level adopting a BMA approach. In doing so, we will use a more comprehensive data set than those of existing studies and will not restrict the sample to the attacks carried out by a particular terrorist group.

3 Methodology

The first study addressing the identification of robust terrorism determinants worldwide was carried out by Gassebner and Luechinger (2011). Using data at the country level, these authors implemented an extreme bounds analysis, which explores whether the significance of a given variable is not altered by considering alternative combinations of a large set of regressors. As pointed out by Rockey and Temple (2016), this methodology may assess the relevance 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 in their statistical significance. These arguments motivated Sanso-Navarro and Vera-Cabello (2018) to introduce model uncertainty into the empirical analysis of the socioeconomic determinants of terror by adopting a BMA approach[4].

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. Proceeding in this manner, estimation and inference are handled simultaneously. It is important to note that the sub-national standpoint embraced in the present paper mitigates the over-dispersed nature of the information about terrorist incidents, allowing us to implement BMA methods within a linear regression model framework. This implies that we will be able to control for the possible presence of spatial dependence and to check the sensitivity of our results to the choice of model-specific parameters and model priors.

A linear regression model establishes that a variable y depends on a vector of covariates x in such a way that the conditional mean of y_i ($i = 1, ..., N$; with N denoting the number of observations) is given by:

$$E(y_i|x_i) = x_i'\beta \tag{1}$$

where β is a set of parameters, estimated using maximum likelihood.

Model uncertainty 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, $j = 1, ..., 2^q$; each of them depending on a set of parameters β^j with conditional posterior probability:

$$g(\beta^j|y, M_j) = \frac{f(y|\beta^j, M_j)g(\beta^j|M_j)}{f(y|M_j)} \tag{2}$$

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

[4]Python, Illian, Jones-Todd, and Blangiardo (2019) have applied a Bayesian hierarchical framework to model the lethality, severity and frequency of terrorist attacks across the world at the sub-national level between 2010 and 2015.

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

$$P(M_j|y) = \frac{f(y|M_j)P(M_j)}{f(y)} \quad (3)$$

Expressions (2) and (3) show that it is necessary to specify priors, updated according to the data, for both model parameters and probabilities. Leamer (1978) assumed that β is a function of β^j in order to obtain the posterior density function of the parameters for all possible models using the law of total probability:

$$g(\beta|y) = \sum_{j=1}^{2^q} P(M_j|y)g(\beta|y, M_j) \quad (4)$$

A common approach to further analyze point estimates and their variances is to take expectations in (4) to calculate their posterior mean and variance:

$$E(\beta|y) = \sum_{j=1}^{2^q} P(M_j|y)E(\beta|M_j) \quad (5)$$

$$Var(\beta|y) = \sum_{j=1}^{2^q} P(M_j|y)Var(\beta|y, M_j) + \sum_{j=1}^{2^q} P(M_j|y)[E(\beta|y, M_j) - E(\beta|y)]^2 \quad (6)$$

It is also possible to obtain posterior inclusion probabilities (PIP) for the q regressors by adding the posterior model probabilities that include them. Actually, Steel (2019) considers these posterior inclusion and model probabilities as virtues of the BMA methodology. The estimation of the whole set of 2^q models has been avoided using a Metropolis-coupled Markov-chain Monte Carlo sampler (MC3, see Madigan, York, and Allard 1995). This model search strategy is based on a birth-death algorithm, which iterates away from a starting model by adding or dropping covariates[5]. The sampler randomly draws an alternative candidate model and then moves to it if improves the value of the marginal likelihood. If not, it is randomly accepted according to a probability that depends on the ratio of marginal likelihoods. Given that the sampler should converge to a suitable distribution, the first 500,000 draws ('burn-ins') have been disregarded. As a baseline, our empirical analysis considers two million subsequent iterations, a hyper-g prior for model-

[5]The methods described in this section have been implemented using the BMS R package (R Core Team 2019; Zeugner and Feldkircher 2015).

specific parameters (Liang, Paulo, Molina, Clyde, and Berger 2008) and a uniform prior over the model space.

4 Data sources and variables

In this paper, terrorism in Colombian departments has been measured using the number of incidents, confirmed fatalities and persons injured, see Table 1. This information has been extracted from the Global Terrorism Database (GTD), maintained by the National Consortium for the Study of Terrorism and Responses to Terrorism (LaFree and Dugan 2007). At this point, it should be clarified that this database 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"*. The GTD reports 1,957 terrorist attacks in Colombia from 2001 to 2014, which caused the death of 2,793 persons and 4,255 injuries. These data have been grouped at departmental level on a yearly basis using the information about the date and the location of each incident. Figure 1 plots cloropleth maps representing the geographical distribution of terrorist attacks across the 33 Colombian departments during the whole sample period and three selected years. Broadly speaking, terrorism has been more widespread in western departments (Antioquía, Cauca, Valle del Cauca, Huila and Tolima) and those on the frontiers with Ecuador (Narino and Putumayo) and, especially, Venezuela (Norte de Santander, Arauca and La Guajira). While Antioquía suffered the largest number of attacks (205), no incidents took place in Archipiélago de San Andrés or Vaupes[6]. It can also be observed that the capital district was notably punished by terrorism in 2008.

[Insert Table 1 and Figure 1 about here]

The sources of information for the potential determinants of terrorism, included with a temporal lag in the estimations to mitigate possible reverse causality concerns, are Universidad de los Andes Data Center (CEDE) and Departamento Administrativo Nacional de Estadística (DANE). Due to the lack of data on some variables, the sample is made up of 24 departments[7] and begins in 2000. The description of the whole set of regressors con-

[6]Other departments that experienced few attacks during 2001-2014 were Amazonas (1), Guainia (1), Quindio (2) and Vichada (3).

[7]Excluded departments are Amazonas, Archipiélago de San Andrés, Casanare, Guainia, Guaviare, Putumayo, Vaupes and Vichada. With the exception of Putumayo, these regions suffered less than one

sidered in the empirical analysis can be found in Table 1. A first group of variables related to demographic conditions includes total population, people per square kilometer and the percentage of urban population. The inclusion of the first two is motivated by the fact that a greater number of targets, victims and perpetrators will be found in large departments. There is also a preconceived idea that urbanization is conducive to terrorism. The proportion of urban population may also be reflecting the forced population displacements generated by violence in Colombia, as 60 per cent of the people moved from rural to urban areas within the same department (Calderón-Mejía and Ibáñez 2016; Depetris-Chauvin and Santos 2018).

A second group of variables tries to capture economic conditions and development at departmental level. This set includes gross domestic product (GDP) per capita[8] and the annual rate of GDP growth, both at 2005 constant prices and expressed in local currency. In the light of the results obtained by existing studies, lower standards of living and economic growth rates are expected to be associated with higher levels of terrorist activity (Poveda 2012; Rodríguez and Daza 2012). For example, the FARC are known to have generally operated in less developed areas (Holmes, Amin Gutiérrez de Piñeres, and Curtin 2007). It has also been taken into account that terrorism may be related to the sectoral composition of the economy. This has been proxied by the percentages over total output of eight economic sectors, thus reflecting departmental idiosyncrasies. Moreover, the importance of the agricultural and mining sectors will capture whether, as in other forms of violence, terrorism is linked to the abundance of natural resources (Holmes, Mendizábal, De La Fuente, Mets, Cárdenas, Armenteras, and Dávalos 2018). Labor market conditions and human capital accumulation have also been found to be associated with terror, especially in fragile states (Okafor and Piesse 2018). This may be the case of Colombia because guerrillas offer higher wages than, among others, traditional agricultural jobs (Holmes, Amin Gutiérrez de Piñeres, and Curtin 2007). Hence, departments with more efficient and inclusive labor markets will be less prone to terrorist attacks. This is measured using the number of persons employed and unemployed as percentages of the labor force. In

attack per year. As has already been pointed out in Section 3, the final composition of the sample spare us from the need of controlling for the over-dispersed count data nature of the information about terrorist incidents.

[8]Total population and real GDP per capita have been introduced in natural logarithms into the estimations to control for skewness.

addition, the proportions of population with primary and secondary education and with a university degree have been used as potential determinants of terrorism.

Finally, our set of candidates to explain terrorism includes variables related to geographical factors and government intervention. In particular, an average index of land usefulness at municipality level has been considered. Although higher values of this index reflect a lower availability of cultivable soil, they are also related to the presence of banana, cocoa and coffee crops. Illicit drug trade has been used by some Colombian terrorist groups to finance their operations. This is primarily the case of the FARC, which is known to have taxed coca crops and controlled the production, processing and export of cocaine and heroin (Vargas 2012). As pointed out by Piazza (2011), one should expect that the more effort made to eliminate illegal agricultural activities the lower the level of violence. Therefore, the percentages of total area where both aerial and manual eradication of illegal coca crops were implemented have also been considered as covariates. The distance between the departmental centroid and Bogotá has also been included as a regressor in order to capture the influence of the central government, see Rodríguez and Daza (2012). The violent activity carried out by the ELN and, especially, the FARC disproportionately increased in Colombian municipalities next to the border with Venezuela after Hugo Chávez became president of this country (Martínez 2017). This fact has been proxied using an indicator variable that takes a value of one in frontier departments and zero otherwise.

5 Results

5.1 Bayesian variable selection and model averaging

Our empirical analysis begins with the implementation of the BMA in a linear regression framework using three alternative measures of terrorism as the endogenous variable and the 24 covariates reported in Table 1. All estimations include time fixed effects to take into account the panel structure of the data. Regional fixed effects have not been introduced because the regressors that capture geographical factors are time-invariant. The first three columns of results in Table 2 show, for each variable and when terror is measured as the total number of incidents at departmental level, the PIP and the mean and standard deviation of estimated parameters. While inclusion probabilities reflect the importance of the variables in explaining the data, the mean and standard deviation can be interpreted, respectively, as a BMA point estimation and standard error.

[Insert Table 2 about here]

Together with the Venezuelan border dummy, four variables related to departmental sectoral composition display the highest inclusion probabilities. These regressors have positive mean estimated parameters. The employment rate and the percentage of urban population receive PIPs of over 85 per cent. Contrarily, these variables have a negative link with terror. The figures reported in the lower panel of Table 2 show that more than one million models have been visited by the MC3 sampler, with an average size of around 28 covariates, including time fixed effects. The correlation between iteration counts and analytical posterior model probabilities (PMP) for the 500 best models (0.98) indicates a good degree of convergence. In addition, the average shrinkage factor over all models, which can be interpreted as a Bayesian goodness-of-fit measure, is 0.87. The other columns in Table 2 show the results for two alternative measures of terrorism that refelct the severity of the incidents: the total number of confirmed fatalities and persons injured. The number of regressors robustly related to terror is much lower when these two variables are used. This is the case of the importance of the business sector, the employment rate and, especially, the percentage of social, communal and personal services over departmental GDP. Although the sign of the mean estimated coefficients for these covariates coincides with that obtained using the number of attacks as the explained variable, the degrees of convergence and the average shrinkage factors are slightly lower.

[Insert Table 3 about here]

Whatever the measure of terrorism under scrutiny, population tends to display a high inclusion probability. In order to check whether this finding is driven by analyzing regions of different sizes, and following the arguments in Mueller (2016) and Jetter and Stadelmann (2017), the same BMA analysis presented before has been applied to terror measures expressed in relative terms with respect to population. The corresponding results are reported in Table 3. The high PIPs of the variables reflecting departmental sectoral composition, the employment rate and the Venezuelan border dummy do not change when incidents are considered per million inhabitants. However, the percentage of urban population (total population) displays a much higher (lower) inclusion probability. The variables that measure the importance of the business sector and, especially, social, communal and personal services sectors have a more robust relationship with relative indicators of violence intensity. Estimation results also show that terrorist attacks implied a greater number of injuries in regions with higher GDP per capita levels.

[Insert Figure 2 about here]

A visual summary of the results described above is shown in Figure 2. Each graph ranks, vertically, the potential determinants of terrorism according to their PIPs. Likewise, the best 500 models are ordered, horizontally, taking into account their posterior probability. A colored rectangle reflects that the covariate is included in the model and indicates the sign of its estimated influence (blue when positive, red when negative). The variables that display high PIPs for all terror measures, regardless of their specification in absolute or relative terms, are the importance of the social, communal and personal services sector and the labor market indicators. Figure 2 corroborates that regressors reflecting the economic structure, the percentage of urban population and the Venezuelan border dummy have a robust relationship with the number of incidents suffered at departmental level. The importance of the business sector shows a higher inclusion probability when fatalities and injuries are considered as the endogenous variable. It can also be observed that there are more variables robustly related to the number of terrorist attacks than to their intensity. This may explain that the posterior probabilities received by the best models are lower when the severity of the incidents is analyzed. For this reason, and from now on, we are going to explore in greater depth the determinants of the number of attacks.

5.2 Prior sensitivity and spatial dependence

Given that the choices of parameters and model priors can be crucial for the final outcomes of BMA exercises (Steel 2019), it is worth studying the sensitivity of the findings described before. The results obtained from this robustness check are depicted in Figure 3. The graphs in the upper panel display inclusion probabilities for the potential determinants of terrorist incidents under different specifications of the prior on model-specific parameters, see Zeugner and Feldkircher (2015) and Forte, Garcia-Donato, and Steel (2018) for a description. When the number of attacks is considered in absolute terms, PIPs of the variables reflecting the sectoral composition of economic activity and the percentage of urban population are not affected by the choice of the prior. With the exception of the local empirical Bayes prior ('EBL') for the parameters, inclusion probabilities for the other regressors are lower when constant g priors are used. This is especially the case of the risk inflation criterion ('RIC') and benchmark ('BRIC') priors. It can also be observed that the sensitivity of the results presented in the previous subsection to the specification of the prior for model-specific parameters is slightly higher when incidents are expressed per million inhabitants.

[Insert Figure 3 about here]

In order to assess the impact of the uniform model prior assumption, which assigns more probability mass to models of intermediate size, we have considered (i) a fixed common prior inclusion probability for each regressor such that the expected value of the model size is $q/2$ ('Fixed'), (ii) a binomial-beta hyperprior on the a priori inclusion probability ('Random'), and (iii) a custom inclusion probability of 0.5 ('PIP'). The results obtained for each regressor under these model priors are plotted in the lower panel of Figure 3. Irrespective of incidents being expressed in absolute or relative terms, inclusion probabilities under these alternative prior specifications are very similar and, at the same time, lower than those calculated with the uniform model prior. The more important differences are found for the regressors with lower inclusion probabilities. To sum up, these results allow us to state that the conclusions drawn about the variables that have a more robust relationship with terrorist attacks at departmental level in Colombia are not significantly affected by changes in the specification of parameters and model priors.

[Insert Table 4 about here]

The cloropleth maps presented in Figure 1 show that terrorist attacks are geographically concentrated across departments. This corroborates the spatial variation of violence in Colombia highlighted by, among others, Feldmann (2018), Holmes, Mendizábal, De La Fuente, Mets, Cárdenas, Armenteras, and Dávalos (2018) and Rozo (2018). The presence of spatial dependence in terrorist activity has been formally tested applying the global

Moran's I test and six alternative specifications of the spatial weights matrix (Bivand and Wong 2018). The resulting test statistics, along with their p-values, for the number of attacks during the whole sample period and in three selected years are reported in Table 4. Except in 2008, when the lowest number of incidents took place, the null hypothesis of no spatial autocorrelation can be rejected at conventional significance levels. This is especially the case when neighbors are defined using a graph representation - through Delaunay ('Gabriel') and Sphere of Influence ('SOI') triangulations - or considering the five nearest departments ('5nn'). These findings lead us to check whether the possible presence of spatial autocorrelation may be driving the results described in subsection 5.1.

Crespo Cuaresma and Feldkircher (2013) developed a procedure to carry out BMA inference in the presence of spatial autocorrelation. This technique is based on a filtering method that implements an eigenvector decomposition of the transformed spatial weights matrix (Griffith 2000; Tiefelsdorf and Griffith 2007). The main aim is to simultaneously deal with the uncertainty regarding the choice of model covariates and the form of spatial interactions[9]. Assuming a spatial autoregressive specification, each eigenvector reflects a unique autocorrelation pattern and is associated with a particular level of spatial dependence. The introduction of these eigenvectors into a standard linear regression framework is intended to control for spatial structures in the regressors, on the one hand, and in the residuals, on the other. Given that eigenvectors may be highly correlated across and within spatial weights matrices, each step of the MC3 sampler is divided into two sub-steps. The model space is first sampled by choosing between two models with a different set of covariates and, subsequently, a decision is made over two models that differ in the eigenvectors included to control for spatial dependence (i.e., in the spatial weights matrix).

[Insert Tables 5 and 6 about here]

Table 5 reports BMA results when the eigenvectors of six spatial weights matrices are included in the estimations. In general, and independent of whether incidents are expressed in absolute or in relative terms, PIPs tend to be lower than those presented in the previous subsection. This results in smaller average model sizes and lower correlations between iteration counts and analytical PMPs. Despite this, the main conclusions drawn

[9]Crespo Cuaresma and Feldkircher (2013) show that ignoring the uncertainty that affects the specification of the spatial weights matrix may have non-negligible effects on parameter estimates.

about the regressors that display a more robust relationship with terrorist attacks do not meaningfully change with the consideration of spatial effects. Table 6 shows, for different combinations of parameters and model priors, posterior probabilities of models averaged across spatial weight matrices. The contiguity matrix ('Queen') receives the highest posterior probability when incidents are expressed in absolute values. The eigenvalues for a five nearest neighbors matrix show inclusion probabilities between 11 and 16 per cent when a prior other than a hyper-g is established for model-specific parameters. The contiguity matrix also tends to display high PIPs when attacks are expressed in relative terms. In this case, the proximity effects are restricted to the three nearest departments. To wrap things up, all these findings suggest that terror spillovers across space in Colombian departments are highly concentrated.

5.3 Assessing differences across perpetrators

Terrorist incidents have been treated equally so far, regardless of the perpetrator. However, it has been established in the related literature that the determinants of terror depend on its motivations (Kis-Katos, Liebert, and Schulze 2014). This may also be the case of Colombia as the grievances prompting the attacks of the different terrorist groups that operated in this country are not the same[10], see Feldmann (2018) for a recent comparison between the ELN and the FARC. To further explore this issue, and given that 87 per cent of the incidents in our sample can be attributed to a particular terrorist group[11], the attacks have been classified according to their ideology. BMA results obtained from this exercise are shown in Table 7. The first three columns report inclusion probabilities and the mean and standard deviation of estimated coefficients for right-wing attacks. The correlation between iteration counts and analytical PMPs and the average shrinkage factor indicate, respectively, a good convergence and fit. In spite of this, no variable displays a clear robust relationship with the number of attacks. The regressors that receive the highest inclusion probabilities are the index of land usefulness, the percentage of people with a university degree and the importance of the primary sector. These findings reflect that right-wing

[10] The 'paradox of power' (Hirshleifer 1991) claims that poorer contenders in conflicts tend to fight more aggressively in order to alter income distribution.

[11] According to the GTD, 18 groups operated in Colombia from 2001 to 2014, both left-wing (9) and right-wing (9).

groups mainly operated in departments with higher levels of human capital and where the agricultural sector had a less important role.

[Insert Table 7 about here]

The next three columns show the results for the attacks carried out by left-wing groups. Given that the great majority of the incidents in the GTD are attributed to organizations in this political spectrum, the figures are very similar to those reported in Table 2. In the light of the last three columns, estimates seem to be principally determined by the incidents perpetrated by the FARC. The main difference with respect to the attacks attributed to the ELN in the GTD is that, in this case, the Venezuelan frontier dummy is always included in the model. This may be reflecting that, during the sample period, the FARC mainly operated in the departments located in the border area with this neighboring country. Finally, it should be emphasized that the results presented in this subsection corroborate the idea that terrorism of leftist ideology is primarily driven by socioeconomic conditions (Meierrieks 2014).

6 Discussion

BMA results allow us to conclude that, among the potential determinants considered in our empirical setup, those displaying a more robust relationship with terrorism in Colombia are the importance of the social, communal and personal services sector and the employment rate. Other variables that are important for explaining the differences in the number of attacks experienced at departmental level are several indicators of the sectoral composition, the percentage of urban population and the Venezuelan border dummy. However, it is much more difficult to find regressors with high inclusion probabilities when the severity of the incidents is analyzed. These findings are robust to the use of relative measures of terrorism or alternative specifications of model-specific parameters and models. Moreover, the results obtained are not significantly affected by controlling for the possible presence of spatial spillovers.

The analysis of the variables that receive high posterior support facilitates the description of terrorism determinants in Colombian departments. Nevertheless, it is the full posterior distribution of the estimated parameters that contains the relevant information about the effects we are interested in. That is to say, it is the entire posterior density of the coefficients that should be looked at. This distribution has been plotted, together with the expected value and standard deviation conditional on inclusion, for the regressors that receive PIPs of over 85 percent in Figure 4. None of these densities have a substantive probability mass around zero, which can be interpreted as evidence that these covariates influence the number of terrorist attacks.

[Insert Figure 4 about here]

The posterior distributions of the parameters attached to the regressors measuring the composition of departmental productive sector are positively skewed. The estimated coefficients suggest that there is a direct relationship between their corresponding covariates and terrorism. On the one hand, this may be reflecting that, to a considerable extent, the attacks were carried out in more developed regions during the years 2001-2014, see Holmes, Amin Gutiérrez de Piñeres, and Curtin (2007). On the other hand, and as is commonly found in the related literature (Holmes, Mendizábal, De La Fuente, Mets, Cárdenas, Armenteras, and Dávalos 2018; Vargas 2012), the positive sign of the parameter for the mining sector suggests that violence is linked with the presence of natural resources. It should be taken into account that these variables may be receiving high inclusion probabilities because they capture idiosyncrasies that would have been proxied using fixed effects at departmental level, not included because there are time-invariant regressors in our set of potential determinants of terrorism.

The distributions of the estimated coefficients for the Venezuelan border dummy, the employment rate and the percentage of urban population are relatively symmetric. In line with Martínez (2017), the positive sign for the border dummy reflects that departments on the frontier suffered a higher number of attacks. On the contrary, regions with higher employment rates and shares of urban population were less exposed to violence. Hence, it can be stated that people were less likely to join terrorist groups in areas with better labor market prospects. It is also known that violence in Colombia had, principally, a rural nature. In fact, the FARC typically operated in non-urban areas with coca crops and limited govermental control (Lemus 2014). Lastly, the marginal posterior density of the estimated parameter for total population presents a slight negative skew. Most of the probability mass is assigned to positive values, capturing that more populated departments experienced a higher number of attacks.

The results presented in the previous subsection suggest that illicit coca crop eradication is not a relevant predictor for terrorism. Actually, the related regressors receive low inclusion probabilities and only display negative mean coefficients when spatial effects are controlled for. Although no causal claims have been made, our empirical analysis highlights robust relationships with policy implications. The importance of the social services sector and the employment rate in explaining differences in terrorist activity across Colombian departments is in line with the seminal contribution of Becker (1968), who posited that agents rationally optimize the distribution of their time between legal and non-legal activities according to economic criteria. Therefore, it can be stated that our findings reinforce the standpoint of Meierrieks and Gries (2012) according to which the best way to fight terrorism is to increase its opportunity cost, see also Sanso-Navarro and Vera-Cabello (2018) and the references therein.

7 Conclusions

Colombia is experiencing one of the most complex and long-lasting conflicts in recent history, with important economic and social consequences (Depetris-Chauvin and Santos 2018; Fernández and Pazzona 2017). A pervasive manifestation of the violence carried out by the adversaries involved in this confrontation has been terrorism. A first step to put into place successful measures to cope with this type of violence is to try to disentangle its main driving factors. Adopting a sub-national level, this has been the main goal of the present paper. In particular, the determinants of both the number and the intensity of terrorist incidents in Colombian departments during 2001-2014 have been studied using BMA techniques and a more comprehensive data set than those of related work to date. By proceeding in this way, we have been able to identify the variables that display a robust relationship with terrorism. Further, the sensitivity of the results to alternative choices of parameters and model priors and specifications of terror measures, to the possible presence of spatial dependence, and to heterogeneity across perpetrator groups has been analyzed.

It is important to acknowledge that no causal relationship has been established due to potential endogeneity concerns between terrorism and its determinants. Time-varying explanatory variables have been included lagged one year to mitigate the possible presence of reverse causation. Nevertheless, this might not be a completely satisfactory solution if terrorism persists over time because past levels of violence might have also affected lagged regressors (Kis-Katos, Liebert, and Schulze 2011). That being said, the employment rate, the importance of the social services sector and the percentage of urban population are found to be robustly linked to terrorism. This implies that an efficient labor market will be in detriment to the informal sector, making violence less attractive to both perpetrators and their supporters. Hence, inclusive socioeconomic development should be promoted to fight terrorism, especially in rural areas. Policies should be aimed at increasing the opportunity cost of violence through a better matching between the supply and demand of job vacancies and more attractive wages in the formal sector. Following the arguments put forward by Frey and Osterloh (2018), satisfactory job prospects will reduce the incentives of joining terrorist groups.

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Table 1: Measures and potential determinants of terrorism: Description of variables and data sources.

Variable	Description	Source
incidents	Number of terrorist incidents	GTD
deaths	Confirmed fatalities	GTD
injuries	Persons injured	GTD
popul	Total population; in natural logarithms	DANE
popdens	Population density; people per square kilometer	DANE
urban	Urban population; as percentage of total population	CEDE
gdppc	Gross domestic product (GDP) per capita, 2005 constant prices (local currency); in natural logarithms	DANE
growth	GDP growth, 2005 constant prices (local currency); annual, per cent	DANE
agric	Agriculture, livestock, hunting, forestry and fisheries; as percentage of GDP	DANE
mining	Exploitation of mines and quarries; as percentage of GDP	DANE
manuf	Manufacturing industries; as percentage of GDP	DANE
elect	Supply of electricity, gas and water; as percentage of GDP	DANE
constr	Construction sector; as percentage of GDP	DANE
business	Commerce, repair, restaurants and hotels; as percentage of GDP	DANE
transp	Transportation, storage and telecommunications; as percentage of GDP	DANE
finance	Financial institutions, insurance, real estate activities and services to companies; as percentage of GDP	DANE
social	Social, communal and personal services; as percentage of GDP	DANE
empl	Total persons employed; as percentage of the labor force	DANE
unemp	Unemployment; as percentage of the labor force	DANE
primary	Persons with primary education; as percentage of total population	CEDE
secondary	Persons with secondary education; as percentage of total population	CEDE
university	Persons with a university degree; as percentage of total population	CEDE
use	Average index of land usefulness at municipality level	CEDE
aerial	Aerial eradication of illicit coca crops; as percentage of total area	CEDE
manual	Manual eradication of illicit coca crops; as percentage of total area	CEDE
distcap	Distance to Bogotá; from regional centroid, in kilometers	Own construction
venez	Border with Venezuela; dummy variable	Own construction

Note: Data sources are Universidad de los Andes Data Center (CEDE), Departamento Administrativo Nacional de Estadística (DANE) and the Global Terrorism Database (GTD). The sample period covers the years from 2000 to 2014.

Table 2: Bayesian model averaging: Terrorism measures in absolute values.

	Incidents			Deaths			Injured		
Variable	PIP	Mean	SD	PIP	Mean	SD	PIP	Mean	SD
popul	0.87	3.62	2.08	0.77	4.76	3.63	0.89	14.93	7.91
popdens	0.71	-0.00	0.00	0.46	-0.00	0.00	0.41	0.00	0.00
urban	0.85	-0.09	0.05	0.44	0.04	0.08	0.37	-0.02	0.13
gdppc	0.48	-1.54	2.85	0.38	-0.60	3.74	0.56	7.90	11.93
growth	0.28	0.01	0.04	0.38	-0.05	0.11	0.31	0.00	0.18
agric	0.49	0.05	0.22	0.41	0.10	0.29	0.41	-0.06	0.55
mining	0.93	0.28	0.21	0.50	0.06	0.27	0.66	0.30	0.56
manuf	0.72	0.22	0.33	0.58	-0.09	0.41	0.57	-0.09	0.81
elect	0.58	-0.30	0.37	0.33	0.05	0.42	0.46	-0.70	1.32
constr	0.99	0.78	0.28	0.51	0.24	0.40	0.67	0.87	0.95
business	0.47	-0.08	0.26	0.96	-1.19	0.50	0.78	-1.29	1.06
transp	0.47	0.20	0.33	0.39	-0.17	0.44	0.34	-0.14	0.81
finance	0.98	0.56	0.23	0.58	0.28	0.38	0.59	0.66	0.89
social	0.95	0.50	0.26	0.95	0.69	0.33	0.96	1.73	0.74
empl	0.89	-0.18	0.10	0.42	-0.08	0.14	0.90	-0.84	0.47
unemp	0.32	0.02	0.08	0.51	0.16	0.24	0.64	0.59	0.63
primary	0.64	-0.23	0.24	0.31	0.03	0.24	0.33	-0.08	0.56
secondary	0.36	0.08	0.21	0.31	0.05	0.30	0.37	-0.31	0.83
university	0.33	-0.05	0.16	0.30	0.00	0.25	0.32	-0.02	0.60
use	0.58	0.01	0.02	0.75	0.03	0.02	0.63	0.04	0.05
aerial	0.33	0.34	1.11	0.66	4.20	4.22	0.53	5.47	7.80
manual	0.28	0.49	2.78	0.33	-1.70	7.03	0.36	5.12	16.11
distcap	0.31	-7.45	0.00	0.53	0.01	0.01	0.47	0.01	0.03
venez	0.93	2.38	1.16	0.30	-0.01	1.13	0.33	0.38	2.64
Models		1,074,502			1,476,488			1,437,152	
Size		27.78			25.07			25.86	
Correlation		0.98			0.76			0.85	
Shrinkage		0.87			0.84			0.81	

Note: The number of observations is 336. All specifications include time fixed effects. The birth-death MC3 sampler has been implemented with 500,000 burn-ins and two million iteration draws. The hyper-g and uniform priors have been established, respectively, for parameters and models. PIP denotes the posterior inclusion probability of each variable. Mean and SD are the posterior mean and standard deviation from model averaging. The lower panel reports the number of models visited, their average size, the correlation between iteration counts and analytical posterior model probabilities, and the mean of the shrinkage factor.

Table 3: Bayesian model averaging: Terrorism measures in relative terms (per million inhabitants).

	Incidents			Deaths			Injured		
Variable	PIP	Mean	SD	PIP	Mean	SD	PIP	Mean	SD
popul	0.39	0.29	0.77	0.39	0.58	1.92	0.41	0.93	2.45
popdens	0.74	-0.00	0.00	0.38	-0.00	0.00	0.57	-0.00	0.00
urban	0.99	-0.11	0.03	0.52	0.07	0.12	0.42	-0.03	0.10
gdppc	0.38	0.59	1.43	0.45	2.48	5.42	0.94	18.66	9.14
growth	0.26	-0.00	0.03	0.50	-0.11	0.18	0.63	-0.22	0.24
agric	0.54	-0.08	0.18	0.49	0.15	0.28	0.37	0.02	0.22
mining	0.88	0.18	0.19	0.38	-0.03	0.17	0.37	-0.00	0.14
manuf	0.82	0.17	0.28	0.38	-0.04	0.26	0.36	-0.02	0.22
elect	0.57	-0.23	0.28	0.39	0.18	0.56	0.35	-0.02	0.59
constr	0.94	0.50	0.23	0.37	0.07	0.27	0.35	0.07	0.28
business	0.47	-0.10	0.20	0.97	-1.26	0.55	0.86	-0.94	0.60
transp	0.82	0.47	0.32	0.40	-0.21	0.53	0.34	-0.00	0.47
finance	0.84	0.27	0.18	0.38	-0.06	0.23	0.37	0.00	0.23
social	0.94	0.46	0.20	0.98	0.84	0.30	1.00	1.58	0.37
empl	0.86	-0.12	0.07	0.39	0.06	0.16	0.57	-0.20	0.27
unemp	0.28	-0.00	0.05	0.35	-0.04	0.19	0.33	0.01	0.20
primary	0.58	-0.14	0.16	0.45	0.25	0.48	0.43	0.25	0.54
secondary	0.29	-0.02	0.12	0.38	-0.15	0.52	0.51	-0.54	0.82
university	0.41	-0.08	0.15	0.57	-0.47	0.62	0.52	-0.48	0.71
use	0.46	0.00	0.01	0.47	0.01	0.02	0.46	0.01	0.02
aerial	0.37	0.47	1.01	0.46	2.18	4.07	0.62	5.29	6.08
manual	0.26	0.13	1.93	0.34	1.39	8.53	0.35	2.37	10.41
distcap	0.43	-0.00	0.00	0.60	0.01	0.02	0.75	0.03	0.02
venez	0.84	1.38	0.88	0.33	-0.12	1.42	0.33	-0.26	1.62
Models	1,089,701			1,724,186			1,580,214		
Size	27.38			24.35			25.19		
Correlation	0.98			0.53			0.82		
Shrinkage	0.88			0.76			0.78		

Note: The number of observations is 336. All specifications include time fixed effects. The birth-death MC3 sampler has been implemented with 500,000 burn-ins and two million iteration draws. The hyper-g and uniform priors have been established, respectively, for parameters and models. PIP denotes the posterior inclusion probability of each variable. Mean and SD are the posterior mean and standard deviation from model averaging. The lower panel reports the number of models visited, their average size, the correlation between iteration counts and analytical posterior model probabilities, and the mean of the shrinkage factor.

Table 4: Spatial autocorrelation test: Incidents in Colombian departments and the capital district.

	Weights matrix					
Year(s)	Queen	Gabriel	SOI	3nn	5nn	7nn
2001-2014	0.77	2.12	1.47	1.76	2.06	0.87
	(0.22)	(0.02)	(0.07)	(0.04)	(0.02)	(0.19)
2001	1.36	1.50	1.46	0.68	1.62	1.89
	(0.09)	(0.07)	(0.07)	(0.25)	(0.05)	(0.03)
2008	1.04	1.07	0.70	1.20	0.50	-0.09
	(0.15)	(0.14)	(0.24)	(0.12)	(0.31)	(0.54)
2014	1.22	2.49	1.48	1.73	2.07	1.17
	(0.11)	(0.01)	(0.07)	(0.04)	(0.02)	(0.12)

Note: This table reports Moran's I test statistic calculated under different specifications of the spatial weights matrix, all row-standardized. Queen: contiguity criterion; Gabriel: Delaunay triangulation graph; SOI: sphere of influence graph; jnn: j nearest neighbors. P-values in parentheses.

Table 5: Bayesian model averaging and spatial filtering: Incidents by department.

	Absolute values			Relative terms		
Variable	PIP	Mean	SD	PIP	Mean	SD
popul	0.79	2.87	2.11	0.31	-0.06	0.63
popdens	0.63	-0.00	0.00	0.61	-0.00	0.00
urban	0.64	-4.85	5.02	0.91	-8.48	4.38
gdppc	0.67	-3.56	3.64	0.35	-0.29	1.52
growth	0.28	-0.01	0.04	0.59	-0.05	0.06
agric	0.50	-0.00	0.22	0.70	-0.14	0.16
mining	0.89	0.22	0.22	0.64	0.07	0.13
manuf	0.61	0.13	0.33	0.60	0.05	0.20
elect	0.60	-0.35	0.40	0.69	-0.33	0.30
constr	0.87	0.42	0.31	0.85	0.27	0.19
business	0.44	0.03	0.26	0.45	-0.04	0.18
transp	0.33	0.08	0.26	0.32	0.04	0.17
finance	0.97	0.50	0.25	0.68	0.15	0.16
social	0.81	0.31	0.27	0.94	0.29	0.16
empl	0.83	-0.15	0.10	0.66	-0.07	0.07
unemp	0.29	-0.01	0.08	0.27	0.06	0.05
primary	0.33	-5.49	14.66	0.27	-1.67	8.29
secondary	0.38	10.71	21.23	0.26	0.10	10.32
university	0.28	-2.68	13.75	0.35	-5.94	13.30
use	0.62	0.01	0.02	0.40	0.00	0.00
aerial	0.27	-0.05	0.95	0.28	-0.06	0.82
manual	0.27	-0.46	2.67	0.31	-0.95	2.51
distcap	0.40	-0.00	0.01	0.74	-0.01	0.01
venez	0.91	2.30	1.16	0.97	2.09	0.77
Models		1,113,354			1,267,180	
Size		21.72			20.13	
Correlation		0.66			0.28	

Note: The number of observations is 336. All specifications include time fixed effects and the eigenvectors calculated for alternative weights matrices (see Table 4) and assuming a spatial autoregression model. The birth-death MC3 sampler has been implemented with 500,000 burn-ins and two million iteration draws. The hyper-g and uniform priors have been established, respectively, for parameters and models. PIP denotes the posterior inclusion probability of each variable. Mean and SD are the posterior mean and standard deviation from model averaging. The lower panel reports the number of models visited, their average size, the correlation between iteration counts and analytical posterior model probabilities.

Table 6: Bayesian model averaging and spatial filtering: Eigenvalues' posterior inclusion probabilities and prior sensitivity.

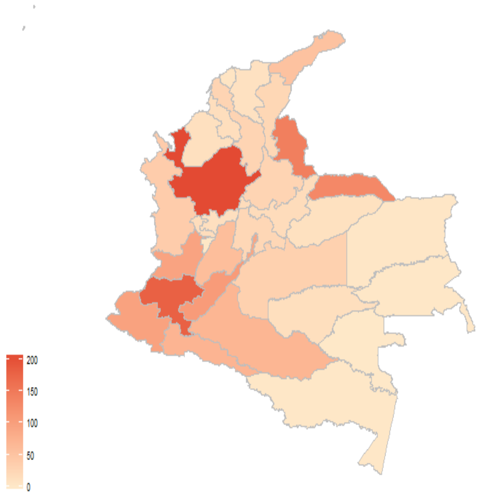
Absolute values							
Prior		Weights matrix					
Parameters	Model	Queen	Gabriel	SOI	3nn	5nn	7nn
Hyper	Uniform	0.99	0.00	0.00	0.01	0.00	0.00
UIP	Uniform	0.85	0.00	0.00	0.01	0.14	0.00
BRIC	Uniform	0.83	0.00	0.00	0.01	0.16	0.00
RIC	Uniform	0.83	0.00	0.00	0.01	0.16	0.00
HQ	Uniform	0.86	0.00	0.00	0.01	0.13	0.00
EBL	Uniform	0.87	0.00	0.00	0.02	0.11	0.00
Hyper	Fixed	0.99	0.00	0.00	0.01	0.00	0.00
Hyper	Random	0.99	0.00	0.00	0.01	0.00	0.00
Hyper	PIP	0.99	0.00	0.00	0.01	0.00	0.00
Relative terms							
Prior		Weights matrix					
Parameters	Model	Queen	Gabriel	SOI	3nn	5nn	7nn
Hyper	Uniform	0.06	0.00	0.00	0.94	0.00	0.00
UIP	Uniform	0.83	0.00	0.00	0.17	0.00	0.00
BRIC	Uniform	0.77	0.00	0.00	0.23	0.00	0.00
RIC	Uniform	0.78	0.00	0.00	0.22	0.00	0.00
HQ	Uniform	0.86	0.00	0.00	0.14	0.00	0.00
EBL	Uniform	0.90	0.00	0.00	0.10	0.00	0.00
Hyper	Fixed	0.06	0.00	0.00	0.94	0.00	0.00
Hyper	Random	0.34	0.00	0.00	0.66	0.00	0.00
Hyper	PIP	0.06	0.00	0.00	0.94	0.00	0.00

Note: Probabilities refer to the eigenvalues calculated for alternative weights matrices and assuming a spatial autoregressive model, see Tables 4 and 5.

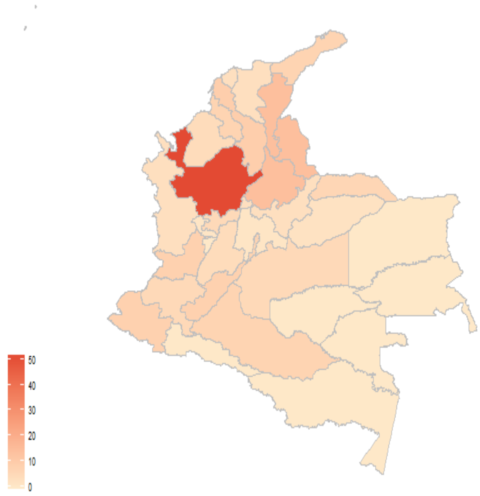
Table 7: Bayesian model averaging: Incidents classified by perpetrator.

	Right-wing			Left-wing			ELN			FARC		
Variable	PIP	Mean	SD	PIP	Mean	SD	PIP	Mean	SD	PIP	Mean	SD
popul	0.53	0.11	0.15	0.84	2.67	1.69	0.49	0.12	0.34	0.87	2.24	1.30
popdens	0.31	0.00	0.00	0.75	-0.00	0.00	0.51	-0.00	0.00	0.67	-0.00	0.00
urban	0.31	-0.00	0.00	0.91	-0.09	0.04	0.61	0.01	0.02	0.99	-0.12	0.03
gdppc	0.40	-0.10	0.21	0.45	-0.97	2.20	0.71	-0.86	0.90	0.35	0.13	1.27
growth	0.23	-0.00	0.00	0.33	0.01	0.04	0.37	0.00	0.01	0.31	0.01	0.03
agric	0.55	-0.01	0.02	0.54	0.08	0.23	0.42	-0.01	0.03	0.59	0.12	0.23
mining	0.39	0.00	0.01	0.92	0.26	0.23	0.46	0.00	0.02	0.95	0.30	0.24
manuf	0.36	-0.00	0.01	0.73	0.24	0.35	0.44	-0.01	0.03	0.78	0.32	0.37
elect	0.27	-0.00	0.02	0.61	-0.28	0.33	0.71	-0.11	0.11	0.39	-0.06	0.20
constr	0.29	0.00	0.01	0.99	0.66	0.28	0.40	0.01	0.03	1.00	0.67	0.27
business	0.41	-0.01	0.02	0.49	-0.00	0.25	0.63	-0.05	0.07	0.52	0.13	0.26
transp	0.46	-0.02	0.03	0.62	0.31	0.37	0.37	-0.01	0.05	0.74	0.42	0.38
finance	0.54	0.01	0.02	0.97	0.48	0.23	0.80	0.06	0.04	0.97	0.45	0.23
social	0.42	0.01	0.01	0.94	0.42	0.26	0.49	0.01	0.03	0.97	0.43	0.25
empl	0.43	-0.01	0.01	0.85	-0.14	0.09	0.43	-0.01	0.02	0.83	-0.11	0.07
unemp	0.24	0.00	0.01	0.34	0.02	0.07	0.43	0.01	0.03	0.32	0.01	0.06
primary	0.27	-0.00	0.01	0.62	-0.18	0.20	0.66	-0.07	0.09	0.44	-0.07	0.13
secondary	0.29	0.01	0.02	0.35	0.05	0.16	0.76	0.13	0.11	0.32	-0.02	0.12
university	0.60	0.03	0.03	0.42	-0.08	0.17	0.44	-0.03	0.06	0.37	-0.05	0.12
use	0.63	0.00	0.00	0.54	0.01	0.01	0.78	0.00	0.00	0.50	0.00	0.01
aerial	0.25	0.02	0.11	0.33	0.21	0.93	0.40	0.09	0.39	0.30	0.06	0.72
manual	0.32	-0.19	0.47	0.30	0.22	2.43	0.60	1.38	1.68	0.33	-0.79	2.43
distcap	0.27	0.00	0.00	0.33	0.00	0.00	0.46	-0.00	0.00	0.34	0.00	0.00
venez	0.24	0.01	0.06	0.90	1.93	1.03	1.00	1.11	0.30	0.37	0.21	0.53
Models		1,432,269			1,119,680			1,619,665			1,161,175	
Size		22.01			28.08			26.38			27.27	
Correlation		0.89			0.98			0.84			0.98	
Shrinkage		0.91			0.84			0.70			0.84	

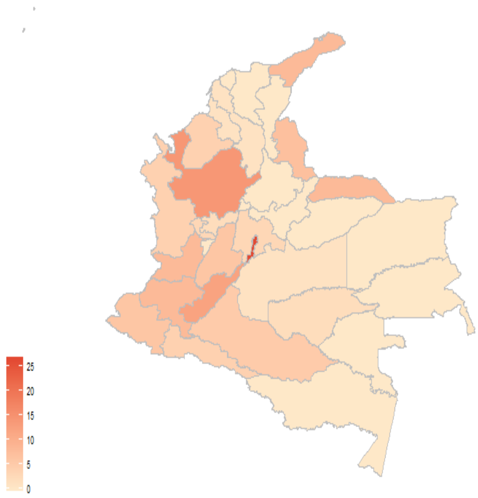
Note: All specifications include time fixed effects. The birth-death MC3 sampler has been implemented with 500,000 burn-ins and two million iteration draws. The hyper-g and uniform priors have been established, respectively, for parameters and models. PIP denotes the posterior inclusion probability of each variable. Mean and SD are the posterior mean and standard deviation from model averaging. The lower panel reports the number of models visited, their average size, the correlation between iteration counts and analytical posterior model probabilities and the mean of the shrinkage factor.



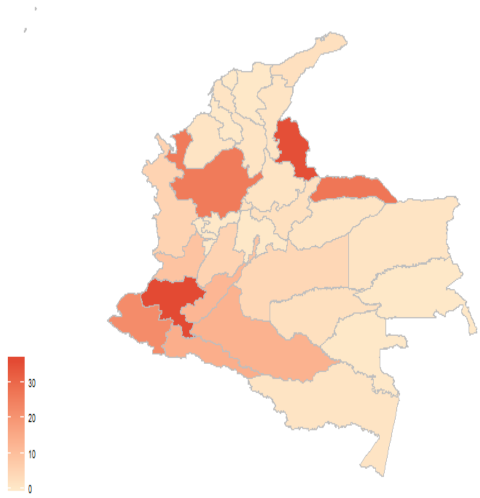
(a) Period 2001-2014



(b) Year 2001

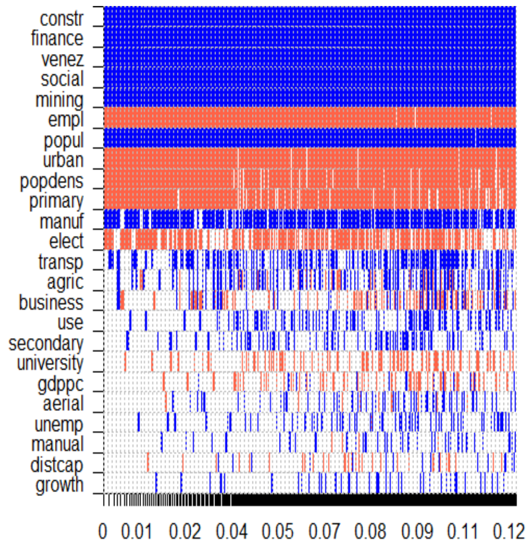


(c) Year 2008

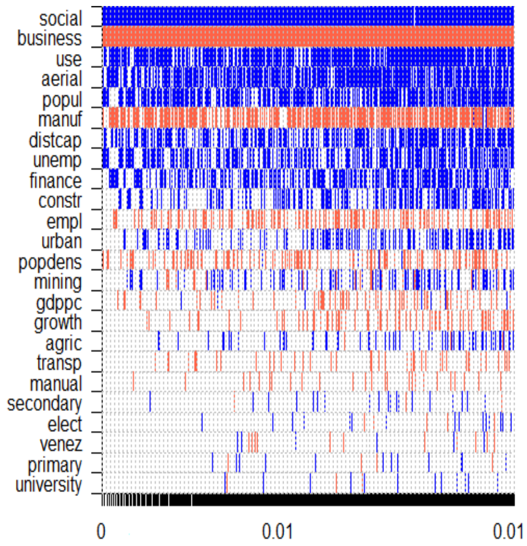


(d) Year 2014

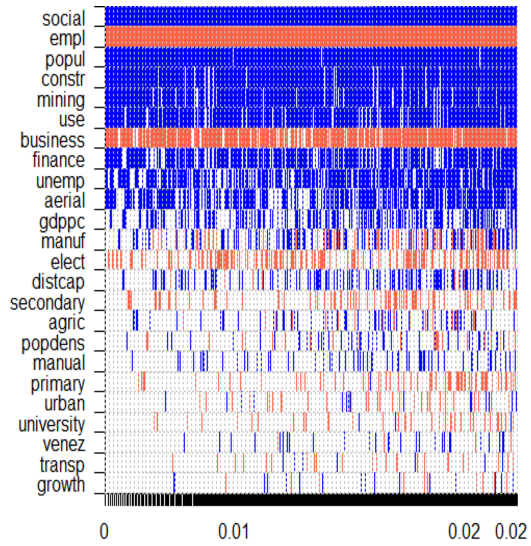
Figure 1: Cloropleth maps: Terrorist incidents in Colombian departments and the capital district.



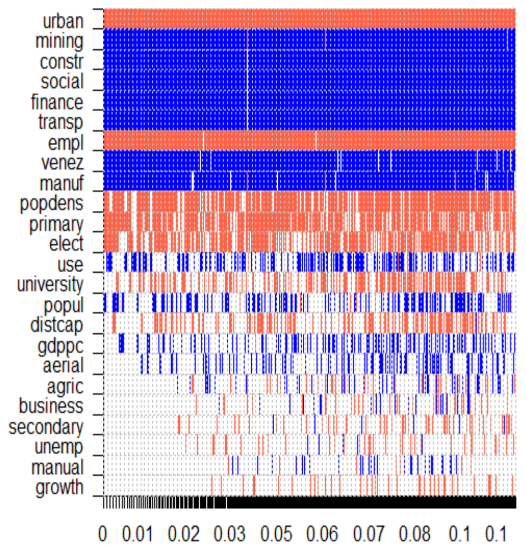
(a) Incidents, absolute values



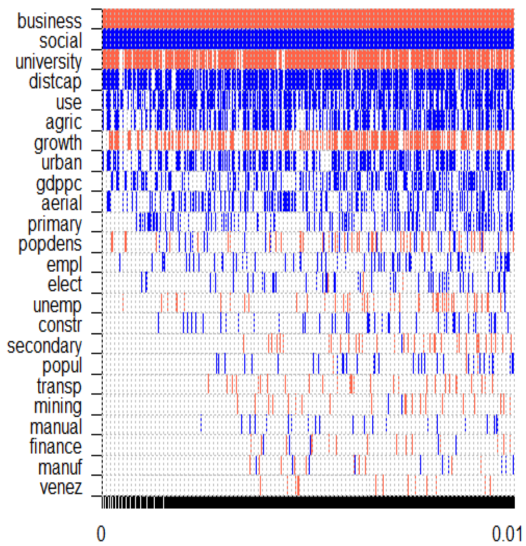
(b) Deaths, absolute values



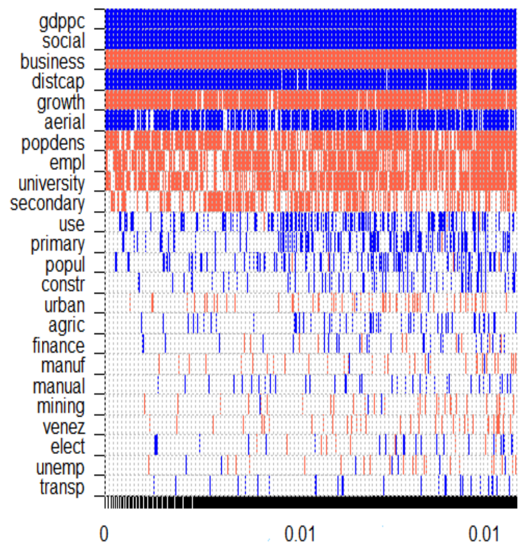
(c) Injured, absolute values



(d) Incidents, relative terms

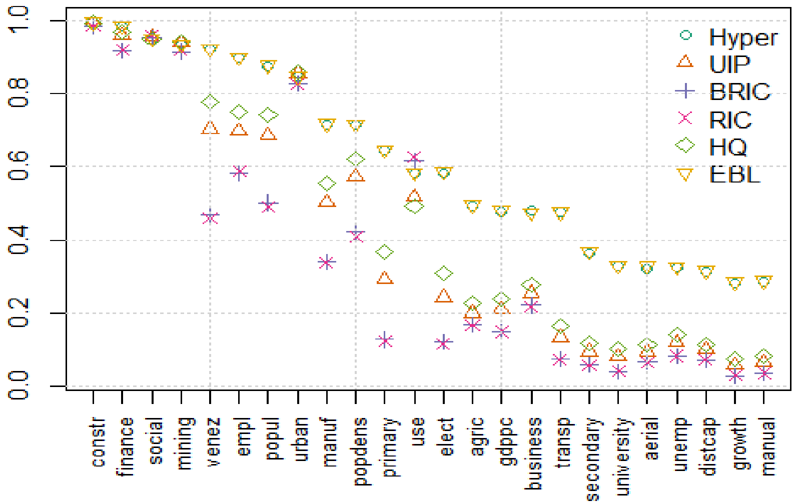


(e) Deaths, relative terms

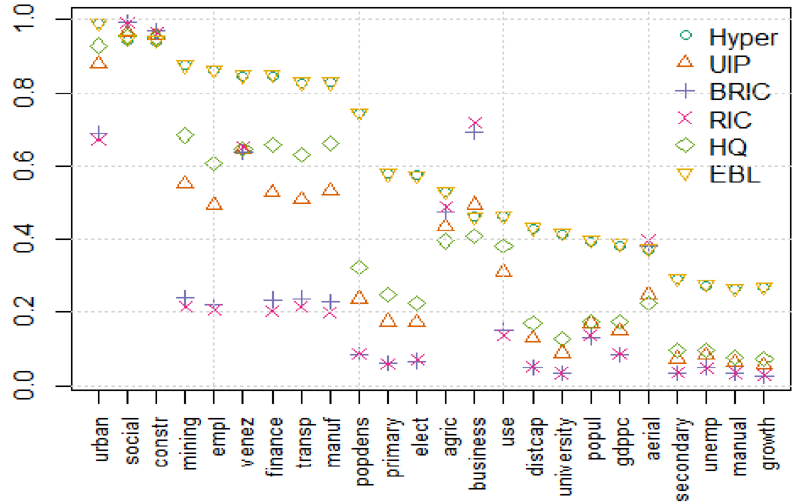


(f) Injured, relative terms

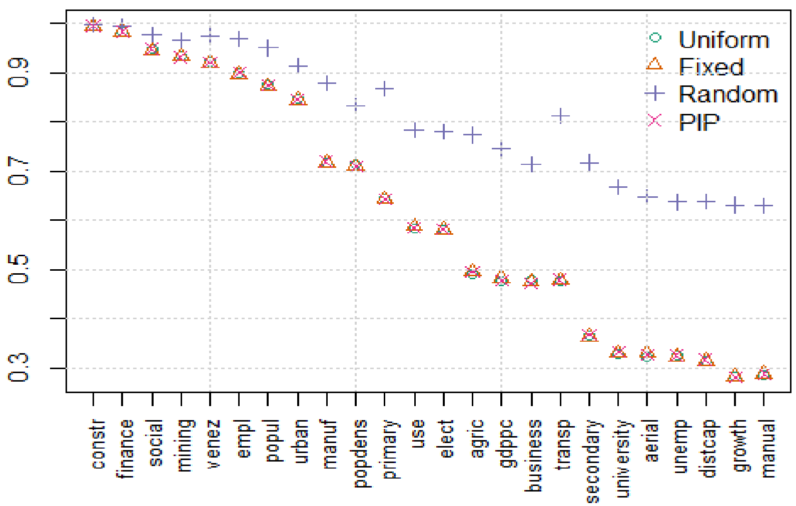
Figure 2: MC3 sampler results: Best 500 models. Colored areas reflect the inclusion of variables in the model and whether their estimated parameters are positive (blue) or negative (red). The horizontal axis represents cumulative model probabilities.



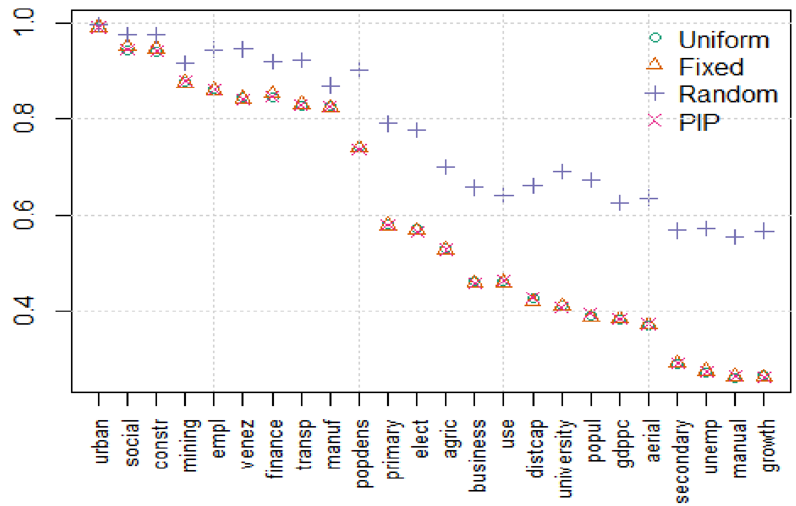
(a) Incidents, absolute values



(b) Incidents, relative terms

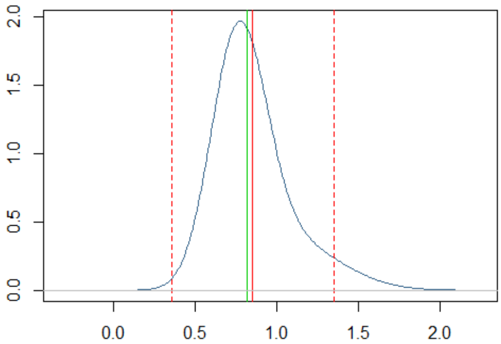


(c) Incidents, absolute values

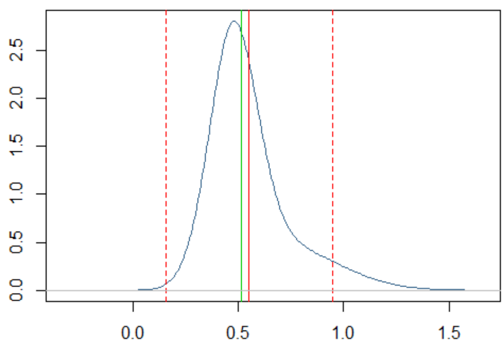


(d) Incidents, relative terms

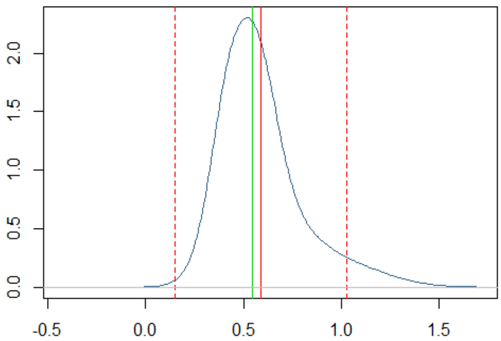
Figure 3: Posterior inclusion probabilities: Sensitivity analysis to alternative specifications of model-specific parameters (top) and model (bottom) priors.



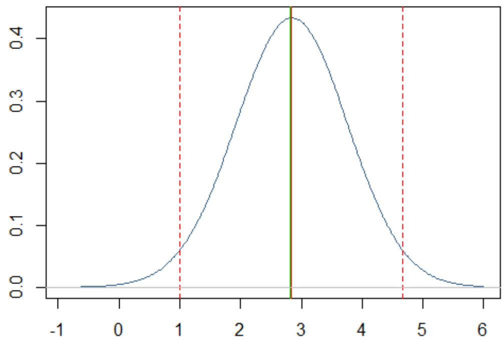
(a) constr (0.99)



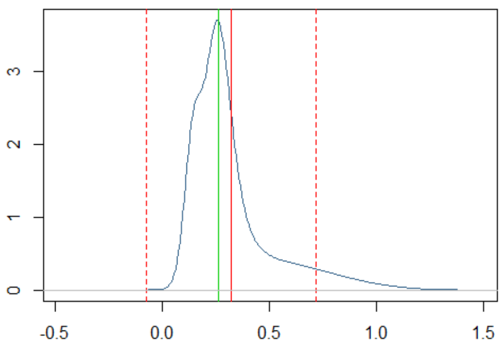
(b) finance (0.98)



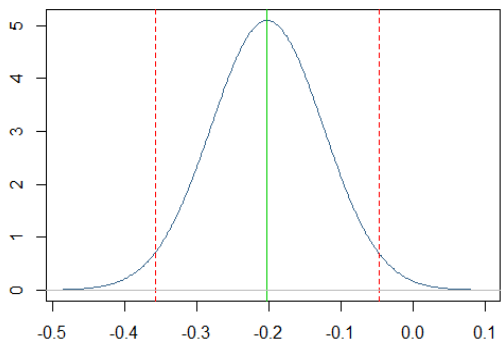
(c) social (0.95)



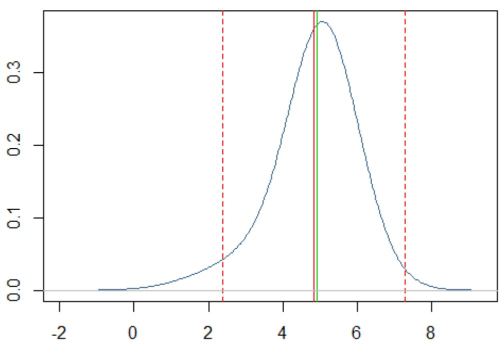
(d) venez (0.93)



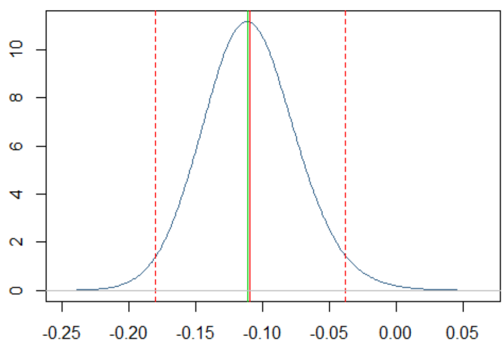
(e) mining (0.93)



(f) empl (0.89)



(g) popul (0.87)



(h) urban (0.85)

Figure 4: MC3 sampler results, terrorist incidents in absolute values: Marginal posterior densities of estimated parameters for selected regressors (PIP$\geq$ 0.85, in parentheses). Conditional on inclusion, solid vertical lines represent the posterior expected value (red) and median (green). Dashed lines are two times standard deviation bounds.