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, together with the increase in the number of attacks across the globe during the last two decades (Gaibulloev and Sandler 2019). 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 (Jetter and Stadelmann 2019; Morris and LaFree 2016; 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 of general validity, see Kis-Katos, Liebert, and Schulze (2014) and the references therein. Therefore, 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.

Taking the previous arguments into consideration, this paper studies the driving factors of terrorism in Colombian departments from 2001 to 2014. There are several aspects that make this analysis interesting. Colombia is the third largest economy of Latin America and has strong commercial and military links with the United States (US). Colombia is well endowed with natural resources and, in comparison with its neighbors, has a long-lasting and solid democracy (Grassi 2014). This country has the second most unequal distribution of wealth in America (Holmes et al. 2018) and - according to data from the United Nations Office on Drugs and Crime[1] - produced more than half of the world's coca in 2019. It is also well known that Colombia has endured a severe, complex and multidimensional conflict during six decades, see Fernández and Pazzona (2019) for some recent figures on

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

its magnitude and implications. As a result, this country suffered the highest level of terrorist activity worldwide during 1970-2004 (Feldmann and Hinojosa 2009).

The length and magnitude of the Colombian conflict has made it a testing ground to study the social and economic consequences of violence. Despite this, further evidence is necessary to properly know the socioeconomic factors driving terrorist activity in Colombia. Poveda (2012) analyzes the determinants of violence in the seven largest cities between 1984 and 2006, concluding that economic growth, coca seizures, and human capital exert a significant negative influence. Population density, income inequality, and poverty are found to be positively related to homicide rates. Rodríguez and Daza (2012) study the drivers of civil conflict in Colombia using data from all 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 Colombian conflict at municipality level decreases (increases) with institutional quality and military operations (illegal rents from coca cultivation).

Holmes et al. (2018) implement a multilevel analysis with data for Colombian municipalities and departments during 2000-2010. They claim that reducing unemployment and incorporating the deprived into public services will reduce leftist guerrilla violence. These authors also find that the shares of the mining and energy sectors are directly associated with violence. Using a similar modeling approach, Holmes et al. (2019) analyze the determinants of paramilitary violence at the municipal level from 2002 to 2015. They conclude that, although the demobilization process lessened paramilitary violence against leftist guerrilla, coca cultivation and ranching still display a significant direct relationship with it. Holmes, Amin Gutiérrez de Piñeres, and Curtin (2006) study the link between departmental coca production and activities of the Revolutionary Armed Forces of Colombia (FARC) during the 1990s. They 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 directly related to exports (legal and illegal), and inversely to gross domestic product (GDP) per capita and the presence of the state in the territory.

The present paper tries to make several contributions to this literature about the socioeconomic determinants of terrorism in Colombia at the sub-national level. In contrast to previous studies, we do not restrict the sample to the attacks carried out by a particular terrorist group, and use a more comprehensive set of covariates. To deal with it, and similarly to Python et al. (2019) and Sanso-Navarro and Vera-Cabello (2020), our empirical analysis is grounded on the implementation of Bayesian model averaging (BMA) techniques (Raftery 1995; Raftery, Madigan, and Hoeting 1997). By proceeding in this way, we are able to introduce model uncertainty in this context and, therefore, identify robust correlates of terrorism. That is to say, BMA allows us to deal with the uncertainty over the control variables by checking the robustness of our estimates in a more systematic way than under a frequentist approach. Moreover, 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. Terrorist incidents have also been expressed in relative terms to population (Jetter and Stadelmann 2019; 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 2020), and to the possible presence of spatial dependence (Crespo Cuaresma and Feldkircher 2013; Sandler 2014) has also been assessed. To the best of our knowledge, this last issue has only been addressed in the present context by Holmes et al. (2018) and Holmes et al. (2019).

The rest of the paper is structured as follows. Section 2 briefly characterizes the Colombian conflict and its development. Section 3 motivates the potential determinants of terrorism considered in our empirical analysis. Section 4 presents the data sources and BMA techniques. Section 5 shows the results obtained and an assessment of their robustness. The main findings are discussed in Section 6 and, finally, Section 7 concludes.

2 The Colombian conflict

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. 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 emerged in rural areas with the objective of establishing a communist state in Colombia. Among a great variety of groups, the two more important are the National Liberation Army (ELN) and the Revolutionary Armed Forces of Colombia (FARC). Therefore, it can be stated that terrorism in this country has ideological roots. In their first two decades, the impact of these organizations was low and restricted to those areas where they acted as substitutes of a missing state.

In the 1980s the drug traffickers - Pablo Escobar and the Medellín Cartel - came into play in the conflict between the state and the guerrillas. Although the justification for the existence of pro-Soviet and pro-Cuban guerrillas was put into question with the end of the Cold War, their violent activity intensified during the 1990s for two reasons. First, and mainly due to financial needs, the FARC became involved in the illicit drug trade. Second, rural landowners and dealers created right-wing paramilitary groups to defend themselves against the extortion of guerrillas, being the United Self-Defence Groups of Colombia (AUC) the more relevant, having several regional branches. Presidents Andrés Pastrana (1998-2002) and Bill Clinton signed the so-called *Plan Colombia*, that came with financial and military aid from the US after the year 2000. This is another proof that the Colombian conflict has been characterized by the successive appearance of new contenders that had changed their original motivations and behavior. In fact, it is difficult to define the role played in this context by coca cultivation. Holmes and Amin Gutiérrez de Piñeres (2014) claim that, rather than drugs or coca production and trade, the main problem faced by Colombia is state fragmentation. Piazza (2011), building on Kleiman (2004), argue that the link between drugs and terrorism in Colombia is determined by the fact that coca generates revenues (cash argument), on the one hand, and that it induces political instability (chaos argument), on the other.

President Álvaro Uribe (2002-2010) established *Plan Patriota* to fight, with the military support of the US, against ELN and FARC. This plan had a mixed success and, in any case, revealed the necessity of a negotiated path to the end of violence in Colombia. This was finally achieved by Juan Manuel Santos (2010-2018), who signed a peace agreement with the FARC in November 2016, for what he was awarded with the Nobel Peace Prize that year. Although the intensity of the conflict has significantly decreased with respect to previous decades, violence has not ceased during President Iván Duque's term (2018-nowadays). The disarmament of FARC created a power vacuum regarding the control of the territory and drug trafficking that has been filled by violent paramilitary groups and new criminal organizations (*Bandas criminales*, BACRIM). In addition, the failure of peace negotiations with the ELN has intensified the activities of this guerrilla. For these reasons, it can be stated that there is still a way to go for a complete cessation of violence in Colombia.

3 Potential determinants of terrorism

Demographic variables

Due to a scale effect, terrorist attacks are more likely to be perpetrated in populous areas (Gassebner and Luechinger 2011). In addition, the results obtained by Krieger and Meierrieks (2011) suggest that larger countries have a greater probability of suffering terrorist incidents. Drakos and Gofas (2006) also show that terrorism is directly related to population density, what is interpreted as a reflection of resource scarcity. These empirical findings have motivated us to include total population and people per square kilometer in order to capture that larger and denser departments are expected to host a greater number of targets, victims and perpetrators.

There is also a preconceived idea that urbanization is conducive to terrorism because it is easier to organize and carry out violent activities in cities, as well as to reach a larger audience (Kis-Katos, Liebert, and Schulze 2011). However, Glaeser and Shapiro (2002) point out that, despite there is a strong link between cities and violence, its final outcome is not clear. The reason is that while terrorist attacks are directly related to the size of the target (target effect), cities provide protection to their citizens (safe harbor effect). This has lead us to consider the percentage of urban population as a potential determinant of terrorism in Colombia. In line with the *'safe harbor effect'* and the prevailing rural nature of violence in this country, the expected sign for the relationship between urbanization and terrorism is negative. Actually, the FARC typically operated in non-urban areas with coca crops and limited governmental control (Lemus 2014). The share of urban population may also be reflecting the forced population displacements generated by violence, as 60 per cent of the people moved from rural to urban areas within the same department (Calderón-Mejía and Ibáñez 2016).

Economic conditions and development indicators

Economic theory has provided foundations for the explanation of terrorism. A first strand of the theoretical literature on this phenomenon was pioneered by the rational choice model proposed by Becker (1968). This author considered criminals to be rational economic agents that allocate their time to legal and illegal activities. Their optimal behavior consists of choosing the level of criminal activities that maximizes the value of an utility function, subject to several constraints. In equilibrium, the marginal opportunity cost of illegal activities is equal to their marginal revenue. This theoretical framework has been adapted to model terrorist behavior by assuming that the objective function depends on the achievement of political goals, see Landes (1978) and Sandler, Tschirhart, and Cauley (1983) among others. The relevance of the rational choice model for terrorism has been advocated by Caplan (2006), who claims that deterrence is a viable strategy to fight against this type of violence.

According to the rational choice theoretical framework, lower standards of living and economic growth rates are expected to be associated with higher levels of terrorism[2] (Poveda 2012; Rodríguez and Daza 2012). The reason is that the opportunity cost of terrorist activities increases with economic prospects (Freytag et al. 2011). Moreover, the FARC are known to have generally operated in less developed areas of Colombia (Holmes, Amin Gutiérrez de Piñeres, and Curtin 2007). These arguments have been taken into account by including GDP per capita[3] and the annual rate of GDP growth, both at 2005 constant prices and expressed in local currency, as explanatory variables.

[2]Krueger and Malevckova (2003) and Abadie (2006) have not found evidence that poor countries experience higher levels of transnational terrorism. Similarly, Kis-Katos, Liebert, and Schulze (2011) show that terror increases with GDP per capita levels. As pointed out by Blomberg, Hess, and Weerapana (2004), this result may be reflecting that a greater state capacity reduces the risk of rebellions and civil wars, but makes terrorism more probable. These conflicting findings have been tried to be reconciled by Enders and Hoover (2012) assuming that the relationship between terrorism and development is nonlinear.

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

Our set of potential determinants of terrorism also includes variables measuring the sectoral composition of the economy. They are intended to capture that, in principle, wages will tend to be higher in those departments where the manufacturing and service sectors represent a higher percentage over GDP. Hence, according to an opportunity cost argument, local economies geared towards the primary sector will be more likely to produce terrorism[4]. The importance of the agricultural and mining sectors will also capture whether, as in other forms of violence, terrorism is linked or not to the abundance of natural resources (Holmes et al. 2018). Moreover, there is a well-established empirical evidence about the direct relationship between income inequality and violence - see, among others, Piazza (2011), Poveda (2012), and Schneider, Brück, and Meierrieks (2015) - that has motivated the consideration of the Gini index for the distribution of income at department level as a regressor.

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). Therefore, 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, which should display, respectively, an inverse and a direct relationship with violence. In addition, the proportions of population with primary and secondary education and with a university degree have been used as potential determinants of terrorism. These variables are included in the empirical analysis to reflect the economic aspirations of the population and, in this sense, these variables should be inversely related to violence, given the positive correlation between the level of human capital and expected wages. The classical argument of the opportunity cost of terrorism associated to the rational choice model also applies to these labor market indicators and educational variables.

[4]The authors acknowledge an anonymous reviewer for pointing out this issue.

Government intervention

Another relevant and vast strand of the literature analyzes terrorism using game theory, see the selective reviews Sandler and Arce (2003) and Sandler and Siqueira (2009), or the editorial note of Mathews and Sanders (2019). The interactions between the government, a terrorist organization, and potential terrorist volunteers have been studied in De Mesquita (2005). The strategic interplay between the government, the electorate, and a terrorist organization is analyzed by De Mesquita (2007). In this line, Powell (2007) deals with governmental optimal resource allocation in the presence of a terrorist group. Jindapon and Neilson (2009) develop a zero-sum game model where terrorists (the government) minimize (maximizes) the expected utility of the median voter. These authors find that, while risk aversion leads to less frequent but more severe attacks, it does not imply an increase in the amount of resources devoted to fight terrorism.

Berman, Shapiro, and Felter (2011) propose a model where the government, violent rebels, and civilians play a three-way contest, concluding that improved service provision reduces insurgent violence. Following this argument, the percentage over total output of the social services and private health sector has been included as a covariate in the estimations. Government intervention has also been tried to be captured using the importance of the public administration and defence sector, which is expected to display a direct relationship with terrorism. One should anticipate that the more effort made to eliminate illegal agricultural activities the lower the level of violence (Piazza 2011). For this reason, the percentages of total area where both aerial and manual eradication of illegal coca crops were implemented have also been considered as covariates.

4 Data and methods

As pointed out by Feldmann and Hinojosa (2009), terrorism can be considered as a specific strategy within all the manifestations of violence observed in Colombia. In fact, these authors claim that non-state armed groups adopted terrorism as a pivotal element of their ways of action. In order to analyze the main determinants of this type of violence in Colombian departments, terrorism has been measured using the number of incidents, confirmed fatalities, and persons injured. This information has been extracted from the

Global Terrorism Database[5] (GTD), maintained by the National Consortium for the Study of Terrorism and Responses to Terrorism (LaFree and Dugan 2007). This database 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. The sources of information for the potential determinants of terrorism, included with a one-period 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[6] and begins in 2000. The description of the measures of terrorism and of the whole set of regressors considered in the empirical analysis can be found in Table 1. Summary statistics and the correlation matrix for these variables are reported, respectively, in tables A1 and A2 in the Appendix.

[Insert Table 1 about here]

BMA techniques are useful to estimate the influence of a large number of possible predictors, especially when there are several measures of the same theoretical concept (Montgomery and Nyhan 2010). These methods consist of estimating all candidate models and then computing a weighted average of their results, taking into account the implicit uncertainty conditional on a given model and across different models. Proceeding in this manner, model selection, estimation, and inference are handled simultaneously. Although count data regression models are commonly employed in the analysis of terrorism, we are implementing BMA within a linear regression framework. The main reason is that, as a contribution to related studies, we are also considering relative measures of the incidence and severity of terror, which take non-integer values. The adoption of a linear model will allow us to control for the possible presence of unobserved heterogeneity because various fixed effects can be more appropriately accommodated in this framework. In addition, it is more difficult to introduce spatial dependence in count data models because they do not

[5]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"*.

[6]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 attack per year.

establish a direct connection between the regressors and the dependent variable, see Glaser (2017).

A linear regression model assumes 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, and for a total number of q regressors, 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.

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

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

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:

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

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

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

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

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 (2020) 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[7]. 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-specific parameters (Liang et al. 2008), and a uniform prior over the model space.

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 dependent variable and the whole set of covariates reported in Table 1. All estimations include departmental fixed effects to control for unobserved heterogeneity such as local political conditions and institutional factors. Time fixed effects have also been introduced to further take into account the panel structure of the data. 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 (SD) 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.

[7] The methods described in this section have been implemented using the BMS R package (R Core Team 2020; Zeugner and Feldkircher 2015).

[Insert Table 2 about here]

The employment rate, the percentage of urban population, and the shares of the mining and business sectors receive inclusion probabilities of over 70 per cent. These regressors have negative mean estimated coefficients, reflecting that terrorism in Colombia is mainly a rural phenomenon. Moreover, the inverse relationship of the employment rate and of the importance of the business sector with terror corroborate the opportunity cost argument described in Section 3. The explanation for the link between the number of incidents and the mining sector is not so straightforward. Although the sign of the correlation between violence and natural resources endowments is expected to be positive, there are arguments that may justify an inverse relationship between these two variables in this country because oil-producing regions have been prioritized for security and enjoy a more intense state presence (Holmes et al. 2019). The Gini coefficient of income distribution also displays a high PIP (0.59), and its mean estimated coefficient suggests that inequality is directly related to the number of incidents. All these results are similar to those obtained from the estimation of a conventional OLS regression, displayed in Table A3 in the Appendix.

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 45 covariates, including department and time fixed effects. The correlation between iteration counts and analytical posterior model probabilities (PMP) for the 500 best models (0.99) indicates an adequate degree of convergence. In addition, the average shrinkage factor over all models, which can be interpreted as a Bayesian goodness-of-fit measure, is 0.88. The other columns in Table 2 show the results for two alternative measures of terrorism that reflect the severity of the incidents: the total number of confirmed fatalities and persons injured. The regressors that are robustly related to terror when these two variables are used as the dependent variable are the percentages of the business, manufacturing, and public administration and defence sectors over departmental GDP. As expected, there is a direct link between defence expenditure and violence. Although the sign of the mean estimated coefficients for these covariates coincides with that obtained when the number of attacks is used as the dependent variable, the degrees of convergence and the average shrinkage factors are slightly lower.

[Insert Table 3 about here]

Although population does not tend to display a high inclusion probability, and following the arguments in Mueller (2016) and Jetter and Stadelmann (2019), we are going to check whether previous findings are driven by analyzing regions of different sizes. For this reason, 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 employment rate, the importance of the mining sector, the percentage of urban population, and income inequality do not change when incidents are considered per million inhabitants. However, the share of the financial (business) sector displays a much higher (lower) inclusion probability. The percentage of population with a university degree, the GDP growth rate and, especially, the importance of the public administration and defence sector have a more robust relationship with relative indicators of violence intensity. Estimation results also show that the attacks implied a greater number of injuries in regions with a more developed manufacturing sector, and with higher GDP per capita levels and employment rates; the percentages of population with secondary and university education exert, on the contrary, a negative influence.

[Insert Figure 1 about here]

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, 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 tend to display high PIPs for all terror measures, regardless of their specification in absolute or relative terms, are the importance of the business sector, the employment rate, and the Gini coefficient for the distribution of income. Figure 1 corroborates that the percentage of urban population has a robust relationship with the number of incidents suffered at departmental level. The importance of the public administration and defence sector shows a higher inclusion probability when fatalities and injuries are considered as the dependent variable. It can also be observed that there are more regressors robustly related to the number of terrorist attacks than to their intensity, especially when it is measured by the number of confirmed fatalities. 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 only the determinants of the number of incidents.

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 2020), it is worth assessing the sensitivity of the findings described before. The results obtained from this robustness check are depicted in Figure 2. 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, the PIP of the employment rate is 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, and of those covariates with inclusion probabilities lower than 0.50. 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 2 about here]

In order to evaluate 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 ('Custom'). The results obtained for each regressor under these model priors are plotted in the lower panel of Figure 2. Irrespective of incidents being expressed in absolute or relative terms, and with the exception of the binomial-beta hyperprior, inclusion probabilities under these alternative specifications are very similar to those calculated with the uniform model prior. 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 Figure 3 and Table 4 about here]

Figure 3 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[8]. It can also be observed that the capital district was notably punished by terrorism in 2008. Figure 3 shows that terrorist attacks are geographically concentrated across departments, what corrobotates the spatial variation of violence in Colombia highlighted by, among others, Feldmann (2018), Holmes et al. (2018) and Rozo (2018).

Consequently, 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 is 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

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

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 covariates, 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 regressors 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 similar to those presented in the previous subsection. The main exceptions are the variables that reflect the sectoral composition of the economy. Despite this, the conclusions drawn about the robust relationship of the employment rate, the percentage of urban population, and income inequality 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. Nonetheless, the eigenvalues for a three nearest neighbors matrix ('3nn') display inclusion probabilities higher than 30 per cent for some prior combinations. 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

[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.

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, the attacks have been classified according to their ideology. Reflecting the multiplicity of agents involved in the Colombian conflict, the incidents included in our data set were perpetrated by, at least, sixteen terrorist groups, both left-wing[11] and right-wing[12]. The former were more active, in terms of both incidence and severity. In fact, FARC are attributed around 60 per cent of the incidents and casualties during our sample period. It is also worth mentioning that, although the most-active right-wing group (AUC) perpetrated 3 per cent of the attacks, they represent 10 per cent of confirmed fatalities.

[Insert Table 7 about here]

In order to capture the nature of the Colombian conflict, the number of terrorist incidents attributed to groups of an opposite ideology has also been introduced as a regressor [13]. BMA results obtained from this exercise are shown in Table 7. The correlations between iteration counts and analytical PMPs, and the average shrinkage factors reported in the lower panel indicate, respectively, good convergence and fit. With the exception of the FARC, the highest inclusion probabilities correspond to the number of attacks carried out by groups of opposite sign. This result reflects a revengeful behavior of terrorist organizations in Colombia, probably driven by the vigilantist character of right-wing groups. An important difference with respect to the attacks attributed to the ELN is that, in this case, the educational variables receive much higher inclusion probabilities. This is also the case of the percentage of area with manual eradication of coca crops, while the influence of labor market conditions on terrorist activities takes place through the unemployment rate. Finally, it should be noted that the results displayed in the last three columns, corresponding to the attacks carried out by the FARC, are very similar to those reported in Table 2. This is a consequence of the relative importance of this group in our data set.

[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]Extremists, Guerrillas, Guevarist Revolutionary Army, National Liberation Army of Colombia, Paraguayan People's Army, People's Revolutionary Army, Popular Liberation Army, Rebels, Revolutionary Armed Forces of Colombia.

[12]Black Eagles, Death Squad, Gunmen, Los Rastrojos, Paramilitaries, People's Revolutionary Army, United Self-Defence Units of Colombia.

[13]The authors acknowledge an anonymous reviewer for bringing this point to our attention.

6 Discussion

BMA results allow us to conclude that, among the potential determinants of terrorism considered in our empirical setup, those displaying a more robust relationship are the employment rate, the percentage of urban population, and income inequality. It is more difficult to find regressors with high inclusion probabilities when terrorism is measured using the number of confirmed fatalities. Other variables that are important for explaining the differences in terrorist incidence at departmental level are several indicators of the sectoral composition. This is especially the case of the importance of the business sector for the number of incidents, and of the public administration and defence sector when the severity of terrorism 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 coefficients what contains the relevant information about the effects we are interested in. That is to say, it is the entire posterior density of the coefficients what 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 50 per cent in Figure 4. None of these densities have a substantive probability mass around zero, what can be interpreted as evidence that these covariates influence the number of terrorist attacks. It can also be observed that the posterior distributions of the parameters attached to these regressors are symmetric. The estimated coefficients for the employment rate, the percentage of urban population, and the importance of the business sector suggest that these variables are inversely related to terrorism. On the contrary, regions with higher Gini coefficients for the distribution of income are more 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).

[Insert Figure 4 about here]

The results presented in the previous subsection suggest that illicit coca crop eradication is not a relevant predictor for terrorism because the related regressors receive low inclusion probabilities. Although no causal claims have been made, our empirical analysis highlights robust relationships with policy implications. The importance of the business 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, our findings reinforce the standpoint of Meierrieks and Gries (2012), who establish that the best way to fight terrorism is to increase its opportunity cost, see also Sanso-Navarro and Vera-Cabello (2020) and the references therein. This is in line with the Territorial Spaces for Training and Reincorporation created in the context of the peace agreement signed between the Colombian government and the FARC. These local programmes are intended to reinsert former members of this group and their families into civilian life through technical training and the development of productive projects. Unfortunately, and although our results support the implementation of this plan, it is facing difficulties due to the lack of financial resources. This may worsen the insecurity and threat felt by FARC members during the disarmament process (Thomson 2020) and, consequently, jeopardize the peace deal.

7 Conclusions

Colombia is experiencing one of the most complex and long-lasting conflicts in recent history, with important economic and social consequences (Fernández and Pazzona 2019). A pervasive manifestation of the violence carried out by the adversaries involved in this confrontation has been terrorism. Therefore, 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 a more comprehensive data set than those of related work to date, and applying BMA techniques. By proceeding in this way, we have been able to identify the variables that display a more 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 assessed.

It is important to acknowledge that no causal relationship has been established due to potential endogeneity concerns between terrorism and its determinants. 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 percentage of urban population, and the importance of the business sector are found to be inversely and robustly linked to terrorism. On the contrary, income inequality displays a direct relationship with this type of violence. These results imply 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 (Nieto-Matiz 2019; Tellez 2019). Our findings corroborate those of an important strand in the literature according to which policies should be aimed at increasing the opportunity cost of violence. This can be achieved 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
injured	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, including oil extraction; as percentage of GDP	DANE
manuf	Manufacturing industries; as percentage of GDP	DANE
business	Commerce, repair, restaurants and hotels; as percentage of GDP	DANE
finance	Financial institutions, insurance, real state activities and services to companies; as percentage of GDP	DANE
socserv	Social services and private health; as percentage of GDP	DANE
public	Public administration and defence; as percentage of GDP	DANE
gini	Gini index; income distribution	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
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

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	0.27	0.15	5.44	0.32	-1.45	12.17	0.46	-23.33	42.94
popdens	0.29	-0.00	0.00	0.38	0.00	0.01	0.98	-0.08	0.03
urban	0.89	-112.89	62.31	0.36	-25.24	73.14	0.56	-195.59	258.53
gdppc	0.33	-1.23	3.69	0.46	-5.81	10.12	0.36	-2.24	17.10
growth	0.29	0.01	0.04	0.47	-0.08	0.13	0.32	-0.01	0.18
agric	0.39	-0.08	0.18	0.32	0.02	0.26	0.34	-0.09	0.65
mining	0.73	-0.14	0.12	0.36	0.04	0.16	0.42	-0.12	0.41
manuf	0.34	0.06	0.15	0.65	0.50	0.52	0.77	1.56	1.25
business	0.88	-0.89	0.51	0.99	-2.72	0.81	0.73	-2.55	2.25
finance	0.32	0.06	0.19	0.38	0.20	0.49	0.49	0.83	1.34
socserv	0.34	0.20	0.52	0.44	0.73	1.35	0.44	1.50	2.93
public	0.27	0.00	0.15	1.00	2.67	0.64	0.69	1.70	1.63
gini	0.59	11.83	13.54	0.31	0.57	15.57	0.52	41.61	60.62
empl	0.99	-0.34	0.10	0.45	-0.10	0.19	0.68	-0.60	0.58
unemp	0.26	0.00	0.08	0.40	0.11	0.23	0.47	0.36	0.64
primary	0.34	-6.87	16.12	0.31	-2.56	28.13	0.32	4.06	63.53
secondary	0.27	3.11	16.43	0.31	-4.25	38.88	0.41	-54.93	117.31
university	0.27	-1.83	12.43	0.34	-9.64	33.72	0.32	-8.60	67.57
aerial	0.29	-0.30	1.16	0.61	4.27	4.88	0.41	3.57	7.67
manual	0.35	1.61	3.73	0.40	-3.91	8.66	0.36	5.51	17.22
Models		1,343,808			1,657,348			1,663,681	
Size		44.70			45.25			46.05	
Correlation		0.99			0.91			0.94	
Shrinkage		0.88			0.80			0.78	

Note: The number of observations is 336. All specifications include department and 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	0.29	1.13	4.47	0.37	0.45	16.09	0.47	-14.41	27.90
popdens	0.26	0.00	0.00	0.45	0.01	0.01	0.36	-0.00	0.01
urban	0.68	-43.67	40.99	0.41	25.41	92.79	0.46	-68.22	131.79
gdppc	0.29	0.49	2.53	0.41	2.81	10.04	0.54	11.79	17.39
growth	0.26	0.00	0.03	0.51	-0.11	0.17	0.53	-0.14	0.21
agric	0.49	-0.12	0.17	0.37	0.00	0.35	0.51	-0.39	0.64
mining	0.90	-0.15	0.09	0.39	0.02	0.17	0.43	-0.10	0.29
manuf	0.29	0.02	0.10	0.39	0.11	0.40	0.67	0.75	0.78
business	0.32	-0.05	0.19	0.62	-0.85	1.01	0.36	-0.01	0.74
finance	0.65	-0.27	0.27	0.37	-0.01	0.51	0.38	0.16	0.71
socserv	0.27	-0.03	0.30	0.37	-0.07	1.23	0.36	0.25	1.50
public	0.26	-0.00	0.11	1.00	3.42	0.82	1.00	3.94	0.97
gini	0.60	9.16	10.17	0.45	-13.00	27.79	0.53	27.41	39.97
empl	1.00	-0.32	0.07	0.39	0.04	0.18	0.66	-0.35	0.37
unemp	0.28	-0.02	0.07	0.37	-0.04	0.24	0.37	-0.01	0.31
primary	0.26	-1.50	8.56	0.38	8.38	41.41	0.37	12.74	48.92
secondary	0.24	1.01	10.94	0.45	-34.71	71.53	0.63	-99.34	112.92
university	0.24	0.90	8.55	0.69	-78.83	78.09	0.64	-81.25	88.75
aerial	0.24	-0.03	0.71	0.40	1.33	4.00	0.42	2.14	5.05
manual	0.33	1.17	2.72	0.37	-1.40	9.29	0.36	1.66	10.76
Models	1,319,339			1,867,066			1,820,006		
Size	44.16			45.17			46.06		
Correlation	0.99			0.82			0.82		
Shrinkage	0.90			0.67			0.72		

Note: The number of observations is 336. All specifications include department and 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.

Variable	Absolute values PIP	Absolute values Mean	Absolute values SD	Relative terms PIP	Relative terms Mean	Relative terms SD
popul	0.39	0.54	1.56	0.37	0.16	0.87
popdens	0.34	0.00	0.00	0.35	0.00	0.00
urban	0.80	-13.74	9.70	0.68	-7.42	7.63
gdppc	0.34	-0.26	1.67	0.34	0.28	1.37
growth	0.24	-0.00	0.03	0.24	-0.00	0.02
agric	0.28	0.01	0.07	0.37	-0.03	0.08
mining	0.35	0.01	0.04	0.39	-0.02	0.05
manuf	0.31	-0.00	0.07	0.34	0.01	0.07
business	0.32	-0.01	0.14	0.42	0.07	0.15
finance	0.71	0.24	0.22	0.36	0.00	0.10
socserv	0.43	-0.26	0.44	0.47	-0.27	0.41
public	0.37	0.06	0.14	0.63	0.22	0.22
gini	0.83	22.42	14.77	0.53	7.07	9.06
empl	0.86	-0.16	0.10	0.97	-0.18	0.07
unemp	0.28	0.02	0.07	0.27	0.01	0.05
primary	0.28	-3.83	11.83	0.26	-1.05	7.66
secondary	0.30	6.31	17.05	0.38	8.47	16.71
university	0.25	-1.52	10.66	0.24	0.82	7.94
aerial	0.26	-0.06	0.95	0.29	0.10	0.85
manual	0.29	1.01	3.11	0.25	0.31	1.98

Note: The number of observations is 336. All specifications include department and time fixed effects, and the eigenvectors calculated for alternative weights matrices (see Table 4), 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.

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

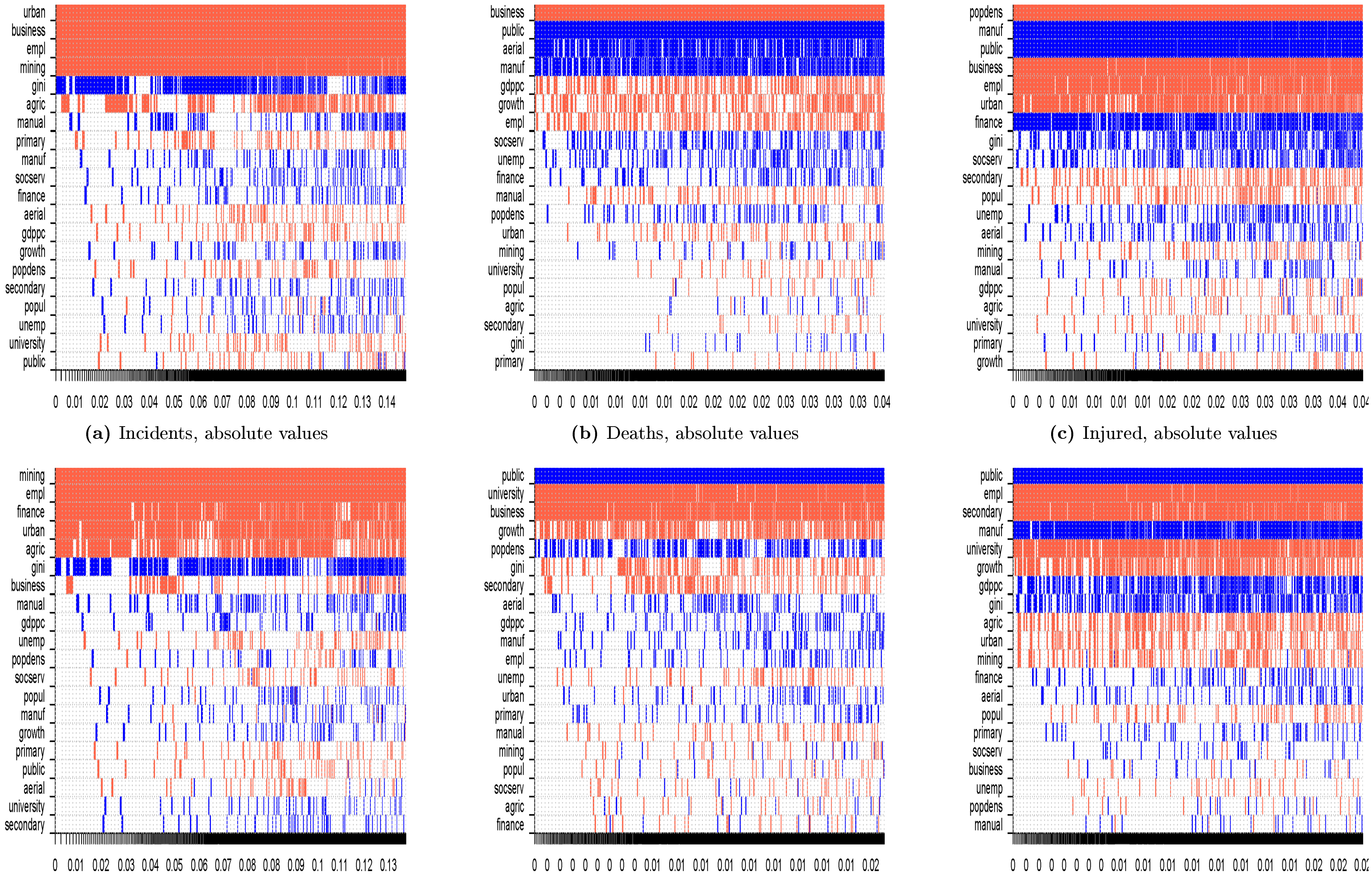
Absolute values							
Prior		Weights matrix					
Parameters	Model	Queen	Gabriel	SOI	3nn	5nn	7nn
Hyper	Uniform	0.99	0.00	0.00	0.01	0.00	0.00
UIP	Uniform	0.90	0.00	0.00	0.10	0.00	0.00
BRIC	Uniform	0.65	0.00	0.00	0.35	0.00	0.00
RIC	Uniform	0.66	0.00	0.00	0.34	0.00	0.00
HQ	Uniform	0.93	0.00	0.00	0.07	0.00	0.00
EBL	Uniform	0.97	0.00	0.00	0.03	0.00	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					
Coefficients	Model	queen	gabriel	soi	3nn	5nn	7nn
Hyper	Uniform	0.64	0.00	0.00	0.36	0.00	0.00
UIP	Uniform	1.00	0.00	0.00	0.00	0.00	0.00
BRIC	Uniform	1.00	0.00	0.00	0.00	0.00	0.00
RIC	Uniform	0.99	0.00	0.00	0.01	0.00	0.00
HQ	Uniform	1.00	0.00	0.00	0.00	0.00	0.00
EBL	Uniform	0.99	0.00	0.00	0.00	0.00	0.01
Hyper	Fixed	0.64	0.00	0.00	0.36	0.00	0.00
Hyper	Random	0.63	0.00	0.00	0.37	0.00	0.00
Hyper	PIP	0.64	0.00	0.00	0.36	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	0.34	-0.37	0.91	0.29	0.94	5.04	0.34	-0.87	2.03	0.33	1.60	5.35
popdens	0.27	2.95	0.00	0.29	-0.00	0.00	0.99	0.01	0.00	0.60	-0.00	0.00
urban	0.27	-0.53	3.71	0.83	-69.91	47.52	0.30	-2.80	9.48	0.79	-59.18	44.30
gdppc	0.48	-0.50	0.75	0.30	0.40	2.66	0.27	-0.09	0.82	0.37	1.25	3.30
growth	0.29	-0.00	0.01	0.38	0.02	0.04	0.25	0.00	0.01	0.38	0.02	0.04
agric	0.27	0.00	0.01	0.30	-0.01	0.11	0.29	0.01	0.04	0.34	-0.04	0.12
mining	0.29	-0.00	0.01	0.46	-0.04	0.07	0.33	0.01	0.02	0.60	-0.07	0.08
manuf	0.34	0.01	0.02	0.36	0.06	0.13	0.65	0.07	0.08	0.29	0.00	0.09
business	0.99	-0.16	0.05	0.36	-0.09	0.25	0.44	-0.06	0.10	0.32	-0.02	0.19
finance	0.98	0.14	0.05	0.33	-0.06	0.17	0.27	0.01	0.05	0.41	-0.10	0.20
socserv	0.36	-0.03	0.07	0.54	0.49	0.63	0.64	0.25	0.25	0.44	0.28	0.49
public	0.62	-0.04	0.05	0.35	0.07	0.18	0.28	0.01	0.05	0.31	0.03	0.13
gini	0.27	0.07	0.93	0.47	6.69	10.15	0.26	-0.17	2.07	0.63	10.51	11.10
empl	0.27	-0.00	0.01	0.99	-0.27	0.08	0.29	-0.00	0.02	0.99	-0.25	0.08
unemp	0.28	0.00	0.01	0.28	-0.01	0.07	0.61	0.04	0.05	0.38	-0.04	0.09
primary	0.28	-0.43	1.81	0.30	-3.50	11.81	0.90	-15.78	8.27	0.29	1.62	9.67
secondary	0.28	0.47	2.41	0.26	1.33	13.54	0.39	4.27	7.94	0.28	-0.89	12.39
university	0.36	1.23	2.63	0.33	-5.41	13.89	0.96	-20.35	8.27	0.28	1.07	9.74
aerial	0.27	-0.02	0.15	0.31	-0.38	1.11	0.26	-0.01	0.31	0.34	-0.38	1.04
manual	0.71	-0.99	0.88	0.44	2.38	3.97	0.80	2.82	1.97	0.29	0.48	2.30
leftw	1.00	0.03	0.01									
rightw				1.00	1.19	0.32	1.00	1.44	0.11	0.32	-0.06	0.18
Models	1,521,002			1,473,435			1,267,188			1,544,010		
Size	44.52			45.18			46.53			45.00		
Correlation	0.97			0.96			0.99			0.94		
Shrinkage	0.86			0.87			0.89			0.86		

Note: The number of observations is 336. All specifications include department and 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) Incidents, absolute values

(b) Deaths, absolute values

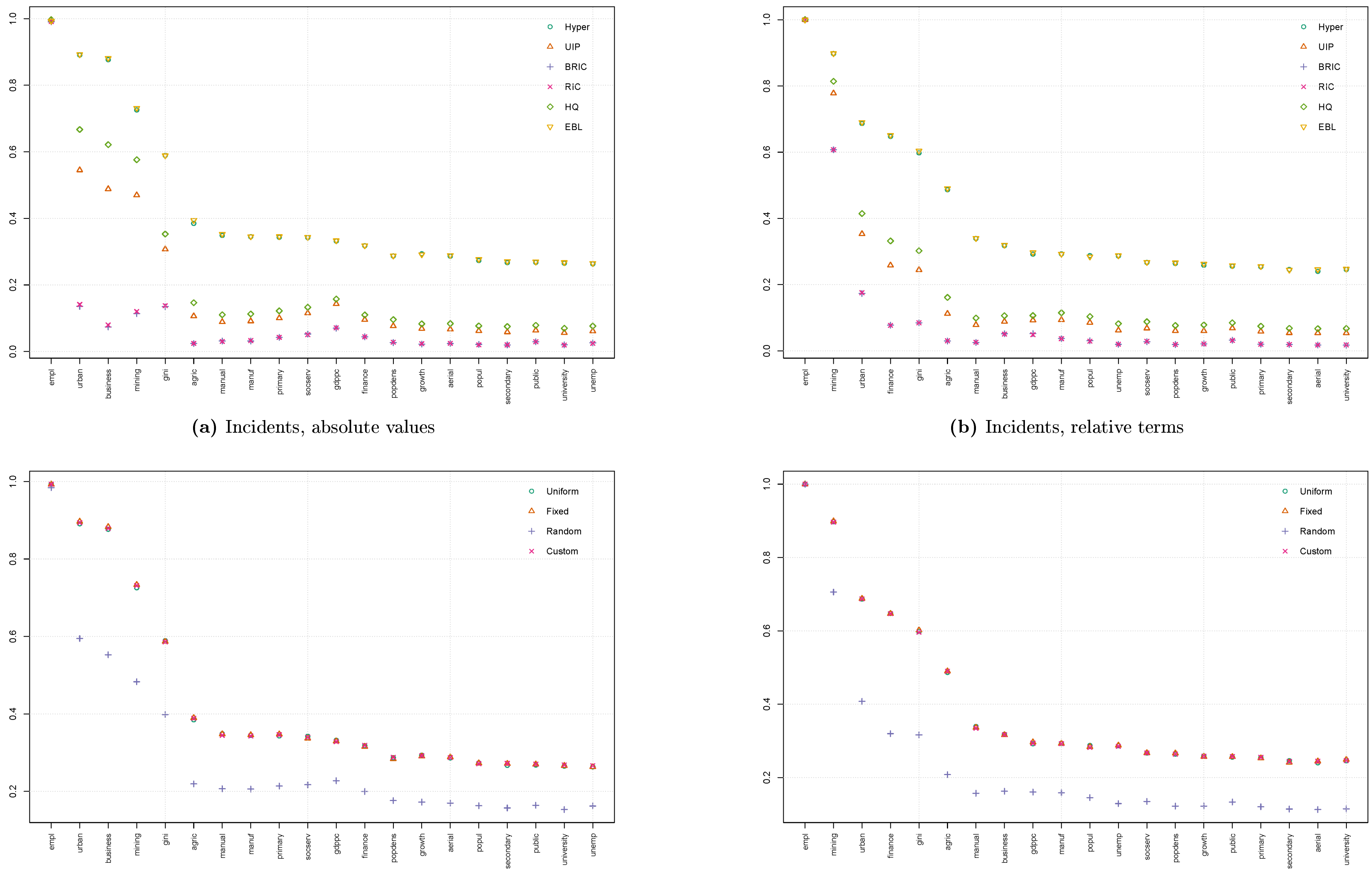
(c) Injured, absolute values

(d) Incidents, relative terms

(e) Deaths, relative terms

(f) Injured, relative terms

Figure 1: 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.



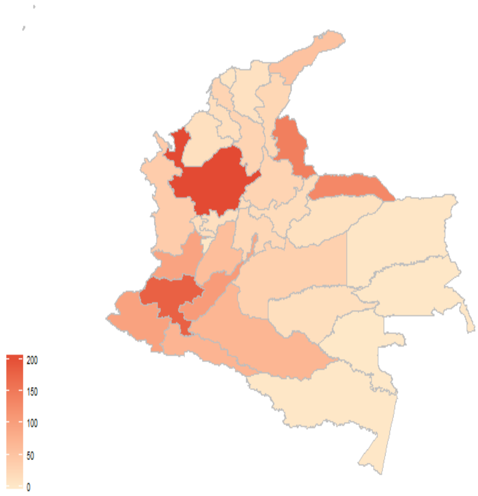
(a) Incidents, absolute values

(b) Incidents, relative terms

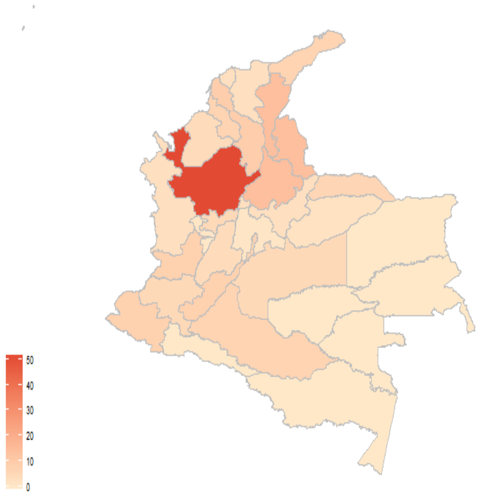
(c) Incidents, absolute values

(d) Incidents, relative terms

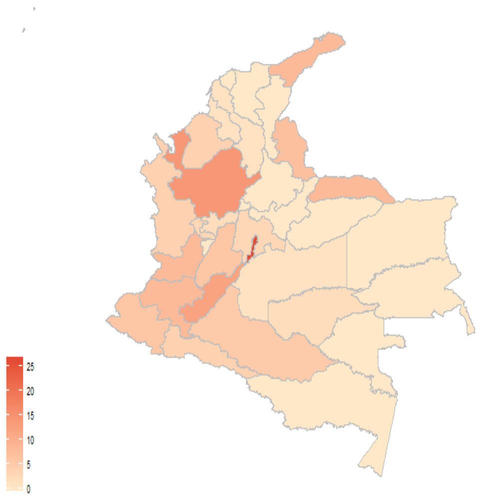
Figure 2: Posterior inclusion probabilities: Sensitivity analysis to alternative specifications of model-specific parameters (top) and model (bottom) priors.



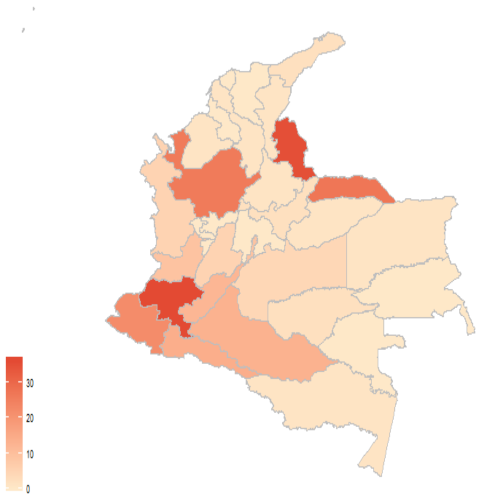
(a) Period 2001-2014



(b) Year 2001

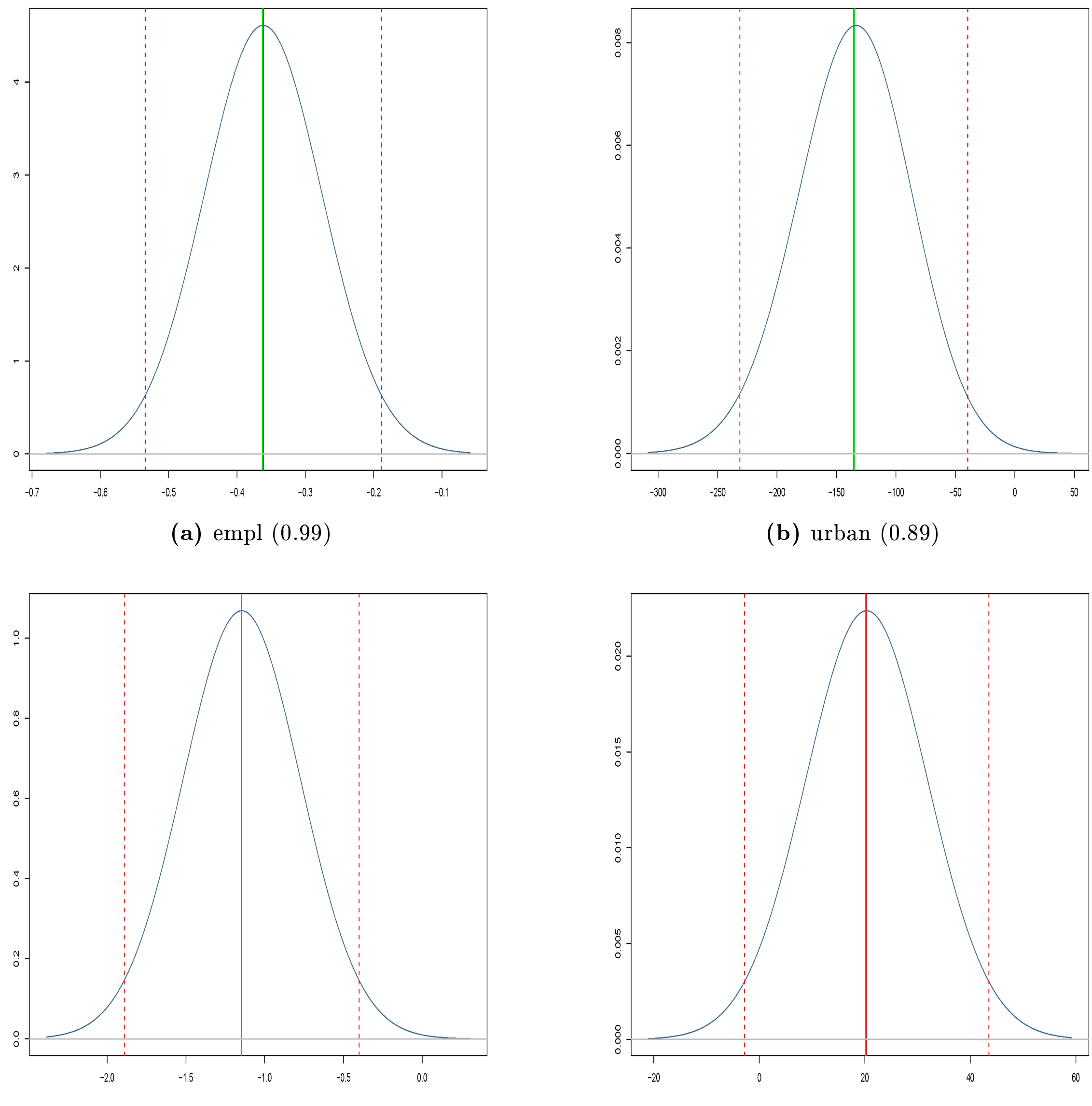


(c) Year 2008



(d) Year 2014

Figure 3: Cloropleth maps: Terrorist incidents in Colombian departments and the capital district.



(a) empl (0.99)

(b) urban (0.89)

(c) business (0.88)

(d) gini (0.59)

Figure 4: MC3 sampler results, terrorist incidents in absolute values: Marginal posterior densities of estimated parameters for selected regressors (PIPs 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.

Appendix

Table A1: Measures and potential determinants of terrorism: Descriptive statistics.

	Mean	SD	Minimum	Maximum
incidents	4.01	6.29	0.00	51.00
deaths	5.73	13.29	0.00	143.00
injuries	10.44	29.07	0.00	275.00
popul	14.10	0.70	12.90	15.85
popdens	281.82	863.16	4.48	4,781.54
urban	0.68	0.15	0.37	1.00
gdppc	-5.07	0.43	-6.13	-3.68
growth	4.07	4.78	-16.23	25.17
agric	12.33	6.02	0.00	27.40
mining	9.25	15.43	0.10	69.90
manuf	10.93	6.96	0.90	29.20
business	11.98	3.39	3.30	21.00
finance	12.74	6.80	2.60	33.10
socserv	2.94	1.13	0.70	7.00
public	7.54	4.09	2.70	25.00
gini	0.52	0.03	0.44	0.62
empl	52.77	4.73	40.43	65.58
unemp	11.89	3.18	5.87	22.29
primary	0.09	0.03	0.02	0.15
secondary	0.07	0.02	0.02	0.11
university	0.08	0.02	0.02	0.12
aerial	0.09	0.23	0.00	1.80
manual	0.03	0.07	0.00	0.64

Note: These variables and their sources are described in Table 1. The number of observations is 336.

Table A2: Measures and potential determinants of terrorism: Correlation matrix.

	incidents	deaths	injuries	popul	popdens	urban	gdppc	growth	agric	mining	manuf	business	finance	socserv	public	gini	empl	unemp	primary	secondary	university	aerial	manual
incidents	1.00																						
deaths	0.55	1.00																					
injuries	0.61	0.66	1.00																				
popul	0.25	0.12	0.31	1.00																			
popdens	0.05	0.01	0.22	0.52	1.00																		
urban	-0.08	-0.11	0.08	0.48	0.52	1.00																	
gdppc	0.02	-0.13	0.08	0.57	0.40	0.59	1.00																
growth	-0.09	-0.19	-0.07	-0.02	-0.01	0.02	0.23	1.00															
agric	-0.16	0.02	-0.18	-0.61	-0.48	-0.62	-0.67	-0.11	1.00														
mining	-0.08	-0.08	-0.12	-0.31	-0.17	-0.22	0.19	0.25	-0.09	1.00													
manuf	0.02	0.01	0.07	0.55	0.07	0.32	0.42	-0.04	-0.42	-0.52	1.00												
business	0.01	0.05	0.07	0.13	0.12	0.15	-0.37	-0.27	0.30	-0.66	-0.01	1.00											
finance	0.22	0.12	0.31	0.77	0.64	0.67	0.40	-0.13	-0.60	-0.53	0.44	0.24	1.00										
socserv	0.04	0.05	-0.04	-0.45	-0.29	-0.44	-0.78	-0.10	0.46	-0.27	-0.38	0.39	-0.28	1.00									
public	0.04	0.15	0.04	-0.52	-0.05	-0.38	-0.61	-0.10	0.46	-0.19	-0.42	0.22	-0.27	0.60	1.00								
gini	0.25	0.20	0.26	0.08	0.09	-0.25	-0.12	-0.15	0.04	0.06	-0.14	-0.10	0.05	0.05	0.02	1.00							
empl	0.07	0.05	0.04	0.38	0.25	0.02	0.34	0.05	-0.18	-0.00	0.15	-0.05	0.21	-0.27	-0.18	-0.08	1.00						
unemp	0.05	0.11	0.18	0.12	0.10	0.27	0.01	-0.23	0.05	-0.24	0.08	0.27	0.33	-0.12	-0.13	0.18	-0.16	1.00					
primary	-0.04	0.10	-0.11	-0.55	-0.57	-0.46	-0.53	-0.02	0.35	0.31	-0.42	-0.15	-0.49	0.34	0.23	0.18	-0.29	-0.19	1.00				
secondary	-0.04	0.03	-0.18	-0.59	-0.60	-0.41	-0.51	-0.03	0.38	0.23	-0.35	-0.13	-0.50	0.39	0.22	0.16	-0.36	-0.14	0.81	1.00			
university	-0.00	-0.01	-0.14	-0.47	-0.60	-0.34	-0.38	0.03	0.22	0.23	-0.29	-0.18	-0.37	0.35	0.12	0.13	-0.34	-0.13	0.73	0.79	1.00		
aerial	0.15	0.10	0.12	0.06	-0.10	-0.29	-0.24	0.03	0.07	-0.12	-0.07	0.33	-0.04	0.28	0.12	0.01	0.04	0.04	0.10	0.05	0.12	1.00	
manual	0.15	-0.00	0.08	0.12	-0.11	-0.22	-0.10	0.02	0.04	-0.08	-0.04	0.18	-0.01	0.22	0.01	0.01	0.01	0.08	0.04	0.05	0.08	0.60	1.00

Table A3: Estimation results for OLS regression models.

	Absolute values			Relative terms		
Dependent variable	Incidents	Deaths	Injured	Incidents	Deaths	Injured
popul	-1.96	-13.92	-77.04	2.48	8.13	-28.11
	(11.76)	(27.87)	(61.82)	(8.44)	(40.23)	(44.13)
popdens	0.00	0.02	-0.09***	0.00	0.02	-0.00
	(0.01)	(0.01)	(0.03)	(0.00)	(0.02)	(0.02)
urban	-158.70***	-93.04	-601.70**	-85.35**	16.62	-376.05*
	(56.33)	(133.50)	(296.10)	(40.44)	(192.70)	(211.40)
gdppc	-1.65	-20.33	-6.35	1.46	8.95	44.69*
	(6.58)	(15.59)	(34.58)	(4.72)	(22.50)	(24.69)
growth	0.04	-0.15	-0.04	-0.00	-0.38	-0.50*
	(0.07)	(0.17)	(0.38)	(0.05)	(0.25)	(0.27)
agric	-0.21	0.32	-0.25	-0.36*	-0.03	-1.41
	(0.26)	(0.61)	(1.36)	(0.19)	(0.89)	(0.97)
mining	-0.19	0.44	0.02	-0.31***	-0.07	-0.67
	(0.15)	(0.36)	(0.79)	(0.11)	(0.51)	(0.56)
manuf	0.16	1.41**	3.12**	-0.05	0.46	1.39
	(0.25)	(0.59)	(1.31)	(0.18)	(0.86)	(0.94)
business	-1.21***	-3.91***	-5.56**	-0.37	-2.22	-0.86
	(0.43)	(1.03)	(2.29)	(0.31)	(1.49)	(1.63)
finance	0.13	0.67	1.93	-0.57**	0.18	0.42
	(0.37)	(0.87)	(1.92)	(0.26)	(1.25)	(1.37)
socserv	0.44	3.16	4.45	-0.25	0.22	0.62
	(0.83)	(1.96)	(4.34)	(0.59)	(2.82)	(3.10)
public	-0.03	3.35***	2.76	-0.08	5.14***	5.34***
	(0.32)	(0.76)	(1.69)	(0.23)	(1.10)	(1.20)
gini	24.77*	-8.78	98.15	20.79**	-42.03	70.26
	(14.00)	(33.19)	(73.61)	(10.05)	(47.90)	(52.55)
empl	-0.39***	-0.19	-0.69	-0.40***	0.09	-0.60
	(0.13)	(0.30)	(0.66)	(0.09)	(0.43)	(0.47)
unemp	-0.05	0.26	0.64	-0.00	0.03	-0.15
	(0.17)	(0.40)	(0.88)	(0.12)	(0.57)	(0.63)
primary	-22.35	-6.88	35.02	-5.92	29.22	67.55
	(23.90)	(56.67)	(125.70)	(17.16)	(81.78)	(89.73)
secondary	14.51	-19.47	-161.30	1.64	-121.40	-224.60*
	(33.05)	(78.35)	(173.80)	(23.73)	(113.10)	(124.00)
university	-8.35	-30.49	-20.72	4.88	-165.40*	-195.10**
	(25.76)	(61.06)	(135.40)	(18.49)	(88.12)	(96.68)
aerial	-1.02	9.79*	11.04	-0.28	4.87	3.68
	(2.17)	(5.14)	(11.41)	(1.56)	(7.42)	(8.14)
manual	6.21	-14.70	17.25	4.91	-10.76	4.69
	(5.64)	(13.36)	(29.63)	(4.05)	(19.28)	(21.15)
constant	195.10	203.40	1,673*	83.88	-57.90	969.70
	(181.80)	(431.00)	(955.90)	(130.50)	(622.10)	(682.50)
R^2	0.57	0.46	0.45	0.61	0.33	0.39

Note: The number of observations is 336. All estimations include department and time fixed effects. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.