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A SPATIAL ANALYSIS OF TERRORIST ATTACKS IN PAKISTAN

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Abstract. The objective of this study is to analyze the temporal and spatial spread of the terrorist attacks in Pakistan. The study uses spatial lag and spatial error models to explain spatial variation in terrorist attacks in the districts of Pakistan for the years 2009 and 2011. The number of attacks in focal districts is associated with the poverty of the neighbouring districts. Another source of variation is the general public's contentment (voter turnout is used as a proxy) with the current regime, which turns out to be negatively correlated with terrorist attacks. A significant spatial variation in terrorism is explained by Federally Administered Tribal Areas (FATA) and Khyber Pakhtunkhwa (KP province). The results also show that clusters of attacks extended to other parts of the country between 2009 and 2011 and terrorism spread through the diffusion of attacks to other districts and provinces. More importantly, the attacks are spatially correlated; hence, hot spots are identifiable.

Keywords: Democracy; poverty; violence; terrorism; spatial analysis

JEL Classification: C32, K42, Z10

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I. INTRODUCTION

The study aims to find out the determinants of terrorism attacks by using temporal and spatial models using the district-level data for the years 2009 (109 districts) and 2011 (113 districts). The data of multidimensional poverty at the district level is developed by Jamal (2012).

Pakistan is among the top five countries with the most terrorist incidents since the violent attack on the World Trade Center on September 11, 2001 (Global Terrorism Index, 2016). In the last one-and-a-half decades, terrorism became a major social, economic, security, and religious issue in Pakistan. Since 9/11, terrorist attacks and terrorism-thwarting security measures have cost Pakistan the precious lives of 60,000 citizens, including 3,500 security personnel, and almost 118 billion dollars.[1] While one may be able to identify many factors that require attention and that may lead to a decline in terrorism in the long-run, short-term measures to control violence are currently the pressing need. Although terrorism, security, and law and order are the most challenging problems facing the country, the problem of terrorism requires thorough investigation.

Based on the literature provided in the next section, one may believe that the regions with the most violence are those with the lowest economic well-being. Pakistan has experienced a devastating wave of violence in terms of terrorist attacks and casualties for the last decade. However, such violence is not uniform across the entire country. The attacks are more concentrated in some districts, while there are fewer in others. Initially, attacks were limited to the tribal region, and only the military and law enforcement agencies were targeted. However, the attacks later spread to various adjacent districts in Khyber Pakhtunkhwa (KP) province. Although lower in intensity, attacks have also taken place in various other parts of the country. Thus, there is an apparent spatial variation in violence in the country. Although various studies have been carried out to investigate the causes of terrorism in Pakistan, none of them has empirically modelled the spatial variation in terrorist attacks across the country (see, for instance, Abbas and Syed 2020; Syed et al.

[1] *Pakistan Economic Survey* (2016).

2015; Rehman et al. 2017; Ismail and Amjad 2014; Syed and Ahmad 2013; Nasir et al. 2012). The identification of the hot spots (or clusters) of violence as well as the intensity of spill over to the neighbouring regions is important for the formulation of security policy. Therefore, there is a need to investigate both the pattern of terrorist attacks as well as their determinants. The current study is an attempt to fill this gap in the literature by using spatial analysis of terrorist attacks across the various districts of Pakistan. The study uses district-level data to identify the determinants of attacks as well as the diffusion process of these attacks by employing a spatial econometric approach.

Using spatial lag and spatial error models on cross-sectional data for the years 2009 and 2011, the study finds that poverty within a district is negatively associated with violence in that district.[2] However, poverty in neighbouring districts is linked with a high number of attacks in that district. The voter turnout, a proxy for the general public's contentment with the incumbent government, is negatively correlated with terrorism incidents. Federally Administered Tribal Areas (FATA) and Khyber Pakhtunkhwa (KP) are found to explain a significant amount of the spatial variation in terrorism. The results also show that clusters of attacks also spread to other parts of the country between 2009 and 2011.

The rest of the study is organized as follows: Section II discusses the relevant literature on the issue of terrorism. Section III provides a preview of the spatial and temporal variations in terrorist attacks in Pakistan. The theoretical framework is discussed in Section IV. Section V presents the data and relevant econometrics methodology. Section VI provides the results, while Section VII concludes the study with some policy suggestions.

II. REVIEW OF LITERATURE

There are two broadsides of the issue that have been investigated: the determinants of terrorism and the consequences of terrorist attacks. Both aspects have been extensively researched. While there is general agreement regarding the consequences of terrorism, academicians usually

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[2] For the years 2009 and 2011, we have used data on voters turn out from the elections in 2008 and 2013, respectively.

differ on what drives terrorist activities. A point of concern here is that these studies tend to ignore the spatial aspect of the issue of terrorism. Studies on terrorism that consider the spatial aspect are very limited[3]. This study will be an addition to such literature generally and contribute to the spatial dynamics of terrorism of Pakistan specifically.

The literature on violence and terrorism dates to the 1960s. Nonetheless, it was the unfortunate event of 9/11 that attracted enormous attention from political and development economists to explore this issue with more intensity. One school of thought, led by Gurr (1970), relates variables such as poverty and inequality to political violence and terrorism. The other, led by Tilly (1978), associates violence and terrorism with the structure of political opportunity. Both ideas have received empirical support.

The original work that considered economic variables to be responsible for violence is that of Gurr (1970), who coined the term "relative deprivation" to describe the feeling of discontent resulting from discrimination by the 'haves' against the 'have-nots' that eventually translates into violence. Other works that found support for the economic dimension include Seligson (1987) for income disparity; Landon and Robinson (1989) for income inequality within domestic economies; Blomberg et al. (2002) for dissatisfaction with the economic environment; Fearon and Laitin (2003) for poverty, political instability, and rough terrain; and Bravo and Dias (2006) for low values on the Human Development Index (HDI).

On the other hand, Tilly (1978) was supported by Hamilton and Hamilton (1983), Muller (1985), Muller and Weede (1990), Abadie (2004) and Testas, (2004). Piazza (2006) argued that the structure of party politics is also important. Another stream of literature tries to apply the rational-choice framework to predict terrorists' behavior [see, for example, Wilkinson (1986); Hoffman (1998); Pape (2005); Dugan et al. (2005); Kydd and Walter (2006); Enders and Sandler (2006); and Clarke

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[3] Some distinguished Spatial terrorism studies include the work of Siebeneck et al. (2009), Braithwaite and Li (2007), LaFree et al. (2012).

and Newman (2006)]. It is obvious from this literature that there is no consensus concerning the causes of terrorism. One reason could be that these studies were conducted on diverse regions across different periods using different techniques.

Siebeneck et al. (2009), who conducted a geographic and temporal analysis of terrorist incidents in Iraq for the period 2004-2006. The study concluded that terrorists' actions are predictable and are not random events. Similarly, Braithwaite and Li (2007) explored transnational terrorism hot spots and their geography. The study argued that countries within the range of hot spots were expected to experience an increase in terrorist attacks in the future. In a recent attempt, LaFree et al. (2012) examined the spatial and temporal patterns of terrorist attacks by the Spanish group ETA between 1970 and 2007. The study found that after the ETA moved towards a more attrition-based attack strategy, the subsequent attacks were significantly more likely to occur outside the Basque region and to target non-adjacent regions. This outcome is consistent with the hierarchical diffusion argument.

III. TERRORISM IN PAKISTAN: SPATIAL AND TEMPORAL VARIATIONS

Throughout the world, terrorism has become a major concern as it has developed into a potential threat to national security. Consequently, efforts are being made to curb terrorism. While long-term solutions may require changes in the political structure and improvements in the economic conditions of the country being affected, short-term strategies rely heavily on pre-empting such acts. The most dangerous aspect of this issue is the randomness of terrorist attacks. Thus, the success of any security strategy is linked to how accurately the time and place of attacks are anticipated. The correct identification of the time and place of attacks can help the government and security agencies develop effective counter-terrorism measures through the efficient allocation of time and resources.

After the 9/11 attacks, the US and coalition forces attacked Afghanistan to end the Taliban regime in the country. The Taliban had no answer to the invaders' airstrikes and were ordered to disperse by their supreme commander, Mulla Omer. However, after a couple of years, they emerged from their hideouts and started attacking the coalition forces in

Afghanistan. The perception was that militants and their supporters had found safe sanctuary in the rugged Pakistan-Afghanistan border region. This led Pakistan to conduct a military operation in 2004 in Waziristan, one of the seven agencies in the FATA of Pakistan. This military operation together with drone attacks by the US-led to the creation of what is now called the Pakistani Taliban in 2006. The Tahreek-e-Taliban Pakistan (TTP) - one of the most influential and dangerous groups among the Pakistani Taliban -initially declared war against the Pakistan Army. In retaliation for the collateral damage, this war spread to the entire FATA region. Later, the terrorist attacks spread to the rest of Pakistan, resulting in numerous casualties. This domestic terrorism in Pakistan has become a serious problem for the major Pakistani cities. Maps 1 to 4 show the temporal and spatial spread of the terrorist attacks in Pakistan (see Appendix Figure A).

IV THEORETICAL MODEL

This section discusses the theoretical underpinnings of the determinants of terrorism. The theoretical model utilizes the rational-choice framework to generate predictions of terrorism. In the context of the terrorism literature, this framework assumes a rational decision-making process by a representative terrorist group that maximizes expected payoffs from terrorist activities given resource constraints [Enders and Sandler (1993); Landes (1978); Sandler et al. (1983)]. This approach can be demonstrated by modifying a simplified version of the rational-choice terrorism equilibrium model developed by Lakdawalla and Zanjani (2005).

Suppose there exists a terrorist group that holds a total of M resources that can be used for terrorist activities. Let there be K potential targets for the terrorist group. The group invests resources m_i into attacking target *i*. If the attack is successful, it acquires value W_i, which may vary across targets. To bring in the spatial aspect, we assume that these targets vary across space. Spending more resources raises the probability of success, but success may be easier to achieve with one target than another. In other words, the marginal productivity of a given amount of resources varies across targets and therefore across space. A productive attack is a successful attack that results in destruction/damage that hurts the government, gains media attention, and spreads terror. Let this productivity be represented by d_i. The probability of a successful attack on target *i* can be defined as $\phi(m_i, d_i)$, where $\phi_m > 0$ and $\phi_d > 0$. The parameter d_i is the 'bang for the buck', or the marginal productivity of a given amount of investment at location *i*. In this environment, the terrorist group maximizes its expected utility according to the following equations:

$$\max_{m_i} \sum_{i=1}^{K} \phi(m_i, d_i) W_i \qquad (1)$$

subject to

$$\sum_{i=1}^{K} m_i = M \qquad (2)$$

The group's optimal behaviour is characterized by the following first-order conditions:

$$\phi_m(m_i, d_i) W_i = \lambda_i \ ; \ i = 1, \ldots\ldots K \qquad (3)$$

where λ is the group's marginal utility of financial resources. Equation (3) states that the terrorist group tries to diversify its attacks over a wider range of space up to the extent where the expected marginal payoff from its resources is equal to λ for all potential targets.[4] In other words, all else equal, more resources will be spent on striking higher-value targets and targets where spending is more productive (i.e., those with higher values ofd). Hence, resources will be diverted from lower-value (or productivity) targets to higher-value (or productivity) targets.

Because W_i shows the value that is acquired through a successful attack, it is higher for high-value targets. In our empirical model, we capture this by using a multidimensional poverty measure for a district. High poverty in a district means lower importance of that district; hence, targeting it would result in a lower value for the terrorist group. Instead,

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[4] This result requires that we impose the condition of an interior solution, which therefore implies that this model considers only those districts that have experienced at least one attack. This is a caveat of the model because the empirical model also includes districts with zero attacks.

the terrorist group would want to target a district that is economically well off and is, therefore, more important to the government. In this sense, we would expect a negative relationship between poverty and terrorism in a district.

The probability of a successful attack using resources m_i increases with the ease of attacks d_i. In other words, the terrorist group will prefer to attack those targets that are easily accessible, as accessibility reduces the cost of an attack (in terms of being caught or the use of other financial resources). Easily accessible targets are those that are closer to their home base. Additionally, lower-cost targets include those areas where the terrorists can easily sneak. In our empirical model, we capture this aspect by using a FATA dummy. FATA stands for the Federally Administered Tribal Areas, which is a region full of mountains and difficult terrain that provides natural hideouts for terrorists. Moreover, FATA shares a large border with Afghanistan, which is useful for terrorists to cross the border in times of military operations in the region.[5] Hence, it is less costly for the terrorists to enter settled areas, execute the attacks, and escape back to FATA. The Khyber Pakhtunkhwa (KP) province shares a border with the FATA region through its 10 districts. Hence, attacking KP province is always easier than attacking other provinces for terrorist groups, which is why we also include a KP dummy in our analysis. We expect positive coefficients for both dummy variables.

Another important factor that can contribute to decreasing the cost of terrorism by a terrorist group is sympathy among the public for the terrorist group. If the masses are dissatisfied/discontent with the prevailing regime and system, there is a higher likelihood that they may tend to support the terrorist group by providing it with financial aid and/or shelter/hideouts. Prominent reasons for such discontent may be relative deprivations, both economic and political. Deprivation enhances rebellious tendencies in the public. There are three types of individuals in any functional democracy. The first is fully satisfied with the system and whole-heartedly participates in democratic processes. The second type is dissatisfied but still believes that positive change may be possible

[5] This border is so large that it is practically impossible for both countries to safeguard it at each point.

through constitutional/democratic means; hence, this type participates in democratic processes despite their grievances. The third type is those who feel completely dissatisfied with the system. In their opinion, any positive change is impossible within the constitutional/democratic framework, so they pull themselves out of the democratic processes by either abstaining or boycotting. This type is also the most vulnerable to becoming either facilitators/aides or active members of a terrorist group. In the context of the present study, a plausible gauge of peoples' satisfaction with the regime is their participation in the electoral process through voting. Hence, a low voter turnout is expected to have a positive correlation with terrorism incidents in any specific area.

We make another modification to the model of Lakdawalla and Zanjani (2005) by allowing for resource constraints to change in our empirical model. We do so by including the poverty of neighbouring districts in the analysis. A high poverty rate should lead to more unemployed people whose opportunity cost of being involved in terrorist activities may not be very high. From the terrorist group's perspective, they can hire more people, obtain logistical support, or improve their support base for a lower price. That is the real resource constraint changes. In other words, the budget line will shift outward, resulting in the availability of more resources (in real terms) for the terrorist group to use. This increase in resources could in turn lead to an increase in terrorism. Hence, we expect a positive association between poverty in neighbouring districts and terrorist attacks in that district. Considering the above theory, we estimate the following equation and its variants:

$$\ln(TA) = \beta_0 + \beta_1 Pov + \beta_2 Neighbor\_Pov + \beta_3 Turnout + \beta_4 FATA + \beta_5 KP + \varepsilon \tag{4}$$

where *TA*, *Pov*, *Neighbour*, *Turnout*, *FATA*, and *KP* respectively denote the number of terrorist attacks in the district, the poverty index for the district, the poverty index in the neighbouring (or adjacent) district, voter turnout, the FATA dummy, and the KP dummy, which take the value of one of the districts is in FATA and PK, respectively.

The above model distinguishes between the preferences and productivity of terrorists when deciding on their attacks. They will attack targets that are easily accessible and that are highly valued. However, in practice, it might be difficult to make this distinction. A target may be easily accessible and highly valued at the same time. For example, the district of Peshawar is not only easily accessible because it is contagious to the FATA region, but it is also highly valued because it is the economic hub of KP province. These characteristics may explain why this district has experienced the highest number of attacks in KP province.

V. DATA AND ECONOMETRIC METHODOLOGY

DATA AND VARIABLES

In this section, we will discuss the data and variables used in the analysis. The unit of analysis is the district.[6] The analysis is conducted for the years 2009 and 2011. The sample size is 109 for 2009 and 113 for 2011. Because the sample sizes are different for the two years, we did not create a panel and run the regressions separately for both years. The dependent variable, terrorism, is quantified by the number of terrorist attacks in a given district in a year. The data for this variable are obtained from the Global Terrorism Database (GTD) of the "National Consortium for the Study of Terrorism and Responses to Terrorism." The dependent variable is in log form.[7]

The continuous variable in the covariates is the value on the Index of Multidimensional Poverty (IMP). Unfortunately, district-level data for many important variables are not available from the official statistics for Pakistan. Researchers have therefore made individual efforts to create data for some variables. In line with the theoretical model's prediction, we utilize data from the Index of Multidimensional Poverty (IMP) developed by Jamal (2012). The index ranges from 0 to 100, where higher values mean more poverty. The study uses the unit record household-level data from the Pakistan Social and Living Standard

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[6]In Pakistan, a district is the second order of administrative division after a province.

[7] Some districts have zero attack in a year, we added 1 for log transformation.

Measurement (PSLM) surveys, which were conducted in 2010-11 and 2008-09 and covered 77,500 households across all provinces in Pakistan, to construct the Index for Multidimensional Poverty for the two years. Jamal (2012) used the Principal Component Method, which combined indicators for human poverty, poor housing, and deprivation in household physical assets to generate a district-level multidimensional poverty index for the years 2009 and 2011. Data on voter turnout are taken from the website of the Election Commission of Pakistan (ECP).[8] These data are available at the constituency level in terms of the percentage of votes polled to total votes. In our analysis, the estimation is conducted at the district level, so a simple average is calculated from the constituencies falling in any district. The FATA_Dummy is a dummy variable where the value of 1 is assigned to any district that is contiguous with the FATA region. This information is obtained from the website of the Global Security Organization.[9] The KP_Dummy is a dummy for districts in the KP province. Table 1 shows the summary statistics for these variables for the two years.

TABLE 1

Summary Statistics

Variable	Observations	Mean	Std Dev.	Minimum	Maximum
Log (Attacks_2009)	109	0.840	1.057	0	4.22
IMP_2009	109	62.201	23.146	8.04	99.43
Neighbour_IMP_2009	109	61.960	17.561	20.903	91.796
FATA_Dummy_2009	109	0.119	0.325	0	1
KP_Dummy_2009	109	0.220	0.416	0	1
Log (Attacks_2011)	113	1.153	1.078	0	5.25
IMP_2011	113	63.638	23.251	6.06	98.58
Neighbour_IMP_2011	113	63.592	6.971	22.843	92.357
FATA_Dummy_2011	113	0.115	0.320	0	1
KP_Dummy_2011	113	0.212	0.410	0	1

8http://www.ecp.gov.pk.htm

9http://www.globalsecurity.org/military/world/pakistan/fata.htm

ECONOMETRIC METHODOLOGY

We now discuss the econometric methods that are used in the analysis. The objective of the study is to investigate the correlates of terrorism across districts. We can begin with the classical OLS regression in the following form:

$$Y = X\beta + \varepsilon \qquad (5)$$

Here, Y is the $n \times 1$ vector of the dependent variable, X is the $n \times k$ data matrix of the explanatory variables, β is a vector of k parameters, and ε is the $n \times 1$ vector of error terms, which are assumed to be normally distributed with constant variance. This specification is useful only if the assumptions of a classical linear regression model are met. However, if there is a locational aspect to the data, then there will be spatial dependence between observations. This violates the Gauss-Markov assumptions. Spatial dependence occurs in a collection of sample data where one observation that is associated with a location labelled i depends on other observations at locations $j \neq i$. Formally, we might write this as:

$$y_i = f(y_1 \ldots y_j \ldots y_n); \; j \neq i \qquad (6)$$

Here, the dependence can be among several observations, as the index i can take any value from 1 to n. There are two main reasons commonly given for spatial dependence among observations. In the words of LeSage (1998):

"First, data collection of observations associated with spatial units such as zip codes, counties, states, census tracts, and so on, might reflect measurement error. This would occur if the administrative boundaries for collecting information do not accurately reflect the nature of the underlying process generating the sample data. A second and perhaps more important reason we would expect for spatial dependence is that the spatial dimension of economic activity may truly be an important aspect of a modelling problem. Regional science is based on the premise that location and distance are important forces at work in human geography and market activity. All of these notions have been formalized in regional science theory that relies on notions of spatial interaction and diffusion effects, hierarchies of place and spatial spillovers."

Therefore, to account for spatial dependence among observations, we follow Anselin (1988) and introduce a spatial lag model of the following form:

$$\begin{aligned} Y &= \rho WY + X\beta + \varepsilon \\ \varepsilon &\approx N(0, \sigma^2 I_n) \end{aligned} \qquad (7)$$

The 'reduced form' of equation (7) is given by:

$$Y = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1}\varepsilon \qquad (8)$$

where ρ is the coefficient of the spatially lagged dependent variable that captures the diffusion process, and W is a known $n \times n$ spatial weight matrix, usually containing first-order contiguity relations or functions of distance. Equation (8) states that the value of the dependent variable (the log of terrorist attacks in this case) at each location is not only determined x_i at that location but also by x_j all other locations through the spatial multiplier $(I - \rho W)^{-1}$.

The spatial dependence may be due to omitted variables that also happen to be spatially correlated, which would result in the spatial correlation of the error terms. In that case, the spatial error model is used. Formally, this model can be written as:

$$\begin{aligned} Y &= X\beta + u \\ u &= \lambda Wu + \varepsilon \\ \varepsilon &\approx N(0, \sigma^2 I_n) \end{aligned} \qquad (9)$$

The "reduced form" for this model is given as:

$$Y = X\beta + (I - \lambda W)^{-1}\varepsilon \qquad (10)$$

where λ is the spatial autoregressive coefficient, and W is the spatial weight matrix. Both the spatial lag and spatial error models are estimated using the Maximum Likelihood method. An important concept used in the above equations is that of the spatial weight matrix (W). This matrix features the prior structure of dependence between spatial units, which is essential due to insufficient information for the specification of a full matrix of interaction $(n \times n)$ from observations into a single cross-section of n observations. Each row of a spatial weight matrix has nonzero elements for the columns that correspond to neighbouring units. By this principle, the diagonal elements are set to zero because a unit cannot be its neighbour. To make this point clear, let us consider a $(n \times n)$ spatial weight matrix W given as:

$$W = \begin{bmatrix} w_{11} & w_{12} \ldots\ldots\ldots\ldots\ldots\ldots w_{1n} \\ w_{21} & w_{22} \ldots\ldots\ldots\ldots\ldots\ldots w_{2n} \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ w_{n1} & w_{n2} \ldots\ldots\ldots\ldots\ldots\ldots w_{nn} \end{bmatrix} \tag{11}$$

with the following characteristics:

$$wij = \begin{cases} 1 & if\ i\ is\ contigous\ to\ j \\ 0 & otherwise \end{cases} \tag{12}$$

and $w_{ii} = 0$ for all $i = 1, \ldots\ldots, n$. For ease of interpretation, the elements of each row are standardized such that they sum to one. Consequently, the spatial value of a variable is calculated as the weighted average of the neighbouring units as follows:

$$\bar{y}_j = \sum_j w_{ij} y_j \tag{13}$$

where w_{ij} are row-standardized weights, and y_j is the unit's value as the weighted average of the values of its neighbours.

VI. RESULTS AND DISCUSSION

This section discusses the estimation results. We perform the analysis for two years 2009 and 2011. The analysis begins by testing for the existence of spatial autocorrelation in terrorist attacks. We do so by using the Global Moran's I. For this purpose, the first-order queen contiguity weight matrix is used.[10] As discussed earlier, the queen continuity matrix considers all districts as neighbours that either share a boundary with the district under consideration or just touch it at a particular point. The Global Moran's I values for terrorist attacks in both years are provided in Table-2. It is obvious from the table that the coefficients are positive and significant, meaning that a high amount of terrorist attacks in a district is associated with a high number of attacks in the neighbouring districts, and a lower number of attacks is associated with a lower number of attacks in neighbouring districts for both years of analysis. However, the value for the year 2011 is higher, which indicates that the attacks became more concentrated in certain districts. One should be careful when interpreting this result, however. Looking at the data, it is obvious that the attacks spread to other districts that did not experience any attack in 2009. However, the intensity of the attacks in the already-affected areas increased significantly, such that they stand out as hot spots in Figures B and C in the Appendix.

Next, we attempt to determine whether this spatial autocorrelation in the attacks is due to spatial relationships in the explanatory variables. Hence, we also examine the Moran's I values for the covariates, which are also provided in Table-2. The Moran's I values for all the covariates are positive and highly significant, thus suggesting the existence of spatial relationships for these variables as well. However, the strength of the univariate spatial relationship varies across the covariates for a particular year. Also, to be noted is the observation that the Moran's I values for terrorist attacks increased in 2011 compared to 2009. However, the Moran's I values for the explanatory values declined during the same period. Because FATA and KP are regional dummies, we did not include them here, as the administrative units did not change significantly during this period. Note that the Moran's I value for the Index of Multidimensional Poverty (IMP) declined compared to 2009. However, it is still very high in absolute terms, which should be a point of concern for policymakers.

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[10] The results were similar when the second-order queen continuity matrix is used.

TABLE 2

Results of Univariate Moran's I

Variables	Moran's I_2009	Moran's I_2011
Log (Attacks)	0.215*** (0.049)	0.318*** (0.522)
IMP	0.566*** (0.048)	0.508*** (0.049)
Neighbour _IMP	0.821*** (0.029)	0.807*** (0.030)
Turnout	0.494*** (0.054)	0.581*** (0.046)

Note: Standard errors are given in parentheses, and *** indicates significance at 1% level of significance.

Next, turn to the regression results using the queen continuity weight matrix. Table 3 shows the estimation results for various models for the year 2009, while Table 4 presents the results for the year 2011. We begin with the classical OLS regression. Model 1 provides the OLS results from the regression of the log of terrorist attacks on the IMP of a district, and for both years, the coefficients are negative and statistically significant at the 1% level of significance. However, the coefficients on Neighbour_IMP, which is the weighted average of the index of multi-dimensional poverty in neighbouring districts, are positive for both years and are statistically significant at the 5% and 1% levels, respectively. This result suggests that poverty within a district is negatively associated with terrorist attacks in that district. One can justify this result considering the theoretical framework described in Section-4. A high level of poverty in a district is evidence of a lack of concern by the government for that district. Also, a high level of poverty likely means that the district is not doing well economically (in terms of not being an important economic hub). On the other hand, terrorists want to attack high-value targets that hurt the government and gain media attention to spread terror. Because terrorists are assumed to be rational and terrorist resources are limited, they want to utilize such resources optimally. The optimal use of resources (both physical and financial) would mean that they attack targets that can cause the greatest destruction and so that they gain more media attention to spread terror among the masses. Such targets, however, are generally found in districts that are either economic hubs or that are at least doing economically well. In addition to spreading fear, attacking such districts will also hurt the government. Hence, there is a negative relationship between poverty within a district and the number of terrorist attacks in that district.

The positive association between the terrorist attacks in a district and the level of poverty in neighbouring districts can also be justified using the theoretical model.[11] As suggested by the model, terrorist groups have resource constraints. The existence of a high level of poverty in neighbouring districts provides them with the opportunity to garner more resources and services (for example, foot soldiers and logistical support) at a lower cost. For instance, it would be easier for a terrorist group to find someplace to hide at a lower cost in a poor district that happens to be a neighbour of a high-value target district. The terrorists can go to the high-value target district, execute the attack, and return to their hiding place in less time. This proximity also reduces the probability of the terrorists being caught, which would be the gain for the terrorist group. In other words, given their budget constraints, terrorists can increase their real resources, which can lead to an increase in attacks in the given district.

It is evident from the empirical results shown in both Tables 3 and 4 that voter turnout has a negative impact on terrorism incidents, and the results remain highly significant in all variants of the model. The estimated coefficients also show consistency and robustness, as the signs stay negative among different specifications of the models. These results bring an important dimension to the issue of terrorism, which is its linkage to political deprivation and the general public's discontent with the regime. Our results are quite consistent with the expectations of the theoretical model that it is much easier for terrorists to operate and disguise themselves in safe hideouts in an area where the population is generally averse to the current regime. Therefore, when devising any strategy to combat the devastation from terrorism, due consideration must

[11] We also tried various regressions using the Index of Multiple Deprivation (IMD) separately in the model because of the high correlation between IMP and IMD (approximately 0.85). The results were almost similar but were less strong than with the IMP and hence are not reported here.

be given to political factors in addition to military-cum-administrative aspects.

In the search for a better specification, however, we include the FATA dummy in Model 2 (Table 3). Although the coefficients of IMP and Neighbour_IMP do not change significantly in terms of sign, significance, and magnitude, the R^2 value indicates that this model now explains 32% of the variation in terrorist attacks in 2009. The coefficient on the FATA dummy is positive and statistically significant. This result confirms the model's prediction that terrorists will attack those targets that are closer to their home bases and hence less costly. Because terrorist groups hide in the mountainous terrain of FATA, it is effective for them to attack the agencies that are at the boundaries of this tribal region because they can execute their attacks with relative ease and go back into hiding.[12] The data also support this outcome. The districts that are contiguous to the FATA region have experienced the highest number of attacks.

More important is the statistics for the Moran's I for the residuals in this model, which are now reduced to 0.058. This result means that the regional variable (FATA_Dummy) explains 47% of the spatial variation in terrorist attacks, and this value is still significant. This result shows that even after controlling for the spatial autocorrelation in terrorist attacks, due to the covariates, there is still a significant amount of the spatial relationship that is left unexplained. This illustrates the inability of the classical OLS model to capture spatial autocorrelation and calls for better estimations of the spatial relationship. The search for the best alternative among these models calls for Lagrange Multiplier (LM) tests. The results of these tests are presented in the diagnostics of the classical model. As is evident, LM_Lagis highly significant, but LM_Error is insignificant. This result suggests that a spatial lag specification should be estimated. However, we estimate both spatial specifications for comparison purposes.

Model 3 in Table 3 provides the results of the spatial lag specification. All the coefficients are statistically significant and have the

[12] An "agency" is an administrative unit in the FATA region. Roughly speaking, an agency is equivalent to a district.

same signs as in Model 2. The spatial autoregressive coefficient is estimated at 0.401 and is highly significant. It is important to note that not only the magnitude of the estimated coefficient of the FATA dummy decreased in value, but it also became insignificant. This result suggests that the explanatory power of this variable that was attributed to its in-district value was due to the neighbouring locations; thus, we were overestimating the value of its coefficient. This discrepancy is now picked up by the coefficient of the spatially lagged dependent variable. This result is also confirmed by the Moran's I value for the residuals, which illustrates that the model has addressed the spatial autocorrelation. In terms of diagnostics, it is worth noting that R^2 and PseudoR^2 are not comparable. The proper measures of fit are the Log-Likelihood and the Akaike Information Criterion (AIC). A comparison of these criteria for the OLS and Spatial Lag models shows an improvement of the spatial lag specification.[13]

The results of the spatial error specification are provided in Model 4. Once again, the results are similar in terms of signs and significance except for the FATA dummy, which is now insignificant. The spatial autoregressive coefficient is also statistically non-significant. Except for IMP and Neighbour_IMP, the magnitudes of all the coefficients on the covariates are smaller than in the classical model in absolute terms. The Moran's I show that the spatial autocorrelation has been addressed. Although this model also addresses the spatial relationship, the diagnostics reinforce the decision of the Robust LM tests that the Spatial Lag model is the best alternative for this specification.

Ten districts in Khyber Pakhtunkhwa (KP) province share a boundary with FATA. Also, the people of the FATA region and KP province share the same culture, as most of the population of this province are Pashtuns. Consequently, KP has always been vulnerable to terrorist attacks, and it, therefore, suffered the most from the surge in terrorist attacks. Hence, in Model 5 (Table 3), we control for this observation by including the KP dummy. The coefficients on the other variables in the model are like those obtained for the earlier model in

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[13] A lower value of AIC and a higher value of Log Likelihood represent an improvement in the model fit.

terms of sign, significance, and magnitude. The coefficient on the dummy variable is positive and statistically significant. Interestingly, the Moran's I value for the residuals was reduced in magnitude and became statistically insignificant. This result suggests that the spatial variation in terrorist attacks is significantly explained by the KP dummy. In other words, the clustering or the hot spots were mostly limited to KP province. This result also accords with the model's prediction that terrorists use their scarce resources as effectively as possible. Because KP is contiguous to the FATA region, terrorists can easily sneak into the province, attack their target, and escape back to the mountains. Although the value of the residuals' Moran's I is insignificant, thereby suggesting that all the spatial variation is explained by these explanatory variables, we run the two spatial models to confirm this finding. Thus, Models 6 and 7 present the results for the spatial lag and spatial error models with the KP dummy included. All the coefficients are statistically significant and have the same signs as in the previous models. As expected, the spatial autoregressive coefficients are non-significant in both models. These results confirm the outcomes observed in Model 5.

Next, we include both regional variables (FATA and KP dummies) in the model. The OLS results of this specification are presented in Model 8. As is obvious from the model, including both regional variables leave the FATA dummy insignificant. This result is not surprising because out of the 13 districts that are contiguous to FATA, 10 are in KP province. Once we control for the KP dummy, the FATA effect mostly vanishes. This result also suggests that the two districts in Baluchistan province and the one in Punjab province that is contiguous to FATA have not experienced significant terrorist attacks. This is also supported by the data. For the period 2005-2011, these three districts experienced only 11 attacks in total. On the other hand, Peshawar, a district in KP province, alone has witnessed 256 attacks over the same period. The coefficients on the other variables in the model are the same as in the previous models. The Moran's I value for the residuals suggests that the entire spatial variation has already been explained. Hence, its coefficient is non-significant. The spatial lag and spatial error models provided in Models 9 and 10 in Table 3 validate this finding. The spatial autoregressive coefficients are non-significant in both models.

TABLE 3

Regression Results [Dependent Variable is Ln(attacks_2009)]

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Constant	2.798*** (0.677)	2.454*** (0.691)	2.002*** (0.678)	2.284*** (0.733)	1.472** (0.724)	1.316* (0.708)	1.449** (0.734)	1.461** (0.728)	1.312* (0.708)	1.439** (0.735)
IMP	-0.020*** (0.005)	-0.020*** (0.005)	-0.022*** (0.005)	-0.020*** (0.005)	-0.021*** (0.005)	-0.022*** (0.005)	-0.020*** (0.005)	-0.021*** (0.005)	-0.022*** (0.005)	-0.020*** (0.005)
Neighbour_IMP	0.018** (0.008)	0.019** (0.008)	0.021*** (0.007)	0.020*** (0.008)	0.026*** (0.007)	0.026*** (0.007)	0.025*** (0.007)	0.026*** (0.007)	0.026*** (0.007)	0.025*** (0.007)
Turnout_2008	-0.045*** (0.009)	-0.040*** (0.009)	-0.034*** (0.009)	-0.037*** (0.010)	-0.027*** (0.010)	-0.025*** (0.009)	-0.026*** (0.010)	-0.027*** (0.010)	-0.025** (0.009)	-0.026*** (0.010)
FATA_Dummy	---	0.528* (0.272)	0.382 (0.259)	0.374 (0.285)	---	---	---	0.125 (0.288)	0.087 (0.277)	0.052 (0.289)
KP_Dummy	---	---	---	---	0.842*** (0.219)	0.723*** (0.236)	0.870*** (0.239)	0.797*** (0.243)	0.694*** (0.257)	0.851*** (0.257)
Delta	---	---	0.401** (0.121)	---	---	0.182 (0.131)	---	---	0.178 (0.131)	---
Lambda	---	---	---	0.220 (0.126)	---	---	0.174 (0.146)	---	---	0.167 (0.147)
Diagnostics										
R^2	0.301	0.325	---	---	0.388	---	---	0.389	---	---
PseudoR^2	---	---	0.364	0.340	---	0.401	0.398	---	0.401	0.397
Moran's I_R	0.110**	0.058*	-0.033	0.004	0.061	0.001	0.005	0.054	-0.001	0.005
LM_Lag	6.829***	4.632**	---	---	1.724	---	---	1.611	---	---
Robust_LM_Lag	3.928**	6.910***	---	---	0.663	---	---	0.888	---	---
LM_Error	3.663*	1.011	---	---	1.122	---	---	0.895	---	---
Robust_LM_Error	0.762	3.288*	---	---	0.061	---	---	0.173	---	---
Log-Likelihood	-140.711	-138.774	-136.425	-138.057	-133.496	-132.632	-132.902	-133.396	-132.582	-132.886
AIC	289.423	287.548	284.851	286.115	276.992	277.263	275.804	278.792	279.164	277.773
Observations	109	109	109	109	109	109	109	109	109	109

Note: Standard errors are given in parentheses. The statistics marked by ***, **, and * are significant at 1%, 5% and 10% levels of significance, respectively. Moran's I_R represents Moran's I values for the residuals.

Next, we conduct the same analysis for the year 2011. The results for all the models are provided in Table-4. Model 1 simply includes the IMP, Neighbour_IMPand Turnout_2013 variables. Once again, we obtain the same signs for the coefficients as in Table-3. Therefore, the interpretation is also the same. Model 2 includes the FATA dummy, which significantly improves the model specification, as suggested by the R^2 value. The coefficient on the FATA dummy is positive and significant, suggesting that FATA was still an important factor in 2011 regarding terrorism. The magnitude of the coefficient is larger in 2011 compared to 2009. Although FATA explains the significant spatial variation in terrorist attacks in 2011, the Moran's I for the residuals is still statistically significant, which calls for the use of a spatial model. The LM test points in favour of the spatial lag model, but we estimate both spatial lag and spatial error models to allow a comparison. The results of the spatial lag specification are provided in Model 3. The spatial autoregressive coefficient (Delta) is estimated at 0.365, which is highly significant. Once again, the absolute value of the coefficient of the FATA dummy has decreased because the neighbouring-locations effect has now been addressed by the spatial autoregressive coefficient. Model 4 is estimated for comparison purposes, and it provides the result for the spatial error model. Although the spatial autoregressive term (Lambda) is also significant, the PseudoR^2, Log Likelihood, and AIC suggest that the spatial lag model should be preferred over the spatial error model.

The next three models include the KP dummy instead of the FATA dummy, as was performed for the year 2009. An interesting finding that calls for attention is the spatial autoregressive coefficient in Model 5. Its value is very high (0.73), and it is highly statistically significant in the presence of the KP dummy. This result implies that the clustering (or the hot spots) is not only in the KP province but has spread to other parts of the country as well. Considering the theoretical model's predictions that terrorists try to use their scarce resources effectively, this empirical result suggests that terrorists have also found support bases in the settled areas of other provinces. The LM test in Model 5 favours the spatial lag model. Although both spatial autoregressive terms (Delta and Lambda) in Models 6 and 7 are statistically significant, the diagnostics favour the spatial lag specification.

Finally, both the FATA and KP dummies are combined in one model. Model 8 provides the OLS results for this specification. As was the case in 2009, the KP dummy captures all the effect and leaves the FATA dummy insignificant. This result is not surprising because the geography during this period did not change much. Interestingly, however, the three districts in the other two provinces that border FATA were still not exploited by terrorists. The terrorists mainly use the KP province channel to attack the cities. Once again, the best alternative to the OLS models is found to be the spatial lag model for this specification. Looking over all the models for both years, one can observe that the diagnostics always favour the spatial lag specifications. This result supports the view that there is a possible diffusion of terrorism across the districts, especially in 2011, when the values of the coefficient of Delta are greater than those of 2009 for all the specifications. Nonetheless, the significance of the spatial term in the spatial error models in some specifications also indicates that this spatial dependence might be due to spatially correlated omitted variables. However, the special lag model by construction addresses that problem (see Equation 8). One might consider using a mixed model that combines the spatial lag and spatial error models. However, a crucial issue would be finding the appropriate weight matrices for the two specifications. If we take the simple approach of using the same weight matrix for both models, we could run into identification issues, which is why such models are not used in the literature.

TABLE 4

Regression Results [Dependent Variable is Ln(attacks_2011)]

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Constant	3.078*** (0.694)	2.803*** (0.677)	2.004*** (0.684)	2.625*** (0.781)	1.984*** (0.749)	1.365* (0.720)	1.828** (0.840)	2.124*** (0.748)	1.499** (0.722)	1.903 (0.827)
IMP	-0.019*** (0.005)	-0.019*** (0.005)	-0.020*** (0.004)	-0.017*** (0.004)	-0.019*** (0.005)	-0.020*** (0.004)	-0.017*** (0.004)	-0.019*** (0.005)	-0.020*** (0.004)	-0.017*** (0.004)
Neighbour_IMP	0.021*** (0.007)	0.021*** (0.007)	0.021*** (0.006)	0.019*** (0.007)	0.026*** (0.007)	0.024*** (0.006)	0.022*** (0.007)	0.025*** (0.007)	0.024*** (0.006)	0.022*** (0.007)
Turnout_2013	-0.040*** (0.008)	-0.037*** (0.008)	-0.027*** (0.008)	-0.032*** (0.009)	-0.027*** (0.009)	-0.020** (0.008)	-0.023** (0.009)	-0.029*** (0.009)	-0.021** (0.008)	-0.024** (0.009)
FATA_Dummy	---	0.798*** (0.269)	0.553** (0.253)	0.563** (0.282)	---	---	---	0.501 (0.303)	0.325 (0.282)	0.267 (0.299)
KP_Dummy	---	---	---	---	0.730*** (0.228)	0.550*** (0.228)	0.823*** (0.282)	0.521** (0.260)	0.427* (0.254)	0.713** (0.296)
Delta	---	---	0.365*** (0.115)	---	---	0.367*** (0.117)	---	----	0.342*** (0.119)	---
Lambda	---	---	---	0.310*** (0.132)	---	---	0.370*** (0.126)	---	---	0.336*** (0.130)
Diagnostics										
R^2	0.270	0.325	---	---	0.333	---	---	0.350	---	---
PseudoR^2	---	---	0.349	0.360	---	0.403	0.392	---	0.408	0.393
Moran's I_R	0.183***	0.105**	-0.060	-0.006	0.165***	-0.025	-0.010	0.130***	-0.034	-0.008
LM_Lag	16.742***	10.534***	---	---	12.042***	---	---	9.718***	---	---
Robust_LM_Lag	7.911***	12.230***	---	---	4.025**	---	---	6.137**	---	---
LM_Error	10.398***	3.453*	---	---	8.455***	---	---	5.252**	---	---
Robust_LM_Error	1.567	5.149**	---	---	0.438	---	---	1.672	---	---
Log-Likelihood	-150.487	-146.061	--141.519	-144.142	-145.394	-140.632	-141.697	-143.972	-139.994	-141.333
AIC	308.974	302.122	295.038	298.285	300.787	293.264	293.396	299.945	293.988	294.668
Observations	113	113	113	113	113	113	113	113	113	113

Note: Standard errors are given in parentheses. The statistics marked by ***, **, and * are significant at 1%, 5% and 10% levels of significance, respectively. Moran's I_R represents Moran's I values for the residuals.

VII. CONCLUSION

This study addresses the spatial dependence in terrorist attacks in Pakistan using data for the years 2009 and 2011 for 109 and 113 districts, respectively. For this purpose, the study uses the first-order queen contiguity weight matrix. The coefficients are estimated using the classical OLS, Spatial Lag, and Spatial Error models under various specifications.

The results indicate that poverty in neighbouring districts is associated with a higher level of terrorist attacks in that district. The poverty within a district and voter turnout are negatively related to terrorism in that district. FATA is found to be an important factor in the spread of terrorism. The results also reveal that clusters of attacks extended to other parts of the country between 2009 and 2011 and that terrorism has spread through the diffusion of attacks in other districts and provinces. Most importantly, the attacks are spatially correlated; hence, hot spots are identifiable. That is, terrorist attacks are not random across districts, although they may be random within a district.

Considering these findings, one can propose several short-run and long-run policy suggestions. For example, in the short run, the spillover of terrorism from FATA to the settled districts can be restricted by the allocation of more resources to those districts that are contagious to the FATA region. This may include an increase in the deployment of police and military forces and the installation of scanners at the borders of these districts. These measures should be taken on a priority basis for KP province for frontline defence in the war on terror, as it is a hot spot that has become one of the terrorists' main targets because it is easily approachable.

The spread of terrorist attacks to other parts of the country that do not border either FATA or KP province indicates that terrorists have been able to find support bases in areas that provide them with logistics. It is simply not possible for them to execute attacks and go into hiding without having sympathizers in the same or neighbouring districts. In response, the government needs to improve its street-level intelligence to try to locate such sympathizers. Because civil intelligence institutions such as the police already have an established structure, this responsibility should be assigned to them. However, the police should be strengthened in terms of training and resources. Because terrorists have resource constraints, a better plan for security checks would increase their probability of arrest, thereby increasing their cost. There should be several security checkpoints on the border of each province to prevent the free movement of terrorists and the explosives that they use. A sound security plan to protect high-value targets would also increase the costs for terrorists.

In the long run, however, the government needs to review its economic policies. It should not just focus on increasing the national income because the distribution of that income also needs to be more equitable. It is not enough to make one district an economic hub and ignore the rest. Pakistan's economic policy should be inclusive to bring more people out of poverty, thereby increasing the opportunity cost of being involved in terrorist activities. The view that this war is fought only on an ideological basis no longer carries weight. People have also started to join terrorist groups because of their economic conditions. The confessions of some of the perpetrators of recent attacks are clear evidence of this reality.

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APPENDIX

Figure A

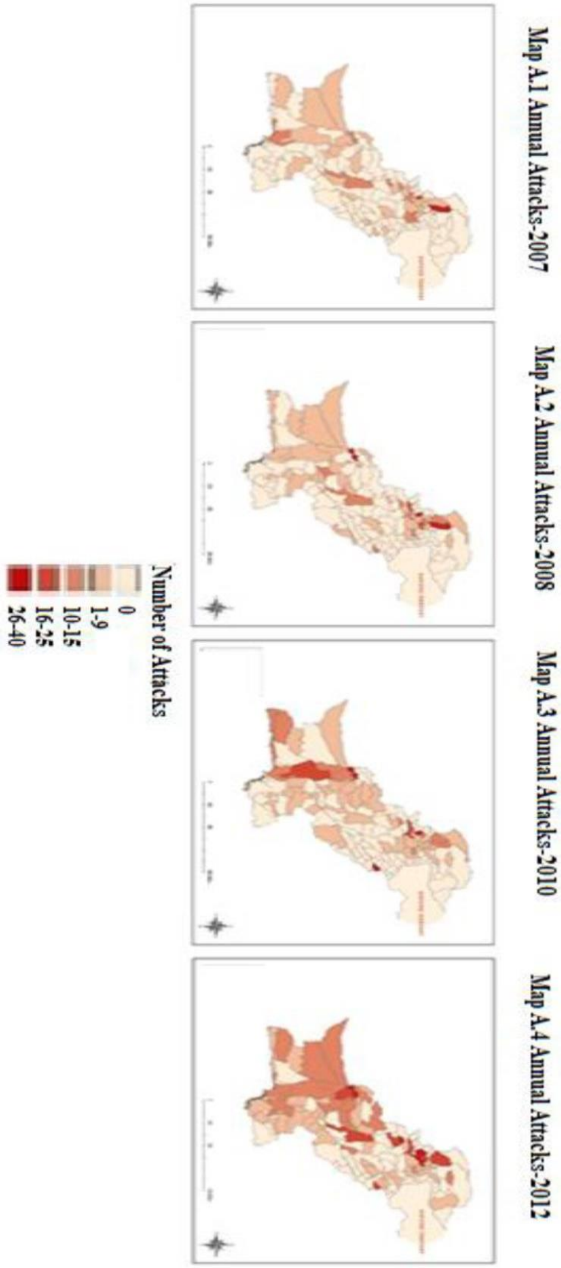

Figure B

Hotspots for Attacks in 2009

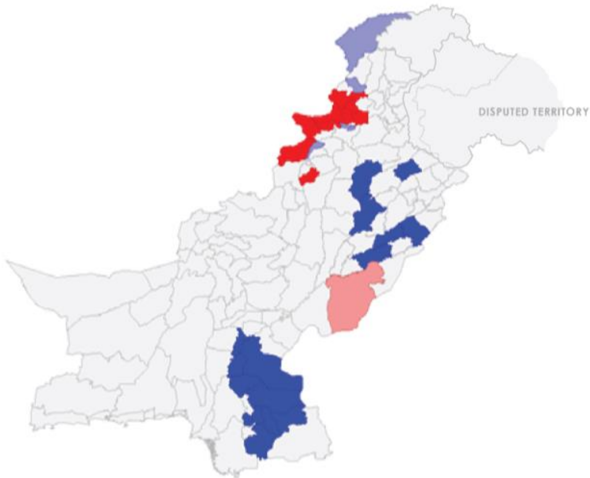

Figure C

Hotspots for Attacks in 2011