Category Clustering Phenomenon of Terrorist Attacks: A Target Similarity Lens

An Shao\textsuperscript{a}, Qian Hu\textsuperscript{b} and Aping Ye\textsuperscript{c}

\textsuperscript{a}Associate Professor, Department of Counterterrorism, Zhejiang Police College, Hangzhou, China; shaoan1981@gmail.com.

\textsuperscript{b}Associate Professor, School of Public Administration, University of Central Florida, Orlando, FL, USA; Qian.Hu@ucf.edu.

\textsuperscript{c}Assistant Professor, Zhejiang University of Science and Technology, Hangzhou, China; alison1019@sina.com.

Abstract: This exploratory study focuses on the relationship of target category to terrorist attacks and examines how similarity in value of terrorist attacks coincides with similarity in target category. A total of 19,289 terrorist attacks that happened in North America and Western Europe from 1970 to 2015 are sorted into four groups by target categories: Public-Designated, Public-Undesignated, Private-Designated, and Private-Undesignated. Utilizing spatial autocorrelation analysis that was adapted for studying this context, this study defines the similarity of target categories as the category weight. Global Moran’s I statistic indicated there was a significant category clustering phenomenon of terrorist attacks. Moran Scatter Plot showed each of four groups had its own cluster. Another interesting finding is that the clustering was weakening in the group of Government-Designated while strengthening in the group of Private-Undesignated. These findings can shed light on research and practice to better allocate counterterrorism resource and harden potential terrorist targets.

Keywords: Terrorist target, Target similarity, Category clustering, Moran’s I

CONTACT An Shao shaoan@zjjcxy.cn Department of counterterrorism, Zhejiang Police College, 555 Binwen Road Binjiang District, Hangzhou, 310057, Zhejiang, China.
Recently, the risk of terrorist attacks in North America and Western Europe has risen sharply. Especially, there has been a succession of terrorist incidents in Britain in 2017. Since a number of attacks happened in concert, street, market, etc., those public places have been enhanced security measures. When terrorist attacks occurred in governmental places such as the House of Parliament, many metropolitan cities such as London, Paris, Berlin, and New York have strengthened the security force around their city landmarks shortly afterwards. This security reaction is typical of governments to rely passively on the previous experiences. Namely, Governments, because of reactionary nature of the response, usually allocated most manpower and material resources for those types of place where have been attacked frequently or have just been attacked in the recent past. The logic behind this security reaction is partly based on the concept of “hot spots” that law enforcement agencies can focus limited resources in areas where terrorist attack is most likely to occur. In some cases, it would be rather effective and efficient in a short term.

However, this security reaction is still not effective enough for the prevention of terrorist attacks. Firstly it sometimes could lag behind current reality because it seems all the high-valued objects are also high likely to be next terrorist targets. Just as the displacement phenomenon of “hot spots” in crime control field, terrorists are also likely to attack those non-“hot category” targets when “hot category” target had been hardened. Secondly, comparing to ordinary crime, terrorist attack is more goal-oriented and less subject to geographic space. Usually terrorists just want to find the ideal category of target to achieve their goal no matter where it is. Therefore, security department should pay more attention on the displacement phenomenon in the level of “hot category” of terrorist targets than in the
level of “hot spots” of geographic space. Thirdly and more important, those non-“hot category” targets that have similar attribution to “hot category” target are more likely being “alternative targets”. It is partly because some terrorist organizations always preferred to target the public sector, and others preferred to target the private sector. And contagion theories indicated some terrorists would like to attack similar targets by imitating previous terrorist incidents. Therefore, it is probably to cause attack clustering phenomenon in a particular group of terrorist targets, namely a target category with high attacks are likely to be surrounded by similar category with high attacks, or vice versa. These deductions suggest that terrorist attacks happened in different target categories may not be independent but have category autocorrelation.

Concentrating on “category” aspect of data, this study analyzes how the target clusters are distributed and how “hot categories” targets affect “non-hot categories.” This study defines Category Clustering of Terrorist Attack as the distribution phenomenon that the pattern of attacks happened within similar target categories may be closer than the counterpart within dissimilar target categories. By investigating the clustering pattern of terrorist attacks from a target similarity lens, we can better understand the selection of terrorist targets. Findings from this study can shed new light on research and practice to better allocate counterterrorism resource and harden potential terrorist targets.
Literature Review

In order to analyze the difference among terrorist targets, researchers, analysts, and policy makers need to categorize these targets by certain standards. The simplest standard is to categorize targets by their affiliation with the public and private sectors. Santifort, Sandler and Brandt (2013) divided the terrorist target into four groups: Private Parties, Business, Military, and Officials.8 Austin (2013) grouped the terrorist targets as Political Leadership, Security, Civilian, and Rival Terrorists.9 Global Terrorism Database (GTD) of University of Maryland, divided targets into 22 categories10, which are similar with the industry classification standard. These categorizing methods above are obviously based on concept of industries or sectors.

Targeting different industries or sectors reflect attacker’s objective and capability.11 On the one hand, attack objective could have been come down to two types: a violence-based approach, where terrorists pursued to maximize the physical damage or casualty as much as possible, and a signaling-based approach, where terrorists pursued the symbolic value of their attack.12 The potential targets that achieve several objectives are more likely to be attacked than those that have just one. On the other hand, attack capability is related to the risk or cost that terrorists can afford to. The security hardenings of different targets are diverse. The governmental targets are generally more difficult to attack while the private targets are much easier to do so.13 Based on the two variables of attack objective and attack capability, some scholars constructed the targets categorizing matrix, such as Cost-Benefit,14 Potential Mass Casualties and Easy to Obtainment,15 Expected Return and Risk.16 In contrast to categorizing targets based on industries or sectors, these matrices more directly reflect the potential attack
objective and attack capability behind different targets selection.

Based on target categorizing, some scholars began to pay more attention to the distribution of terrorist attacks. One research branch is investigating how terrorist attacks have been distributed from the target category angle. For example, Brandt and Sandler (2010) had utilized Bayesian Poisson changepoint regression models to identify the changepoint of each of four target types, and explained how transnational terrorists adjusted their choices among four target types. \(^{17}\)Charlinda, Sandler, and Brandt (2013) had used Herfindahl index to observe the trend of target diversity. \(^{18}\)Meanwhile, Li (2014) had applied Gini coefficient to analyses 22 target categories in global and national level, and all the calculating results show there are significant centralization phenomenon in those target categories. \(^{19}\)Yet the research remain limited on the interaction and correlation among different categories of terrorist targets.

On another research branch, there are quite a few scholars focused on spatial clustering of terrorist attacks from the geographic angle. Spatial econometrics methods had been applied to detect spatial clustering pattern of terrorist attacks and aims to analyze the spatial autocorrelation among terrorist targets. Siebeneck et al (2009) employed Geographic Information Science to conduct a series of spatial and temporal cluster identification analyses on terrorist incidents in Iraq. \(^{20}\)Lafree et al (2012) conducted Local Indicators of Spatial Autocorrelation statistic to detect the spatial shift patterns of terrorist attacks in Spain. \(^{21}\)The results from all these studies demonstrated the spatial clustering phenomenon of terrorist attacks and the effectiveness of spatial autocorrelation method in applying to the counterterrorism field.
Reviewing and comparing previous research, this study will combine both research branches, and use spatial autocorrelation method to examine the clustering pattern of terrorist attacks from the target category angle, which not only fill in the literature gap theoretically but also shed light on counterterrorism policy. To this end, this study focuses mainly on three research questions: (1) Is there any category clustering phenomenon of terrorist targets?; (2) How does the category clustering develop in each target?; And (3) What affects the development of category clustering?
Data and Methods

The data for this study was from Global Terrorism Database (GTD) including 19,289 terrorist attacks in North America and Western Europe from 1970 to 2015. Using this long-term period could allow this study to avoid making conclusions based on short-term fluctuations in terrorist attacks. The dataset includes information regarding the date of terrorist attack, country, and target categories which are necessary in this study. In order to answer three research questions in this study, we applied three methods gradually: (1) Global Moran’s I; (2) Moran Scatter Plot; and (3) Diffusion Pathway Analysis.

Global Moran’s I

To examine the category clustering phenomenon of terrorist targets, we used the Global Moran’s I. Spatial clustering is a particular attribute self-correlation of observed values according to the geographical distance of the values. Global Moran’s I statistics measure the whole spatial autocorrelation of one particular attribute in a area. The Global Moran’s I statistic is defined as:

\[
I = \frac{\sum_{i} \sum_{j} W_{ij} (y_i - \bar{y})(y_j - \bar{y})}{\sum_{i} (y_i - \bar{y})^2}
\]

The values of Moran’s I range from -1 to +1. In this study context, \(N\) is the number of targets categories indexed by \(i\) and \(j\); \(y\) is the variable of interest; \(\bar{y}\) is the mean of \(y\); and \(W_{ij}\) is the weight (e.g., 0, 1) for categories \(i\) and \(j\).

For the weight setting of this study, the physical spatial distance was replaced with
virtual “category distance”. Terrorist targets consist of 22 categories in GTD data. This study further sorts these categories into groups by designated/undesignated (x-axis) and public/private (y-axis) in Figure 1. Each quadrant could be seen as a group. To some extent, this matrix’ connotation is essentially identical with previous research. Except for the important difference that the public/private sector (y-axis) are about sectoral characteristic of target, while the designated/undesignated (x-axis) are about objective of terrorist attack that aim at the designated victim or not. The targets of group 1 (upper right) are undesignated and belong to the private sector. These targets are easier to be attacked and more likely to cause mass casualty. Group 3 (lower left) contains targets that are designated and belong to the public sector. These targets are more difficult to be attacked and have more signal meaning to terrorists. Terrorist will need to take much more risk when they attack these targets because governments have more security measures. The same is true with Group 2 and Group 4.

![Figure 1. Four Terrorist Target Groups](image)

The next is to define what the “category distance” means, i.e., a similarity measure

1 In this study, we exclude four categories from the GTD database: terrorist, unknown, others. And we also made another data test including the four categories, and the result still show there are a significant clustering phenomenon.
should be determined to the relationships between the two categories of targets. In this study, category distance means the extent to which the target categories are similar. Targets in the same group are more similar in two dimensions of designated/undesignated and public/private, and their category distance is closer than those in different groups. Referring to method of Contiguity Weights, the rules of weights setting are that the weight was set as 1 between two categories of targets if they are neighbors in the same group, which also means these targets have closer category distance (e.g. Police and Military). And the weight was set as 0 between targets if they are non-neighbors in different groups, which suggests these two categories of targets have further category distance (e.g. Police and Non-governmental Organization; Police and Business). By using this weight setting, this study calculated Global Moran’s I to examine the whole clustering pattern of 19,289 terrorist attacks from 1970 to 2015.

**Moran Scatter Plot**

To examine the category clustering within each target group, we used the Moran Scatter Plot. It allows us evaluating how an interest variable spread out to its neighboring variable in a visual way. This Moran Scatter Plot displays the value of interest variable on the horizontal axis and the spatial lag of the neighboring variable on the vertical axis. All these values are standardized. The scatter plot has been divided into four quadrants, both high-high (upper right) and low-low (lower left) represent positive spatial autocorrelation, while high-low (lower right) and low-high (upper left) represent negative spatial autocorrelation. This study will calculate the data not only in the whole data but also in each of five year’s period from 1970 to 2015, and plot the temporal trend of the Moran Scatter Plot.
**Diffusion Pathway Analysis**

To investigate what affects the development of category clustering, this study conducted diffusion pathway analysis. This method aims to determine whether the change value within a target category be affected by the neighbor categories or the non-neighbor categories.

This study modifies two aspects of the diffusion pathway method. Firstly, we further sorted the stationary status into two kinds: one is absolutely stationary when no change happened; another is comparably stationary when the local unit had no change but the neighbor unit had changed (i.e. from quadrant Low-Low to Low-High). The first “Low” in the Low-Low is about local category, and the second “Low” is about neighbor categories. Secondly, we contrast the value of LISA statistics at 5-year period $t$ with those at 5-year period $t + 1$, which could fully take temporal lag effect into account. Table 1 offers a summary of how to interpret these changes. Each cell in the table designates whether the transitions is stationary or not, or the transitions is from the neighbor categories, or from the non-neighbor categories.

Table 1. Summary of Diffusion Pathways (Gary et al 2012)

<table>
<thead>
<tr>
<th>Period t+1</th>
<th>L-L</th>
<th>H-L</th>
<th>L-H</th>
<th>H-H</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period t</td>
<td>Stationary</td>
<td>Increase</td>
<td>Stationary</td>
<td>Increase</td>
</tr>
<tr>
<td>L-L</td>
<td>Absolutely</td>
<td>Non-neighbor</td>
<td>Comparably</td>
<td>Non-neighbor</td>
</tr>
<tr>
<td>H-L</td>
<td>Decrease</td>
<td>Stationary</td>
<td>Decrease</td>
<td>Stationary</td>
</tr>
<tr>
<td></td>
<td>Neighbor</td>
<td>Absolutely</td>
<td>Neighbor</td>
<td>Comparably</td>
</tr>
<tr>
<td>L-H</td>
<td>Stationary</td>
<td>Increase</td>
<td>Stationary</td>
<td>Increase</td>
</tr>
<tr>
<td></td>
<td>Comparably</td>
<td>Non-neighbor</td>
<td>Absolutely</td>
<td>Neighbor</td>
</tr>
<tr>
<td>H-H</td>
<td>Decrease</td>
<td>Stationary</td>
<td>Decrease</td>
<td>Stationary</td>
</tr>
<tr>
<td></td>
<td>Non-neighbor</td>
<td>Comparably</td>
<td>Non-neighbor</td>
<td>Absolutely</td>
</tr>
</tbody>
</table>
Result
A temporal trend description of terrorist attack in North America and Western Europe through 2015 is shown in Figure 2. The annual data in the model are the sum events in every category of target. The statistics relating to the amount of each category of target through 2015 are presented in Figure 3. Obviously, the top 5 of all target categories in frequency are much higher than others.

Figure 2. Amount of terrorist attack in North America and Western Europe 1970–2015

Figure 3. Amount of Target Categories Distribution 1970-2015
Global clustering of target category

The global Moran’s I test statistic (0.38, p < 0.001) showed statistically significant category clustering of terrorist target in overall data from 1970 through 2015. This positive autocorrelation of target categories demonstrated the self-correlation of the target selection according to the ordering of target category, and also suggested some “hot categories” (high frequency target) cluster in same group while some other “cold categories” cluster in other same group. More specifically, the “hot categories” can affect the rest categories of target in its same group to be “hot” while the “cold categories” can affect the rest categories of target in its same group to be “cold”. This evidence suggested the selection of terrorist target was definitely not random.

Data analysis in 5-year periods identified the category clustering was quite persistent over time, which ranged from 0.11 to 0.31. The lowest global Moran’s I is 0.11 in the period of 2011-2016 while the highest is 0.31 in the period of 1986-1990 (Figure 4). Target selection always had strong positive autocorrelations despite the extent of autocorrelation is fluctuating. As Global Moran’s I provide just a single measure of categories clustering, it still needs to apply Moran Scatter Plot to detect how the clustering is developing in each target group.

Figure 4. Trend of annual Moran’s I
**Distribution of target categories in Moran Scatter Plot**

Figure 5 was produced by Geoda software, and additionally marked out each category with different colors and the first they have by hand. This graph identified two clusters with high number of terrorist attack were in high-high quadrant. The cluster of the Public-Designated group was identified with 3 categories of target: Government (General), Military, and Police, another includes 2 categories of target of the Private-Undesignated group: Business, Private Citizens and Property. There were other two clusters with significantly low number of terrorist attacks were in low-low quadrant. One had 7 categories of target of the Public-Undesignated group: Telecommunication, Utilities, Food or Water Supply, Airports & Aircraft, Maritime, Transportation, and Educational Institution; another had 4 categories of target of the Private-Designated group: Non-governmental Organization, Journalists and Media, Religious Figure/Institutions, and Abortion Related. Additionally, the remaining two categories of target were in low-high: Tourists, Government (Diplomatic), which mean there have less autocorrelation between the two and other categories of target. Now Moran Scatter Plot analysis showed us each target group has its own cluster, next this study further detect how these clusters are developing over time.

![Figure 5 Moran scatter plot of overall data 1970 through 2015](image-url)
In order that we can better understand what it’s like in each group, I transformed this scatter plot into the map of target category group (Figure 6). The volumes of rectangle represent correspondingly the attack number of target category, namely the bigger the rectangle are, the more attack events happened.

Figure 6. Category Clustering Map of Four Groups

In the end, Figure 7 shows a clear variation trend that clustering has been weakening in group of Public-designated. Conversely, clustering has been strengthened in group of Private-undesignated. This trend suggests choice of terrorist targets have been shifting from the public sector to the private sector. We could draw a preliminary conclusion that recently and in the near future, terrorists have more interesting on those categories of target that could cause mass casualty easily, such as Business, Private Citizens & Property.
Lagged Attacks

Figure 7. Trend of Moran Scatter Plot in 5-year

**Diffusion Pathway of category clustering**

To get a more systematic view, the study counted the move of each category of target and observed the clusters change in each of five-year periods in Moran Scatter Plot. In general, most of targets (91%) remain in same quadrant; they didn’t change their quadrant location over time. Only 9% targets changed location and move to other quadrant. This evidence
demonstrated not only the clustering phenomenon is persistent but also the member of cluster is stable. The middle two columns of Table 3 contrast the increases by diffusing from neighbor targets or non-neighbor. The last two columns in table 3 show neighbor decrease and non-neighbor decrease.

Table 3. Summary of Target transition

<table>
<thead>
<tr>
<th></th>
<th>Stationary</th>
<th>Stationary</th>
<th>Increase</th>
<th>Decrease</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Absolutely</td>
<td>Comparably</td>
<td>Neighbor</td>
<td>Non-neighbor</td>
</tr>
<tr>
<td>Total</td>
<td>N(%)</td>
<td>N(%)</td>
<td>N(%)</td>
<td>N(%)</td>
</tr>
<tr>
<td>1970-2015</td>
<td>149(91)</td>
<td>16(4)</td>
<td>1(0.6)</td>
<td>2(1.2)</td>
</tr>
</tbody>
</table>

We analyze these changes in each target group, which involves not only individual groups but also inter-groups. First of all, as to the group of Public-Designated, Government (Diplomatic) moved from Low-High to High-High in 1981-1985, which can be interpreted Government (Diplomatic) had been affected by other neighbor targets such as Government (General), military, and police. Nevertheless, it should be seen as being affected by non-neighbor when Government (Diplomatic) moved from High-High to Low-High in 1986-1990. For the same reason, Military moved from High-High to Low-High at 1991-1995, which means this shift had not been affected by neighbor target categories because all other group member still kept a high value. In addition, Government (General) moved to High-Low from High-High in 1996-2000 and 2011-2015. This study calls such move as stationary comparably. It’s because the value of Government (General) itself was high no matter it was before
moving or after, and Government (General) had been moved passively as values of Government (Diplomatic) and Military had decreased during the period. It applies to Police as well when Police moved from High-High to High-Low in 2011-2015. Anyway, all the change in group of Government-Designated demonstrates that Government (General) and police have much more attractive to terrorists than other two.

Interestingly, all the targets in the group of Public-Undesignated stayed in Low-Low all the time. This suggests terrorists were less likely to attack Telecommunication, Utilities, and Food or Water Supply etc. Also, there is strong positive autocorrelation among these target categories.

With respect to the group of Private-Designated, Journalists & Media had moved from High-Low to Low-Low twice in 1976-1980 and 1986-1990, which definitely attributed to neighbor targets according to Table 1. In large part because values of Non-governmental Organization, Religious Figure/ Institutions and others in same group are all very low, and these low values affected value of Journalists & Media being low. As it was, there have strong autocorrelation in this group, and this situation couldn’t be changed easily in a short time. Also it’s important to note that Religious Figures/Institutions moved from Low-Low to High-Low at 2011-2015, which indicates terrorist were more interested in Religious Figures/Institutions than ever, and this change could have been driven by non-neighbor target categories.

As to the group of Private-Undesignated, Business and Private Citizens & Property have always stayed in High-High, which indicate there are very strong and stable autocorrelation between them. Furthermore, Business and Private Citizens & Property could be seen as “hot
spot” and the two could reinforce one another. Meanwhile Tourist has always stayed in Low-High. It seems like Business and Private Citizens & Property did not have any influence on Tourist. In fact, many tourists are victims of attacks that happened in malls, and shopping centers, and those tourist victims have been sorted into Business and Private Citizens & Property instead of Tourist.

Discussion

Global Moran’s I test statistic suggests there are statistically significant category clustering of terrorist targets both throughout the whole time and in each five-year periods. Why did terrorist attacks cluster in target categories? There are two theories could help us to better understand the clustering phenomenon. One is Path-dependence theory.\textsuperscript{30} As different target have different security model, terrorists could be easier to attack the familiar target (e.g. target categories in the same target group) again on the base of previous technical, personnel, and experience. This dependence on target selecting could be self-reinforcement continuously with time. More importantly, this dependence on target selecting could lower attack risk or cost, and cause increasing returns to terrorists. Terrorists need to calculate their costs if they try to attack total new categories of targets (e.g. target categories in different target group).

The second useful theory is contagion theory.\textsuperscript{31} The contagion phenomenon has recently been observed in the terrorist attacks. This behavior is “copycat” acts of terrorism where the terrorist seeks to imitate their predecessor.\textsuperscript{32} When certain target had been attacked successfully and caused mass casualty, this attack mode would have a great influence on other terrorist individuals or organizations. This study enriches our understanding of the
copycat effect of terrorist based on the categories clustering phenomenon of terrorist target. Firstly, the choice of terrorist targets can be contagious. Besides imitating to attack the same category target, terrorist are also very likely to attack the similar targets. Secondly, when there come out a new attack method or new tool, it is very likely to be imitated by other terrorists. Take truck-crush as an example, this study preceded a statistics of attacks in which terrorist used vehicles as the main weapon. There were a total of 10 terrorist incidents of vehicle attacks, in which terrorists all used cars, not truck, as their main weapon from 1970 to 2015 in North America and Western Europe. However, after 2016 Nice Attack in which a 19-ton cargo truck was deliberately driven into crowds, there are at least three similar truck attacks and several car attacks subsequently happened in one year, including 2017 Barcelona Attack and 2017 Berlin Attack.

Moran Scatter Plot indicated each target group has its cluster. This suggests obvious segregation in category distribution of terrorist attacks in North America and Western Europe. Evidence from the diffusion pathway analysis indicated that the rise of terrorism attacks on Journalists, Media and Government (Diplomatic) had been affected by respective neighbor targets in their own group. This finding has implication for counterterrorist decision-making. Decision-maker need to establish the concept of “target group” and avoid viewing certain targets as static and isolated. When allocating security resources, similar targets have to be taken into account as a whole. Moreover, the Public-Designated group and the Private-Undesignated group should be top priority among priorities. If certain category of target in these two groups could be “hot spot”, the rest categories of target in same group should be also reinforced by security forces. The Public-Undesignated group and the Private-
Designated group require quite different strategies. Although certain categories of target in those two groups might have been attacked, the security forces may not be allocated too much on the rest categories of target in same group.

Diffusion pathway analysis showed the whole trend of Public-Down & Private-Up, which clustering has been weakening in the group of Public-Designated while reinforcing in the group of Private-Undesignated. Attacks in group of Private-undesignated rise steadily over ten years, and account for 44% of all attacks in 2010-2015. Meanwhile, those of the Public-Designated group indicated a downtrend, and account for 23% of all attacks in 2010-2015, which is a record low. It is important to pay more attention and resources to protect the private sector nowadays, especially in Business and Private Citizens & Property. As Tourists are easy to be affected by Business and Private Citizens & Property, Tourists require corresponding security forces even though attacks of Tourist are low currently.

**Conclusion**

In order to inform government departments to better allocate counterterrorism resources, this study has applied the concept of category clustering of terrorist targets to discover the autocorrelation among target categories. First of all, we categorized all categories of targets into four groups by two dimensions Public/Private and Designated/Undesignated.

Next, the finding from Global Moran’s I test statistic suggests there have been statistically significant category clustering of terrorist targets throughout the whole time, namely there have been strong autocorrelation among the selecting of terrorist target. Additionally, this autocorrelation has existed continuously throughout of the five-year periods.
Then Moran Scatter Plot identified each of four target groups has its own cluster. The results from the method of diffusion pathways indicated the attack frequency of most targets remain in a stable situation. There are only a few targets that moved to other quadrant, in which 50% moves are affected by neighbor target categories and 50% are by non-neighbor. Last and most important, there is a clear trend that clustering have been weakening in the group of government-designated while clustering have been keeping stable in the group of private-undesignated, even being strengthened between Business and Private Citizens & Property.

Finally, this study definitely belongs to interdisciplinary topic. More emphasis on theoretical construction and target grouping method are priority among priorities in the future research.

Notes


3. Hot Spots Policing National Institute of Justice

https://www.crimesolutions.gov/PracticeDetails.aspx?ID=8


