maps in Figure 8.6 support this argument, showing that the pattern of alarm distribution in the neighborhoods is closely connected to the distribution of the different population age groups.

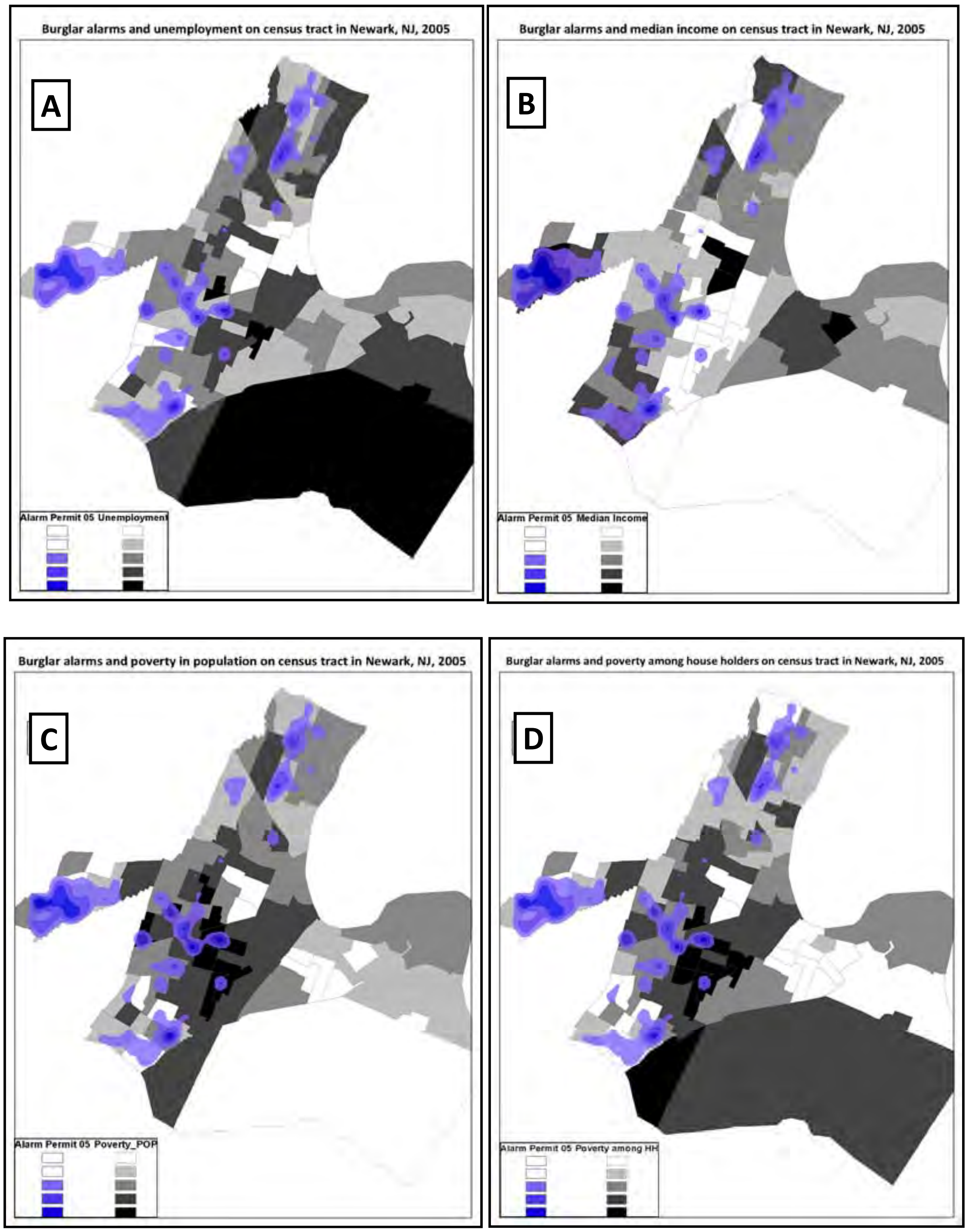
On the contrary, the map for the age group over 75 (map E) shows the opposite pattern of distribution to the age groups below 14 and between 15 and 17. The correlation coefficient and direction of the relationship for the population age group over 75 are relatively weak and negative, indicating that as the residents over 75 in a neighborhood increase, the installation rate of burglar alarms decreases.

(3) Burglar alarms and socio-economic composition

Among the three variables in the socio-economic category (e.g., median income, unemployment, and poverty level), only unemployment demonstrates a sporadic statistical significance with burglar alarms in the correlation statistics (see Appendix 4). Though the other two variables do not have statistical relationships, it may be meaningful to examine their patterns in the census tracts.

Figure 8.7 presents census-tract maps for the socio-economic variables, including the variable poverty level in householders, with density maps of burglar alarms. Census tracts with higher unemployment rates (map A) are located in the northeastern and central parts of the city, whereas lower unemployment rates are in the western and central eastern parts of the city. A definitive pattern between the installation of burglar alarms and unemployment in census tracts cannot be determined, but the census tracts with higher rates of alarm installation do cluster in and around the census tracts with a relatively lower unemployment rate. A clearer pattern between median income (map B) in the population and alarm installation exists, indicating that neighborhoods with a higher median income tend to have a higher rate of alarm installation, whereas a lower median income (e.g., in the central and northern parts of the city) has the lowest rate of alarm installation.

[Figure 8.7] Census tract maps of socio-economic characteristics with density maps of burglar alarms in Newark, NJ, 2005



Furthermore, Figure 8.7 displays spatial patterns between burglar alarms and poverty levels among the general population (map C) and householders (map D). The distribution patterns of the poverty levels of both the population and householders are similar with relatively higher levels in many of the central parts of the city. These maps show that the census tracts with comparatively higher population and number of householders living below the poverty level tend to have a higher rate of alarm installation. This is an unexpected observation because, first of all, the residents living in higher unemployment neighborhoods may not be able to afford to buy burglar alarm systems, and, second, unemployment conditions may keep adult family members in their houses longer, producing extended occupant hours for the houses. In short, this observation indicates that the neighborhoods with higher unemployment rates do not necessarily have fewer residential burglar alarms installed. More analyses with other socio-economic factors are needed to explain and verify these results.

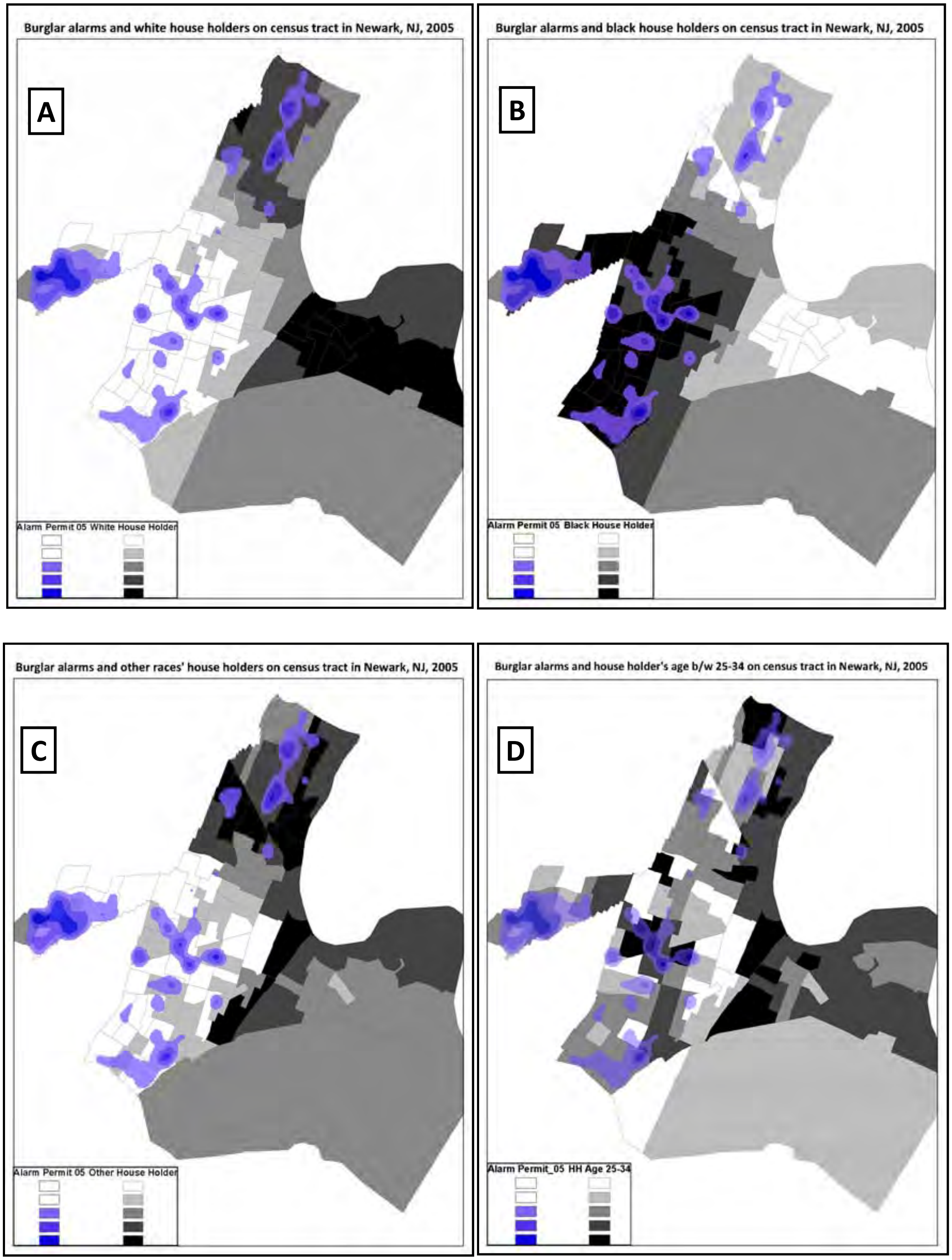
(4) Burglar alarms and householders' race and age composition

The variable householders by race is one of the housing characteristic categories with a statistically moderate and significant relationship with burglar alarms when using correlation statistics. But the direction of these statistical relationships is positive one for 'black' householder and negative for 'white' and 'others' householders.

Maps A, B, and C in Figure 8.8 display an explicit pattern between burglar alarms and householders by race on the census-tract level. The census tracts with white (map A) and others (map C) householders are predominantly located in the northeastern and some eastern parts of the city, whereas black householders (map B) predominantly reside in the western central part of the city. The neighborhoods with higher proportions of white or others householders tend to have fewer residential burglar alarms than those of black householders. This pattern is intriguing because it becomes more concrete when compared with the census-tract maps between burglar alarms and the race of the general population in Figure 8.5, implying that black householders in the city tend to have more burglar alarms being installed in their houses.

In addition, map D in Figure 8.8 illustrates the census-tract map of householders in the age group from 25 to 34 with a density map of burglar alarms. Among the eight householder's age groups, only the ages 25 to 34 variable has intermittent significance depending on the year, but also significant in the overall time period from 2001 to 2005, with a moderate and positive relationship using correlation statistics (see Appendix 4). Compared with the map for the population age group from 25 to 34 in Table 8.6, which displays that the pattern of population distribution of this age group, the census map of the householders' age group from 25 to 34, except in the central part of the city, does not show a clear pattern. However, the census tracts with a relatively higher rate of householders in the age group from 25 to 34 reside in sections in the northeastern, central, eastern, and western parts of the city, corresponding to areas with higher rates of alarm installation. Thus, younger householders tend to have more burglar alarms being installed.

[Figure 8.8] Census-tract maps of householders by race and age with density maps of burglar alarms in Newark, NJ, 2005

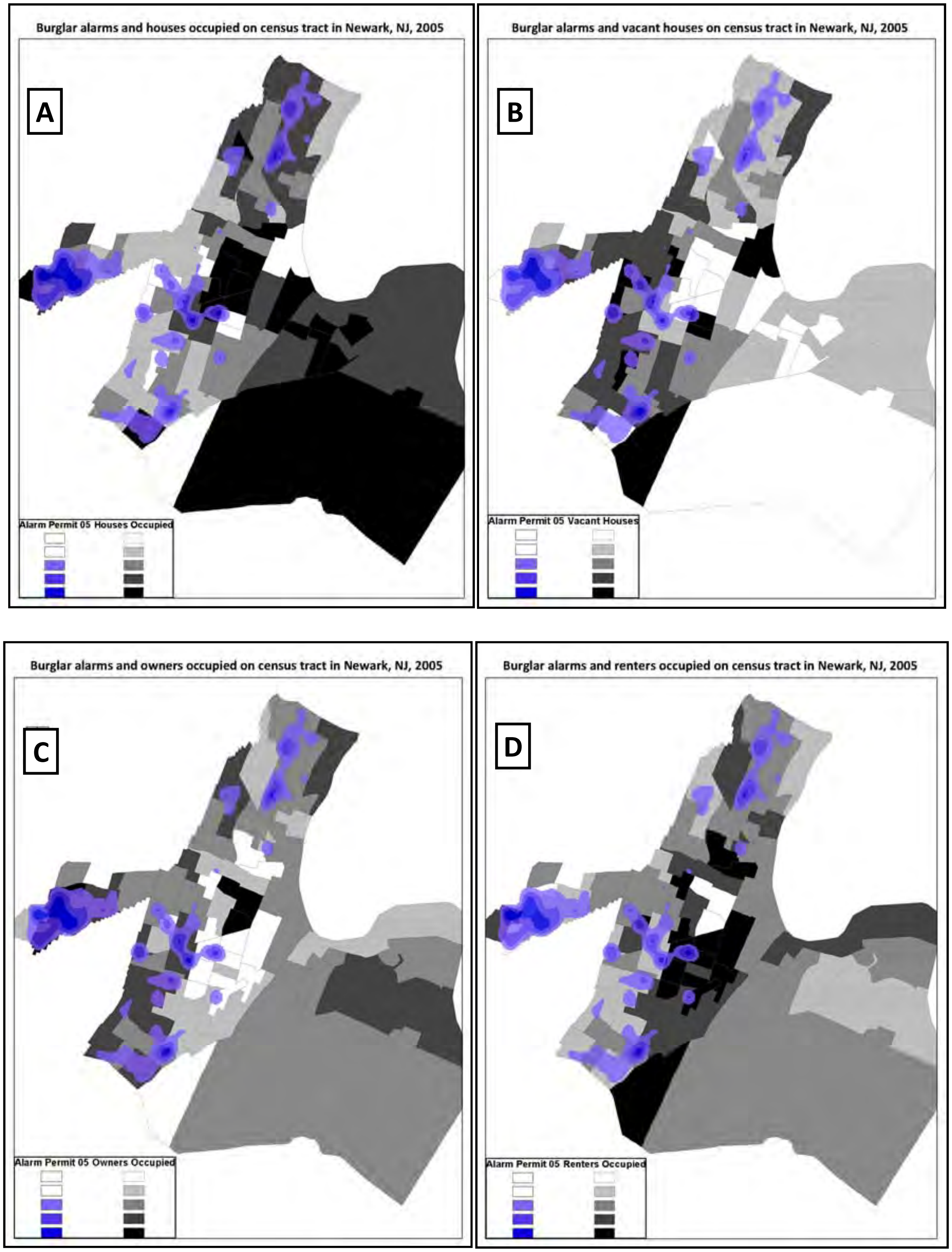


(5) Burglar alarms and housing characteristic composition

Two core variables in housing characteristic composition are house occupancy and owner occupancy. Maps A and B in Figure 8.9 display census-tract maps of house occupancy and vacancy. The western, northern, and eastern parts of the city maintain higher rates of housing occupancy than the central and southwestern parts. At first glance, in tracts where houses are occupied, it seems that the houses have fewer burglar alarms than in areas with more vacant houses. In addition, maps C and D show that the western, southwestern, and northern parts of the city have relatively higher rates of owner occupancy with more burglar alarms being installed.

However, these maps in Figure 8.9 do not illustrate a clear pattern between residential burglar alarms and the status of house occupancy and owner occupancy, indicating that these two variables are not substantial factors in deciding to install a burglar alarm. Other factors may be more plausible in explaining the installation pattern of residential burglar alarms.

[Figure 8.9] Census-tract maps of housing characteristics with density maps of burglar alarms in Newark, NJ, 2005



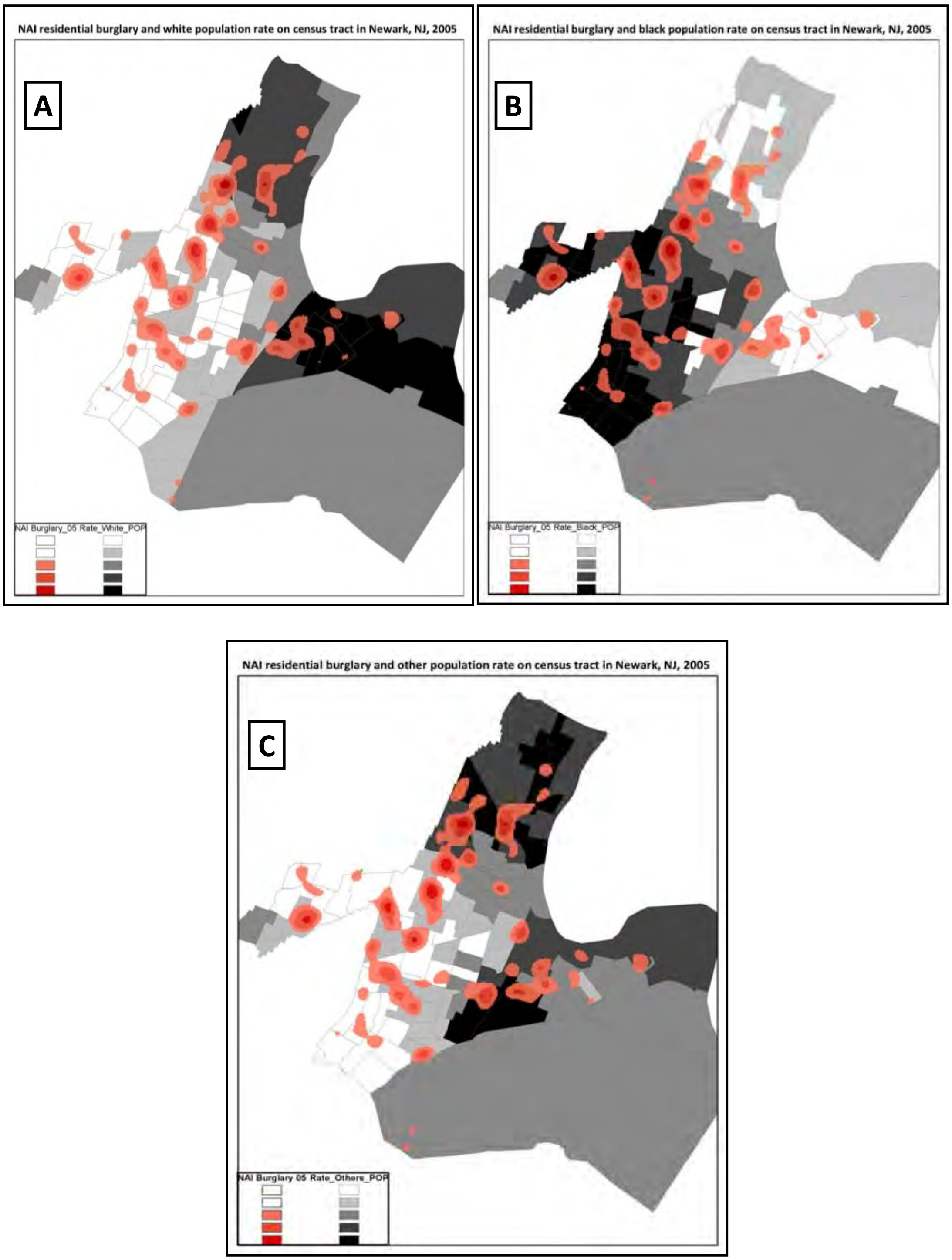
2. Spatial Characteristics of NAI Residential Burglary

(1) NAI residential burglary and demographic composition

As discussed before, the dense areas of NAI burglary are spread across the city. Figure 8.10 presents the map of those areas superimposed on census tracts of the population. The same census-tract maps are used as they were for the analyses of burglar alarms. A clear pattern is observed between two population groups: 'black (map B)' and 'white and others (maps A and C).' Census tracts with higher black population as the number one population category share a more highly concentrated rate of NAI burglary than those with white and others population. This observation is fairly similar to the pattern of burglar alarms, indicating that the distribution of burglar alarms and NAI burglary are closely linked to the distribution of race among the population.

Combining the information, black-dominant neighborhoods, comparatively, have more highly concentrated spots of burglar alarms and burglary, explaining a causal relationship between alarm installation and NAI burglary. As discussed in Chapter 7, the quantitative analyses could not explain which one of them might cause the other to happen, but spatial approaches show that census tracts dominated by black populations have more burglar alarms installed and NAI burglary. Under such circumstances, it could be assumed that the higher installation rate of burglar alarms might cause more NAI burglary incidents. However, it is more reasonable to presume that higher NAI burglary rate may urge residents in certain neighborhoods to install more burglar alarms. Thus, for a causal argument, a higher NAI burglary rate may precede burglar-alarm installation. But further analyses are necessary to verify this argument.

[Figure 8.10] Census-tract maps of the general population by race with density maps of NAI burglary in Newark, NJ, 2005

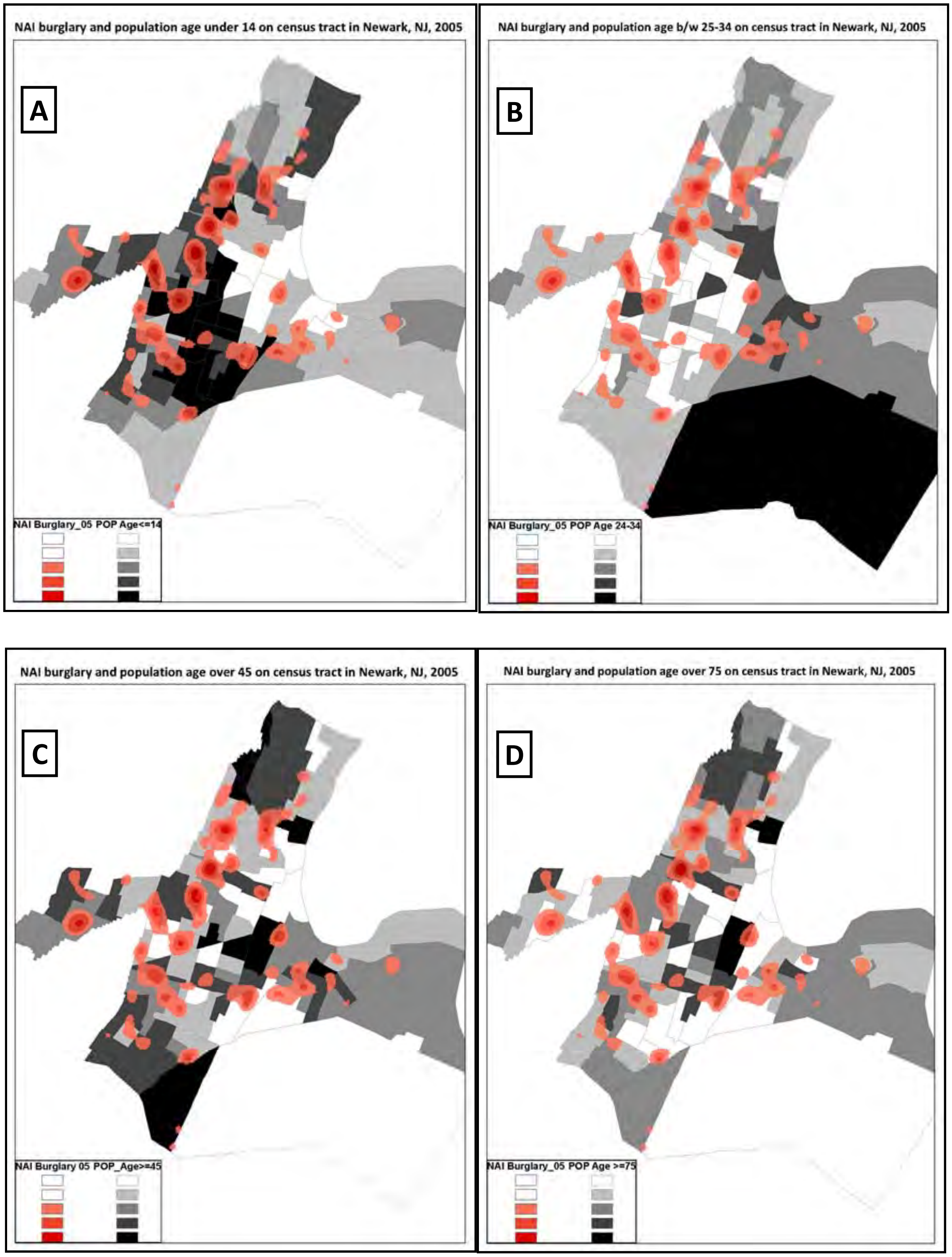


(2) NAI residential burglary and general population age composition

In the above section, residential burglar alarms showed a clear pattern in relationship to the general population age groups. As Figure 8.11 illustrates, an explicit pattern exists between NAI burglary and the distribution of the general population according to census tract. For example, map A shows that census tracts with a higher density of the population below 14 years old coincide with many highly concentrated areas of NAI burglary, though those spots are spread across the city. However, the remaining three maps B, C, and D do not have a clear pattern. Thus it can only be confidently argued that the population age group below 14 years old is strongly related to the distributions of NAI burglary.

However, scrutinizing the data leads to an interesting observation. One common pattern is found among the four maps in Figure 8.11; almost all census tracts with white colors, which represent the lowest degree of general population density, do not overlap the most highly concentrated spots of NAI burglary. For instance, the central eastern section in map A containing data from ages below 14, the central section in map B of ages 25 to 34, the upper eastern section in map C of ages over 45, and the upper eastern and southern sections in map D of ages over 75 do not share highly dense spots of NAI burglary.

[Figure 8.11] Census-tract maps of population age groups with density maps of NAI burglary in Newark, NJ, 2005



This observation implies two points. First, as discussed in Chapter 7 and shown in Figure 8.11, both NAI burglary and the age groups of the general population are not distributed evenly throughout the city, generating an obvious pattern of distribution, which relates to underlying socio-economic conditions in the neighborhoods. Second, the distributions of both NAI burglary and the age groups of the general population have a strongly linked pattern, suggesting that NAI burglary is more likely to be associated with younger population age groups, in particular below 14 years old, and that NAI burglary is definitely less likely to correlate with thinly populated neighborhoods beyond any distinctive age groups. Thus, connecting those arguments, the data demonstrate that residential burglary is, to a large extent, related to the distribution of the general population and associated with a younger population.

(3) NAI residential burglary and socio-economic composition

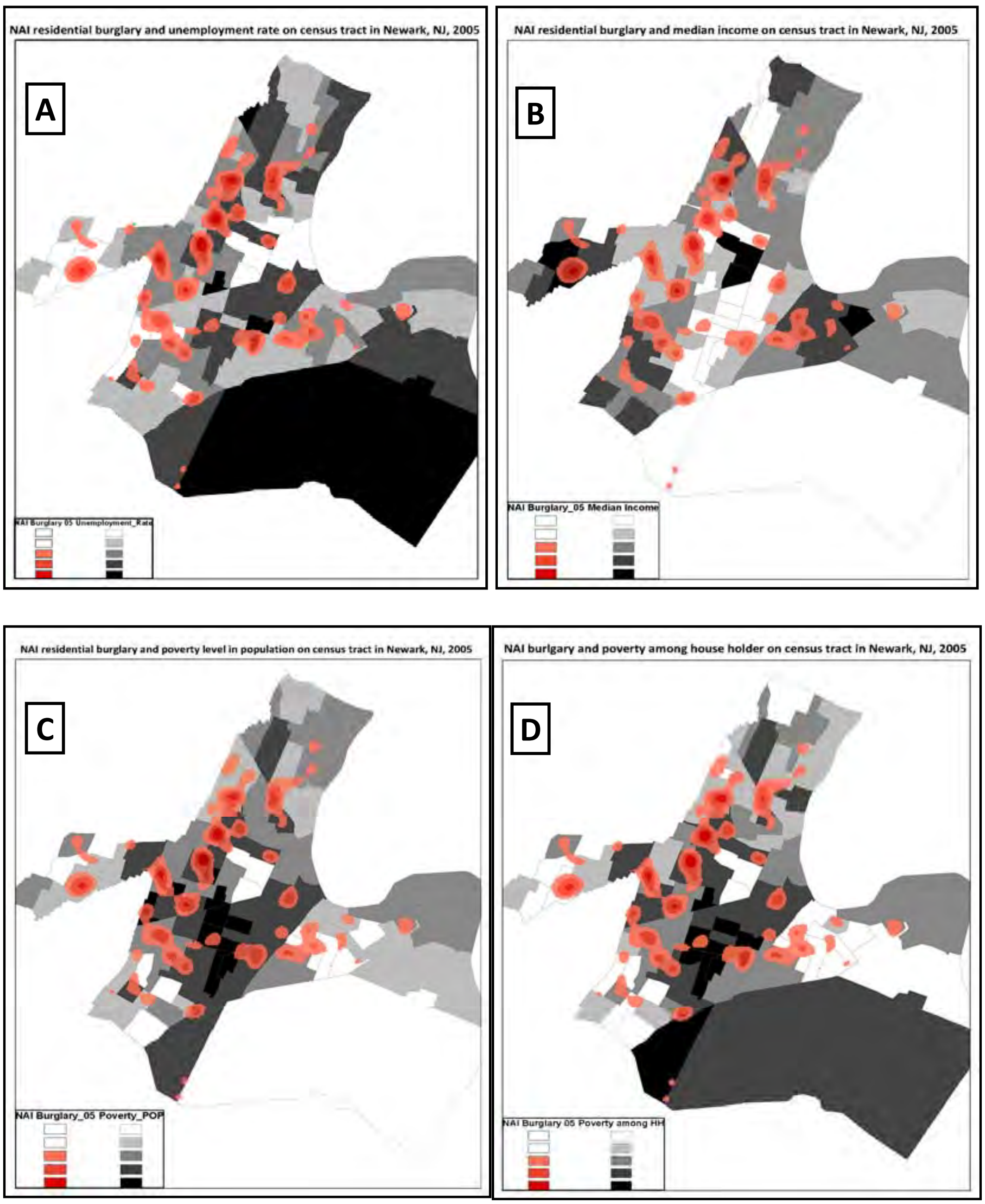
In the above section, the spatial pattern between burglar alarms and four socio-economic variables was discussed. The same variables are used to examine possible relationships with the spatial distribution for NAI burglary. Figure 8.12 illustrates census tract maps of socio-economic variables overlaid with NAI burglary. At first glance, no explicit patterns appear. For example, NAI burglary does not have an obvious pattern with the unemployment rate (maps A) on the census tract level—one of the reasons being that dense spots of NAI burglary are spread across the city. Unless independent variables (e.g., unemployment, median income, and poverty levels) maintain overt and consistent patterns in the spatial dimension, it is not easy to find and confidently argue that a spatial relationship between those variables exists. However, Figure 8.12 shows some insight into this relationship. Regarding the unemployment rate in map A, several highly dense spots are superimposed with areas of NAI burglary, though it is not the case in the western section of the city.

The median income in map B has an explicit pattern with the distribution of NAI burglary. The central section and some of the northern parts of the city have a lower-level median income, whereas most other parts of the city maintain a relatively higher-level median income. This observation is reliable when compared with map A because the levels of unemployment and median income are presupposed to be opposite, meaning that the higher the unemployment rate, the lower the median-income level. The western section of the city, in particular, illustrates this relationship. Thus, map B clearly shows that median-income is associated with NAI burglary in that the densest spots of NAI burglary reside in and around the census tracts with relatively higher median-income, whereas most census tracts with lower median-income in the central and northern parts of the city do not coincide with NAI burglary.

Poverty levels both in the general population (map C) and among householders (map D) have a similar pattern in that most of the central section maintains a comparatively higher level. Furthermore, census tracts in this area are closely associated with high levels of NAI burglary. On the other hand, lower levels of poverty in the population and among householders is less likely to be related to NAI burglary.

Linking these observations, socio-economic conditions demonstrate an explicit pattern that neighborhoods with higher levels of unemployment tend to have a lower-level median income and higher levels of poverty in the population and among householders. The central section of the city illustrates this pattern on all four maps, indicating that NAI burglary is greatly affected by socio-economic conditions.

[Figure 8.12] Census-tract maps of socio-economic conditions with density maps of NAI burglary in Newark, NJ, 2005

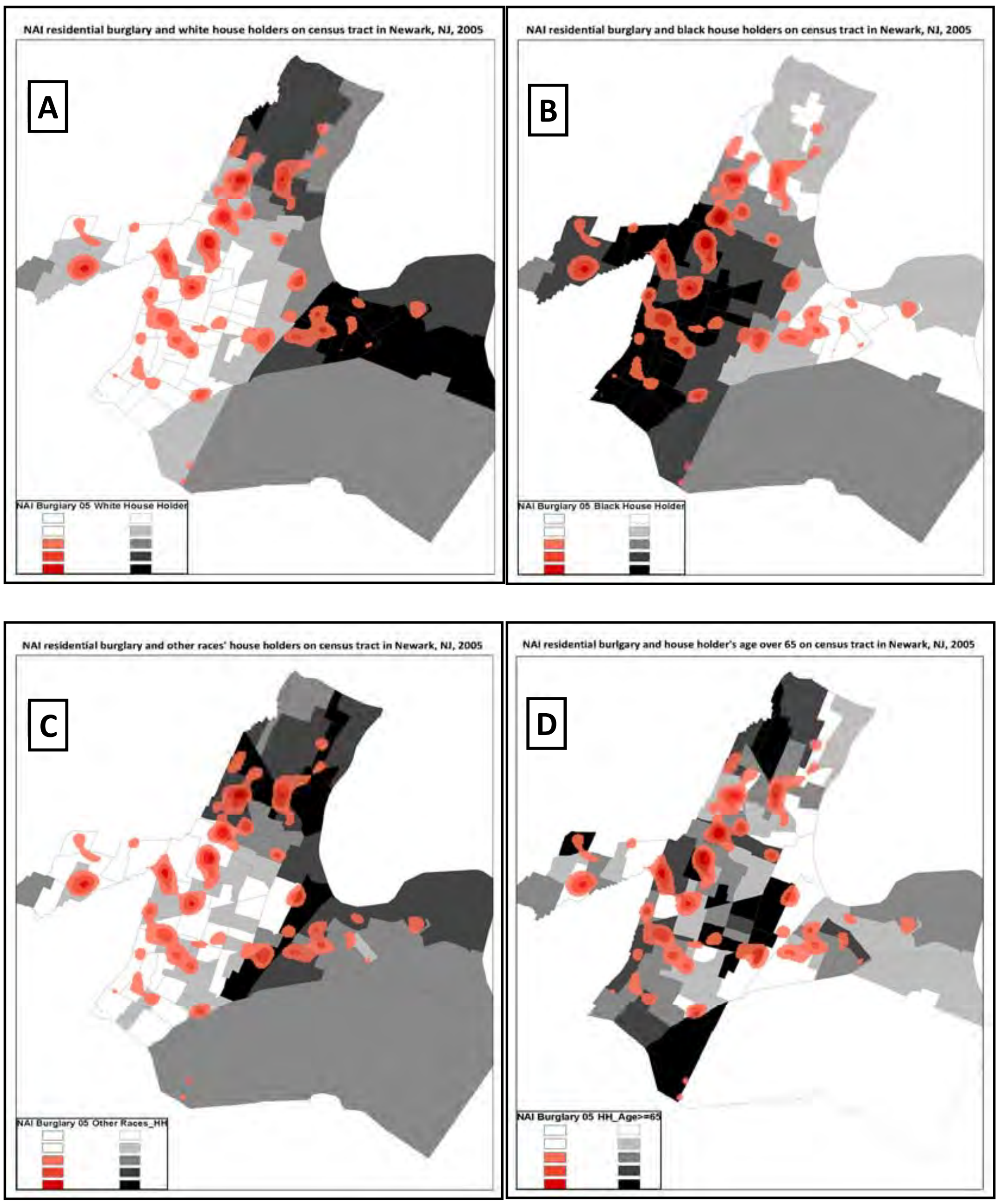


(4) NAI residential burglary and householders' race and age compositions

The distributions of householders by race in Figure 8.13 are similar to those of the general population in Figure 8.11, illustrating that census tracts with white (map A) and other race (map C) householders primarily reside in the eastern and northern sections of the city, whereas those with black householders (map B) are predominantly located in the western and central sections of the city. Some areas dominated by white and other have dense spots of NAI burglary, but most areas with high levels of NAI burglary overlap with neighborhoods with high concentrations of black. The pattern indicates that the neighborhoods dominated by black are more likely to be victimized by residential burglary than neighborhoods dominated by white and others.

This observation can link the causal relationship between burglar alarms and NAI burglary with the pattern of the general population by race. As discussed with quantitative statistics in Chapter 7, a statistically significant correlation between the increase of burglar alarms and the decrease of NAI burglary existed, but the order of causality was unclear. Spatial analyses can incorporate those observations to obtain a better explanation and understanding of this issue. The neighborhoods with dense NAI burglary also tend to have a higher rate of burglar alarms, but the number of NAI burglaries begins decreasing. Although the neighborhoods dominated by black population and householders enjoy declining residential burglary over the years along with the other neighborhoods, those neighborhoods still have comparatively higher rates of residential burglary. Consequently, they are more likely to install burglar alarms than neighborhoods with the population and householders dominated by white and others. On the other hand, neighborhoods with white and others population and householders have relatively lower rates of NAI burglary, which may directly connect to the lower rate of installation of burglar alarms. But, the results are not conclusive.

[Figure 8.13] Census-tract maps of householders by race and age with density maps of NAI burglary in Newark, NJ, 2005

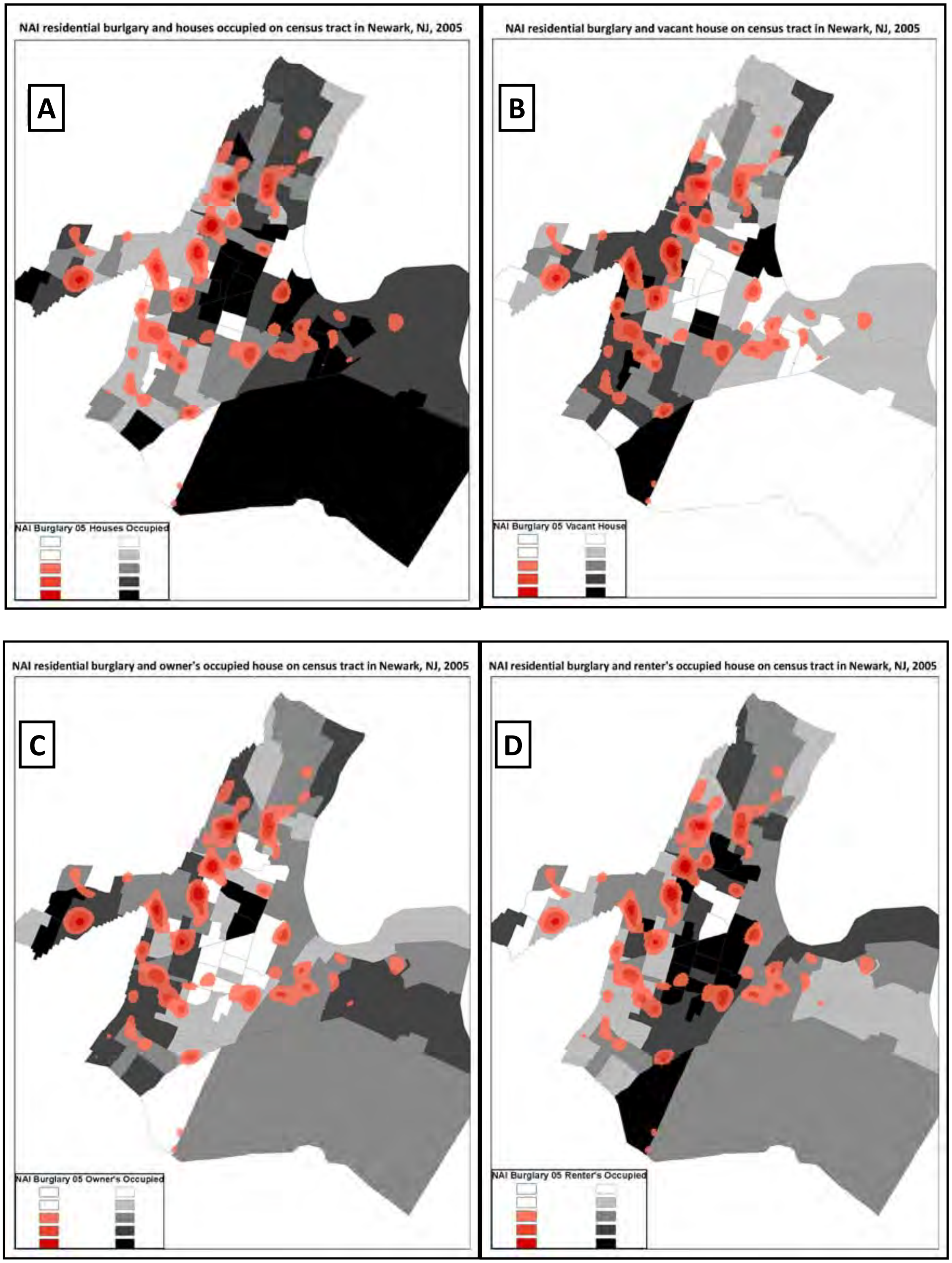


(5) NAI residential burglary and housing characteristic composition

Maps A and B in Figure 8.14 present the distribution of house occupancy with NAI burglary. The western, eastern, and northern parts of the city have dense rates of housing occupancy (map A), whereas the central west and southwestern sections show relatively dense rates of housing vacancy (map B). A clear pattern is not conclusive, but many of the densest spots of NAI burglary existing along the central west line of the city in map B share the same spatial dimensions with tracts having higher vacancy rates.

In addition, maps C and D illustrate that the neighborhoods with relatively higher rates of house occupancy by owners, in particular in the western and southwestern sections of the city, tend to have more NAI burglary than other neighborhoods. The existence of an explicit pattern cannot be conclusively argued.

[Figure 8.14] Census-tract maps of housing characteristics composition with density maps of NAI burglary in Newark, NJ, 2005



IV. Chapter Conclusion

Spatially descriptive analyses were conducted to examine Research Question 4 with two primary focuses: (1) to examine the spatial distributions and patterns of both burglar alarms and residential burglaries; and (2) to verify the findings based on quantitative analyses presented in Chapter 7. All addresses of burglar alarms and residential burglaries were geocoded for the purpose of map projection on a street-line city map using GIS computer program. Several spatial statistical techniques (e.g., point maps, density maps, and overlaying maps with independent variables) were used to examine the spatial relationships of burglar alarms and residential burglaries with other selective demographic, socio-economic, and housing characteristic variables by incorporating with and overlaying over the census tract-based maps.

First, point and density mapping methods were used as a macro-level approach. The point mapping approach by pinpointing all events onto a city map illustrated some indication of isolated patterns between burglar alarms and residential burglaries, but did not demonstrate clear spatial pattern over the years. On the other hand, the density mapping approach by creating a smooth continuous surface to represent the density or volume of the events distributed across the city clearly visualized several gradually concentrated areas of both burglar alarms and NAI residential burglary, showing that the patterns of burglar alarms installations and residential burglary incidents were not evenly distributed throughout the city. Though many of streets and city blocks had burglar alarms installed and were affected by residential burglaries, certain areas or neighborhoods obviously existed with either more burglar alarms or more burglary incidents. Such patterns occurred dependent upon neighborhoods' conditions, such as demographic, socio-economic, and housing characteristics.

In addition, superimposed density maps between burglar alarms and NAI burglary plainly demonstrated that in most parts of the city, the heavily dense spots of both burglar alarms and NAI burglary did not overlap, showing that street blocks or small sectors of the city with high installation rates of burglar alarms had less NAI burglary incidents, whereas street segments or some sectors with higher residential incidents had less burglar alarms installed. These mapping analyses indicated that the installation pattern of residential burglar alarms showed some positive impact on residential burglary by pushing away potential burglar(s) from the highly concentrated areas of burglar alarms.

An overlaying mapping method was used: (1) to examine spatial characteristics of both burglar alarms and residential burglaries with some independent variables (e.g., population race and age group, unemployment, median income, householders' race and age group, house occupancy, and owner occupancy); and (2) to examine the consistency and reliability of the early quantitative observations by linking them to census-tract mapping analyses. Regarding the spatial installation pattern of residential burglar alarms, neighborhoods with a higher black population had more burglar alarms had more burglar alarms being installed than neighborhoods with a higher number of people of other races. Neighborhoods with a higher proportion of the younger population—ages below 17—had more burglar alarms installed because of its parent's concern of safety.

Neighborhoods with greater burglar alarms did cluster in and around the neighborhoods with a relatively lower unemployment rate, while neighborhoods with a higher median income level had more burglar alarms than those of a lower median income. Furthermore, neighborhoods with higher proportion of white or others householders had less burglar alarms installed than those of black householders.

With regard to the pattern of NAI burglary, neighborhoods with a relatively higher black population shared a more highly concentrated rate of NAI burglary than those with a white and others population. In short, black-dominant neighborhoods had more highly concentrated spots of burglar alarms and residential burglary. Neighborhoods with a highly density of the population below 14 years old coincided with many highly concentrated areas of NAI burglary, showing that NAI burglary was, though not a personal crime, to a large extent, related to the distribution of the general population and associated with a younger population. Neighborhoods with higher levels of unemployment had a lower-level median income and higher levels of poverty in the general population and among householders, showing that NAI burglary was greatly affected by socio-economic conditions in the neighborhoods. In short, these descriptive spatial analyses generally confirmed most of the earlier findings based on quantitative statistics in Chapter 7.

In the next chapter, spatial impact analyses of both burglar alarms and residential burglaries will be conducted and discussed to answer Research Question 5, which primarily focuses on spatial impact. Using GIS program, some simple spatial statistics (e.g., spatial centrality and spatial dispersion analyses) and advanced spatial statistics (e.g., spatial autocorrelation analyses and spatial clustering analyses) for burglar alarms and residential burglaries will be employed.

CHAPTER 9. SPATIAL ANALYSES OF THE IMPACT OF BURGLAR ALARMS ON RESIDENTIAL BURGLARIES

I. Introduction

In Chapter 7, the analyses and discussions focused on quantitative statistics to examine the relationship between burglar alarms and residential burglaries. In Chapter 8, the descriptive spatial analyses examined the distribution and pattern of burglar alarms and residential burglaries in conjunction with quantitative analyses. In particular, the combined descriptive-spatial approach with quantitative statistics in the present study is an advanced method in the sense that research on burglary previously has lacked a unified analysis using both these methods.

As discussed and observed in Chapter 8, in many cases producing and presenting a map portraying the relevant variables can be enough to get the answers to the research questions. But examining a series of maps and trying to draw conclusions from those maps are not always easy, particularly when they are based on a descriptive approach. One shortcoming of such descriptive spatial analyses is that they do not provide statistical scrutiny. Thus, conducting a geographic analysis using spatial statistics is imperative. This statistical approach on a spatial dimension can produce more reliable and valid conclusions. Research Question 5 with the emphasis on spatial impact analyses of both burglar alarms and residential burglaries is directly related to this chapter.

With this in mind, this chapter focuses on geographic analysis using spatially statistical approaches to determine the impact of residential burglar alarms on residential burglary and vice versa. The two primary questions related to this analysis are: (1) How are the features of residential burglar alarms and burglaries distributed in a spatial dimension; and (2) Where are the clusters? Answering these questions involves finding clusters of burglar alarms and residential burglaries to examine the cause of clusters, to determine whether those features occur together and to measure the strength of the relationship. By identifying a relationship, it may be possible to predict where these features will occur. Several spatially analytical tools are employed.

II. Spatial Centrographic Analyses for Burglar Alarms and Residential Burglaries

Geographic statistics can unveil the distribution and characteristics of features (e.g., burglar alarms, non-alarm-installed (NAI) residential burglary, and alarm-installed (AI) residential burglary), such as their geographic centers, the extent to which the features are clustered or dispersed around the center, or whether the features trend in a particular direction. The primary purpose of using this spatial centrographic approach is to examine a graphic representation and dispersion of both burglar alarms and NAI/AI burglaries.

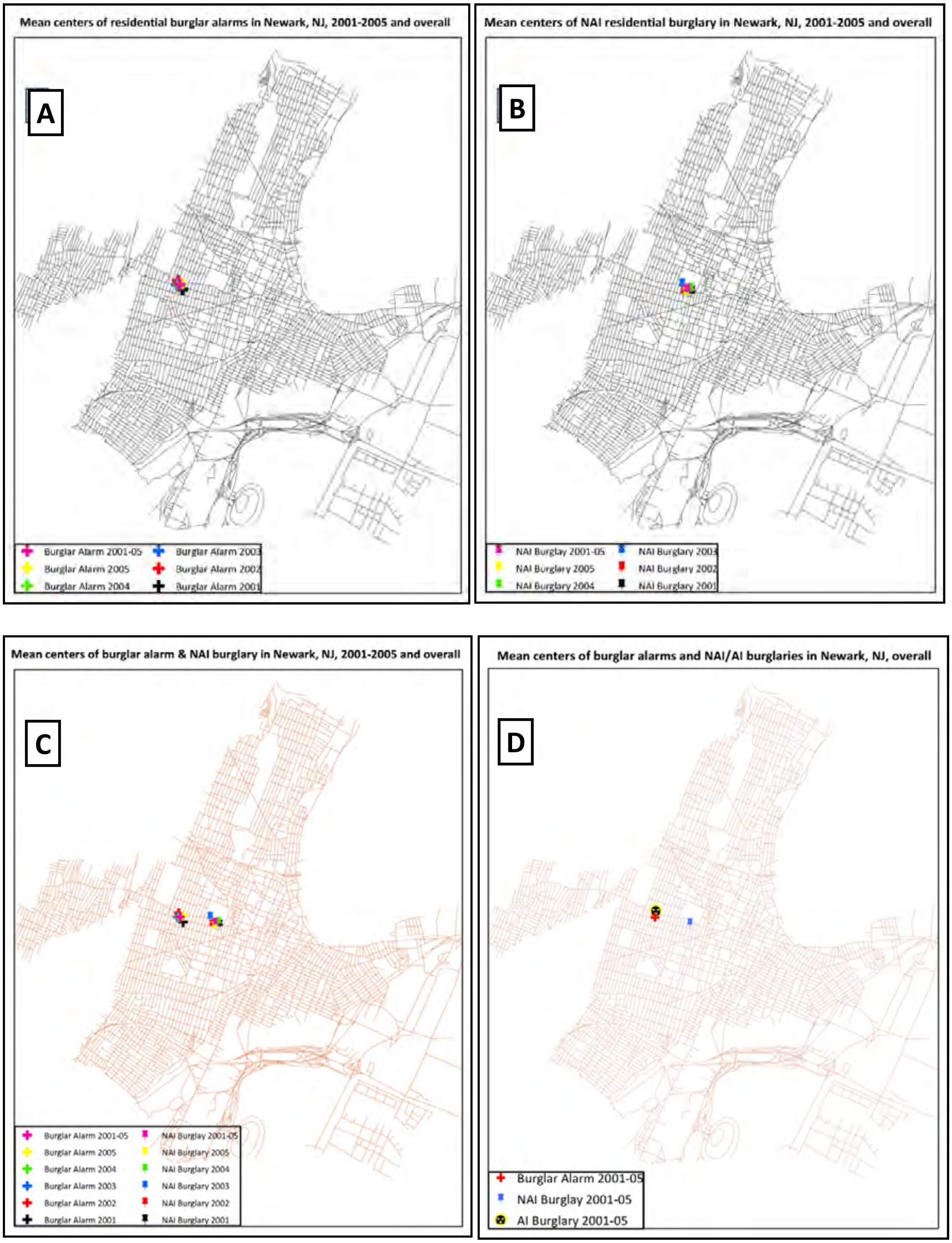
1. Measures of Spatial Centrality for Burglar Alarms and Residential Burglaries

Finding the geographic center of a group of features is useful for tracking change in the distribution. Three measures of such a center are used: mean center, median center, and central feature. The underlying concepts and assumptions of these features are quite similar to those in quantitative statistics (e.g., mean, mode, and median). For example, the mean center is the average x-coordinate and y-coordinate of all the features in the region this study covers. The median center is the location that has the shortest total distance to all features in the study area, being calculated using the straight-line distance from the x-coordinate and y-coordinate. The central feature is the feature that is the shortest total distance from all other features (Mitchell, 2005). Among these three, the mean center, which represents the most centrally located feature, is primarily used.

As observed and discussed in the previous chapter, the distribution of residential burglar alarms and NAI burglary were spread throughout the city, though many highly concentrated spots existed, and were unevenly located, in the city. In addition to these concentrated areas, it also is worthwhile to map the spatial points of representation of all spots for burglar alarms and NAI/AI burglaries.

Figure 9.1 shows the geographic mean centers of burglar alarms and NAI/AI burglaries. Maps A and B illustrate that the mean centers of residential burglar alarms are located to the left of the mean centers of NAI burglary, which reside in the center of the city. Map C puts these mean centers together, showing that each spatial mean center for both burglar alarms and residential burglary is closely clustered in one proximate geographic area within two distinctive parts of the city. The mean center for AI burglary is near the mean centers of residential burglar alarms.

[Figure 9.1] Mean centers of burglar alarms and residential burglaries annually in Newark, NJ



The distribution of mean centers is a reflection of the overall distribution of burglar alarms and NAI/AI burglaries. As discussed in Chapter 8, the areas with more burglar alarms were more likely to be located in the western and central sections of the city, whereas those of NAI burglary resided in the same sections of the city, as well as in the eastern section of the city (see Figure 8.3). This pattern pushes the mean centers for NAI burglary toward the eastern boundary of the city, away from those of burglar alarms, indicating that the distributive pattern of burglar alarms tends to be clustered more geographically than that of NAI burglary, which is less clustered, or more spatially dispersed, throughout the city. In other words, the city itself is, to a large extent, affected by residential burglary, while some certain sections of the city are influenced by burglar alarms. In particular, some eastern parts of the city definitely have fewer burglar alarms installed than other sections of the city with similar levels of NAI burglary (see Figure 8.3).

It should be noted that, like with any quantitative statistic, one or more outliers can skew the mean center or median center. An outlier may be a feature that is located incorrectly—especially if the street address was incorrectly geocoded. Furthermore, multiple events at a single location are stored as individual features in the geographic information system (GIS) database.

2. Measures of Spatial Dispersion for Burglar Alarms and Residential Burglaries

Measuring the compactness of distribution provides a single value representing the dispersion of features around a geographic center. There are two measures for spatial compactness of any distribution: standard distance deviation and standard deviational ellipse. Standard distance deviation is the spatial equivalent of the standard deviation, a statistic mainly employed to describe the dispersal of values around the mean. The difference lies in that the standard distance deviation is a distance, so the compactness can be represented on a map by drawing a circle with the radius equal to the value. The value can be used to compare two or more distributions or to compare the same type of feature over different time periods (e.g., daytime and nighttime burglaries). The standard distance deviation value is expressed in the units in which the features are represented. The greater the standard distance value, the greater the distance varies from the average, and the more widely dispersed the features are around the center (Chainey and Ratcliffe, 2005; Mitchell, 2005).

On the other hand, the standard deviational ellipse measures the orientation and direction of spatial compactness. It can be thought of as a directional equivalent of the standard distance. The ellipse measures the standard deviation of the features from the mean center on the x-coordinates and the y-coordinates individually. An ellipse can be drawn using two, or more, standard deviations. An ellipse calculated using one standard deviation shows where features are concentrated. An ellipse calculated using two or more standard deviations shows where most of the features occur (Mitchell, 2005).

Thus, the standard deviational ellipse provides an accurate examination if the distribution of features is elongated, and hence has a particular orientation. It gives a more accurate picture than using the standard distance circle because the result is based on a statistical calculation rather than a visual interpretation of map output. The information also can be used in comparing the distributions of categories of features and for comparing a single feature at different times (Chainey and Ratcliffe, 2005). These two analytical tools can be incorporated in conjunction with the mean centers.

Maps A and B in Figure 9.2 present the standard distance deviations and standard deviational ellipse of burglar alarms (red) and NAI burglary (blue), together with the mean centers. Both the standard distances and ellipses share the same spatial point as mean centers and use one standard deviation distance from the mean, which contains about 68 percent of the addresses of both burglar alarms and NAI burglary. The standard distance deviation circle of burglar alarms is larger than that of NAI burglary, showing that the distribution of burglar alarms tends to be more dispersed from the mean center than residential burglary and indicating that an equal measure of the standard distance from the mean center for all burglar alarm points is longer and less concentrated than NAI burglary, despite the fact that the overall geographic area covered by the densest distributions of burglar alarms is smaller than that of NAI burglary (see Figure 8.1 and Figure 8.3). On the other hand, the distribution of NAI burglary seems to be more clustered around the mean center in comparison with the wider distribution of burglar alarms, implying that the measure of the standard distance for NAI burglary is shorter than that of burglar alarms.

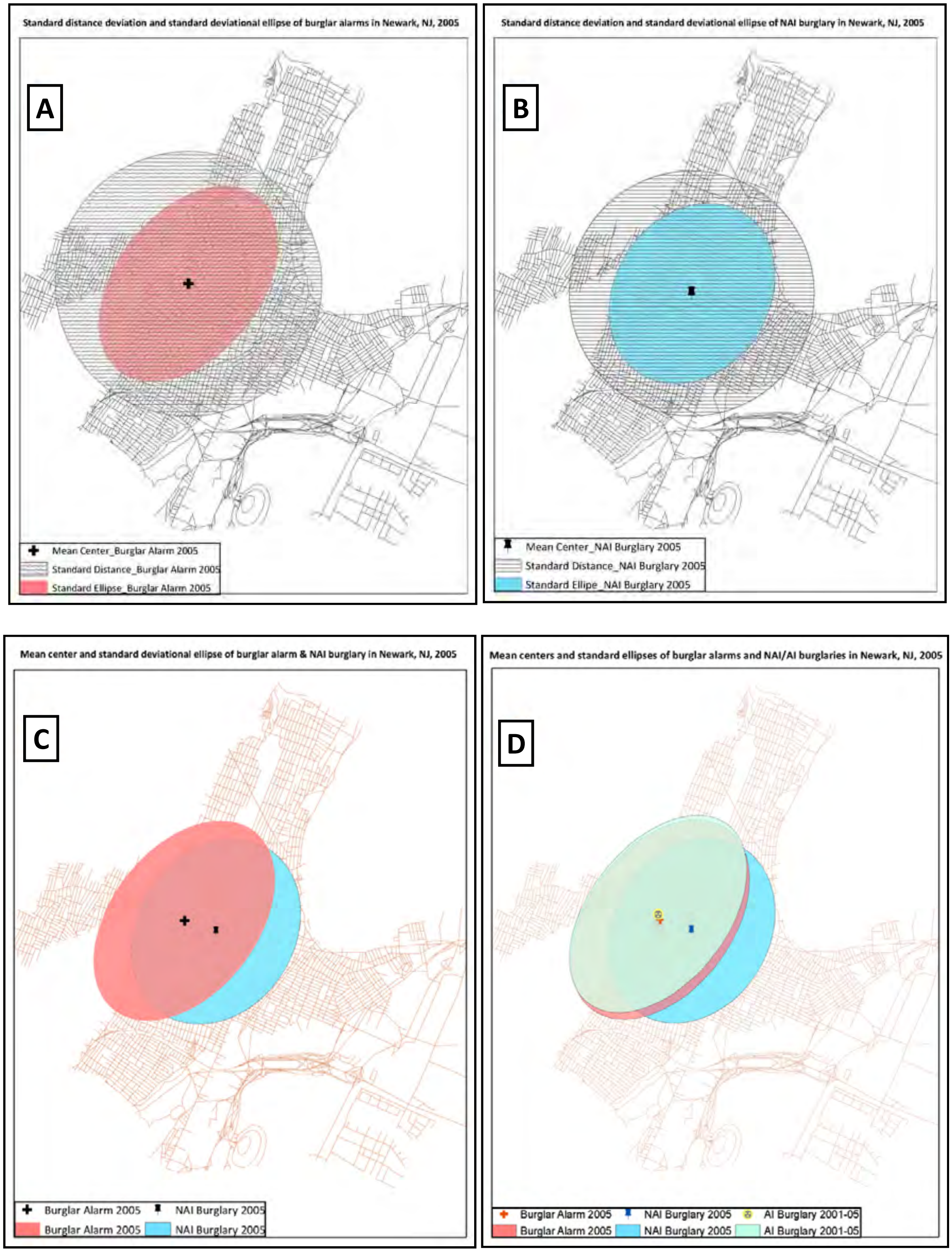
Regarding the standard deviational ellipse in Figure 9.2, both ellipses for burglar alarms and NAI burglary (map C) show an explicit orientation, both being inclining toward the east because both distributions for burglar alarms and NAI burglary in the city have dense areas toward the upper northeastern and lower southwestern sections (see Figure 8.3), which elongate the standard deviation distances into the current shapes.

But though the ellipses have the same orientation, the sizes are different. For example, map C, which overlays burglar alarms and NAI burglary data from Figure 9.2, illustrates that the ellipse shape for burglar alarms (red) is a thinner oval than that of NAI burglary (blue). This observation indicates that while many dense areas of burglar alarms reside in the western section of the city, NAI burglary has dense areas of distributions in the same western section, but also in the eastern section of the city (see Figure 8.3). In other words, the distribution of NAI burglary is wider spread than that of burglar alarms. It stretches the oval shape of the standard deviational ellipse for NAI burglary wider toward the western and eastern boundaries of the city than burglar alarms.

Map D overlays the standard deviational ellipse for AI burglary on the ellipses for burglar alarms and NAI burglary, together with the mean centers. The orientation of the three features is fairly similar, and the size for AI burglary is matches the other two features. The similar pattern can be explained mainly by the distribution of AI burglary being based upon those of NAI burglary.

Figure 9.2 clearly demonstrates that the standard deviational ellipse is more sensitive to the geographic distributions of burglar alarms and residential burglaries than the standard distance deviation. Thus, its measures provide better information and understanding about geographic distributions and patterns of these features.

[Figure 9.2] Standard distance deviation, standard deviational ellipse, and mean center of burglar alarms and NAI/AI burglaries in Newark, NJ, 2005



But some of these observations contradict the factual observations from the previous chapter (see Figure 8.3). The number of dense areas of burglar alarms in the city are fewer than that of NAI burglary and cover smaller geographic sections of the city, in particular, in the western section of the city. At the same time, the areas of NAI burglary are spread more widely throughout the city because, it can be assumed, a smaller geographic area covered by the features should have a smaller standard deviation distance. Thus, the size of the standard distance deviation for burglar alarms should be smaller than that of NAI burglary. But the actual maps above show the opposite.

This phenomenon is closely associated with the assumption that the standard distance deviation is an equal measure in every direction from the mean. As observed in Figure 9.2, the geographic area covered by both the dense spots and the overall distribution of burglar alarms is smaller than that of NAI burglary, but this does not mean that the size of the standard distance also coincides with the geographic area of burglar alarms and, thus, is smaller in size in comparison to NAI burglary. The same assumption for the standard deviation in quantitative statistic explains this phenomenon in the sense that though distributions of burglar alarms cover a smaller geographic area, the standard deviational distance can be larger when all points of those features are clustered near each other but located farther from the mean center, because both the standard deviation and standard deviational distance are solely based on the mean and mean center. Thus, both the standard deviational distances and standard deviational ellipses, in conjunction with the points and density maps in Chapter 8, indicate that the distribution of residential burglar alarms covers a relatively smaller geographic area than NAI burglary, but burglar alarms are much clustered than NAI burglary.

In addition, two issues should be mentioned. First, the standard distance deviation lacks directional focus (Chainey and Ratcliffe, 2005). Irrespective of the spread of the points in a particular direction, the standard distance is an equal measure in every direction. A more useful type of global dispersal measure is the standard deviational ellipse. Second, both the standard distance deviational and the standard distance ellipse are affected by outliers. In particular, regarding the orientation or size of the ellipse, the latter can be skewed by a few outlying features and, thus, not provide an accurate picture of the distribution.

Furthermore, though those analyses are useful and necessary to examine spatial patterns and characteristics for burglar alarms and residential burglaries, they have been analyzed and discussed without statistical tests. In other words, without a statistical approach for the spatial data, the geographic observations presented and discussed previously cannot be confirmed and, the null hypotheses for the spatial pattern analysis cannot be tested. Thus, it is imperative to conduct spatially statistical tests. But even with these limitations and issues, standard deviational ellipses are an improvement over standard distance deviations in terms of indicating point dispersion and direction of that dispersion.

III. Spatial Autocorrelation Analyses for Burglar Alarms and Residential Burglary at the Macro-Level

In the above section, the geographic representation and dispersion of the features for burglar alarms and NAI burglary at the city level were presented and discussed.

But spatial statistics measuring patterns is more accurate than identifying patterns by examining maps. For spatial statistic measures, the concepts of global and local statistics are used. Global statistics focus on whether the features form a pattern across the study area and the type of pattern that exists, whereas local statistics focus on individual features and their relationship to nearby features (Mitchell, 2005). In other words, the global method calculates a single statistic that summarizes a geographic pattern for the study area, while the local method calculates a statistic for each feature based on its similarity to its neighbors.

For example, the spatial impact of residential burglar alarms on residential burglary can be examined on the city level as a single unit of analysis, rather than on the neighborhood level or by sections within the city. This approach can be a global statistic in order to identify and measure overall geographic patterns. If the approach focuses on local or neighborhood variations for the impact of burglar alarms on residential burglary within the city, it would be considered local statistic.

This section uses the first approach, a global statistic to identify a clustered pattern in the city at different times looking for the geographic distribution impact between burglar alarms and residential burglary. Any distribution of features or values within a defined area can create a pattern. Geographic patterns range from completely clustered at one extreme to completely dispersed at the other. A pattern that falls at a point between these extremes is said to be random. Thus, knowing if there is a pattern in the data is useful to have a better understanding of a geographic phenomenon, monitor conditions on the ground, compare patterns, or track changes.

One way of identifying patterns in geographic data is to use statistics to measure the extent to which features or values are clustered, dispersed, or random. With that measure, it can be possible to compare the patterns for different sets of features or compare patterns over time. Using statistics to measure patterns is more accurate than identifying patterns by looking at a map. Global statistics are used to determine whether the features form a pattern across the study area and on what type of pattern exists.

For instance, as seen and discussed in the previous chapter (see Figure 8.3), many heavily dense spots exist across the whole city for the distribution of both burglar alarms and NAI burglary. One observation from the data is that all the points of burglar alarms and NAI burglary are not randomly distributed but have explicit patterns, which implies that residential burglar alarms have some positive impact on residential burglary by pushing away NAI burglary. If a spatial statistical test confirms this observation as being statistically significant, the spatial relationship between burglar alarms and NAI burglary is more reliable and supportive of the positive impact of burglar alarms on residential burglary.

Two primary approaches can be applied for spatial autocorrelation at the global statistic level: (1) measurement of the spatial pattern by discrete features[23] (e.g., points, lines, or noncontiguous areas), using quadrant analysis, nearest neighbor index (NNI), and k-function; and (2) measurement by attribute values

[23]) Discrete features can be points, lines, or areas. Points are used to represent either stationary features or events that occur at a specific place and time. Lines can be disjunctive or connected in a network. Discrete areas are usually distinct and separate, but may share a border or even overlap as fire boundaries often do (Mitchell, 2005).

associated with the features (e.g., census tracts or census blocks), using join count, Geary's C and global Moran's *I*, and general G (Chainey and Ratcliffe, 2005; Mitchell, 2005). Among these measures, NNI and global Moran's *I* approaches are most commonly applied to crime data.

1. Measure of the Nearest Neighbor Index (NNI) for Burglar Alarms and Residential Burglaries

As observed in Chapter 8, several dense areas of burglar alarms and residential burglaries exist across the city. A critical question about those areas is whether the distribution of the points within each area is clustered or dispersed with statistical significance, which can explain the spatial impact of residential burglar alarms on residential burglaries.

The NNI is a distance statistic for point pattern data sets that gives an indication of the degree of clustering of the points. The simple assumption for the NNI analysis is based on the comparison of the actual (or observed) distribution of features to a hypothetical random (or expected) distribution of the same number of features over the same study area, which enables the null hypothesis test for spatial data. Thus, the analysis compares the characteristics of an observed set of distances between pairs of closest points with distances that would be expected if points were randomly placed. It finds the distance between each feature and its closest neighbor, then calculates the average (or mean) of these distances. The results of NNI values are used for statistical significance (Chainey and Ratcliffe, 2005).

There are three general types of geographic pattern (see Table 9.1). A clustered pattern is often the most common form of spatial pattern seen with crime data because neither opportunities nor the routine activities of offenders and victims are randomly distributed. If a pattern is more widespread, it is possible that is exhibits the second type of spatial pattern: a random distribution. In this type of pattern, although there may be some local clusters, the overall pattern of the crime series is spread across the study area without any apparent pattern—an event has an equal chance to appear anywhere in the study area. The third type of pattern is a dispersed distribution. This occurs where points are spaced roughly the same distance apart (Chainey and Ratcliffe, 2005; Mitchell, 2005).

[Table 9.1] Nearest Neighbor Index (NNI) ratios and results

NNI Ratio	Pattern
Ratio = 1	**Random** (no apparent pattern)
Ratio < 1	**Clustered** (similar values are found together)
Ratio > 1	**Dispersed** (high and low values are interspersed)

(Source: Mitchell, 2005)

NNI ratios can range from 0.0, for the distribution of features (e.g., burglar alarms and NAI/AI burglaries) that have all the points at the same geographic location, through 1.0, for a random distribution of points, up to a maximum value of 2.15. Values less than 1.0 indicate a clustered pattern (Chainey and Ratcliffe, 2005). Thus, if the NNI value is less than 1.0 and the *p*-value is less than 0.05, the probability that the distribution of the features is clustered due to random variation is less than 5 percent, which is a statistically significant finding.

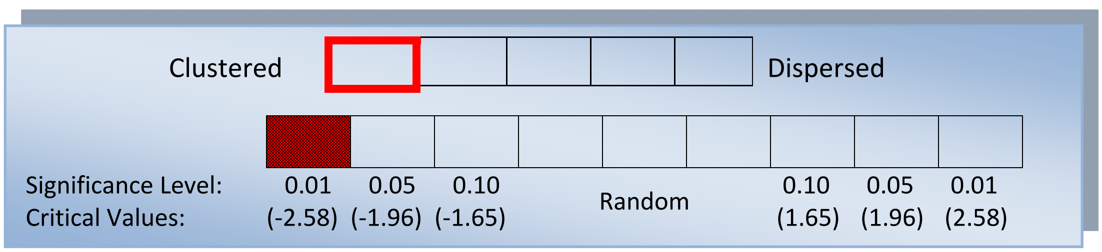
Table 9.2 displays the values of NNI ratio and z-scores with the statistical significance level for burglar alarms and NAI/AI burglaries. Figure 9.3 demonstrates two positioning continua of NNI ratio values and z-scores: one at the five-class continuum between clustered and dispersed, and the other at the nine-class continuum for the position of z-scores between plus (+) and minus (-) three standard deviations.[24] The null hypothesis is that the features (e.g., burglar alarms and NAI/AI burglaries) are randomly distributed in the city.

[Table 9.2] NNI rations and z-scores for burglar alarms and NAI/AI burglaries annually in Newark, NJ

Type	Residential Burglar Alarms						NAI Residential Burglary						AI
Year	2001	2002	2003	2004	2005	overall	2001	2002	2003	2004	2005	overall	overall
NNI Ratio	0.39	0.42	0.38	0.37	0.37	0.13	0.38	0.39	0.37	0.40	0.44	0.24	0.49
Z-score	-39.3**	-34.5**	-45.1**	-49.8**	-53.8**	-142.5**	-58.9**	-57.6**	-55.9**	-52.3**	-40.9**	-150.4**	-18.6**

** Statistically significant at the .01 level

[Figure 9.3] The results of NNI analyses



Regarding the NNI ratio for residential burglar alarms, the values are around 0.4, on average, with a statistical significance at the 0.01 level, rejecting the null hypothesis that burglar alarms are randomly distributed in the city and indicating that the distribution of burglar alarms is not randomly scattered but heavily clustered at certain geographic spots being affected by socio-economic conditions.

24) These two positioning continua are a typical, visual output for geographic statistical analysis in the ArcGIS computer software.

The results clearly support earlier observations and discussions in Chapter 8 about the pattern of burglar alarms.

The NNI ratios for both NAI/AI burglaries also are around 0.4, on average, with a statistical significance at the 0.01 level, which implies that NAI/AI burglaries are not evenly scattered across the city, but clustered within certain areas or neighborhoods. This finding also supports the earlier observations about the distribution of NAI/AI burglaries in Chapter 8. A substantially spatial relationship between burglar alarms and residential burglaries exists. Thus, for both burglar alarms and NAI burglary, the null hypotheses that the features are randomly distributed throughout the city are rejected.

Furthermore, combining Table 9.2 and Figure 9.3, this observation proposes that the distributions of both burglar alarms and NAI/AI burglaries are influenced by neighboring locations. This phenomenon is called a "spatial autocorrelation (or spatial dependency)," which means that, in general, places closer together are more likely to have a similar value (Chainey and Ratcliffe, 2005).

This can explain the installation pattern of residential burglar alarms by residents in certain neighborhoods. For example, when the NNI ratio for burglar alarms shows a clustered pattern with statistical significance, an installation of a alarm system at one geographic point directly affects the proximate or nearest location causing the installation of burglar alarms, and from the next nearest location to the surrounding area, and so forth. Then, after a certain time period, a relatively dense, but limited, geographic area for residential burglar alarms can be created. Once such a specific spot is created, it becomes self-sustaining and growing.

Such a process and phenomenon can occur in many small geographic areas in the city simultaneously or according to different timelines.

Thus, these dense spots of residential burglar alarms throughout the city tend to be clustered together in a geographic dimension, to provide protective seals over these particular areas and to keep residential crime rates comparatively lower than the areas without enough burglar alarms by pushing away residential burglar(s). One burglar alarm system at a house creeps into the next house. Such a spatial phenomenon demonstrates the positive impact of burglar alarms on residential burglaries. The descriptive geographic analyses in Chapter 8 visualize such spatial distributions (see Figure 8.1 and Figure 8.3). In particular, most of the heavily dense spots of burglar alarms are isolated from those areas of NAI burglary. More importantly, this is the basic concept of the "diffusion of benefits" of crime prevention schemes, which will be discussed in greater detail in the following chapter. Nonetheless, residential burglar alarms can be self-sustainable and can spread the diffusion of benefits of crime prevention to the neighborhood.

By the same token, the victimization pattern of residential burglary can be explained by a similar process and phenomenon using the pattern for residential burglar alarms. In other words, two crucial questions can be answered based on the values of the NNI ratios and z-scores with statistical significance: (1) Why is NAI burglary not spread evenly throughout the city?; and (2) Why do many heavily dense areas of NAI burglary exist across the city? The same spatial effect may occur for the pattern of crime victimization by residential burglary.

2. Measure of the Global Moran's *I* for Burglar Alarms and Residential Burglaries

Moran's *I* is a classic measure of global spatial autocorrelation and is commonly applied to crime data. The advantage of Moran's *I* over NNI analysis is that while NNI measures the clustering in points, Moran's *I* can show if there is significant clustering in a variable (Chainey and Ratcliffe, 2005). This means, for example, that the process is able to determine whether there is clustering in the patterns for burglar alarms or residential burglaries, even if those patterns are aggregated to the same set of polygons. Thus, global Moran's *I* can determine whether the dense areas of both burglar alarms and residential burglaries also are surrounded by other dense areas of burglar alarms and residential burglaries, and whether less dense areas are surrounded by other less dense areas. If so, then the patterns of burglar alarms and residential burglaries are said to display positive spatial autocorrelation. If, however, less dense areas are surrounded by dense areas of burglar alarms and residential burglary, and dense areas are surrounded with less dense areas, the series would display negative spatial autocorrelation. If there is no pattern to the distribution of dense and less-dense areas, then the series would have zero spatial autocorrelation (Mitchell, 2005).

Table 9.3 shows the range of possible values of Moran's *I* index from - 1 to 1. If all neighboring features have close to the same value, the index value will be near 1 with a positive z-score, indicating complete clustering of values. Conversely, if the values are completely dispersed, the value of the index is near - 1 with a negative z-score.

[Table 9.3] Global Moran's *I* Index values and results

Moran's *I* Index	Pattern
Ratio = 0	**Random** (zero spatial autocorrelation)
Ratio < 1	**Clustered** (positive spatial autocorrelation)
Ratio > -1	**Dispersed** (negative spatial autocorrelation)

(Source: Mitchell, 2005)

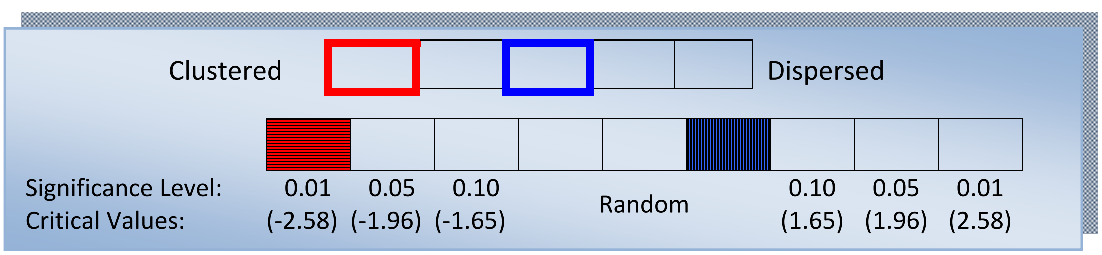
Table 9.4 displays index values of Moran's *I* for burglar alarms and NAI/AI burglaries to examine the spatial relationships. Figure 9.4 demonstrates the position of Moran's *I* indexes in the continuum between clustered and dispersed and the position of z-scores in the continuum between plus (+) and minus (-) three standard deviations.

[Table 9.4] Global Moran's *I* values for burglar alarms and NAI/AI burglaries annually in Newark, NJ

Type	**Residential Burglar Alarms**						**NAI Residential Burglary**						**AI**
Year	2001	2002	2003	2004	2005	overall	2001	2002	2003	2004	2005	overall	overall
Moran's Index	0.04	0.04	0.09	0.09	0.05	0.08	0.00	-0.01	0.00	0.00	0.00	0.00	0.00
Z-score	3.7**	3.9**	7.4**	7.6**	5.0**	6.5**	1.4	0.9	1.4	1.4	1.2	1.3	0.8

** Statistically significant at the .01 level

[Figure 9.4] The results of Global Moran's *I* analysis for burglar alarms and NAI/AI burglaries



For residential burglar alarms
For NAI/AI residential burglaries

For residential burglar alarms, the average value of Moran's *I* Index is about 0.06 with a statistical significance at the 0.01 level. Figure 9.4 shows that the spatial pattern of residential burglar alarms is clustered, confirming the previous finding with the NNI analysis and demonstrating that features near each other are more alike than features far apart. Many dense areas of burglar alarms in the city exist because, as discussed in the previous section, the distribution of burglar alarms in a certain dense area is not isolated from other dense areas, but surrounded by dense areas of distribution of burglar alarms, which consequently creates a heavily dense spot in the city. Furthermore, the dense areas of burglar alarms themselves are not isolated from other spots but surrounded by them, which enables all these dense areas to be clustered.

Thus, not only do heavily dense spots of burglar alarms exist in the city, but also these spots reside in considerable proximity, being bound by the mutual gravitation of surrounding dense spots. This observation supports the positive impact of residential burglar alarms to neighboring geographic areas. In other words, the effect of diffusion of benefits of burglar alarms delivers a comparatively high level of diffusion of benefits to the neighborhoods where burglar alarms have been installed.

NAI residential burglary, however, the average value of Moran's *I* index is 0.00 with no statistical significances (but the z-scores are not close to 0.0), which indicates that unlike burglar alarms, statistical analysis does not support spatial clustering for NAI burglary. The results do not mean that spatial clustering completely does not exist throughout the city. It does show that although the individual distribution of points within individual spots is clustered and many dense spots of NAI burglary exist, the distribution of these dense spots at the city level is not clustered, but rather dispersed, because those spots are not distributed closely to each other, but are instead randomly spread throughout the city.

Three issues for the above observations of the Moran's *I* value should be noted. First, unlike burglar alarms with a statistical significance at the 0.01 level, NAI burglary has almost 0 spatial autocorrelation with no statistical significance. However, by and large, this finding may coincide with the distribution of burglar alarms and NAI burglary because the positive spatial autocorrelation for burglar alarms is associated with the most heavily dense spots, located in the western, central, and southwestern sections of the city, whereas the 0 spatial autocorrelation for NAI burglary is related with many heavily dense spots spread throughout the city. In other words, the former is concentrated in smaller geographic sections of the city, while the latter is scattered around the city, which global Moran's *I* test does not show a statistical significance.

Second, the different observations between burglar alarms and NAI burglary according to the Moran's *I* are closely related to the geographic density map discussed in the previous chapter (see Chapter 8). The average number of burglar alarms and NAI burglary over the five years are 2,138 and 2,269, respectively (see Table 5.1), though each year has discrepancies. Thus, the total number of burglar alarms and NAI burglary per year is similar, but the geographic distribution of them shows a quite different pattern. The distribution of dense spots for burglar alarms is concentrated in the western, central, and southwestern areas of the city, whereas the distribution of NAI burglary is spread across the city. The overall size of the geographic area for burglar alarms is definitely smaller than that of NAI burglary. It produces a higher geographic compactness for burglar alarms and a lower compactness for NAI burglary. Therefore, global Moran's *I* shows the positive spatial autocorrelation for burglar alarms and the zero spatial autocorrelation for NAI burglary.

Third, such global spatial statistics as NNI ratio and Moran's *I* may provide little insight into the location, relative scale, size, shape, and extent of hotspots. Those spatial association statistics examine whether the number of point events in an area is similar to the number of point events in neighboring areas. In general, they explore the spatial autocorrelation between data variables and can determine if positive spatial autocorrelation is said to exist. But these global statistical measures often tend to summarize an enormous number of possible disparate spatial relationships in crime data (Chainey and Ratcliffe, 2005). It is imperative to examine the spatial impact of burglar alarms on residential burglaries at the micro-level with local spatial statistics. Nevertheless, the critical point here is that this observation from the Moran's *I* analysis is not contradictory to the positive impact of burglar alarms on residential burglary.

IV. Spatial Clustering Analyses for Burglar Alarms and Residential Burglaries at the Micro-Level

In the above section, the spatial pattern and impact for both residential burglar alarms and burglaries were presented and discussed on a city level with the overall features of all distributions of burglar alarms and residential burglaries, using global geographic statistics. Local spatial statistics also can be used to focus on individual features and their relationship to nearby features.

Local spatial statistics are useful to identify the spatial association between a single value and its neighbors. Using a local statistic can help find hotspots when a global statistic indicates that there is a clustered pattern. In other words, if a global statistic indicates there is spatial autocorrelation, the measure of local variation can help pinpoint which feature or features are contributing to it. For example, the clearly clustered pattern for both burglar alarms and NAI residential burglaries are identified at the entire city level in the previous section. Are those observations consistent even at the local level within the city? Local indicators of spatial association statistics (Chainey and Ratcliffe, 2005) can be used to provide a better understanding and insight of the geographic patterns and impact between burglar alarms and residential burglaries.

Unlike the spatial autocorrelation statistics with the whole city as a unit of analysis, census tract of the city are used as a unit of analysis for local indicators of spatial association statistics. Thus, local spatial statistics can show consistency and validity of the earlier observations and discussions regarding the spatial relationship and impact for burglar alarms and residential burglaries, and provide better insight into the spatial patterns and relationships at the micro-level.

Three measures of spatial local statistics are available: local Geary's *C*, local Moran's *I*, and General Gi*. They are calculated and used in different ways each with its strengths and weaknesses. For example, local Geary's *C* compares the values of neighboring features by calculating the difference between them. It emphasizes how features differ from their immediate neighbors because it compares the values of neighboring features directly with each other. On the other hand, Local Moran's *I* compares each value in the pair to the mean value for all the features in the study area. Thus, it emphasizes how features differ from the values in the study area as a whole because it compares the value of each feature in a pair to the mean value for all features in the study area. Gi* compares neighboring features within an area that a researcher specifies. It is useful to find hotspots or coolspots because the results indicate the extent to which each feature is surrounded by similarly high or low values (Mitchell, 2005). Among them, local Moran's *I* and Gi* are employed here for spatial clustering analyses.

1. Geographic Clustering Analyses

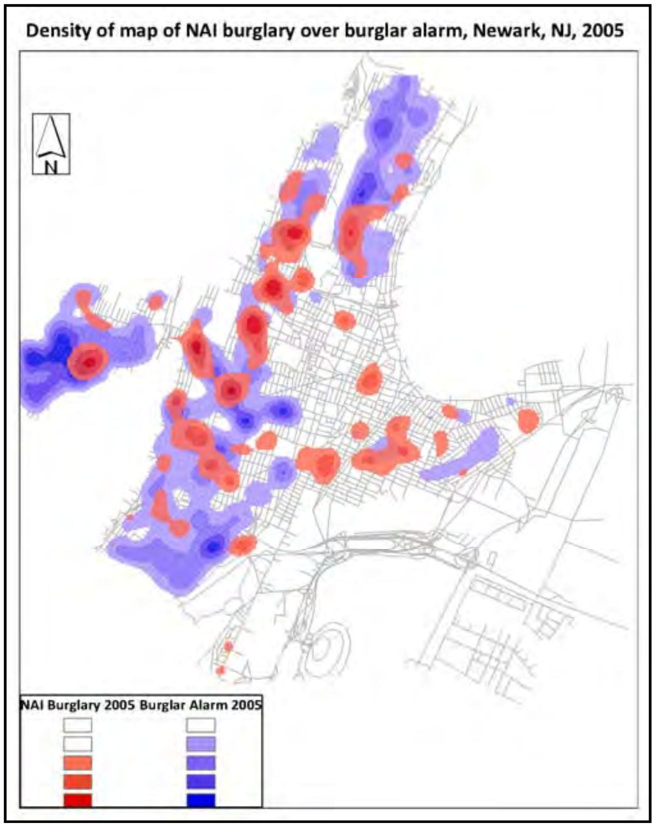
To measure the impact of burglar alarms on residential burglaries, two approaches will be used: macro-level and micro-level. As observed and discussed previously, the macro-level analysis could be employed to examine the impact of alarm systems on crimes at a city level. For this approach, the density function was used to identify the dense spots of residential burglar alarms and NAI/AI burglaries. This method is useful in analyzing the pattern between burglar alarms and residential burglaries, as well as for visually examining whether the dense spots of burglar alarms and residential burglaries overlap.

Further global statistical measures with the NNI ratio and Moran's *I* index are used to test spatially statistical significance for the geographic pattern. Those analyses presented the macro-level impact and directionality (e.g., positive or negative impact) of alarm systems on residential burglaries. One shortcoming of the macro-level approach with aggregated data is that it lacks a micro-level analysis at the level of the single house, census block, or census tract. It is necessary to have more sensitive spatial analyses with disaggregated data at a micro-level in order to examine the impact of burglar alarm systems on residential burglaries.

The fundamental concept for this level's approach is cluster. Clusters occur in a geographic distribution either when features are found in close proximity or when groups of features with similarly high or low values are found together (Mitchell, 2005). In the context of crime analysis, the concept of a hotspot is similar to that of a cluster of features. For example, when similarly high values of features are found closely clustered, it can be identified as a hotspot. The method can be applied to both burglar alarms and residential burglaries.

Clustering at the macro-level is used to examine the impact of burglar alarms on crime at a city-level and can be done by using the density function (or smoothing-out) in ArcGIS. With this method, the individual data points depicting the addresses of either residential burglaries or burglar alarms are "smoothed out" to create an image that shows the areas with the highest density or concentration. Two comparison density estimations for burglar alarms and NAI burglary are produced. The outcome is two separate images of hotspots. An examination of distinctive distribution patterns can determine if they overlap, and statistical tests can show their relationship. Thus, seeing the impact of alarm systems on residential burglaries can be useful. Figure 9.5 is one example of a density map of NAI burglary overlaid with information for burglar alarms in the city in 2005. The map visually displays multiple hotspots for both burglar alarms (blue) and NAI burglary (red). In both cases, darker colors show higher numbers.

[Figure 9.5] Overlaid density map of burglar alarms and NAI burglary in Newark, NJ, 2005



One drawback of the macro-level approach with a larger study area is that it lacks a micro-level analysis at levels of a single house, census block, or census tract. For example, as presented in Figure 9.5, the overlapping hotspots between burglar alarms and NAI burglary exist, in particular, in the western and central sections of the city. Such a spatial observation may lead to misinterpreting the impact of alarm system on residential burglaries. In other words, because of those overlapping hotspots, the issues of displacement and diffusion of benefits are questionable.

Furthermore, it can be argued that the spatial relationship between burglar alarms and residential burglary does not exist. Therefore, more sensitive spatial analyses with disaggregated data at the micro-level are required in order to examine the impact of alarm systems on crime.

2. Local Moran's *I* Analyses for Burglar Alarms and Residential Burglaries

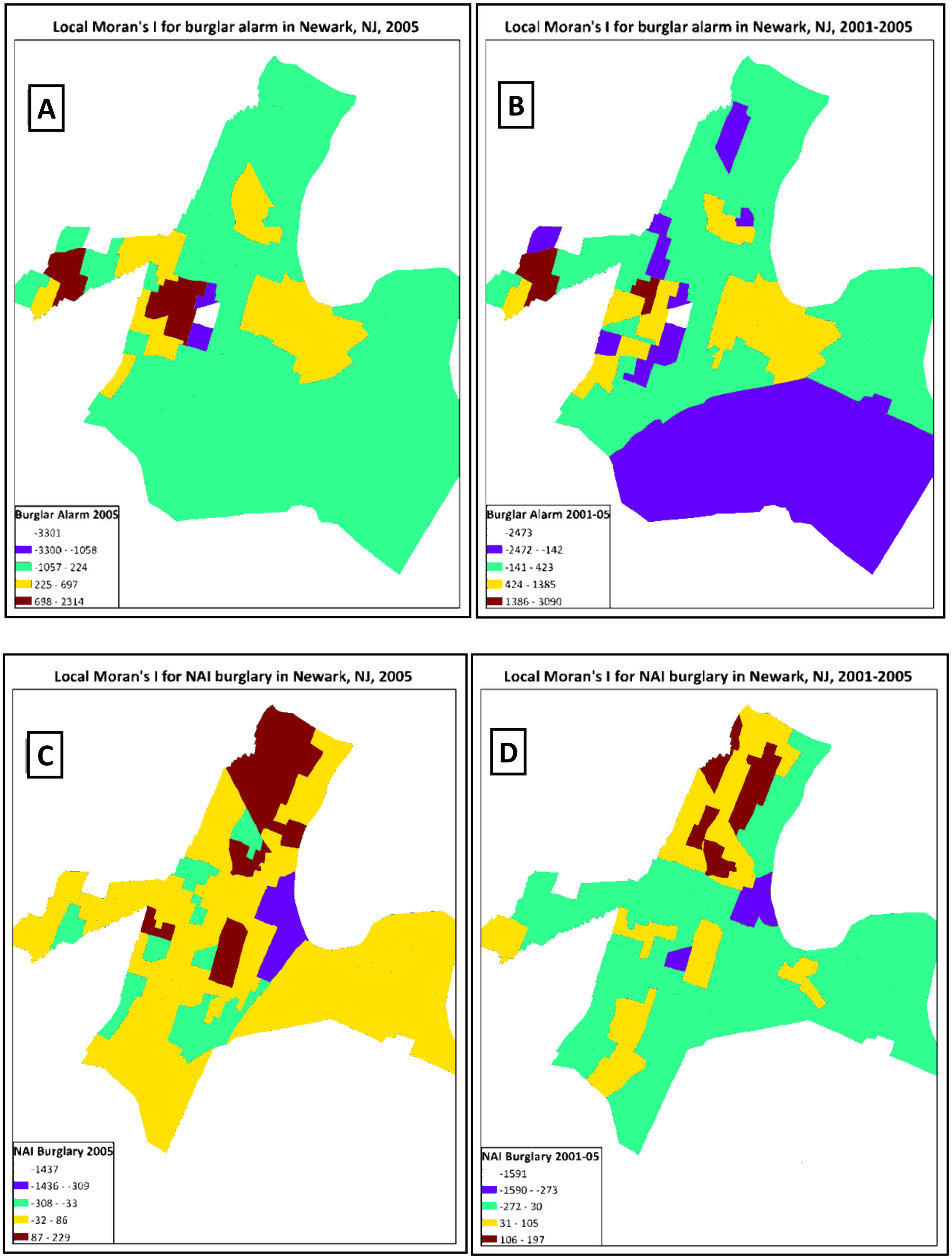
Local Moran's *I* cluster is used to identify the locations of statistically significant hotspots. In particular, it identifies those clusters of points with values similar in magnitude and those clusters of points with heterogeneous values. The cluster analysis output is a Local Moran's *I* value with an associated z-score for each feature. The z-score represents the statistical significance of the index value. It, in effect, indicates whether the apparent similarity or dissimilarity in values between the feature and its neighbors is greater than would be expected by chance.

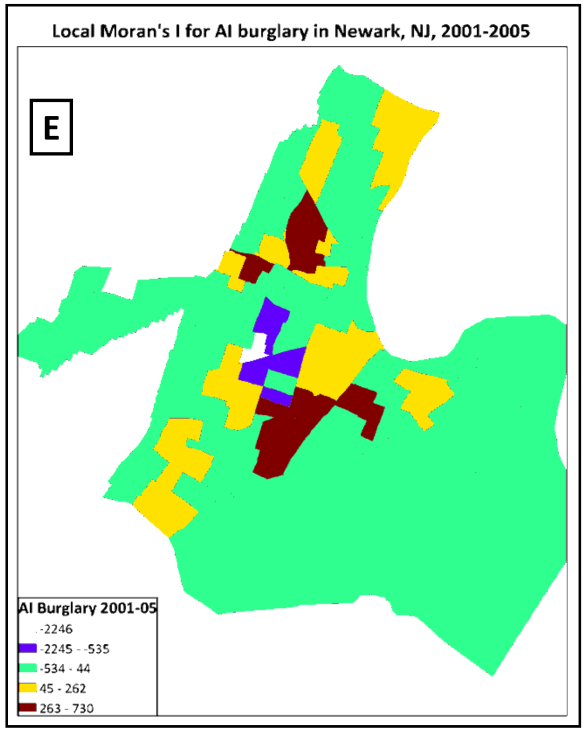
A high positive z-score for a feature indicates that the surrounding features have similar values, either high or low. A group of adjacent features having high z-score indicates a cluster of similarly high or low values. A low negative z-score for a feature indicates that the feature is surrounded by dissimilar values—that is, if a feature has a negative z-score, its value is different than its neighbors (i.e., a high value relative to a neighborhood that has low values or a low value relative to a neighborhood that has high values) (Mitchell, 2005).

This approach can determine the degree to which each feature is similar or dissimilar to its neighbors—where high values are surrounded by high values or low values are surrounded by low values. This method calculates a statistic for each feature and maps the features based on this value to find the locations of features with similar values. It also can locate hotspots and coolspots as this approach looks at values of adjacent features or features within a specified distance and compares the average value for the neighborhood to the average value for the study area. The method also indicates whether clusters are composed of high or low values. Thus, Local Moran's *I* shows local variation, that is what is occurring immediately surrounding each feature. For this approach, 90 census tracts in the city were used as a unit of analysis. Census-tract maps based on Local Moran's *I* analysis illustrate geographic clustering for the attributes (e.g., burglar alarms and NAI/AI burglaries) among the features (e.g., census tract).

Figure 9.6 presents the census maps of Local Moran's *I* for burglar alarms and NAI/AI burglaries for 2005 and the overall. For this analysis, all counts of both burglar alarms and residential burglaries were regrouped and geocoded according to the 90 census tracts. The best way to view and interpret these maps is to examine whether the same color census tract appear next to each other or share the same tract boundaries. The greater the number of areas with the same color gather, the more tracts that are similar. Maps A and B for burglar alarms in Figure 9.6 present the same level of burglar alarms neighboring each other. For example, yellow-colored census tracts with high rates of burglar alarms gather together in the central, eastern, and central northern sections of the city, whereas brown-colored census tracts with the highest rates of burglar alarms are next to each other in the western and central parts of the city.

[Figure 9.6] Local Moran's *I* for burglar alarms and NAI/AI burglaries in Newark, NJ, 2005 and overall





The similar patterns of spatial clustering for NAI and AI burglaries are identified in the remaining maps of C, D, and E in Figure 9.6, showing that census tracts with NAI/AI burglaries are surrounded by neighboring census tracts with substantially similar rates of residential burglaries at several geographic sections within the city.

Several indications are observed from these maps based on Local Moran's *I* analysis. First, as discussed in the previous section and chapters, the distributions of both burglar alarms and residential burglaries on the census-tract level are not evenly scattered across the city. The same geographic observation was found on the city level. Thus, not only on the city level, but also on the census level, the distribution of burglar alarms and residential burglaries are spatially clustered, meaning that the local variations of the levels of alarm installation and NAI burglary exist and those local variations are strongly linked to each other by forming spatial closeness. Therefore, geographic clustering of both burglar alarms and NAI burglary based on the Global and Local Moran's *I* analyses are consistent over the years. In other words, these observations do not occur by random chance, but are closely link to neighborhoods' socio-economic factors.

Second, some of the densest spots of both burglar alarms and NAI burglary, in dark brown, are scattered across the city because the same levels of burglar alarms and NAI burglary tend to gather next to each other on the census-tract level, with the result being relatively large geographic areas occupied with the same color. This observation confirms the earlier findings and discussions based on the NNI ratio and Global Moran's *I* index regarding the spatial clustering of the distributions of burglar alarms and NAI burglary, which are spread evenly throughout the city but spatially clustered in neighborhoods with dense spots forming across the city. These spatial observations from Local Moran's *I* are moderately consistent over the years (see Appendixes 13 and 14).

Third, these geographic observations confirm that the effect of diffusion of benefits can explain the installation pattern of burglar alarms and NAI burglary in Newark, N.J. The densest census tract, shown with a dark brown color, of burglar alarms can affect the neighboring tract and create both yellow and green colors, which eventually creates a group of census tracts. Its group, thus, produces one geographic boundary with the densest rate of alarm installation. The same process can be used to explain NAI burglary. However, the diffusion of benefits of burglar alarms (maps A and B in Figure 9.6) is more apparent and visual than that of NAI burglary.

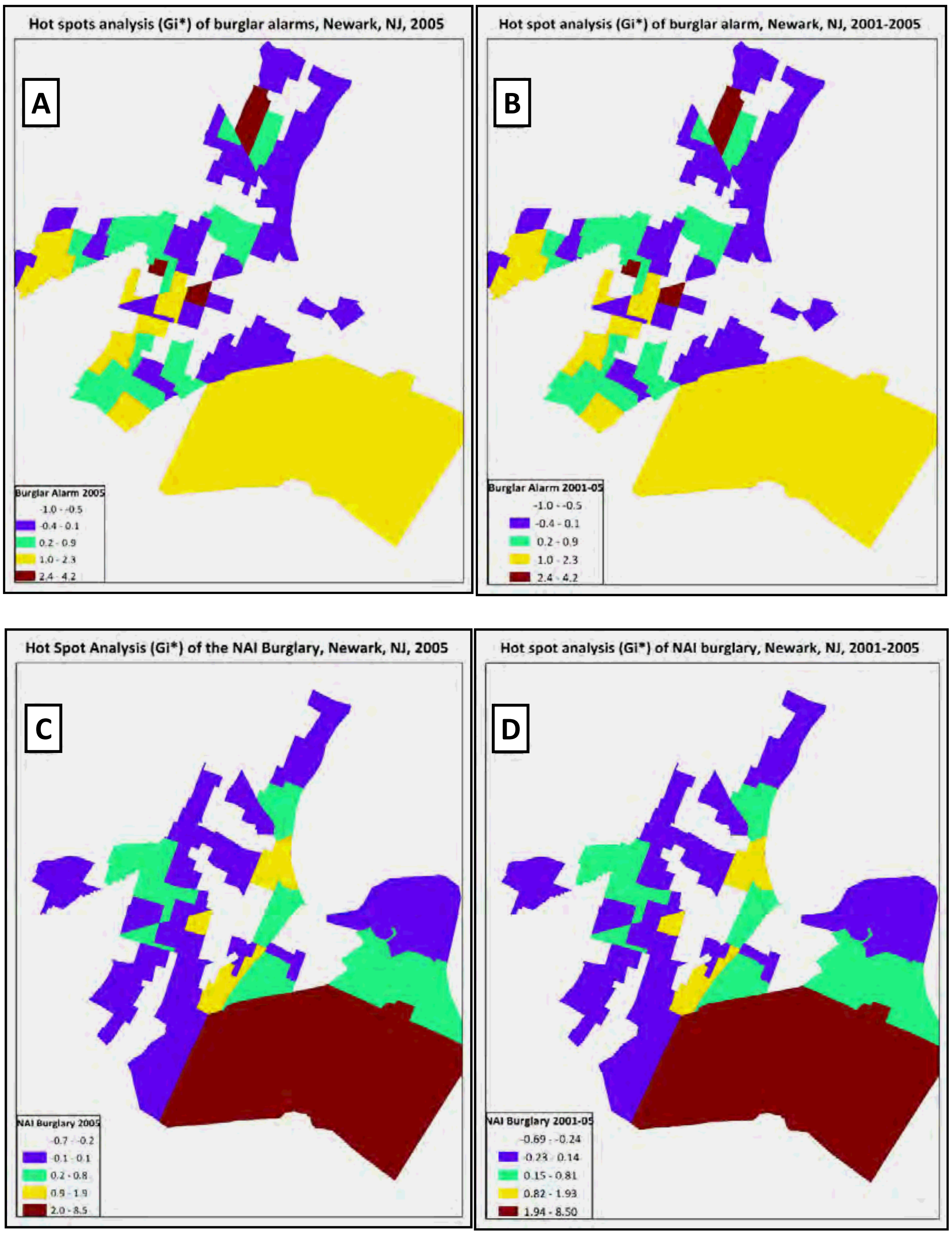
3. Local Hotspots (Gi*) Analysis for Burglar Alarms and Residential Burglaries

The local Gi* analysis describes where geographic clusters of high or low values are located. Gi* statistics identify the extent to which each feature is surrounded by similarly high or low values in an effort to find hotspots or coolspots. A group of features with high Gi* values indicates a cluster or concentration of features with high attribute values. Conversely, a group of features with low Gi* values indicates a coolspot. Thus, a Gi* value near 0 indicates there is no concentration of either high or low values surrounding the target feature (Mitchell, 2005).

Figure 9.7 presents the census-tract maps of Gi* for burglar alarms and NAI burglaries. Like the Local Moran's *I*, the best way to observe and interpret these maps is to examine whether census tracts of similar colors gather together or share boundaries with other similar tracts. The higher the number of same-color clusters, the more each tract in a group is similar. In addition, a census tract with the densest color (brown) can be identified as a hotspot, and the census tract with the lightest color (white) can be recognized as a coolspot. Yellow-colored census tracts with a relatively higher level of both burglar alarms and NAI burglary also can be identified as hotspots.

Maps A and B for burglar alarms by census tract in Figure 9.7 show that most of the same-colored tracts, depending on different levels of the Gi* values, are clearly neighboring each other, forming a group of census tracts with the same level. For example, the first level of several hotspots (brown-colored census tracts) of burglar alarms is seen in the central and northern sections of the city. In addition, the second level of hotspots (yellow-colored census tracts) for burglar alarms is located in the western and southwestern neighborhoods in the city. But the coolspots for burglar alarms are found in some central sections, most of the eastern section, and the central northern section of the city.

[Figure 9.7] Gi^* for burglar alarms and NAI burglary in Newark, NJ, 2005 and overall



A similar pattern of spatial clustering for NAI burglary is identified in maps C and D in Figure 9.7, showing that most of census tracts for NAI burglary are surrounded by the neighboring census tracts with a substantially similar rate of residential burglaries at several geographic sections in the city. In particular, the first and second levels of hotspots (brown- and yellow-colored tracts) for NAI burglary are found in the southern and central eastern sections of the city, while the coolspots are observed throughout the city.

As discussed earlier, the Gi* approach can be used to identify both hotspots and coolspots of distribution of burglar alarms and NAI burglary. The maps in Figure 9.7 illustrate that the hotspots and coolspots for both features exist throughout the city. This observation is consistent with the earlier findings in Chapters 7 and 8. For example, in Chapter 7, it was argued that the distribution of both burglar alarms and residential burglaries was not evenly spread throughout the city, indicating that the variation was due to several key variables of the neighborhoods' characteristics (e.g., burglar alarms, NAI burglary, black population, owner's occupancy, unemployment, population age group over 45 years old, and householder age group of 60 to 64 years old). In Chapter 8 with a series of geographic mapping approaches, those descriptive mapping analyses supported most of the findings from quantitative approaches in Chapter 7. In particular, those maps indicated that the installation pattern of residential burglar alarms had some positive impact on residential burglaries. Furthermore, several statistically geographic analyses confirmed those earlier findings and the existence of the effect of diffusion of benefits of burglar alarms.

V. Chapter Conclusion

Research Question 5 was related to the spatial impact analyses of both burglar alarms and residential burglaries. Using GIS program, some simple spatial statistics (e.g., spatial centrality and spatial dispersion analyses) and advanced spatial statistics (e.g., spatial autocorrelation and spatial clustering analyses) were employed for burglar alarms and residential burglaries.

With regard to spatial centrographic analyses with the focus on spatial distributions of burglar alarms and residential burglaries, three geographic centers were used: mean center, median center, and central feature (which are quite similar to those in quantitative statistics, such as mean, mode, and median). The distribution of mean centers reflected the overall distributions of burglar alarms and NAI/AI burglaries. For example, as seen in Chapter 8, the areas with more burglar alarms were more likely to be located in the western and central sections of city, whereas those of NAI burglary resided in the same sections of the city, as well as in the eastern section of the city. This pattern pushed the mean centers for NAI burglary toward the eastern boundary of the city, away from those of burglar alarms. It showed that the distributive pattern of burglar alarms tended to be clustered more spatially than that of NAI burglary throughout the city. In other words, the city itself was, to a large extent, affected by residential burglary, while some certain sections of city are influenced by burglar alarms.

Spatial dispersion analyses showed that the distribution of burglar alarms was more dispersed from the mean center than residential burglary and that the oval shape of the standard deviational ellipse for NAI burglary stretched wider toward the western and eastern boundaries of the city than burglar alarms, because many dense areas of burglar alarms resided in the western section of the city, whereas NAI burglary had dense areas in the same western section, as well as in the eastern section of the city.

With regard to spatial autocorrelation analyses, both the NNI ratio and global Moran's *I* for burglar alarms and residential burglaries showed that the distribution of them was not randomly scattered but heavily clustered at certain geographic spots across the city being affected by socio-economic conditions. Both findings clearly supported earlier observations about the distributions of burglar alarms and residential burglaries that a substantially spatial relationship between them with other variables existed.

More importantly, the distributions of both burglar alarms and residential burglaries were influenced by neighboring locations, meaning that places closer together were more likely to have a similar value, which is called a spatial autocorrelation. In other words, an installation of a burglar alarm at one geographic point directly affected the proximate or nearest location causing the installation of burglar alarms, and from the next nearest location to the surrounding area, and so forth. Then, after a certain time period, a relatively dense, but limited, geographic are for burglar alarms can be created. Once such a specific spot is created, it becomes self-sustaining and growing. Thus, these dense spots of burglar alarms throughout the city were clustered together in a geographic dimension, provided protective seals over these particular areas, and kept residential crime rates comparatively lower than the areas without enough burglar alarms installed by pushing away residential burglar(s). As a result, most of the heavily dense spots of burglar alarms, as visualized in Chapter 8, were isolated from those areas of NAI burglary. Thus, not only do heavily dense spots of burglar alarms existed in the city, but also these spots resided in considerable proximity, being bound by the mutual gravitation of surrounding dense spots. Such a spatial observation is the basic concept of the "diffusion of benefits" of crime prevention schemes, supporting that burglar alarms had the positive impact on the decrease of residential burglary incidents to neighboring geographic areas.

Regarding spatial clustering analyses, local Moran's *I* for burglar alarms and residential burglaries showed that, on both the city level but also the census level, the distribution of burglar alarms and residential burglaries were spatially clustered, demonstrating that the local variations of the levels of alarm installation and NAI burglary existed and those local variations were strongly linked to each other by forming spatial closeness. In other words, these spatial distributions did not occur by random chance, but were closely link to neighborhoods' socio-economic factors.

Furthermore, local hotspots (Gi*) analysis for burglar alarms and NAI burglary showed that either hotspots or coolspots was clearly neighboring each other by forming a group of census tracts with the same level, indicating that the installation pattern of burglar alarms had some positive impact on the decrease of residential burglaries.

In the following chapter, Research Question 6 will be examined and discussed, which focuses on the spatial displacement and diffusion of benefits of burglar alarms on residential burglaries. Acknowledging the absence of a standardized study design for the measurement of spatial displacement and diffusion of benefits of criminal prevention programs, nonequivalent-group quasi-experimental research design will be discussed. In addition, the theoretical approach of the weighted displacement quotient (WDQ) will be discussed and utilized with nested buffer and control zones approach at the individual household level to devise the research design to measure the spatial displacement and diffusion of benefits. A land parcel map using GIS program also will be used.

CHAPTER 10. DISPLACEMENT/DIFFUSION OF BENEFITS OF BURGLAR ALARMS ON RESIDENTIAL BURGLARIES

I. Introduction

This chapter is directly related to Research Question 6, which examines the spatial displacement and diffusion of benefits of burglar alarms on residential burglaries. In the previous chapters, spatial analyses were conducted to scrutinize the relationship between burglar alarms and residential burglaries. Those analytical approaches used datasets from two primary agency data sources (e.g., police department and city hall) to create new sub-datasets by grouping, regrouping, recounting by topic, and analyzing. Units of analysis were the addresses of both burglar alarms and non-alarm-installed (NAI)/alarm-installed (AI) residential burglaries for quantitative analyses and the entire city and the census tracts for spatial analyses. Those approaches produced insightful and useful knowledge to understand the relationship between burglar alarms and residential burglaries by answering Research Questions 1 through 5. In addition, no specified research design was used for the previous analyses. The primary research method was a secondary data analysis, which, by and large, uses agency data (e.g., federal, state, and local criminal justice agencies) (Maxfield and Babbie, 2008).

However, in order to answer Research Question 6, it is necessary to devise a customized research design at the street and/or single household level. The question requires a whole different approach for research design, measurement, and analysis. It should fit to the theoretical background, and its analytical process should be reasonable and clear to obtain an accurate answer to Research Question 6.

Nonequivalent-groups quasi-experimental research design with buffer function at the individual household level can be employed to examine the spatial displacement and diffusion of benefits of burglar alarms on residential burglaries.

II. Nonequivalent-Groups Research Design for the Measurement of Displacement and Diffusion of Benefits

1. Measurement Issues

One of the most potentially negative consequences of crime prevention programs is that of crime displacement, whether such programs are aimed at well-defined geographic locations or specific population groups. The idea of preventing crime through the manipulation of environmental factors has been plagued with the issue of whether or not crimes prevented are simply displaced to other types of crime, times, places, or tactics (Bowers and Johnson, 2003).

In an effort to understand the extent to which displacement occurs, some researchers have compiled information from a number of studies that have examined crime displacement in general. For instance, Hesseling's (1994) review found that reported cases of spatial and other forms of displacement were in the minority. Eck's (1993) review also found that spatial and other forms of displacement in crime prevention programs were minor. Reppetto (1974) argues that displacement, whether geographic or functional, looms as one of the major obstacles to any strategy for the control of residential crime.

Though literature review shows that spatial displacement is generally not a common phenomenon, rigor for scrutinizing such an observation in crime prevention research has been required. As Bowers and Johnson (2003) noted, the measurement of displacement is notoriously difficult, and different researchers have used a variety of techniques to quantify the phenomenon. Several relevant issues are worth discussing.

One of the problems of the lack of rigorous studies is the absence of a standardized method. As Weisburd and Green (1995) argued, finding the right size for a buffer zone is an important issue in displacement and diffusion of benefit analysis. It should not be so large that any increase in crime due to displacement will be imperceptible, but large enough to ensure that any change is detectable.

2. Measurement at the Individual and Household Levels

In particular, the household-level approach is imperative to examining spatial displacement and diffusion of benefits of burglar alarms on residential burglaries. A number of studies have examined the displacement and diffusion of benefits of crime-prevention initiatives targeting burglaries. The units of analysis for those studies were relatively large geographic areas, such as a census tract and police district (Bowers, Johnson, and Hirschfield, 2003; Ratcliffe, 2005) or street block (Weisburd et al., 2006). In addition, a few studies used the time-series approach to study a burglary-reduction program in Australia (Ratcliffe, 2004). This approach incorporated geographic boundaries (e.g., hotspots).

The previous chapters of this study employed similar approaches and demonstrated that residential burglar alarms maintained a positive impact on residential burglary, showing an effect of diffusion of benefits by creating an invisible protective seal over the dense spots of burglar alarms. However, these methods lack any examination of the displacement and diffusion of benefits of crime-prevention schemes at a household-level in their research design and analysis. Though burglar alarms positively impact residential burglary at the city level or in a relatively large geographic area (e.g., census tract and police district), a household-level analysis may produce similar or quite different spatial analyses.

Thus, it is necessary to examine the displacement and diffusion of benefits of residential burglar alarms on residential burglaries. In the context of studying the impact of burglar alarms on residential burglaries, it is imperative to examine the nature of crime displacement caused by alarm systems in the targeted area and to investigate the potential for diffusion of benefits from alarm security measures, which have been given little attention in the research literature. This approach has several benefits. First, unlike other studies that used a large geographic unit to test this issue, this approach is a first attempt to use the single house as a unit of analysis to closely investigate the spatial displacement and diffusion of benefits of residential burglar alarms on crime.

Second, this examination may or may not confirm the previous observations and findings in Chapters 7 through 9, which indicate that there is a statistically significant relationship between burglar alarm systems and residential burglaries and identifies a spatially positive impact of burglar alarms on residential burglaries. If this analysis shows the same outcome, it proves that alarm systems have a positive impact on reducing or preventing residential burglaries. On the other hand, if this spatial approach reveals the opposite result, it contradicts the previous observations and arguments, meaning that it is not conclusive that burglar alarm systems act as a deterrent in preventing residential burglaries.

As Barnes (1995) argued, however, the measurement of displacement is notoriously difficult, and in the absence of a standardized approach, several researchers have used a variety of techniques to quantify the phenomenon. For this measurement, the buffer function as a micro-level spatial analysis at the single-house level will be used. The buffer and control zones approach will be generated to detect the displacement and diffusion of benefits of alarm systems on crime over time. The nested buffer and control zones have three rings (the inner target area [e.g., house with burglar alarm], middle buffer area, and outer control area). To measure the extent to which alarm systems have an impact on residential burglary, the Weighted Displacement Quotient (WDQ) will be modified and applied. The WDQ examines the rates of burglar alarms and NAI burglaries in the buffer and control zones in a particular year and compares them with the previous year's rate. WDQ values will show the size (e.g., net effect, no effect, or no benefit) and directionality (e.g., positive, negative, or no effect) of the impact of alarm systems on residential burglary.

3. Nonequivalent-Groups Quasi-Experimental Research Design

Quasi-experimental research design (Maxfield and Babbie, 2008; Shadish, Cook, and Campbell, 2002) can be used when randomization[25] is not possible. In most cases,

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[25]) The classical experiment has several requirements and components. The most conventional type of experiment in the natural and the social sciences involves three major pairs of components: (1) independent and dependent variables; (2) pretesting and posttesting; and (3) experimental and control groups. But before beginning any experiment, two crucial decisions must be made: (1) who will participate; and (2) how particular members of the target population will be selected for the experiment. Ideally, these processes must meet the scientific norm of generalizability. For that purpose,

quasi-experiments do not randomly assign subjects to treatment and comparison groups and, therefore, may suffer from the internal validity threats that are well controlled in true experiments. Maxfield and Babbie (2008) regroup quasi-experimental research designs into two categories: (1) nonequivalent-groups designs and (2) time-series designs.

One of the assumptions of random assignment is the equivalence in experimental and control groups. But if a nonrandom procedure is used to construct groups, the design uses nonequivalent-groups. On the other hand, a time-series design involves examining a series of observations of variables over time. In particular, an interrupted time series is a special type of time-series design that can be used in cause-and-effect studies (Maxfield and Babbie, 2008).

It should be noted that there are no simple formulas for designing an experimental or quasi-experimental study. Each category has several modified approaches, depending on the nature of research topic and subject. For the present study, a time-series design is not appropriate because one of the requirements of it is to have a specific time order in the datasets. In other words, a series of observations is compared before and after some form of intervention is introduced. The unit of analysis in this study is the address of burglar alarm permits and NAI/AI burglaries. If the current dataset of burglar alarms had the date of alarm installation, the time-series design would have been a better method. But such information is

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randomization is required. Thus, randomization is a central feature of the classical experiment. The important characteristic of randomization is that it produces experimental and control groups that are statistically equivalent. However, in most criminal justice research, randomization is not easy to execute (Maxfield and Babbie, 2008).

not available, even though the date of NAI/AI burglaries is available. Thus, no proper comparison groups exist for burglar alarms and NAI/AI burglaries if comparing exact dates. As a consequence, the nonequivalent-groups research design is more feasible to adopt for the present analysis. Maxfield and Babbie (2008) suggest three different nonequivalent-groups design examples. Table 10.1 illustrates a diagram of them, using the *X* (intervention program), *O* (data measurement) and *t* (time order) notation.

[Table 10.1] Three examples of nonequivalent-groups quasi-experimental designs

Widom (1989)		**Clarke (1997)**		**Gill and Spriggs (2005)**	
Treatment group	*X* *O*	Treatment group	*O* *X* *O*	Target area 1	*O* X_1 *O*
Comparison group	*O*	Comparison group	*O* *O*	Comparison area 1	*O* *O*
	t_1 t_2		t_1 t_2 t_3	Target area 2	*O* X_2 *O*
				Comparison area 2	*O* *O*
				---	---
				Target area 13	*O* X_i *O*
				Comparison area 13	*O* *O*
					t_1 t_2 t_3
X=official record of child abuse *O*=counts of juvenile or adult arrest		*X*=caller identification and call tracing *O*=customer complaints of obscene calls		X_i=CCTV installation in area *i* *O*=police crime data, survey data on fear of crime	

Source: Maxfield and Babbie (2008)

As Maxfield and Babbie (2008) argue, the first example used by Widom (1989) for the study of the relationship between child abuse and later arrest was produced using experimental and comparison groups matching individual subjects without having a before-and-after research design. The second example was used for the study of deterring obscene phone calls by Clarke (1997a) and employed the before-and-after design because the study has data on the treatment and comparison groups with pre- and post-intervention measures. The third example, used for the evaluation study of CCTV and crime prevention by Gill and Spriggs

(2005), was designed to evaluate 13 CCTV projects installed in a variety of residential and commercial settings. It employed the before-and-after design by creating two types of comparison areas: (1) comparison areas with similar socio-demographic and geographic characteristics and crime problems, and (2) buffer zones as in the area within a 1-mile radius of the edge of the target area where CCTV cameras were installed.

These quasi-experimental design examples above reflect the nature of the research topic and data collected. For example, in the child abuse study (Widom, 1989), it was not possible to assign children randomly to groups in which some were abused and others were not. Thus, a research design was developed without pre- and post-intervention measures. The second example, the study of the effectiveness of newly introduced caller-identification (ID) and call-tracing programs against obscene or threatening phone calls (Clarke, 1997b), was designed based on two criteria: (1) the new telephone services were available (the treatment group); and (2) the services were not (the comparison group). The records of formal customer complaints about annoying phone calls in these two groups were compared to examine whether the number of formal complaints in the treatment group dropped. This design employed pre- and post-intervention measures with the treatment and comparison groups.

The third example, the evaluation study of CCTV on crime (Gill and Spriggs, 2005), is similar to the second example of research design using both the treatment and comparison groups and pre- and post-intervention measures. The unique feature of the study's design is that it uses the concept of buffer zones as a comparison area. The buffer zones have been divided into three concentric rings around a target area. The rationale for buffer zones as comparison areas is that if CCTV is effective in reducing crime, either crime should decline in target areas but not in buffer areas, or any reduction in crime should be greatest in the target areas and the degree of the reduction should decline moving away from the target areas.

As seen in Table 10.2, for the current study, a modified research design from the second and third examples of nonequivalent-groups design is devised and employed by borrowing the assumptions of treatment and comparison groups, pre- and post-intervention measures, and buffer zones. It is not possible to use the same treatment and comparison groups, but instead the two nonequivalent groups of residential burglar alarms and NAI burglary are used. However, as discussed briefly in the previous section, a clear time order for the installation date of all residential burglar alarms is not available. Only aggregate installation data by year (from 2001 to 2005) is available. It would be better to use the year as a unit of intervention time order. Detailed dates of all residential burglaries are on hand, but they also should be aggregated by year for comparison purposes with burglar alarms.

[Table 10.2] Nonequivalent-groups quasi-experimental design for the current study

The Impact of Burglar Alarms on Residential Burglaries		
Burglar alarms 2001	O X_1 O	
NAI residential burglary 2001	O Y_1 O	
		X_i=Residential burglar alarm permits by year i
Burglar alarms 2002	O X_2 O	Y_i=Number of instances of NAI residential burglary by year i
NAI residential burglary 2002	O Y_2 O	O_a=Police incident report data on NAI residential burglary
---	---	O_b=City Hall data on residential burglar-alarm permit record
Burglar alarms 2005	O_a X_i O_a	t_1 and t_2=Consecutive two years
NAI residential burglary 2005	O_b Y_i O_b	
	t_1 t_2	

The buffer zone approach will be incorporated with the WDQ approach, which calculates WDQ ratios to interpret spatial displacement and diffusion of benefits of the crime prevention scheme. Thus, together with this buffer zone approach, the concept of WDQ is utilized to develop a flexible and usable nonequivalent-groups quasi-experimental research design for this study in the following section.

4. Weighted Displacement Quotient (WDQ)

The nested buffer and control zone approach is based on a statistical technique, the WDQ (Bowers and Johnson, 2003), which aims to measure spatial displacement of crime prevention programs. The rationale is that the displacement and diffusion of benefits can only be attributed to crime prevention schemes if crime is reduced in the target area. Thus, the WDQ not only measures what occurs in the buffer zone, but also relates changes in the buffer zone to those in the target area over the years. WDQ values will show the size and directionality of the impact of alarm systems on residential burglary.

As seen in Figure 10.1, the conceptual approach of the WDQ has three concentric zones nested within each other. The target zone (A) is the area in which a crime prevention scheme is applied. Surrounding the target zone is a buffer zone (B), which may have been influenced by the operation of the crime prevention in the target zone and represents the displacement or diffusion of benefits zone. Surrounding the buffer zone is a wider control zone (C), which is unlikely to be affected by changes within the target or buffer zone. In addition, it is equally possible to have one, or several, control zones that do not surround the buffer and target zones. Bowers and Johnson (2003) argued that since it was possible to define more than one control zones in this way, the reliability of any analysis conducted could be increased using this procedure.

[Figure 10.1] Nested buffer and control zones

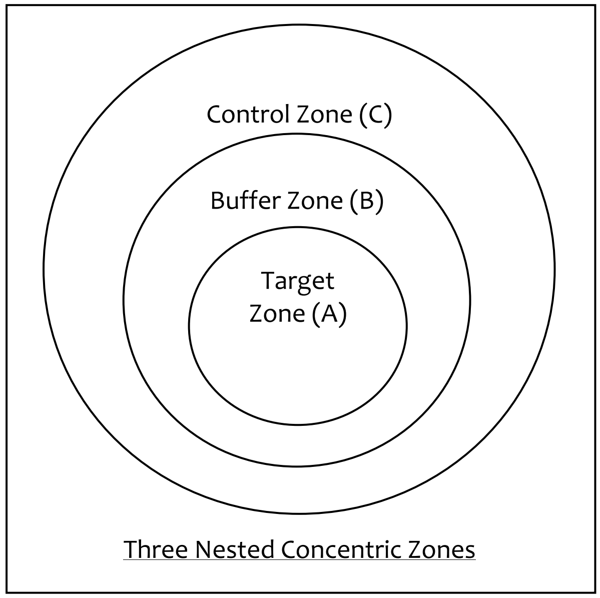
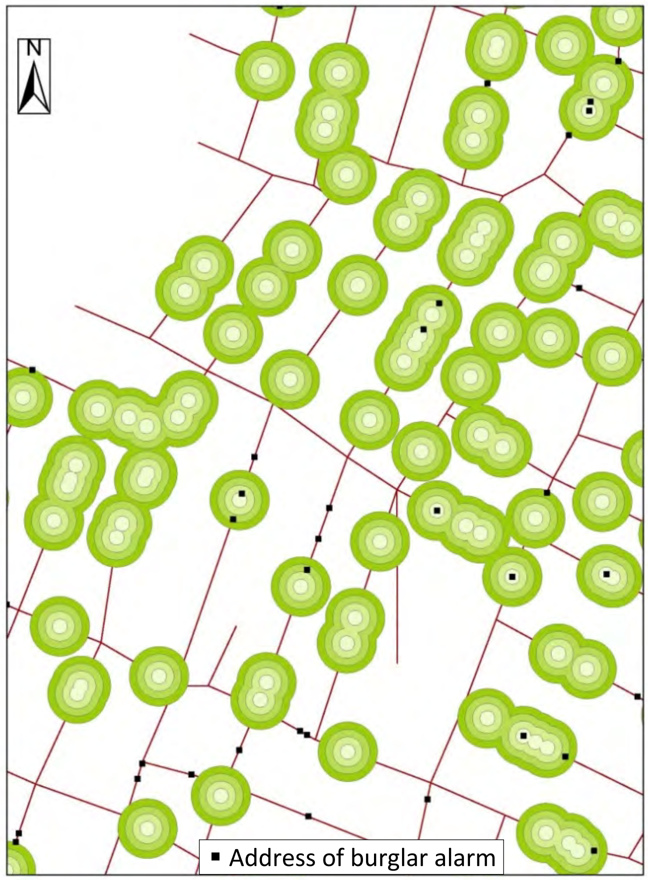


Figure 10.1 is based on a theoretical approach. However, it is limited in its explanation and application to a real-life situation. For example, in Figure 10.2 the four buffer rings can be used as a universal and consistent method to view all residential alarm permits in the city. Black dots represent the addresses of houses with residential burglar alarms installed. Thus, the program can produce four same-size buffer rings with the same radii throughout the city because this pin-map application is based on a theoretical assumption, and not on the real size of houses or the distance between houses. Though most urban neighborhoods have well-planned street blocks and housing arrangements, some parts of neighborhoods have different structures. It is necessary to apply the WDQ conceptual approach into a

real situation. Doing so may produce different-shaped buffer zones (B) and control zones (C).

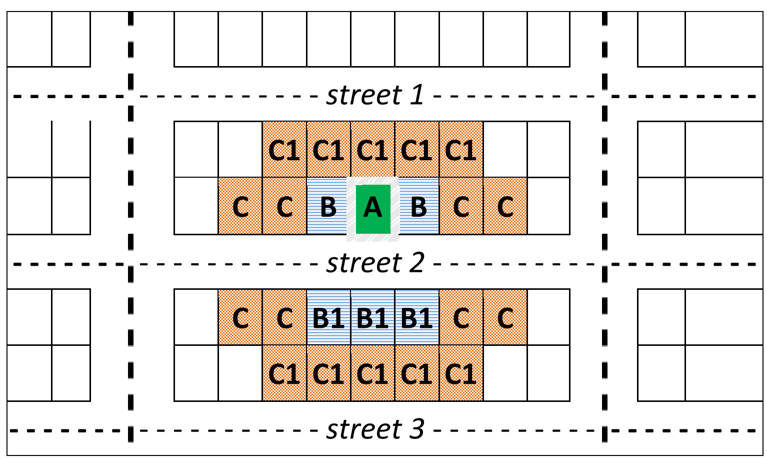
[Figure 10.2] Four-ring buffering maps of burglar alarms and NAI burglary in the western and northeastern parts of Newark, NJ, 2005



5. Application of the Nonequivalent-Groups Design and WDQ

Figure 10.3 shows a typical street block and housing arrangement. The entrances of each house face the streets. For example, houses A, Bs, B1s and Cs have the same entrances facing Street 2. On the other hand, all C1s face either Street 1 or Street 3. The target zone with a burglar alarm (A – green color) is surrounded by the five buffer houses (B and B1 – blue color), which, then, border the outer control zone with 18 houses (C and C1 – red color). The reason the C1 houses, which are located directly behind house A, are not included among the buffer houses is that their entrances face Street 1, meaning that even though they are located next to each other, in order to check whether the C1 houses have burglar alarms, an offender must use Street 1 or Street 3, rather than Street 2. More time is needed to check and enter the house Bs on Street 2 because the offender must walk the entire street block. As a consequence, C1 houses directly behind house A may be less likely targets of crime than the house Bs, which are next to house A on both sides of Street 2.

[Figure 10.3] Application of the nested buffer and control zones in a typical housing layout

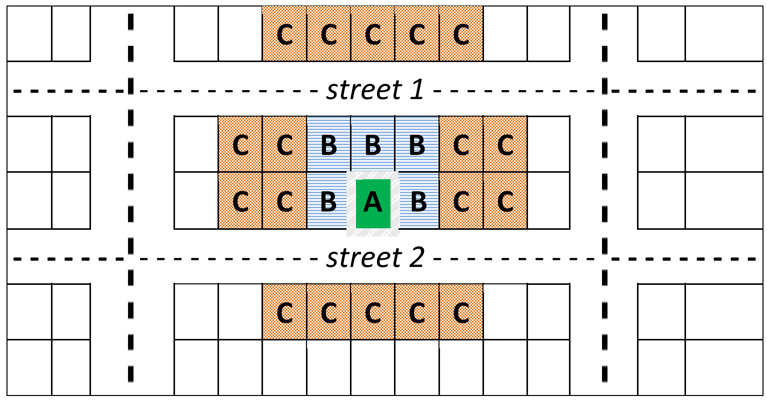


Also, the four C houses next to the house Bs are included to the control zone with all C1 houses. The rationale for this assignment is that, first, according to the literature on displacement and diffusion of benefits of crime prevention programs (Bowers and Johnson, 2003; Bowers, Johnson, and Hirschfield, 2003; Johnson, Bowers, Young, and Hirschfield, 2001), the buffer area directly neighbors the target area, while the control area covers a relatively wider area beyond the buffer area. Secondly, assuming that an offender spends 5 to 10 minutes on one street to check for a house with a burglar alarm, and then, finds house A, the offender may spend the remaining time carefully seeking other possible targets around house A. The offender would not spend a longer period of time to spy out crime targets, but use as short a period as possible. Thus, the time period would be less than 5 minutes, and the four house Cs can be vulnerable alternative targets to house A.

In addition, the three B1 houses across Street 2 are included in the buffer area, the assumption being that if an offender finds that house A has a burglar alarm installed, the offender may seek a nearby target for crime. Even though these houses are on the other side of the street, due to their close proximity and the alarm-system yard signs for house A, they would be included in the buffer zone houses to examine the impact of displacement and diffusion of benefits of burglar-alarm systems on residential burglaries. Thus, each target house with a burglar alarm has five buffer houses and 18 control houses.

Figure 10.3 shows a typical layout of single-family housing units in urban neighborhoods. However, some parts of the city display different layouts and do not conform to the pattern in Figure 10.3. Thus, the selection process should be flexible and adaptable based on the layout of the housing units or street blocks, even though the same principle of the nested buffer and control zones applies in the selection of buffer and control areas. Accordingly, the shape of buffer and control areas may be different from that of Figure 10.3. Figure 10.4 is one example of a slightly different shape of buffer and control zones. But the concept and assumptions of the nested buffer and control zones will still apply. It should be noted that the simple street map of a city is inappropriate for this detailed approach. The city parcel map, which is based on the real size and location of houses, is necessary for this analysis.

[Figure 10.4] Application of the nested buffer and control zones



6. Measuring Process of Applied Nonequivalent-Groups Design and WDQ Analysis

The assumption of this WDQ approach is that over any given time period, the buffer zone (Bs and B1s) would account for a particular proportion of the crime committed within a control area (Cs and C1s). If a burglar alarm has some positive impact on residential burglary, the diffusion of benefits should spread from the target zone into the buffer zone that surrounds it with the crime rate in the buffer zone decreasing. The unit of analysis for this method is a single address of homes with burglar alarms.

The selection process of the three distinct areas follows as:

① To select the addresses of repeated alarm permits from 2001 to 2005. These addresses will be the target zones (A in Figure 10.3).

② To select the buffer houses (B and B1 in Figure 10.3) surrounding the target zone, each target zone with a burglar alarm installed may have five neighboring houses without burglar alarms. If the neighboring houses have burglar alarms installed, they each can be one target zone with five buffer houses.

③ To select the control houses without burglar alarms (C and C1 in Figure 10.3) surrounding the buffer zone. The control area will include 18 houses in a typical housing layout.

④ To count the number of crimes in the three areas over the five-year period and calculate the changes in the burglary rate in the buffer zone (expressed as a proportion of that in the control area) for different times. Then this figure is weighted by an index that measures crime rate in the target area by the control area.

The equation is:

$$\frac{\frac{B}{C}}{\frac{A}{C}} \qquad \text{[Equation 10.1]}$$

where B = crime rate in buffer zone, C = crime rate in control area, and A = crime rate in target area. This index only examines the differing proportions in the various areas at one point of time. Thus, it is necessary to examine the changes over years. The modified equation for the WDQ above is:

$$WDQ = \frac{\frac{Bt_1}{Ct_1} - \frac{Bt_0}{Ct_0}}{\frac{At_1}{Ct_1} - \frac{At_0}{Ct_0}} \qquad \text{[Equation 10.2]}$$

Equation 11.2 takes into account the changes observed in the control area over time by comparing the situation after implementation (t_1) with the situation before implementation (t_0). Instead of the before-after time frame, a five-year time frame can be applied for this study.

There are two possible outcomes for the numerator. If it is positive, this is indicative of possible displacement. But if it is negative, it may suggest that there may have been a diffusion of benefits because the buffer zone (B) suffered proportionally less crime in comparison with the control area (C) over the years examined. There are also two possible outcomes for the denominator. If it is negative, it shows that a burglar alarm was successful in reducing burglary relative to the control area (C). If it is positive, then this means that a burglar alarm has been unsuccessful, and thus, it is difficult to relate any change in the buffer zone (B) to the target area (A).

Then, as Table 10.3 shows, the WDQ can be interpreted in several ways (Bowers and Johnson, 2003; Chainey and Ratcliffe, 2005). Positive WDQ values indicate diffusion of benefits to the buffer zone, and negative WDQ values indicate geographic displacement of crime. With the WDQ values, a figure of + 1 shows a diffusion of benefits where the burglary reduction in the buffer zone is equal to that in the target area. In other words, there is a positive net impact of burglar alarms on residential burglaries. A value of - 1 indicates a displacement where a burglary reduction is offset entirely by an increase in the buffer zone. A WDQ of 0 represents a scenario where there was apparently no change in the buffer zone, or where this change could not be attributed to changes in the control area.

[Table 10.3] Interpretation guide for WDQ ratios

WDQ Ratios	Displacement/Diffusion	Overall Intervention Effect
WDQ>1	Diffusion greater than direct effect	Positive net effect of the intervention
WDQ near 1	Diffusion about equal to direct effect	
1>WDQ>0	Diffusion, but less than direct effect	
WDQ=0	No displacement or diffusion	
0>WDQ>-1	Displacement, but less than direct effect	
WDQ near -1	Displacement about equal to direct effect	No net benefit to intervention
WDQ <-1	Displacement greater than direct effect	Intervention worse than doing nothing

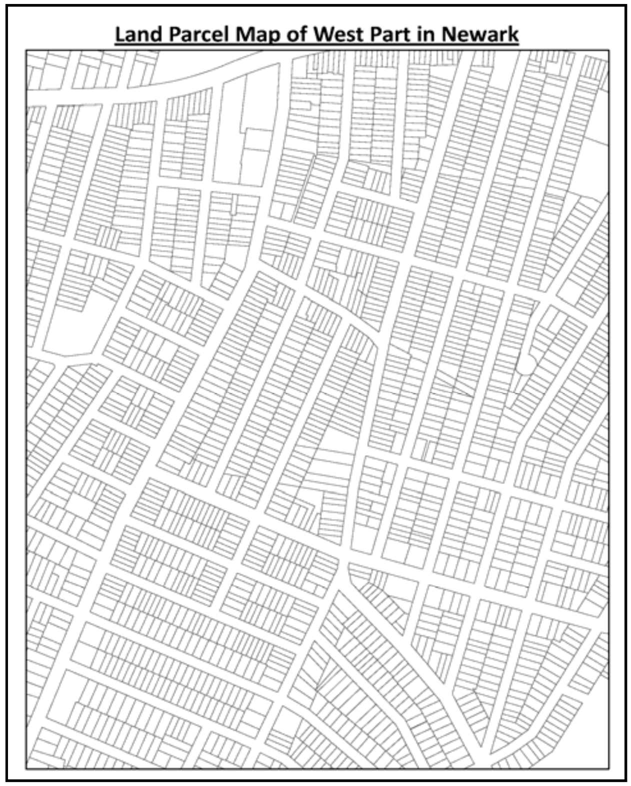
Source: Chainey and Ratcliffe (2005)

III. Applied WDQ Analysis of Burglar Alarms on Residential Burglaries

1. A Land Parcel Map

The previous analyses used a regular street map of the city of Newark, N.J. But for applied WDQ analysis, a parcel map is necessary. The parcel map is based on a polygon feature, a multisided figure represented by a closed set of lines. Examples of polygon features are census tracks, police beats, and land parcels (Boba, 2001). This valuable tool, unlike regular street maps, allows for detailed spatial analyses of a small area. It also is more specific and precise than a centerline map in indicating the exact location of a feature, such as an incident of residential burglary or a permit record of a burglar alarm. Figure 10.5 shows one example of the land parcel map in the western part of the city. The land parcel map of Newark identifies 48,249 parcels. Each rectangle shape lot is an exact land parcel and identified as a single polygon. When an address of an alarm permit is goecoded, the point is placed in the exact middle of the polygon.

[Figure 10.5] Example of the land parcel map of the western part in Newark, NJ



2. The Selection Process of Buffer and Control Zones

The WDQ analysis for the study of displacement of crime and/or the diffusion of benefits of burglar alarms on residential burglaries involves several sequential selection processes with a parcel map of the city.

The first step is to identify all polygons of residential burglar alarm permits on the city's land parcel map by overlaying the addresses of each year's alarm permit records. This step can be accomplished using the join function in the ArcMap computer software. The address-level point data (e.g., each year's addresses of alarm permit records) are joining to the polygon data (e.g., a land parcel map of the city). This produces a new layer that includes a new variable, called count, on the original land parcel map. The count variable has the number of points occurring in each polygon annually. The second row in Table 10.4 shows the number of residential burglar alarm records annually after being joined with the polygon data on the city's parcel map.

The second step is to identify the spatial target zone (A) on the joined land parcel map. The process starts by using the selection function in the ArcMap software. After uploading the new joined land parcel map, all addresses of NAI burglaries are selected by location. Several selection features[26] are available in the ArcMap. This study used the "Are Completely Within" selection feature, which selects features in one layer that fall completely inside the polygons of another without applying any buffer distance. The same method is repeated five times using each year's NAI burglaries' data. Thus, this approach produces five new layers of the number of NAI burglaries upon the joined land parcel map. The third row in Table 10.4 presents the numbers in the target zone (A).

The third step is to create the spatial buffer zone (B) on the joined land parcel map and to count the number of NAI burglaries in these zones. This method starts by creating the first zone (B) using the buffer function in the ArcMap. The buffer distance for this zone is 9 meters (approximately 29.53 feet), which almost completely covers at least the surrounding three land parcels (see Figure 10.6 with red-color rims). After creating the buffer zones surrounding the target zones, all

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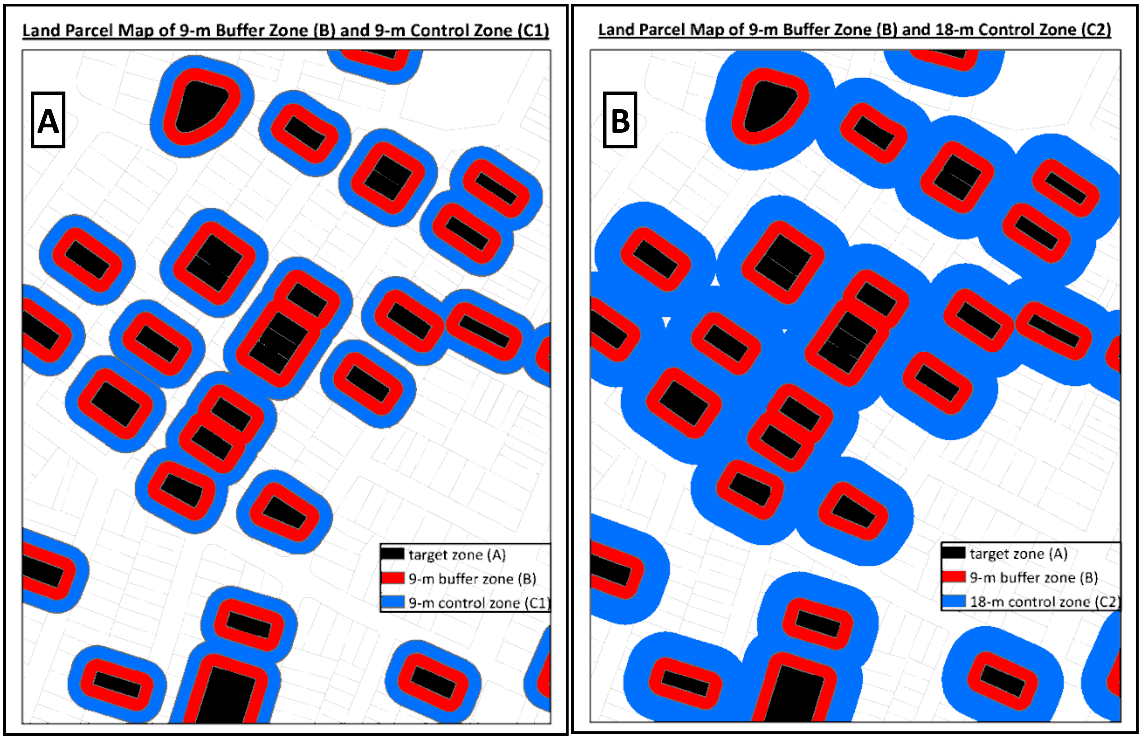
[26]) Examples of available selection features are "Are Crossed By The Outline Of," "Intersect," "Are Within Distance Of," "Have Their Center In," "Are Completely Within," "Completely Contain," "Share A Line Segment With," "Tough The Boundary Of," "Are Identical To," "Contain," and "Are Contained By" (CMAP, 2007).

addresses of NAI burglaries are selected by location by using the selection function in the ArcMap with the "Are Completely Within" selection feature. These steps produce a new layer with the number of NAI burglaries within the 9-meter buffer zone parcel map. The fourth row in Table 10.4 shows the number of NAI burglaries in buffer zones (Bs) throughout the years.

The fourth step is to create the spatial control zone (C_1) on the joined parcel map by using the buffer function in ArcMap and to count the number of NAI burglaries in these zones with the selection function (see map A in Figure 10.6 with blue-color rims). The procedure is the same as the third step. But the buffer distance for the control zone is another 9 meters from the boundary of each of the 9-meter buffer zones (Bs). The fifth row in Table 10.4 shows the number of NAI burglaries in the control zones (C_1s).

In addition, one more spatial control zone (C_2s) is created and identified with an 18-meter (approximately 59.06 feet) buffer distance (see map B in Figure 10.6 with blue-color rims). The last row in Table 10.4 shows the numbers of control zone (C_2s). The primary purpose of having another control zone surrounding the target and buffer zones is that two control zones allows for the calculation and comparison of WDQ values to examine where the values are consistent or discrepant. The assumption is that when WDQ values from two control zones show a similar pattern (e.g., increase or decrease together over the years), the argument over the displacement and/or diffusion of benefits of burglar alarms on residential burglaries is stronger and more reliable.

[Figure 10.6] Land parcel maps of 9-meter control zone (C_1) and 18-meter control zone (C_2) with 9-meter buffer zone (B)



[Table 10.4] Number of parcel-mapped residential alarm records annually, Newark, NJ

ZONES	YEAR				
	2001	2002	2003	2004	2005
Parcel-mapped alarm permits	670	601	921	1,020	1,188
Target zone (*A*)	124	132	149	183	101
Buffer zone (*B*)	77	72	69	109	65
Control zone (C_1) w/ 9 meters	61	54	105	79	75
Control zone (C_2) w/ 18 meters	117	128	171	150	137

3. The Values of Applied WDQ Analysis

After creating the three spatial zones based on the joined land-parcel map (e.g., target, buffer, and control zones) and counting the number of NAI burglary on each of these different zones, WDQ values are calculated by using Equation 10.2 to scrutinize geographic displacement and/or diffusion of benefits of burglar alarms.

Table 10.5 presents the values of the applied WDQ analysis based on the above spatial approaches and numbers. At first glance, all values are positive, showing, according to the interpretation guide for WDQ ratios in Table 10.3, the phenomenon of spatial diffusion of benefits from burglar alarms against residential burglaries. There is no indication of any spatial displacement of residential burglaries due to burglar alarms.

[Table 10.5] Values of applied WDQ analysis in Newark, NJ

Control Zones	2001-2002	2002-2003	2003-2004	2004-2005
Control Zone C_1	0.17	0.66	0.81	0.53
Control Zone C_2	3.28	0.99	0.93	0.53

WDQ values in the control zone C_1 are less than 1, indicating that the diffusion of benefits is no greater than the direct effect. In other words, the positive net effect of burglar alarms against residential burglaries does not exist. However, the "less than direct effort," but "close to direct effect," of burglar alarms is found. For example, the WDQ value of 2003-2004 is 0.81, indicating that there is a positive and substantial impact of burglar alarms on residential burglaries. WDQ values for 2002-2003 and 2004-2005 also indicate that there is no direct effect of burglar alarms, but a sizable impact on the continual decrease of residential burglaries exists over the years. The WDQ value for 2001-2002 is 0.17, which is relatively lower than the other values. Still its value indicates that some geographically positive effect of burglar alarms exists against residential burglaries.

In addition, WDQ values in the control zone C_2 show a similar pattern to those in control zone C_1, except the value from 2001-2002. In general, the values are higher than those in the control zone C_1. In particular, the values for 2002-2003 and 2003-2004 are close to 1, which can be interpreted as the direct effect of diffusion of benefits by burglar alarms on residential burglaries. It is mainly because control zone C_2s cover a wider geographic area and consequently include a larger number of NAI burglaries with 65.8 more burglaries, a 93 percent increase on average.

The WDQ value for 2001-2002 is 3.28. According to the interpretation guide for WDQ ratios in Table 10.3, this unexpected value indicates that there is a far greater than direct effect of diffusion of benefits. In other words, the positive net effect of burglar alarms against residential burglaries is observed. However, concluding that this high WDQ value reflects the true effect of burglar alarms on residential burglaries should be done cautiously because, as discussed in the previous chapters, there also are several other independent variables that could explain the decrease of NAI burglaries over the years. Thus, although the WDQ value is far greater than 1, showing that there is a greater diffusion of benefits, the discussion of the diffusion of benefits of burglar alarms on residential burglaries should be presented in context with other variables.

Nevertheless, it is conclusive that WDQ values in control zone C_2s show the geographic diffusion of benefits of burglar alarms on residential burglaries and that the geographic displacement of residential burglaries due to burglar alarms is not found. Thus, these observations and arguments are consistent with those in control zone C_1s.

Several points are worthy of further discussion. First, the applied WDQ values clearly do not show the geographic displacement of NAI burglaries due to the installation of burglar alarms throughout the years. Instead, the substantial and consistent geographic diffusion of benefits of residential burglar alarms against residential burglaries is found.

Second, although the above findings explain the diffusion of benefits of burglar alarms against residential burglaries, it should be cautiously concluded that such diffusion of benefits is the net effect or absolute benefit. Rather, burglar alarms have a sizeable, direct, and considerable impact on the constant decrease of residential burglaries over the years. There are other factors that could explain the same trend in residential burglaries, such as population composition, householders' age composition, and housing characteristics. However, the above analyses reveal that residential burglar alarm systems do not negatively impact the spatial displacement of residential burglaries, but they maintain a persistent diffusion of benefits on residential burglaries.

Third, an unexpected observation was found in that, according to WDQ values in Table 10.5, residential burglar alarms not only have a short geographic ambit of diffusion of benefits (control zone C_1), but also a wider geographic range of diffusion against residential burglaries based on the higher WDQ values in the control zone C_2, which are higher than those in the control zone C_1. This finding is consistent over the years.

This observation is linked to the current literature on the argument of displacement in crime prevention circles. In particular, it has been argued that with geographic displacement, there is likely to be a displacement gradient, meaning that displacement is most likely to occur within close proximity to a target area where a crime prevention program is introduced and that it will decrease as the distance from the target area increases. This assumption is based on the notion of familiarity decay (Eck, 1993). The alternative to familiarity decay or distance decay effects (Bowers and Johnson, 2003) is that as the effect of geographic displacement weakens with distance from the target zone, the effect of diffusion of benefits of a crime prevention intervention can strengthen. In other words, the distance decay effect of the geographic displacement of crime can be explained by the distance strength effect of the geographic diffusion of benefits. As discussed above, WDQ values in control zone C_2s, with wider geographic areas, are greater than those in control zone C_1s. Though the spatial displacement of NAI burglary due to burglar alarms is not found in two control zones, WDQ values indicate that the geographic diffusion of benefits of alarm systems from target zone As gets stronger in control zone C_2s than control zone C_1s.

4. The Diffusion of Benefits of Burglar Alarms on Residential Burglaries

As discussed in the previous chapters with quantitative analyses, a relationship between burglar alarms and residential burglaries exists, in that the decrease of the total number of NAI burglaries and the increase of the total number of alarm permits over the five-year period maintained a statistically significant relationship. When other independent indicators (e.g., demographic, socio-economic, and housing characteristic variables) were added in advanced statistical analyses, the relationship between these two primary variables (e.g., burglar alarm permits and NAI burglary) still showed a statistically consistent and significant relationship. Based on such observations, the causal relationship between the two variables can be recognized in that the steady decrease of the number of NAI burglary over the years was directly or indirectly impacted by the steady increase in the total number of residential burglar alarms. At the same time, advanced multiple regression models showed that both burglar alarms and NAI burglary, when used as an independent variable, was a strong predictor of the other, when used as a dependent variable. However, any arguments were made cautiously as to the direct and positive impact of the increase of burglar alarms on NAI burglary, pending verification by further spatial analyses.

In addition to the quantitative approach, most spatial analyses confirmed the earlier observations and findings of the quantitative analyses. Furthermore, such analyses strongly suggested that residential burglar alarms had a positive impact on the steady decrease of NAI burglary due to the effect of diffusion of benefits, an invisible protective seal being spread from a house with a burglar alarm installed to the nearest neighboring houses in a relatively small geographic area. The argument is interrelated with the hotspot approach. Such an analysis was done at the macro-level with both the entire city and census tract.

Moreover, a micro-level approach at single-house level was completed in this chapter, utilizing the city's land-parcel map and the applied WDQ method. As discussed above, a geographic displacement of NAI burglary over the years was not observed, but the diffusion of benefits of burglar alarms against NAI burglary was found.

Therefore, it is conclusive that there is not only a statistically significant relationship and causal relationship between the increase of residential burglar alarms and the decrease of residential burglaries, but also a geographic diffusion of benefits of burglar alarms on residential burglaries. The houses with residential burglar alarms installed are less victimized and better protected than the houses without burglar alarms. Houses located next to a house with a burglar alarm installed are also less likely to be victimized and are better protected. These relatively small geographic protected hotspots are spread across the entire city. Such a phenomenon can be explained as the result of the spatial diffusion of benefits of a house with a burglar alarm over the immediate and surrounding houses. Furthermore, this spatial effect also directly links to the distance strength effect of the spatial diffusion of benefits of burglar alarms on residential burglaries.

Having a burglar alarm system at a home definitely brings a positive impact in protecting the home and preventing residential burglaries. A home burglar alarm can be used as a effective and powerful deterrent against residential burglaries.

IV. Chapter Conclusion

Research Question 6 focused on the examination of spatial displacement and diffusion of benefits of burglar alarms on residential burglaries. Unlike the previous analyses with no specified research design, a customized, flexible, and usable measuring design was devised. Acknowledging the absence of a standardized study design for the measurement at the individual household level, the nonequivalent-groups quasi-experimental research design was discussed, borrowing and modifying the assumptions of treatment and comparison groups, pre- and post-intervention measures, and buffer zones. The buffer zone approach was incorporated with the WDQ concept, which aimed to measure geographic displacement of crime prevention programs. The WDQ not only measured what occurred in the buffer zone, but also related changes in the buffer zone to those in the target area over the years. Its values showed the size and directionality of the impact of burglar alarms on residential burglary. For this application to the measurement, the city land parcel map, which is based on the real size and location of house buildings, was utilized.

After creating the three spatial zones based on the joined land parcel map (e.g., target, buffer, and control zones) with burglar alarm permits and counting the number of NAI residential burglary on each of these different zones, WDQ values were calculated. The applied WDQ analyses clearly showed that there was no indication of any spatial displacement of residential burglaries due to the increase of burglar alarm installations and that there was a positive and substantial impact of burglar alarms on the decrease of residential burglaries over the years. Furthermore, WDQ analyses showed that a distance strength effect of the spatial diffusion of benefits of burglar alarms on residential burglaries was observed.

In conclusion, having a burglar alarm system at a home definitely brought a positive impact in protecting the home and preventing residential burglaries. A home burglar alarm can be used as a powerful deterrent against residential burglaries.

In the following chapter, a summary of the previous study findings and policy implications will be presented. Limitations of the present study and further research agenda, focusing on the effect of burglar alarms systems on crime also will be discussed.

CHAPTER 11. DISCUSSION AND CONCLUSION

I. Introduction

This study questioned, analyzed, and examined the impact of home burglar alarms on residential burglaries, using multiple variables. Quantitative and spatial analyses were primarily employed for the present study. This chapter discusses the significance of the findings presented and discussed in Chapters 6 through 10 and offers explanations for these results. Implications for policy and crime prevention, limitations of the present study, and suggestions for further research, focusing on the impact of burglar alarm systems on crime also are discussed.

II. Finding Explanations and Policy Implications

1. Results Summary

The general trend analyses according to the data from police department and city hall showed that residential burglar alarms in use had steadily increased over the five-year period, while both NAI and AI residential burglaries also had progressively decreased. This crossing observation became the deep-seated research question penetrating throughout the present study in order to scrutinize the deterrent effect of burglar alarms on residential burglaries. Of the hypotheses proposed in Chapter 4, most are supported by either the quantitative analyses in Chapter 7 or the spatial analyses presented in Chapters 8 through 10.

The first research question and hypothesis concerned the overall relationship between burglar alarms and residential burglaries over the years. The continual decrease of the number of residential burglaries was closely and statistically associated with the consistent increase of burglar alarm installations in Newark, N.J. Chi-square and changed proportion statistics supported the crossing relation was statistically significant and persistent over the years, which indicated that burglar alarms impacted on the decrease of residential burglary incidents.

Followed by rudimentary quantitative inquiries, correlation and regression statistics not only confirmed the crossing relationship between the increase of burglar alarms in use and the decease of residential burglary incident but also identified key variables with statistical significance to explain about and link to the patterns of burglar alarm installations and residential burglary incidents. Both patterns were dependent on such variables as population race (white, black, and others), population age groups (ages under 17, 25 to 34, and 60 to 64), unemployment rate, householder race and age groups, and house occupied by owner.

For example, regarding increased installation trends of residential burglar alarms, neighborhoods with greater black populations, population ages 12 to 17, black householders, householders within the 25 to 34 age group, and houses occupied by owner were more likely to have burglar alarms installed because of safety issue in their houses. The installation pattern of burglar alarms also was closely related to employment status, showing that neighborhoods with lower unemployment rates were more likely to have burglar alarms installed than neighborhoods with higher unemployment rates.

With regard to the pattern of residential burglaries, neighborhoods with greater population groups of ages under 14, ages 15 to 17, and ages over 45, householder age group over 65 years old were less likely to be victimized by residential burglary. The interrelation between this finding and the installation pattern of burglar alarms clearly revealed that the increase of burglar alarms in use had positive impact on the decrease of residential burglary incidents due to the fact that neighborhoods with greater population ages 12 to 17 were more likely to have burglar alarms installed and less likely to be victimized by residential burglary. The elderly population over 65 years old was less likely to be victimized. But the most vulnerable target for residential burglary was within the 60 to 64 householder age group. Furthermore, neighborhoods with higher unemployment rates tended to have higher number of residential burglary. The unemployment rate was one substantial indicator to explain the patterns of both burglar alarm installations and residential burglaries. In short, both patterns of burglar alarm installations and residential burglaries were dependent upon, and explained by, those key indicators.

The further advanced multiple regression statistics enabled to suggest a group of powerful predictors, rather than to single out the most influential variable on the dependent variable, to both burglar alarms and residential burglaries. The forward selection multiple regression showed that among the group of indicators were black population, owner occupancy, householder ages 25 to 34, NAI burglary, and general population ages under 14 to best explain and predict the installation pattern of residential burglar alarms. On the other hand, the hierarchical selection multiple regression showed that such variables as burglar alarms, unemployment, population ages over 45, and householder ages 60 to 64 were the best indicators, though not necessarily in that order of degree of predictability, to explain and predict the pattern of NAI burglary.

A series of spatial analyses was an eye-popping visualization to examine the spatial distributions and patterns of both burglar alarms and residential burglary and to verify the findings based on quantitative analyses presented in Chapter 7. An overlaying mapping method demonstrated consistent quantitative findings even on a spatial dimension and identified spatial relationships with key indicators which were used in correlation and regression statistics. For example, neighborhoods with the dense spots of higher black population and younger population ages under 17 shared the same or neighboring dense spots of higher installation of burglar alarms.

Point and density mapping methods showed that distribution patterns of both burglar alarm installations and residential burglaries were not evenly distributed throughout the city. Though many of streets and city blocks had burglar alarms installed and were affected by residential burglaries, certain areas or neighborhoods obviously had heavily dense spots cross the city with either more burglar or more burglary incidents. Such a spatial pattern occurred dependent upon neighborhoods' conditions (e.g., demographic, socio-economic, and housing characteristics). More importantly, those dense spots of burglar alarms and residential burglaries did not overlap, showing that street blocks or small geographic sections of the city with high installation rate of burglar alarms had less residential burglary incidents and visa verse. Further spatial statistics and analyses (e.g., spatial autocorrelation and clustering analyses) confirmed this spatial observation that hotspots and coolspots of both burglar alarms and residential burglaries existed and that the distribution of those spots were not randomly scattered but heavily clustered at certain geographic areas across the city, being affected by demographic, socio-economic, and housing conditions. In short, those spatial patterns demonstrated that the increased installation of residential burglar alarms had some positive impact on the decreased number of residential burglary incidents over the years by creating a protective seal around the hotspots of burglar alarm installations and pushing away potential burglar(s) from these hotspots.

Finally, the applied WDQ analysis revealed that no indication of spatial displacement of residential burglary due to the increase of burglar alarm installations was observed and that there was a positive and substantial impact of burglar alarms on the progressive decrease of residential burglaries over the years. Such an analysis explicitly supported spatial diffusion of benefits of burglar alarms on residential crime. In short, all the quantitative and spatial findings were consistent and explained the impact of burglar alarms on residential burglaries.

2. Policy Implications

The research outcomes presented and discussed in Chapters 7 through 10 support prior findings showing that residential burglar alarms have a deterrent effect in reducing incidents of residential burglaries. In addition, this study finds that the geographic displacement of residential burglaries by burglar alarms is not observed, but that the diffusion of benefits of burglar alarms is shown. The study's results throughout the various analyses are reliably consistent and predictable with several key variables. Attached to those findings are some promising implications for policy and practice. The policy implications presented below address the key variables shown to be the strongest predictors of patterns of burglar-alarm installation and residential burglaries in the current study. These policy implications will be directed to the security industry and potential buyers of alarms, as well as the local police departments, governments, insurance industry that are able to address crime problems in our neighborhoods to build safer and more secure communities.

The discussion of policy implications here is directly related to the theoretical background presented in Chapter 3. The theoretical background for studying burglary and the offender's perspective has been built upon well-established theories, such as routine activities theory and rational choice theory. Those theoretical arguments have become the basis for the development of crime prevention approaches for situational crime prevention. One similarity of those theories is that crime is a normal, commonplace aspect of modern society. Burglary also is regarded as a routinely produced form of behavior by the normal patterns of social and economic life, rather than as a deviation from normal civilized conduct. Thus, crime prevention strategies based on those theories identify recurring criminal opportunities and seek to govern them by developing situational controls. Criminogenic situations, hot products, and hotspots are the new objects of control (Garland, 2001).

The key variables in the present study explaining the impact of burglar alarms and residential burglaries are situational indicators. To be effective, crime prevention strategies targeting residential burglaries address these situational variables. The spatial analyses in the current study supported that a burglar is more likely to respond to a residential burglar alarm at the neighborhood, block, or individual residence level. As Cromwell, Olson, and Avary (1991) and Wright and Decker (1994) argued, crime prevention strategies at the macro-level, such as increased levels of prosecution, increasing statutory penalties, and large-scale social change, or at the middle-level, such as neighborhood watch programs, may not be perceived as being effective, except under certain circumstances. Of course, the potential benefits for crime prevention of these macro- and middle-level crime prevention strategies should not be dismissed.

For instance, as discussed in Chapter 7, a powerful predictor of residential burglaries was unemployment. Thus, job creation would seem to be one of the more promising means to keeping both active burglars and would-be burglars away from engaging in criminal activities because the assumption is that burglars also need a stable financial source and would quit offending if they have a good job. However, creating such jobs is a daunting, long-term task. Even if this were accomplished, it is not clear that the offenders actually would be willing or able to take advantage of the new employment opportunities. The persuasive argument is that not only are the majority of them poorly educated and unskilled, but many are unreliable, having drug or alcohol problems. These circumstances may suggest that expanded employment opportunities can be effective in reducing residential burglaries, but it is dubious that a job creation program will impact those already heavily involved in crime (Wright and Decker, 1994).

Rather, micro-level approaches, such as installing a lock on windows and doors or installing a burglar alarm, instituted by the residents of a potential burglary target, are perceived to be more effective because a burglar is more concerned with the possibility of immediate detection and immediate rewards (Felson and Clarke, 1998). Even though burglars cannot be completely kept out through target-hardening means, such as locks, bolts, and alarms, still such means of prevention can delay, frustrate, and deter attempted entries. In other words, they can slow down the burglar by making the burglary difficult for those critical seconds, which may either make the burglar give up or enable him to be observed in the act of residential burglary. Thus, a residential burglar alarm is one such means of an effective micro-level strategy to respond to residential burglaries.

Analyses of the changes in residential burglary in the buffer and control zones throughout the years indicated that geographic displacement was not found, but instead geographic diffusion of benefits of burglar alarms was observed, with houses within these zones experiencing a reduction in the risk of burglary. This important finding suggests that the preventive effects of situational crime reduction measures may extend to unprotected houses within close proximity of a scheme. Thus, the possibility exists that the effectiveness of many situational crime reduction interventions may be increased by adopting targeting strategies that give the illusion of a greater area of coverage (Bowers, Johnson, and Hirschfield, 2003).

One of the most substantial results in this study is that burglar alarms are indeed effective in deterring residential burglar(s) in AI houses and in diffusing the positive benefits of burglar alarms to houses in close proximity and the surrounding geographic area. Spatial density analyses in Chapter 8 and NNI, Moran's *I*s, and Hot Spot (Gi*) analyses in Chapter 9 showed that hotspots of NAI burglary in the city were surrounded by many NAI houses, whereas coolspots of NAI burglary were surrounded by many AI houses. These patterns and relationships between burglar alarms and residential burglaries were continual over the years. Understanding those relationships can help homeowners considering alarm systems for better protection of their residences.

Even when motivated offenders know that a dwelling is unoccupied, situational measures remain that can discourage them from attempting to burglarize it. Foremost among these are occupancy proxies, such as burglar alarms. Few of the offenders were prepared to tackle burglar alarms, and most made a concerted effort to avoid them (Gillham, 1992; Wright and Decker, 1994). Spatial analyses in Chapter 8 supported that neighborhoods in which burglar alarms were heavily installed have fewer incidents of residential burglaries than the neighborhoods with fewer burglar alarms. Thus, the installation of burglar alarms makes dwellings less attractive to the would-be and active burglars.

Technology advances and market competition over the years have brought down the costs of the first-time installation and monthly maintenance. In most cases homeowners can obtain alarm systems for less than the monthly cost of a cell phone, though the initial cost of system installation is relatively pricey to low-income neighborhoods in particular. The alarm industry and insurers should offer discounts in premiums for alarm ownership. Residential burglar alarms indeed have some positive impact on residential burglaries by having a lower number of incidents, being compared with NAI houses, and having diffusion of benefits of alarm systems to surrounding houses. In order to justify awarding discounts to alarm owners, the discount must be considered in the alarm-purchase decision process because burglar alarms can yield financial benefits to insurers even after paying for discounts. Though the initial cost and maintenance costs of burglar-alarm systems have lowered due to market competition and better technology, still this suggestion is recommended. Some affluent communities can afford alarm systems, but many households in the city of Newark, N.J. may be not. The median income was $26,926, with a wide range of variation among neighborhoods in the city, and the black population variable as the largest population category over other population categories was the most important predictor in explaining the pattern of alarm installations. In other words, the neighborhoods with a larger black population tended to have more alarm systems installed than any other population group. But those who live in lower-income neighborhoods and have an alerted concern for safety and security may not be able to afford to buy and install a burglar alarm. Thus, offering discounts in premiums for alarm ownership from both the alarm industry and insurance company is strongly recommended in order to encourage the residents in black population neighborhoods to buy and install alarm systems.

In addition, as discussed in Chapters 7 and 8, house ownership was directly related to the installation pattern of residential burglar alarms. As proposed, more discounts in premiums for alarm ownership for homeowners are recommended. In particular, this suggestion links two critical predictors: householder age group 25 to 34 and general population age group under 14 years old. As discussed in Chapter 7, these younger householders had more burglar alarms installed than other householder age groups. Of course, it is dubious to think that most of them owned their houses. It is more reasonable to assume that most those younger householders were renters rather than homeowners. The data show that the rate of renter-occupied houses in the city is substantially high (76 percent). However, both homeowners and renters are concerned with the safety and security for either owner-occupied or renter-occupied houses. In the case of renter-occupied houses, the original homeowner had installed a burglar alarm. At the same time, this younger householder age group from 25 to 34 years old generally had more babies, toddlers, or children at their houses than older householders with more attention paid to their children's safety. Thus, from a policy-oriented view, it is recommended to offer substantial and persistent discounts in premiums for alarm ownership for targeted homeowners based on demographic, socio-economic, and housing indictors by both the alarm industry and insurance companies. Such a policy will encourage them to buy and install burglar alarms to better protect their homes.

Also, with the insurance industry looking to enhance alarm sales, cooperation between the two industries will be beneficial to both. The insurance industry could cooperate by working toward standardizing discounts and stressing the merits and effectiveness of burglar alarms to clients. These suggestions would require more aggressive activity by the alarm associations. They also propose increased cooperation with police and the insurance industry to increase the credibility and visibility of the industry and to improve service.

Finally, as discussed in Chapters 8 and 9, distinctive spatial hotspots and coolspots of residential burglaries supported that the crime is not spread evenly across the city. These distributions were formed by embedded key indicators in the neighborhoods in the city, such as demographic, socio-economic, and housing characteristics. The existence of such indicators informs the police of hotspots that routinely need patrolled. But a hotspots-oriented police patrol should not be a stand-alone consideration to develop a patrol program or crime prevention strategy. It should be incorporated with the temporal analysis of residential burglaries, which is discussed in Chapter 6. Together, they can guide local police departments to develop an analytical and targeted patrol strategy, utilizing scant police resources in fighting residential burglaries.

III. Limitations of the Present Study

As discussed in Chapter 4, this study resolved several serious methodological issues stemming from the previous studies on the research topic for a better understanding and insight into the relationship between burglar alarms and residential burglaries. But this one study cannot disentangle all possible methodological problems. In other words, several limits inevitably subsist in the current study. It should be noted that though several study limitations exist, they supply further research topics on the broader spectrum for the impact of burglar alarm systems on crime. The following is suggestions for future research.

1. Nonequivalent-Groups Quasi-Experimental Design

As discussed and proposed in Chapter 10, the current study used a nonequivalent-groups quasi-experimental research design. Randomization was not possible because this study utilized the secondary data from the local police department and

City Hall. Then, by definition, experimental and control groups were not equivalent because the experimental and control groups were defined and identified according to spatial proximity to AI houses with a burglar alarm as a crime prevention stimulus. The WDQ approach was modified and applied to examine the spatial impact of burglar alarms on residential burglaries.

Though the nonequivalent-groups quasi-experimental design in the current study was grounded in a theoretical understanding, as Maxfield and Babbie (2008) argued, this study may suffer from a possible threat to validity. Either a more rigorous and theoretically grounded quasi-experimental research design or randomized experimental design should be developed and used to study this topic.

2. The Potential Drawbacks of Recorded Crime Data

The primary data source for this study is "data from agency records." The methodological limitations of the official police record data is well-known among criminologists, especially in regard to the data's failure to capture crimes unreported to authorities. Relying on such a secondary data source presents the problem of the dark figure of crime, or crimes that go unreported to police.

For the current study, the data for NAI and AI burglaries were collected from the police-incident reports database. Due to the proportion of unreported crimes to the police, it is not possible to know the actual number of crimes in the city. This disadvantage underestimates the total number of NAI burglary, and skews the rate of residential burglary, which is calculated by dividing the total number of crimes with the total number of households in the city. Thus, the size of crime rates based on secondary data would be smaller than the size of crime rates based on the true number of crime. Consequently, the ratio of residential alarm permits to NAI burglary would be biased.

3. Some Proportion of In-Use, but Non-Registered, Burglar Alarms Exists

The residential alarm-permit records from City Hall include the total number of applications in a given year. But this record does not present the true total number of burglar alarms in use in the city. According to the Alarm Section in the police department, there are three categories of residential burglar alarm users: (1) the legitimate burglar-alarm user with a city permit; (2) the expired alarm user, who once applied for the city permit but did not renew it; and (3) the unlicensed burglar-alarm user who has installed alarm systems but has never applied for a city permit. The second and third categories are non-registered alarms. Table 11.1 shows the total number of burglar alarms according to different types of residential alarm users from 2001 to 2005.

[Table 11.1] Numbers of three different residential burglar alarms annually in Newark, NJ

Type	Year					Average (%)
	2001	2002	2003	2004	2005	
Legitimate alarm permit	1,261 (0.80)	1,081 (0.74)	1,649 (0.76)	1,887 (0.69)	2,205 (0.75)	0.75
Expired alarm	88 (0.06)	120 (0.08)	124 (0.06)	44 (0.01)	90 (0.03)	0.05
Unlicensed alarm	211 (0.14)	266 (0.18)	391 (0.18)	770 (0.30)	642 (0.22)	0.20
TOTAL	1,560	1,467	2,164	2,701	2,937	1.00

(Source: Newark City Hall and Police Department)

The total number of expired and unlicensed alarms are based on the number of summons issued by the police department. Table 11.1 shows that the number of summons issued to those who have an unlicensed alarm system is higher than that of an expired alarm system. Even though these numbers are substantial, the police department and City Hall cannot estimate even the approximate total number of unlicensed alarm users in the city. It is not known why many homeowners have installed and used burglar-alarm systems without city permits. It also is unclear why some homeowners would not renew their current alarm systems and use them. These issues need to be further studied.

The problem of the number of nonregistered burglar alarm users may overestimate the total number of AI residential burglary. The current dataset of AI burglary does not identify which incidents involved alarm systems. When comparing the rate of AI burglary by total alarm systems, the outcome may be biased toward a lower rate. For example, in 2004 there were 1,887 total registered alarm permits, 814 nonregistered (44 expired alarms and 770 unlicensed alarms), and 54 AI burglary. The rate of AI burglary by total alarm systems without nonregistered alarms is 2.86, while the rate with the nonregistered alarms is 2.0. The combined number of the three types of residential alarm systems in use is treated as the total number for this project.

4. A Sudden Increase in Residential Alarm Permit Records

In 2005, 2,205 residential alarm permits were issued. Table 12.2 shows the percentage change of residential alarm permits over the years. During the five years, the alarm permits increased each year. In particular, when compared with 2001 and 2002 records, the number of permits in 2005 increased by 75 percent and 104 percent, respectively. The change occurred within three years, a relatively short period of time.

[Table 11.2] Number of residential burglar alarm permits annually in Newark, NJ, 2001-2005

	Year					Average (X)
	2001	2002	2003	2004	2005	
Number of permits	1,261	1,081	1,649	1,887	2,205	1,617
Change (%)		***-14.3***	***+52.5***	***+14.4***	***+16.9***	***+17.4***

(Source: Newark City Hall)

Such sudden increases are, to some extent, unusual among general social phenomenon. Several factors may produce this increase, such as a sudden social change, sharp increase of the crime rate, new internal policy, or new laws regulating the alarm industry. When the researcher asked a City Hall public officer, who was in charge of the licensing business, whether there had been any significant policy change or new regulations relating to the alarm-installation businesses or residential alarm permits during the last five years, the officer answered that there were no such changes. At this time, the direct factor(s) for the sudden increase is not clear. This issue could be included in a future research agenda.

This issue may have a bias toward the impact of alarm systems on residential burglaries. For example, in calculating the rate of alarm permits in 2005, a sudden increase in the total number of alarm permits produces an unusual high value compared with the previous year. It can, all other things being consistent (i.e., the decrease of residential burglary was consistent), demonstrate a significantly positive impact of alarm systems on residential burglaries.

5. Some Proportion of Unmatched Geocoding Addresses

In the course of data transformation, all addresses of residential alarm permits, NAI burglary, and AI burglary were geocoded for descriptive and statistical spatial analyses. This process was done by using a GIS software function (e.g., geocode address). But there was some proportion of unmatched addresses from the three different datasets, with the average being 9 percent. The threshold of percent matching in criminal justice research is 85 percent. The current study shows a 93 percent matching point, and thus, is higher than the acceptable threshold in criminal justice research. Several factors may cause this problem, such as problems with handling abbreviations, incorrect spellings, incomplete addresses, addresses of an area of open space, and non-existent addresses.

This issue may cause problems with the spatial analysis processes. For example, in identifying hotspots for both alarm permits and NAI burglary, the unmatched addresses are excluded, and, thus, underestimate the total numbers of hotspots of alarm permits and NAI burglary, producing biased outcomes for macro-level spatial analyses.

6. Lack of a Multiple Factor Approach in Examining the Impact of Alarm Systems on Crime

This study primarily focuses on examining the impact of residential burglar alarms on levels of NAI burglary. But the reality is that other initiatives (e.g., secured lock systems on doors and windows, security yard sign without an actual alarm system, dog, and street lights) by residents also may have an effect at this level. These initiatives can be a confounding factor in investigating the impact of alarm systems on crime. Because the datasets from City Hall and the police department did not have such information with residential burglar-alarm systems, it is not possible to include the information in the various datasets used for this study. This sort of information can be obtained through questionnaire, telephone, or door-to-door surveys. Without such information included, the outcome of analyses in this study can be questionable and biased toward the discussion of the impact of the alarm system on crime. Thus, for a better understanding of the effect of the alarm system on crime, it is necessary for the study to incorporate other research methods (e.g., ethnographic approach and field observation), including more variables which have a possible effect on the levels of residential burglary.

7. The Generalization of the Study Is in Issue

The site for this study is an urban neighborhood close to a metropolitan city. According to the U.S. Census data for 2000, the population of the city was close to 270,000, and the total number of households was approximately 100,000. Even though the population and household numbers remain static, Newark also has diverse ethnicities. Such conditions may not be similar to other urban cities in the United States. Crime patterns and alarm-permit distributions may be different from other urban neighborhoods.

In addition, suburban neighborhoods and metropolitan cities will show different patterns of residential burglaries and distribution of residential burglar alarms than other urban areas. Thus, even if the same research design may be used in other urban and sub-urban neighborhoods or metropolitan cities, the research findings could be different. Originally, two more cities were included as research sites, but due to problems with databases and a lack of cooperation from local police departments, only one city was included in this study. It remains necessary to study the impact of alarm systems on residential burglaries in different cities.

IV. Further Research Agenda

This study focuses on the relationship and impact between burglar alarms and residential burglaries. As discussed in Chapters 6 through 10, some consistent and reliable research findings were observed to argue that burglar alarms have a substantially positive impact on the continuous decrease of residential burglaries over the years and that burglar alarms have a strong spatial diffusion of benefits against residential burglaries at a single-house level.

However, this one approach with three different secondary data sources cannot be the best research method to understand and explain the relationship and impact between burglar alarms and burglaries. For a comprehensive and better understanding of this relationship, it is imperative to expand the current research with available research methods.

The first research agenda should be related to the generalizability issue discussed above. The study area for the current study is Newark, N.J. Other cities with different demographic, socio-economic, and housing characteristics in different geographic areas (e.g., metropolitan, urban, suburban, and rural areas) should be considered. Such a replication can verify the research design and findings presented in the present study.

The second possible research topic related to the current study is relevant to commercial burglary. All analyses and discussions in the present study solely focused on residential burglary, with the topic of commercial burglary being excluded. In most localities, business owners must install a burglar alarm system and update their licenses on a regular basis. But commercial burglaries affect local businesses and economics. A rigorous and scientific-driven research is necessary to bridge the gap between the wide use of burglar alarms and the dearth of the research-based updated body of knowledge.

The third research agenda relates to the research methodological approach. The current study and the above two agendas involve secondary data sources mainly from local police departments and city halls. Another potential approach to study the impact of alarm systems on burglaries is to interview either active burglars or incarcerated inmates. Such an approach may provide in-depth personalized knowledge and insight about the impact of burglar alarms on burglaries.

The fourth research agenda is associated with repeat victimization. The literature on burglary consistently demonstrates that, in general, the risk of victimization doubles following an initial burglary (Bowers, Johnson, and Hirschfield, 2003; Johnson, Bowers, and Hirschfield, 1997; Weisel, 2002). While most people and places do not get victimized by crime, those who are victimized consistently face a higher risk of being victimized again. Previous victimization is the single best predictor of victimization. It is a better predictor of future victimization than any other characteristic of crime (Weisel, 2002). An experimental research design can be used to examine the impact of burglar alarms on burglaries on the reduction of repeat victimization.

Finally, the issue of false alarm activation should be included in future research. As discussed in the previous chapters 7 through 10, burglar alarms have a substantial impact on residential burglaries in reducing criminal incidents and spatial diffusion of benefits. So, it is suggested that financial supports to reduce initial and maintenance costs and premiums from the alarm industry and insurance company are imperative so that homeowners can buy and install burglar-alarm systems. However, such a suggestion may generate opposition from local police departments because more alarm means more false alarm reports directly to the police. For example, in Newark, the rate of false alarm activation is, on average, 97 percent. This problem has drained very limited police resources among local police departments. Thus, it is imperative to study the false activation problem of burglar alarms to explore the scope of the problem and to explain the causal relationship for better crime prevention strategies.

V. Conclusion

The foremost question throughout the current study was "do home burglar alarms have the deterrent effect on residential burglary?" This inquiry was answered by analyzing the phenomenon between the gradual decrease of residential burglaries and the increase of residential burglar alarms and by looking at key explanatory variables. Several quantitative analyses in the present study showed that several key variables played a role in explaining the relationship between burglar alarms and residential burglaries.

Spatial approaches also found and supported a significant relationship between burglar alarms and residential burglaries. Burglar alarms were not installed evenly across the city. Both hotspots and coolspots were observed in many neighborhoods. Residential burglaries also were not spread equally throughout the entire city. Some key variables (e.g., demographic, socio-economic, and housing indicators) were directly linked to these patterns. Spatial analyses suggested that burglar alarms had some positive impact on residential burglaries on the city level by showing that hotspots of burglar alarms did not overlap those of residential burglaries. Several spatial-based analytical approaches (e.g., NNI, Moran's *I*, geographic clustering analysis, and local hotspots [Gi*] analysis) supported this conclusion.

Furthermore, a single-house level analysis using the applied WDQ with the city's land-parcel map supported the lack of geographic displacement of residential burglaries by burglar alarms, but did demonstrate the spatial diffusion of benefits of burglar alarms on residential burglaries. It supported the use of burglar alarms as target-hardening crime prevention tactics. A micro-level approach for a crime prevention strategy in a small geographic area can be effective and substantive in fighting local crime problems, which can then create the effect of diffusion of benefits and produce an overall crime reduction in the city. Those findings were summarized to propose tangible crime prevention and marketing strategies.

By doing so, the present study may bridge the gap between the widespread installation and use of burglar alarms and the dearth of rigorous examination of the impact of such systems on residential burglaries. In addition, this study may update the current body of knowledge on similar and relevant topics so that research findings can be disseminated among academia and practitioners who are working in crime prevention circles.

In conclusion, this study is just one small endeavor and step by both the research institution, AIREF, and the researcher, together with distinguished faculty members, to obtain an in-depth and comprehensive understanding of burglar alarm systems and their use in fighting local residential burglaries.

Appendices

Appendix 1. Chi-Square statistics between burglar alarms and residential burglaries annually in Newark, NJ

		YEAR											
		2002			2003			2004			2005		
		Burglarized		Total	Burglarized		Total	Burglarized		Total	Burglarized		Total
		No	*Yes*		*No*	*Yes*		*No*	*Yes*		*No*	*Yes*	
Burglar Alarm	*No*	92,113	1,359	93,472	97,633	2,089	99,722	95,735	2,647	98,382	96,643	2,772	99,415
	Yes	2,570	108	2,678	2,331	75	2,406	2,254	54	2,308	1,568	57	1,625
Total		94,683	1,467	96,150	99,964	2,164	102,128	97,989	2,701	100,690	98,211	2,829	101,040

Appendix 2. The rates of alarm installation and NAI/AI residential burglaries annually for 90 census tracts in Newark, NJ

Tract ID	YEAR														
	2002			2003			2004			2005			Overall (2001-05)		
	Alarm	NAI_Bur	AI_Bur	Alarm	NAI_Bur	AI_Bur	Alarm	NAI_Bur	AI_Bur	Alarm	NAI_Bur	AI_Bur	Alarm	NAI_Bur	AI_Bur
1	0.022	0.020	0.082	0.031	0.015	0.043	0.039	0.013	0.012	0.035	0.006	0.039	0.029	0.013	0.041
2	0.087	0.042	0.023	0.022	0.018	0.000	0.022	0.022	0.000	0.026	0.011	0.000	0.049	0.023	0.023
3	0.005	0.012	0.000	0.006	0.011	0.000	0.008	0.010	0.000	0.009	0.008	0.000	0.007	0.011	0.000
4	0.010	0.009	0.135	0.022	0.024	0.000	0.011	0.016	0.000	0.016	0.007	0.000	0.012	0.015	0.043
5	0.024	0.033	0.150	0.026	0.005	0.000	0.033	0.031	0.167	0.045	0.015	0.000	0.030	0.020	0.060
6	0.028	0.027	0.028	0.031	0.022	0.000	0.033	0.012	0.024	0.032	0.019	0.024	0.028	0.018	0.017
7	0.006	0.023	0.135	0.017	0.019	0.026	0.023	0.023	0.038	0.022	0.021	0.000	0.015	0.022	0.039
8	0.009	0.013	0.084	0.020	0.015	0.120	0.024	0.022	0.000	0.025	0.021	0.000	0.018	0.016	0.035
9	0.005	0.018	0.000	0.011	0.014	0.000	0.010	0.013	0.000	0.011	0.018	0.063	0.008	0.016	0.033
10	0.018	0.027	0.126	0.015	0.026	0.050	0.024	0.022	0.000	0.015	0.021	0.000	0.019	0.025	0.047
11	0.011	0.033	0.000	0.015	0.029	0.125	0.029	0.029	0.000	0.023	0.016	0.083	0.021	0.028	0.055
12	0.021	0.034	0.168	0.022	0.038	0.083	0.031	0.055	0.000	0.048	0.046	0.000	0.026	0.043	0.055
13	0.008	0.038	0.000	0.020	0.032	0.000	0.024	0.037	0.115	0.033	0.022	0.057	0.019	0.031	0.049
14	0.005	0.022	0.000	0.009	0.022	0.000	0.015	0.026	0.000	0.015	0.019	0.000	0.013	0.020	0.000
15	0.007	0.031	0.000	0.016	0.034	0.000	0.038	0.053	0.000	0.030	0.038	0.000	0.019	0.037	0.000
16	0.013	0.025	0.000	0.014	0.033	0.000	0.024	0.036	0.000	0.019	0.014	0.000	0.014	0.027	0.000
17	0.033	0.045	0.000	0.041	0.050	0.030	0.039	0.039	0.000	0.045	0.026	0.056	0.036	0.043	0.028
18	0.016	0.059	0.299	0.024	0.050	0.000	0.037	0.059	0.067	0.046	0.025	0.027	0.029	0.049	0.067
19	0.017	0.022	0.034	0.017	0.021	0.065	0.025	0.020	0.022	0.026	0.012	0.022	0.019	0.019	0.041
20	0.059	0.036	0.063	0.088	0.045	0.022	0.102	0.029	0.019	0.105	0.013	0.009	0.082	0.032	0.037
21	0.017	0.008	0.042	0.025	0.006	0.028	0.029	0.008	0.000	0.031	0.002	0.011	0.023	0.007	0.027
22	0.040	0.024	0.048	0.067	0.020	0.044	0.056	0.020	0.017	0.073	0.011	0.014	0.055	0.018	0.039
23	0.046	0.033	0.081	0.061	0.036	0.041	0.074	0.034	0.017	0.075	0.025	0.008	0.059	0.033	0.049
24	0.025	0.032	0.061	0.043	0.036	0.055	0.041	0.020	0.000	0.036	0.015	0.043	0.034	0.026	0.032
25	0.020	0.033	0.106	0.030	0.035	0.024	0.027	0.023	0.000	0.034	0.014	0.000	0.025	0.025	0.039
26	0.014	0.049	0.000	0.020	0.044	0.000	0.037	0.026	0.050	0.035	0.043	0.053	0.023	0.042	0.032
27	0.064	0.025	0.000	0.085	0.038	0.037	0.078	0.041	0.040	0.096	0.029	0.033	0.082	0.036	0.031
28	0.054	0.050	0.075	0.087	0.048	0.024	0.090	0.050	0.023	0.090	0.050	0.047	0.070	0.051	0.035
29	0.020	0.048	0.000	0.058	0.058	0.000	0.081	0.053	0.000	0.069	0.019	0.040	0.048	0.046	0.034
30	0.002	0.016	0.673	0.006	0.034	0.400	0.009	0.039	0.143	0.004	0.005	0.000	0.006	0.026	0.182
31	0.094	0.063	0.000	0.115	0.060	0.040	0.130	0.102	0.000	0.279	0.032	0.019	0.135	0.078	0.021
32	0.022	0.047	0.224	0.046	0.038	0.056	0.051	0.025	0.050	0.062	0.015	0.000	0.037	0.033	0.081
33	0.031	0.043	0.052	0.032	0.030	0.000	0.050	0.010	0.065	0.057	0.031	0.029	0.041	0.029	0.055
34	0.012	0.038	0.112	0.023	0.070	0.059	0.051	0.042	0.000	0.048	0.038	0.000	0.030	0.047	0.028
35	0.032	0.046	0.112	0.047	0.028	0.079	0.058	0.040	0.021	0.070	0.019	0.036	0.052	0.034	0.057
36	0.003	0.023	0.000	0.007	0.025	0.000	0.007	0.018	0.143	0.005	0.020	0.000	0.007	0.022	0.056
37	0.009	0.043	0.673	0.014	0.023	0.000	0.020	0.035	0.000	0.026	0.015	0.000	0.015	0.031	0.075
38	0.026	0.020	0.096	0.037	0.028	0.000	0.039	0.015	0.022	0.049	0.020	0.000	0.038	0.023	0.027
39	0.014	0.026	0.061	0.019	0.030	0.043	0.021	0.024	0.000	0.023	0.013	0.000	0.017	0.023	0.030
40	0.030	0.051	0.000	0.035	0.034	0.083	0.052	0.042	0.114	0.060	0.036	0.000	0.043	0.039	0.041
41	0.032	0.026	0.096	0.034	0.021	0.045	0.026	0.032	0.000	0.031	0.021	0.000	0.031	0.025	0.039
42	0.015	0.020	0.096	0.028	0.022	0.079	0.039	0.014	0.020	0.029	0.013	0.026	0.027	0.018	0.049
43	0.025	0.035	0.000	0.033	0.023	0.049	0.047	0.019	0.017	0.042	0.015	0.019	0.035	0.024	0.023
44	0.037	0.020	0.031	0.046	0.012	0.025	0.052	0.008	0.011	0.056	0.007	0.010	0.046	0.012	0.022
45	0.020	0.026	0.052	0.024	0.023	0.000	0.021	0.011	0.000	0.033	0.017	0.031	0.022	0.022	0.036
46	0.003	0.028	0.000	0.009	0.018	0.000	0.008	0.026	0.000	0.008	0.018	0.000	0.007	0.023	0.014

Tract ID	YEAR														
	2002			2003			2004			2005			Overall (2001-05)		
	Alarm	NAI_Bur	AI_Bur	Alarm	NAI_Bur	AI_Bur	Alarm	NAI_Bur	AI_Bur	Alarm	NAI_Bur	AI_Bur	Alarm	NAI_Bur	AI_Bur
47	0.016	0.014	0.071	0.026	0.008	0.043	0.031	0.009	0.037	0.035	0.007	0.032	0.027	0.010	0.038
48	0.020	0.055	0.224	0.027	0.037	0.000	0.042	0.021	0.027	0.051	0.033	0.022	0.034	0.037	0.040
49	0.011	0.020	0.000	0.027	0.019	0.000	0.030	0.011	0.037	0.031	0.014	0.000	0.023	0.015	0.010
50	0.032	0.039	0.000	0.043	0.048	0.000	0.043	0.022	0.000	0.039	0.019	0.056	0.040	0.032	0.022
51	0.031	0.020	0.000	0.037	0.013	0.030	0.038	0.016	0.000	0.036	0.022	0.000	0.034	0.020	0.007
52	0.006	0.017	0.000	0.006	0.009	0.000	0.007	0.015	0.200	0.013	0.008	0.000	0.008	0.013	0.053
53	0.012	0.084	0.269	0.020	0.053	0.000	0.022	0.068	0.077	0.026	0.048	0.067	0.018	0.071	0.129
54	0.019	0.032	0.000	0.017	0.042	0.000	0.022	0.019	0.000	0.019	0.007	0.077	0.017	0.025	0.017
55	0.011	0.014	0.061	0.008	0.005	0.000	0.008	0.007	0.000	0.012	0.001	0.056	0.011	0.009	0.036
56	0.017	0.005	0.135	0.035	0.028	0.000	0.028	0.021	0.000	0.018	0.002	0.000	0.023	0.015	0.039
57	0.000	0.012	0.000	0.000	0.007	0.000	0.000	0.013	0.000	0.002	0.003	0.000	0.001	0.010	0.000
58	0.001	0.012	0.673	0.004	0.010	0.000	0.007	0.014	0.091	0.007	0.009	0.091	0.004	0.014	0.090
59	0.015	0.035	0.056	0.020	0.034	0.043	0.025	0.061	0.034	0.020	0.034	0.000	0.018	0.042	0.038
60	0.005	0.021	0.135	0.006	0.012	0.125	0.009	0.014	0.000	0.019	0.015	0.077	0.010	0.018	0.060
61	0.003	0.025	0.000	0.005	0.022	0.286	0.009	0.019	0.000	0.009	0.013	0.000	0.006	0.019	0.050
62	0.006	0.016	0.000	0.010	0.012	0.000	0.012	0.014	0.000	0.016	0.015	0.000	0.011	0.013	0.000
63	0.002	0.015	0.000	0.005	0.012	0.000	0.003	0.012	0.000	0.008	0.008	0.100	0.005	0.012	0.035
64	0.004	0.014	0.135	0.009	0.011	0.000	0.016	0.013	0.000	0.015	0.011	0.000	0.011	0.013	0.021
65	0.007	0.040	0.000	0.010	0.027	0.000	0.016	0.046	0.000	0.025	0.028	0.000	0.013	0.041	0.000
66	0.005	0.026	0.135	0.011	0.019	0.000	0.009	0.034	0.000	0.009	0.013	0.071	0.009	0.025	0.031
67	0.004	0.016	0.000	0.005	0.026	0.000	0.006	0.033	0.000	0.007	0.020	0.143	0.005	0.024	0.040
68	0.006	0.021	0.000	0.005	0.007	0.000	0.007	0.010	0.000	0.010	0.010	0.000	0.006	0.013	0.000
69	0.005	0.018	0.000	0.005	0.013	0.000	0.012	0.009	0.000	0.006	0.012	0.000	0.008	0.013	0.000
70	0.005	0.012	0.168	0.004	0.011	0.200	0.005	0.012	0.000	0.003	0.011	0.000	0.004	0.012	0.080
71	0.001	0.015	0.000	0.007	0.011	0.000	0.010	0.016	0.063	0.007	0.009	0.000	0.006	0.014	0.021
72	0.007	0.106	0.000	0.008	0.068	0.000	0.015	0.078	0.111	0.018	0.060	0.000	0.010	0.077	0.068
73	0.001	0.016	0.000	0.003	0.017	0.167	0.004	0.016	0.000	0.003	0.006	0.000	0.002	0.015	0.135
74	0.000	0.016	0.000	0.000	0.018	0.000	0.008	0.006	0.000	0.007	0.004	0.000	0.003	0.011	0.000
75	0.009	0.139	0.000	0.016	0.125	0.200	0.016	0.128	0.000	0.019	0.056	0.000	0.015	0.111	0.041
76	0.004	0.004	0.000	0.000	0.016	0.000	0.001	0.019	0.000	0.003	0.009	0.000	0.002	0.011	0.000
77	0.019	0.040	0.090	0.016	0.039	0.000	0.024	0.040	0.000	0.023	0.016	0.036	0.019	0.038	0.026
78	0.034	0.019	0.122	0.035	0.021	0.000	0.046	0.017	0.045	0.037	0.019	0.000	0.033	0.020	0.038
79	0.006	0.027	0.000	0.008	0.015	0.000	0.016	0.008	0.000	0.008	0.007	0.000	0.008	0.017	0.033
80	0.002	0.007	0.000	0.003	0.004	0.000	0.002	0.009	0.000	0.001	0.003	0.000	0.002	0.006	0.000
81	0.015	0.033	0.067	0.024	0.031	0.043	0.027	0.020	0.038	0.021	0.022	0.000	0.020	0.027	0.031
82	0.009	0.029	0.404	0.009	0.036	0.000	0.020	0.031	0.000	0.015	0.007	0.077	0.013	0.030	0.093
83	0.009	0.024	0.067	0.017	0.032	0.071	0.023	0.027	0.000	0.026	0.017	0.024	0.017	0.028	0.043
84	0.021	0.007	0.099	0.025	0.006	0.033	0.029	0.009	0.043	0.037	0.011	0.012	0.027	0.009	0.038
85	0.007	0.008	0.061	0.015	0.013	0.086	0.024	0.008	0.000	0.027	0.007	0.047	0.016	0.009	0.052
86	0.007	0.041	0.269	0.025	0.035	0.037	0.022	0.026	0.083	0.021	0.014	0.043	0.017	0.030	0.063
87	0.004	0.016	0.269	0.010	0.021	0.118	0.014	0.008	0.000	0.023	0.004	0.000	0.012	0.013	0.061
88	0.040	0.347	0.673	0.054	0.297	0.000	0.054	0.459	0.000	0.026	0.237	0.000	0.042	0.358	0.127
89	0.003	0.020	0.000	0.013	0.016	0.000	0.013	0.013	0.000	0.021	0.016	0.083	0.011	0.018	0.063
90	0.000	0.022	0.000	0.002	0.012	0.000	0.001	0.010	0.000	0.002	0.006	0.000	0.001	0.014	0.000

Appendix 3. Lists of the variables for correlation and regression analyses

Category	Variables*
Demographic	White, black, and other
Age	Age <=14, 15-17, 18-24, 25-34, 35-44, 45-54, 55-59, 60-64, 65-74, and >=75 Median age
Socio-Economic	Median income Unemployment Poverty level in population
Housing Characteristic	Householder's race by white, black, and other Householder's age 15-24, 25-34, 35-44, 45-54, 55-59, 60-64, 65-74, over 75 Poverty level in household House occupied and vacant Owner's and renter's occupied

* All variables listed here are calculated with rates, except "median age" and "media income."

Appendix 4. Multiple correlation coefficients (Person's r) for the rates of burglar alarm installations for 90 census tracts annually, in Newark, NJ

Variable	Year					
	2001	2002	2003	2004	2005	Overall
White Population	-.251*	-.258*	-.366**	-.376**	-.305**	-.339**
Black Population	.279**	.258*	.375**	.386**	.319**	.354**
Other Population	-.245*	-.184	-.281**	-.292**	-.250*	-.276**
Population Age <=14	.123	.182	.220*	.241*	.318**	.249*
Population Age 15-17	.215*	.192	.223*	.177	.132	.198
Population Age >=75	-.041	-.093	-.216*	-.208*	-.204	-.178
Median Age (30.2)	-.218*	-.254*	-.318**	-.331**	-.364**	-.331**
Median Income ($26,929)	.119	.118	.238*	.203	.101	.168
Unemployment	-.149	-.134	-.251*	-.248*	-.261*	-.232*
White Householder	-.247*	-.236*	-.339**	-.361**	-.298**	-.324**
Black Householder	.280**	.245*	.352**	.372**	.308**	.340**
Other Householder	-.256*	-.186	-.268*	-.276**	-.231*	-.266*
Householder Age 25-34	.078	.173	.217*	.220*	.279**	.221*
Householder Age >=75	.019	-.051	-.249*	-.288**	-.235*	-.195
Owner Occupied	.243*	.249*	.381**	.363**	.180	.302**
Renter Occupied	-.243*	-.249*	-.381**	-.363**	-.180	-.302**

* Statistically significant at the .05 level

** Statistically significant at the .01 level

Appendix 5. Multiple correction coefficients (Pearson's *r*) of the rates of NAI burglary for 90 census tracts annually in Newark, NJ

Variable	Year					
	2001	2002	2003	2004	2005	Overall
Population Age <=14	-.290**	-.300**	-.302**	-.334**	-.273**	-.306**
Population Age 15-17	-.218*	-.238*	-.207	-.250**	-.178	-.226*
Population Age 25-34	.582**	.578**	.549**	.617**	.550**	.591**
Population Age 35-44	.407**	.448**	.396**	.427**	.462**	.432**
Population Age 45-54	-.234*	-.175	-.189	-.172	-.181	-.197
Population Age 55-59	-.253*	-.222*	-.240*	-.235*	-.177	-.234*
Population Age 60-64	-.251*	-.246*	-.212*	-.296**	-.269*	-.262*
Population Age 65-74	-.299**	-.328**	-.301**	-.302**	-.307**	-.313**
Population Age >=75	-.226*	-.271**	-.240*	-.221*	-.287**	-.250*
Unemployment	.478**	.430**	.400**	.471**	.447**	.457**
Householder Age 60-64	.640**	.600**	.615**	.585**	.567**	.616**
Householder Age 65-74	-.294**	-.320**	-.277**	-.283**	-.255*	-.294**
Householder Age >=75	-.251*	-.278**	-.283**	-.249*	-.279**	-.272**

* Statistically significant at the .05 level
** Statistically significant at the .01 level

Appendix 6. A series of forward selection multiple regressions for burglar alarm annually in Newark, NJ (*N*=90 census tracts)

For Year 2001

Independent Variables	Dependent Variable (=Burglar Alarm)											
	Model 1				Model 2				Model 3			
	b	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*
Black Householder	.014	.005	.280	2.738**	.014	.005	.284	2.855**	.014	.005	.277	2.835**
Owner Occupied					.032	.013	.247	2.483*	.031	.013	.243	2.489*
NAI Residential Burglary									.075	.036	.204	2.093*
F	7.498**				7.052**				6.345**			
Constant	.009				.002				-.001			
R^2	.079				.139				.181			

For Year 2002

Independent Variables	Dependent Variable (=Burglar Alarm)																			
	Model 1				Model 2				Model 3				Model 4				Model 5			
	b	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*
Black Population	.013	.005	.258	2.510*	.013	.005	.259	2.591*	.015	.005	.313	3.17**	.014	.005	.296	3.05**	.008	.006	.166	1.46
Owner Occupied					.031	.013	.250	2.501*	.035	.012	.279	2.87**	.033	.012	.265	2.77**	.040	.012	.317	3.27**
Householder Age 25-34									.091	.034	.266	2.68**	.089	.033	.258	2.65*	.072	.034	.208	2.11*
NAI Residential Burglary													.092	.043	.205	2.16*	.129	.045	.287	2.83**
Population Age <=14																	.066	.032	.250	2.07*
F	6.3000*				6.465**				7.002***				6.635***				6.367***			
Constant	.010				.002				-.019				-.020				-.032			
R^2	.067				.129				.196				.238				.275			

For Year 2003

Independent Variables	Dependent Variable (=Burglar Alarm)																			
	Model 1				Model 2				Model 3				Model 4				Model 5			
	b	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*
Owner Occupied	.058	.015	.381	3.87***	.058	.014	.382	4.22***	.064	.013	.420	5.02***	.060	.012	.394	4.82***	.068	.012	.445	5.49***
Black Population					.022	.005	.376	4.15***	.026	.005	.447	5.26***	.025	.005	.415	4.99***	.016	.006	.265	2.71**
Householder Age 25-34									.147	.036	.352	4.12***	.142	.035	.341	4.12***	.119	.035	.285	3.45**
NAI Residential Burglary													.135	.052	.214	2.61*	.197	.055	.313	3.58**
Population Age <=14																	.088	.033	.275	2.68**
F	14.963***				17.468***				19.425***				17.264***				16.252***			
Constant	.010				-.004				-.037				-.038				-.053			
R^2	.145				.287				.404				.448				.492			

For Year 2004

Independent Variables	Dependent Variable (=Burglar Alarm)																			
	Model 1				Model 2				Model 3				Model 4				Model 5			
	b	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*
Black Population	.025	.006	.386	3.93***	.025	.006	.387	4.26***	.030	.005	.459	5.39***	.029	.005	.446	5.40***	.019	.006	.293	3.08**
Owner Occupied					.060	.015	.364	4.01***	.066	.014	.402	4.79***	.065	.013	.393	4.83***	.075	.013	.457	5.64***
Householder Age 25-34									.162	.039	.356	4.15***	.159	.038	.350	4.22***	.132	.037	.291	3.55**
NAI Residential Burglary													.098	.038	.212	2.62**	.148	.040	.318	3.71***
Population Age <=14																	.103	.035	.297	2.90**
F	15.428***				17.061***				19.249***				17.142***				16.586***			
Constant	.014				-.001				-.038				-.039				-.057			
R^2	.149				.282				.402				.446				.497			

For Year 2005

Independent Variables	Dependent Variable (=Burglar Alarm)															
	Model 1				Model 2				Model 3				Model 4			
	b	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*
Black Population	.030	.010	.319	3.15**	.037	.009	.391	4.05***	.038	.009	.397	4.22***	.028	.010	.290	2.72**
Householder Age 25-34					.240	.065	.357	3.71***	.257	.063	.382	4.05***	.230	.064	.342	3.60**
Owner Occupied									.054	.023	.222	2.40**	.067	.023	.273	2.89**
Population Age <=14													.111	.055	.217	2.01*
F	9.946**				12.565***				10.764***				9.365***			
Constant	.013				-.039				-.055				-.074			
R^2	.102				.224				.273				.306			

* Statistically significant at the .05 level
** Statistically significant at the .01 level
*** Statistically significant at the .001 level

Appendix 7. A series of hierarchical multivariable regressions for NAI residential burglary annually in Newark, NJ (*N*=90 census tracts)

For Year 2001

Independent Variables	Dependent Variable (=NAI Residential Burglary)																			
	Model 1				Model 2				Model 3				Model 4				Model 5			
	b	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*
Burglar Alarm	.599	.285	.219	2.102*	.812	.246	.296	3.303**	.842	.177	.307	4.768***	.606	.149	.221	4.079***	.614	.151	.224	4.07***
Unemployment					.256	.044	.522	5.819***	.244	.032	.497	7.522***	.183	.028	.374	6.532***	.186	.029	.379	6.37***
Population Age <=17									-.163	.077	-.254	-2.135*	-.150	.063	-.233	-2.395*	-.147	.063	-.229	-2.33*
Population Age 25-44									.135	.087	.196	1.548	.072	.072	.105	1.008	.070	.072	.102	.974
Population Age >=45									-.329	.078	-.422	-4.202***	-.340	.064	-.436	-5.32***	-.322	.081	-.413	-3.99***
Householder Age 60-64													.578	.088	.383	6.55***	.575	.089	.381	6.46***
Householder Age >=65																	-.021	.056	-.031	-.365
F	4.419*				19.962***				33.62***				49.145***				41.704***			
Constant	.024				-.074				.024				.026				.024			
R^2	.048				.315				.667				.780				.781			

For Year 2002

Independent Variables	Dependent Variable (=NAI Residential Burglary)																			
	Model 1				Model 2				Model 3				Model 4				Model 5			
	b	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*
Burglar Alarm	.554	.231	.248	2.403*	.695	.205	.311	3.39**	.676	.153	.303	4.407***	.505	.137	.226	3.693***	.516	.138	.231	3.753***
Unemployment					.184	.036	.472	6.14***	.170	.027	.436	6.277***	.126	.026	.324	5.099***	.132	.026	.338	5.141***
Population Age <=17									-.146	.064	-.284	-2.264*	-.131	.056	-.256	-2.349*	-.126	.056	-.246	-2.241*
Population Age 25-44									.108	.073	.198	1.484	.068	.064	.124	1.063	.063	.064	.116	.989
Population Age >=45									-.247	.065	-.398	-3.771***	-.255	.057	-.411	-4.490***	-.218	.071	-.352	-3.069**
Householder Age 60-64													.419	.078	.349	5.368***	.414	.078	.345	5.283***
Householder Age >=65																	-.042	.050	-.080	-.850
F	5.773*				16.939***				28.824***				36.779***				31.522***			
Constant	.023				-.047				.034				.032				.028			
R^2	.062				.280				.632				.727				.729			

For Year 2003

Independent Variables	Dependent Variable (=NAI Residential Burglary)																			
	Model 1				Model 2				Model 3				Model 4				Model 5			
	b	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*
Burglar Alarm	.508	.160	.321	3.18**	.681	.142	.430	4.803***	.673	.110	.425	6.109***	.511	.101	.323	5.062***	.511	.102	.323	5.032***
Unemployment					.166	.030	.495	5.530***	.154	.023	.459	6.663***	.114	.022	.339	5.266***	.115	.022	.342	5.141***
Population Age <=17									-.168	.054	-.381	-3.086**	-.152	.048	-.345	-3.195**	-.151	.048	-.343	-3.131**
Population Age 25-44									.046	.062	.097	.739	.013	.054	.027	.235	.012	.055	.025	.217
Population Age >=45									-.211	.055	-.395	-3.807***	-.221	.048	-.415	-4.58***	-.214	.061	-.402	-3.536**
Householder Age 60-64													.354	.068	.343	5.222***	.353	.068	.342	5.176***
Householder Age >=65																	-.008	.042	-.018	-.196
F	10.096**				22.037***				30.547***				37.964***				32.169***			
Constant	.018				-.047				.049				.050				.049			
R^2	.103				.336				.645				.733				.733			

For Year 2004

Independent Variables	Dependent Variable (=NAI Residential Burglary)																			
	Model 1				Model 2				Model 3				Model 4				Model 5			
	b	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*
Burglar Alarm	.557	.222	.258	2.510*	.862	.189	.400	4.558***	.870	.132	.403	6.607***	.709	.123	.329	5.748***	.710	.124	.329	5.720***
Unemployment					.284	.044	.570	6.497***	.259	.030	.520	8.602***	.212	.029	.425	7.323***	.209	.030	.421	7.020***
Population Age <=17									-.205	.070	-.314	-2.918**	-.191	.063	-.292	-3.016**	-.193	.064	-.296	-3.018**
Population Age 25-44									.155	.080	.221	1.939	.111	.072	.160	1.543	.113	.073	.162	1.556
Population Age >=45									-.274	.072	-.346	-3.805***	-.288	.065	-.364	-4.450***	-.304	.081	-.384	-3.760***
Householder Age 60-64													.412	.090	.269	4.593***	.414	.090	.270	4.579***
Householder Age >=65																	.019	.056	.028	.334
F	6.299*				25.729***				45.173***				50.165***				42.554***			
Constant	.015				-.097				-.004				.000				.002			
R^2	.067				.372				.729				.784				.784			

For Year 2005

Independent Variables	Dependent Variable (=NAI Residential Burglary)																			
	Model 1				Model 2				Model 3				Model 4				Model 5			
	b	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*	*b*	*SE*	*Beta*	*t*
Burglar Alarm	.105	.081	.137	1.300	.208	.073	.273	2.87**	.219	.057	.287	3.820***	.161	.054	.211	3.000**	.161	.054	.210	2.975**
Unemployment					.135	.025	.518	5.455***	.124	.019	.476	6.509***	.096	.018	.368	5.223***	.096	.019	.368	5.028***
Population Age <=17									-.056	.044	-.164	-1.259	-.048	.040	-.140	-1.187	-.048	.041	-.140	-1.175
Population Age 25-44									.116	.051	.318	2.305*	.088	.046	.241	1.908	.088	.047	.241	1.893
Population Age >=45									-.127	.046	-.305	-2.767**	-.135	.041	-.326	-3.265**	-.136	.052	-.328	-2.615*
Householder Age 60-64													.250	.057	.312	4.408***	.250	.057	.312	4.374***
Householder Age >=65																	.001	.036	.003	.027
F	1.690				16.000***				25.630***				29.284***				24.799***			
Constant	.017				-.036				-.019				-.016				-.016			
R^2	.019				.269				.604				.679				.679			

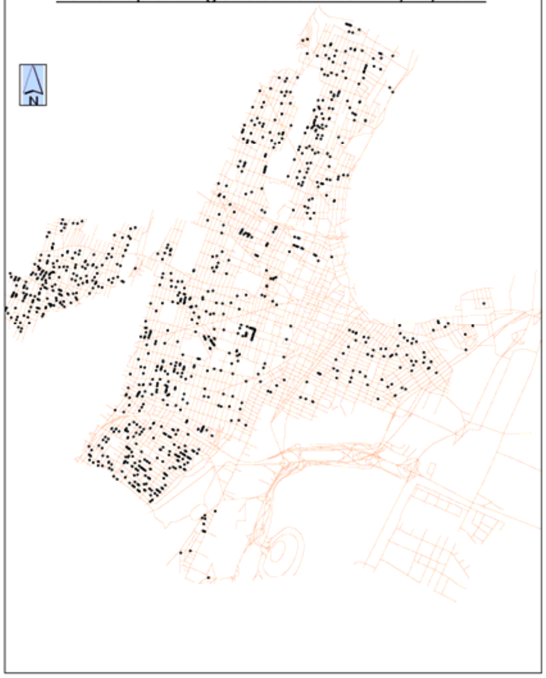
* Statistically significant at the .05 level

** Statistically significant at the .01 level

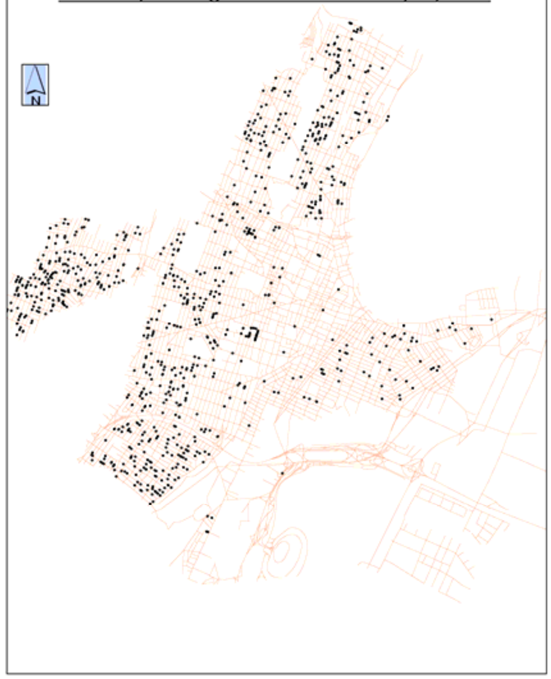
*** Statistically significant at the .001 level

Appendix 8. Points maps of residential burglar alarms annually

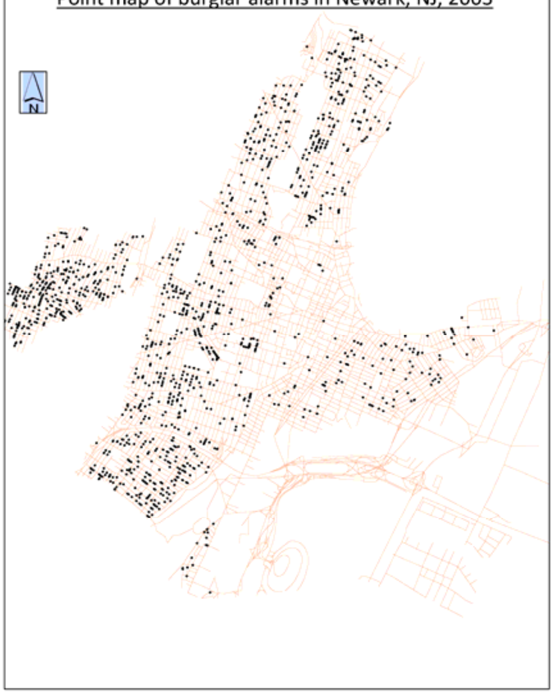
Point map of burglar alarms in Newark, NJ, 2001



Point map of burglar alarms in Newark, NJ, 2002



Point map of burglar alarms in Newark, NJ, 2003



Point map of burglar alarms in Newark, NJ, 2001-2005