# A GEOSPATIAL ANALYSIS OF THE EFFECT OF BLOCK-LEVEL CHARACTERISTICS ON THE DISTRIBUTION OF DOMESTIC BURGLARY

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## ABSTRACT

This study examines the degree to which select block-level characteristics affect burglaries in Lawrence Township, New Jersey. Two regression models were estimated in this study. The first regression model consists of various block-level measures from the U.S. Census, while the second includes a block-level count of burglaries from the prior year, in addition to block-level measures. Overall, the two variables which came to be the strongest predictors of burglary for the 2012 data were the percentage of renters in a given block and the block-level burglary count from 2011. Based on findings for the latter, it was determined that the distribution of burglaries was spatially stable.

## INTRODUCTION

According to the Federal Bureau of Investigation's national statistics, a burglary occurs about every fifteen seconds in the United States (Federal Bureau of Investigation, 2012a). This translates into slightly more than two million burglaries in 2012, almost three-quarters of which (n=1,567,508) targeted residences (Federal Bureau of Investigation, 2012b). The pervasiveness of this crime, and its ability to affect almost anyone, makes it one that deserves a more in-depth analysis. The ultimate goal is the development of more effective preventative strategies which aim to prevent future occurrences.

In an effort to better understand this crime, dispatch data from the Lawrence Township Police Department (LTPD) were studied and used to conduct a geospatial analysis to determine what affects various block-level characteristics had on the overall distribution. Results of this study may be used to aid local police in determining areas of high risk to which they can shift their focus and develop appropriate preventative measures. Data from the U.S. Census such as housing tenure, race and age were used as controls to limit the effects of variables not being analyzed.

## REVIEW OF PRIOR RESEARCH

Prior research of residential burglary has identified different risk factors associated with burglary victimization. Tseloni, Farrell and Pease (2004); Wilcox, Madensen and Tillyer (2008); and Zhang, Messner and Liu (2007) all find that a high occupancy frequency, defined as how often a home is occupied by at least one individual, has a negative effect on burglary risk. Coupe and Laurence (2006) find that home occupancy, in conjunction with environmental factors, are the most influential determinants in defining target attractiveness during the daytime. Their study also concludes that a home left unoccupied is at four times greater risk of victimization. Similarly, Tseloni, Farrell, & Pease, 2004 find that homes in the Netherlands that are left unoccupied are at a 16% greater risk for burglary. D'Alessio, Eitle, and Stolzenberg (2012) find that unemployment rates have a negative effect on burglary rates during weekdays. The reason being unemployed persons are spending more time at home, as opposed to at work. This premise aligns with the guardianship tenet of rational choice theory. Simply, the theory states the presence of a capable guardian can mitigate the risk of victimization (Cohen & Felson, 1979).

Without taking into account unemployment rates, occupancy frequencies are found to be at their lowest during the daytime and twice as high at night during weekdays. This is presumably due to the fact that these times coincide with the average workday. Comparatively, on the weekends occupancy frequencies are high during both the day and night with no significant difference (Coupe & Laurence, 2006). Therefore, during a weekday, a potential burglar would have to weigh the various costs and benefits in two main scenarios. They could either target a house that is more likely to be empty during the day, while exposing himself in the daylight, or using the cover of night to target a house that is more likely to be occupied. It is ultimately up to the offender as to which option is more desirable. Coupe and Laurence (2006) find that younger offenders are more likely to commit a burglary during the day in an attempt to avoid running into any residents, at the same time increasing their likelihood of being seen. They also conclude that older offenders are more willing to encounter a resident at night while using the darkness to their advantage.

An analysis of ten years of burglary data from Hong Kong found different trends in the number of burglaries month-to-month. The author attempted to connect the number of burglaries with Cohen and Felson's (1979) routine activity theory. Following this theory, it is expected that the fewest burglaries would occur in the winter months, when there are fewer people outside, therefore fewer guardians to prevent a crime. The results showed that more burglaries occurred in January and the fewest occurred in February. For the rest of the months there is little variance in the burglary count. However, even with the disparity between January and February, there was found to be no seasonal bias of burglary rates (Yan, 2004). The results do not necessary adhere to the expectations that are set by the routine activities theory.

Family income is also correlated with burglary rates. In Tianjin, China, families with higher incomes greatly increase their risk of burglary following the hypothesis that more affluent families are likely to own a house that is a more appealing target to a potential burglar (Zhang, Messner, & Liu, 2007). Similar effects of family income have been found in Seattle, Washington (Wilcox, Madensen, & Tillyer, 2008). Tseloni, Farrell and Pease (2004) find that in the United Kingdom, high-income households are at about a 30% higher risk of burglary. This corresponds with the results produced in parts of both China and the United States. However, on a national scale, affluent homeowners in the United States experience 33% fewer burglaries compared to those homeowners with average income (Tseloni, Farrell, & Pease, 2004).

Overall, increases in home security result in a decrease in the chance of victimization in Seattle (Wilcox, Madensen, & Tillyer, 2008). However, the same cannot be said for abroad. In the United Kingdom and the Netherlands, homes with an increased security measures were at *least* twice as likely to have been affected by burglary. It is observed, however, that this odd trend is likely due to an increase in security in response to a burglary that occurred before the study was conducted (Tseloni, Farrell, & Pease, 2004).

Zhang, Messner, and Liu (2007) looked at other variables, the effects of which yield results contrasting those found within the United States. In conjunction with occupancy frequency, these researchers analyzed the effects of length of residence, defined as the number of years spent in a residence, on burglaries. They find these variables to have mitigating effects. In their analysis of poverty rates they find that neighborhood poverty level has no contextual effect of victimization risk, contrary to findings in the United States (Zhang, Messner, & Liu, 2007). The reason for this trend is government aid in these regions, which is not offered to the same degree within the United States (Zhang, Messner, & Liu, 2007). This, in turn, limits the destabilization of the area that results from the poverty. Even more surprising is the effect of community stability being positively associated with victimization, wherein more stable neighborhoods are at an increased risk of victimization. The assumption is the expectation that stable neighborhoods are populated with wealthy residents, increasing the number of attractive targets in the area. (Zhang, Messner, & Liu, 2007).

In their study, Rey, Mack, and Koschinsky (2011) took a different approach in predicting the likelihood of victimization. Using Markov chains they have found that attaching probabilities to various grid cells they could predict the likelihood of a burglary occurring there in the future. The prediction is based on prior data from the grid in question. This approach also uses the data from surrounding grids as well.

Occupancy frequency has been found to have a negative effect on burglary rates. Variables such day of the week, unemployment rate, poverty level, building value, family income and environmental factors are also commonly used in burglary analyses. Many prior studies have also tested theories such as routine activities theory (Cohen & Felson, 1979) and social disorganization theory (Sampson & Groves, 1989) to better understand what factors increase the probability of burglary victimization.

## METHODOLOGY

The area under analysis is Lawrence Township, a suburban neighborhood nested within Mercer County, New Jersey, which borders Trenton. According to the 2010 United States Census, the population of Lawrence Township was 33,472 (United States Census Bureau, 2011). The 2010 decennial census describes the racial and ethnic demographics of the area as follows: “White” (70.36%), “Asian” (13.22%), “Black” (12.87%) and “Other” (3.55%) (United States Census Bureau, 2010a).

This study employs a cross-sectional, block-level analysis of dispatch data from the Lawrence Township Police Department (LTPD) for the years of 2011 and 2012. These data include the full enumeration of domestic burglary events reported to the LTPD that took place in those years. Point data for each call contains XY coordinates; no identifying address information was used or made available as part of this study. The unit of analysis is the block-level since this level of data aggregation makes it possible to keep any possible identifying information about victims private. The original data files from the LTPD were modified using SAS 9.4 in order to extract pertinent data from each burglary event, including location and time. These data were then further analyzed utilizing the various statistical procedures available via SAS 9.4.

The original dispatch file, which contains all reported instances of burglary for 2011 and 2012, was subjected to a multi-step exclusion process that limited the events to those of only residential burglaries. This process first involved excluding from U.S. Census data, all blocks that were not located within Lawrence Township, New Jersey by relying on a field labeled “OBJECTID;” only blocks within a shapefile of Lawrence Township were assigned a value for this variable in SAS 9.4. A conditional statement was then implemented to filter out any block for which a null value was reported for “OBJECTID,” leaving only residential blocks within Lawrence Township. Blocks that contain a population of “0” were excluded from the study since an unpopulated block, by definition, contains no occupied residences to be burglarized. Since residential burglary is the focus of the study these blocks were not necessary to include. Finally, another binary variable entitled “Residential” was created in SAS 9.4. This variable was generated using a U.S. Census data file that lists the total number of housing units per block in all of Mercer County, New Jersey. According to the United States Census Bureau (2010b) a housing unit is defined as:

> A house, an apartment, a mobile home, a group of rooms, or a single room that is occupied (or if vacant, is intended for occupancy) as separate living quarters. Separate living quarters are those in which the occupants live and eat separately from any other persons in the building and which have direct access from the outside of the building or through a common hall.

After filtering out non-residential blocks, a total of (n=366) residential blocks remained. This is a reduction of around 36% from the original LTPD file which contained a total of (n=571) blocks. The removal of these blocks had a minimal effect on the total number of burglaries for the year of 2012. The unaltered police file contained a reported (n=126) burglaries before applying the filter. Afterward, there was a count of (n=112), a loss of fourteen events (11%) from the dataset. This 11% represents the burglary events that were not considered domestic burglary according to the parameters set by the conditional statements in SAS 9.4.

An examination of the distribution of events from month to month shows that in 2012, the two highest counts of domestic burglaries occurred in January (n=17) and February (n=11), while the two lowest (n=2) and (n=3) occurred in July and April, respectively. The distribution was similar in 2011. The highest counts occurred in September (n=23) and there was a tie for October and November (n=18). The lowest number of events was in March (n=4) and April (n=5). While the numbers do not coincide between the two years, there is a trend of more burglaries occurring in the winter months. The fewest burglaries occurred from March to July, during the spring and summer. This trend may be due to the shorter days during the winter that give perpetrators the cover of darkness for a longer period of time. This theory contradicts the findings of Yan's (2004) study of burglaries in Hong Kong. While Yan (2004) found differences in the number of events from month to month, he determined there to be no significant seasonal bias.

A shapefile of Mercer County, New Jersey was obtained through the United States Census Bureau's Topographically Integrated Geographic Encoding and Referencing (TIGER) database (United States Census Bureau, Geography Division, 2010). A block-level shapefile of Lawrence Township was created by clipping a larger shapefile of Mercer County using tools available in ArcMAP10. All geospatial analyses in this study were conducted using other features in the program. These analyses include generating choropleth images—which display the distribution of residential burglary events throughout Lawrence Township—as well as a hotspot analysis of the aforementioned distribution. A hotspot analysis determines if there is any significant clustering of events in a given distribution. Any clustering that has been deemed significant as a result of this analysis have been colored a shade of red in Figures 1a and 1b.

The main independent variable in this analysis is home occupancy level. A variable from the U.S. 2010 decennial census called "Average Household Size," which lists the average number of residents in each household per block, was used to represent this variable. Housing tenure, race and age variables are all used as controls. Housing tenure is defined as the percentage of owned and rented residences per block. Race is defined as the percentage of "White", "Black," "Native American," "Asian," "Northern Hawaiian," and "Other" races. The "Other" category contains any race not subsequently mentioned. Age is defined as the percentage of individuals in each of the following age groups: "15-24," "25-34", "45-54," "55-59," "60-64," "65-74," "75-84," and "85 and above." The number of domestic burglary events for the year of 2011 was also used as a control variable in one of the regressions to test for the geospatial stability between the two years; in other words, the goal was to determine whether the same areas of Lawrence Township were experiencing similar numbers of burglaries year over year. Various economic variables such as "unemployment rate," "residential income," "residence value," "length of residence" and "time of day" and "day of the week" were desired for this analysis, but were unavailable at the block-level.

Table 1.*

| Variable | Minimum | Maximum | Mean | Median | Standard Deviation |
|---|---|---|---|---|---|
| Number of Burglary Events in 2011 | 0 | 9 | 0.47 | 0 | 1.12 |
| Number of Burglary Events in 2012 | 0 | 8 | 0.31 | 0 | 0.87 |
| Average Household Size | 1 | 5 | 2.17 | 2 | 0.67 |
| Percent of Rented Housing Units | 0 | 100 | 19.67 | 5.88 | 30.06 |
| Percent of White Residents | 0 | 100 | 73.23 | 82.33 | 26.49 |
| Percent of Black Residents | 0 | 100 | 10.86 | 2.8 | 19.53 |
| Percent of Asian Residents | 0 | 100 | 9.74 | 4.55 | 15.5 |
| Percent of American Indian Residents | 0 | 35.71 | 0.23 | 0 | 2.06 |
| Percent of Native Hawaiian Residents | 0 | 1.06 | 0.01 | 0 | 0.1 |
| Percent of Other Residents | 0 | 100 | 3.43 | 0 | 10.87 |
| Percent of Individuals Age 15-24 | 0 | 100 | 1.91 | 0 | 6.58 |
| Percent of Individuals Age 25-34 | 0 | 50 | 8.38 | 5.09 | 10.66 |
| Percent of Individuals Age 45-54 | 0 | 100 | 21.98 | 22.13 | 15.37 |
| Percent of Individuals Age 55-59 | 0 | 100 | 11.86 | 10 | 12.12 |
| Percent of Individuals Age 60-64 | 0 | 100 | 10.26 | 7.41 | 13.42 |
| Percent of Individuals Age 65-74 | 0 | 100 | 12.17 | 9.57 | 12.84 |
| Percent of Individuals Age 75-85 | 0 | 100 | 8.61 | 5.26 | 11.32 |
| Percent of Individuals Age 85+ | 0 | 68.25 | 3.65 | 0 | 6.84 |

*Description of sample measures for independent and dependent variables

The wide range of ages was included in the study to take into account the general younger age of perpetrators and the notion that those in fifties and sixties and the elderly, who live outside of care facilities, are likely to reside in a low-occupancy household consisting of one to two people. All control variables are at the block-level. Location measures for all variables are listed in Table 1.

After the block-level data tables were downloaded from the U.S. Census database, they were manipulated in SAS 9.4 to match the format of the LTPD file. This was necessary in order to perform analyses. Once the tables were reformatted, they were imported into ArcMAP10 and joined to a shapefile of Lawrence Township using the "GEOID" variable, which all of the files have in common. This variable was already present in the shapefile and was generated in the Census table using the substring function in SAS 9.4 on a similar variable field. While the original variable contained the information for the "GEOID variable, there was extra information that needed to be removed. This function separated the portion of that variable which contained the same information as the "GEOID" variable from that extra information.

A test for spatial randomness of burglary event distribution was using the Global Moran's I tool in ArcMAP10. The goal of this test is to determine whether the distribution of events in the area of observation is random, or if the points are not randomly distributed. A zone of indifference was used as the conceptualization of spatial relationships with Euclidean distance as the distance method. Numerous distance bands were tested for the distribution of points for both the 2011 and 2012 datasets to determine which distance should be implemented in a subsequent hotspot analysis. Values for distance bands were chosen using the staircase method, with a starting point of 1,000 ft., to discover a drop-off point, at which the Z-Scores decrease dramatically. For the 2012 dataset the Z-Score equals 2.176206 at a distance of 1,465 feet and drops to a value of 0.322747 at a distance of 1,300 feet. For the 2011 dataset, the Z-Score is 2.017874 at a distance of 1,150 feet and drops to 0.772746 at a distance of 1,000 feet. The distances of 1,465 ft. and 1,300 ft. were used for the 2012 and 2011 datasets, respectively.

Figure 1a.

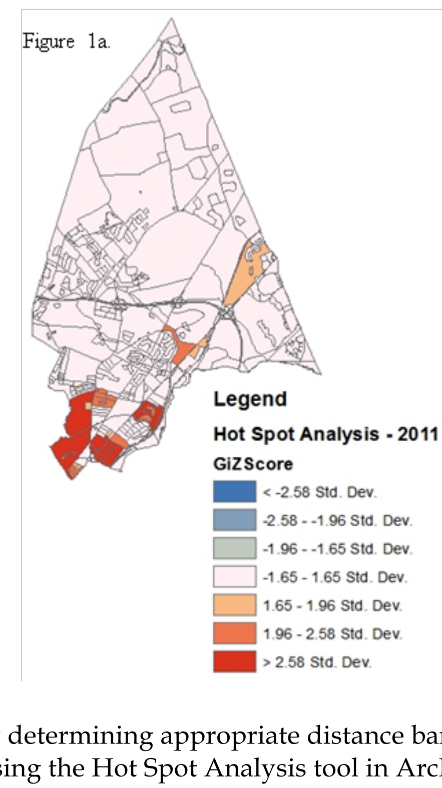
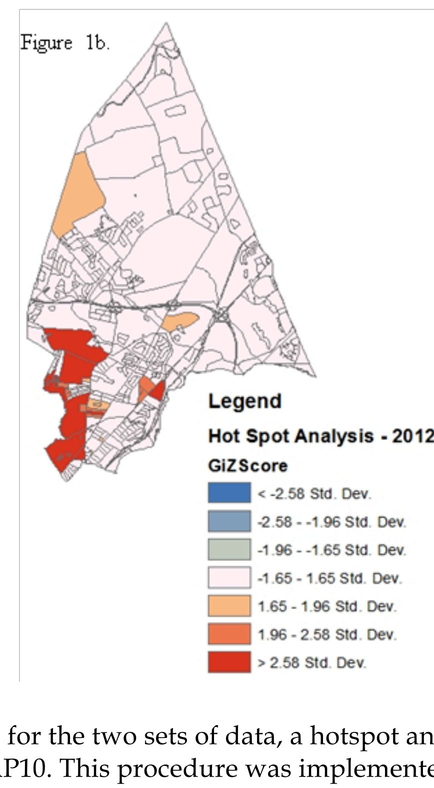



Figure 1b.




After determining appropriate distance bands for the two sets of data, a hotspot analysis was performed using the Hot Spot Analysis tool in ArcMAP10. This procedure was implemented for both the 2011 and 2012 datasets, using the event count as the input feature. The neutral range, the range in which a value is determined as neither a "hot spot" nor a "cold spot," is set at (GiZScore= -1.65< x < 1.65). This range is a default set by the program. In these areas, represented in white, there is no significant clustering of events. Any values for (GiZScore < -1.65) is defined as a "cold spot" and is represented in a shade of blue, while any values for (GiZScore > -1.65) is defined as a "hot spot" and is represented in a shade of red. The results of the hotspot analysis are displayed in Figure 1a. and Figure 1b.

It is evident looking at the figures above that there is significant clustering of events in the southern section of the township for both years. For the year of 2012 there are notably more blocks in the southwest region of Lawrence with significant clustering. A negative binomial regression was used in an attempt to determine whether home occupancy level, in the presence of racial, age, and tenure controls, was a factor in the burglary count.

The distributions for both sets of data are right-skewed, meaning that a preponderance of blocks in the set have no burglary events. Model 1 is a regression of the dependent variable for the 2012 count of domestic burglary on all aforementioned independent variables excluding the 2011 count data. Model 2 is a regression of 2012 count data on all independent variables, including the 2011 count data.

## RESULTS

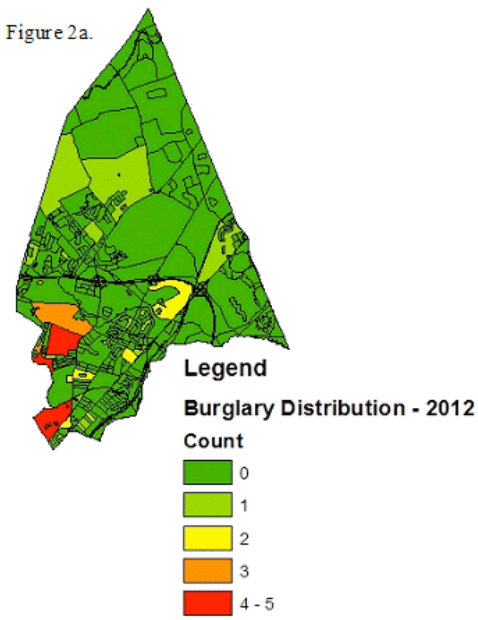
Regression estimations for Model 2 yield interesting results. "Percent of Rented Housing Units" (p=.0282) and "Number of Burglary Events in 2011", included in Model 2, emerged as predictors with low probability values. Therefore, in areas with high numbers of rented housing units within Lawrence Township, there is a higher likelihood of burglary victimization. The positive coefficient estimate for "Number of Burglary Events in 2011" shows that a block that experienced a burglary in 2011 was at an increased risk of experiencing one in 2012; thus, burglaries were spatially stable between 2011 and 2012.

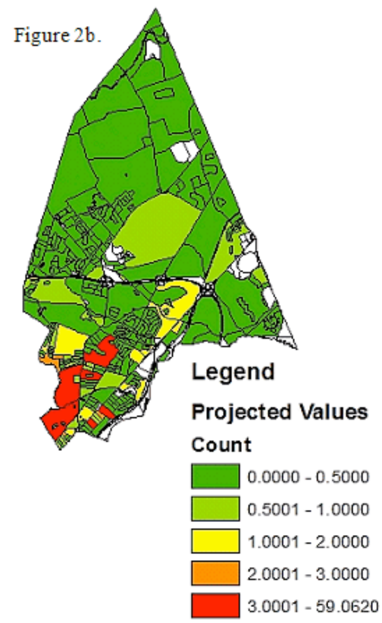
Table 2.

Parameter Estimates

| Parameter | DF | Estimate | Standard Error | t Value | Approx Pr > \|t\| |
|---|---|---|---|---|---|
| Intercept | 1 | -7.654 | 4.718 | -1.62 | 0.1048 |
| Average Household Size | 1 | 0.141 | 0.251 | 0.56 | 0.5742 |
| Percent of Rented Housing Units | 1 | 0.012 | 0.006 | 2.19 | 0.0282 |
| Percent of White Residents | 1 | 0.039 | 0.047 | 0.83 | 0.4069 |
| Percent of Black Residents | 1 | 0.048 | 0.047 | 1.02 | 0.3061 |
| Percent of Asian Residents | 1 | 0.014 | 0.048 | 0.29 | 0.7741 |
| Percent of American Indian Residents | 1 | -0.784 | 0.614 | -1.28 | 0.202 |
| Percent of Native Hawaiian Residents | 1 | 1.394 | 0.919 | 1.52 | 0.1292 |
| Percent of Other Residents | 1 | 0.015 | 0.051 | 0.3 | 0.7662 |
| Percent of Individuals Age 15-24 | 1 | 0.047 | 0.024 | 1.94 | 0.0526 |
| Percent of Individuals Age 25-34 | 1 | 0.007 | 0.017 | 0.41 | 0.685 |
| Percent of Individuals Age 45-54 | 1 | 0.023 | 0.013 | 1.79 | 0.0742 |
| Percent of Individuals Age 55-59 | 1 | 0.018 | 0.017 | 1.09 | 0.2749 |
| Percent of Individuals Age 60-64 | 1 | -0.002 | 0.015 | -0.12 | 0.9026 |
| Percent of Individuals Age 65-74 | 1 | 0.022 | 0.014 | 1.56 | 0.1198 |
| Percent of Individuals Age 75-85 | 1 | 0.020 | 0.015 | 1.37 | 0.1708 |
| Percent of Individuals Age 85+ | 1 | 0.023 | 0.021 | 1.11 | 0.2666 |
| Number of Burglary Events in 2011 | 1 | 0.688 | 0.108 | 6.39 | <.0001 |
| Alpha | 1 | 1.179 | 0.425 | 2.78 | 0.0055 |

Following the calculation of parameter estimates for Model 2, a list of predicted probabilities was generated using the same regression. These values represent the likelihood, as a percent, of a burglary event occurring in a given block and are depicted in the choropleth image in Figure 2b. The actual event count for burglary events in 2012 is represented in Figure 2a. Looking at the images one can see they share similar counts for many blocks.




Even though the event counts may seem similar, the scales used for the two maps are not the same. This is due to the values for the actual count being larger integers, while the predicted values being mostly fractional values. The counts for the choropleth image of predicted values vary to a greater degree than that of the actual count, necessitating the values to be binned differently.[i] Binning is the process of assigning values, or a range of values, to a group. In this instance, values were assigned to a color to be represented on the choropleth image.

## DISCUSSION & CONCLUSION

The goal of this study was to analyze the distribution of domestic burglary events in Lawrence Township, New Jersey and achieve a better understanding as to whether burglary events are spatially stable and correlated with certain block-level characteristics. More specifically, this analysis attempts to determine the effect these various block-level variables had with regards to the occurrence of a burglary for the year of 2012. Another goal is to determine how spatially stable reported burglaries are from the years 2011 to 2012. While most of the independent variables did not result in sizeable estimated changes in the dependent variable when analyzed individually, when combined in a regression, the resulting data are similar to the actual count as depicted in Figure 2a. and Figure 2b. However, while the data represented in the aforementioned figures appear similar, there are areas between the two which vary. Based on the prediction data, the distribution of burglaries would change when taking into account the specific variables that were studied.

The benefit of an area of study such as Lawrence Township, is the ability to avoid sampling data from a larger pool. This is because sample pools may not accurately represent an entire population to which to results would be applied.

It is for this reason this study potentially provides the LTPD the knowledge that burglary, at least according to this study, is spatially stable. Between the years of 2011 and 2012 there are blocks within Lawrence Township that constantly experience significant clusters of domestic burglaries. This information is important for police in their mission of reducing crime, allowing them to predict which areas will need more resources and allocate them appropriately.

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[i] The highest value in the prediction map is 59.062 and is considered an outlier based on the values for the actual counts for both 2011 and 2012.