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What is Near and Recent in Crime for a Homeowner? The Cases of Denver and Seattle

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Abstract

This paper analyzes the effects of the concentration of crime on housing prices using nonparametric methods. Specifically, we use a modified local K-function in order to measure crime concentration. This technique provides us with a crime measure that is not dependent on pre-defined boundaries. Results from this analysis suggest a decrease in housing prices of two percent to seven percent for crimes in the past six months that occur within a quarter of a mile of the house.

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1 Introduction

We are interested in estimating how changes in crime impact property prices across different periods of time and distances. We assess this impact by examining crime measured over different distances in order to ask, "What do property owners consider near?" Secondly, we examine crime that occurs over different periods of time in order to ask, "What do property owners consider recent?" We examine the impact of crime by looking at data from the cities of Denver, Colorado and Seattle, Washington.

Previous literature has found that crime negatively affects housing prices (Ihlanfeldt and Mayock, 2010). Other papers emphasize the perception of future crime based on past behavior by examining when a sex offender moves into, and then out of, a neighborhood. These studies measure the impression of a ''rise in risk'' of crime in the neighborhood using the precise time and location of a sex offender's arrival (increase risk) and departure (reduction of the risk). Housing prices respond by decreasing in areas near to where a sex offender (risk) has moved (Linden and Rockoff, 2008; Pope, 2008). A sex offender moving into the neighborhood is a rare event compared to number of crimes. Our paper explores the impact of all types of crime on property prices.

We measure increased risk around properties using a nonparametric measures of spatial concentration in order to account for the effects of crime on residential property prices; in particular, we focus on the concentration of crime around a property sold at a given point in time. This procedure creates property specific measures of crime. This method overcomes limitations when using crime data aggregated using arbitrary boundaries including zip code, city, and census block boundaries. Furthermore, by varying the length of time over we use to create the concentration measure, we can determine the persistence of the impacts of crime on property prices.

Results suggest that some crimes, including public disorder and automobile theft, negatively affect property prices. As expected, the impact of crime decreases when crime concentration is measured over large distances. We analyze two cities, Seattle and Denver, and find that the effect varies across cities. A one-standard-deviation increase in crime concentration decreases property prices between two percent to seven percent

In Section 2, we provide a summary of the relevant literature. Section 3 explains the methodology applied, describes the data employed in our empirical analysis, and discusses the main results. Finally, in section 4, we draw some conclusions.

2 Literature Review

The relationship between crime and housing prices has been extensively studied in previous research by including measures of crime as an explanatory variables in a hedonic model (Ihlanfeldt and Mayock, 2010). These papers used a variety of variables in order to account for crime intensity. Presumably, crime is thought to decrease the quality of the surrounding neighborhood. An increase in crime is expected to create disutility in the owner/resident of the house. Additionally, as Gibbons (2004) explains, ''the spatial concentration of crime can have dynamic effects driven by households, because their concentration increases the "fear of crime" and discourages new home buyers from moving there. This creates a downward spiral of the neighborhood's quality.''

The hedonic models have typically found evidence of a negative relationship between crime rates and house prices (Thaler, 1978; Rizzo, 1979; Naroff et al., 1980; Taylor, 1995; Lynch and Rasmussen, 2001; Bowes and Ihlanfeldt, 2001; Schwartz et al., 2003; Gibbons, 2004; Tita et al., 2006; Ihlanfeldt and Mayock, 2010). These papers emphasize the relationship between an increase in crime and a decrease in property prices. However, a small number of works have found insignificant correlations between crime and housing prices (Ridker and Henning, 1967; Kain and Quigley, 1970). Furthermore, at least one study finds a positive correlation (Case and Mayer, 1996).

The choice of how to measure of crime and which types of crime to use is important. In studies of residential property, researchers have used a variety of variables including total crime, property crime, violent crime, shopping center crime, assault and vandalism. The choice of one type of crime over another is related to the expected disutility that the person selling the house is facing. As Ihlanfeldt and Mayock (2010) highlight, different crimes have different impacts on house prices. Aggregating all crimes together by using an overall crime rate would incorrectly assume that, ultimately, the measure of crime adequately represents the expected disutility faced by homeowners when selling a property.

Choice of spatial unit in crime analysis is also crucial. Researchers have used different areal units in their analyses including census tract, community, blocks, town, and precinct. Arbia et al. (2015) points out that when using areal data "[any] conclusions are based on the arbitrary definition of jurisdictional spatial units". In other words, using different levels of spatial aggregation can lead to different outcomes. Arbia (1989) defines this problem as the "Modifiable Areal Unit Problem" (MAUP).

More recently, articles have proposed solutions to the MAUP when measuring the value of amenities amenities, accessibility, or the presence of any characteristic that is related to location. For example, when measuring the effect of accessibility on house prices, Baum-Snow and Kahn (2000) use distance to rail stations. Baum-Snow and Kahn (2000) find that reduced distance between census tract and rail transit is associated with an increase in mean property price. Gibbons and Machin (2005) analyze the opening of a new subway line extension in London. They find that properties where the distance between the nearest train decreases experience an increase in house price. The change in price can also be affected by expectations, as McMillen and McDonald (2004) find. McMillen and McDonald (2004) estimates a model in which price changes after plans for a new line of rapid transit in Chicago were released. Their analysis shows that property prices increase in locations where future stations were anticipated, yet not formally announced.

(Pope, 2008; Linden and Rockoff, 2008) investigates the presence of a sex offender living in the neighborhood on property prices. In this study, there is an increase in "risk of crime". The presence of a sex offender was captured by a dummy variable that is assigned a value of 1 if the registered offender lives within a specified distance from a property. The authors find a negative and significant correlation with property price. Further, Pope (2008) find that house prices revert to their previous levels when the sex offender moves.

In the above studies, there is a minimal risk that several sex offenders will live near each other, and that the effects will cumulate. However, it is frequently the case that many crimes can occur within a given area. In order to capture the cumulative effects of these crimes, we incorporate methodologies from the urban agglomeration literature designed to solve the MAUP. Several articles on agglomeration economies using micro data on establishment locations have shown the desired result (Duranton and Overman, 2005, 2008; Arbia et al., 2008; Espa et al., 2010; Ellison et al., 2010; Nakajima et al., 2012). These studies use the firm location when measuring firm concentration and apply the K-function developed in (Ripley, 1976). This analysis avoids the MAUP because it considers the specific location of each firm and provides an un-biased measure of spatial concentration.

The K-function has been used in recent empirical studies by Ellison et al. (2010) and Arbia et al. (2015). These authors propose constructing variables using K-function measures of industrial concentration or agglomeration. Ellison et al. (2010) estimate the concentration by sector, using this K-function variable as a dependent variable when testing for specific sources of coagglomeration. Arbia et al. (2015) uses a local K-function applied to firm location and uses this measure as an independent variable. Arbia et al. (2015) analyzes a hazard function in order to test whether concentration is associated with firm attrition.

3 Empirical Analysis

3.1 Econometric Approach

We are interested in measuring the concentration of crime around individual houses thus avoiding the MAUP. We use the K-function to measure the presence and concentration of crime in areas surrounding a property. Measuring crime at the property level is similar to the approach taken by Gibbons (2004), Linden and Rockoff (2008), and Pope (2008). We propose a variation of the K-function in order to measure local concentrations (Getis, 1984). A similar procedure was used by Arbia et al. (2015). The K-function in equation (1) measures the standardized concentration of events located within a specific distance from a given property.

$$K_i(d,s) = \frac{1}{\lambda_s} E\left[\sum_j I(d_{ij} \leq d) I(s \leq s_{ij} \leq s + s^*)\right] \tag{1}$$

Where $d_{ij} = ||l_i - l_j||$ and $s_{ij} = t_i - t_j$ and $0 \leq s_{ij}$. The values l_i and l_j denote the locations of property i and crime j. The term d_{ij} is the distance in miles between property i and crime j. The crimes included in the K-function are the crimes that are located within d

miles of property i. The terms t_i and t_j are the dates of the sale for property i and the date of crime j. The term s_{ij} measures the time between the sale and the crime. The restrictions $s \leq s_{ij} \leq s + s^*$ imply that the K-function only includes crimes committed less than s^* months prior to the sale.

The variables λ_s is the spatial intensity of crime between time periods s and $s + s^*$ per unit area. We calculate this as $\lambda_s = \frac{1}{|A|} \sum_j I(s \leq s_{ij} \leq s + s^*)$. For two properties i and i' sold at the same time, $t_i = t_{i'}$, we will have $s_{ij} = s_{i'j}, \forall j$ and $\lambda_{is} = \lambda_{i's}$. In other words, the spatial intensity of crime is only determined by the date of sale. [1]

The sale price of property i, p_i is given by

$$p_i = x_i\beta + \sum_{s \in S} \theta_{ds} K_i(d, s) + \epsilon_i \tag{2}$$

where x_i is a vector of property attributes for property i, β is a vector of relative prices, and $\sum_{s \in S} \theta_{ds} K_i(d, s) = \theta_{ds} K_i(d, s) + \theta_{ds+s^*} K_i(d, s + s^*)$. The variable $K_i(d, s)$ is the K-function between the periods s and $s + s^*$, and we include the K-function for different periods.

We are only interested in using values of the K-function for a small number of d and s. The distances should be small to more accurately reflect the property owner's perception of crime. For this reason, we use $D = \{0.25\,miles, 0.5\,miles, 1\,mile\}$. Because real estate cannot be sold immediately, we use $S_{90} = \{0, 90, 180, 270, 360\}$ for $s^* = 90$ days and $S_{180} = \{0, 180, 360\}$ for $s^* = 180$ days. When using S_{90}, the values in $K_i(d, s)$ reflect changes in the K-function over 90 day periods and likewise for S_{180}.

In order to make interpretation of the K-function more straightforward, we modify the formula. The modified K-function is now standardized by the distance that we use as the threshold. This modification redefines the λ parameter to reconsider a variable unit area, which means that when D takes any value, the unit area used to calculate λ is the area for the threshold value. The output of the modified K-function will be based on the average concentration for the specific area in which the K-function is calculated.

$$K_i(d, s) = \frac{1}{\lambda_{d,s}} E\left[\sum_j I(d_{ij} \leq d) I(s \leq s_{ij} \leq s + s^*)\right] \tag{3}$$

As an example, when $s = 0$ and $s^* = 90$ days, $K_i(d, 0)$ is the K-function for crimes 90 days prior to the sale, and $K_i(d, 90)$ is the K-function for crimes 90-180 days prior to the sale. The function $K_i(d, s)$ is the K-function between the period. When $K_i(d, s) > 1$, crime is more concentrated at distance d in locations near property i.

[1] For this reason, there is no subscript i on λ_s.

3.2 Data Description

Crime and property transaction data used in this study come from the Denver and Seattle cities. Denver property transaction data are available from the City and County of Denver Assessment Division.[2] King County (Seattle) transaction data are available from the King County Assessor's office.[3] Denver crime data are available from the City and County of Denver, Denver Police Department.[4] Seattle crime data are the City of Seattle Police Department incident reports.[5] All data are available for public download.

Observations in the crime data sets include the location and date of the crime, as well as its description. Crime categories in the two cities do not coincide. Therefore, we created encompassing categories and sort crimes into categories based on the nature of the crime. The scheme used to group each crime is listed in the appendix. Crime categories and counts for Denver and Seattle are displayed in Tables 1 and 2, respectively.

Crime data are reported at the city level. Because of this, we have excluded all transactions in Denver County and King County that are not in the city of Denver or the city of Seattle. The Denver County transactions data include the city, but King County data do not include the city. Seattle properties are defined as any property within the city limit area.

Transaction data for Denver cover the period, 2008-2015. Transaction data in Seattle cover the period 1990-2015. Each observation contains attribute information on the property, sale date, sale price, and other variables of interest. The data are cleaned using reasonable criteria in order to remove any non-arms-length transactions and outlying observations. Summary statistics for the housing transactions for Denver and Seattle are displayed in Tables 3 and 4, respectively.

The crime data as will be explained in the empirical section of this paper, are used to calculate a concentration index based on distance between the house sold and the crimes that had occurred in a specified period before the sale. The estimated K-function will then rank between 0 and a value that is higher than 1. Such values will explain if the concentration of crime is lower than all the crimes in the city of analysis for the specified period. If the number of crimes concentrated in the area is low with respect to the total distribution and higher values then crime is concentrated around these areas. The behavior of the K-function is shown in Figures 1 and 2. These charts reveal that some areas have a higher presence of crimes and some are free of crimes. The patterns of orange (high crime concentration) and blue (low crime concentration)are often in close proximity.

Figures 3 and 4 show the distribution of K function results within half a mile distance with a time period of 90 to 180 days before the sale of the dwelling and compares the concentration inside a ZIP code area. The results show a pattern change between years in

[2] http://data.denvergov.org/dataset/city-and-county-of-denver-real-property-sales-and-transfers
[3] http://info.kingcounty.gov/assessor/DataDownload/default.aspx
[4] http://data.denvergov.org/dataset/city-and-county-of-denver-crime
[5] https://data.seattle.gov/Public-Safety/Seattle-Police-Department-Police-Report-Incident/7ais-f98f

some of these ZIP codes. Some houses inside the ZIP code that are right next to each other show bright blue and orange colors. Another impression given by the ZIP code contrast is that crime rates are not constant in a one year time frame, and that issue might raise the MAUP in the estimation.

3.3 Results

Our estimation strategy takes advantage of the temporal changes of crime in the neighboring areas of a property. The occurrence of crimes within a certain distance of the house is not constant for all areas. However, it is also important to consider timing. Crimes occurring just prior to the sale should have the greatest impact on price. Obviously, crimes occurring after the negotiation and agreement are not in the information set of the homeowner and will not affect the selling price.

We estimate the model in equation (2). We will focus our discussion on the estimated coefficients of the different K-function measures, which vary by crimes, distance, and specified period. Four tables of results are presented for each city (Denver and Seattle). These four include one table for all crimes, crimes of public disorder, theft from motor vehicle, and automobile theft. Each table has a section for three different K-functions, with rows for different time frames. Each table has columns for three distances used. All regressions include housing characteristics and year fixed effects.

As explained in the introduction, this analysis depends on the velocity of transactions for dwelling sales and the speed with which the information flows. First, dwellings usually sell more quickly during certain seasons of the year when more people move and likely sell more quickly in more dynamic markets. Second, the speed of the spread of information among people about nearby crimes. In addition, the persistence of information on factors such as nearby crimes will affect house prices and sales volume.

We discuss our two cities separately. First we present the results for Denver and explain the reasons for and implications of the different specifications. Then we will do the same for Seattle.

3.3.1 Denver

Public disorder is the crime with greatest frequency in most years. Table 5 presents the OLS results for Denver when the K-functions only consider public disorder crimes. The impact of the K-functions declines almost uniformly as both the distance threshold and length of time increase. Coefficients are statistically significant and negative for the smallest distances and lengths of time. Coefficients decline in magnitude, eventually becoming insignificant as distances and time periods increase. In general, these results suggest that crime is not directly related to the wealth of a neighborhood as noisy or unruly neighbors negatively affect house prices.

Table 6 shows results for theft from motor vehicles (carprowl), defined as the illegal subtraction of property from a car. The coefficients of the K-functions are positive and significant. For the most part, the impact decreases with distance as time frame increases. The impact appears to increase again after nine months. The positive sign could indicate that these kinds of crime signal a wealthy, high income neighborhood that might serve as an attractor for crime but without a strong negative association with a large loss in property prices.

Table 7 shows results for automobile theft. The crime concentration coefficients almost always have a negative and significant coefficient. The coefficients are larger for smaller distance thresholds. Interestingly, the coefficients initially become larger as time increases.

Table 8 shows results for Denver when all crimes are used. As intuition suggests, results appear to become the average of the individual crime results. Very few estimated coefficients are statistically significant outside those for 90-180 days. Comparing Table 8 results with those for Tables 5, 6, and 7, provides further support for analyzing crimes on an individual basis as opposed to aggregating all crimes together.

In Table 9, we summarize of a one standard deviation increase of the K-function on price. Results indicate that dwelling prices decrease 1.8 percent for a one standard deviation increase in all crimes within half a mile and 2.3 percent when the increase is within a quarter of a mile. The comparable results for public disorder crimes are decreases of 5.95 percent and 5.85 percent, respectively, for crimes within half a mile and within a quarter of a mile. The effect from automobile theft is 7.5 percent for crimes within half a mile and 7.6 percent for crimes within a quarter of a mile.

3.3.2 Seattle

Tables 11-14 present results for Seattle. Table 11 presents results for public disorder crimes showing negative and significant coefficients when considering a threshold of a quarter of a mile and half a mile, other than for the 180-270 day period. Effects appear to be larger and more persistent in Seattle, compared with Denver.

Table 12 considers theft from motor vehicles. It is a very common crime in Seattle with more than fifty thousand cases. As with Denver, coefficients are generally positively correlated with housing prices, perhaps reflecting attraction to wealthy areas where autos are likely to have valuable property. This result is very similar to the results for Denver.

Automobile theft results are presented in Table 13. For the most part, results are similar to those for Denver, most coefficients are negative and significant for the three distance periods considered, but with seemingly stronger and persistent effects. Coefficients are much larger especially for longer time frames.

Once again, the “all crimes” model has a mix of results that are a mix of the individual crime results (Table 14). On average this model reflects the stronger, more persistent effects for Seattle with mostly significant negative results for medium-to-long-term time frames.

Table 15 summarizes the effects on dwelling price of a one standard deviation increase in the K-function. Results indicate that dwelling prices decrease 1.8 percent for a one standard deviation increase in all crimes within half a mile and 3.3 percent when the increase is within a quarter mile. The comparable decrease for public disorder crimes are 4.85 percent for crimes within half a mile and 6.47 percent for crimes within a quarter of a mile. The effect from automobile theft is 5.0 percent for crimes within half a mile and 6.26 percent for crimes within a quarter of a mile.

4 Conclusions

The analysis developed by Pope (2008) correctly identifies the timing and distance effect of moving a sex offender to a neighboring area. However, other crimes also affect dwelling price, and the time frame and distance impacts are difficult to estimate when the number of crime events is large. Crime rates considered for some large fixed area such as county or census tract lead to aggregation errors and result in biased estimates for the effect of crime on property price. Considering the crime for a year or some other fixed period of time also leads to estimation error. A crime included in estimating impacts may have occurred after a house was sold or far in the past before a house was sold. As a result, this crime should not impact property prices.

The analysis described in this paper addresses these two issues. We estimate the concentrations of crime at the property level taking into account the time frame of crime as well as the distance between the crime and house. As the distance threshold for "nearness" increases, the crime's impact on property price changes, typically decreasing and eventually becoming statistically insignificant for many cases. Time effects vary greatly depending on the type of crime. For public disorder crimes, the strongest impact is for crimes occurring within 90 days before a property sells. This impact rapidly decreases rapidly for larger time frames. For auto theft, impacts are more persistent and often appear stronger with longer lead times.

Finally, our results show that researchers cannot take a one-size-fits-all approach to estimated crime impacts on property price. First, crime impacts, accounting for distance and time frame vary substantially across types of crime. Even where we find strong negative impacts, such as for public disorder crimes and auto theft, the distance and time frame impacts vary greatly. Other crimes, including theft from motor vehicle, do not even display strong negative impacts. Using total crimes averages the impacts of individual crimes and eliminates the most important information. Second, crime impacts vary across cities, while Denver and Seattle display similar general patterns, the specific distance and time frame patterns were quite different. In general, crime impacts were more persistent in Seattle even though average impacts seemed similar.

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5 Tables and Figures

Table 1: Denver Crime Counts by Year

	2010	2011	2012	2013	2014	2015
Aggravated Assault	1169	1449	1487	1537	1600	680
Arson	129	93	92	96	130	38
Auto Theft	3286	3572	3431	3414	3506	1648
Burglary	4484	4707	4745	4826	4570	1848
Drug Alcohol	1815	1415	1721	4820	6067	2680
Larceny	5444	5983	6699	8456	9325	3402
Murder	33	43	33	40	33	21
Other Crimes Against Persons	1210	1419	1440	2638	3639	1502
Public Disorder	6361	6372	6133	8297	9730	3872
Robbery	957	1137	1216	1068	1075	443
Theft from Motor Vehicle	7228	7608	6649	6291	5121	2362
White Collar Crime	803	1095	957	855	1068	696

Table 2: Seattle Crime Counts by Year

	2010	2011	2012	2013	2014	2015
Aggravated Assault	1346	2391	2482	2555	4359	430
Arson	7	21	32	34	62	7
Auto Theft	2891	4979	4570	5250	10060	765
Burglary	3723	6552	6345	7081	11519	979
Drug Alcohol	1619	1981	1751	1509	1611	183
Larceny	6667	11552	12545	14441	23515	1969
Murder	10	10	10	19	22	1
Other Crimes Against Persons	221	474	375	419	611	48
Public Disorder	8249	13845	12813	13346	20444	1981
Robbery	675	1231	1276	1430	2305	237
Theft from Motor Vehicle	5416	9940	9227	11760	21426	1640
White Collar Crime	2747	3123	3489	3928	9466	472

Table 3: Descriptive Statistics: Denver Transactions

Statistic	N	Mean	St. Dev.	Min	Max
Panel A: Single Family Housing					
PRICE ($1,000s)	25,981	391.163	397.346	0.499	33,500.000
BUILDING SQFT	25,981	1,592.505	847.496	226	8,964
LAND SQFT	25,981	6,998.306	3,002.211	0	97,125
BEDROOMS	25,981	2.816	0.816	1	11
BATHROOMS	25,981	2.133	0.943	1	9
SALE YEAR	25,981	2011.510	2.156	2008	2015
CONDO	25,981	0.000	0.000	0	0
Panel B: Condominium					
PRICE ($1,000s)	8,778	182.696	159.428	0.499	2,725.000
BUILDING SQFT	8,778	1,113.364	437.439	219	5,700
LAND SQFT	8,778	1,837.833	1,539.400	150	20,800
BEDROOMS	8,778	1.821	0.606	1	5
BATHROOMS	8,778	1.569	0.588	1	6
SALE YEAR	8,778	2011.833	2.195	2008	2015
CONDO	8,778	1.000	0.000	1	1

Table 4: Descriptive Statistics: Seattle Transactions

Statistic	N	Mean	St. Dev.	Min	Max
Panel A: Single Family Housing					
PRICE ($1,000s)	91,905	467.933	468.073	0.110	28,031.170
BUILDING SQFT	91,905	2,058.075	938.180	10	15,300
BEDROOMS	91,905	3.366	0.921	1	12
BATHROOMS	91,905	1.512	0.650	1	7
SALE YEAR	91,905	2012.724	1.131	2010	2015
CONDO	91,905	0.000	0.000	0	0
Panel B: Condominium					
PRICE ($1,000s)	24,559	632.618	2,575.069	0.117	26,260.000
BEDROOMS	24,559	1.894	0.654	1	8
BATHROOMS	24,559	1.480	0.527	1	6
SALE YEAR	24,559	2012.780	1.108	2010	2015
CONDO	24,559	1.000	0.000	1	1

Note: Square footage is not available for condominiums in the Seattle data.

Table 5: Regression Results for Hedonic Model including the Modified K-function for Public Disorder Crimes in Denver.

Variable	1/4 mile	1/2 mile	1 mile
K_{0-90}	-0.13791^{**}	-0.02946^{**}	-0.00301^{**}
	(-5.51534)	(-5.6734)	(-2.83067)
K_{90-180}	-0.12891^{**}	-0.0202^{**}	-0.00023
	(-5.15985)	(-3.88023)	(-0.20985)
R^2	0.47941	0.48064	0.47629

Variable	1/4 mile	1/2 mile	1 mile
K_{0-180}	-0.18672^{**}	-0.03929^{**}	-0.00391^{**}
	(-6.48856)	(-6.90703)	(-3.62204)
$K_{180-360}$	-0.08775^{**}	-0.0076	0.00109
	(-3.00797)	(-1.32391)	-1.00615
R^2	0.47971	0.48063	0.47627

Variable	1/4 mile	1/2 mile	1 mile
K_{0-90}	-0.10765^{**}	-0.02716^{**}	-0.00457^{**}
	(-3.95322)	(-4.6602)	(-3.71404)
K_{90-180}	-0.09605^{**}	-0.01732^{**}	-0.00032
	(-3.50595)	(-2.94614)	(-0.25554)
$K_{180-270}$	-0.06945^{**}	-0.00773	-0.00319^{**}
	(-2.56804)	(-1.30656)	(-2.52689)
$K_{270-360}$	-0.02312	0.00133	0.00501^{**}
	(-0.88849)	(0.23476)	(4.1553)
R^2	0.47969	0.48069	0.47685

t - statistics in parentheses. $^{**}p < 0.05$, $^{*}p < 0.1$

Table 6: Regression Results for Hedonic Model including the Modified K-function for Theft from Motor Vehicle crimes in Denver.

Variable	1/4 mile	1/2 mile	1 mile
K_{0-90}	0.20318^{**}	0.0413^{**}	0.00973^{**}
	(8.60116)	(8.02603)	(8.91793)
K_{90-180}	0.13953^{**}	0.02516^{**}	0.00434^{**}
	(5.88403)	(5.03404)	(4.08035)
R^2	0.48211	0.48466	0.49274

Variable	1/4 mile	1/2 mile	1 mile
K_{0-180}	0.19384^{**}	0.02565^{**}	0.0023^{*}
	(6.80306)	(4.42811)	(1.92649)
$K_{180-360}$	0.18596^{**}	0.04314^{**}	0.01134^{**}
	(6.65018)	(7.64095)	(9.8995)
R^2	0.48338	0.48622	0.49524

Variable	1/4 mile	1/2 mile	1 mile
K_{0-90}	0.14506^{**}	0.0249^{**}	0.00482^{**}
	(5.76696)	(4.47273)	(4.03477)
K_{90-180}	0.0642^{**}	0.00418	-0.00228^{*}
	(2.4358)	(0.72329)	(-1.78891)
$K_{180-270}$	0.05928^{**}	0.00921	0.0015
	(2.26984)	(1.59994)	(1.19858)
$K_{270-360}$	0.1402^{**}	0.03675^{**}	0.01084^{**}
	(5.45364)	(6.65546)	(9.21485)
R^2	0.48356	0.48666	0.49627

t - statistics in parentheses. $^{**}p < 0.05$, $^{*}p < 0.1$

Table 7: Regression Results for Hedonic Model including the Modified K-function for Automobile Theft Crimes in Denver.

Variable	1/4 mile	1/2 mile	1 mile
K_{0-90}	-0.13821^{**}	-0.02485^{**}	-0.00315^{**}
	(-5.5945)	(-4.48012)	(-2.64062)
K_{90-180}	-0.19372^{**}	-0.03863^{**}	-0.00483^{**}
	(-7.71315)	(-6.96689)	(-4.05329)
R^2	0.48121	0.48326	0.47997

Variable	1/4 mile	1/2 mile	1 mile
K_{0-180}	-0.19144^{**}	-0.04414^{**}	-0.00991^{**}
	(-6.24827)	(-6.71323)	(-7.29479)
$K_{180-360}$	-0.17417^{**}	-0.01808^{**}	0.0025^{*}
	(-5.72385)	(-2.81078)	(1.88918)
R^2	0.4823	0.4836	0.48031

Variable	1/4 mile	1/2 mile	1 mile
K_{0-90}	-0.06796^{**}	-0.01474^{**}	-0.00361^{**}
	(-2.51602)	(-2.37205)	(-2.66558)
K_{90-180}	-0.11764^{**}	-0.02584^{**}	-0.00486^{**}
	(-4.23643)	(-3.99138)	(-3.4142)
$K_{180-270}$	-0.10977^{**}	-0.02758^{**}	-0.00458^{**}
	(-3.92347)	(-4.32404)	(-3.26439)
$K_{270-360}$	-0.10305^{**}	0.001	0.00519^{**}
	(-3.75102)	(0.16114)	(3.8670)
R^2	0.48246	0.48389	0.48055

t - statistics in parentheses. $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8: Regression Results for Hedonic Model including the Modified K-function for All Crimes in Denver.

Variable	1/4 mile	1/2 mile	1 mile
K_{0-90}	0.01717	0.0086	0.00444**
	(0.45637)	(1.22361)	(3.9687)
K_{90-180}	−0.12518**	−0.02355**	−0.00164
	(−3.32845)	(−3.42628)	(−1.51442)
R^2	0.47617	0.47611	0.4764

Variable	1/4 mile	1/2 mile	1 mile
K_{0-180}	−0.06065	−0.01511**	0.00059
	(−1.66639)	(−2.53201)	(0.66144)
$K_{180-360}$	−0.04398	0.00175	0.00198**
	(−1.22657)	(0.30032)	(2.31148)
R^2	0.47611	0.47592	0.47629

Variable	1/4 mile	1/2 mile	1 mile
K_{0-90}	0.04366	0.00597	0.00255*
	(1.02805)	(0.71641)	(1.79525)
K_{90-180}	−0.0922**	−0.02364**	−0.00203*
	(−2.15176)	(−3.13423)	(−1.76235)
$K_{180-270}$	−0.09226**	−0.01002	−0.00142
	(−2.27387)	(−1.42876)	(−1.31805)
$K_{270-360}$	0.02601	0.01309*	0.00381**
	(0.64263)	(1.83316)	(3.40217)
R^2	0.47633	0.47623	0.47676

t - statistics in parentheses. $^{**}p < 0.05$, $^{*}p < 0.1$

Table 9: Percentage Impact of a One Standard Deviation Increase of the K-function - Denver.

K function for	Half mile	Quarter mile
Total	-1.88%	-2.30%
Public Disorder	-5.95%	-5.85%
Theft from Auto	8.68%	8.14%
Automobile Theft	-7.50%	-7.63%

Table 10: Regression Results for Hedonic Model including the Modified K-function for All Crimes in Seattle.

Variable	1/4 mile	1/2 mile	1 mile
K_{0-90}	-0.18959^{*}	0.01645	0.01895^{**}
	(-1.89527)	(0.79338)	(4.71084)
K_{90-180}	-0.26105^{**}	-0.05026^{**}	-0.01453^{**}
	(-2.63986)	(-2.44829)	(-3.6341)
R^2	0.31255	0.31111	0.31141

Variable	1/4 mile	1/2 mile	1 mile
K_{0-180}	-0.10472	0.02637	0.00474
	(-0.89327)	(1.1304)	(1.05247)
$K_{180-360}$	-0.34068^{**}	-0.05992^{**}	-0.00053
	(-2.94772)	(-2.59031)	(-0.11898)
R^2	0.31268	0.31117	0.311

Variable	1/4 mile	1/2 mile	1 mile
K_{0-90}	-0.04241	0.04297^{*}	0.01838^{**}
	(-0.37732)	(1.85795)	(4.11248)
K_{90-180}	-0.08943	-0.01908	-0.01624^{**}
	(-0.76527)	(-0.77434)	(-3.34992)
$K_{180-270}$	-0.09532	0.0026	0.01466^{**}
	(-0.82511)	(0.108)	(3.14784)
$K_{270-360}$	-0.24576^{**}	-0.06207^{**}	-0.01244^{**}
	(-2.34807)	(-2.8608)	(-2.92659)
R^2	0.31278	0.31135	0.31172

t - statistics in parentheses. $^{**}p < 0.05$, $^{*}p < 0.1$

Table 11: Regression Results for Hedonic Model including the Modified K-function for Public Disorder Crimes in Seattle.

Variable	1/4 mile	1/2 mile	1 mile
K_{0-90}	-0.42986^{**}	-0.04462^{**}	0.00301
	(-6.59421)	(-2.94322)	(0.93766)
K_{90-180}	-0.33458^{**}	-0.04584^{**}	-0.00541^{*}
	(-5.24848)	(-3.11826)	(-1.73534)
R^2	0.31837	0.31564	0.31063

Variable	1/4 mile	1/2 mile	1 mile
K_{0-180}	-0.37861^{**}	-0.04124^{**}	-0.00731^{*}
	(-4.79431)	(-2.28605)	(-1.89376)
$K_{180-360}$	-0.36831^{**}	-0.0442^{**}	0.00509
	(-4.76554)	(-2.48445)	(1.33458)
R^2	0.31862	0.31561	0.31061

Variable	1/4 mile	1/2 mile	1 mile
K_{0-90}	-0.28724^{**}	-0.03172^{*}	-0.00327
	(-3.89892)	(-1.82246)	(-0.85368)
K_{90-180}	-0.18455^{**}	-0.03394^{*}	-0.01212^{**}
	(-2.48035)	(-1.92415)	(-3.17826)
$K_{180-270}$	-0.08588	0.01615	0.01417^{**}
	(-1.17789)	(0.93229)	(3.69815)
$K_{270-360}$	-0.24066^{**}	-0.04166^{**}	-0.00122
	(-3.57726)	(-2.576)	(-0.33762)
R^2	0.31883	0.3158	0.31099

t - statistics in parentheses. $^{**}p < 0.05$, $^{*}p < 0.1$

Table 12: Regression Results for Hedonic Model including the Modified K-function for Theft from Motor Vehicle Crimes in Seattle.

Variable	1/4 mile	1/2 mile	1 mile
K_{0-90}	0.34909**	0.03582**	0.00583**
	(6.2418)	(3.25672)	(2.78173)
K_{90-180}	0.39226**	0.0912**	0.01675**
	(7.24404)	(8.45692)	(8.01871)
R^2	0.31542	0.31754	0.32285

Variable	1/4 mile	1/2 mile	1 mile
K_{0-180}	0.31627**	0.01787	−0.00175
	(4.96129)	(1.4893)	(−0.78264)
$K_{180-360}$	0.56807**	0.12386**	0.02492**
	(9.17558)	(10.47268)	(11.26335)
R^2	0.31757	0.3201	0.3258

Variable	1/4 mile	1/2 mile	1 mile
K_{0-90}	0.15399**	−0.01754	−0.0061**
	(2.57775)	(−1.44839)	(−2.60658)
K_{90-180}	0.18146**	0.03622**	0.00408
	(3.06199)	(2.98606)	(1.67534)
$K_{180-270}$	0.28754**	0.06318**	0.01162**
	(4.87761)	(5.29657)	(4.88389)
$K_{270-360}$	0.31613**	0.069**	0.01535**
	(5.80864)	(6.19593)	(6.96015)
R^2	0.31747	0.32022	0.32607

t - statistics in parentheses. $^{**}p < 0.05$, $^{*}p < 0.1$

Table 13: Regression Results for Hedonic Model including the Modified K-function for Automobile Theft Crimes in Seattle.

Variable	1/4 mile	1/2 mile	1 mile
K_{0-90}	-0.27251^{**}	-0.03773^{**}	0.00102
	(-6.29732)	(-4.05668)	(0.52082)
K_{90-180}	-0.24949^{**}	-0.03574^{**}	-0.00354^{*}
	(-5.71546)	(-3.80782)	(-1.77705)
R^2	0.31404	0.31305	0.31051

Variable	1/4 mile	1/2 mile	1 mile
K_{0-180}	-0.09499^{*}	0.0413^{**}	0.01719^{**}
	(-1.81136)	(3.81199)	(7.82405)
$K_{180-360}$	-0.58236^{**}	-0.13532^{**}	-0.02217^{**}
	(-11.0951)	(-12.26512)	(-9.76834)
R^2	0.31677	0.31637	0.31275

Variable	1/4 mile	1/2 mile	1 mile
K_{0-90}	-0.08995^{*}	0.01114	0.00919^{**}
	(-1.93826)	(1.09638)	(4.25977)
K_{90-180}	-0.03884	0.02622^{**}	0.00775^{**}
	(-0.81288)	(2.43783)	(3.29637)
$K_{180-270}$	-0.35126^{**}	-0.06819^{**}	-0.00874^{**}
	(-7.40134)	(-6.38283)	(-3.77138)
$K_{270-360}$	-0.24889^{**}	-0.07264^{**}	-0.01403^{**}
	(-5.57484)	(-7.29746)	(-6.59055)
R^2	0.31685	0.31646	0.31263

t - statistics in parentheses. $^{**}p < 0.05$, $^{*}p < 0.1$

Table 14: Regression Results for Hedonic Model including the Modified K-function for All Crimes in Seattle.

Variable	1/4 mile	1/2 mile	1 mile
K_{0-90}	-0.18959^{*}	0.01645	0.01895^{**}
	(-1.89527)	(0.79338)	(4.71084)
K_{90-180}	-0.26105^{**}	-0.05026^{**}	-0.01453^{**}
	(-2.63986)	(-2.44829)	(-3.6341)
R^2	0.31255	0.31111	0.31141

Variable	1/4 mile	1/2 mile	1 mile
K_{0-180}	-0.10472	0.02637	0.00474
	(-0.89327)	(1.1304)	(1.05247)
$K_{180-360}$	-0.34068^{**}	-0.05992^{**}	-0.00053
	(-2.94772)	(-2.59031)	(-0.11898)
R^2	0.31268	0.31117	0.311

Variable	1/4 mile	1/2 mile	1 mile
K_{0-90}	-0.04241	0.04297^{*}	0.01838^{**}
	(-0.37732)	(1.85795)	(4.11248)
K_{90-180}	-0.08943	-0.01908	-0.01624^{**}
	(-0.76527)	(-0.77434)	(-3.34992)
$K_{180-270}$	-0.09532	0.0026	0.01466^{**}
	(-0.82511)	(0.108)	(3.14784)
$K_{270-360}$	-0.24576^{**}	-0.06207^{**}	-0.01244^{**}
	(-2.34807)	(-2.8608)	(-2.92659)
R^2	0.31278	0.31135	0.31172

t - statistics in parentheses. $^{**}p < 0.05$, $^{*}p < 0.1$

Table 15: Percentage Impact of a One Standard Deviation Increase of the K-function - Seattle.

K function for	Half mile	Quarter mile
Total	-1.81%	-3.30%
Public Disorder	-4.85%	-6.47%
Theft from Auto	6.62%	6.84%
Automobile Theft	-5.00%	-6.26%

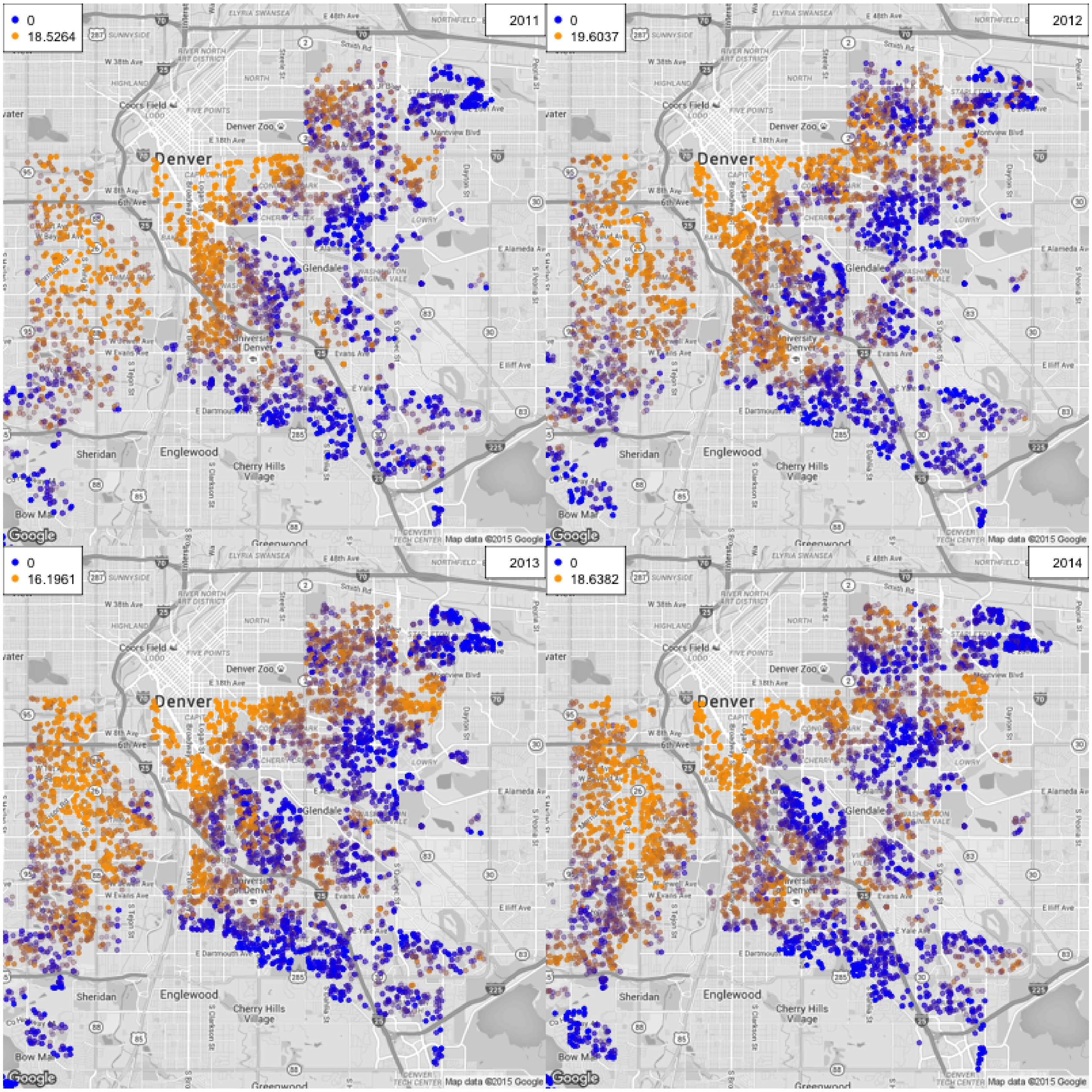

Figure 1: Map of the K-function within Half of a Mile for Public Disorder Crimes in Denver.

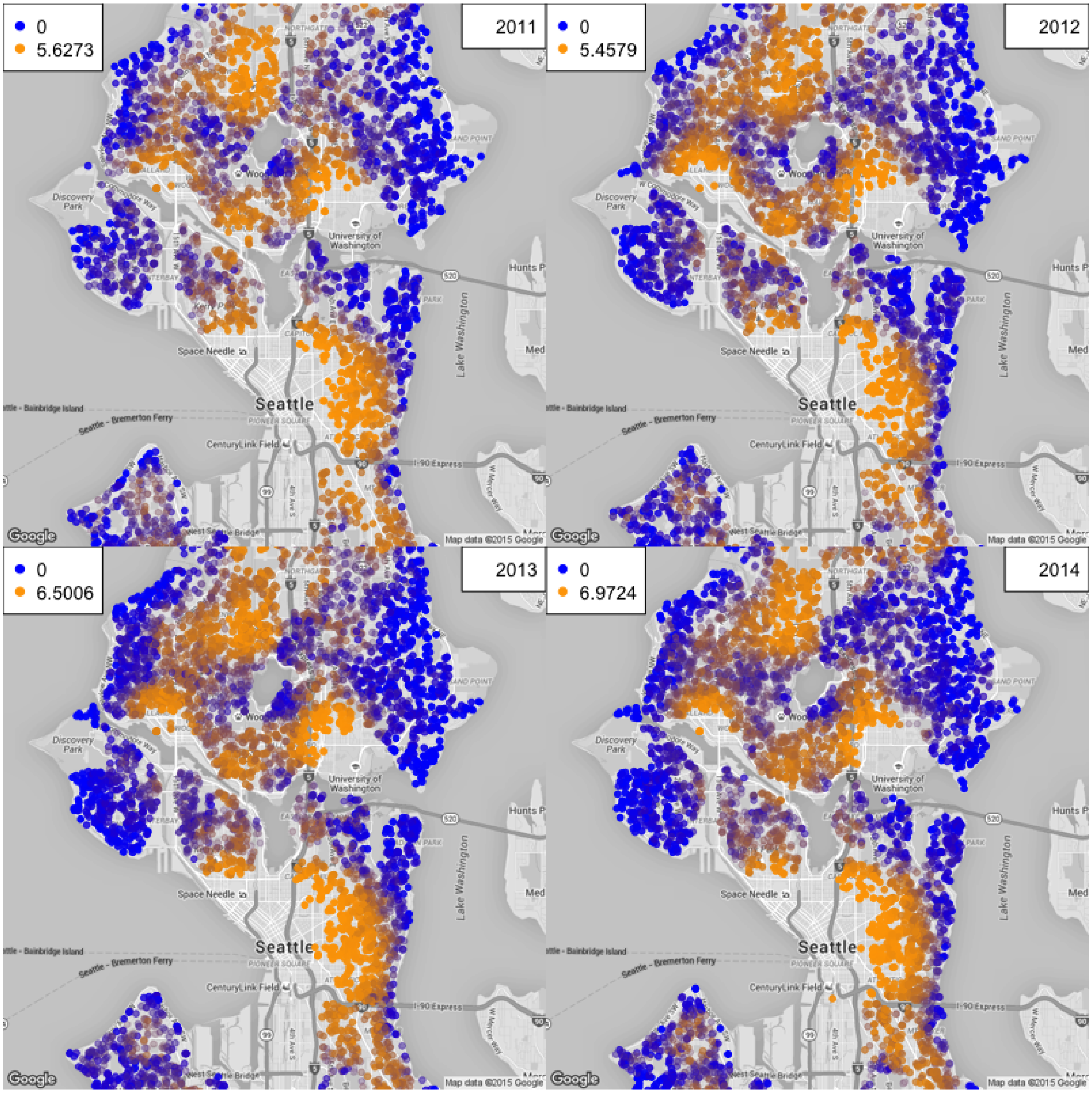

Figure 2: Map of the K-function within Half of a Mile for Public Disorder Crimes in Seattle.

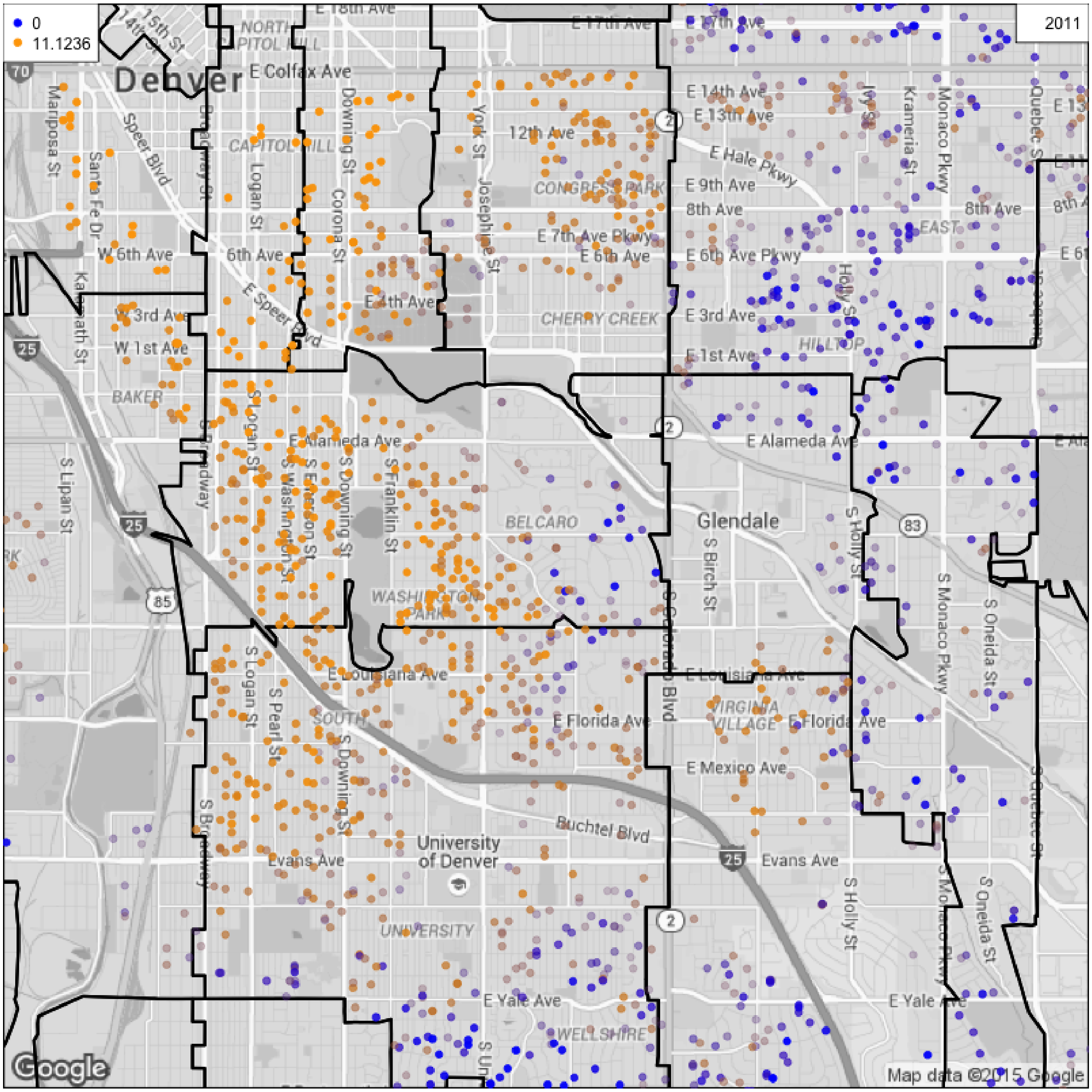

Figure 3: Map of the K-function within Half of a Mile for Public Disorder Crimes in Denver including the ZIP code limits.

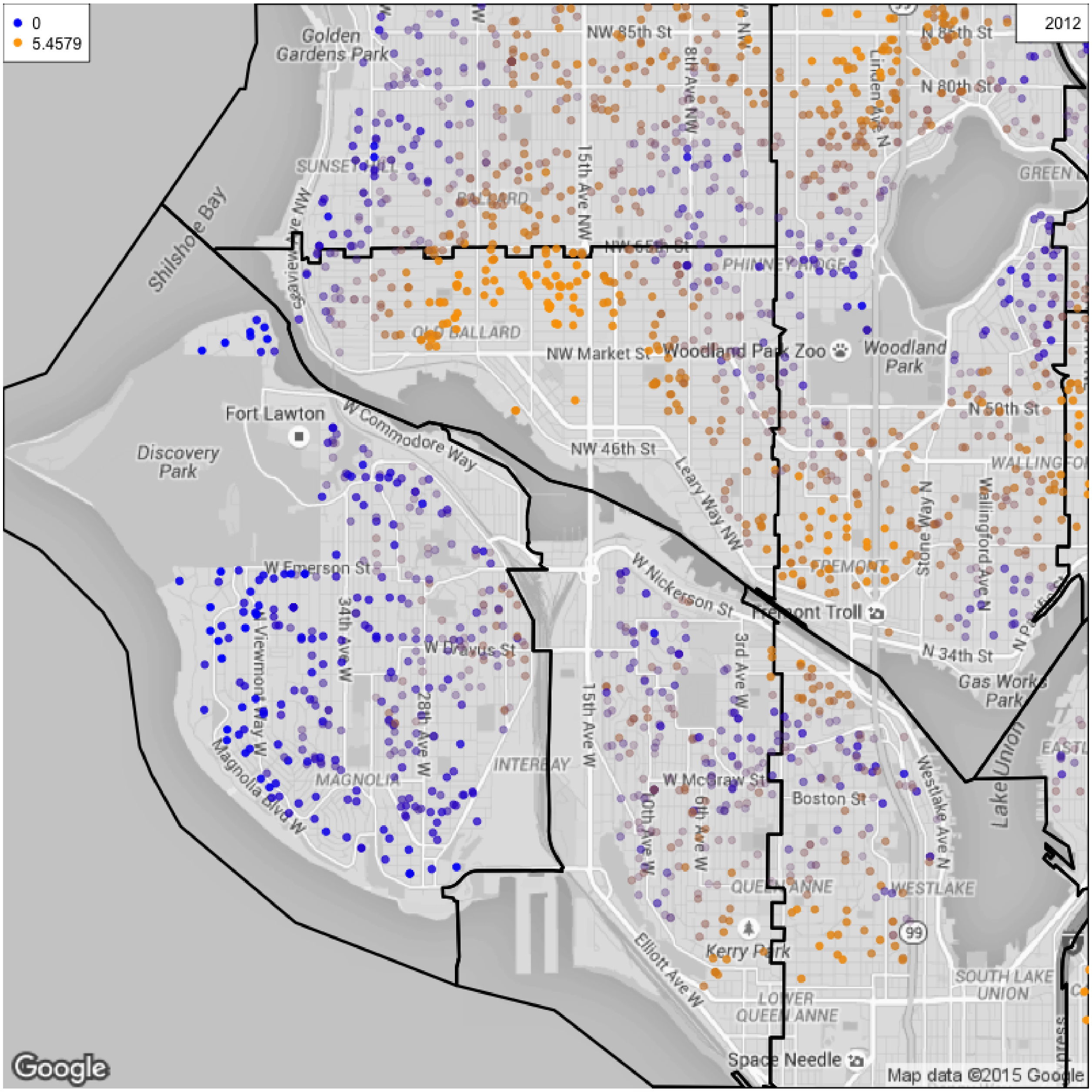

Figure 4: Map of the K-function within Half of a Mile for Public Disorder Crimes in Seattle including the ZIP code limits.