Predicting Urban Crime In Diverse Settings

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Abstract

The distribution of crimes across neighborhoods is still puzzling to Urban Economists as well as to other researchers. I analyze crime in Seattle between 1996 and 2006 on the neighborhood level and use numerous variables to explain the variation I find. Equipped with these findings, I try to predict crime levels in Durham, North Carolina. The results are promising and show that crime predictors such as poverty, income inequality, housing ownership and housing occupancy can be used to approximate crime levels even in diverse settings.

Introduction

Why is crime in some neighborhoods much more prevalent than in others? So far, scholars of Urban Economics and other disciplines have found no clear answer to that question. One school of thought claims that in the short run, crime levels can be independent from the characteristics of a neighborhood. Supporting that claim, sociologists discovered in the 1920s that in some areas, crimes persisted despite changes in cultural and social characteristics. This suggests that "communities like individuals can have careers in crime"(Reiss 1986:12).

Another school of thought has focused on the analysis of neighborhood characteristics to explain differences in crime. The various theories related to this school of thought are hardly coherent as they use a multitude of different indicators and arrive at partly contradictory conclusions.[2] So far, none of the theories has prevailed in empirical studies. As Hipp (2007: 666) claims, this might result from the use of large units of analysis, for example counties and cities, in early studies. Hipp argues that using data disaggregated to the neighborhood (that is, most fittingly, the census tract[3]) level promises clearer conclusions about the situation *in* rather than *across*

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[2] See Hipp (2007: 668-72) for a comprehensive discussion.

[3] Census tracts comprise between 2,500 and 8,000 persons. They are relatively homogeneous with respect to population characteristics, economic status, and living conditions, see http://www.census.gov/geo/www/cen_tract.html. This is obviously the closest to a neighborhood possible with census data.

neighborhoods. In his own study, Hipp relates crime rates mainly to the distribution of income and the racial heterogeneity within and across neighborhoods in 19 cities. He finds significant effects for these social characteristics as well as for differing levels of homeownership. Poverty alone, he concludes, has no influence on crime when income inequality is included as another explanatory variable (687).

In this paper, I roughly adopt Hipp's method to examine the case of Seattle, Washington. While Hipp includes Seattle in his analysis, I believe that a deeper analysis of this case provides further insights, especially because of the vast amount of crime data available for that city. After a description of my data and variables, I provide an overview of the reported criminal activity in Seattle between 1996 and 2006. Using census tract data, I construct five explanatory models and conduct a regression analysis that tests for the importance of numerous neighborhood characteristics in explaining property and violent crimes. Lastly, I move to the opposite corner of the United States, to Durham, North Carolina. After a brief description of Durham's characteristics concerning crime, population and housing, I try to predict crime in Durham using the results from Seattle. The results, while not perfect, are promising, and show that even without knowing the "criminal history" of a neighborhood, its crime level can be predicted fairly accurately.

Data and Variables

Collecting data on crimes on the census tract level is difficult mainly for two reasons. First, most Police Departments that offer publicly accessible crime datasets do not categorize them into census tracts. Often, crimes are listed separately for police districts. Police districts are usually far larger and unrelated to census tracts. Police beats are an alternative and come closer in size to the common understanding of a neighborhood, but can equally be unrelated to census tracts (see also Hipp: 672). Second, most publicly available crime datasets cover only short periods of time, often going back no more than to the previous month. Due to these limitations and the often incomplete time series included in these datasets, the analysis of neighborhood crime over an extended time period is often difficult.

For this paper, I use crime data from the Police Departments of Seattle and Durham. To build my models, I rely on the Seattle dataset because of the large number of observations that were collected for Seattle between 1996 and 2006. The great advantage of this dataset is that it is available in disaggregated form - both to the census tract level and to various types of crime. The Durham dataset covers the entire year 2006 and the year 2007 from January to July. It is used to briefly test my findings, contrasting a smaller city in the Southeast with a larger city in the Northwest. Concerning neighborhoods and crime types, the Durham dataset is – thanks to the generous help I received from the Durham Police Department - equally disaggregated.

A minor data issue results from the fact that the Seattle Police Department uses the tract boundaries from the 1990 Census for its entire dataset. This made some changes necessary. Where the 2000 Census joined previously separated areas, I use the 2000 definition and aggregate the number of crimes. Where the Census Bureau split 1990 tracts, I use the 1990 tract boundaries and aggregate or average the Census information. With this method, I arrive at a total of 123 tracts for the Seattle metropolitan area.

The Durham crime dataset conveniently uses 2000 Census tracts. However, I exclude the two tracts containing Duke University's East and West Campus for three reasons. First, the security measures provided in these tracts are hardly comparable to those in the rest of Durham. Duke has its own Campus Police that regularly patrol the area and can be reached over numerous SOS-telephones.[4] Second, public transportation is also much more advanced on the two Campuses. Duke's students and employees can use the free and convenient bus system and the nightly, free "SafeRide" van service.[5] The DATA bus service covering the rest of Durham operates less frequently and stops earlier at night.[6] Third, it is difficult to use the census information for these tracts because most "households" on Campus are administrative buildings. Consider poverty, for example: The 2000 Census reports that on West Campus, 93.2 percent of the population lives below the poverty line while apparently nobody does so on East Campus. Keeping this information in my dataset would lead to skewed results. Without the Duke Campuses, I arrive at a total of 51 census tracts for Durham.

The dependent variables used in this study are the criminal activities in their various forms, as reported by the two police departments. Following the FBI definition of the Uniform Crime Reports (FBI 2007), I distinguish property crimes (burglary, larceny-theft, motor vehicle theft, arson) and

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[4] See the website of the Duke University Police Department at http://www.duke.edu/web/police/

[5] See http://siren.auxserv.duke.edu/parking/transportation/transit_schedules.htm for Duke's bus transit schedules and http://siren.auxserv.duke.edu/parking/saferides/saferides.htm for SafeRide information.

[6] DATA stands for Durham Area Transit Authority. DATA's schedules are available at http://data.durhamnc.gov/howto.cfm

violent crimes (murder and nonnegligent manslaughter, forcible rape, robbery, aggravated assault). Non-aggravated assaults are included separately. These variables are adjusted for the population of the census tracts. During the text and in the summary statistics, I work with crimes per 1000 persons and in the regression analysis with crimes per person.

My explanatory variables are mostly neighborhood characteristics from the Census 2000 Summary Files. This census conveniently cuts the 1996-2006 time period for which Seattle crime data are available. The 1990 Census is used to obtain information on preceding population growth. The first explanatory variable is the percentage of the population living below the poverty line. Poverty alone is a common explanation for crime. As mentioned earlier in this paper, however, Hipp denies its explanatory power. With the second variable, I approximate the income inequality within neighborhoods using the Gini coefficient.[7] The 2000 Census provides information on 1999 household income in 16 discrete categories. With the exception of the highest category ($200.000 or more), which can not be included due to its open character, these are integrated in the analysis by multiplying the number of households and the median income in the respective category. Hipp finds income inequality to be an important predictor of crime. My third and fourth variables cover housing characteristics. They are the rate of owner-occupied as opposed to renter-occupied and the rate of occupied as opposed to vacant housing. The fifth variable is the proportion of a neighborhood's population that is between 18 and 29 years old. It was included because young people are more likely to be both criminal offenders and victims of crime (Steffensmeier et al. 1989, Perkins 1997). The sixth variable is the degree of racial heterogeneity in the neighborhoods. The Census 2000 asks respondents to identify themselves as white, black or African American, American Indian or Alaska Native, Asian, Native Hawaiian or Other Pacific Islander, as members of other races or of two or more races. Hispanics or Latinos, the fastest growing minority group in the US, are included as an ethnic group in the census. Since self-identified Latinos also pick a race, I can include them in the calculation of the racial heterogeneity index. To do so, I plug Census 2000 data into a Herfindahl-Index.[8] In addition to the heterogeneity measure, I include the proportion of the larger racial and

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7 Defined as $G = \frac{2}{\mu n^2} \sum_{i=1}^{n} i x_i - \frac{n+1}{n}$. Explanation: Households are sorted from i to n, x_i is the 1999 household income taken from the 2000 Census and μ the mean income, G=0: perfect equality, G=1: perfect inequality.

8 Defined as $H = 1 - \sum_{j=1}^{J} G_j^2$. Explanation: G is the proportion of racial group j out of J racial groups.

ethnic groups, namely African Americans, Hispanics, Asian Americans and American Indians. Table 1 provides summary statistics of those variables for Seattle.

Table 1: Summary Statistics for Seattle, dependent and explanatory variables

Variable	Mean	SD	Min	Max
Crime per 1000 inhabitants and year, 1996-2006	109.91	128.46	0.12	1004.34
Property crimes per 1000 inhabitants and year, 1996-2006	88.71	102.02	0.03	776.14
Violent crimes per 1000 inhabitants and year, 1996-2006	8.38	13.23	0.08	101.76
Non-aggravated assaults per 1000 inhabitants and year, 1996-2006	12.79	16.31	0.02	126.44
% Houses occupied, 2000	0.96	0.03	0.84	0.99
% Homeowners, 2000	0.50	0.23	0.77	0.94
% Below poverty level, 2000	0.13	0.10	0.02	0.50
Income inequality, 2000 (Gini coefficient)	0.45	0.09	0.21	0.65
% Between 18 and 29 years old	0.22	0.13	0.06	0.92
Racial heterogeneity, 2000 (Herfindahl-Index)	0.40	0.19	0.10	0.77
% African American, 2000	0.08	0.10	0.01	0.51
% Hispanic, 2000	0.05	0.04	0.01	0.37
% Asian, 2000	0.12	0.12	0.02	0.58
% American Indian, 2000	0.01	0.01	0.01	0.03

N=123
Source: Seattle Police Department 2007, Census 2000

Overview: Crime in Seattle

Before getting into the modeling and the regression analysis, I give an overview of the criminal activity in Seattle between 1996 and 2006. Within this time period, the overall number of crimes decreased by 22.33 percent to 49,925 in 2006 (see Graph 1 in the Appendix). This was a remarkably constant process, closely accompanied by the development of property crimes. The only significant deviation happened in 2003, when the number of crimes increased by 7.6 percent to 56,445. This was due to seven more murders and 1,159 more residential robberies, which resulted in an increase by 25.9 and 23.1 percent in the respective categories. However, this peak turned out to be only temporary, and in 2004 crime decreased again, reaching the lowest number of the entire time period by 2006.

<u>By crime type</u>

The analysis by crime type shows that the decrease happened not as uniformly as it was hitherto assumed (see Graph 2 in the Appendix and Table 2). Indeed, the number of most violent crimes decreased during the period under study. In 2006, 30 murders corresponded to a decrease of 18.9 percent from the 37 murders in 1996. The number of rapes declined by more than half after 1996 and reached 127 in 2006. Despite that strong general development, the numbers for 1998 and 2003 constitute stark exceptions. The number of rapes went up by 24 and 22, or 11 and 14.5 percent, respectively. The figure for robberies decreased by 15.1 percent between 1996 and 2006, rather modestly when compared to the general development. The only exception among violent crimes is aggravated assaults. These went up until 1998 and decreased until 2004, only to rise again later. In 2006, their number was at 2,322, almost unchanged from the 2,282 in 1996.

Table 2: Crime in Seattle 1996-2006 by crime type

Crime type	**Total Number**	**Percent**	**Average per year**	**Percent change 1996-2006**
Murder	381	0.06	34.64	-18.92
Rape	1,991	0.32	181.00	-51.34
Robbery	18,607	3.02	1,691.55	-15.08
Aggravated Assault	25,787	4.18	2,344.27	1.75
Residential Burglary	53,950	8.75	4,904.55	8.75
Non-Residential Burglary	26,133	4.24	2,375.73	-27.38
Theft	322,393	52.31	29,308.45	-35.17
Auto Theft	91,636	14.87	8,330.55	28.06
Arson	2,313	0.38	210.27	-6.40
Non-Aggravated Assault	73,160	11.87	6,650.91	-28.57
Total	616,351	100.00	56,031.91	-22.33

Source: Seattle Police Department

The development of property crimes was generally less clear and fluctuation was greater. At first glance, burglaries seem to shift from non-residential to residential targets. However, this trend is not that obvious for the individual years. Overall, the figure for residential burglaries increased modestly. While it fell below 4,000 in the year 2000, it rose above 6,000 in 2003. Both developments were in line with previous years. In 2005, the number decreased below 5,000 again and reached 5,417 in 2006. This corresponds to an increase of 8.8 percent from 1996. Non-residential burglaries, on the other hand, decreased, after an initial fall by 18.4 percent in 1998, rather slowly during almost the whole time period. By 2006, non-residential burglaries had dropped by 27.4 percent since 1996. In an even stronger manner, thefts seem to shift towards cars. The overall most common crime type, theft, plummeted until 2000, and decreased somewhat more slowly since. In 2006, its figure was 35.2

percent lower than in 1996. The number of auto thefts, however, increased strongly until 2005. In 2006, the number went down by 14.9 percent or 1,420 cases. Still, the development over the eleven years resulted in an overall surge of 28.1 percent. Arson, finally, decreased by 6.4 percent between 1996 and 2006. This number obscures that in 1999, the figure was 34.8 percent or 87 cases lower than in 1996. Afterwards, it rose again and reached 234 in 2006.

The number of non-aggravated assaults fell below 6,000 for the first time during the period under study in 2002. In 2005, it again reached 6,262, and fell to 5,992 in 2006. This last figure corresponds to an overall drop of 28.6 percent since 1996.

By census tract

Criminal activity was distributed very unequally across the census tracts and thus the 572,600 inhabitants (2004) of Seattle (Seattle Population and Demographics). Of the 123 tracts, 40 had a yearly crime rate higher than 100 crimes per 1000 persons, 12 had a rate above 200 and in three tracts, more than 500 crimes per 1000 persons happened. With the only crime rate beyond 1.000 (actually, it was 1.004), census tract 81 stood out widely. Statistically, each of the 3,477 inhabitants of this tract is once a year involved in a crime. Of course, this assumes that only tract inhabitants are involved in crimes and ignores non-residents as both criminals and victims of crimes. Yet, it is an astonishingly high figure. For this tract, the division into property and violent crimes and non-aggravated assaults changes surprisingly little and the crime rate in tract 81 is the highest in all categories. The same five census tracts (71, 72, 92, 93, and 109) follow, in changing order, always suit. Map 1 (in the Appendix) shows the location of these high-crime neighborhoods. They stretch along the Eastern side of the bayou that cuts into the city, from Lake Union in the North down to King County International Airport in the South. While not all tracts are located next to the waterfront, they are all geographically connected. That points to the mobility of criminals and the spreading of crime resulting from it.

In looking at changes of crime over the years in these six neighboring areas (see Graph 3 in the Appendix), it is striking how strongly crime rates change within individual years. The high average number for Census tract 81 hides the intense transformation this neighborhood went through, as the crime rate per 1000 inhabitants fell from 1,560 in 1996 to 710 in 2006. This is all the more remarkable because according to the two most recent Censuses, the population increased by 88.6 percent between 1990 and 2000. Across all Census tracts, I find the opposite effect. Population growth and crime rates are generally positively correlated and when crime rates are regressed against population change, tract 81 is the main outlier.

Table 3 presents the degree of correlation between the crime levels in the six high-crime tracts between 1996 and 2006. In all cases but one, the crime levels were positively correlated over time. However, the correlation between two neighboring tracts is not necessarily stronger than between more distant areas. Between the two small central-area tracts 71 and 72, the connection is rather weak. Likewise, crime rates in the two largest tracts, 93 and 109, move only lightly in the same direction. This excludes explanations referring to the size of a neighborhood as a predictor of the influence of its crime level on other neighborhoods. Another interesting fact is that the only – if weak – negative correlation is that between the two neighborhoods farthest removed from each other (tracts 71 and 109). From this, I conclude that geographical proximity is indeed often strongly related to changes in crime levels. However, as the exceptions in this small and, concerning the dependent variable, also biased sample show, distance is by no means a generally applicable predictor. It is, however, not the aim of this paper to provide a thorough and comprehensive study of this relationship. From the description and analysis of Seattle's crime patterns I now move on to the modeling for my regression analysis.

Table 3: Correlation - crime rates per 1000 inhabitants 1996-2006 in the 6 high-crime Census tracts

Census tracts	**71**	**72**	**81**	**92**	**93**	**109**
71	1					
72	**0.2434**	1				
81	0.0539	**0.9168**	1			
92	0.3512	0.8812	**0.9029**	1		
93	0.0277	0.566	0.6354	**0.4632**	1	
109	-0.046	0.2879	0.5233	0.4754	**0.3127**	1

The correlations between neighboring tracts are printed in bold.
Source: Seattle Police Department, Census 2000

Modeling

In the following paragraphs, I construct five models, separately for property and violent crimes. These relate the crime rates in the neighborhoods to four of their social and housing characteristics. These characteristics are their poverty level, their income inequality and their proportion of owner-occupied and occupied housing. All of these variables have been related to crime in the past (see, for example, Hipp 2007: 677). The fifth model combines all four variables. Moreover, all models include measurements of racial composition, specifically the racial heterogeneity of the neighborhoods and the percentage of inhabitants that is African American, Hispanic, Asian and American Indian.

The first and the second models assess the respective influence of income inequality and poverty on crime rates. Poverty is probably the most common explanation for crime. In this study, it is measured as the percentage of the population living below the poverty line. As mentioned before, Hipp (2007: 682-3) finds that poverty has virtually no influence on crime. He claims that income inequality, especially within racial groups, is a by far stronger predictor. This finding confirms the relative deprivation theory. This theory claims that the subjective perception of income inequality in a neighborhood leads people to commit crimes against a supposedly advantaged reference group. Property crimes are committed to "balance" the perceived injustice, and violent crimes are carried out of frustration against the reference group (Hipp: 669).

The third model relates crime to homeownership rates. The rationale behind this assumptive relationship is that homeowners make a higher investment in their neighborhood by building or buying a house. Renters do not have as much to lose when they leave the area as they are only bound to pay their rent payments until the contract duration ends. Homeowners, on the other hand, have to sell their house before they can leave the neighborhood. This can be difficult, especially when crime rates have increased. To prevent such a situation, the argument continues, homeowners also engage more in crime prevention and in neighborhood organizations than renters do (Hipp: 675, White 2001: 326).

The fourth model is closely knit to the third and not as common in the literature. It links house occupancy rates to crime. Housing occupancy, I argue, is a stronger predictor of crime than ownership. If crime rises above a certain threshold, owners willing to sell or rent their houses will no longer find interested buyers or renters willing to pay the price they demand. Unable to sell their homes, owners living in the area leave it and abandon the house. If the owners do not live in the area and already rented the house before, the outcome is the same: If there is no demand for renting their property, they abandon the house.

The fifth model combines the other four. It is used to assess the interdependences between the explanatory variables. I do not assume that the income and housing variables are fully independent from each other. This is also part of the theories that explain their use. Consequently, I analyze the results of this last model more carefully than those of the other models.

Regression analysis

Table 4: Ordinary least squares regression analysis for Seattle[9]					
	Property crimes (Standard errors in parentheses)				
Model	1	2	3	4	5
Poverty level	.324** (.120)				.233* (.106)
Income Inequality		.034 (.116)			.273* (.120)
Housing Ownership			-.149** (.054)		-.097 (.064)
Housing Occupancy				-2.384** (.273)	-2.197** (.276)
Population 18-29	.028 (.069)	.133 (.070)	-.067 (.091)	.004 (.050)	-.102 (.072)
Racial heterogeneity	-.245 (.127)	-.252 (.131)	-.167 (.131)	-.031 (.105)	.021 (.106)
African American	.214 (.147)	.306* (.149)	.189 (.149)	-.013 (.120)	-.085 (.119)
Hispanic	-.049 (.253)	-.107 (.261)	-.208 (.254)	-.294 (.202)	-.221 (.200)
Asian	-.006 (.108)	.068 (.108)	.020 (.105)	.003 (.084)	-.061 (.083)
American Indian	9.676** (1.867)	12.463** (1.707)	9.435** (1.903)	6.105** (1.456)	3.944* (1.614)
R-squared	0.4195	0.3831	0.4208	0.6289	0.6643
N	123	123	123	123	123
*p < .05 (two-tail test): **p < .01 (two-tail test)					

Tables 4 and 5 present the results of an ordinary least squares analysis using my five models. Table 4 covers property crimes and Table 5 violent crimes. Poverty is a significant predictor for both crime types according to Model 1. A one percent increase in poverty contributes to a rise in the property crime level per 1000 persons by 324 points. The violent crime level per 1000 persons increases by 72 points with a one percent rise in poverty. This influence remains significant even if poverty is included only as one of the explaining factors as in Model 5.

The influence of inner-neighborhood income inequality in Model 2 is less pronounced. It is significant at the 95 percent level only in combination with the other explanatory variables. Taken

[9] How to read this table: The .324** in the first cell of the table (Poverty level/Property crimes Model 1) is a coefficient. It shows that a one percent increase in poverty increases the property crime level per person by 0.324 points (or the crime level per 1000 persons by 324 points). The two stars signal that the probability that this relationship between poverty and property crimes is only due to chance is equal to or below one percent. One star signals a probability equal to or below five percent. The (.120) below is the standard error. It measures the expected variation in the size of the coefficient in my sample – in this case between .204 (= .324 - .120) and .444 (= .324 + .120).

together, these findings turn Hipp's claim on its head: In Seattle, income inequality becomes relevant only if poverty is also taken into account. The two variables are correlated at -.65, implying that inequality is much greater in richer neighborhoods and measures something different – or indeed the opposite - of poverty. Moreover, the R-squared is larger in Model 1 than in Model 2, implying that poverty explains the variation in Seattle's crime rates better than does income inequality.

Table 5: Ordinary least squares regression analysis for Seattle

	Violent crimes (Standard errors in parentheses)				
Model	1	2	3	4	5
Poverty level	.072** (.013)				.065** (.013)
Income Inequality		-.004 (.014)			.033* (.014)
Housing Ownership			-.022** (.006)		-.010 (.008)
Housing Occupancy				-.239** (.036)	-.209** (.033)
Population 18-29	-.014 (.008)	.006 (.008)	-.021 (.011)	-.004 (.007)	-.025** (.009)
Racial heterogeneity	-.024 (.014)	-.026 (.016)	-.013 (.016)	-.004 (.014)	.002 (.013)
African American	.030 (.016)	.049** (.018)	.033 (.018)	.018 (.016)	.002 (.014)
Hispanic	.011 (.028)	-.005 (.032)	-.018 (.030)	-.022 (.027)	-.004 (.024)
Asian	-.002 (.012)	.014 (.013)	.007 (.013)	.008 (.011)	-.007 (.010)
American Indian	.955** (.208)	1.524** (.206)	1.112** (.226)	.917** (.193)	.412* (.195)
R-squared	0.5710	0.4643	0.5139	0.6114	0.7082
N	123	123	123	123	123
*p < .05 (two-tail test): **p < .01 (two-tail test)					

Another interesting finding is that the coefficients for racial heterogeneity and the racial minority groups, with the exception of Hispanics, are largest when income inequality is taken as the only crime predictor in Model 2. This poses a puzzle to me that I fail to explain at the moment. To approximate a solution, the context may be relevant. In Seattle, income inequality and racial heterogeneity are correlated at -.50. Income inequality and poverty are correlated at -.50. This means that incomes tend to differ more within rich neighborhoods. Taken together, this means that rich tracts tend to be racially homogeneous and that racial segregation is accompanied by income segregation.

Similar to income inequality, housing ownership loses its role as a significant predictor of both property and violent crimes once the other variables are also included in Model 5. Housing occupancy is more relevant than ownership, both taken alone and together with the other variables, as its influence remains significant in both cases. Resulting from the small variation between the neighborhoods in respect to housing occupancy, an increase in occupancy of one percent in Model 3 reduces the property crime level per 1000 persons by 2,384 points, or more than three times its maximum value.

The percentage of the population between the age of 18 and 29 and the racial heterogeneity of a tract are in most models not significant predictors of either type of crime. Surprisingly, if all explanatory variables are included in Model 5, violent crimes become less likely once this fraction of the population increases. Across all tracts, violent crime levels and the population between 18 and 29 are almost uncorrelated at .03.

One finding common to all models is that American Indians tend to live in neighborhoods that experience high levels of crime. Again, the high coefficients are due to the generally small number of Indians living in Seattle, but nevertheless the effect is significant across all models. A possible solution to this puzzle is that on average, American Indians are relatively poor. The percentage of Indians in a tract is correlated with the tract's poverty at .60, indicating that American Indians tend to live in poor neighborhoods. These neighborhoods are – as Model 1 and Model 5 clearly show – more likely to experience high levels of crime.

A comparison of the two regression tables shows that the R-squared is larger for violent crimes in most Models. With the variables I selected for my analysis, I was able to better explain violent crimes. The only exception is Model 4 in Table 4 that manages to explain a greater amount of the variation in property crimes with housing occupancy than does Model 4 in Table 5 for violent crimes.

It is hard to explain these relationships to the fullest. For the moment, I am interested in how well they are applicable to other criminal settings in the United States. With this aim in mind, I move on to a short description of my second urban area, Durham, North Carolina.

Overview: Crime in Durham

With a population of 210,553 in 2000, Durham, North Carolina is much smaller than Seattle. It is also located in the Southeast, on the "opposite" side of the United States. Between January 2006 and July 2007, 22,820 crimes were reported for Durham, excluding Duke University. This corresponds to an average crime rate of 68.5 crimes per 1000 persons and year. 21,388 crimes were assigned to a Census tract and thus included in my dataset. Of these, 17,460 (81.6 percent) were property crimes and 2,536 (11.9 percent) violent crimes. Table 6 presents summary statistics for Durham similar to those included for Seattle in Table 1.

Table 6: Summary Statistics for Durham, dependent and explanatory variables

Variable	Mean	SD	Min	Max
Crime per 1000 inhabitants and year, 2006-2007	131.56	113.64	0.39	814.18
Property crimes per 1000 inhabitants and year, 2006-2007	71.31	94.63	0.39	673.48
Violent crimes per 1000 inhabitants and year, 2006-2007	10.53	14.20	0.00	95.78
Non-aggravated assaults per 1000 inhabitants and year, 2006-2007	49.72	28.29	0.00	139.95
% Houses occupied, 2000	0,93	0,04	0,80	1,00
% Homeowners, 2000	0,50	0,27	0,00	0,95
% Below poverty level, 2000	0,16	0,13	0,02	0,45
Income inequality, 2000 (Gini coefficient)	0,45	0,11	0,28	0,93
% Between 18 and 29 years old	0,21	0,10	0,06	0,57
Racial heterogeneity, 2000 (Herfindahl-Index)	0,41	0,18	0,04	0,72
% African American, 2000	0,45	0,29	0,06	0,98
% Hispanic, 2000	0,08	0,07	0,01	0,25
% Asian, 2000	0,02	0,03	0,00	0,13
% American Indian, 2000	0,00	0,00	0,00	0,01

N=51
Source: Durham Police Department 2007, Census 2000

Durham's overall crime rate is about a fifth higher than is Seattle's. This difference builds mainly on non-aggravated assaults which are almost four times as numerous as in Seattle. Property crimes are less common in Durham but violent crimes happen more often. At 45 percent, the African American population of Durham is far larger than the one of Seattle that corresponds to 8 percent. Durham's Hispanic population is smaller than Seattle's but its Asian population is at two percent - only at a sixth of Seattle's.

I analyzed the Durham crime data in a regression similar to the one for Seattle (see Tables 7 and 8 in the Appendix). However, the results are different in some respects. In Durham, poverty and income inequality are both strong predictors of crime. In the case of property crimes, poverty becomes irrelevant if income inequality is also considered. Contrary to the Seattle results, this confirms Hipp's findings. For violent crimes, however, both poverty and income inequality remain relevant also in Model 5. This shows no more than the general relationship of poverty and inequality is not clear and dependent on the city setting.

The effect of ownership and occupancy rates is also reversed. Ownership plays a much more important role in Durham than it does in Seattle. In Durham, home ownership remains relevant when other variables are included in the analysis in Model 5. For the explanation of crime, Durham's occupancy rates are significant only at the 95 percent confidence level, making ownership a more important predictor for crime than occupancy. As I argued before, the decision to abandon a house can be interpreted as the last option if its owner cannot find anybody willing to invest in it. It is thus surprising that ownership is a more powerful predictor of crime than is occupancy. A comparison of the summary statistics in Tables 1 and 6 suggests that these differences are not due to differences in the means or variances of these variables but are indeed related to differences inherent in the cities and their unique distribution of crime.

Predicting crime in Durham

The previous analysis has shown that crime in Durham differs from crime in Seattle in many respects. Can the Seattle results be used to approximate crime rates in Durham nevertheless? Which proportion of the disparities is due to different characteristics of the two cities and which can be explained with the different behavior of its inhabitants? To answer this question, I use the coefficients from Seattle's Model 5 and the neighborhood characteristics of Durham. The findings are pictured in Table 9.

Table 9: Actual and predicted crime rates for Durham, 2006-2007

Variable	Mean	SD	Min	Max
Actual property crimes per 1000 inhabitants and year	71.31	94.63	0.39	673.48
Predicted property crimes per 1000 inhabitants and year	101.01	93.75	-9.72	456.23
- Difference	-29.70	0.88	10.11	217.25
Actual violent crimes per 1000 inhabitants and year	10.53	14.20	0.00	95.78
Predicted violent crimes per 1000 inhabitants and year	15.23	14.63	-3.40	66.66
- Difference	-4.70	-0.42	3.40	29.12

N=51
Source: Durham Police Department 2007, Census 2000

My model tends to overestimate the prevalence of both types of crime in Durham. In 31 census tracts, the actual crime rate is lower than the one predicted by the model while in the other 20 tracts, the actual crime rate is higher than the predicted one. At 101, the average predicted property crime rate per 1000 persons by far surpasses the real one of 71.3 by almost a half. However, the prediction shows different results at the extremes. The property crime prediction even includes four census tracts with negative crime rates and underestimates the maximum crime rate by 217.3 points. The same is true for the predicted violent crime, where three tracts show negative crimes rates and the maximum crime rate is underestimated by a third.

These differences may seem large, but as a comparison of the differences across neighborhoods shows, they are not really. In only seven neighborhoods is the property crime rate over- or underestimated by more than the average crime rate of 71.3. These false estimations are fairly large and thereby manage to distort the whole picture that looks better for most tracts. Concerning violent crimes, the underestimation seems more systematic. The real violent crime rate is higher than the predicted one in only eleven tracts, while in all other tracts, crime is overestimated. Nevertheless, real crime levels differ from the predicted ones by more than the average 10.5 points in only another eleven census tracts. The patterns in census tract 17.10 seem to resemble Seattle the most. Here, the real crime rate is underestimated by only 0.00006 points.

From these results, I can assess the relative influence of neighborhood characteristics and behavior on crime. The difference of roughly 30 crimes per 1000 persons between the predicted and the actual crime rate is due to different behavior. Estimating from the results of Seattle, its characteristics would render Durham a more criminal city than it actually is.

Conclusion

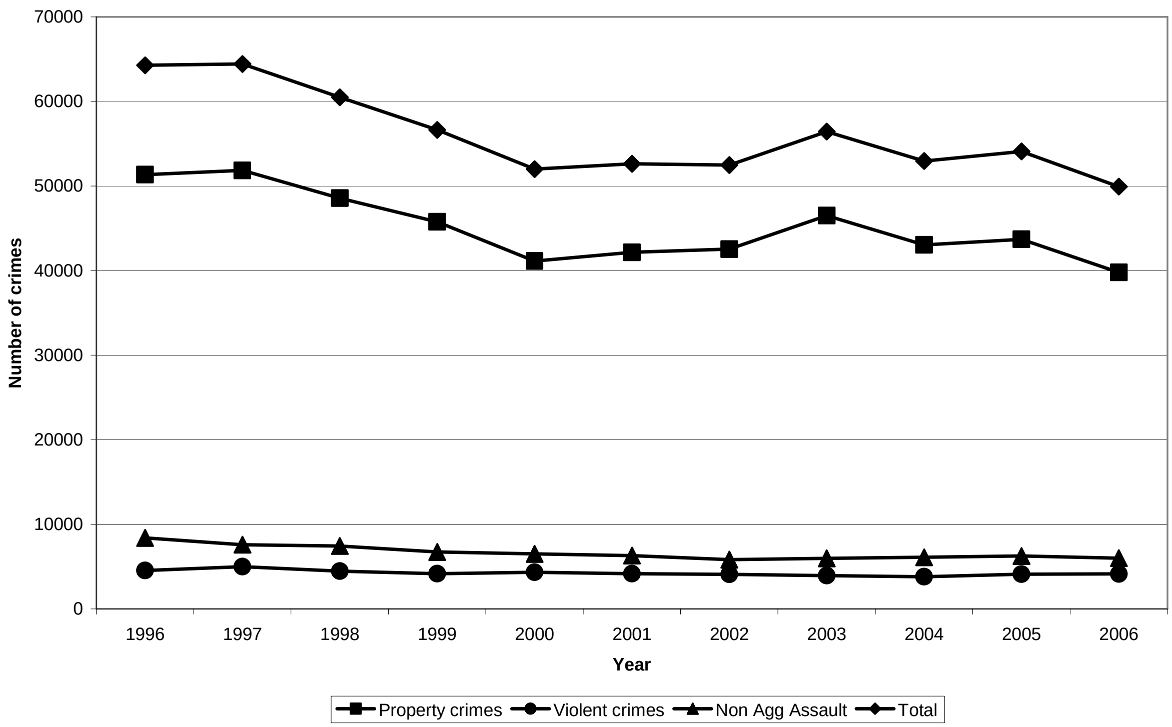
In this paper, I assessed the explanatory power of four variables commonly associated with crime by applying them to two cities in the US. None of these variables emerged as dominant in both cities, but instead they mattered to different degrees. It became apparent that poverty and income inequality are interrelated, as are housing occupancy and ownership. When combined, these variables reached very far in explaining variations in crime.

Durham and Seattle differ both in their structural circumstances and the behavior of their inhabitants. Nevertheless, the prediction of crime from one city to another was relatively successful.

In sum, this paper marks a starting point for more refined future studies. These may use indicators for crime that are both better applicable to different settings and more closely related to crime.

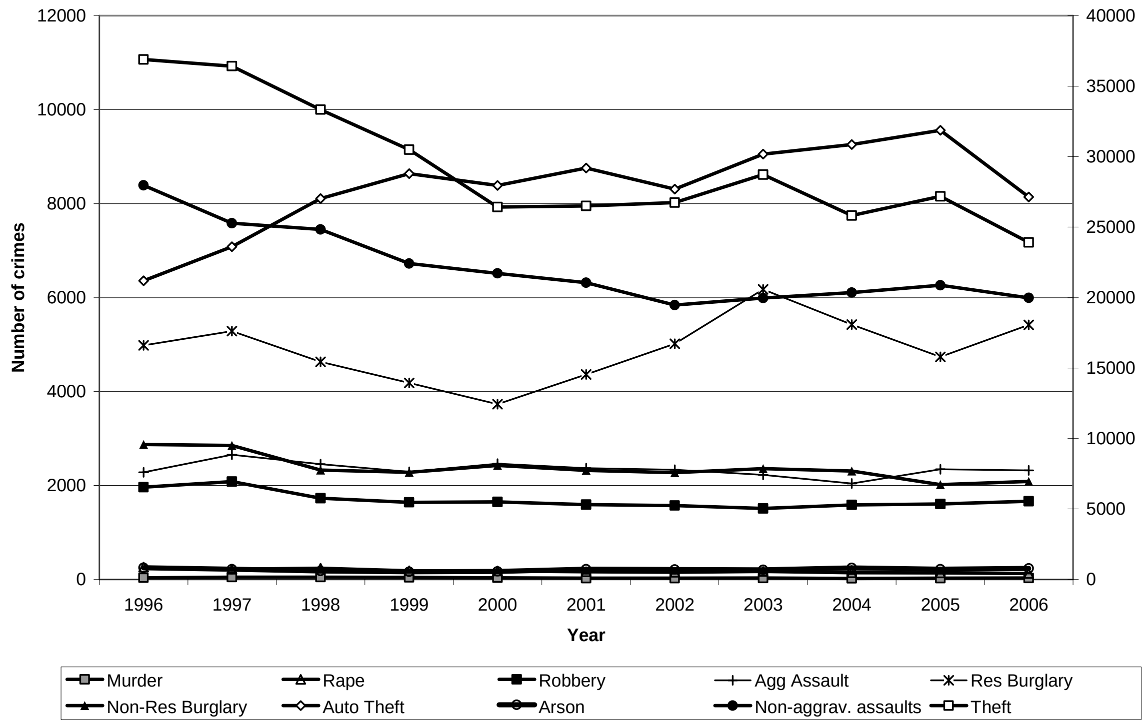
Appendix

Graph 1: Crimes in Seattle 1996-2006



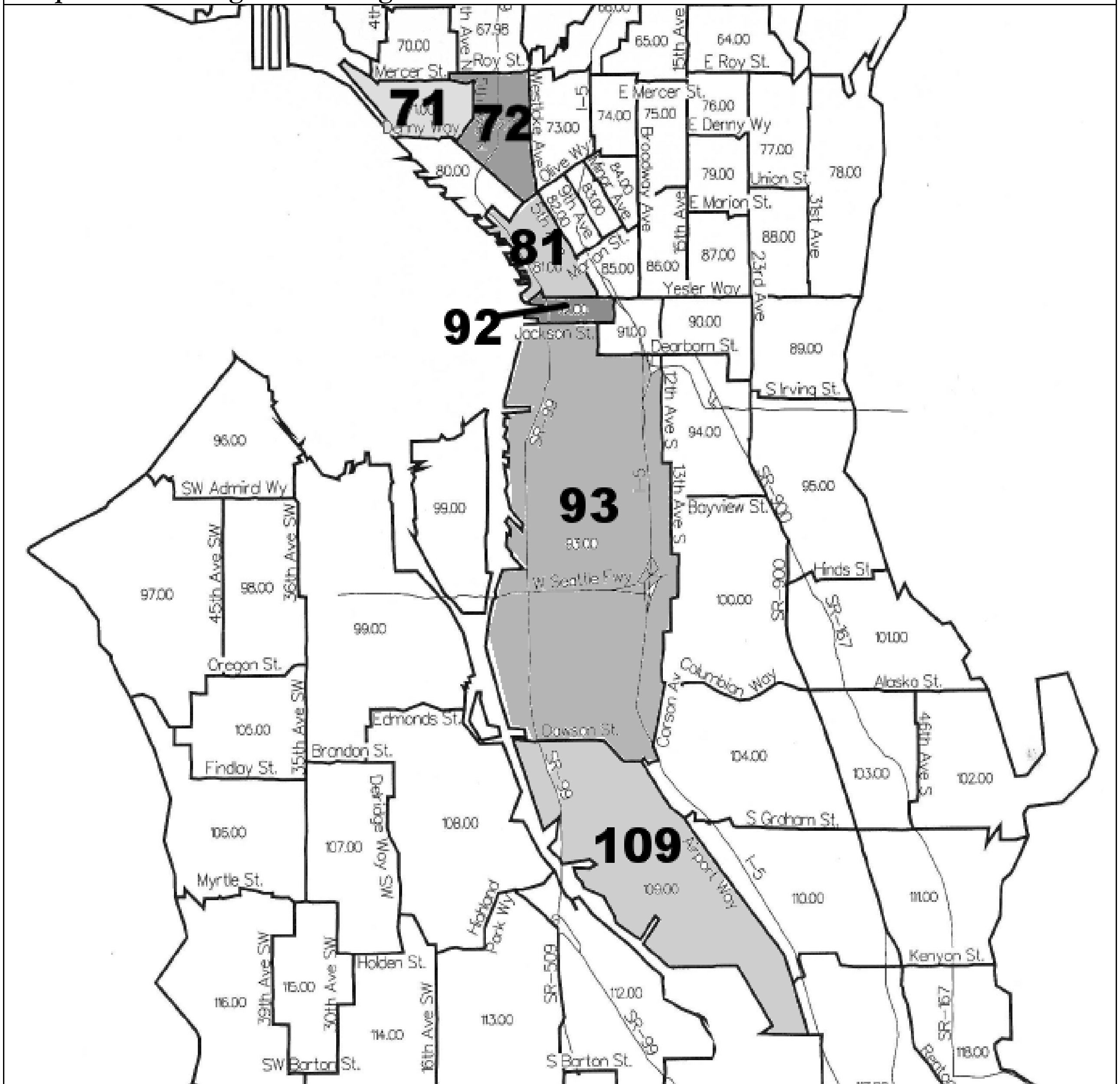
Source: Seattle Police Department

Graph 2: Crimes by type in Seattle 1996-2006



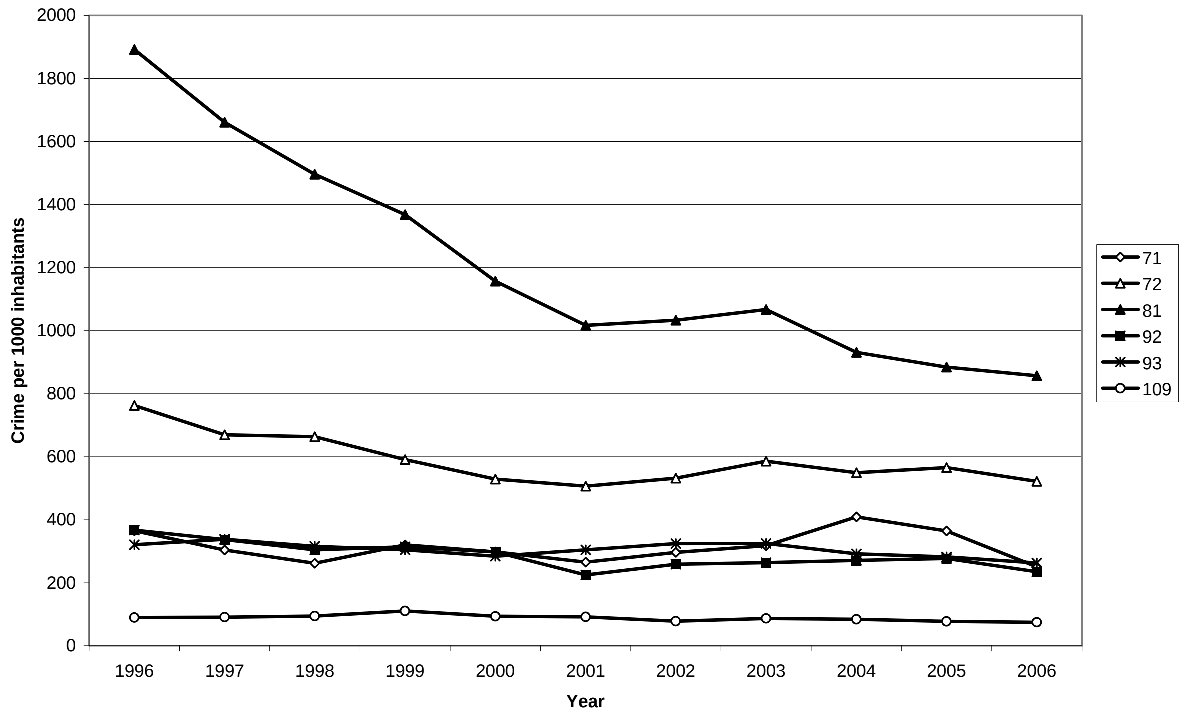
Source: Seattle Police Department

Map 1: Seattle's high-crime neighborhoods



Source: Seattle Police Department

Graph 3: Crimes in the high-crime neighborhoods of Seattle 1996-2006



Source: Seattle Police Department

Table 7: Ordinary least squares regression analysis for Durham					
	Property crimes (Standard errors in parentheses)				
Model	1	2	3	4	5
Poverty level	.683** (.152)				.087 (.133)
Income Inequality		.686** (.123			.675** (.076)
Housing Ownership			-.338** (.067)		-.257** (.064)
Housing Occupancy				-.959* (.403)	-.536* (.217)
Population 18-29	.062 (.154)	.147 (.142	-.195 (.158)	.013 (.178)	-.115 (.098)
Racial heterogeneity	.212* (.100)	.092 (.088	.070 (.092)	.123 (.110)	.123 (.061)
African American	-.101 (.065)	.139** (.047	-.057 (.056)	.046 (.060)	-.014 (.038)
Hispanic	-.820** (.248)	.411 (.230	-.715** (.224)	-.385 (.249)	-.091 (.163)
Asian	-.611 (.517)	-.315 (.473	-.785 (.502)	-.448 (.587)	-.777* (.292)
American Indian	12.302* (5.654)	4.578 (5.437)	15.541** (5.443)	12.264 (6.451)	5.591 (3.358)
R-squared	0.4487	0.5321	0.4913	0.2849	0.8398
N	51	51	51	51	51
*p < .05 (two-tail test): **p < .01 (two-tail test)					

Table 8: Ordinary least squares regression analysis for Durham					
	Violent crimes (Standard errors in parentheses)				
Model	1	2	3	4	5
Poverty level	.118** (.019)				.057** (.015)
Income Inequality		.103** (.017)			.096** (.009)
Housing Ownership			-.049** (.010)		-.023** (.007)
Housing Occupancy				-.121* (.0590	-.064* (.025)
Population 18-29	-.005 (.020)	.009 (.020)	-.041 (.023)	-.010 (.026)	-.018 (.011)
Racial heterogeneity	.027* (.013)	.006 (.012)	.003 (.013)	.009 (.016)	.018* (.007)
African American	-.010 (.008)	.030** (.007)	.002 (.008)	.017 (.009)	.002 (.004)
Hispanic	-.091** (.032)	.106** (.032)	-.060 (.032)	-.010 (.036)	.013 (.019)
Asian	-.066 (.066)	-.015 (.065)	-.083 (.072)	-.032 (.085)	-.079* (.033)
American Indian	.843 (.720)	-.291 (.752)	1.340 (.776)	.887 (.937)	-.219 (.382)
R-squared	0.6027	0.6032	0.5409	0.3301	0.9079
N	51	51	51	51	51
*p < .05 (two-tail test): **p < .01 (two-tail test)					

Literature and other sources

FBI (2007): "Uniform crime reports", http://www.fbi.gov/ucr/ucr.htm

Hipp, J.R. (2007): "Income Inequality, race and place: Does the distribution of race and class within neighborhoods affect crime rates?". Criminology, 45(3), 665-697.

Perkins, Craig (1997): "Age Patterns of Victims of Serious Violent Crime". Bureau of Justice Statistics Special Report, July 1997, http://www.ojp.usdoj.gov/bjs/pub/pdf/apvsvc.pdf

Reiss, A. J. (1986): "Why are Communities Important in Understanding Crime?". Crime and Justice, 8, pp. 1-33

Seattle Population and Demographics (2007): "Seattle-at-a-glance", http://www.seattle.gov/dpd/Research/Population_Demographics/Seattle_at_a_Glance/default.asp

Steffensmeier, Darrell, **Allan**, Emilie, Harer, Miles, Streifel, Cathy (1989): "Age and the Distribution of Crime". The American Journal of Sociology, Vol. 94, No. 4., pp. 803-831

White, G.F. (2001): "Homeownership: Crime and the tipping and trapping processes". Environment and Behavior, 33(3), 325-342.

Census 1990 and 2000, American Factfinder
http://factfinder.census.gov/home/saff/main.html?_lang=en

Durham Crime Mapper
http://www.durhampolice.com/crimemapper.cfm

Durham, NC
http://www.durham-nc.com

Seattle Police Department Crime Data
http://www.seattle.gov/police/crime/stats.htm