Theory and Evidence Regarding the Effects of Segregation on Crime Rates

David Bjerk*
McMaster University and RAND Corp.

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Abstract

This paper empirically examines whether greater segregation by poverty status or race affects citywide crime rates. To control for the potential endogeneity of segregation (of either type) with respect to crime, I instrument for segregation using information regarding how public housing assistance is allocated in each city, as well as the structure of local public finance in each city. The results indicate that greater segregation by poverty status or race has no impact on basic property crimes such as larceny and motor vehicle theft, actually leads to somewhat lower burglary rates, but most notably, leads to substantially higher rates of aggravated assault and robbery. The second part of this paper then develops a model of criminal participation that explicitly accounts for why segregation may have these differing effects on different types of crime.

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1 Introduction

While crime rates have generally been falling throughout the last decade in the United States, crime remains a topic of tremendous concern for Americans. In a 2004 Pew Survey of American adults regarding legislative priorities, individuals ranked reducing crime at or above such issues as providing health insurance to the uninsured, the budget deficit, programs for the poor and the needy, and protecting the environment (Pew, 2004). Moreover, concerns about crime appear to be particularly acute for those living in primarily black neighborhoods with very high rates of poverty. For example, individuals who signed up for the Moving To Opportunity residential relocation subsidy program came from neighborhoods where the average poverty rate was over 30 percent and the average fraction of the neighborhood that were minorities was over 80 percent. Among these individuals, fear of crime and gangs, not a better apartment or higher quality schools, was overwhelmingly cited as the primary reason for wanting to enroll in the program (Kling, Ludwig, and Katz, 2005).

These high rates of criminal participation and victimization in poor black neighborhoods have been described by numerous journalists and scholars (Wilson, 1987, 1996; Krivo and Peterson, 1996; Kotlowitz, 1991; Patterson, 1991; Messner and Tardiff, 1986, to name just a few), leaving little doubt that crime is a large part of life in such neighborhoods. However, what is less clear is whether the high rates of crime in these neighborhoods arise simply because those most prone to crime are concentrated in these areas, or whether the existence of such highly economically and racially segregated neighborhoods actually causes the individuals who live in such neighborhoods to be more prone to criminal activity than they would if they were dispersed more uniformly across the city. In other words, does the degree of economic and racial segregation in a metropolitan area have a direct effect on the overall amount of crime committed in that area or does it simply affect who is victimized by such crime?

In the first part of this paper, I focus on this task of estimating the degree to which greater segregation (by poverty status or race) in a metropolitan area affects overall metro area crime rates. The primary difficulty in this task is that segregation might not only affect the overall amount of crime in a metro area, but since crime may influence individual residential location choice, crime rates may also affect the level of segregation in a metro area. This simultaneity concern means that even after conditioning on a variety of metro area characteristics, simple estimates of the correlation between segregation and crime may not be very informative regarding the effect of greater segregation on crime.

To overcome this potential endogeneity bias in estimating the effect of segregation on crime, I employ a Two-stage least squares approach using two distinct instruments for economic and racial segregation. The first instrument uses data regarding the fraction of government housing assistance that is allocated in the form of government owned public housing projects rather than through vouchers or other subsidies to private property owners. The second instrument follows from Cutler and Glaeser (1997), and uses data regarding the historic structure of local public finance revenue.

The key results of this empirical analysis indicate that greater segregation (by poverty status or race) has different effects on different types of crimes. Specifically, greater segregation has little direct impact on basic property crimes such as larceny and motor vehicle thefts, and if anything, may lead to slightly lower burglary rates. However, the strongest results indicate that greater segregation leads to large and significant increases in the rates of violent crimes such as robbery and aggravated assault.

One potential explanation for these results is that some individuals' behavior with respect to crime is affected by their neighbor's characteristics or behavior—what has generally been called "neighborhood effects." Another hypothesis is that these results arise from segregation affecting crime indirectly, for example through worsening schools or job opportunities, which in turn affect crime. However, neither current models of neighborhood effects with respect to criminal behavior, nor the indirect effect hypothesis, make distinctions by type of crime. Therefore, current models of either type cannot directly account for the apparently differential effects of segregation on violent interpersonal crimes versus more basic property crimes.

In the second part of this paper, I develop a new model of criminal behavior that distinguishes between basic property crimes and violent interpersonal crimes in an attempt to provide plausible mechanisms behind the empirical results discussed above. The key assumptions of the model are only that individuals incur diminishing marginal utility in consumption, and can differ in both their legal income and their underlying taste for being a criminal, where this taste is independent of income and independent between neighbors. With respect to *basic property* crimes, I show that such assumptions mean that poorer individuals will indeed be more likely to engage in such crimes, but an individual's decision to do so is not affected by the characteristics of his neighbors. This means that with respect to basic property crimes, the simplest version of this model suggests there will be no neighborhood effects and therefore no direct effect of segregation on such crimes.

However, if this simple model of basic property crime is amended to assume that the monetary payoff to a given property crime is greater when an individual has more non-poor neighbors, then neighborhood effects can arise, but such effects will actually mean that citywide basic property crime rates will be *negatively* related to segregation. Therefore, this model suggests that greater segregation can have either no effect or a negative effect on *basic property crimes*—a result consistent with the previously discussed empirical findings regarding the basic property crimes of larceny, motor vehicle theft, and burglary.

Alternatively, with respect to *violent interpersonal* crimes, the model additionally assumes that individuals choose whether to become the type of individual who will engage in violent behavior against all of those he encounters in his neighborhood (i.e. a "thug"), or the type who will not (i.e. a "pacifist"). Thus, when a thug encounters a pacifist, the thug acts violently while the pacifist does not, which I assume results in the thug both imposing pain and suffering and taking money from the pacifist. On the other hand, when two thugs encounter one another, both act violently, which I assume causes both thugs to incur pain and suffering, but causes neither to lose or gain any money. This means that, similar to basic property crimes, by being a thug an individual can potentially gain money beyond his legal income in a given period. However, unlike with respect to basic property crimes, by being a thug an individual can avoid having money taken from him by other thugs. Importantly, this latter benefit depends on the fraction of other thugs that live in his neighborhood, which is a function of the fraction of his neighbors that are poor. I show that, in contrast to basic property crimes, these incentives imply that greater segregation will have a *positive* impact on the overall amount of robberies and assaults in a city. This implication is once again consistent with the previously discussed empirical results regarding violent crimes.

2 Estimating the Effects of Segregation on Crime

This section attempts to empirically estimate the direct effect of segregation (by both poverty status and race) on crime. This analysis will be done at the MSA/PMSA level ("MSAs" from here on). In general, the data I use for this analysis come from two primary sources—the FBI's Uniform Crime Reports for

2000 and the 2000 Census. I will talk about each of these data sources, as well as the variables obtained from them, separately.

FBI Uniform Crime Reports

The FBI Uniform Crime Reporting Program is a nationwide program where nearly 17,000 city, county, university, and state law enforcement agencies report the number of crimes of different types that were brought to their attention. The reporting agencies covered roughly 94 percent of the total U.S. population, and 96 percent of the population living in MSAs. The program's primary objective is to generate a reliable set of criminal statistics to be used by both law enforcement agencies, legislators, the media, and researchers (Federal Bureau of Investigation, 2000).[1]

In this analysis, I look separately at the five most common *Index* crimes—robbery, aggravated assault, burglary, larceny-theft, and motor vehicle theft.[2] For clarity, it is important to precisely describe what is meant by each of these crime categories. The Uniform Crime Reports define Aggravated Assault to be "the unlawful attack by one person upon another," where the attacker used a weapon, or inflicted "serious or aggravated injury" on the victim. Robbery is defined to be "taking or attempting to take anything of value from the care, custody, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear." By contrast, Burglary is defined to be "the unlawful entry of a structure to commit a felony or theft," while Larceny is defined to be "the unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another. It includes crimes such as shoplifting, pocket-picking, purse-snatching, thefts from motor vehicles, thefts of motor vehicle parts and accessories, bicycle thefts, etc., in which no use of force, violence, or fraud occurs." Finally, motor vehicle thefts are simply the "theft or attempted theft of a motor vehicle" (Federal Bureau of Investigation, 2000).

As the above definitions make clear, a major distinction between these crime

[1] This data was made available through the National Archive for Criminal Justice Data (NACJD) and the Inter-University Consortium for Political and Social Research (ICPSR) study #3451.

[2] I do not look at the three other Index crimes—rape, murder, and arson—because the number of these crimes are relatively small, especially in smaller cities, making the rates somewhat uninformative. In particular, in many smaller cities there are less than 5 of such crimes reported in a given year, meaning for example that one more murder in a given year will increase the murder rate in that city by 20 percent or more.

categories is that Aggravated Assault and Robbery are violent crimes involving a direct confrontation with the victim, while Burglary, Larceny, and Motor Vehicle Thefts are non-violent property crimes that explicitly do not involve a direct confrontation with the victim.[3] Therefore, I will refer to Aggravated Assault and Robbery as "violent interpersonal crimes," and Burglary, Larceny, and Motor Vehicle Thefts as "basic property crimes." The importance of these distinctions will become clear later in the paper.

I also use the FBI Uniform Crime data from 1999 to obtain crime clearance rates for each type of crime in each MSA, where the clearance rate is measured to be the fraction of all reported crimes where at least one person is arrested, charged with the commission of the offense, and turned over to the court for prosecution (Federal Bureau of Investigation, 2000). This measure will be used as a measure of the efficiency of the police force in each MSA, under the assumption that higher clearance rates in the prior year may have deterrence effects and indicate more effective police forces.

Since the FBI UCR crime data are reported at the county level, I determined crime rates and clearance rates for each MSA by aggregating all crime data for counties that fall within a particular MSA. Because most counties either fall in one MSA or fall in zero MSAs, this generally provided accurate MSA crime information. However, several New England counties are divided between two or more distinct MSAs. Since I could not determine which MSA to assign the reported crimes in these counties to, I had to exclude these New England MSAs that contained shared counties from the analysis.[4]

MSA Population Characteristics

Data regarding MSA population characteristics come for the most part from the 2000 United States Census Summary File 3. These data are compiled from a sample of approximately 19 million housing units (about 1 in 6 households) that received the Census 2000 long-form questionnaire. I use these data to obtain measures of the fraction of each MSA living at or below the poverty line, the racial make-up of each MSA, the population of each MSA, the fraction of each MSA that is made up of first generation immigrants, the fraction of adults in the MSA who have a college degree, the fraction of households in each MSA

[3] Car-jacking, or taking an individual's car by threat or force, is counted as robbery, not a motor vehicle theft.

[4] The Miami FL MSA was not included in the subsequent analysis because no UCR crime information was available. The Lawrence KS MSA was also excluded from the subsequent analysis since no robberies occurred in 1999, precluding calculation of the relevant clearance rate.

headed by a single mother, the fraction of the workforce in each MSA that is unemployed, and a measure of the fraction of the MSA that lived in an "urban area" or "urban cluster".[5]

I also use data from the Department of Housing and Urban Development's "A Picture of Subsidized Households - 1998" to determine the total number of households in each MSA that receive housing assistance. This data set contains data on all subsidized household units for each housing agency in the United States. From this data, I determine the number of all households in each MSA that receive housing subsidies, which I then divide by the number of households in the MSA to determine the fraction of households in each MSA that receive housing assistance.[6]

Measures of Racial Segregation

In this analysis I will look at both segregation by poverty status and segregation by race. While there exist several plausible measures of segregation of either type within a community, I employ the two measures used by Cutler, Glaeser, and Vigdor (1999), both constructed for each MSA using data at the census tract level.[7] The first measure is referred to as the *dissimilarity index*, originally proposed by Duncan and Duncan (1955) and Taeuber and Taeuber (1965). In the context of segregation by poverty status, this index is high when the poor disproportionately reside in some areas of the city relative to the non-poor. The actual index is constructed to be

$$\text{Poverty Dissimilarity Index} = \frac{1}{2}\sum_{i=1}^{N} \left| \frac{\text{poor}_i}{\text{poor}_{total}} - \frac{\text{non-poor}_i}{\text{non-poor}_{total}} \right|,$$

where poor_i is the number of individuals in census tract i living in households with income below the poverty line, poor_{total} is the total number of individuals in the whole city living below the poverty line, and the non-poor terms are analogously defined. As discussed by Cutler, Glaeser, and Vigdor (1999) (but within the context of race), this index ranges from zero as the lowest level of

[5] "Urban Area" consists of densely settled territory that contains 50,000 or more people. "Urban Cluster" consists of densely settled territory that has at least 2,500 people but fewer than 50,000 people

[6] The HUD data did not contain information on public housing for several MSAs that were not classified as MSAs prior to 1998. Therefore, these MSAs were also excluded from the subsequent analysis.

[7] For further discussion of these different measures, see Taeuber and Taeuber (1965), Massey and Denton (1988), and Glaeser and Scheinkman (1997).

segregation, to one as the highest level of segregation, and answers the question what share of the poor population would need to change areas for the poor and non-poor to be evenly distributed within a city?

The second measure of segregation I employ is what is generally referred to as an *isolation index*. First proposed by Bell (1954), this index attempts to measure the extent to which individuals of one group are likely to interact with individuals of another group in their neighborhoods. With respect to segregation by poverty status, this index is constructed to be the following

$$\text{Poverty Isolation Index} = \frac{\sum_{i=1}^{N}(\frac{\text{poor}_i}{\text{poor}_{total}}\frac{\text{poor}_i}{\text{persons}_i}) - (\frac{\text{poor}_{total}}{\text{persons}_{total}})}{\min(\frac{\text{poor}_{total}}{\text{persons}_\ell}, 1) - (\frac{\text{poor}_{total}}{\text{persons}_{total}})},$$

where persons_ℓ is the number of persons in the census tract with the lowest population with in the city and i once again denotes census tract. The first term in the top part of the above equation is the fraction poor in the census tract occupied by the average poor individual. From this, we can subtract the percentage poor in the city as a whole to eliminate the effect coming from the overall size of the poor population. This whole term is then normalized to be between zero and one, with one indicating the city is the most segregated it can possibly be.

In both cases, I use 2000 Census data to create these indices. Not surprisingly, the two indices are highly correlated, with a correlation coefficient of roughly 0.8.

As discussed above, I also construct analogous measures using black versus non-black, rather than poor versus non-poor, to measure *racial* segregation in each MSA. As is expected, segregation by poverty status and segregation by race are also relatively highly correlated, with correlation coefficients of greater than 0.4 for the both the dissimilarity indices and the isolation indices.

Weather Measures

Finally, weather may have an effect on criminal activity (see Jacob, Lefgren, and Moretti, 2004). In particular, cities with a high number of very hot days may have more days where people are out in the street, meaning there will be more potential interactions in which crimes may take place. Alternatively, the opposite will hold true in cities with a high number of very cold days. Moreover, tempers might run higher on very hot days, while the importance of obtaining money quickly may be greater on very cold days (e.g. if is harder to sleep outside, food and clothing become more important). Therefore, I obtained information on the average number of very hot days (i.e. temperature of 90 degrees or higher) per 100 days for each state, as well as the average number of very cold days (i.e. temperature of 32 degrees or lower) per 100 days for each state. This data comes from the National Climatic Data Center, a U.S. government funded archive of weather data.[8]

Table I summarizes all of the above variables for the sample used in this analysis. See the Data Appendix for complete description of this sample.

2.1 The Correlation between Segregation and Crime

We can begin by looking at the relationship between crime and segregation using simple OLS specifications regressing the MSA crime rate, for each type of crime separately, on an index of the degree of segregation (by poverty or race) in the MSA and a variety of other MSA characteristics that may also influence MSA crime rates. Table II(a) shows the results of such regressions using the two indices of segregation by poverty status, while Table II(b) shows the analogous results using the two indices of segregation by race.

In Tables II(a) and II(b), there are two specifications in each table for each type of crime, where the first specification uses the dissimilarity index to measure segregation and the second specification uses the isolation index (both standardized to have a mean of zero and standard deviation of one). For each type of crime, the dependant variable is the rate of that crime per 100,000 residents, standardized to have a mean of zero and standard deviation of one. I use these standardized rates in order to facilitate comparing magnitudes across crimes, as the overall rates per 100,000 residents differ dramatically across crimes (as can be seen in Table I). The other MSA characteristics I control for were discussed above and are also shown in Tables II(a) and II(b).

Looking at the first two rows of Table II(a), we can see that the correlation between segregation by poverty status and crime rates is quite weak across all crime categories. Only with respect to robbery is the coefficient on either of the segregation indices statistically significant (although the coefficients are

[8]Measures are calculated to be the average for all cities for which weather data is reported in each state. The measures for each city are calculated as the average over several years, ranging from 11 years to over 100. Data and further information regarding the NCDC is available at www.ncdc.noaa.gov/oa/ncdc.html.

still relatively small in magnitude). Looking at the results regarding segregation by race in Table II(b), there similarly appears to be very little correlation between racial segregation and the rates of the non-confrontational property crimes of burglary, larceny, and motor vehicle theft, using either measure of racial segregation, but there appears to be some positive and significant correlation between racial segregation and the interpersonal crimes of aggravated assault and especially robbery. However, once again, the magnitudes of these estimated coefficients are quite small, with the largest indicating that a one standard deviation increase in the racial isolation index is correlated with less than one third of a standard deviation increase the robbery rate. The estimated coefficients on the other variables generally conform to expectations.

2.2 Controlling for the Potential Endogeneity of Segregation

While the results presented in Tables II(a) and II(b) reveal some small but interesting differences in the correlation between economic or racial segregation and crime across different types of crime, these results are not necessarily very informative about the degree to which segregation may *affect* MSA-wide crime rates for these different types of crimes. In particular, as discussed in the introduction, the level of economic and racial segregation in an MSA may be endogenous since people generally have substantial choice about where to live within a city.

Such selection may bias the causal interpretation of the OLS results for several reasons. To take one example, Cullen and Levitt (1999) argue that rising crime rates may lead to flight from central cities, especially by the wealthy and whites. This means that any positive relationship between crime and economic or racial segregation may arise not because greater segregation increases crime, but because greater crime leads to greater economic or racial segregation. Therefore, the OLS results presented above may be upwardly biased.

Alternatively, as violent crime increases in a city, for example as gangs become more prominent, individuals living in the neighborhoods where these gangs operate have a greater incentive to take on the expenses associated with moving. Indeed, as discussed in the introduction, escaping from gangs and crime was the primary reason participants in the MTO housing relocation program gave for signing up for the program. Given that these neighborhoods where violence and gang activity are greatest are often the poorest and most predominantly black neighborhoods in a city, those emigrating from these neighborhoods will generally be poorer and more frequently non-white than the residents of the neighborhoods they move to. Therefore, it is also possible that as crime increases, a city becomes somewhat less economically and/or racially segregated, meaning the OLS results presented above could also be downwardly biased.[9]

In order to obtain plausibly unbiased estimates of the causal effect of segregation on different types of crime rates we therefore must find some characteristics that vary across Metropolitan areas that affect economic and racial segregation, but can be credibly excluded from having any direct relationship to current levels of criminal activity. Given we can find instruments that meet this exclusion restriction, we can estimate the effect of segregation on the different types of crime using Two-stage Least Squares (2SLS).

The first instrument for segregation (of both types) that I employ is the fraction of public housing assistance that was allocated in the form of apartments in government owned public housing structures as opposed to allocated via Section 8 housing vouchers or certificates (or other types of subsidies to non-government property owners). The data used to create this instrument once again comes from the Department of Housing and Urban Development's "A Picture of Subsidized Households - 1998" described above. By design, public housing structures group poor individuals together to a greater extent than do housing vouchers which can generally be used anywhere in the city. To the extent that a substantially higher fraction of black households are poor and in need of housing assistance than white households, cities that provide a greater fraction of housing assistance via providing space in a public housing project, as opposed to through vouchers or certificates, should have higher levels of both economic and racial segregation. Indeed, the HUD data shows that the census tracts surrounding Public Housing Structures are roughly 36 percent poor and 60 percent minority on average, compared with an average of only 20 percent poor and just over 40 percent minority for census tracts surrounding those units procured via vouchers or certificates.

Moreover, since public housing projects constitute a stock of facilities that generally have existed for a considerable number of years prior to the year 1998 (the year in which the measures come from for this analysis), it is unlikely that the overall fraction of housing assistance provided via apartments in public housing projects in 1998 was directly related to the factors determining the crime

[9] For more formal and detailed discussions of racial and economic segregation that are not related to crime, see Sethi and Somanathan (2004) and Bayer, McMillan, and Rueben (2004).

conditions in the MSA in the period around 2000, especially after controlling for a variety of other MSA characteristics (including the overall fraction of households receiving housing subsidies of either form in each MSA). Indeed, data from "A Picture of Subsidized Housing in the 1970s" (also made available by HUD) confirms that the number of in-kind public housing units used to provide housing assistance throughout U.S. cities in 1998 was essentially determined several decades ago. Specifically, over 87 percent of the public housing projects that existed in 1977 still existed and were in use in 1998. Moreover, very few public housing projects were built between the 1970s and 1998, with 62 percent of the public housing projects that existed and were in use in 1998 being constructed prior to 1977. Even more notably, extremely few *large* public housing projects were added between 1977 and 1998. In particular, of the public housing projects in use in 1998, almost 85 percent of those projects larger than 100 units, and over 92 percent of those projects larger than 200 units, were constructed prior to 1977. Overall, this evidence reveals that most of the current use of public housing project units was determined by decisions made in the 1970s or before, well prior to the large increases in crime that occurred in the 1980s or any of the decreases in crime that took place over the 1990s.

The second variable I use as an instrument for segregation was first used by Cutler and Glaeser (1997) and is the share of local government revenue in an MSA that comes from the state or federal government in 1962.[10] With more money coming from outside sources, there is less of an incentive for individuals within a city to segregate by income, since a smaller fraction of local public goods are funded through local taxes. Moreover, state and federal money may have often been tied to more state and federal oversight meant to prevent discriminatory and segregatory practices by local officials. Therefore, a greater fraction of local revenue coming from the state or federal government should lead to less segregation by poverty and race in an MSA.[11]

[10] This data comes from the Census of Governments 1962, made available by the Inter-University Consortium for Political and Social Research (ICPSR) website.

[11] Cutler and Glaeser (1997) also employ another instrument for segregation, namely the number of municipality and township governments in each MSA in 1962. However, adding this instrument provides very little further explanatory power beyond the two discussed above. In fact, in most specifications, the F-statistic for the joint significance of the instruments in the first stage regressions is essentially unchanged or actually falls when this third instrument is added. Moreover, when this third instrument is added, overidentification tests reject the validity of this instrument under some specifications. Even with this caveat, the 2SLS results are essentially the same with or without using this third instrument. The results when this third instrument is used in addition to the other two are shown in Appendix Tables A1(a) and A1(b).

Table III shows the results of the first stage regressions of the two measures of segregation by poverty status (first two columns) and the two measures of segregation by race (latter two columns) on these two instruments and the other MSA characteristics included in the original regressions from Tables II(a) and II(b).[12] As can be seen, the two instruments discussed above are significantly related to both measures of segregation by poverty status and segregation by race in the predicted manner. The last line of Table III shows the F-statistics for the joint significance of both instruments (i.e. the excluded variables). Not only are these F-statistics significant at below the 1 percent level in all specifications, but also their sizes are sufficient to alleviate concerns about a substantial weak instruments bias (Staiger and Stock, 1997, Stock and Yogo, 2002).

Tables IV(a) and IV(b) show the results from the 2SLS specifications instrumenting for the poverty and racial segregation indices respectively. As can be seen, the results of this analysis show quite striking differences across the different types of crimes. The first two columns in Table IV(a) give some evidence that as segregation by poverty status increases (using either measure), burglary actually decreases. While these results are only statistically significant when using the dissimilarity index (at the 10 percent level), they are relatively large in magnitude, suggesting that a one standard deviation increase in either of the poverty segregation indices leads to a decrease in burglary rates by roughly one third of a standard deviation, which translates to an almost 15 percent lower burglary rate (computed using the mean and standard deviation for burglaries from Table I).

On the other hand, the results shown in Table IV(a) with respect to larceny and motor vehicle theft reveal little effect of segregation by poverty status on these crimes. Finally, and most notably, the results in the last four columns of Table IV(a) reveal that greater segregation by poverty status (using either measure) leads to much higher rates of the violent interpersonal crimes of robbery and aggravated assault, with these effects all being statistically significant at the 5 percent level or higher. The point estimates indicate that a one standard deviation increase in poverty segregation leads to an over one standard deviation increase in robbery rates and an over 0.9 standard deviation increase in the rate of aggravated assault. Given the mean and standard deviation for

[12] The first stage regression results shown are from the Burglary specification, but the regressions are almost identical across the different crime type specifications. Indeed, the only variable that differs across crime type specifications is the clearance rate variable. For burglaries, I use the clearance rate for burglaries, for larcenies I use the clearance rate for larcenies, and so forth.

robbery rates per 100 thousand residents are 127 and 97 respectively, the above estimates suggest that a one standard deviation increase in poverty segregation leads to a roughly 75 percent higher robbery rate, all else equal. Similarly, given the mean and standard deviation for aggravated assault rates are 319 and 180 respectively, the above estimates suggest that a one standard deviation increase in poverty segregation leads to roughly 50 percent higher aggravated assault rate, all else equal.

Table IV(b) shows that the 2SLS results using the racial segregation indices are very similar to those using the poverty segregation indices, but somewhat smaller in magnitude. Specifically, higher racial segregation appears to have no effect on larceny and motor vehicle theft rates, leads to lower burglary rates, and leads to higher rates of robbery and aggravated assault. Translating the point estimates using the means and standard deviations shown in Table I indicate that a one standard deviation increase in the racial segregation indices lead to a roughly 15 percent lower burglary rate, a 50 to 60 percent higher robbery rate, and a 35 to 44 percent higher aggravated assault rate. These somewhat more muted findings are consistent (though not conclusive) with the notion that racial segregation is simply acting as an noisy indicator for economic segregation, and it is economic segregation which is the key mechanism behind these results.

When evaluating all of the 2SLS results discussed above, recall from Table III that both of the excluded instruments are significantly related to segregation in the predicted manner. Indeed, the strength of these instruments are actually somewhat surprising, especially the fraction of public housing allocated in-kind variable given that on average only just over 2 percent of households receive housing subsidies of any form.[13] One reason for this may be that historically, large housing projects were sometimes built in already segregated neighborhoods in order to maintain existing racial and economic segregation patterns (Cohen and Taylor, 2001). This suggests that the relative frequency of using space in public housing facilities as opposed to vouchers and rent certificates as a means of subsidizing housing may also be seen as an indicator of a more segregationist historical legacy. Again, however, I would argue that such a segregationist historical legacy is not directly related to crime conditions around the year 2000 other than through how these historical conditions contribute to current levels of segregation in that city. Therefore, the fact that the fraction of public housing given in-kind may be acting as an indicator of other historical forces leading to

[13] Although, in several cities in the sample this percentage is ranges from 5 to 8 percent of the metro area population.

segregation does not necessarily negate its validity as an instrument.

Moreover, given we have more excluded instruments than potentially endogenous variables, the model is overidentified, meaning we can directly test whether it is inappropriate to exclude the instruments discussed above from being directly related to crime in 2000. In particular, we can take the R-squared that results from regressing the residuals obtained from two-stage least squares regressions on all of the exogenous variables including the excluded instruments, and multiply this value times the number of observations. The excluded instruments can be argued to be invalidly excluded from directly affecting the dependant variable of interest if this test statistic, often referred to as the Sargan statistic, is significantly different from zero. As can be seen in the bottom row of Tables IV(a) and IV(b), these statistics are never significantly different from zero at any standard level of significance in any of the specifications.[14]

Furthermore, another potential test of the validity of these instruments is to see if they have a significant relationship to other key metro area characteristics, such as the poverty rate or fraction black, after controlling for segregation by poverty status or race and the other metro area characteristics. If they do, this suggests that these proposed instrumental variables may directly influence a variety of characteristics of a city in addition to segregation, possibly including crime.[15] However, running similar first stage regressions to those shown in Table III, but using "percent living in poverty" as the dependant variable and adding either of the poverty segregation indices to the right-hand side variables, the coefficients on the two excluded instruments are small and statistically insignificant at any standard level of significance. Similarly, regressing "percent black" on the instruments, either of the racial segregation indices and remaining right-hand side variables, again reveals small and statistically insignificant coefficients on the two instruments. These findings reinforce the above arguments regarding the validity of these instruments in this context.

In general, these findings are roughly consistent with those coming from Kling, Ludwig, and Katz 's (2005) analysis of the Moving to Opportunity (MTO) demonstration project. Specifically, the MTO project randomly allocated volunteer families who all lived in very high poverty census tracts in several large

[14] The Sargan Statistic, will asymptotically have a Chi-squared distribution with degrees of freedom equal to the number of excluded instruments minus the number of endogenous regressors (Wooldridge, 2002). With 1 degree of freedom the critical value for significance at even the 10 percent level is 2.706 (with critical values for greater levels of significance obviously being much higher).

[15] Thanks to Francisco Martorell for suggesting this.

U.S. cities, to either a control group or one of two treatments. One of these treatments provided housing vouchers and relocation assistance to families subject to the restriction that they move to a relatively low poverty census tract. As discussed by Kling, Ludwig, and Katz (2005), the results of this experiment suggest that "moving to lower poverty neighborhoods leads to fewer violent and property crimes for females, and fewer violent but more property crime arrests for males."

However, it is important to note that Kling, Ludwig, and Katz (2005) also found that the decrease in violent crime arrests associated with moving for males is much smaller than it is for females, and there is some evidence that this effect for males appears to recede over time. However, even if the decrease in violent crime arrests for males were to fully disappear over time, such a finding would not necessarily be contradictory to the findings of this paper, as the sample of youth Kling, Ludwig, and Katz (2005) analyze consists only of youth who moved during their adolescent or teenage years, and the results may be different for males who move from high poverty neighborhoods while still very young or for males who move after their teen years. In general, while related, the empirical results in this paper and those in Kling, Ludwig, and Katz (2005) look at somewhat different questions examining somewhat different populations.

3 Discussion of Empirical Results

As alluded to in the introduction, a variety of explanations have been put forth linking criminal activity to neighbor and neighborhood characteristics. For example, an individual's information about payoffs to crime may evolve differently depending on the number of criminals in his neighborhood (see Lochner and Heavner, 2002; Calvo-Armengol and Zenou, 2004). Similarly, lack of role models and peer conformity pressures may increase an individual's proclivity to engage in crime in poor high crime neighborhoods (see Glaeser, Sacerdote, and Sheinkman,1996; Brock and Durlauf, 2001). These neighborhood effects models suggest that individual criminal behavior may be affected by the behavior and characteristics of those around him, highlighting one reason why segregation could have a direct impact on the total amount of crime committed in a city. However, these models do not provide any rationale for why such neighborhood effects should differentially affect violent crime compared to more basic property crimes. Therefore, such models cannot directly account for the findings discussed above.

Another argument is that greater economic and racial segregation may impact crime indirectly, for example by worsening schools and job access for the poor and for African-Americans, or increasing racism and classism, which in turn contribute to greater economic hardship and therefore greater criminality for African-Americans and the poor (Verdier and Zenou, 2004). Indeed, Cutler and Glaeser (1997) show that greater racial segregation leads to a variety of negative outcomes for black Americans. However, once again, these arguments do not directly suggest that segregation should have a differential impact on different type of crime. If anything, they seem to suggest that segregation should have at least as strong of a positive impact on basic property crimes as violent crimes, an implication contradictory to the empirical findings discussed above.

Two models, Silverman (2004) and O'Flaherty and Sethi (2007), examine how neighbor behavior and segregation may affect more specific types of crime—namely assault and robbery respectively. The key insight of Silverman's model is that becoming a street thug, or becoming the type of person who assaults his neighbors, may serve a strategic role. Specifically, within his model, if neighbors are sufficiently connected to each other and individuals do not discount their future too much, then some individuals who would prefer not to act violently toward others in the short run engage in such behavior while young in order to gain a reputation as a street tough that will deter others from attacking them in the future. However, in Silverman's basic model, individuals are not differentiated by wealth, income, or race, so the model cannot speak directly to how individual violent behavior would be affected by his own income or the income characteristics of his neighbors, or how the overall fraction of individuals choosing to engage in violent behavior will be affected by the degree to which poor and/or black individuals are segregated from others.[16]

O'Flaherty and Sethi (2007) look explicitly at the relationship between segregation and robbery. An important contribution O'Flaherty and Sethi's model

[16] At the end of his paper, Silverman does suggest that his model could potentially incorporate differences in behavior across income groups through assuming that rich individuals incur a smaller utility loss from behaving passively when attacked than do poor individuals. This added assumption is motivated by saying that the rich may have lower marginal utilities from wealth, which implicitly assumes that part of the payoff (loss) from attacking (being attacked) is monetary, which is explicitly not part of the motivation for the assumptions he makes in the original model and also is not accounted for in the payoff structure to the game. Therefore, it is not straightforward to generalize the model to think about how the reputation effects and criminal behavior of individuals will be altered by the economic characteristics of their neighbors, or how overall crime rates would be affected by changing the level of economic segregation in a city.

is that both criminal activity (namely robbery) and segregation are endogenously determined. However, in contrast to the empirical results presented above, O'Flaherty and Sethi's model actually suggests that more segregated cities should experience lower robbery rates, as robbers would expect to meet more resistance to robbery attempts when a city is more segregated.

The section below attempts to develop a new model of crime that explicitly accounts for why greater segregation appears to directly increase violent interpersonal crime rates, but has a negligible or even negative effect on basic property crime rates. Unlike O'Flaherty and Sethi's (2007) model, the framework developed below does not endogenously model segregation. However, the model does explicitly take into account both monetary and physical costs to being attacked, and moreover, the key assumptions of the model are quite simple—namely that individuals incur diminishing marginal utility in money, and that by becoming the type to engage in violent behavior, an individual can stop other violent individuals from taking his money.

4 Model of Segregation and Crime

Assume a community is made up of a large number of individuals who live for an infinite number of periods, where each individual can be classified as having either low income or high income. In the absence of committing any crime, assume that low income individuals have ω_ℓ dollars available for consumption each period, while high income individuals have ω_h dollars available for consumption each period, and individuals cannot save across periods. Let individuals value consumption in any given period according the a utility function u, where u is an increasing strictly concave function in consumption. Finally, suppose the overall community can be divided up into a collection of neighborhoods, where each individual lives in one and only one neighborhood. Let λ_k denote the fraction of residents in a given neighborhood k who have low income, and let λ denote the community-wide fraction of residents who have low income.

4.1 Participation in Basic Property Crimes

Let us first consider an individual's decision to become a thief, or to engage in a property crime that does not involve a direct confrontation with other individuals (e.g. Burglary, Larceny, Motor Vehicle Theft), in any given period. Assume that by becoming a thief, an individual adds b units of additional consumption above and beyond the consumption possible though consuming his income that period. However, by engaging in such criminal activity, an individual must also incur a utility cost of ϵ^i, where ϵ^i is a normally distributed random variable with mean μ_ε and variance σ_ε (meaning any given ε^i can be positive or negative).[17] In words, ϵ^i represents each individual i's disutility (or possibly his utility) associated with being a criminal, meaning it captures any feelings of guilt or pleasure associated with criminal activity, any physical disutility associated with criminal activity, as well as the expected disutility associated with the possibility of receiving a jail sentence. For ease of reference, this parameter will be referred to as each individual's "criminal propensity," with a lower ϵ^i indicating a higher criminal propensity.

A key assumption of this paper is that ϵ^i is an i.i.d random draw across individuals. This means that this model explicitly does not allow for correlated or interpersonal preferences regarding criminal participation across neighbors, which is implicitly the key assumption behind the social interactions models of neighborhood effects (Brock and Durlauf, 2001; Glaeser, Sacerdote, and Scheinkman, 1996).

Given the discussion from above, we can say that an individual chooses to become a thief if and only if $u(\omega^i + b) - \epsilon^i \geq u(\omega^i)$. This means the equilibrium fraction of individuals of income level ω_j (for $j \in \{\ell, h\}$) living in neighborhood k who choose to become thieves in any given period equals

$$\pi_j^* = \Phi(u(\omega_j + b) - u(\omega_j)), \tag{1}$$

where Φ is the cumulative distribution for a normally distributed random variable.

Because of the strict concavity of the u function, it is straightforward to see that it will be true that $\pi_h^* < \pi_\ell^*$. In words, because the utility benefit associated with any fixed monetary payoff for stealing is lower for high income individuals, high income individuals are less likely to become thieves. Hence, the greater the overall fraction of a neighborhood who are of low income, the greater the fraction of the neighborhood who become thieves. This argument also holds at the community-wide level. This means that, according to this simple model, the rate of basic property crimes committed in a neighborhood (or a whole community), should be increasing in the fraction of neighborhood

[17] The assumption that ϵ^i is distributed normally is used for simplicity only. Only Proposition 3 is affected by this assumption. However, as slightly modified version of Proposition 3 will hold under more general distributional assumptions for ϵ^i as well.

(community) made up of poor individuals.

A second thing to notice about π_j^* as given in equation (1) is that it does not depend on λ_k. In words, the probability that an individual becomes a thief does not depend on the income of his neighbors, meaning there are no "neighborhood effects" with respect to basic property crimes in this model without making further assumptions. This in turn means that after controlling for the overall fraction of the community made up of poor individuals, the distribution of income across neighborhoods within the community should have no independent effect of the overall rate on basic property crimes in the community as a whole, meaning segregation should have no direct effect on basic property crimes.

One reasonable extension to this model is to assume that the monetary benefit to being a thief is greater when fewer of one's neighbors are poor, or that the monetary benefit to being a thief is given by $b(\lambda_k)$, where $b'(\lambda_k) < 0$. In this case, equation (1) would become

$$\pi_j^*(\lambda_k) = \Phi(u(\omega_j + b(\lambda_k)) - u(\omega_j)),$$

Clearly, since $b(\lambda_k)$ is decreasing in λ_k, the above equation implies that the fraction of individuals of any given income level j who choose to become thieves is decreasing in λ_k. Therefore, when the monetary benefit to being a thief depends on the economic status of one's neighbors, there will exist neighborhood effects with respect to becoming a thief. Moreover, note that the change in expected criminality from moving an individual of income level ω_j from a neighborhood k to neighborhood k', where $\lambda_k < \lambda_{k'}$ (meaning $b(\lambda_k) > b(\lambda_{k'})$), will equal

$$\Delta\pi_j^* = \Phi(u(\omega_j + b(\lambda_k)) - u(\omega_j)) - \Phi(u(\omega_j + b(\lambda_{k'})) - u(\omega_j)).$$

Further note that the concavity of the u function implies $[u(\omega_j+b(\lambda_k))-u(\omega_j)]-[u(\omega_j + b(\lambda_{k'})) - u(\omega_j)]$ will be larger given ω_ℓ than ω_h. Therefore, a sufficient condition for $\Delta\pi_\ell^* > \Delta\pi_h^*$ is for Φ to be weakly convex when evaluated at or before $u(\omega_\ell + b(\lambda_k)) - u(\omega_\ell)$. Given Φ is the cdf of a normal distribution, this would be true for example if $\pi_\ell^*(0) \leq 0.5$, or if the distribution of criminal propensity is such that less than half of the poor individuals would choose to become thieves even if they were the only poor person in their neighborhood.

Recalling that $\Delta\pi_j^*$ denotes the expected change in criminality with respect to basic property crimes from moving an individual of income level ω_j from a richer to a poorer neighborhood, we can infer that an important implication of $\Delta\pi_\ell^*$ being greater than $\Delta\pi_h^*$ is that there will be bigger increase in expected criminality when moving a poor individual from a poorer neighborhood to a richer neighborhood than would be offset by the decrease in expected criminality from moving a rich individual from the richer neighborhood to the poorer neighborhood. This in turn implies that in this environment, when the monetary benefit to committing a given basic property crime is inversely related to the fraction of the neighborhood that is poor, *less* segregation will actually *increase* this type of basic property crime and vice versa.

The simple model laid out in this section shows that in the absence of assuming preferences for abstaining from crime are correlated across neighbors, greater segregation by income (or race given a strong correlation between race and income) will either have no effect, or a negative effect on community-wide basic property crimes, depending on whether the monetary benefit of the crime does or does not depend on neighbor's income. Therefore, this model is consistent with the empirical findings described above if the payoffs to burglaries often depend on neighbor income, but the payoffs to larceny and motor vehicle theft generally do not. One reason this could be true is if individuals who engage in burglaries generally do so in or near their own neighborhoods, since they have better information regarding who has valuable objects to break in and steal when it comes to their own neighbors versus those who live further away. On the other hand, since larceny and motor vehicle theft generally involve taking things which are directly or at least more easily observed, those prone to such crimes may be more willing to travel to less familiar neighborhoods to engage in them.

4.2 Participation in Interpersonal Violent Crime

Now consider crimes against persons, such as muggings, robberies, and assaults. In modelling these crimes, assume each individual decides whether to be a "thug" or a "pacifist," then proceeds to encounter other individuals in his neighborhood at a rate of one person per period. By choosing to be a pacifist, an individual commits to acting passively when encountering anyone in his neighborhood. Alternatively, by choosing to be a thug, an individual commits to violently attacking anyone he encounters in his neighborhood. Therefore, when a pacifist and a thug encounter each other, the one-sided violence will allow the thug to successfully rob the pacifist, thereby increasing the thug's consumption in that period by b, while decreasing the pacifist's consumption that period by b

and further imposing a cost of c on the pacifist due to pain and suffering.[18] On the other hand, when two thugs encounter each other, the violence is mutual, meaning no money will change hands, but causing both individuals to incur a cost of c due to pain and suffering. Finally, when two pacifists encounter each other, no violence takes place, meaning no money changes hands and no pain and suffering arises.

The above assumptions can be motivated two ways. First, choosing to be a thug can be interpreted as an individual learning the fighting skills and/or obtaining the weapons necessary to take possessions from pacifists, who do not have such skills and/or weapons. However, since other thugs also have fighting skills and/or weapons, thugs cannot take possessions from each other, but will incur substantial pain and suffering when they fight. A second, somewhat complementary interpretation of the above assumptions is that choosing to be a thug is equivalent to joining a street gang, where once in a gang an individual can be assured of taking property from the non-gang members he encounters in his neighborhood (and is often expected to do so), while at the same time he must periodically engage in violence when he encounters rival gang members.

Finally, analogous to above, assume that by choosing to be a thug, an individual i must further incur a utility cost ϵ^i each period. As before, this criminal propensity parameter ϵ^i captures the effort and any feelings of guilt (or pleasure) associated with being a thug and engaging in violence, as well as the expected disutility of being arrested and punished for being a thug.

If we denote the per period discount rate as β, then the above assumptions mean that the expected utility for an individual i of income level ω_j living in neighborhood k associated with becoming a thug is given by

$$\sum_{t=0}^{\infty}\beta^t[\hat{\pi}_k[u(\omega_j)-c]+(1-\hat{\pi}_k)u(\omega_j+b)-\epsilon^i],$$

where $\hat{\pi}_k$ is the individual's beliefs concerning the likelihood he encounters a thug as opposed to a pacifist in his neighborhood in a given period. Alternatively, the expected utility from being a pacifist for an individual i of income level ω_j living in neighborhood k is given by

[18] I assume that b does not depend on the income of one's victim. While the model is robust to loosening this assumption a little bit, I feel that such an assumption is generally justified. Afterall, it is not clear that poor individuals carry less cash on them than do rich individuals, especially since poor individuals are less likely to store their wealth in bank accounts or credit cards. A similar assumption and justification is made by O'Flaherty and Sethi [2007].

$$\sum_{t=0}^{\infty}\beta^t[\hat{\pi}_k[u(\omega_j - b) - c] + (1 - \hat{\pi}_k)u(\omega_j)],$$

where, once again, $\hat{\pi}_k$ is the individual's beliefs concerning the relative frequency he will encounter a thugs as opposed to pacifists in his neighborhood k.

Given the above expected utilities, we can derive that optimal behavior for an individual i of income level j living in neighborhood k is to become a thug if and only if

$$\hat{\pi}_k[u(\omega_j) - u(\omega_j - b)] + (1 - \hat{\pi}_k)[u(\omega_j + b) - u(\omega_j)] \geq \epsilon_i. \tag{2}$$

Like with basic property crimes, the above expression indicates that it will generally be those with a low ϵ^i, meaning those with high criminal propensities, who will choose to become thugs.

In order to further simplify equation (2), define $\delta_t(\omega_j)$ to equal $u(\omega_j) - u(\omega_j - b)$. In words, $\delta_t(\omega_j)$ is the utility cost associated with the monetary loss incurred by not being a thug when encountering a thug, for an individual with income ω_j. Similarly, define $\delta_p(w_j)$ to equal $u(\omega_j + b) - u(\omega_j)$, meaning $\delta_p(\omega_j)$ is the utility cost associated with the monetary loss incurred by not being a thug when encountering a pacifist, for an individual with income ω_j. Intuitively, $\delta_t(\omega_j)$ is the price, in utility terms, an individual of income ω_j pays for being a pacifist when encountering a thug. In the same way $\delta_p(\omega_j)$ can be interpreted as the price, in utility terms, an individual of income level ω_j pays for being a pacifist when encountering another pacifist.

Given these definitions and beliefs $\hat{\pi}_k$, equation (2) becomes

$$\hat{\pi}_k\delta_t(\omega_j) + [1 - \hat{\pi}_k]\delta_p(\omega_j) \geq \epsilon_i. \tag{3}$$

This equation highlights the important components with respect to the decision individuals make regarding whether or not to become a thug in this environment. Namely, the fraction of individuals in a neighborhood choosing to become thugs is increasing in both the monetary benefit that can be obtained from doing so (i.e. $\delta_p(\omega_j)$), as well as the monetary cost that can be avoided (i.e. $\delta_t(\omega_j)$) by doing so. This latter benefit to being a thug is one thing that makes the decision to become a thug different from the decision to become a thief. Moreover, also unlike the decision regarding whether or not to become a thief, the decision to become a thug depends on the individual's beliefs regarding the fraction of other individuals in the neighborhood who are going to be thugs (i.e. $\hat{\pi}_k$).

From equation (3), we can now derive the fraction of individuals of income level ω_j living in neighborhood k choosing to be a thug to be

$$\pi_j = \Phi(\hat{\pi}_k \delta_t(\omega_j) + [1 - \hat{\pi}_k]\delta_p(\omega_j)). \tag{4}$$

For simplicity, I will refer to the fraction of individuals of a given group who choose to be a thug as the criminal participation rate for this group.

A Perfect Bayesian Equilibrium in this environment will be for individuals to behave optimally with respect to becoming a thug given their beliefs, and for their beliefs to be consistent with Bayes' rule given each other individual behaves optimally. If we define $\pi_j^*(\lambda_k)$ as the equilibrium criminal participation rate for individuals of income level j living in neighborhood k, we can state the following Theorem.

Theorem 1 *For any $\lambda_k \in [0, 1]$, there exists a Perfect Bayesian Equilibrium characterized by criminal participation rates $\{\pi_\ell^*(\lambda_k), \pi_h^*(\lambda_k)\}$ and beliefs $\hat{\pi}_k = \pi^*(\lambda_k) = \lambda_k \pi_\ell^*(\lambda_k) + (1 - \lambda_k)\pi_h^*(\lambda_k)$, such that the following two equations hold:*

$$\pi_\ell^*(\lambda_k) = \Phi(\pi^*(\lambda_k)\delta_t(\omega_\ell) + [1 - \pi^*(\lambda_k)]\delta_p(\omega_\ell)),$$

$$\pi_h^*(\lambda_k) = \Phi(\pi^*(\lambda_k)\delta_t(\omega_h) + [1 - \pi^*(\lambda_k)]\delta_p(\omega_h)),$$

Proof. In Appendix. ■

Given the existence of an equilibrium, a first thing to examine is how the likelihood of becoming a thug within a particular neighborhood depends on an individual's income level, or the difference between $\pi_\ell^*(\lambda_k)$ and $\pi_h^*(\lambda_k)$. In examining these equilibrium criminal participation rates, the first thing to note is that the strict concavity of the u function implies that $\delta_t(\omega_\ell) > \delta_p(\omega_\ell) > \delta_t(\omega_h) > \delta_p(\omega_h)$.[19] In words, being a pacifist will be "more expensive" for individuals when they encounter thugs than when they encounter other pacifists,

[19] Technically, this result is only guaranteed when $\omega_h - b > \omega_\ell + b$. In other words, when the changes in wealth associated with mugging or being mugged are small compared to the overall income differences between high income and low income individuals.

and being a pacifist will be "more expensive" for individuals with low income, regardless of who they interact with. This is shown graphically in Figure 1.

The intuition here is similar to that with respect to basic property crimes. Since each individual's utility function exhibits diminishing marginal utility in consumption (and therefore income), the greater the individual's income each period, the smaller is the utility lost from getting a relatively small amount of money taken from them in any given period, and the smaller is the utility gained by taking a relatively small amount of money from someone else.

These differing incentive across income types leads to Proposition 1.

Proposition 1 *In any neighborhood k, a greater fraction of low income individuals will participate in interpersonal violent crimes (i.e. be thugs) than high income individuals, or $\pi_\ell^*(\lambda_k) > \pi_h^*(\lambda_k)$.*

Proof. See Appendix. ■

The next thing we want to examine is how the likelihood of becoming a thug in this environment depends on λ_k, or the poverty rate of one's neighbors. Unlike with respect to the basic property crimes modeled above, "neighborhood effects" will arise in this model with respect to interpersonal violent crimes without further assuming that criminal propensity (i.e. ϵ^i) is correlated across neighbors or that the monetary payoff to crime depends on neighborhood composition. Rather, as long as there is sufficient variance in criminal propensity over the population (namely $\sigma_\varepsilon > \frac{\delta_t(\omega_\ell)-\delta_p(\omega_\ell)}{\sqrt{2\pi}}$) the following proposition holds.

Proposition 2 *For both high and low income individuals, the fraction choosing to participate in interpersonal violent crimes is increasing in the fraction of their neighborhood that has low income, or $\frac{\partial \pi_j^*(\lambda_k)}{\partial \lambda_k} > 0$ for $j = h, \ell$.*

Proof. In Appendix. ■

Proposition 2 shows that, in this model, an individual with income level j is more likely to become a thug if he lives in a relatively poor neighborhood than if he lives in a relatively rich neighborhood, or that indeed there exist *neighborhood effects* with respect to violent crime. Intuitively, when an individual expects a relatively high fraction of his neighbors to be thugs (as he would in a high poverty neighborhood), his own incentive to become a thug is primarily defensive, in the sense of being able to prevent other thugs from taking his property. Alternatively, when an individual expects very few of his neighbors to be thugs (as he would in a low poverty neighborhood), his own incentive to become a thug is primarily to offensive, in the sense of being able to successfully take property from others. Due to the diminishing marginal utility of consumption, the defensive incentive in a poor neighborhood is greater than the offensive incentive in a richer neighborhood.

Pushing the model a little bit further, we can examine whether the strength of this neighborhood effect (i.e. $\frac{\partial \pi_j^*(\lambda_k)}{\partial \lambda_k}$) differs by the income level of the individual. This leads to Proposition 3.

Proposition 3 *If* $\pi_\ell^*(1) \leq 0.5$*, the neighborhood effect will be stronger for low income individuals than high income individuals, or* $\frac{\partial \pi_\ell^*(\lambda_k)}{\partial \lambda_k} > \frac{\partial \pi_h^*(\lambda_k)}{\partial \lambda_k}$.

Proof. In Appendix. ■

Intuitively, from Figure 1 we know that the utility gains (losses) associated with the monetary rewards (costs) for being a thug are greater for poor individuals than richer individuals all else equal. Moreover, an individual's expected utility from being a thug versus a pacifist depends on his expectations regarding the relative number of thugs in his neighborhood, which in turn depends on the poverty level in the individual's neighborhood. Therefore, poor individuals will be more influenced by the income characteristics of their neighbors than will richer individuals when it comes to committing violent crimes.

The sufficient condition for this result, namely $\pi_\ell^*(1) \leq 0.5$, essentially says that this result will always hold if a relatively large fraction of poor individuals incur sufficient disutility from choosing to engage in the thug life such that they will still choose not to become thugs even if all of their neighbors are poor (i.e. a large fraction of individuals have a low criminal propensity or high ϵ^i). It is worth noting that this is a sufficient condition for Proposition 3 to hold, but is not necessary.[20]

[20] As can be seen in the Appendix, if we drop the assumption that ϵ^i is normally distributed, a sufficient condition for Proposition 4 is that the cumulative distribution of ϵ^i is simply weakly convex prior to $\pi_\ell^*(1)$.

Using the results from Propositions 1-3, we can now analyze how the income distribution within a neighborhood, as well as how income is distributed across neighborhoods within a community, affect the rate of interpersonal crime. To start this analysis, first recall that the equilibrium fraction of individuals in any particular neighborhood k choosing to become thugs is given by $\pi^*(\lambda_k) = \lambda_k \pi_\ell^*(\lambda_k) + (1 - \lambda_k)\pi_h^*(\lambda_k)$. Taking the derivative of this equation and re-arranging gives

$$\frac{\partial \pi^*(\lambda_k)}{\partial \lambda_k} = (\pi_\ell^*(\lambda_k) - \pi_h^*(\lambda_k)) + \lambda_k \frac{\partial \pi_\ell^*(\lambda_k)}{\partial \lambda_k} + (1 - \lambda_k)\frac{\partial \pi_h^*(\lambda_k)}{\partial \lambda_k}.$$

From Proposition 1 we know that the first expression in parentheses in the above equation is positive, and from Proposition 2 we know that the second and third expressions in the above expression are also positive. Therefore, if we assume the overall rate of interpersonal violent crime within a neighborhood at any given point time is a strictly increasing function of the fraction of the residents in the neighborhood who are thugs at that time, then increasing the fraction of the neighborhood made up of low income individuals will increase the overall rate of interpersonal violent crime in the neighborhood. In this way, interpersonal violent crimes are similar to basic property crimes.

However, note that if we take the second derivative of $\pi^*(\lambda_k)$ and re-arrange, we obtain

$$\frac{\partial^2 \pi^*(\lambda_k)}{\partial \lambda_k^2} = 2\left(\frac{\partial \pi_\ell^*(\lambda_k)}{\partial \lambda_k} - \frac{\partial \pi_h^*(\lambda_k)}{\partial \lambda_k}\right) + \lambda_k \frac{\partial^2 \pi_\ell^*(\lambda_k)}{\partial \lambda_k^2} + (1 - \lambda_k)\frac{\partial^2 \pi_h^*(\lambda_k)}{\partial \lambda_k^2}.$$

From Proposition 3, we know the expression in parentheses in the above equation is positive. Moreover, as shown in the Appendix, as long as we again assume $\pi_\ell^*(1) \leq 0.5$, both of the latter two terms in the above expression are also positive, implying $\frac{\partial^2 \pi^*(\lambda_k)}{\partial \lambda_k^2} > 0$. This leads to Proposition 4.

Proposition 4 *The rate of interpersonal violent crime in the community as a whole is increasing in the degree to which its neighborhoods are segregated by income.*

Proof. Given $\frac{\partial \pi^*(\lambda_k)}{\partial \lambda_k} > 0$ and $\frac{\partial^2 \pi^*(\lambda_k)}{\partial \lambda_k^2} > 0$, we know the fraction of a neighborhood that chooses to become thugs is an increasing strictly convex function of the fraction of the neighborhood that is poor. Therefore, for any given community wide fraction poor λ, the interpersonal crime rate in the overall community is minimized when all neighborhoods have the same fraction of the poor. Alternatively, the rate of interpersonal crime in the community as a whole becomes greater the more its neighborhoods are segregated by income. ■

The intuition for Proposition 4 comes from Proposition 3, which showed that neighborhood effects more strongly influence poor individuals than rich individuals. Specifically, moving a poor individual from a richer neighborhood to a poorer neighborhood leads to a greater expected increase interpersonal violent crime than would be offset by the expected drop in interpersonal violent crime associated with moving a rich individual from the poorer neighborhood to the richer neighborhood. Therefore, the rate of interpersonal violent crime should necessarily be higher the more poor individuals are segregated from rich individuals all else equal. Given a strong correlation between race and income, a similar statement could be made with respect to racial segregation and violent interpersonal crime. Note that just the opposite was true with respect to the basic property crime model developed above, and moreover, that this implication coincides with the empirical results regarding robberies and aggravated assaults presented previously.

5 Conclusion

This first part of this study used MSA level data to examine the relationship between segregation (by poverty status and race) and crime. The key methodological hurdle to overcome was that not only might segregation affect criminal activity, but that criminal activity might also affect segregation. Therefore, in order to obtain plausible estimates for the effects of segregation on criminal activity I instrumented for current segregation using information regarding the degree to which public housing assistance in each city is allocated via government owned housing projects (as opposed to rental vouchers), as well as information regarding how local public works were historically financed in each city.

This analysis lead to some interesting results. In particular, the effect of greater segregation on crime depends substantially on the type of crime in question. With respect to the rate of basic property crimes, greater economic or racial segregation has a negligible impact (in the cases of larceny and motor vehicle theft), or even has an arguably negative impact (in the case of burglary).

By contrast, my findings indicate that greater segregation by poverty status or race clearly and substantially increases interpersonal violent crimes such as robberies and aggravated assaults.

The fact that segregation has a direct effect on crime can be accounted for by a variety of neighborhood effects type models, where individual criminal participation decisions are affected by the characteristics of those around them. Relatedly, it is also plausible that greater economic or racial segregation affects school quality and job opportunities, as well as classicism and racism, and it is though these mechanisms that segregation affects crime. However, while these hypotheses cannot be definitively ruled out, they generally cannot account for these empirical results showing that greater segregation appears to increase violent crimes, but has little effect or even a negative effect on basic property crimes.

The second part of the paper derived a new model of crime that explicitly differentiates between basic property crimes and interpersonal violent crimes. The model shows that under relatively simple assumptions, neighborhood effects, and therefore segregation, should either have no effect or a negative affect on basic property crimes such as burglary, larceny, motor vehicle theft, but a strictly positive effect on interpersonal violent crimes such as robbery and aggravated assault.

While consistent with the empirical findings discussed above, certainly more evidence is necessary to definitively conclude that this model is the key explanation underlying the previously discussed empirical findings. However, if true, this theoretical model leads to a very important conclusion. Namely, that when it comes to some types of crime, not only do an individual's own economic characteristics matter, but so do the economic characteristics of his neighbors. Therefore, while it is clear that policies dictating how public housing is allocated and how an urban area is developed will affect who is *victimized* by crime, such policies may also have a significant direct effect on who *commits* crime and the overall amount of crime that occurs, particularly when it comes to violent crime.

6 Data Appendix

As discussed in the text, the sample of MSAs used for this analysis was constrained in a couple of ways. First, those New England MSAs that share counties with other MSAs were dropped since the FBI crime data is at the county level, and it was unclear how to allocate the crimes that were reported in counties that were split across multiple MSAs. This criteria excluded the following MSAs: Bangor ME, Boston MA-NH, Burlington VT, Hartford CT, Lewiston-Auburn ME, Manchester NH, Pittsfield MA, Portland ME, Portsmouth-Rochester NH-ME, Springfield MA.

The following MSAs were dropped because the HUD data did not contain information on their public housing since they were not classified as MSAs until 1998 and the HUD data used pre-1998 MSA classifications: Brazoria TX, Enid OK, Dover DE, Greenville SC, Jonesboro AR, Rocky Mount NC, Sumter SC, Pocatello ID, Hattiesburg MS, Corvalis OR, Goldsboro NC, Yolo CA, Flagstaff AR, Grand Junction CO, Auburn AL, Punta Gorda FL, Myrtle Beach SC, San Luis Obispo CA.

Finally, Lawrence KS was excluded since no robberies were reported in 1999, making robbery clearance rates impossible to calculate, and the Miami FL MSA was excluded because the FBI UCR reports did not provide crime data for this MSA in 2000.

7 Proofs Appendix

7.1 Proof of Theorem 1

As discussed in Theorem 1, a Perfect Bayesian Equilibrium (PBE) in this environment will be for individuals to behave optimally with respect to becoming a thug given their beliefs, and for their beliefs to be consistent with Bayes' rule given each other individual behaves optimally. In the context of this model, given beliefs $\hat{\pi}_k$, optimal behavior will imply that the fraction of individuals of income level $j \in \{h, \ell\}$ who become thugs will equal $\pi_j = \Phi(\hat{\pi}_k \delta_t(\omega_j) + [1 - \hat{\pi}_k]\delta_p(\omega_j))$. Moreover, for beliefs to be consistent with Bayes's rule given everyone behaves optimally, it must be that $\hat{\pi}_k = \lambda_k \pi_\ell + (1 - \lambda_k)\pi_h$. Therefore, for each neighborhood k, an equilibrium will be characterized by a pair $\{\pi_\ell(\lambda_k), \pi_h(\lambda_k)\}$ that jointly solve

$$\pi_\ell(\lambda_k) = \Phi([\lambda_k\pi_\ell(\lambda_k) + (1-\lambda_k)\pi_h(\lambda_k)]\delta_t(\omega_\ell) + [1 - [\lambda_k\pi_\ell(\lambda_k) + (1-\lambda_k)\pi_h(\lambda_k)]]\delta_p(\omega_\ell)) \quad (5)$$

$$\pi_h(\lambda_k) = \Phi([\lambda_k\pi_\ell(\lambda_k) + (1-\lambda_k)\pi_h(\lambda_k)]\delta_t(\omega_h) + [1 - [\lambda_k\pi_\ell(\lambda_k) + (1-\lambda_k)\pi_h(\lambda_k)]]\delta_p(\omega_h)) \quad (6)$$

If we define the right-hand side of equation (6) as $g(\pi_h(\lambda_k))$, it will be the case that $g : [0,1] \to [0,1]$ is a continuous function from a non-empty compact, convex set to itself. Therefore, by Brouwer's fixed point theorem we know that for any $\pi_\ell(\lambda_k)$ there exists a $\pi^*(\pi_\ell(\lambda_k))$ such that $\pi_h(\lambda_k) = \pi^*(\pi_\ell(\lambda_k))$ solves equation (6). Plugging $\pi^*(\pi_\ell(\lambda_k))$ in for $\pi_h(\lambda_k)$ in equation (5), we get

$$\pi_\ell(\lambda_k) = \Phi([\lambda_k\pi_\ell(\lambda_k) + (1-\lambda_k)\pi^*(\pi_\ell(\lambda_k))]\delta_t(\omega_\ell) + [1 - [\lambda_k\pi_\ell(\lambda_k) + (1-\lambda_k)\pi^*(\pi_\ell(\lambda_k))]]\delta_p(\omega_\ell). \quad (7)$$

Similar to above, we can define the right-hand side of equation (7) as $h(\pi_\ell(\lambda_k))$, and it will once again be the case that $h : [0,1] \to [0,1]$ is a continuous function from a non-empty compact, convex set to itself. Therefore, once again by applying Brouwer's fixed point theorem we know that there exists a $\pi_\ell(\lambda_k)$ that solves equation (7) which we can denote $\pi_\ell^*(\lambda_k)$. If we then define $\pi_h^*(\lambda_k)$ as being equal to $\pi^*(\pi_\ell^*(\lambda_k))$, we know the pair $\{\pi_\ell^*(\lambda_k), \pi_h^*(\lambda_k)\}$ jointly solve equations (5) and (6), confirming the existence of an PBE.

7.2 Proof of Proposition 1

Say $\pi_h^*(\lambda_k) \geq \pi_\ell^*(\lambda_k)$. From Theorem 1 (and the fact that the distribution Φ must be an increasing function), we then know that this would imply

$$\pi^*(\lambda_k)\delta_t(\omega_h) + [1 - \pi^*(\lambda_k)]\delta_p(\omega_h) \geq \pi^*(\lambda_k)\delta_t(\omega_\ell) + [1 - \pi^*(\lambda_k)]\delta_p(\omega_\ell).$$

Re-writing the above expression we get

$$\pi^*(\lambda_k)[\delta_t(\omega_h) - \delta_t(\omega_\ell)] + (1 - \pi^*(\lambda_k))[\delta_p(\omega_h) - \delta_p(\omega_\ell)] \geq 0.$$

Recalling that $\delta_t(\omega_\ell) > \delta_p(\omega_\ell) > \delta_t(\omega_h) > \delta_p(\omega_h)$, we can see that the above equation cannot hold. Therefore, it cannot be true that $\pi_h^*(\lambda_k) \geq \pi_h^*(\lambda_k)$, meaning $\pi_h^*(\lambda_k) < \pi_h^*(\lambda_k)$, confirming Proposition 1.

7.3 Proof of Proposition 2

From Theorem 1 and the definition of $\pi^*(\lambda_k)$, we know that for $j = h, \ell$, the following equation must hold

$$\begin{aligned}\pi_j^*(\lambda_k) &= \Phi([\lambda_k \pi_\ell^*(\lambda_k) + (1-\lambda_k)\pi_h^*(\lambda_k)]\delta_t(\omega_j) \\ &\quad + [1 - \lambda_k \pi_\ell^*(\lambda_k) - (1-\lambda_k)\pi_h^*(\lambda_k)]\delta_p(\omega_j)).\end{aligned}$$

Taking the derivative of the above equation with respect to λ_k and re-arranging we get

$$\frac{\partial \pi_j^*(\lambda_k)}{\partial \lambda_k} = \phi(x_j^*(\lambda_k))[\delta_t(\omega_j) - \delta_p(\omega_j)]\left[\Delta\pi^* + \lambda_k \frac{\partial \pi_\ell^*(\lambda_k)}{\partial \lambda_k} + (1-\lambda_k)\frac{\partial \pi_h^*(\lambda_k)}{\partial \lambda_k}\right] \tag{8}$$

where ϕ is the pdf of the normal distribution evaluated at $x_j^*(\lambda_k) = [\lambda_k \pi_\ell^*(\lambda_k) + (1-\lambda_k)\pi_h^*(\lambda_k)]\delta_t(\omega_j) + [1 - \lambda_k \pi_\ell^*(\lambda_k) - (1-\lambda_k)\pi_h^*(\lambda_k)]\delta_p(\omega_j)$ and $\Delta\pi^* = \pi_\ell^*(\lambda_k) - \pi_h^*(\lambda_k)$ (where $\Delta\pi^*$ is known to be strictly positive by Proposition 1). Next, note that the above equation implicitly defines two equations of the following form:

$$A = \phi(x_\ell^*(\lambda_k))\Delta\delta_\ell[\Delta\pi^* + \lambda_k A + (1-\lambda_k)B] \tag{9}$$

$$B = \phi(x_h^*(\lambda_k))\Delta\delta_h[\Delta\pi * + \lambda_k A + (1-\lambda_k)B], \tag{10}$$

where $A = \frac{\partial \pi_\ell^*(\lambda_k)}{\partial \lambda_k}$, $B = \frac{\partial \pi_h^*(\lambda_k)}{\partial \lambda_k}$, and $\Delta\delta_j = [\delta_t(\omega_j) - \delta_p(\omega_j)]$ (where $\Delta\delta_j$ can easily be confirmed to be strictly positive). Solving equation (9) for A then substituting into equation (10) and re-arranging we get

$$\frac{B}{\phi(x_h^*(\lambda_k))\Delta\delta_h} = \Delta\pi^* + \frac{\lambda\phi(x_\ell^*(\lambda_k))\Delta\delta_\ell(1-\lambda)}{1-\phi(x_\ell^*(\lambda_k))\Delta\delta_\ell\lambda}B + (1-\lambda)B.$$

Simplifying the above equation we can get

$$B = \frac{\phi(x_h^*(\lambda_k))\Delta\delta_h[1-\phi(x_\ell^*(\lambda_k))\Delta\delta_\ell\lambda]}{1-\phi(x_\ell^*(\lambda_k))\Delta\delta_\ell\lambda-(1-\lambda)\phi(x_h^*(\lambda_k))\Delta\delta_h}\Delta\pi^*.$$

Note that the above equation implies $B > 0$ as long as (i) $1-\phi(x_\ell^*(\lambda_k))\Delta\delta_\ell\lambda > 0$, and (ii) $1-\phi(x_\ell^*(\lambda_k))\Delta\delta_\ell\lambda-(1-\lambda)\phi(x_h^*(\lambda_k))\Delta\delta_h > 0$. Clearly, condition (i) will hold if condition (ii) holds.

To prove that condition (ii) will hold true, first recall the assumed regularity condition that $\frac{\delta_t(\omega_\ell)-\delta_p(\omega_\ell)}{\sqrt{2\pi}} < \sigma_\varepsilon$, which implies $\frac{1}{\sigma_\varepsilon\sqrt{2\pi}}\Delta\delta_\ell < 1$ or equivalently (given ε is normally distributed) that

$$1-\phi(\mu_\varepsilon)\Delta\delta_\ell > 0. \tag{11}$$

Moreover, given that ε is normally distributed we know $\phi(\mu_\varepsilon) \geq \phi(x)$ for all x. Finally, recalling that $0 < \lambda_k < 1$ and $\Delta\delta_\ell > \Delta\delta_h$ (as can be confirmed in Figure 1), then we know equation (11) implies that condition (ii) (and therefore also condition (i)) hold. Therefore, $B > 0$, confirming $\frac{\partial\pi_h^*(\lambda_k)}{\partial\lambda_k} > 0$. An analogous argument can be made to show $\frac{\partial\pi_\ell^*(\lambda_k)}{\partial\lambda_k} > 0$ by solving equation (10) for B and substituting into equation (9).

7.4 Proof of Proposition 3

First, recall equation (8) above

$$\frac{\partial\pi_j^*(\lambda_k)}{\partial\lambda_k} = \phi(x_j^*(\lambda_k))[\delta_t(\omega_j)-\delta_p(\omega_j)]\left[\Delta\pi^* + \lambda_k\frac{\partial\pi_\ell^*(\lambda_k)}{\partial\lambda_k} + (1-\lambda_k)\frac{\partial\pi_h^*(\lambda_k)}{\partial\lambda_k}\right].$$

From the above expression we can see that $\frac{\partial\pi_\ell^*(\lambda_k)}{\partial\lambda_k} > \frac{\partial\pi_h^*(\lambda_k)}{\partial\lambda_k}$ if (i) $\delta_t(\omega_\ell)-\delta_p(\omega_\ell) > \delta_t(\omega_h)-\delta_p(\omega_h)$ and (ii) $\phi(x_\ell^*(\lambda_k)) \geq \phi(x_h^*(\lambda_k))$. Given our assumption that u in an increasing strictly concave function, we know condition (i) will always be true (see Figure 1). Regarding condition (ii), given our assumption that Φ is the cdf of the normal distribution and therefore convex for all x such that $\Phi(x) \leq 0.5$, we know $\phi(x_1) \geq \phi(x_2)$ for all $x_2 \leq x_1 \leq 0.5$. Therefore, recalling that

$$\pi_j^*(\lambda_k) = \Phi(x_j^*(\lambda_k))$$

and $\pi^*_\ell(\lambda_k) > \pi^*_h(\lambda_k)$, we know that $\phi(x^*_\ell(\lambda_k)) \geq \phi(x^*_h(\lambda_k))$ as long as $\pi^*_\ell(\lambda_k) < 0.5$. Given $\pi^*_\ell(\lambda_k) < \pi^*_\ell(1)$ (as implied by Proposition 2), this confirms that if $\pi^*_\ell(1) < 0.5$ then $\frac{\partial \pi^*_\ell(\lambda_k)}{\partial \lambda_k} > \frac{\partial \pi^*_h(\lambda_k)}{\partial \lambda_k}$ for all $\lambda_k \leq 1$.

7.5 Proof that $\frac{\partial^2 \pi^*_j(\lambda_k)}{\partial \lambda_k^2} > 0$ for $j = h, \ell$

From the proof of Proposition 2 we know

$$\frac{\partial \pi^*_j(\lambda_k)}{\partial \lambda_k} = \phi(x^*_j(\lambda_k))[\delta_t(\omega_j) - \delta_p(\omega_j)] \left[\Delta\pi^* + \lambda_k \frac{\partial \pi^*_\ell(\lambda_k)}{\partial \lambda_k} + (1 - \lambda_k) \frac{\partial \pi^*_h(\lambda_k)}{\partial \lambda_k} \right].$$

Taking the derivative of the above expression we get

$$\frac{\partial^2 \pi^*_j(\lambda_k)}{\partial \lambda_k^2} = \phi'(x^*_j(\lambda_k))[\delta_t(\omega_j) - \delta_p(\omega_j)] \left[\Delta\pi^* + \lambda_k \frac{\partial \pi^*_\ell(\lambda_k)}{\partial \lambda_k} + (1 - \lambda_k) \frac{\partial \pi^*_h(\lambda_k)}{\partial \lambda_k} \right]. \tag{12}$$

Noting that the cdf of the normal is convex for all x such that $\Phi(x) < 0.5$, we know that $\phi'(x) > 0$ for all x such that $\Phi(x) < 0.5$. Once again, recalling that

$$\pi^*_j(\lambda_k) = \Phi(x^*_j(\lambda_k))$$

and $\pi^*_\ell(\lambda_k) > \pi^*_h(\lambda_k)$, we know that $\phi'(x^*_j(\lambda_k)) > 0$ given the assumption that $\pi^*_\ell(\lambda_k) < 0.5$ for all $0 \leq \lambda_k \leq 1$. Further recalling that $[\delta_t(\omega_j) - \delta_p(\omega_j)] > 0$ (see Figure 1), $\Delta\pi^* > 0$ (from Proposition 1), and $\frac{\partial \pi^*_j(\lambda_k)}{\partial \lambda_k} > 0$ for $j = h, \ell$ (from Proposition 2), we then can confirm from equation (12) that $\frac{\partial^2 \pi^*_j(\lambda_k)}{\partial \lambda_k^2} > 0$ for $j = h, \ell$.

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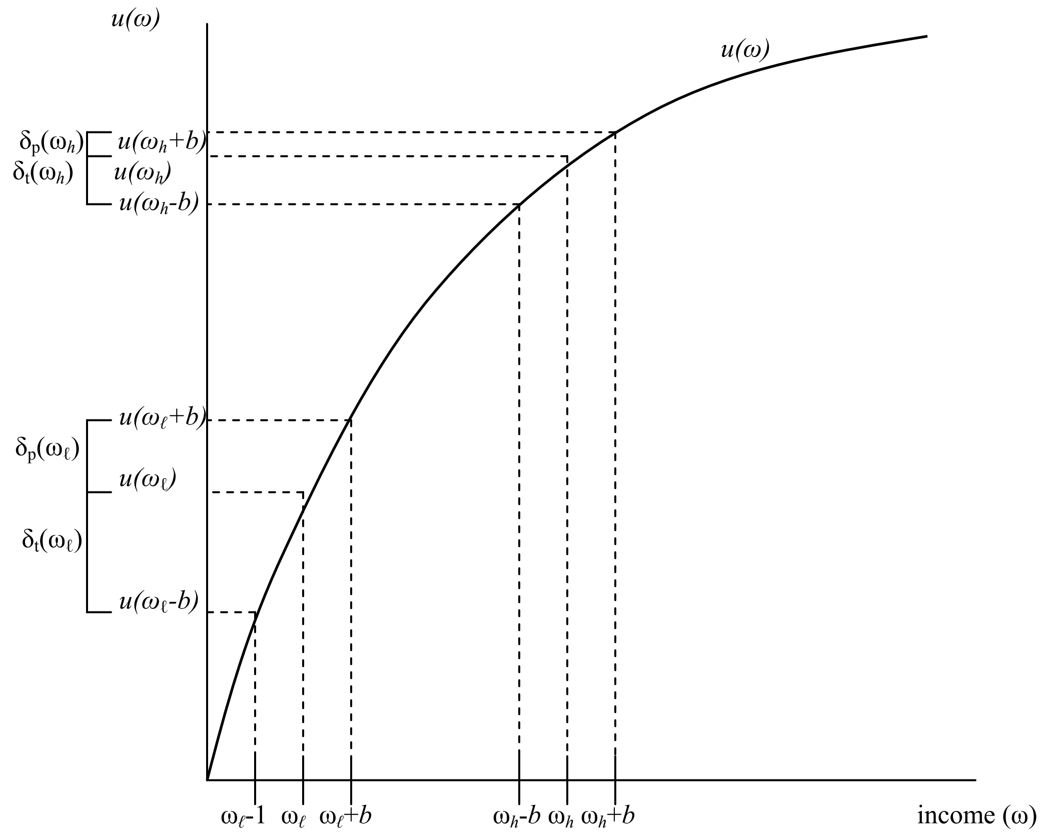

Figure 1 – Graphical depiction showing that $\delta_t(\omega_\ell) > \delta_p(\omega_\ell) > \delta_t(\omega_h) > \delta_p(\omega_h)$ will be true with strictly concave *u* function.

Table I - Descriptive Statistics of Data

Variable	Mean	Std. Dev.
Crime Data (FBI UCR)		
Basic Property Crimes (in 2000)		
burglaries per 100K residents	821.3	342.4
larcenies per 100K residents	2858.4	931.3
motor vehicle thefts per 100K residents	357.8	211.9
Interpersonal Crimes (in 2000)		
robberies per 100K residents	127.0	97.0
aggravated assaults per 100K residents	318.9	179.8
Clearance Rates per 100 reported crimes (in 1999)		
burglary	13.4	6.8
larceny	18.9	7.8
motor vehicle thefts	20.3	12.4
robbery	30.6	13.9
violent crimes	55.9	19.1
MSA Characteristics (2000 Census)		
percent living in poverty	12.4	4.3
total population	837,700	1,405,790
percent urban	80.1	11.9
percent immigrant	1.1	0.9
percent black	10.9	10.3
percent hispanic	10.2	14.7
percent of adults with college degree	23.2	7.0
percent of households headed by single mother	7.4	1.7
percent of households receiveing housing assistance	2.2	1.0
unemployment rate	5.9	1.8
percent of days over 100 degrees	10.8	8.0
percent of days below 32 degrees	23.7	13.7
Segregation		
Dissimilarity Index of Poverty Segregation	0.32	0.07
Isolation Index of Poverty Segregation	0.08	0.04
Dissimilarity Index of Racial Segregation	0.53	0.12
Isolation Index of Racial Segregation	0.22	0.18
Number of observations	297	

Table II(a) - OLS Regession Results (Segregation by Poverty Status)

	Dependant Variable									
	std. burglary rate		std. larceny rate		std. motor veh. theft rate		std. robbery rate		std. agg. assault rate	
Variable	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**
std. poverty dissimilarity index	-0.015		-0.005		0.070		0.111		-0.000	
	(0.066)		(0.067)		(0.056)		(0.051)**		(0.063)	
std. poverty isolation index		-0.061		-0.028		0.058		0.114		-0.009
		(0.063)		(0.060)		(0.055)		(0.054)**		(0.065)
1999 clearance rate	-0.039	-0.039	-0.034	-0.035	-0.019	-0.019	-0.012	-0.012	-0.009	-0.009
	(0.007)***	(0.008)***	(0.007)***	(0.007)***	(0.003)***	(0.003)***	(0.004)***	(0.004)***	(0.003)***	(0.003)***
percent living in poverty	0.039	0.049	0.066	0.071	0.007	0.002	-0.003	-0.016	0.024	0.025
	(0.022)*	(0.024)**	(0.024)***	(0.027)***	(0.015)	(0.017)	(0.016)	(0.018)	(0.024)	(0.028)
log of population	-0.112	-0.107	-0.168	-0.166	0.386	0.388	0.380	0.382	0.148	0.149
	(0.059)*	(0.058)*	(0.061)***	(0.060)***	(0.056)***	(0.056)***	(0.070)***	(0.069)***	(0.071)**	(0.071)**
percent urban	0.013	0.014	0.022	0.023	0.019	0.020	0.017	0.018	0.008	0.008
	(0.007)*	(0.007)**	(0.007)***	(0.006)***	(0.005)***	(0.005)***	(0.004)***	(0.004)***	(0.007)	(0.007)
percent immigrant	-0.048	-0.051	-0.025	-0.027	-0.073	-0.080	0.031	0.023	-0.031	-0.032
	(0.050)	(0.050)	(0.054)	(0.055)	(0.049)	(0.050)	(0.045)	(0.045)	(0.057)	(0.057)
percent black	0.017	0.019	-0.018	-0.017	0.004	0.005	0.053	0.053	0.017	0.017
	(0.012)	(0.012)	(0.011)	(0.011)	(0.009)	(0.009)	(0.010)***	(0.009)***	(0.013)	(0.013)
percent hispanic	-0.009	-0.010	-0.018	-0.018	-0.012	-0.012	0.004	0.005	0.003	0.003
	(0.006)	(0.006)	(0.006)***	(0.006)***	(0.005)**	(0.005)**	(0.004)	(0.004)	(0.006)	(0.006)
percent with college degree	-0.013	-0.010	0.010	0.011	-0.012	-0.012	-0.016	-0.017	-0.008	-0.008
	(0.009)	(0.009)	(0.009)	(0.009)	(0.007)*	(0.007)	(0.007)**	(0.007)**	(0.008)	(0.008)
percent of HH with single mother	0.123	0.118	0.256	0.254	0.114	0.118	-0.041	-0.033	0.080	0.079
	(0.067)*	(0.068)*	(0.062)***	(0.062)***	(0.052)**	(0.052)**	(0.056)	(0.055)	(0.060)	(0.060)
percent of HH subsidized	-0.122	-0.130	-0.060	-0.064	-0.083	-0.083	0.018	0.023	-0.093	-0.095
	(0.050)**	(0.050)**	(0.060)	(0.060)	(0.046)*	(0.047)*	(0.034)	(0.034)	(0.058)	(0.059)
unemployment rate	-0.011	-0.015	-0.083	-0.085	0.076	0.076	0.054	0.055	0.023	0.022
	(0.042)	(0.041)	(0.049)*	(0.049)*	(0.034)**	(0.034)**	(0.039)	(0.039)	(0.046)	(0.046)
percent of days above 90 deg.	0.086	0.082	0.075	0.072	0.055	0.054	0.065	0.065	0.099	0.099
	(0.029)***	(0.028)***	(0.032)**	(0.031)**	(0.028)**	(0.028)*	(0.028)**	(0.028)**	(0.032)***	(0.032)***
sq. of percent of days above 90	-0.002	-0.002	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002	-0.003	-0.003
	(0.001)**	(0.001)**	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)**	(0.001)**	(0.001)***	(0.001)***
percent of days below 32 deg.	0.019	0.020	0.035	0.035	0.012	0.013	0.045	0.046	-0.041	-0.041
	(0.015)	(0.015)	(0.017)**	(0.017)**	(0.015)	(0.015)	(0.014)***	(0.014)***	(0.016)**	(0.016)**
sq. of percent of days below 32	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.001	-0.001	0.001	0.001
	(0.000)*	(0.000)*	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)***	(0.000)***	(0.000)***	(0.000)***
N	297	297	297	297	297	297	297	297	297	297
R - square	0.46	0.47	0.43	0.43	0.61	0.61	0.66	0.66	0.38	0.38

Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Coefficient on constant not shown.

Table II(b) - OLS Regession Results (Segregation by Race)

	Dependant Variable									
	std. burglary rate		**std. larceny rate**		**std. motor veh. theft rate**		**std. robbery rate**		**std. agg. assault rate**	
Variable	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**
std. poverty dissimilarity index	0.031		-0.058		0.056		0.212		0.100	
	(0.070)		(0.061)		(0.063)		(0.056)***		(0.061)	
std. poverty isolation index		0.055		-0.085		0.075		0.316		0.279
		(0.077)		(0.072)		(0.078)		(0.081)***		(0.081)***
1999 clearance rate	-0.039	-0.039	-0.035	-0.036	-0.019	-0.019	-0.012	-0.011	-0.008	-0.007
	(0.007)***	(0.007)***	(0.007)***	(0.007)***	(0.004)***	(0.004)***	(0.004)***	(0.004)***	(0.003)***	(0.003)**
percent living in poverty	0.036	0.036	0.069	0.068	0.009	0.010	-0.008	-0.005	0.018	0.016
	(0.023)	(0.022)*	(0.024)***	(0.024)***	(0.016)	(0.015)	(0.017)	(0.015)	(0.024)	(0.023)
log of population	-0.127	-0.135	-0.144	-0.138	0.370	0.367	0.301	0.277	0.105	0.046
	(0.068)*	(0.066)**	(0.066)**	(0.065)**	(0.066)***	(0.064)***	(0.064)***	(0.060)***	(0.074)	(0.068)
percent urban	0.012	0.012	0.023	0.023	0.021	0.020	0.017	0.016	0.006	0.003
	(0.007)*	(0.007)*	(0.006)***	(0.006)***	(0.005)***	(0.005)***	(0.004)***	(0.004)***	(0.006)	(0.007)
percent immigrant	-0.038	-0.036	-0.037	-0.037	-0.072	-0.073	0.060	0.062	-0.009	0.011
	(0.050)	(0.050)	(0.058)	(0.058)	(0.051)	(0.051)	(0.043)	(0.042)	(0.055)	(0.054)
percent black	0.015	0.013	-0.015	-0.011	0.004	0.001	0.047	0.034	0.012	-0.004
	(0.013)	(0.014)	(0.011)	(0.012)	(0.009)	(0.009)	(0.009)***	(0.009)***	(0.013)	(0.015)
percent hispanic	-0.008	-0.008	-0.019	-0.019	-0.012	-0.012	0.006	0.007	0.004	0.006
	(0.006)	(0.006)	(0.007)***	(0.007)***	(0.005)**	(0.005)**	(0.004)	(0.004)*	(0.006)	(0.005)
percent with college degree	-0.011	-0.011	0.006	0.006	-0.006	-0.006	0.000	-0.001	-0.003	0.001
	(0.010)	(0.009)	(0.009)	(0.009)	(0.007)	(0.006)	(0.007)	(0.006)	(0.009)	(0.009)
percent of HH with single mother	0.129	0.128	0.245	0.248	0.124	0.121	-0.001	-0.012	0.099	0.106
	(0.073)*	(0.068)*	(0.064)***	(0.062)***	(0.053)**	(0.051)**	(0.052)	(0.050)	(0.061)	(0.058)*
percent of HH subsidized	-0.122	-0.121	-0.056	-0.058	-0.096	-0.094	-0.011	-0.004	-0.100	-0.099
	(0.051)**	(0.050)**	(0.058)	(0.059)	(0.047)**	(0.047)**	(0.033)	(0.033)	(0.055)*	(0.053)*
unemployment rate	-0.006	-0.005	-0.090	-0.089	0.078	0.076	0.072	0.069	0.036	0.045
	(0.042)	(0.041)	(0.050)*	(0.049)*	(0.034)**	(0.034)**	(0.039)*	(0.039)*	(0.045)	(0.045)
percent of days above 90 deg.	0.092	0.092	0.067	0.068	0.056	0.054	0.083	0.078	0.114	0.123
	(0.031)***	(0.029)***	(0.033)**	(0.032)**	(0.029)*	(0.028)*	(0.029)***	(0.028)***	(0.031)***	(0.029)***
sq. of percent of days above 90	-0.002	-0.002	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002	-0.003	-0.003
	(0.001)**	(0.001)**	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)***	(0.001)***	(0.001)***	(0.001)***
percent of days below 32 deg.	0.018	0.017	0.035	0.035	0.014	0.014	0.047	0.045	-0.042	-0.044
	(0.015)	(0.015)	(0.017)**	(0.016)**	(0.015)	(0.015)	(0.014)***	(0.014)***	(0.016)***	(0.015)***
sq. of percent of days below 32	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.001	-0.001	0.001	0.001
	(0.000)*	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)***	(0.000)***	(0.000)***	(0.000)***
N	297	297	297	297	297	297	297	297	297	297
R - square	0.46	0.47	0.43	0.43	0.61	0.61	0.67	0.68	0.38	0.40

Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Coefficient on constant not shown.

Table III - First Stage of 2SLS Regession Results

	Dependant Variable			
Variable	std. poverty dissimilarity index (a)	std. poverty isolation index (b)	std. racial dissimilarity index (a)	std. racial isolation index (b)
EXCLUDED INSTRUMENTS				
fraction of housing assistance via public housing	0.005	0.004	0.007	0.006
	(0.002)**	(0.002)**	(0.002)***	(0.002)***
share of local rev. coming from State & Fed gov't.	-0.014	-0.014	-0.021	-0.016
	(0.005)***	(0.005)***	(0.005)***	(0.004)***
NON-EXCLUDED				
clearance rate for burglaries	-0.003	0.001	-0.005	-0.006
	(0.006)	(0.006)	(0.006)	(0.005)
percent living in poverty	0.060	0.173	0.042	0.016
	(0.020)***	(0.021)***	(0.020)**	(0.017)
log of population	0.127	0.109	0.424	0.367
	(0.052)**	(0.055)**	(0.052)***	(0.045)***
percent urban	0.030	0.020	0.011	0.013
	(0.006)***	(0.006)***	(0.006)**	(0.005)***
percent immigrant	-0.212	-0.137	-0.291	-0.217
	(0.051)***	(0.053)**	(0.051)***	(0.044)***
percent black	0.034	0.037	0.047	0.073
	(0.009)***	(0.009)***	(0.009)***	(0.008)***
percent hispanic	-0.005	-0.012	-0.008	-0.009
	(0.005)	(0.005)**	(0.005)*	(0.004)**
percent with college degree	0.047	0.052	-0.048	-0.028
	(0.008)***	(0.008)***	(0.008)***	(0.007)***
percent of HH with single mother	0.017	-0.055	-0.158	-0.067
	(0.050)	(0.053)	(0.051)***	(0.043)
percent of households subsidized	-0.129	-0.166	0.074	0.031
	(0.045)***	(0.047)***	(0.045)	(0.039)
unemployment rate	-0.071	-0.081	-0.116	-0.067
	(0.043)*	(0.045)*	(0.043)***	(0.037)*
percent of days above 90 deg.	-0.089	-0.087	-0.123	-0.064
	(0.025)***	(0.026)***	(0.025)***	(0.022)***
sq. of percent of days above 90	0.002	0.002	0.003	0.002
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
percent of days below 32 deg.	0.032	0.029	0.004	0.008
	(0.014)**	(0.014)**	(0.014)	(0.012)
sq. of percent of days below 32	-0.000	-0.000	-0.000	-0.000
	(0.000)*	(0.000)*	(0.000)	(0.000)
N	297	297	297	297
R - square	0.57	0.52	0.60	0.72
F-stat for excluded instruments	7.86***	6.59***	17.63***	16.23***

Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Coefficient on constant not shown.

Table IV(a) - 2SLS Regession Results (Segregation by Poverty Status)

	Dependant Variable									
	std. burglary rate		std. larceny rate		std. motor veh. theft rate		std. robbery rate		std. agg. assault rate	
Variable	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
std. poverty dissimilarity index	-0.486		-0.031		0.038		1.029		0.919	
	(0.297)		(0.286)		(0.243)		(0.345)***		(0.389)**	
std. poverty isolation index		-0.508		-0.036		0.039		1.070		0.973
		(0.308)*		(0.297)		(0.252)		(0.374)***		(0.431)**
1999 clearance rate	-0.041	-0.039	-0.035	-0.035	-0.019	-0.019	-0.006	-0.008	-0.007	-0.005
	(0.007)***	(0.007)***	(0.006)***	(0.006)***	(0.004)***	(0.004)***	(0.005)	(0.005)	(0.003)**	(0.004)
percent living in poverty	0.072	0.131	0.068	0.073	0.010	0.005	-0.070	-0.193	-0.041	-0.154
	(0.032)**	(0.061)**	(0.030)**	(0.059)	(0.026)	(0.050)	(0.037)*	(0.075)***	(0.041)	(0.085)*
log of population	-0.049	-0.055	-0.165	-0.165	0.389	0.390	0.274	0.286	0.027	0.045
	(0.073)	(0.070)	(0.069)**	(0.066)**	(0.059)***	(0.058)***	(0.081)***	(0.083)***	(0.094)	(0.094)
percent urban	0.029	0.025	0.023	0.023	0.020	0.021	-0.013	-0.003	-0.023	-0.014
	(0.012)**	(0.010)***	(0.011)**	(0.009)**	(0.010)**	(0.008)***	(0.013)	(0.011)	(0.015)	(0.013)
percent immigrant	-0.126	-0.092	-0.029	-0.028	-0.078	-0.081	0.172	0.101	0.120	0.051
	(0.076)*	(0.064)	(0.072)	(0.061)	(0.061)	(0.052)	(0.085)**	(0.076)	(0.098)	(0.086)
percent black	0.034	0.036	-0.017	-0.017	0.005	0.005	0.022	0.018	-0.015	-0.020
	(0.015)**	(0.015)**	(0.014)	(0.015)	(0.012)	(0.013)	(0.017)	(0.018)	(0.019)	(0.021)
percent hispanic	-0.013	-0.016	-0.018	-0.018	-0.012	-0.012	0.012	0.019	0.010	0.017
	(0.006)**	(0.007)**	(0.006)***	(0.007)***	(0.005)**	(0.006)**	(0.007)	(0.009)**	(0.008)	(0.010)*
percent with college degree	0.006	0.010	0.011	0.011	-0.010	-0.011	-0.054	-0.061	-0.046	-0.054
	(0.015)	(0.017)	(0.014)	(0.016)	(0.012)	(0.014)	(0.017)***	(0.020)***	(0.019)**	(0.023)**
percent of HH with single mother	0.120	0.084	0.256	0.253	0.114	0.117	-0.035	0.041	0.084	0.154
	(0.059)**	(0.063)	(0.056)***	(0.060)***	(0.048)**	(0.052)**	(0.068)	(0.076)	(0.076)	(0.085)*
percent of HH subsidized	-0.185	-0.207	-0.064	-0.066	-0.087	-0.086	0.147	0.192	0.031	0.076
	(0.066)***	(0.075)***	(0.064)	(0.072)	(0.054)	(0.061)	(0.078)*	(0.091)**	(0.086)	(0.103)
unemployment rate	-0.048	-0.055	-0.085	-0.086	0.073	0.074	0.131	0.144	0.097	0.113
	(0.055)	(0.057)	(0.052)	(0.054)	(0.045)	(0.047)	(0.065)**	(0.069)**	(0.072)	(0.078)
percent of days above 90 deg.	0.039	0.037	0.072	0.072	0.052	0.052	0.161	0.163	0.193	0.200
	(0.042)	(0.042)	(0.041)*	(0.041)*	(0.035)	(0.035)	(0.050)***	(0.052)***	(0.055)***	(0.059)***
sq. of percent of days above 90	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.005	-0.005	-0.006	-0.005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)***	(0.001)***	(0.002)***	(0.002)***
percent of days below 32 deg.	0.036	0.035	0.036	0.036	0.013	0.014	0.013	0.015	-0.073	-0.070
	(0.019)*	(0.019)*	(0.018)**	(0.018)**	(0.015)	(0.015)	(0.022)	(0.022)	(0.025)***	(0.025)***
sq. of percent of days below 32	-0.001	-0.001	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.001	0.001
	(0.000)**	(0.000)**	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)***	(0.000)***
N	297	297	297	297	297	297	297	297	297	297
F-stat on excl. instruments	7.86***	6.59***	7.58***	6.40***	7.68***	6.52***	7.78***	6.51***	7.58***	6.11***
Sargan Overid Stat.	0.72	0.70	1.32	1.32	0.14	0.14	0.26	0.21	0.39	0.41
p-val on Sargan Stat.	0.40	0.40	0.25	0.25	0.71	0.71	0.61	0.65	0.53	0.52

Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Coefficient on constant not shown.

Table IV(b) - 2SLS Regession Results (Segregation by Race)

	Dependant Variable									
	std. burglary rate		std. larceny rate		std. motor veh. theft rate		std. robbery rate		std. agg. assault rate	
Variable	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**
std. poverty dissimilarity index	-0.314		-0.013		0.028		0.666		0.623	
	(0.190)*		(0.191)		(0.161)		(0.183)***		(0.227)***	
std. poverty isolation index		-0.373		-0.012		0.037		0.808		0.783
		(0.232)		(0.237)		(0.197)		(0.218)***		(0.271)***
1999 clearance rate	-0.041	-0.042	-0.035	-0.035	-0.019	-0.019	-0.012	-0.009	-0.006	-0.004
	(0.007)***	(0.007)***	(0.006)***	(0.007)***	(0.004)***	(0.004)***	(0.003)***	(0.003)***	(0.003)**	(0.003)
percent living in poverty	0.056	0.049	0.067	0.066	0.011	0.011	-0.035	-0.021	-0.012	0.002
	(0.025)**	(0.024)**	(0.025)***	(0.023)***	(0.021)	(0.020)	(0.024)	(0.022)	(0.029)	(0.026)
log of population	0.023	0.027	-0.163	-0.164	0.382	0.381	0.104	0.096	-0.119	-0.140
	(0.102)	(0.106)	(0.099)*	(0.103)	(0.085)***	(0.088)***	(0.098)	(0.098)	(0.119)	(0.119)
percent urban	0.018	0.019	0.022	0.022	0.021	0.021	0.010	0.007	-0.002	-0.005
	(0.007)***	(0.007)***	(0.007)***	(0.007)***	(0.006)***	(0.006)***	(0.006)	(0.007)	(0.008)	(0.008)
percent immigrant	-0.115	-0.105	-0.027	-0.026	-0.079	-0.079	0.161	0.138	0.104	0.088
	(0.070)	(0.067)	(0.068)	(0.065)	(0.059)	(0.056)	(0.067)**	(0.062)**	(0.081)	(0.074)
percent black	0.032	0.045	-0.017	-0.017	0.005	0.004	0.024	-0.003	-0.014	-0.041
	(0.014)**	(0.020)**	(0.013)	(0.020)	(0.011)	(0.017)	(0.013)*	(0.019)	(0.016)	(0.023)*
percent hispanic	-0.013	-0.013	-0.018	-0.018	-0.012	-0.012	0.011	0.013	0.010	0.012
	(0.006)**	(0.006)**	(0.006)***	(0.006)***	(0.005)**	(0.005)**	(0.006)*	(0.006)**	(0.007)	(0.007)*
percent with college degree	-0.031	-0.027	0.009	0.009	-0.007	-0.008	0.027	0.017	0.027	0.018
	(0.014)**	(0.012)**	(0.014)	(0.012)	(0.012)	(0.010)	(0.013)**	(0.011)	(0.016)*	(0.013)
percent of HH with single mother	0.063	0.088	0.253	0.255	0.119	0.117	0.086	0.034	0.199	0.153
	(0.067)	(0.061)	(0.066)***	(0.060)***	(0.057)**	(0.052)**	(0.065)	(0.057)	(0.079)**	(0.068)**
percent of HH subsidized	-0.099	-0.110	-0.059	-0.059	-0.094	-0.093	-0.040	-0.014	-0.133	-0.111
	(0.053)*	(0.052)**	(0.051)	(0.050)	(0.044)**	(0.043)**	(0.051)	(0.048)	(0.061)**	(0.057)*
unemployment rate	-0.050	-0.038	-0.084	-0.084	0.074	0.073	0.130	0.108	0.105	0.087
	(0.054)	(0.052)	(0.053)	(0.051)*	(0.046)	(0.043)*	(0.052)**	(0.048)**	(0.064)*	(0.058)
percent of days above 90 deg.	0.043	0.059	0.073	0.074	0.052	0.051	0.147	0.118	0.190	0.164
	(0.039)	(0.034)*	(0.039)*	(0.034)**	(0.033)	(0.029)*	(0.038)***	(0.032)***	(0.047)***	(0.039)***
sq. of percent of days above 90	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.004	-0.004	-0.005	-0.005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)***	(0.001)***	(0.001)***	(0.001)***
percent of days below 32 deg.	0.022	0.023	0.035	0.035	0.015	0.014	0.041	0.037	-0.046	-0.049
	(0.015)	(0.016)	(0.015)**	(0.015)**	(0.013)	(0.013)	(0.015)***	(0.015)**	(0.018)**	(0.017)***
sq. of percent of days below 32	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.001	-0.001	0.001	0.001
	(0.000)	(0.000)*	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)**	(0.000)**	(0.000)***	(0.000)***
N	297	297	297	297	297	297	297	297	297	297
F-stat on excl. instruments	17.63***	16.23***	16.83***	15.07***	17.34***	15.76***	17.53***	16.05***	16.66***	14.88***
Sargan Overid Stat.	0.91	1.02	1.33	1.34	0.13	0.13	0.76	1.03	0.35	0.24
p-val on Sargan Stat.	0.34	0.31	0.25	0.25	0.72	0.72	0.38	0.31	0.55	0.62

Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Coefficient on constant not shown.

Table A1(a) - 2SLS Regession Results (Segregation by Poverty Status - Using 3 instruments)

	Dependant Variable									
	std. burglary rate		std. larceny rate		std. motor veh. theft rate		std. robbery rate		std. agg. assault rate	
Variable	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**
std. poverty dissimilarity index	-0.402		0.003		-0.072		0.960		0.746	
	(0.277)		(0.273)		(0.235)		(0.322)***		(0.349)**	
std. poverty isolation index		-0.398		0.005		-0.088		0.969		0.766
		(0.280)		(0.279)		(0.240)		(0.336)***		(0.376)**
1999 clearance rate	-0.040	-0.039	-0.034	-0.034	-0.019	-0.019	-0.007	-0.008	-0.007	-0.006
	(0.007)***	(0.007)***	(0.006)***	(0.006)***	(0.004)***	(0.004)***	(0.005)	(0.004)*	(0.003)**	(0.003)*
percent living in poverty	0.066	0.111	0.066	0.065	0.018	0.028	-0.065	-0.174	-0.029	-0.116
	(0.030)**	(0.056)**	(0.029)**	(0.056)	(0.026)	(0.048)	(0.035)*	(0.068)**	(0.038)	(0.074)
log of population	-0.060	-0.068	-0.169	-0.169	0.403	0.404	0.282	0.296	0.050	0.067
	(0.070)	(0.067)	(0.068)**	(0.066)***	(0.059)***	(0.058)***	(0.078)***	(0.078)***	(0.087)	(0.085)
percent urban	0.027	0.022	0.022	0.022	0.024	0.024	-0.011	-0.001	-0.017	-0.010
	(0.011)**	(0.009)**	(0.011)**	(0.009)**	(0.009)***	(0.008)***	(0.013)	(0.010)	(0.014)	(0.012)
percent immigrant	-0.112	-0.082	-0.024	-0.024	-0.096	-0.093	0.162	0.093	0.091	0.034
	(0.073)	(0.061)	(0.070)	(0.060)	(0.061)	(0.052)*	(0.081)**	(0.072)	(0.090)	(0.078)
percent black	0.031	0.032	-0.018	-0.018	0.009	0.010	0.025	0.021	-0.009	-0.012
	(0.014)**	(0.014)**	(0.014)	(0.014)	(0.012)	(0.012)	(0.016)	(0.017)	(0.017)	(0.019)
percent hispanic	-0.012	-0.015	-0.018	-0.018	-0.013	-0.014	0.011	0.018	0.009	0.014
	(0.006)*	(0.007)**	(0.006)***	(0.007)***	(0.005)**	(0.006)**	(0.007)	(0.008)**	(0.008)	(0.009)
percent with college degree	0.003	0.005	0.009	0.009	-0.006	-0.005	-0.051	-0.056	-0.039	-0.044
	(0.014)	(0.015)	(0.014)	(0.015)	(0.012)	(0.013)	(0.016)***	(0.018)***	(0.018)**	(0.021)**
percent of HH with single mother	0.121	0.093	0.256	0.256	0.113	0.107	-0.036	0.033	0.084	0.138
	(0.057)**	(0.060)	(0.056)***	(0.060)***	(0.048)**	(0.052)**	(0.065)	(0.072)	(0.071)	(0.078)*
percent of HH subsidized	-0.174	-0.188	-0.059	-0.059	-0.102	-0.108	0.138	0.174	0.008	0.040
	(0.064)***	(0.070)***	(0.063)	(0.070)	(0.054)*	(0.060)*	(0.074)*	(0.085)**	(0.079)	(0.092)
unemployment rate	-0.042	-0.045	-0.082	-0.082	0.065	0.062	0.125	0.135	0.083	0.094
	(0.054)	(0.054)	(0.052)	(0.054)	(0.045)	(0.046)	(0.062)**	(0.065)**	(0.067)	(0.071)
percent of days above 90 deg.	0.047	0.048	0.076	0.076	0.040	0.039	0.154	0.153	0.176	0.179
	(0.040)	(0.040)	(0.040)*	(0.040)*	(0.034)	(0.034)	(0.047)***	(0.048)***	(0.050)***	(0.053)***
sq. of percent of days above 90	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.005	-0.004	-0.005	-0.005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)***	(0.001)***	(0.001)***	(0.002)***
percent of days below 32 deg.	0.033	0.031	0.034	0.034	0.017	0.018	0.015	0.018	-0.067	-0.064
	(0.018)*	(0.018)*	(0.018)*	(0.017)**	(0.015)	(0.015)	(0.021)	(0.021)	(0.023)***	(0.023)***
sq. of percent of days below 32	-0.001	-0.001	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.001	0.001
	(0.000)**	(0.000)**	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)***	(0.000)***
N	297	297	297	297	297	297	297	297	297	297
F-stat on excl. instruments	5.72***	4.97***	5.54***	4.81***	5.64***	4.91***	5.60***	4.83***	5.51***	4.52***
Sargan Overid Stat.	1.77	1.95	1.49	1.49	2.36	2.31	0.87	1.04	3.18	3.27
p-val on Sargan Stat.	0.41	0.38	0.48	0.48	0.31	0.31	0.65	0.60	0.20	0.19

Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Coefficient on constant not shown.

Table A1(b) - 2SLS Regession Results (Segregation by Race - Using 3 instruments)

	Dependant Variable									
	std. burglary rate		std. larceny rate		std. motor veh. theft rate		std. robbery rate		std. agg. assault rate	
Variable	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**
std. poverty dissimilarity index	-0.171		0.026		-0.095		0.467		0.324	
	(0.153)		(0.158)		(0.135)		(0.142)***		(0.176)*	
std. poverty isolation index		-0.293		0.019		-0.066		0.725		0.620
		(0.215)		(0.223)		(0.186)		(0.200)***		(0.249)**
1999 clearance rate	-0.040	-0.041	-0.034	-0.034	-0.019	-0.019	-0.012	-0.009	-0.007	-0.005
	(0.007)***	(0.007)***	(0.006)***	(0.007)***	(0.004)***	(0.004)***	(0.003)***	(0.003)***	(0.003)***	(0.003)*
percent living in poverty	0.048	0.047	0.065	0.065	0.018	0.014	-0.023	-0.018	0.005	0.006
	(0.024)**	(0.023)**	(0.024)***	(0.023)***	(0.021)	(0.020)	(0.022)	(0.022)	(0.026)	(0.025)
log of population	-0.039	-0.003	-0.179	-0.176	0.435	0.418	0.190	0.126	0.009	-0.080
	(0.088)	(0.100)	(0.089)**	(0.099)*	(0.077)***	(0.085)***	(0.082)**	(0.091)	(0.099)	(0.111)
percent urban	0.016	0.018	0.021	0.022	0.023	0.023	0.013	0.009	0.003	-0.002
	(0.006)**	(0.007)***	(0.006)***	(0.007)***	(0.006)***	(0.006)***	(0.006)**	(0.006)	(0.007)	(0.008)
percent immigrant	-0.083	-0.092	-0.019	-0.022	-0.106	-0.095	0.117	0.125	0.039	0.063
	(0.064)	(0.065)	(0.064)	(0.064)	(0.056)*	(0.056)*	(0.059)**	(0.060)**	(0.071)	(0.071)
percent black	0.025	0.039	-0.019	-0.019	0.012	0.012	0.034	0.003	0.001	-0.029
	(0.012)**	(0.019)**	(0.012)	(0.019)	(0.011)	(0.016)	(0.011)***	(0.017)	(0.014)	(0.021)
percent hispanic	-0.011	-0.012	-0.018	-0.018	-0.014	-0.013	0.009	0.012	0.007	0.010
	(0.006)*	(0.006)**	(0.006)***	(0.006)***	(0.005)***	(0.005)**	(0.005)*	(0.006)**	(0.006)	(0.007)
percent with college degree	-0.023	-0.024	0.011	0.010	-0.014	-0.011	0.015	0.014	0.010	0.013
	(0.012)*	(0.011)**	(0.012)	(0.012)	(0.011)	(0.010)	(0.011)	(0.010)	(0.014)	(0.012)
percent of HH with single mother	0.090	0.095	0.261	0.258	0.095	0.107	0.048	0.027	0.142	0.138
	(0.062)	(0.060)	(0.063)***	(0.060)***	(0.055)*	(0.052)**	(0.058)	(0.055)	(0.070)**	(0.065)**
percent of HH subsidized	-0.109	-0.113	-0.061	-0.060	-0.086	-0.091	-0.028	-0.012	-0.114	-0.107
	(0.050)**	(0.051)**	(0.051)	(0.050)	(0.044)*	(0.043)**	(0.047)	(0.047)	(0.056)**	(0.055)*
unemployment rate	-0.032	-0.032	-0.079	-0.081	0.058	0.065	0.105	0.102	0.066	0.073
	(0.051)	(0.051)	(0.052)	(0.050)	(0.045)	(0.043)	(0.047)**	(0.047)**	(0.057)	(0.056)
percent of days above 90 deg.	0.064	0.065	0.079	0.077	0.034	0.043	0.119	0.111	0.146	0.151
	(0.035)*	(0.033)**	(0.036)**	(0.034)**	(0.031)	(0.028)	(0.032)***	(0.030)***	(0.040)***	(0.037)***
sq. of percent of days above 90	-0.001	-0.001	-0.001	-0.001	-0.000	-0.001	-0.003	-0.003	-0.004	-0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)***	(0.001)***	(0.001)***	(0.001)***
percent of days below 32 deg.	0.020	0.022	0.034	0.034	0.016	0.016	0.044	0.038	-0.044	-0.047
	(0.015)	(0.015)	(0.015)**	(0.015)**	(0.013)	(0.013)	(0.014)***	(0.014)***	(0.017)***	(0.017)***
sq. of percent of days below 32	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.001	-0.001	0.001	0.001
	(0.000)*	(0.000)*	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)***	(0.000)**	(0.000)***	(0.000)***
N	297	297	297	297	297	297	297	297	297	297
F-stat on excl. instruments	17.80	12.27	17.28	11.54	17.79	12.14	17.81	12.15	16.81	11.07
Sargan Overid Stat.	2.98	2.20	1.46	1.48	1.95	2.34	5.27	2.50	7.00	4.27
p-val on Sargan Stat.	0.23	0.33	0.48	0.48	0.38	0.31	0.07	0.29	0.03	0.12

Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Coefficient on constant not shown.