Spreading the wealth: The effect of the distribution of income and race/ethnicity across households and neighborhoods on city crime trajectories

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Abstract

This study tests the effect of the composition and distribution of economic resources and race/ethnicity in cities, as well as how they are geographically distributed within these cities, on crime rates over a 30-year period. Using data on 352 cities from 1970 to 2000 in metropolitan areas that experienced a large growth in population after World War II, this study theorizes that the effect of racial/ethnic or economic segregation on crime is stronger in cities in which race/ethnicity or income are more salient (due to greater heterogeneity or inequality). We test and find that higher levels of segregation in cities with high levels of racial/ethnic heterogeneity leads to particularly high overall levels of the types of crime studied here (aggravated assaults, robberies, burglaries, and motor vehicle thefts). Similarly, higher levels of economic segregation lead to much higher levels of crime in cities with higher levels of inequality.

Keywords: Macro-crime, longitudinal, inequality, race/ethnicity, segregation.

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Whether studying neighborhoods, cities, counties, or even larger aggregations, researchers often posit and test whether two key constructs—the racial/ethnic and economic composition in a geographic unit—are related to higher levels of crime. Various theories posit why the presence of more racial/ethnic heterogeneity within geographic units leads to more crime (Hunter, 1995; Sampson and Groves, 1989; Shaw and McKay, 1942). Likewise, theories posit why the lack of economic resources, or greater levels of economic inequality, within geographic units leads to more crime (Agnew, 1985; Agnew, 1999; Hipp, 2007b; Jasso, 1980). A key issue is determining the proper level of aggregation when measuring such structural characteristics. Do they operate at the level of neighborhoods, some broader area, or at the level of larger geographic units such as cities or counties (Hipp, 2007a)?

The geographic unit of analysis at which these mechanisms operate has important implications for prior research studying these questions. Studies comparing neighborhoods within the same city can determine whether mechanisms actually operate at the neighborhood-level. However, these studies cannot ascertain whether these structural characteristics indeed *increase* the amount of crime, or simply *shift* its location from other neighborhoods. Studies using larger geographic units of analysis may find a relationship between some structural characteristic and crime levels, but often cannot determine whether the mechanisms operate at the city level, or simply at the neighborhood level and then scale up to the city level, in instances in which the neighborhood effects are linear. However, if these structural characteristics have a nonlinear effect at the neighborhood level, then how these constructs are distributed geographically *throughout* the city (e.g., segregation) may have important implications for crime

rates. For both race/ethnicity and economic resources, we can consider their composition and distribution *within* neighborhoods, as well as how they are distributed *across* neighborhoods. At root, the question is whether these constructs indeed exhibit a degree of scale invariance (Land, McCall, and Cohen, 1990). With the exception of a recent cross-sectional study viewing homicide rates of African-Americans in central cities (Lee and Ousey, 2007), studies have generally failed to test this proposition. As we describe in more detail below, when focusing on distribution measures (e.g., racial/ethnic heterogeneity and inequality), defining the proper unit of analysis is particularly crucial when testing their effects on crime.

Addressing these questions is challenging due to the data requirements. On the one hand, multilevel data containing information on crime rates in neighborhoods within a large number of cities would be one useful way to address these questions. However, such data are hard to come by, especially when looking for longitudinal data. Since we are interested in the generation of crime, and not just whether it is shifted across neighborhoods, we test these hypotheses using city-level data, but accounting for the geographic distribution of income and race/ethnicity across the neighborhoods of these cities. Thus, if the spatial distribution of income and race/ethnicity affects crime rates, we would be able to detect this when measuring city-level crime rates as the outcome.

We begin by describing prior research studying the effects of race and class for crime rates across neighborhoods and cities. We then consider issues regarding the appropriate unit of analysis. Following that, we discuss the unit of analysis for these posited mechanisms, and consider how the distribution of race and class within and across neighborhoods may have different implications for city crime rates. We then describe our study sample, along with the measures used in the study and our research methods. We describe the results, and then conclude.

Income, race, and crime

Prior research

Researchers have studied the effect of the racial/ethnic composition and economic resources on crime rates for various geographic units of analysis. Numerous studies have focused on neighborhoods when testing the effect of the racial/ethnic and economic composition on crime rates. Studies focusing on the relationship between neighborhood racial/ethnic heterogeneity and crime rates have generally found a strong positive relationship (Bellair, 1997; Hipp, 2007b; Sampson and Groves, 1989; Smith and Jarjoura, 1988; Veysey and Messner, 1999; Warner and Pierce, 1993; Warner and Rountree, 1997). Studies have also generally found a positive relationship between the presence of racial/ethnic minorities and levels of crime in neighborhoods (Crutchfield, 1989; Hannon and Knapp, 2003; Krivo and Peterson, 1996; Ouimet, 2000; Peterson, Krivo, and Harris, 2000; Roncek, 1981). Occasional studies have accounted for the level of racial/ethnic heterogeneity in the neighborhood when testing the effect of the presence of racial/ethnic minorities and found a positive effect (Hipp, 2007b; Roncek and Maier, 1991). Regarding the effects of economic resources, studies have generally found that neighborhoods with higher levels of poverty have more crime (Crutchfield, 1989; Hipp, 2007b; Krivo and Peterson, 1996; McClain, 1989; Messner and Tardiff, 1986; Warner and Pierce, 1993; Warner and Rountree, 1997), and that neighborhoods with higher levels of inequality have more crime (Crutchfield, 1989; Hipp, 2007b).

Another body of research has focused on the relationship between crime rates and structural measures of income and racial composition measured for larger geographic units such as cities. For example, studies have tested the relationship between poverty and crime for units such as cities, counties, or even MSA's, with some finding a positive relationship (Bainbridge, 1989; Chamlin and Cochran, 1997; Messner and Blau, 1987), although many have found mixed

results (Beyerlein and Hipp, 2005; Crutchfield, Geerken, and Gove, 1982; Gibbs and Erickson, 1976; Harer and Steffensmeier, 1992; Liska and Bellair, 1995; Liska, Logan, and Bellair, 1998; Shihadeh and Ousey, 1996) or even negative results (Hipp, Bauer, Curran, and Bollen, 2004). A series of studies assessed the effects of economic inequality on levels of crime using large units of analysis, with some finding a positive relationship (Harer and Steffensmeier, 1992; McVeigh, 2006), whereas others found only sporadic positive effects (Blau and Blau, 1982; Chamlin and Cochran, 1997; Golden and Messner, 1987; Kposowa, Breault, and Harrison, 1995; Land, McCall, and Cohen, 1990; Messner and Golden, 1992; Ousey, 1999; Simpson, 1985). One study found that inequality among African Americans led to higher race-specific violent crime rates across U.S. cities (Shihadeh and Steffensmeier, 1994). Although numerous studies have tested and frequently found a positive relationship between the percentage of African-Americans or non-whites in a city and rates of crime (Beyerlein and Hipp, 2005; Chamlin and Cochran, 1997; Kawachi, Kennedy, Lochner, and Prothrow-Stith, 1997; Kovandzic, Vieratis, and Yeisley, 1998; Land, McCall, and Cohen, 1990; Liska and Bellair, 1995; Messner, 1983b; Miethe, Hughes, and McDowall, 1991; Ousey, 1999; Sampson, 1985; Wilkinson, 1996), fewer studies have tested whether racial/ethnic heterogeneity in larger units of analysis affects crime rates, though two studies did so and found significant positive effects in counties (McVeigh, 2006), and cities (Hipp, Bauer, Curran, and Bollen, 2004), and others have included a quadratic term for percent African-American to test this (Messner, 1983a; Williams, 1984).

Considering the proper level of aggregation

In reviewing this large body of prior work using varying levels of aggregation to test these relationships, it becomes clear that it is important to consider the posited mechanisms in order to determine the appropriate level of aggregation (Hipp, 2007a). Disentangling the unit of analysis at which these processes operate is challenging. Studies positing that these processes

operate at the level of neighborhoods and then comparing rates of crime across the neighborhoods of a particular city can test whether these structural characteristics are indeed associated with more crime in such neighborhoods. However, a limitation of these studies is that they cannot assess whether these structural characteristics bring about *more crime* within those neighborhoods, or simply *shift it* from other neighborhoods. To assess whether these characteristics bring about more overall crime would require also showing that cities with more of a particular structural characteristic also have higher crime rates. For example, if higher levels of poverty in neighborhoods create more crime and this is a linear relationship, then there will also be a linear relationship between the poverty rate and crime rate across cities. However, if poverty simply shifts crime from one neighborhood to another, then the overall poverty rate in a city would have no relationship with the crime rate. Thus, city-level analyses that find such an effect cannot be certain that the observed relationship operates at the geographic level of the city, or at some smaller geographic unit and simply scales up to the geographic level of the city.

To complicate matters further, there are situations in which neighborhood-level measures would not simply scale up to the city-level. One situation occurs when the variable of interest has a nonlinear effect at the neighborhood level; for example, if poverty nonlinearly increases neighborhood crime, then the effect of poverty on crime at the level of the city would depend not only on the total level of poverty in the city, but also on its distribution across the neighborhoods within the city (Stretesky, Schuck, and Hogan, 2004).[1] When the variable of interest is a *distribution* measure (e.g., racial/ethnic heterogeneity and economic inequality) rather than a measure of central tendency (e.g., poverty rate, median income, percent minorities), the effects would not necessarily scale up to the larger unit of analysis.

[1] It is worth point out that spatial effects from nearby neighborhoods will not affect city-level crime if they are linear effects, or if they only shift the location of crime. It is only if such spatial effects are nonlinear in some fashion (e.g., a polynomial relationship, or an interaction effect) that it would be necessary to account for the spatial distribution of the measure when explaining the amount of crime in the city.

This issue is particularly salient for our research question, as correctly identifying the unit of analysis is crucial with distribution variables. For example, if two subareas that each have low inequality (but one with high income households and one with low income households) are incorrectly combined into a single neighborhood, this combined "neighborhood" will appear to have a relatively high level of inequality. Therefore, understanding the geographic unit of analysis at which this mechanism operates is crucial. There is no a priori reason to assume that summing up the inequality levels of neighborhoods in a city will yield the level of inequality in the city overall. It is logically possible for a city to have a high degree of inequality overall, but virtually no inequality within its neighborhoods if there is complete segregation based on income level. Likewise, a city with a high rate of overall ethnic heterogeneity could in principle have completely homogeneous neighborhoods. Indeed, the voluminous empirical evidence of high levels of segregation in cities by race/ethnicity (Iceland and Nelson, 2008; Logan, Stults, and Farley, 2004; Massey and Denton, 1993) implies that there can be cities with little heterogeneity *within* neighborhoods, but high levels of heterogeneity *across* neighborhoods.

Considering theoretical mechanisms

Given this background, we next consider some of the theoretical mechanisms posited to explain the relationships between the racial/ethnic or economic composition and the level of crime, as well as their geographic scale. The most prominent theory employed to explain the relationship between racial/ethnic heterogeneity and crime rates is social disorganization theory. This model posits that higher levels of racial/ethnic heterogeneity reduce social interaction and therefore informal social control, leading to more crime (Hunter, 1995; Sampson and Groves, 1989; Shaw and McKay, 1942). The focus on social interactions implies that this operates at a relatively small geographic scale, generally at the level of neighborhoods. Another perspective adopts a political explanation, arguing that greater levels of racial/ethnic heterogeneity reduce

the community's political resolve to work together to address problems (Putnam, 2000). This implies a larger scale, such as a city.

There are several theoretical explanations for the relationship between economic inequality and crime. At least three models operate at a smaller geographic scale such as a neighborhood. One perspective builds on social disorganization theory and posits that inequality fosters social distance between households and reduces the provision of informal social control, leading to higher levels of crime (Hipp, 2007b; Hipp and Perrin, 2009). A second theory, routine activities theory, hypothesizes that a combination of potential targets (the wealthy) and motivated offenders (the poor), along with the absence of guardians will lead to more crime (Cohen and Felson, 1979). The third perspective, general strain theory, posits that inequality fosters a sense of injustice and subsequent increased violence on the part of those who are disadvantaged (Agnew, 1985; Agnew, 1999; Jasso, 1980). Additionally, at least two models posit that inequality at larger scales will increase crime rates. First, it is plausible that residents may not simply compare themselves to nearby residents when assessing their level of deprivation, but may compare themselves to residents throughout the broader community and therefore the effect of relative deprivation may operate at the geographic scale of the city (Merton, 1968). Second, inequality at the city level may reduce the solidarity and social capital of the community (Putnam, 1995), lowering the resolve to provide the political resources necessary to address crime when it becomes a problem in some neighborhoods (Bollen and Jackman, 1985; Tolbert, Lyson, and Irwin, 1998).

These competing theories positing that the distribution measures of inequality and racial/ethnic heterogeneity might operate at either the neighborhood level or the larger geographic level of cities or counties highlight the need to simultaneously account for the overall level of inequality (or heterogeneity) in a city and the degree of segregation (economic or racial)

across its neighborhoods in order to tease apart these competing perspectives. For example, if racial/ethnic heterogeneity is more important at the neighborhood level, then a measure of racial/ethnic segregation in the city will have a stronger effect on the amount of crime and its trajectory over time than will a measure of racial/ethnic heterogeneity. This is because reduced segregation brings different groups into contact in neighborhoods. In contrast, cities with higher levels of segregation would have neighborhoods with low heterogeneity. Although some studies have included a measure of the level of segregation in the city predicting crime along with a measure of percent nonwhite (Liska and Bellair, 1995) or percent African-American (Ousey, 1999), such an approach does not measure the effect of city level racial/ethnic *heterogeneity*. Similarly, studies including a segregation measure along with no other measures of racial/ethnic composition are not able to speak to this question (Shihadeh and Flynn, 1996). This has not been tested on cross-sectional data, much less longitudinal data.

The moderating effect of the inequality or heterogeneity context

A rarely considered possibility is that the racial/ethnic (or economic) composition of a city may have different effects on crime rates based on the geographic distribution of race/ethnicity (or economic resources) across the neighborhoods of the city. For example, economic class may be more salient to the residents in a city with more economic inequality. This builds on the notion of priming, which posits that individuals will be more focused on picking out a pattern of segregation when it is related to a dimension which is particularly pronounced for some reason (Margolis, 1987). Thus, a city with more overall inequality might foster a milieu of heightened injustice and competition between neighborhoods that could result in higher crime rates overall if it is accompanied by high levels of economic segregation. Whereas economic segregation into different neighborhoods of rich and poor households may bring about a sense of division and a lack of common interests between neighborhoods for cities

in general, this perception may be particularly heightened for the residents of cities in which class is particularly salient (due to high levels of inequality). This could happen for various reasons. It might occur if high inequality cities foster perceived competition between neighborhoods that are economically unequal, leading to crime events between neighborhoods. Or it might occur because these economic differences result in less cooperation in crime fighting activity among the neighborhoods in such a city, leading to more overall crime. As suggestive evidence, one study found that economic isolation of low-income blacks from other blacks led to higher crime rates (Shihadeh, 2009). The implication is that in cities with low levels of inequality, the differences in economic resources between neighborhoods would be less salient. In low inequality cities, the micro effect of inequality as postulated by routine activities and social disorganization theories may increase crime rates in the high inequality neighborhoods, but not crime across neighborhoods. A somewhat similar argument was made by Messner and Golden (1992) who suggested that inter-racial violence between blacks and whites may be heightened by segregation that occurs in the context of high overall inequality between the groups.

Likewise, the consequences of the geographic distribution of racial/ethnic groups across neighborhoods of a city may differ based on the degree to which race/ethnicity is salient in a city. We argue that race/ethnicity is a more salient issue to the residents in cities with higher levels of racial/ethnic heterogeneity. In the extreme, race would have little meaning to the residents of a completely homogeneous city. In a city in which race/ethnicity is more salient, how racial/ethnic groups are geographically distributed may have important implications for crime rates. This might lead to more crime events from residents in one neighborhood upon residents in other neighborhoods, or it might lead to more crime due to a lack of cooperation among neighborhoods in crime-fighting behavior. Note that this process of competition between neighborhoods could

co-occur with a process of higher crime in highly heterogeneous neighborhoods as specified earlier: thus, both processes could be occurring simultaneously. We are aware of no tests of these hypotheses.

Finally, the defended neighborhood theory has important implications for short-run changes in the racial/ethnic composition of neighborhoods (Suttles, 1972). In this short-run theory, neighborhood residents who create a common identity based on certain characteristics (such as race/ethnicity) may respond with violence to an influx of members of other groups. This implies that cities experiencing *decreasing* segregation (as groups move into neighborhoods together) would experience increasing rates of violence. We hypothesize that in cities in which race has more salience due to higher racial/ethnic heterogeneity, this effect may be exacerbated. The neighborhoods in such cities would therefore be expected to have particularly high levels of aggravated assaults in the short-run, given that inter-group violence frequently manifests itself as this type of violent crime (Green, Strolovitch, and Wong, 1998; Hipp, Tita, and Boggess, 2009; Lyons, 2007).

Data and methods

A challenge for studies viewing city trajectories of crime is the need to compare cities at similar "developmental" levels. In the child development literature, where trajectory models have frequently been used, researchers are aware of the need to compare children's trajectories at similar age levels. Analogously for cities, the issues facing older rust belt cities arguably are different from those facing newer sprawling cities in the south and west. This implies that it is not appropriate to simply compare the trajectories of cities from these different milieus over a specific period of time. Rather, it is more appropriate to compare a group of cities over the same time period that developed at a similar point in time. By adopting this approach, we are effectively controlling for other city characteristics in isolating the effect of economic and

racial/ethnic distribution across households and neighborhoods in cities for trajectories of crime rates.

We analyzed city-level data from the 1970-2000 period to understand crime trajectories of 352 cities in 29 counties in 14 areas that have experienced a booming population in the post-World War II era. The term "boomburbs" has been coined to describe these growing suburbs (Lang and Simmons, 2001). They face similar issues as all have experienced rapid growth of tract housing that sprawls at a relatively low density over large areas away from a regional center. The following areas are included in the study, with their population growth rate since the beginning of their boom period in parentheses: Atlanta (18.2); Dallas (3.6); Denver (9.0); Houston (4.2); Las Vegas (28.5); Miami: (4.6); Orange County, CA (13.2); Orlando (7.8); Phoenix (9.3); Riverside (9.1); San Bernardino (6.1); San Diego (5.1); Silicon Valley (Santa Clara) (5.8); Tampa/St. Pete (5.8).[2]

Dependent variables

We employed crime data from the Uniform Crime Reports of cities over the 1970-2000 period (downloaded from http://www.icpsr.umich.edu/NACJD/index.html). Our key outcome measures are crime rates of these cities for four key Type I crimes: aggravated assaults, robberies, burglaries, and motor vehicle thefts. These rates are computed per 10,000 residents and log transformed.[3]

Independent variables

[2] The counties are: Gwinnett, Cobb, and Clayton in the Atlanta area; Dallas, Collin, Denton, and Tarrant in the Dallas area; Adams, Arapahoe, Boulder, and Jefferson in the Denver area; Harris, Fort Bend, Montgomery, and Brazoria in the Houston area; Clark in the Las Vegas area; Dade, Broward, and Palm Beach in the Miami area; Orange County, CA; Orange in the Orlando area; Maricopa in the Phoenix area; Riverside County, CA; San Bernardino County, CA; San Diego County, CA; Santa Clara in the Silicon Valley area; Pinellas and Hillsborough in the Tampa/St Petersburg area.

[3] We do not include larcenies, as they are a more minor form of crime that is more vulnerable to under-reporting. We also do not include homicides, as the rareness of this type of crime resulted in estimation difficulties.

We used data from the U.S. decennial censuses to construct our key exogenous measures. At the city level, we computed the percentage of two key racial/ethnic minority groups: African-American and Latino. We constructed a measure of the racial/ethnic heterogeneity in the city with a Herfindahl index (Gibbs and Martin, 1962: 670) of five racial/ethnic groups (white, African American, Latino, Asian, and other race), which takes the following form:

$$H = 1 - \sum_{j=1}^{J} G_j^{\,2} \tag{1}$$

where G represents the proportion of the population of ethnic group *j* out of *J* ethnic groups.

We capture the economic composition with an index of concentrated disadvantage. This index is constructed by combining the following four variables with a principal components analysis (PCA): percent unemployed, percent of individuals below the poverty line, the average family income, and the percent single parent households. We created a factor score by multiplying the weights from the PCA by the value of the variables divided by their standard deviations; thus, although this factor score is measured in standard deviations, by not subtracting the mean at each time point (as is done in full standardization) we allow the mean of this factor score to vary over time (and this measure is perfectly correlated with the typical standardized factor score). We measured overall income inequality with the Gini coefficient, which is defined as:

$$G = \frac{2}{\mu n^2} \sum_{i=1}^{n} i x_i - \frac{n+1}{n} \tag{2}$$

where x_i is the household's income, μ is the mean income value, the households are arranged in ascending values indexed by *i*, up to *n* households in the sample. Because the data are binned (as income is coded into various ranges of values), we take this into account by utilizing the Pareto-

linear procedure (Aigner and Goldberger, 1970; Kakwani and Podder, 1976), which Nielsen and Alderson (1997) adapted from the U.S. Census Bureau[4]

We also constructed measures that account for the spatial distribution across the tracts in a city. To measure economic segregation in these cities, we computed the variance in logged median income across the tracts in a city (Lobmayer and Wilkinson, 2002). To capture the degree of racial/ethnic segregation in the city, we computed Theil's information theory measure (*H*) of multiple groups (Theil, 1967) for the five racial/ethnic groups in each city. To calculate this, we first computed the entropy score of the city (*E*) as:

$$E = \sum_{j=1}^{J} (\Pi_j) \ln[1/\Pi_j] \quad (3)$$

where Π_j represents the racial/ethnic group j's proportion of the entire city population, and ln is the natural log. We then computed the entropy score of each census tract (E_i) as:

$$E_i = \sum_{j=1}^{J} (\Pi_{ji}) \ln[1/\Pi_{ji}] \quad (4)$$

where Π_{ji} represents the racial/ethnic group j's proportion of tract *i*'s population. Using these two measures, we calculated Theil's H index (H) for the entire city as the weighted average deviation of each tract's entropy from the city-wide entropy:

$$H = \sum_{i-1}^{I} \left[\frac{t_i (E - E_i)}{ET} \right] \quad (5)$$

where t_i is the population of tract *i*, *T* is the city population, *E* is the city area entropy, E_i is tract *i*'s entropy of *I* tracts. This measure ranges from a value of 0 when all tracts contain the same composition as the overall city, to 1 when all areas contain a single group only, representing complete segregation.

[4] We used the prln04.exe program provided by Francois Nielsen at the following website: http://www.unc.edu/~nielsen/data/data.htm.

We included several additional city-level measures to minimize the possibility of spurious results. We captured residential stability by summing two variables (divided by their standard deviations): percent homeowners and percentage of households in the same unit five years previously. To capture increased crime possibilities of abandoned buildings, we included the percentage of residential units that are occupied. We accounted for crowding by including a measure of the percentage of households living in crowded conditions (defined as more than one person per room). We accounted for population size, as prior evidence suggests that larger cities will suffer from higher rates of crime (Baumer, Lauritsen, Rosenfeld, and Wright, 1998; Liska and Bellair, 1995; Ousey, 1999; Sampson, 1985; Sampson, 1987; Williams and Flewelling, 1988). Given that recent work has suggested that college towns exhibit a different trajectory of crime, we included a measure of the percentage of young residents (those aged 19 to 29) who attend college (McCall, Land, and Parker, 2010). To account for the fact that a few of these cities are somewhat older than the others in this sample of relatively young cities, we included a measure of the average age of the housing structures in the city.

To account for change over the decade, we computed differenced versions of the above measures. That is, we computed the difference in the measure at the beginning of the decade from the value at the end of the decade. The one exception is that instead of computing the change in racial/ethnic heterogeneity (which can have differential meaning whether the city is at the beginning or near the end of a transition period from one dominant group to another), we computed a measure of the racial/ethnic churning (EC) in the city (Pastor, Sadd, and Hipp, 2001). This captures the degree to which a city *k* undergoes racial/ethnic change during the decade by:

(6) $$EC_k = \sqrt{\sum_{1}^{J} (G_{jt} - G_{jt-1})^2}$$

where G represents the proportion of the population of racial/ethnic group *j* out of *J* racial/ethnic groups at time *t* and time *t-1*. This is a sum of squares of differences, and we take the square root to return it approximately to the original metric (Hipp, 2010). The summary statistics for the variables used in the analyses are presented in Table 1.

<<<Table 1 about here>>>

Methods

We use latent trajectory models to describe the trajectories of crime for the cities in the study from 1970 to 2000 (Bollen, Christ, and Hipp, 2003; Bollen and Curran, 2006). We estimate each decade separately as a multiple groups analysis, implying the following equation:

(7) $$y_{tjj(g)} = \alpha_{ij(g)} + \lambda_t \beta_{ij(g)} + \varepsilon_{tij(g)}$$

where y is the crime rate at time *t* in city *i* in county *j* in decade *(g)*, α is a random intercept that varies over cities, β is a random slope that varies over cities and has a λ effect on *y* (where lambda is structured to take into account time), and ε is a disturbance term for each city at each time point with an assumed normal distribution and mean of zero. Thus, this model is estimating a separate trajectory for each city, within each decade. Given the size of these cities, the logged crime rate distributions approximate a normal distribution, meaning that treating these as continuous measures rather than counts yield appropriate results. We found a linear model to provide a satisfactory approximation to these trajectories.[5]

The second step in the analyses after estimating the trajectories of crime in cities within counties is attempting to explain these differing trajectories. This uses characteristics of a city to

[5] In the LTM, the λ's can be structured to estimate various forms of trajectory: linear, logarithmic, or even unstructured (in which only the first and last time points are specified, and the remaining λ's are estimated) (for a more complete discussion of such modeling, see Bollen and Curran, 2006). Note that more elaborate nonlinear functions can be estimated—such as exponential or Gompertz curves—and additional random slope terms can be included to estimate cubic trajectories over time, higher order polynomials, or even a cosine function (Hipp, Bauer, Curran, and Bollen, 2004). However, we constrain our perspective to more simple polynomial models here because we do not hypothesize these trajectories heading to any particular asymptote.

explain the level of crime at one point in time, and changes in the characteristics of a city to explain the trajectory of crime over the following decade. This implies augmenting the previous equation to yield these second-level equations:

(8) $$\alpha_{ij(g)} = \kappa_{\alpha(g)} + \Gamma_{\alpha(g)}X_{ij(g)} + \zeta_{1ij(g)}$$

(9) $$\beta_{ij(g)} = \kappa_{\beta(g)} + \Gamma_{\Delta\beta(g)}\Delta X_{ij(g)} + \zeta_{2ij(g)}$$

where α and β are as defined before, the κ's represent the fixed intercepts for these random terms, X is a matrix of our city-level variables of interest which has $\Gamma_{\alpha(g)}$ effect on the random intercept in decade *(g)* (the amount of crime in the city at the beginning of the decade), which captures the long run relationship (or, equilibrium) between the construct and crime rates [6], ΔX is a matrix of the changes in our city-level variables of interest over the decade which has a $\Gamma_{\Delta\beta(g)}$ effect on the random slope (capturing the short-term change in crime in the city over the decade)[7], and the ζ's are disturbance terms with an assumed zero mean and normal distribution[8]. We tested and found that we could constrain these parameters to be equal over decades without a

[6] It is well-known that cross-sectional models capture equilibrium relationships. That is, although the model implies that changes in *x* lead to changes in *y* (over some suitably short time period), a cross-sectional model is only able to compare across units at a point in time. Thus, over a long period of time, many small changes in *x* would lead to higher levels of *y* (for a positive relationship), and this would be observed in a cross-sectional model. In contrast, the trajectory portion of the model captures the effect of the change in *x* over the decade affecting changes in *y* over the decade (short term change).

[7] Note that because of perfect collinearity, we cannot include both the X_{ij} and the ΔX_{ij} variables simultaneously in the model. We therefore estimated two separate models: the first uses the X_{ij} variables as predictors (in which we only report the coefficients from equation 8), and the second uses the ΔX_{ij} variables as the predictors in equation 9.

[8] Handling possible spatial autocorrelation in latent trajectory models is not straightforward. Nonetheless, although there are two possible forms of spatial effects—a spatial autocorrelation (or, error) effect, or a spatial lag effect—the consequences of these are not deleterious for our study. If spatial autocorrelation exists (in which there is an additional relationship between the *residuals* of neighboring tracts), only the standard errors are affected by ignoring this problem. Ignoring this often inflates the standard errors, suggesting that our test here is somewhat conservative, and that accounting for spatial autocorrelation—if it is indeed present—would simply strengthen the significance of the observed relationships (Anselin, 2002). If the data contain a spatial lag effect (in which the crime rate in one city increases crime in adjacent cities), then ignoring this would imply that we are capturing *total* effects of our predictors, rather than *direct* effects. That is, the presence of poverty in a city may be associated with higher levels of crime, and these higher levels of crime then impact the amount of crime in adjacent cities. This implies that the presence of poverty in one city *indirectly* increase the amount of crime in adjacent cities. Because our goal is not to parse apart these direct and indirect effects, we suggest that these total effects are of interest to academics and policy makers. Furthermore, there is limited spatial contiguity given that these cities come from 14 geographically dispersed areas.

decrement in model fit, implying that these effects are relatively constant over the decades of the period of study.[9] We also tested for possible nonlinear effects for inequality and segregation by including polynomials of these measures and retained them whenever statistically significant. After grand-mean centering the data, there was no evidence of collinearity problems as all variance inflation factors were less than 10.

Results

We first briefly describe the results for the main effects of our measures in these models, before turning to the key questions of possible interaction effects. Regarding the effects of the racial/ethnic composition, we see that cities with a higher proportion of African Americans have higher levels of the two violent crimes (1.034 for aggravated assaults and .423 for robbery) cross-sectionally (the first and third columns of Table 2 predicting the random intercept). Thus, the long run equilibrium is higher levels of violent crimes (but not property crimes) for cities with a higher percentage of African Americans. We also see evidence that an increase in the percentage African American over the decade results in a steeper increase in the robbery (.021) and burglary (.113) rates (but not the other two types of crime), as seen in columns 4 and 6 in Table 2. Although we see no evidence that cities with more racial/ethnic heterogeneity have higher levels of crime in the long run equilibrium (based on the nonsignificant effects predicting the random intercepts), we do see evidence that racial/ethnic churning during the decade results in greater increases in the two types of violent crime. The effects for Latinos are nearly nonexistent, as the only significant effect we detect is that cities with more Latinos have higher levels of motor vehicle thefts in the long run equilibrium (.390). Finally, the effects for racial/ethnic segregation are quite strong. Cities with higher levels of racial/ethnic segregation

[9] This was accomplished by estimating models with and without constraining the coefficients in the Γ matrices to be equal over all three decades. Given our large sample size, it is more informative to compare these models using the Bayesian Information Criterion (BIC). The results showed that for nearly all of the models, a more satisfactory BIC value was obtained when constraining these coefficients equal over the decades. That is, the parsimony in the model from estimating fewer coefficients outweighed any gain in absolute model fit.

have higher robbery, burglary and motor vehicle theft rates (see columns 3, 5 and 7 in Table 3). The short-run effect is the opposite as increasing racial/ethnic segregation over the decade results in decreasing aggravated assault, robbery, and burglary rates. This short-run effect for aggravated assaults is consistent with the defended neighborhood hypothesis that decreasing segregation will lead to more assaults as it brings groups into contact in neighborhoods.

<<<Table 2 about here>>>

The measures of economic resources and inequality show weak effects. Higher levels of concentrated disadvantage lead to higher aggravated assault rates in the long run equilibrium (6.333), and increasing levels of concentrated disadvantage over the decade are accompanied by increasing burglary and motor vehicle theft rates (columns 6 and 8). We see that cities undergoing increasing inequality experience increasing aggravated assault and motor vehicle theft rates during the same decade. We also see a strong nonlinear relationship between inequality and burglary rates in the long run equilibrium: Figure 1 shows that although there are minimal differences in the burglary rate among cities with below average levels of inequality, burglary rates sharply increase for cities with higher levels of inequality.

<<<Figure 1 about here>>>

In the long run equilibrium, cities with higher levels of economic segregation have higher aggravated assault rates (column 1 of Table 2), but no other significant effects. It is worth noting that when we estimated ancillary models that did not include economic or racial/ethnic segregation, in the long run equilibrium income inequality showed strong nonlinearly increasing effects on robbery rates. Thus, accounting for the geographic distribution of economic resources throughout the community changed our interpretation.

Interaction of income segregation and inequality

We next turn to a key focus of this study: to what extent are the measures of income segregation and racial/ethnic segregation moderated by the level of racial/ethnic heterogeneity or income inequality in the city? We first focus on the question of the interaction between the level of inequality in the city and the level of economic segregation. We present the results as figures to aid in interpretation. We plot each of these variables at their mean values, and at values one standard deviation above and below the mean. We do not plot the points for cities with low inequality and high economic segregation, or cities with high inequality and low economic segregation, given that such cities were rarely observed in our sample (the average correlation between inequality and economic segregation over these waves was .39).

There are strong interaction effects for these economic measures. In the model predicting aggravated assault, we see in Figure 2 that for cities with low levels of inequality, income segregation has little effect on aggravated assault rates (the left side of the Figure). Thus, segregating households by their income level does not increase aggravated assault rates in cities with relatively low levels of inequality. On the other hand, in cities with average levels of inequality, aggravated assault rates increase as the degree of economic segregation increases. This effect is accentuated in cities with high levels of inequality: cities with very high levels of inequality and economic segregation—walled off fortresses of wealth—will have the highest assault rates of any of these combinations.

<<<Figure 2 about here>>>

Turning to the results for robbery rates, we see that at low levels of inequality economic segregation actually reduces the robbery rate in the city overall, as seen in Figure 3. Thus, the cities with the lowest robbery rates are those with relatively low inequality and average levels of economic segregation. For cities with average levels of inequality, economic segregation has no effect on the robbery rate. On the other hand, the effect reverses in high inequality cities, as

increasing levels of economic segregation increase the robbery rate. The cities with the highest robbery rates are those with high levels of both inequality and economic segregation—again, the walled off fortresses of wealth.

<<<Figure 3 about here>>>

Turning to our two property crime types, we see in Figure 4 for burglary rates and in Figure 5 for motor vehicle theft rates that economic segregation also reduces these crime types in cities with very low levels of inequality. Thus, burglary rates tend to be highest in cities with low levels of economic segregation, regardless of the level of inequality. This is consistent with routine activities theory as such cities are more likely to combine households of different economic levels in the same neighborhood. The one exception is that in cities with high levels of inequality, the level of economic segregation makes little difference. The pattern for motor vehicle thefts is similar to that for robberies: this type of crime is highest in two extreme types of cities: those with low levels of economic segregation and inequality, and those with high levels of economic segregation and inequality, as seen in Figure 5.

<<<Figures 4 and 5 about here>>>

Interaction of racial/ethnic segregation and racial/ethnic heterogeneity

We next ask whether the effect of racial/ethnic segregation in the city is moderated by the level of heterogeneity in the city. In these models, we do not plot the values for cities with low levels of racial/ethnic heterogeneity and high levels of racial/ethnic segregation as they were essentially not empirically present in our data (the average correlation between racial/ethnic heterogeneity and segregation was .36 over these years). We see a similar pattern to that observed for inequality and economic segregation. In Figure 6 we see that segregation actually reduces the aggravated assault rate when it occurs in a city with a relatively low level of racial/ethnic heterogeneity. In fact, cities with the lowest aggravated assault rates are those with

very low heterogeneity, but average levels of segregation for these small numbers of minority members. In contrast, segregation has a strong positive effect on assault rates in cities with high levels of racial/ethnic heterogeneity. Thus, racial/ethnic mixing within neighborhoods seems to be least deleterious in cities with a great amount of heterogeneity overall of racial/ethnic groups.

<<<Figure 6 about here>>>

The general pattern holds for robbery rates, as illustrated in Figure 7. Whereas segregation actually reduces robbery rates in cities with low levels of racial/ethnic heterogeneity, segregation increases robbery rates in cities with average levels of heterogeneity. In high heterogeneity cities the degree of segregation is crucial: such cities with quite mixed neighborhoods will have the lowest robbery rates, whereas those with high levels of segregation will have the highest robbery rates.

<<<Figure 7 about here>>>

The property crimes of burglary and motor vehicle theft rates show very similar patterns to each other. We see in Figure 8 for burglaries that the level of segregation has very little effect on the burglary rate in cities with low levels of heterogeneity. However, in cities with average or high levels of heterogeneity, increasing levels of segregation result in increasing rates of burglaries or motor vehicle thefts. Thus, for both burglaries and motor vehicle thefts, cities with high levels of heterogeneity accompanied by high levels of segregation have the highest rates of each of these crime types. Furthermore, each of these crime types can be ameliorated considerably in high heterogeneity cities if there is a high degree of ethnic mixing within the neighborhoods of these cities.

<<<Figures 8 and 9 about here>>>

Finally, we tested our hypothesis regarding the defended neighborhood theory with an interaction between the increase in racial/ethnic segregation and racial/ethnic churning during the

decade. Consistent with our expectations, Figure 10 shows that although increasing segregation always results in falling assault rates over the decade, this negative effect is particularly pronounced in cities undergoing high levels of ethnic churning. Stated differently, the cities experiencing the greatest increases in assault rates are those undergoing large levels of churning in which that churning is bringing together in neighborhoods members of different racial/ethnic groups (and therefore reducing segregation—see the right hand side of this figure). This is consistent with prior research in the defended neighborhoods tradition arguing that such inflows of different racial/ethnic group members can lead to a violent response of the part of the residents currently living in the neighborhood (Green, Strolovitch, and Wong, 1998; Hipp, Tita, and Boggess, 2009).

<<<Figure 10 about here>>>

We briefly note the effects for our control variables. There is some evidence consistent with the protective effect of residential stability, as the long run equilibrium shows that cities with more stability have lower rates of all four crime types (thought aggravated assault is not significant), and the short-run effect shows that cities with increasing residential stability experience a simultaneous drop in the robbery and burglary rates during that decade. We see that higher vacancy rates lead to higher assault and burglary rates in the long run equilibrium. Cities with more crowding have higher aggravated assault and robbery rates in the long run equilibrium, but a falling burglary rate in a short-term change. As expected, cities with more college students have lower assault rates, and they have somewhat lower burglary rates both in the short-term and in the long run equilibrium.

Conclusion

This study has shown the importance of simultaneously considering both the micro and the macro social context when comparing crime rates across cities. We have demonstrated that it

is not enough to simply focus on neighborhoods within a particular city, nor can scholars simply create ecological measures at the level of the city when assessing across-city crime comparisons. Instead, it is necessary to focus on both simultaneously. Although the spatial distribution of certain social characteristics has important consequences for how crime is distributed across the neighborhoods of a city, it is also the case that the distribution of certain social characteristics affects the total amount of crime in cities. These social phenomena are not simply shifting crime about the neighborhoods of a city, but are impacting the overall amount of crime in the city.

We showed that the economic resources and the racial/ethnic composition of the city matter in their aggregation at the city level and how they are distributed across the neighborhoods of a city in this study of rapidly growing cities since World War II. It is interesting to note that in our models not taking into account these interactions, racial/ethnic heterogeneity in the city had little effect on long run crime rates. However, racial/ethnic heterogeneity had important contextual effects: this study was the first to show that there are important interactions between racial/ethnic heterogeneity and segregation. Whereas the consistent findings of the neighborhoods and crime literature that racial/ethnic heterogeneity leads to more crime would imply that segregation should actually reduce the amount of crime (since it reduces heterogeneity within the neighborhoods of the city), this was not always the case. In fact, this segregation had extremely different effects depending on whether it occurred within the context of a city with a high level of racial/ethnic heterogeneity or a relatively homogeneous city. We argued that in cities with high levels of racial/ethnic heterogeneity, race becomes salient and therefore is particularly notable when it results in segregation of groups into separate neighborhoods (Wilson, 1987), and thus leads to higher overall levels of crime.

We found analogous effects for the distribution of economic resources within the city as a whole and how they are spatially distributed across the neighborhoods of the city. It is worth

highlighting that in ancillary models not taking into account economic segregation, inequality appeared to have a nonlinear positive effect on robbery rates. However, this effect greatly diminished when accounting for the geographic distribution of economic resources across the neighborhoods of the city. Whereas some prior research has found that neighborhoods with higher levels of inequality have higher levels of crime, we found that cities with more economic *segregation* have higher levels of crime. This is surprising given that cities with high levels of economic segregation in fact have neighborhoods with lower levels of inequality, which should lead to lower crime rates within those neighborhoods which would then aggregate up to lower crime rates for the city as a whole. Furthermore, we found an important interaction which has never before been detected in the literature: cities with both high inequality and high economic segregation have higher overall rates of crime. We argued that the high level of inequality in such cities makes economic differences particularly salient to residents, which may lead to a perception of walled-off neighborhoods with strikingly different economic resources. We also found that inequality within neighborhoods appears to increase crime the most when it occurs in cities with overall low levels of inequality. We have argued that these results may be explained by two simultaneous processes: one in which the social differences fostered by inequality within neighborhoods as postulated by social distance theory increase neighborhood crime, and one characterized by the micro-macro process we described leading to crime between neighborhoods.

These are paradoxical findings that are unique in the literature and demand new theorizing. Exactly why do we observe such patterns? We have suggested that racial/ethnic differences and economic differences become most salient within cities in which these differences are the greatest. In such instances, these structural characteristics may lead to awareness of differences across neighborhoods, which may lead to increasing crime rates. Clearly, this is speculative given our inability to measure the actual processes within

neighborhoods. Nonetheless, the pattern of results is intriguing and suggests that future research will want to test these implications more directly. We point out that it may not be enough to use multilevel data of neighborhoods nested within cities, as it may also be necessary to know the neighborhood of the offender and the victim to assess whether this increases *across-neighborhood* crime (Bernasco and Block, 2009).

We acknowledge some limitations to our study. First, as just mentioned, we were unable to actually test these processes with individual or neighborhood-level data. Although obtaining multilevel data of neighborhoods nested within multiple cities is difficult, this will be necessary as one approach to more carefully explore the implications of these findings. Second, our study focused on cities that have grown dramatically in the post World War II era. An advantage of our approach was capturing cities that experienced population growth during the same time period. However, a limitation is that we cannot be certain that these important contextual effects of inequality and heterogeneity will indeed be present in samples of cities at a different stage of their lifecycle. Future research will be necessary to assess whether this is indeed the case. Third, beyond measuring these characteristics at the neighborhood level, it would also be preferable to actually measure the mechanisms hypothesized to bring about these effects. Again, data limitations make measuring such processes particularly challenging. Nonetheless, the pattern of results we have detected suggest that future research attempting to measure such mechanisms in a smaller sample of areas might be fruitful. Finally, any study using longitudinal UCR data is subject to the effect of reporting changes over time (Lynch and Addington, 2007). It is well-known that the reporting of crime by police units to the UCR is a social process that produces these numbers and reduces their validity as measures of actual crime rates. It is important to keep these social processes in mind; nonetheless, we know of no reason why cities exhibiting

these particular patterns of inequality or heterogeneity and segregation would be likely to over-report their levels of crime, or to systematically change such reporting over time.

To conclude, our findings suggest the need for both a broader, as well as a narrower, lens. It is not enough for researchers to simply focus on what explains the distribution of crime across the spatial landscape of a city. Although such studies are clearly useful in understanding why some neighborhoods have higher crime rates than others, it is important to be able to distinguish between instances in which the spatial distribution of certain characteristics affects the distribution of crime—that is, act as crime attractors—and other instances in which they actually affect the overall amount of crime in the city—that is, act as crime generators (Brantingham and Brantingham, 1984). In the fast-growing cities of this study, it appears that high overall inequality and high overall racial/ethnic heterogeneity make these salient dimensions for citizens. In these instances, isolating citizens into neighborhoods based on their race or economic resources appears to have the most explosive effect on the overall level of crime.

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Tables and Figures

Table 1. Summary statistics for variables used in analyses

	1970		1980		1990	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Outcome variables						
Aggravated assault rate (avg over decade)	26.1	35.0	36.8	42.9	41.5	41.6
Robbery rate (avg over decade)	12.7	15.4	17.6	22.2	17.5	21.5
Burglary rate (avg over decade)	164.7	97.5	173.8	98.7	118.9	75.6
Motor vehicle theft rate (avg over decade)	36.7	27.5	50.0	41.8	60.1	50.9
Independent variables						
Percent black	6.67	11.24	6.60	11.73	8.53	12.74
Percent Latino	7.75	9.81	10.23	12.76	14.41	15.38
Racial/ethnic heterogeneity	22.81	16.51	26.77	17.82	34.67	18.71
Racial/ethnic segregation	0.15	0.20	0.10	0.15	0.08	0.11
Concentrated disadvantage	0.84	1.03	0.88	0.92	1.09	0.91
Income inequality	34.08	5.75	34.35	5.80	36.27	5.82
Income segregation	0.29	0.17	0.24	0.13	0.25	0.13
Residential stability	7.61	1.22	6.98	1.30	6.95	1.38
Percent occupied units	93.62	4.62	90.85	8.17	87.77	10.60
Percent crowded households	3.36	1.89	4.39	4.75	6.38	6.57
Percent enrolled in college	18.35	12.12	26.67	15.54	39.52	17.69
Age of buildings	14.11	4.55	16.68	5.41	18.68	6.71
Population	73,897	163,300	69,833	167,053	84,555	195,173

N = 352 cities. Crime rates are expressed per 10,000 persons and log transformed

Table 2. Latent Trajectory Models of four types of crime over three decades: 1970-80, 1980-90, and 1990-2000

	Aggravated assault rate		Robbery rate		Burglary rate		Motor veh
	(1)	(2)	(5)	(4)	(5)	(6)	(7)
	Intercept	Slope	Intercept	Slope	Intercept	Slope	Intercept
Percent black	1.034 **	-0.037 †	0.423 **	0.021 **	0.609 †	0.113 *	0.141
	(6.34)	-(1.75)	(5.79)	(2.67)	(1.74)	(2.52)	(1.02)
Percent Latino	-0.099	-0.028	0.070	0.014 †	0.008	0.016	0.390 **
	-(0.57)	-(1.26)	(0.93)	(1.78)	(0.02)	(0.35)	(2.58)
Racial/ethnic heterogeneity	-0.087	0.059 **	-0.115 *	0.013 **	0.284	0.059 *	0.017
	-(0.77)	(4.76)	-(2.52)	(2.82)	(1.24)	(2.12)	(0.19)
Racial/ethnic segregation	6.075	-8.110 **	16.473 **	-1.760 **	156.017 **	-16.487 **	22.351 **
	(0.53)	-(4.91)	(3.45)	-(3.12)	(6.01)	-(3.84)	(2.58)
Concentrated disadvantage	6.333 **	0.113	0.136	0.024	4.700	0.531 **	0.421
	(3.28)	(1.24)	(0.19)	(0.72)	(1.11)	(2.86)	(0.29)
Income inequality	0.841	0.056 *	1.320	0.011	11.373 *	-0.010	0.076
	(0.36)	(2.37)	(1.42)	(1.26)	(2.26)	-(0.21)	(0.04)
Income inequality squared					10.381 **		
					(4.18)		
Income segregation	4.291 **	0.065	0.522	0.029	-2.549	0.046	-0.610
	(3.92)	(0.79)	(1.31)	(1.04)	-(0.99)	(0.22)	-(0.81)

continued

Residential stability	-1.096	-0.185 †	-0.887 *	-0.121 **	-6.062 **	-0.842 **	-3.142 **
	-(1.06)	-(1.72)	-(2.11)	-(3.29)	-(2.70)	-(3.29)	-(3.87)
Percent occupied units	-0.583 **	-0.003	0.015	-0.005	-1.774 **	0.050	-0.130
	-(4.13)	-(0.22)	(0.24)	-(0.97)	-(5.89)	(1.37)	-(1.15)
Percent crowded households	0.812 *	0.040	0.387 *	-0.011	0.911	-0.223 **	-0.027
	(2.02)	(1.14)	(2.53)	-(0.93)	(1.09)	-(2.94)	-(0.09)
Percent enrolled in college	-0.424 **	-0.011	-0.029	0.005	-0.347 †	-0.040 †	-0.055
	-(4.64)	-(0.96)	-(0.75)	(1.07)	-(1.74)	-(1.67)	-(0.75)
Age of buildings	0.650 **	-0.070 *	0.105	-0.010	0.619	-0.072	0.163
	(3.14)	-(2.15)	(1.22)	-(0.87)	(1.41)	-(1.16)	(0.90)
Population	-0.057	-0.014	0.117 †	0.025 *	-0.476 †	0.087	0.026
	-(0.46)	-(0.43)	(1.78)	(2.20)	-(1.69)	(1.48)	(0.19)

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). T-values in parentheses. N = 352 cities. Crime rates are per 10,000 persons, and log transformed. Co represent the effects of the measure on the latent intercept and slope, respectively, for each of the three decades in the latent trajectory model (constrained equal over decades)*

Figure 1. Burglary rate at one time point, predicted by inequality

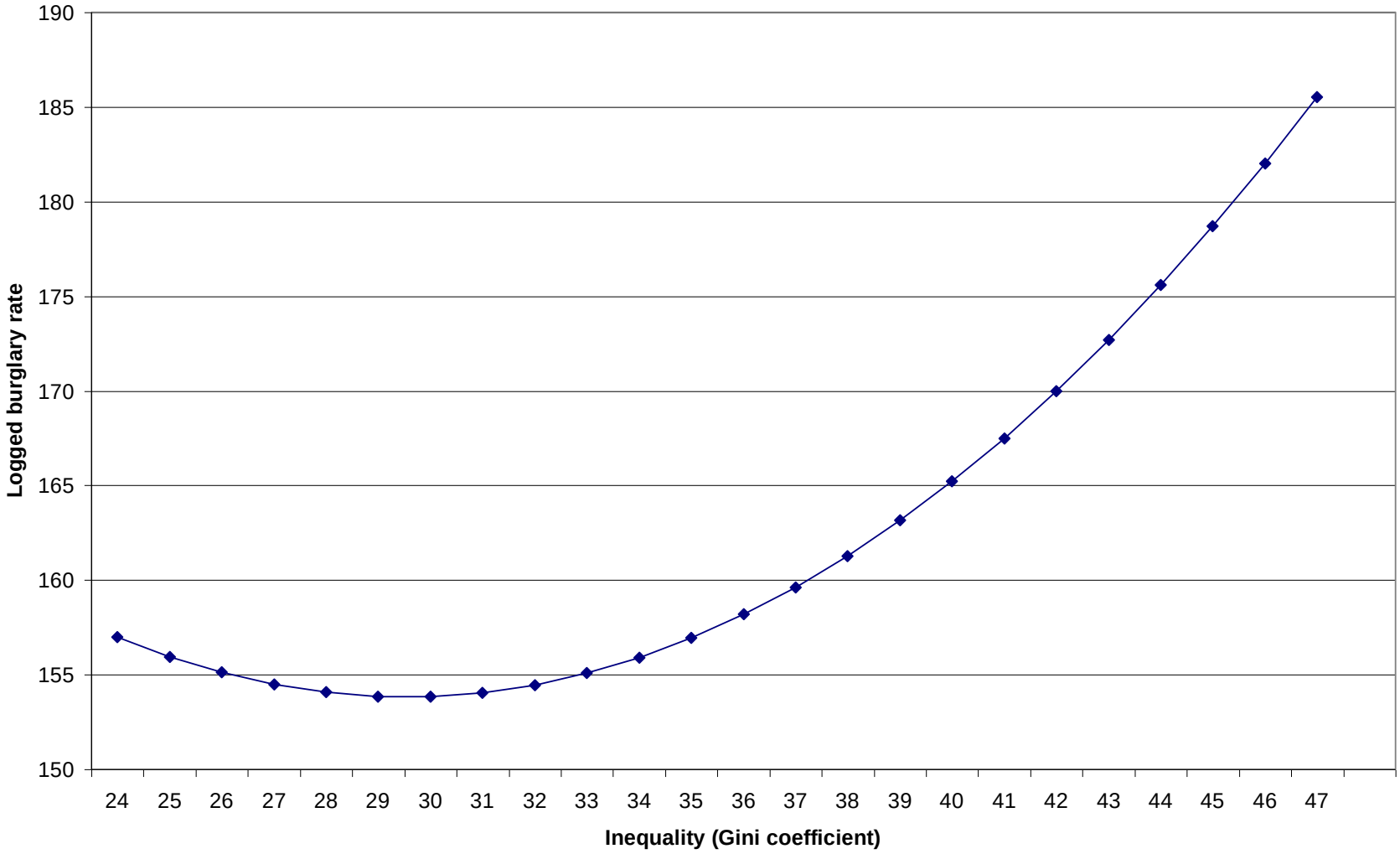

Figure 2. Aggravated assault rates predicted by interaction of inequality and economic segregation

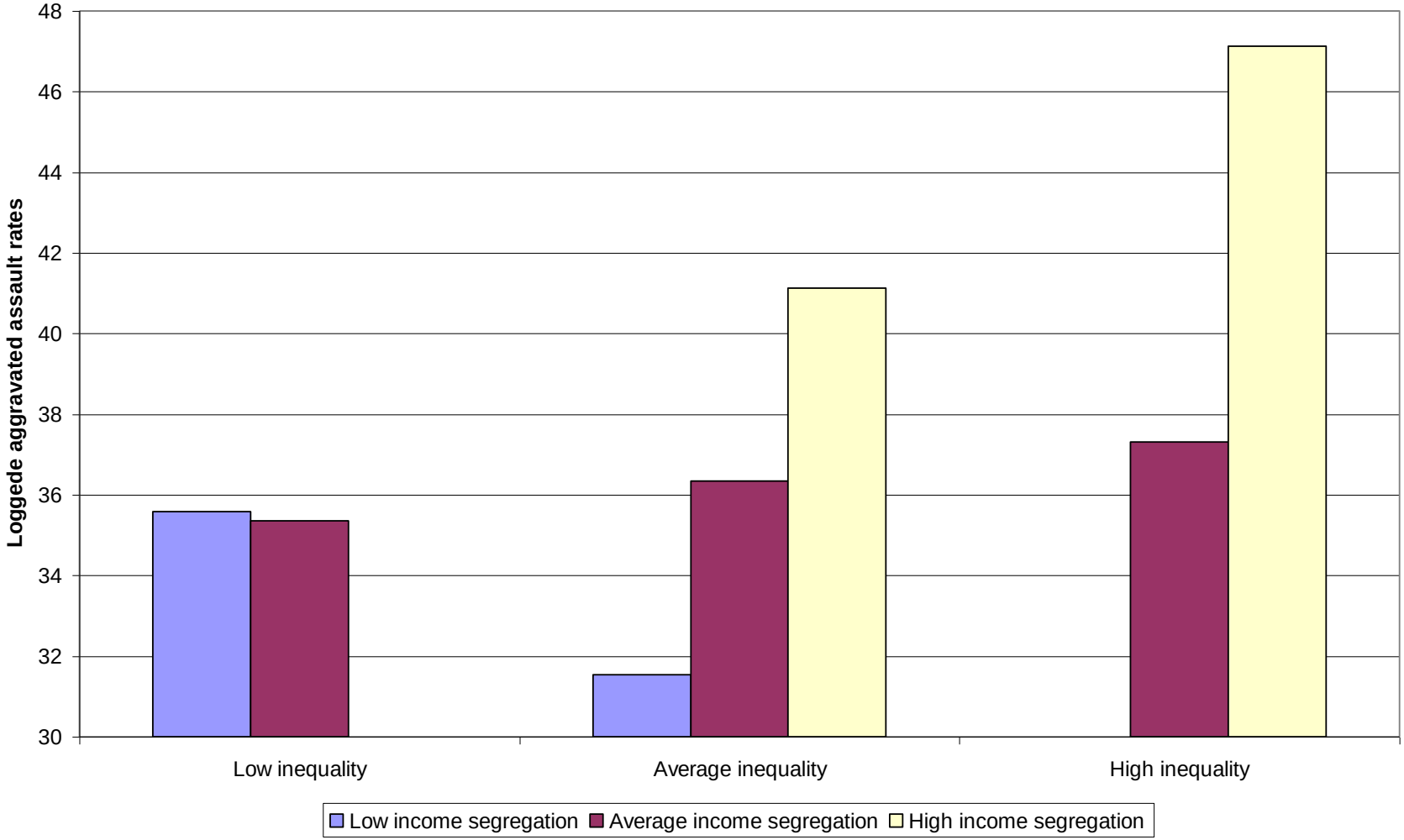

Figure 3. Robbery rates predicted by interaction of inequality and economic segregation

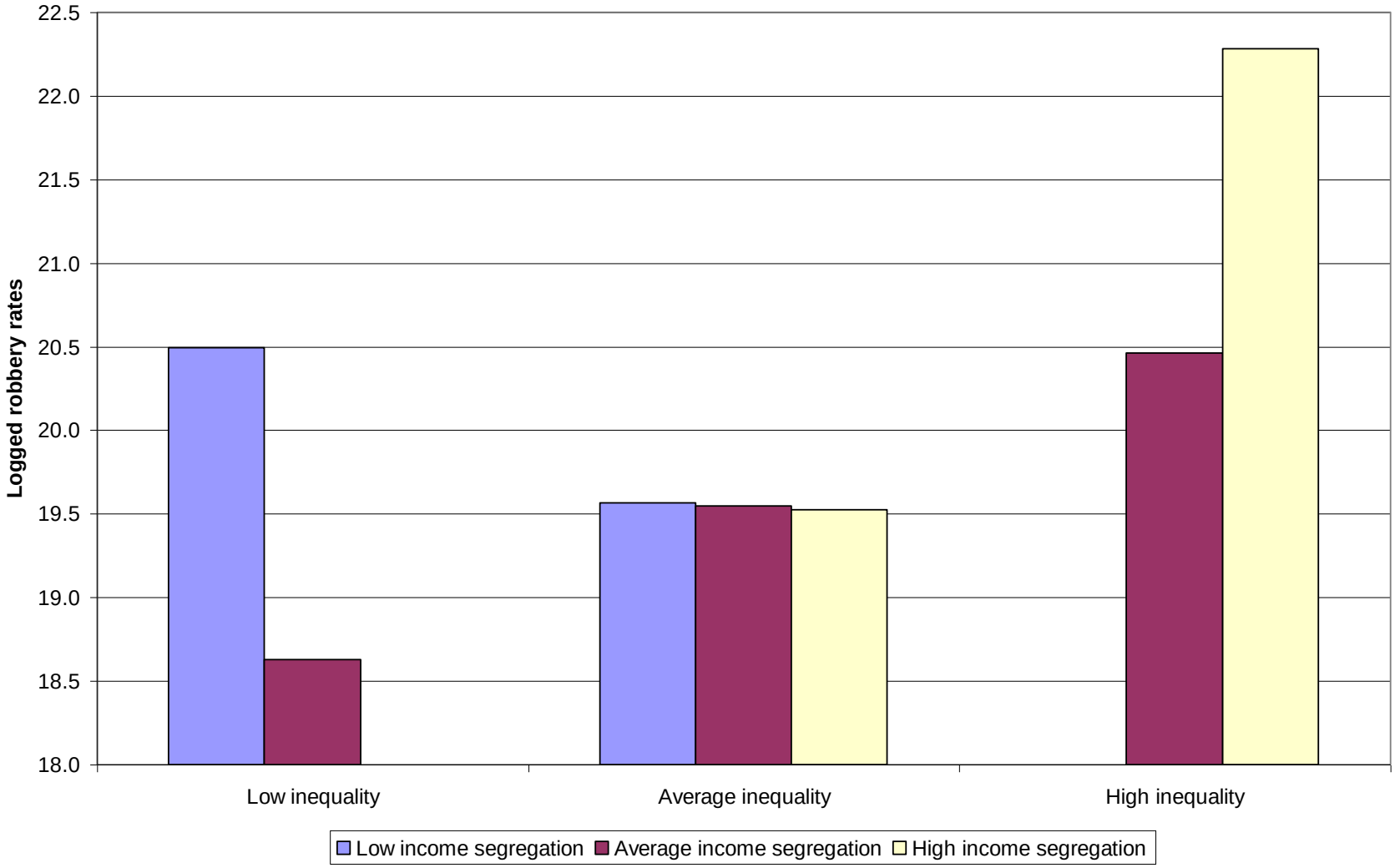

Figure 4. Burglary rates predicted by interaction of inequality and economic segregation

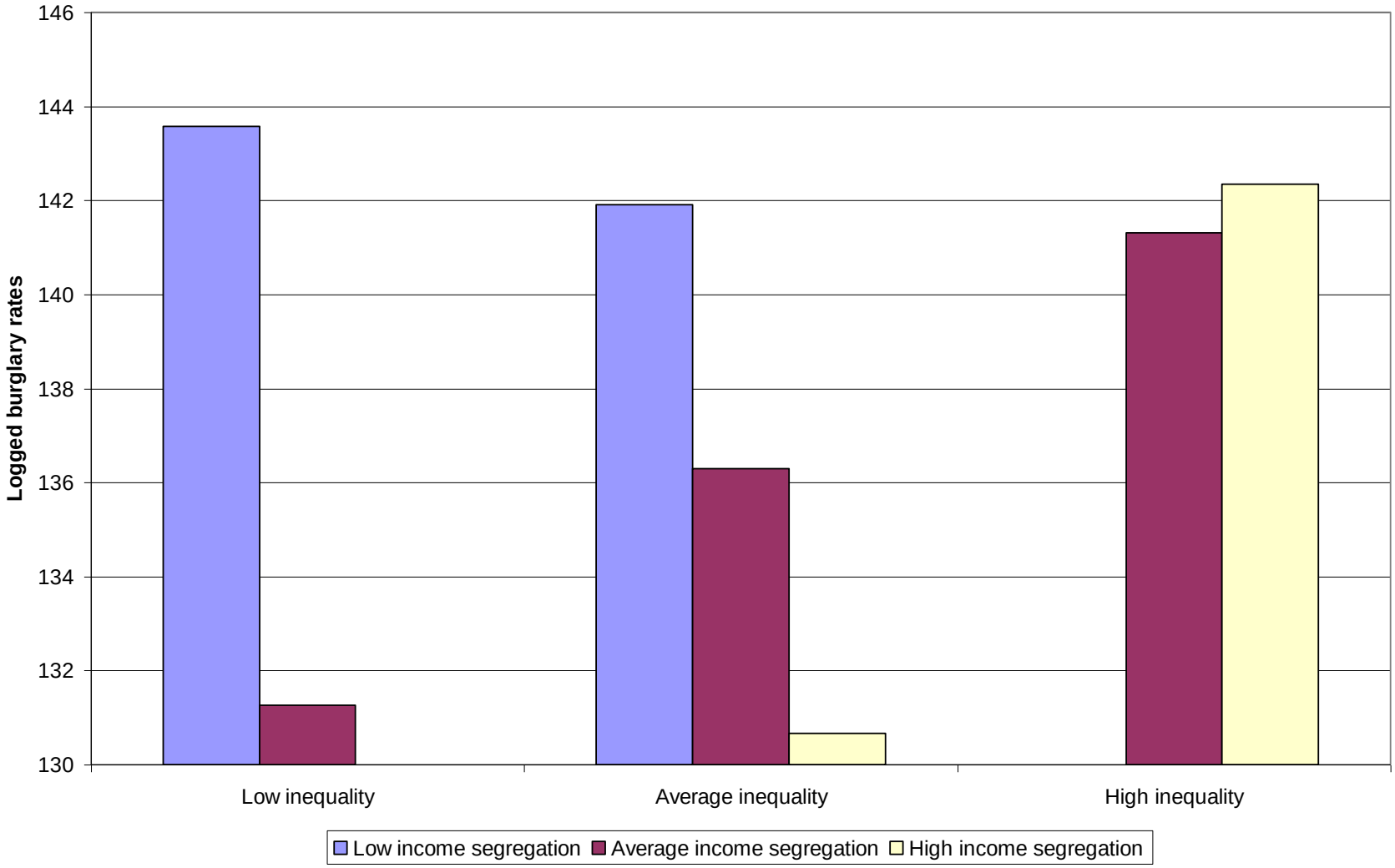

Figure 5. Motor vehicle theft rates predicted by interaction of inequality and economic segregation

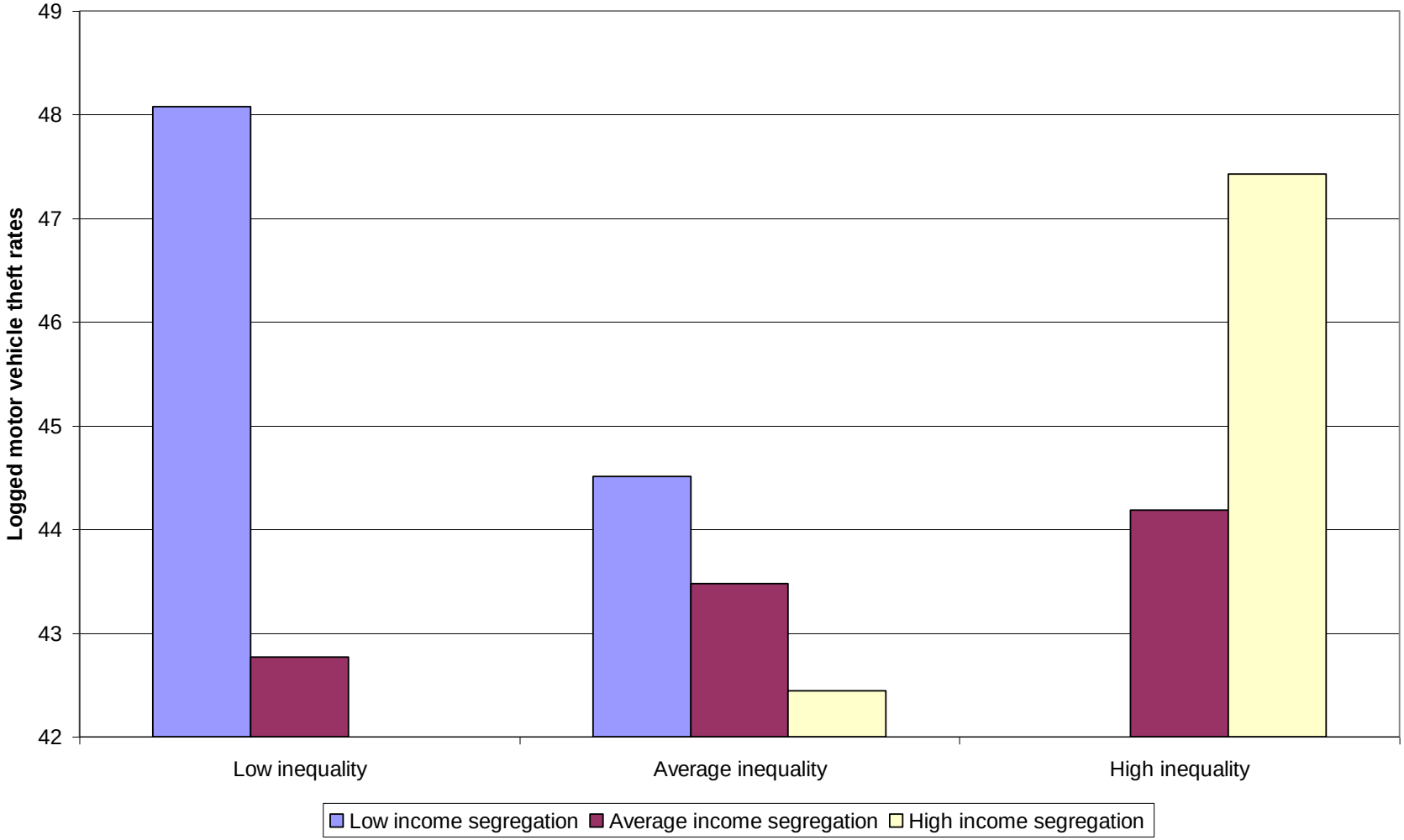

Figure 6. Aggravated assault rates predicted by interaction of racial/ethnic heterogeneity and racial/ethnic segregation

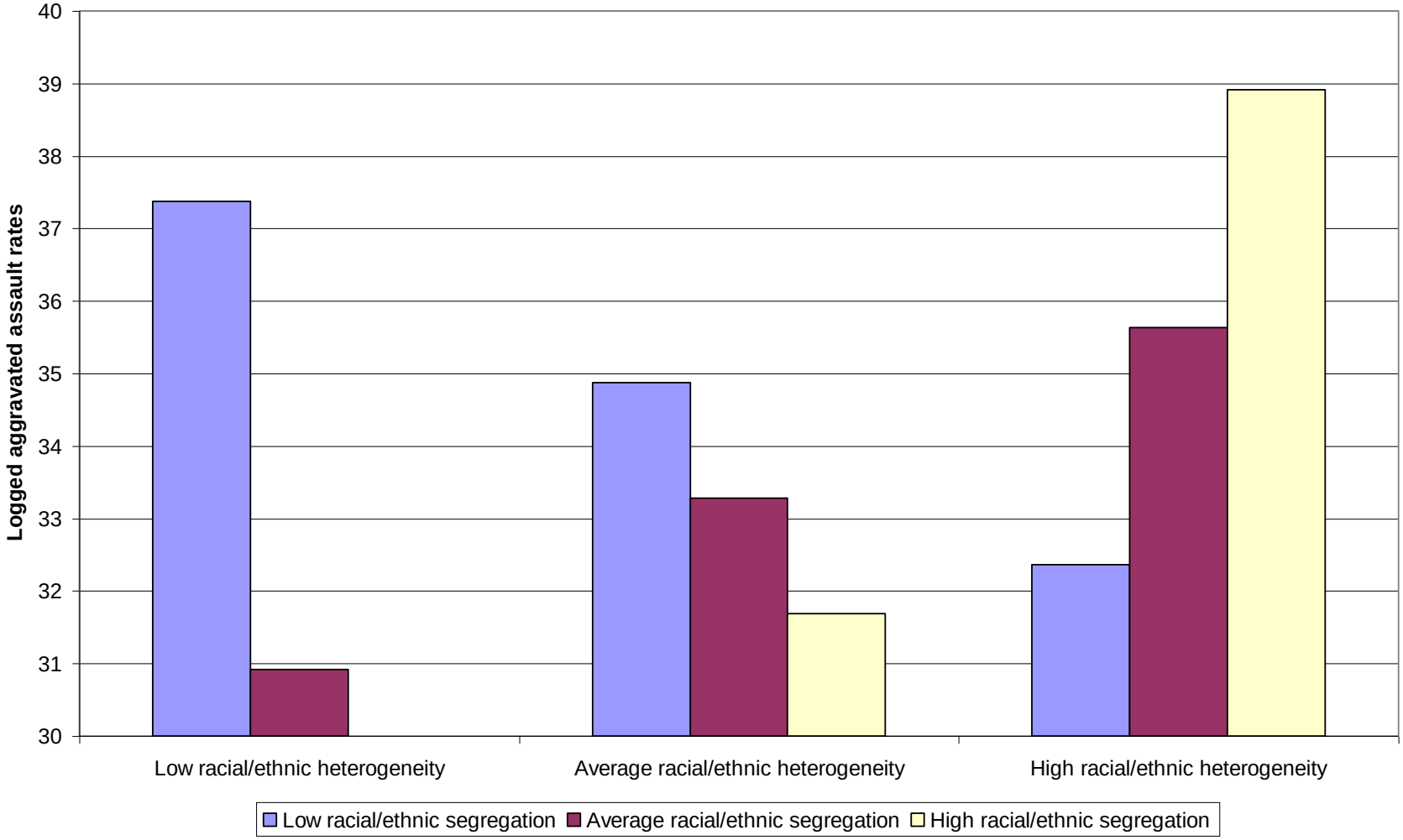

Figure 7. Robbery rates predicted by interaction of racial/ethnic heterogeneity and racial/ethnic segregation

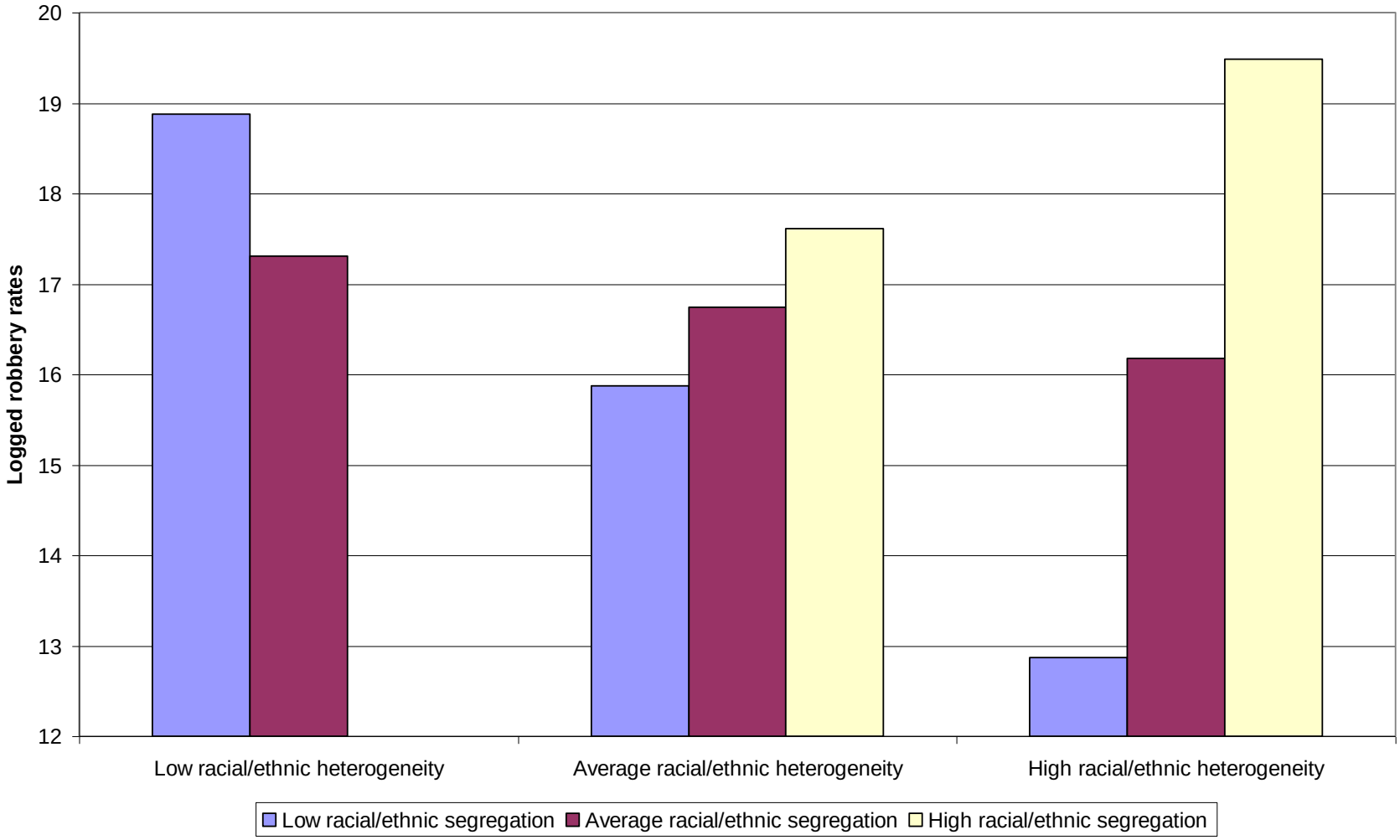

Figure 8. Burglary rates predicted by interaction of racial/ethnic heterogeneity and racial/ethnic segregation

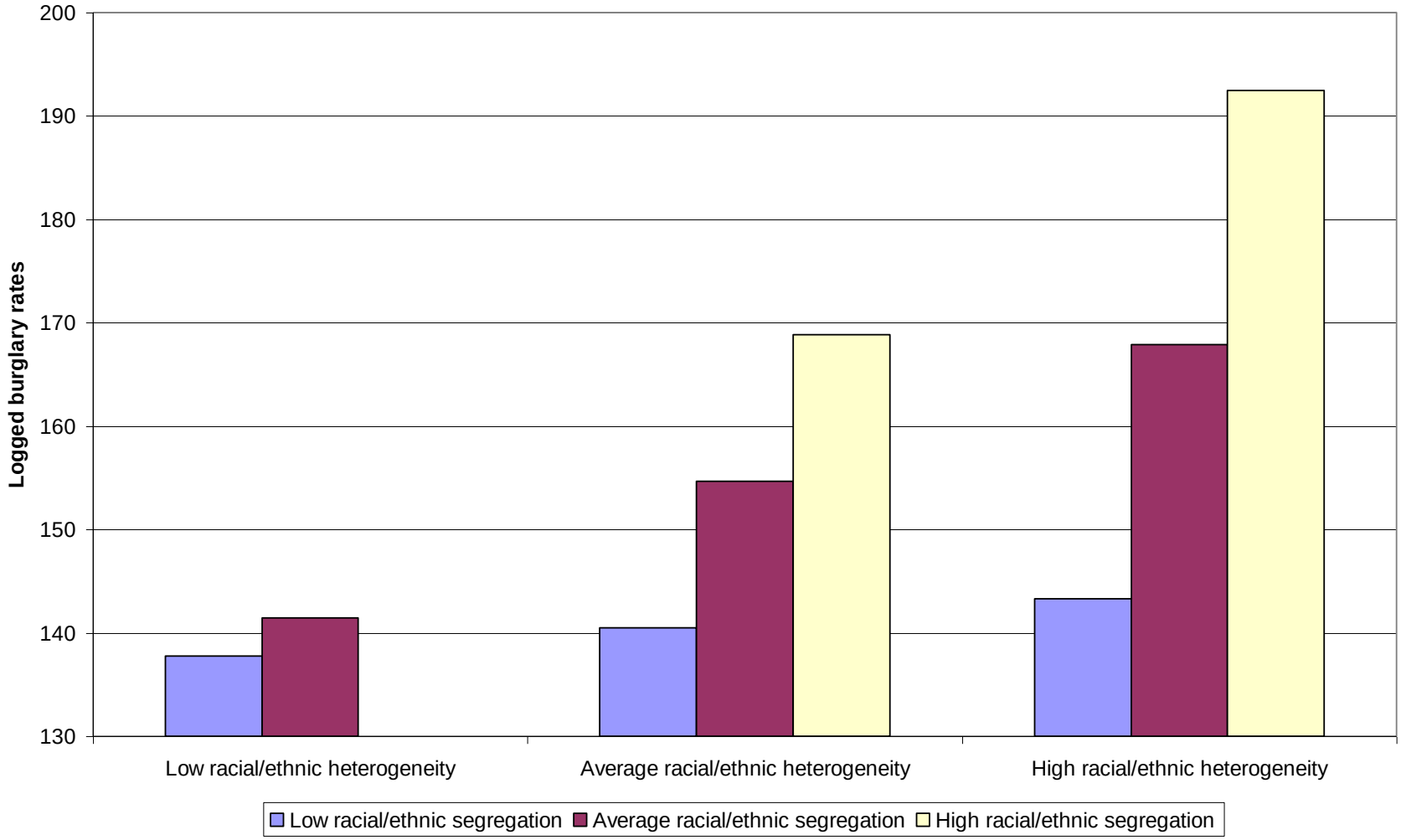

Figure 9. Motor vehicle theft rates predicted by interaction of racial/ethnic heterogeneity and racial/ethnic segregation

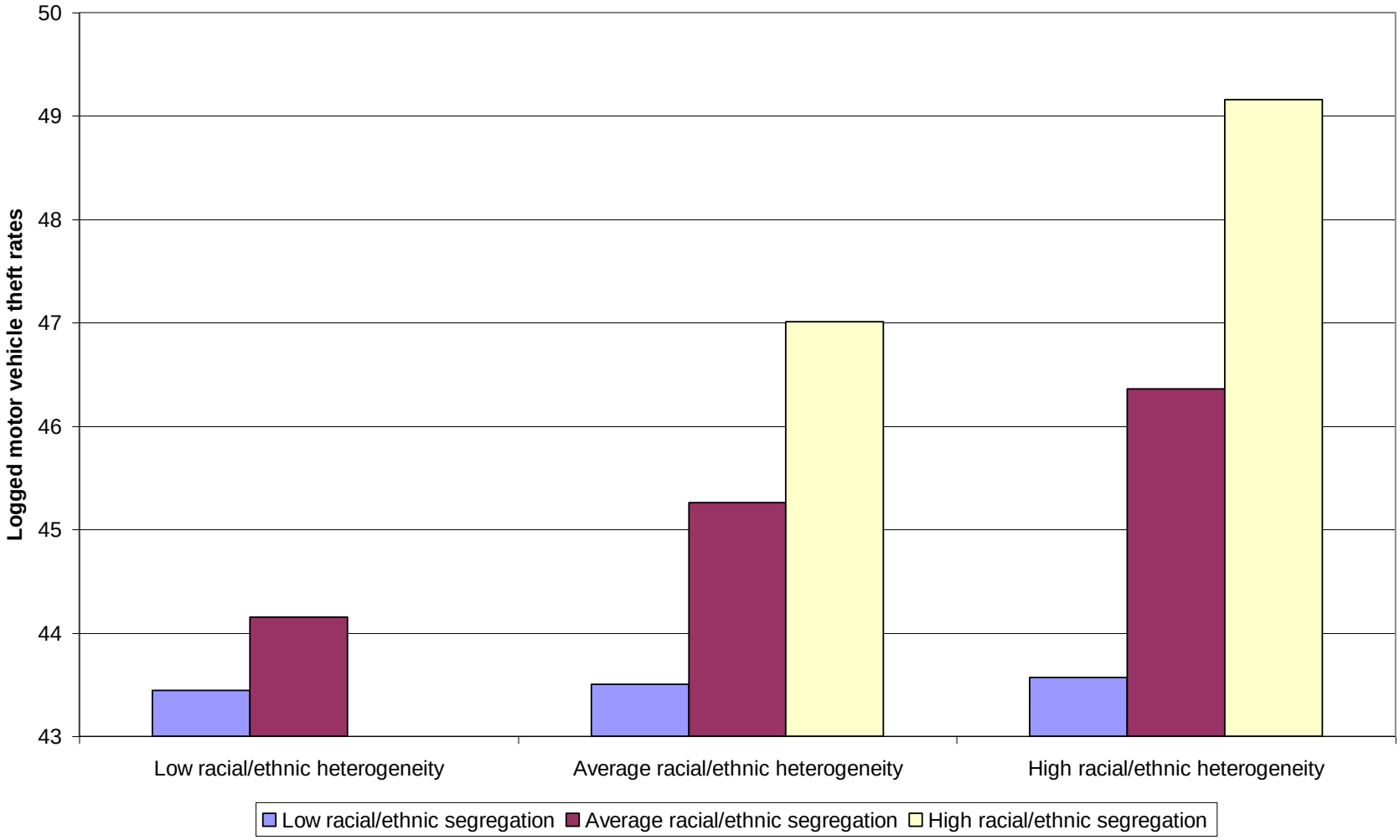

Figure 10. Change in aggravated assault rates over decade predicted by interaction of racial/ethnic churning and change in racial/ethnic segregation