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The Spatial Scale of Inequality: Comparing Egohoods across Four Cities

John R. Hipp

Abstract

This Chapter explores the question of how inequality impacts neighborhood crime at various spatial scales in four key ways. First, I utilize a strictly spatial measure of neighborhoods—*egohoods*—which relax the assumption of non-overlapping boundaries of most existing neighborhood definitions. Existing strategies for constructing neighborhood boundaries typically minimize the amount of inequality present across the social landscape *by design*, and therefore may underestimate the relationship between inequality and crime in neighborhoods. Second, I assess whether the level of inequality in the broader 2.5 mile area around the ½ mile egohoods further impacts the level of crime. Third, I move beyond cross-sectional analyses and estimate models across 10 years of data. Finally, I extend existing research that often studies a single city, and instead select four cities that differ in key ways: two are Sun Belt cities (Atlanta and Dallas) and two are Rust Belt cities (Chicago and Cincinnati). There was strong evidence of the impact of spatial inequality, as greater inequality in a ½ mile egohood was associated with higher robbery rates, and greater inequality in a broader 2.5 mile area around egohoods was related to even higher robbery rates. Nonetheless, spatial inequality may be context specific, as inequality in the larger ¾ mile egohoods better captured crime patterns in Atlanta, a city with lower population density and more similar inequality levels across the landscape.

Keywords: inequality; crime; spatial scale; longitudinal.

Bio

John R. Hipp is a Professor in the Departments of Criminology, Law and Society, and Sociology, at the University of California Irvine. His research interests focus on how neighborhoods change over time, how that change both affects and is affected by neighborhood crime, and the role networks and institutions play in that change. He approaches these questions using quantitative methods as well as social network analysis.
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The Spatial Scale of Inequality: Comparing Egohoods Across Four Cities

There are numerous theories positing why we should expect to observe a positive relationship between levels of inequality and crime. Nonetheless, a recurring challenge for these theories is specifying the proper spatial scale at which we would expect them to operate, and then operationalizing research studies that appropriately account for this proper spatial scale. Failing to do so can lead to faulty inferences. Furthermore, given that different theories posit varying spatial scales at which inequality should be related to crime—including the neighborhood level, nearby neighborhoods, or even the city—measuring inequality at these different scales provides one way to distinguish between the mechanisms posited by competing theories. A related challenge is defining neighborhoods, particularly if one hypothesizes that inequality matters either within or across neighborhoods for crime levels. I will argue here that a neighborhood unit that flexibly captures such spatial patterns is useful for exploring the relationship between spatial inequality and crime, and therefore I will utilize the concept of egohoods (Hipp and Boessen 2013). Egohoods are defined by selecting a block at their center, and then including all blocks within some predefined radius. This results in overlapping units that arguably better capture inequality across the spatial landscape.

In this chapter I consider how the spatial scale of inequality may be related to robbery and burglary levels. Furthermore, a limitation of much existing research is that the neighborhood inequality and crime relationship is assessed within a single city. I will instead assess this by using data from four cities that differ in their history: two are traditional Rust Belt cities in the Midwest—Chicago and Cincinnati. And the other two are Sun Belt cities that have shown considerable population growth over the last several decades—Atlanta and Dallas. Comparing across these four different cities will give us a better sense of how generalizable the inequality and crime relationship is across different macro environments. Yet another limitation of much existing research is that it assesses the relationship between inequality and neighborhood crime at a single point in time. This leaves unanswered the question of whether changing levels of inequality similarly impact crime levels, or whether such changes have different consequences for how crime changes compared to the relationship at a point in time. Therefore, I will assess both how inequality is related to crime levels at one point in time (2010), as well as how the relationship between inequality and crime changed between two time points (2000 and 2010).

In the next section I will describe the existing literature regarding the relationship between inequality and neighborhood crime, and the theoretical expectations. I will highlight the spatial uncertainty of this possible relationship, and then describe how egohoods can be useful in addressing this question. I will then present empirical examples of both types of analysis for each of the four US cities. I then conclude with a discussion of the implications of these results for scholars and policymakers interested in the relationship between inequality and crime in neighborhoods.

Background

There is a long tradition of literature focusing on the question of whether inequality is related to levels of crime. An early theoretical explication of this idea comes from the economist Isaac Ehrlich (1973). In his rational choice model, those with fewer economic resources are more likely, on average, to turn to crime to supplement their income. Given that persons and households with more income are more attractive targets, the implication is that inequality will bring together more attractive targets along with potential offenders. Nonetheless, the proper spatial scale remains a source of challenge for exploring this theory.

There are various mechanisms that could bring about such a relationship. One mechanism is an opportunity effect, especially for property crime. That is, based on routine activity theory (Cohen and Felson 1979), higher income households can serve as attractive targets, so to the extent that there are more economically challenged households nearby there is the possibility that they may be more likely to act as motivated offenders. This mechanism requires at least a certain degree of spatial proximity between potential offenders and targets, so this inequality arguably needs to play out at a more moderate spatial scale for it to impact crime. One implication is that this would induce a positive relationship between inequality and crime within neighborhoods. However, it is well-documented that offenders typically travel distances to crime that exceed the size of the "neighborhoods" as typically defined (e.g., Rossmo 2000), and therefore we would expect additional spillover effects into nearby neighborhoods.

A second possible mechanism is that inequality can result in conflict between economic groups, which could increase the likelihood of crime. In part based on relative deprivation theory (Agnew 1999; Messner and Golden 1992; Taylor and Covington 1988), high levels of inequality can cause members of the disadvantaged group to feel deprived, angered, or humiliated, especially if this inequality is perceived as unjust. In this mechanism, there is a lack of specificity on the likely spatial scale on which it would occur. It is possible that inequality within the neighborhood could bring about such frustration and criminal response. It could even occur if there are large amounts of inequality *between* neighborhoods. In this case, residents of a poorer neighborhood might commit crime against residents in higher income neighborhoods—even if there is little inequality *within* the two sets of neighborhoods. Furthermore, it could also be that this plays out on the larger scale of a city.

A third possible mechanism is that economic inequality creates social distance between residents, which can reduce the ability of the neighborhood to provide guardianship through informal social control capability (Hipp 2007). Whereas social disorganization theory has focused on racial/ethnic heterogeneity as important for creating difference between residents that reduces their ability to collaborate to address neighborhood problems (Kubrin and Weitzer 2003; Sampson and Groves 1989), I have generalized this idea to the more general construct of *social distance* (Hipp 2007, 2010). Social distance can be created across numerous social dimensions in societies, such as age, marital status, the presence of children, level of education, politics, etc. (Hipp 2010). A particularly important social dimension is economic resources, and therefore inequality can be seen as a particular form of social distance (Hipp 2007). For example, there is evidence from a study of a single community that households are less likely to interact with one another as the gap in their home values increases, even accounting for the physical distance between them (Hipp and Perrin 2009). This mechanism is expected to play out at the spatial scale of a neighborhood.

A fourth possible mechanism is that the broader city is capable of providing resources to neighborhoods that need them, and in cities with higher levels of inequality or spatial inequality between neighborhoods there may be less willingness to provide this help. This ties in with the idea of public social control, in which a neighborhood obtains external resources for addressing problems within the neighborhood (Bursik and Grasmick 1993). While the public social control literature often focuses on the ability of the neighborhood to *obtain* such resources, it is also possible that some cities may simply be less willing to provide such resources to neighborhoods in need due to a lack of social capital *across* neighborhoods (Putnam 1995). Indeed, a study found evidence that cities with higher levels of inequality *combined with* spatial inequality (measured as economic segregation) experienced higher levels of crime, with the hypothesized mechanism being that this combination reduces the willingness to provide needed resources to lower income neighborhoods within the city (Hipp 2011).

Whereas each of the four mechanisms I have just discussed argues that higher levels of inequality will be related to higher levels of crime, these focus on the distribution of income within some defined area. We can also consider the *average* level of income in an area. This can be important for comparing spatial inequality across neighborhoods, as already mentioned. However, there is a further question of whether the level of inequality has different effects depending on the average level of income of residents. That is, consider a neighborhood with a range of incomes, but most skewed towards the higher end of the income distribution, and another neighborhood with a range of incomes, but mostly skewed towards the lower end of the income distribution. While each of these neighborhoods has similar levels of inequality, do they equally impact the level of crime in the neighborhood? I explore this question in the analyses.

On What Spatial Scale Does Inequality Matter?

The previous discussion of potential mechanisms makes clear that it is important to consider the spatial scale at which we measure inequality. For some theories, the level of inequality at a smaller geographic scale—such as a neighborhood—is clearly what is of interest. A challenge for these approaches is defining what a neighborhood is. Given that inequality is a function of some defined geographic area, correctly defining this spatial scale is crucial. For example, if a homogeneous low income area is adjacent to a homogeneous high income area, defining these two areas as separate neighborhoods would result in two low inequality neighborhoods, but defining them as a single neighborhood would result in a high inequality neighborhood. Thus, the identification and definition of the proper boundary is crucial. I will return to this issue shortly.

In earlier years, there were fewer studies focusing on neighborhood inequality and crime levels. For example, one study used 57 neighborhoods across three cities, but found no relationship between inequality and crime (Patterson

1991). Likewise, a study of 26 neighborhoods in New York City also failed to detect a relationship between inequality and crime (Messner and Tardiff 1986). However, the limited statistical power of these studies, as well as the challenges of appropriately defining neighborhoods, were limitations of this early work. A more recent study that did not simply focus on neighborhoods from a single city, but instead used census tracts across 19 cities, found a strong positive relationship between inequality and neighborhood violent crime levels (Hipp 2007). This same study also asked whether inequality within or between racial groups impacted crime, and while there was little evidence that inequality between racial groups was associated with higher crime levels, neighborhoods with more within group inequality tended to have higher crime levels. A study of police precincts in South Africa also tested whether inequality within or between racial groups impacted crime levels; the study found that greater levels of across racial group inequality were associated with more property crime, whereas precincts with greater within group inequality experienced more burglaries and aggravated assaults (Demombynes and Özler 2005). Nonetheless, inequality within and across racial groups has received few empirical tests.

A second possibility is that the proper scale is some broader area. In this view, focusing only on the local neighborhood would miss out on an important context of the surrounding area. This surrounding area could simply be adjacent neighborhoods, and some research has shown that large gaps in economic disadvantage between neighborhoods can result in higher levels of property crime (Chamberlain and Hipp 2015). Some, therefore, conceive of spatial inequality as based on the differences in income levels *between neighborhoods*. In this view, the average level of income in neighborhoods is computed—as opposed to inequality, which is the distribution of income—and then the difference in these average levels across neighborhoods is assessed. If there is a sense of "us against them", then it may be that higher levels of this spatial inequality will create a sense of injustice among the residents in the low income neighborhoods, which would manifest either as frustration—which may lead to violent crime, or just general disorder—or else as retributive property crime.

A number of studies have focused on this question of whether inequality between neighborhoods results in more crime. As one example, Metz and Burdina (2016) used crime data from three cities and defined neighborhoods based on block groups. They asked whether the gap in average income between a block group and either its poorest neighboring block group, or the richest one, results in more property crime. Although they found no evidence that a neighborhood that is richer than its neighbors has more property crime, neighborhoods that were poorer than their neighbors had lower property crime rates. In the same model, they found no evidence that higher inequality *within* these block groups resulted in more property crime, although this may be related to how block groups are defined, an issue to which I will return shortly.

Demombynes and Özler's (2005) study of South African neighborhoods also explored how inequality both within and across neighborhoods was related to different crime levels. Using police precincts as their geographic unit of analysis, they found that higher levels of inequality within the precinct were associated with higher levels of property crimes, but not violent crimes. Furthermore, they found that both property and violent crime rates were notably higher if the precinct was the wealthiest among its neighbors, implying that it may serve as a target. These precincts were quite large, with average population of nearly 20,000, which is about the size of five neighborhoods in the U.S., which may be too large to capture offender behavior.

A study using data for neighborhoods in the Brazilian city of Recife tested whether neighborhood and nearby inequality impacted homicide rates (Menezes et al. 2013). Whereas the study found that neighborhood inequality levels were associated with higher homicide rates, there was an unexpected negative impact from inequality in nearby neighborhoods. In contrast, a longitudinal study of Los Angeles census tracts found that high income neighborhoods with greater increases in home values experienced larger increases in aggravated assaults when they were surrounded by lower home value neighborhoods (Boggess and Hipp 2016).

Finally, a study of neighborhoods in Indianapolis likewise focused on inequality within and across neighborhoods (Stucky, Payton, and Ottensmann 2015). The authors found a robust positive relationship between neighborhood level inequality and all types of crime. There was also consistent evidence that neighborhoods with higher average income compared to their neighbors had higher levels of all types of crime. Thus, in this study, inequality both within and across neighborhoods was associated with higher levels of crime. Nonetheless, this also highlights that there can be idiosyncracies in studies of a single city: for example, whereas a study of over 90 cities also found a robust positive relationship between neighborhood inequality and crime, the pattern for inequality across neighborhoods differed for violent and property crime (Chamberlain and Hipp 2015). For property crime, there was indeed an opportunity effect in which neighborhoods with higher average income than their neighbors had higher property crime levels; however, violent crime rates were highest in high disadvantage neighborhoods surrounded by high levels of disadvantage.

Defining neighborhoods, and consequences for inequality

A key question underlying much of this discussion is how to properly measure neighborhoods. The key issue is this: most definitions of "neighborhood" in the U.S. are based on similarity (Duque, Ramos, and Suriñach 2007). That is, smaller geographic units that are similar based on key social measures—such as race/ethnicity and socio-economic status—are combined together into a neighborhood. Indeed, numerous algorithms are constructed to accomplish this very task (Duque, Ramos, and Suriñach 2007). Therefore, breaks in the social landscape where social differences occur between smaller areas are then defined as the boundaries between these neighborhoods. However, this becomes particularly problematic when measuring inequality. This is because this strategy, *by design*, artificially reduces the level of inequality existing across the spatial landscape. That is neighborhoods are constructed to have as little internal inequality as possible given this effort to maximize similarity. To then assess how neighborhood inequality is related to crime based on these units is problematic given that inequality has largely been defined away. That is, the definition of the neighborhood minimizes the amount of inequality within the boundaries, and maximizes the inequality *across* neighborhoods. If these boundaries are indeed accurate social markers that capture the social world, this would not be so problematic (though it would still require carefully measuring the presence of inequality with nearby neighborhoods). However, such neighborhood boundaries rarely so clearly mark deep social boundaries given the evidence of residents' social activity patterns, as I describe shortly.

Given the spatial uncertainty of inequality, one study adopted a novel strategy and explicitly measured it across various spatial scales (Whitworth 2012). Using data across the U.K. cities of London and South Yorkshire, it measured neighborhoods about the size of two U.S. census tracts. The study then measured the level of inequality in successively increasing buffers around these neighborhoods. In London, the positive relationship between inequality and crime levels was larger when inequality was measured in a larger spatial scale compared to a smaller scale. In South Yorkshire, there was little relationship between inequality and crime.

Given the challenge of defining neighborhood boundaries, in a study with a colleague we proposed a new definition of neighborhood that explicitly accounts for spatial scale: *egohoods* (Hipp and Boessen 2013). In short, egohoods, take a block as the center, and then draw some sized buffer around it and include all the blocks in the buffer. The process is continued for all other blocks in the city. The result is overlapping units, as opposed to the non-overlapping neighborhood units created by nearly all other strategies. We gave several reasons as justification for this strategy. For one, the activity patterns of residents almost always exhibit a spatial decay pattern around their home, as opposed to all residents in an area constraining their activity space to be the same as would be expected if non-overlapping units truly captured social patterns (Sastry, Pebley, and Zonta 2002).

Relatedly, studies asking residents to report on their perceived neighborhood generally have two broad findings: 1) general disagreement among residents about the boundaries of the neighborhood, and 2) a tendency for respondents to place themselves at the center of their neighborhood (Coulton et al. 2001: 375; Grannis 2009: 99-101). Third, we noted that numerous studies have shown that the spatial networks of residents are based on a distance decay, and not constrained to their own specific "neighborhood" (Caplow and Forman 1950; Festinger, Schachter, and Back 1950; Hipp and Perrin 2009). Finally, the travel to crime literature consistently shows that offenders exhibit a distance decay in where they travel, and do not constrain themselves to their own neighborhood (Rossmo 2000). For all these reasons, we argued that an egohood approach is more appropriate than the non-overlapping unit strategy.

We found that egohoods better captured the social world in general when assessing the relationship between key sociodemographic measures and crime. However, particularly notable was how much stronger the inequality and crime relationship was in egohoods compared to traditional Census units such as block groups or tracts. Again, this should not be surprising given that these traditional units construct neighborhoods that *minimize* inequality within them (and maximize it across them). Egohoods appropriately capture the level of social heterogeneity across the spatial landscape of a city, and this is particularly important for capturing levels of inequality.

Does The City Context Matter?

It is also possible that the proper spatial scale might be an area even broader than the adjacent neighborhoods. As I discussed earlier, it may be the city that has important consequences—perhaps because higher levels of inequality across a city reduce the ability and willingness to provide much needed resources to lower income neighborhoods within the city (Hipp 2011). In this case, the city is a political unit that can provide resources. Another possibility is that perceptions of inequity are fostered by a larger scale area that is unrelated to city boundaries. This can occur because in many relatively dense urban areas city boundaries will not provide a substantively important break in the social environment between cities (Hipp and Roussell 2013). If the spatial patterns among residents or offenders transgress city boundaries, then ignoring such spatial patterns may miss important impacts of inequality at this broader spatial scale. For example, a study showed evidence in the city of Los Angeles that increasing levels of inequality in a broader area around a neighborhood (a 2.5 mile buffer) were related to increasing levels of crime during the 2000s (Hipp and Kubrin 2017).

Another strategy measures the spatial inequality across neighborhoods within a city and assessed how that is related to *city-level* crime rates. One study of about 500 metropolitan counties across a 30-year period found little evidence that greater concentrations of high poverty neighborhoods near low poverty ones resulted in higher homicide rates (Baumer et al. 2021). A study of the 200 largest U.S. counties from 1990 to 2010 found that higher levels of across-tract inequality was associated with more city-level violent and property crime at a point in time (but there was no evidence of a longitudinal effect) (Kang 2015). However, higher levels of within-tract inequality were not related to city-level violent crime, and were actually negatively related to property crime. Likewise, a study of 350 cities over a 30-year period found that high economic segregation—combined with high city-level inequality—resulted in higher violent crime rates (Hipp 2011). Given that high levels of economic segregation will result in neighborhoods with low levels of inequality, the implication was that higher levels of inequality in the city combined with *low* levels of neighborhood inequality resulted in higher violent crime rates. For property crime, it was *either* high levels of city *or* neighborhood inequality that resulted in more property crime, but not both in combination.

Given the importance of the city context, a question is whether the relationship between inequality within or between neighborhoods and crime can differ across city contexts? There are important distinctions between cities in the

Sun Belt of the United States that are experiencing booming population growth versus older industrial cities in the northeast or Midwest of the country (the so-called 'Rust Belt') that might be experiencing more stagnation and/or abandonment. The built environment of such cities differs, as older industrial cities are built on a tighter street grid network, whereas newer Sun Belt cities often have wider roads and longer street blocks. A consequence is that the spatial scale of economic inequality may differ between these sets of cities. For example, Reardon and Bischoff (2011) showed evidence that increasing inequality in cities over the last few decades has resulted in economic segregation at a broader scale within cities rather than segregation at smaller scales. In addition, the relative economic vibrancy across these cities may have important consequences for the inequality and crime relationship within them. In more economically stagnant cities, it may be that inequality has a stronger impact on crime if some neighborhoods are being abandoned.

Yet another theoretical question that has received less empirical attention is whether we should expect the relationship between inequality and crime to be the same as the relationship between changing inequality and changing crime? On the one hand, we might expect these two ways of modeling the relationship to move in lockstep and yield similar results. On the other hand, the change in inequality might be particularly noticeable to residents, and be particularly likely to engender hostility between income groups. If this is the case, we would expect a stronger relationship between changing inequality and changes in crime, but this would then slow down over time as a location achieves a new equilibrium level of inequality and a particular level of crime. In the next section I describe the data I use from four cities to test these questions of spatial scale between inequality and crime both in 2000, and as change from 2000 to 2010.

Data and Methods

Data

To explore these questions, I use data from four cities that differ based on their social histories. I use data for two cities that are older Midwest, Rust Belt cities—Chicago and Cincinnati. I also use data for two cities in the Sun Belt that are experiencing considerable population growth—Atlanta and Dallas. The incident-level crime data for each of these cities from 2000 to 2010 are created from crime reports officially coded and reported by the respective police departments. I combine these with Census data capturing demographics: the 2000 U.S. Census and the 2010 Census combined with the 2008-12 5-year estimates from the American Community Survey (ACS). The data are combined into egohoods, in which a ½ mile buffer is created around a particular block and includes all blocks whose centroids are contained in the buffer. The number of egohoods in a city is thus equal to the number of blocks.

Dependent variables

I constructed measures of two types of acquisitive crime: robberies and burglaries. These two crime types differ in that robbery has a more violent component to it. Although we might also study a more direct measure of violence, this is outside the scope of this chapter. The crime incident data for each city was geocoded to a latitude-longitude location, and then aggregated to the proper census block. The crime measures are averaged over three years at the beginning (2000-02) and end (2008-10) of the study period to minimize yearly fluctuations. These blocks were then aggregated to egohoods by computing the number of robbery or burglary incidents within a ½ mile buffer of a focal block.

Independent variables

The primary measures of interest in this study were measures of *average household income (logged)* and *income inequality*. I constructed measures of these in ½ mile egohoods in 2010. I also constructed similar measures in 2000, and then computed the difference between the two time points. There are twin challenges for constructing the average income and inequality measures from Census data: the data is presented in income bins, and it is aggregated to block groups. I follow the approach of Hipp and Kubrin (2017) in constructing these measures. First, I need to impute the binned income data from block groups to blocks. The imputation strategy used employs information on the income distribution by racial/ethnic group in each block group and the fact that I know the racial/ethnic composition of each block. I therefore compute the proportion of racial group members of the block group that live in a particular block, and impute the binned income data based on this proportion. This provides a more principled estimate of the binned income data in each block. I then aggregate this information for all blocks in an egohood. I assigned household incomes within a bin to the midpoint value, log transformed this value, and then computed the average logged income based on this information.[1] I measured income inequality by computing the standard deviation of income based on these values.

I constructed several other measures in the ½ mile egohoods to minimize the possibility of obtaining spurious results. To account for the racial/ethnic composition, I constructed measures of the *percent African American*, *Latino*, and *Asian* (with percent white and other race as the reference category). I measured *racial/ethnic heterogeneity* with the Herfindahl index of the same five racial/ethnic groups, which is constructed as a sum of squares of proportions and then subtracted from 1. I included a measure of the *percent immigrants*, given evidence

[1] In the highest range I assigned the value as 25% greater than the bottom value in this range.

that such neighborhoods often have less crime. There is evidence that home owners are more willing to provide social control capability, so I constructed a measure of the *percent owners*. To account for the possibility that vacant units can be crime generators (Kubrin and Hipp 2014; Rice and Smith 2002; Smith, Frazee, and Davison 2000) I computed a measure of *percent vacant units*. Life course literature finds that 16 to 29 is the prime age of offenders, so I constructed a measure of the *percent of people aged 16 to 29*. The density of population is likely important, so I constructed a measure of *logged population* in the egohood—given that egohoods are a constant areal size, this is effectively population density. I calculated difference versions of these measures for the change analyses.

<u>Independent variables in the broader spatial scale (2.5 miles)</u>

I accounted for the characteristics of the broader area around the egohood by computing four measures within a 2.5 mile egohood around the block that were constructed similarly to the measures in ½ mile egohoods. I only include measures that are theoretically expected to impact crime at such a large scale. I therefore constructed measures of *average household income (logged), income inequality, racial/ethnic heterogeneity*, and *logged population*.

Methods

I estimated two sets of models. For the models using crime data for 2010, I estimated negative binomial regression models (given that less than 2 percent of observations had zero crimes, zero inflated models were not necessary). These account for the count nature of the data, as well as the over-dispersion present. By including the logged population in the model, this is effectively transforming the outcome measures into rates. For the models in which the outcome measure was the difference in crime from 2000 to 2010 and the independent variables were difference measures from 2000 to 2010, I estimated ordinary least squares regression models.

Results

I begin by describing the summary statistics for the sample across these four cities. The first row in Table 1 displays the count of robberies in egohoods across the four cities during 2010, and shows that the highest average count occurs in Chicago egohoods. However, egohoods have much higher population density in Chicago compared to the other cities: the second row from the bottom shows that the average ½ mile egohood in Chicago has just over 11,000 residents, whereas the averages are about 3,700 in Cincinnati and Dallas, and just 3,200 in Atlanta. Adjusting the crime counts into rates per 1,000 residents, the third row in the table shows that Dallas has the highest average robbery rate (30.5), whereas Chicago has the lowest robbery rate (7.0). Atlanta experienced the largest average decrease in robberies over the decade, declining 13.3 robberies on average per egohood. The highest burglary rate is observed in Cincinnati (31.9), whereas Chicago also has the lowest burglary rate (12.0). However, the largest drop in burglaries over the decade occurred in Cincinnati, whereas Chicago actually experienced a slight increase.

<<<Table 1 about here>>>

Of particular interest to us are the income and inequality measures. The highest average income inequality across ½ mile egohoods is observed in Atlanta (1.04), with Cincinnati having nearly equally high inequality. Dallas has the lowest average inequality across egohoods. This relative ranking of inequality measures remains the same when measured in 2.5 mile egohoods. We also see that the largest increases in inequality between 2000 and 2010 in ½ mile and 2.5 mile egohoods occurred in Cincinnati and Atlanta. Regarding logged average household income, Atlanta has the highest average across egohoods (11.11), with Dallas and Chicago at similar values. Only Cincinnati has appreciably lower average income across its egohoods. Earlier I noted that spatial inequality can capture inequality *across* neighborhoods: that can be seen here in the *standard deviations* of logged income across egohoods. Thus, the greatest variability across egohoods in average income occurs in the two Sun Belt cities: Dallas (SD = .77) and Atlanta (SD=.64). The variability across egohoods in average income is lower in the two Rust Belt cities: Cincinnati (SD=.43) and Chicago (SD=.38). As one final note: to get a sense of how large the population is within the 2.5 mile buffers, there are between 65,000 and 75,000 persons in these buffers in three of the cities, whereas there are over 210,000 persons in these buffers, on average, in Chicago. Thus, these buffers are capturing relatively large populations.

Robbery models

I next ask how these measures of inequality are related to robbery levels across the four cities. In Table 2, the first four columns present the results for the cross-sectional robbery models, and the last four columns present the results for the change models. The first row of Table 2 shows that there is a strong positive relationship between inequality in ½ mile egohoods and robberies in three of the four cities. The strongest effect occurs in Dallas, as a one standard deviation increase in inequality is associated with 7.1% more robberies (exp(.682*.10)= 1.071). One standard deviation increases in inequality in Cincinnati and Chicago are associated with 6% and 4% more robberies, respectively. Only in Atlanta is there a negative relationship, as a one standard deviation increase in inequality is actually associated with 6% fewer robberies. There is also an additional effect from inequality in the broader 2.5 mile area in three of the cities. A one standard deviation increase in inequality in this broader area is associated with 20% more robberies in Atlanta, 18% more in Dallas, and 10% more in Chicago. Thus, this is a much stronger effect than that observed in the local ½ mile egohood, highlighting the importance of inequality in this broader spatial scale (except for Cincinnati).

<<<Table 2 about here>>>

Higher average incomes in the local egohood or the broader 2.5 mile egohood mostly have negative relationships with robberies. Egohoods with one standard deviation higher income have between 2% and 15% fewer robberies (though an exception is Chicago with 3% more robberies in higher income egohoods). The pattern is even stronger in the larger 2.5 mile egohoods, especially in the two Sun Belt cities. Higher income in the broader area is associated with 3-5% fewer robberies in the Rust Belt cities, but fully 23-29% fewer robberies in the Sun Belt cities.

The last four columns of this Table 2 show the results for the change models. We see similar effects for inequality as in the cross-sectional models. A one standard deviation increase in inequality in the egohood over the decade is associated with .04-.07 standard deviations increase in robberies in three of the cities. Again, Atlanta is the exception as increasing inequality is associated with a falling robbery rate. There are weaker effects for changing inequality in the 2.5 mile buffer compared to the cross-sectional models. Whereas increasing inequality in this broader area is associated with increasing robberies in Dallas and, especially, Chicago, it is associated with falling robbery rates in the other two cities. And whereas changing average income in the local egohood has minimal relationship with changing robberies, changing average income in the broader area has a strong negative relationship with robberies. Thus, a one standard deviation increase in average income in the 2.5 mile egohood is associated with between .16 and .40 standard deviation decreases in robberies. These are quite strong effects, suggesting that the income level change in this broader area has strong consequences for how robberies change over the decade.

Burglary models

I next turn to the burglary results in Table 3. The relationship between inequality and burglaries is less consistent compared to the relationship with robberies. In each city, it is only inequality at one particular scale that has a positive relationship with burglaries. In Cincinnati and Dallas, egohoods with higher inequality have higher burglary rates, although inequality in the broader 2.5 mile area has a negative relationship with burglary in these two cities. And the pattern is opposite in Chicago and Atlanta, as it is inequality in the broader 2.5 mile area that has a positive relationship with burglaries. In all cases, the size of the effect is much larger for the 2.5 mile buffer compared to the local ½ mile egohood. We do see that egohoods with higher average income have lower burglary rates—between 5% and 25% lower. However, egohoods surrounded by higher average income in the 2.5 mile buffer around them actually have somewhat more burglaries.

<<<Table 3 about here>>>

Turning to the change models for burglary in the last four columns of Table 3, there is no evidence that increasing inequality in the ½ mile egohood is associated with an increase in burglaries. Whereas increasing inequality in the ½ mile egohood is negatively associated with changing burglaries in Atlanta, this is balanced by the positive effect of increasing inequality in the broader 2.5 mile egohood. In Chicago and Atlanta there is evidence that increasing inequality in the broader area is associated with increasing burglaries. Thus, there is modest evidence that increasing inequality is associated with increasing burglary rates. There is, however, strong evidence that increasing average income (both in the local egohood and the broader area) is associated with falling burglary rates. This relationship is particularly strong with increasing average income in the broader 2.5 mile egohood.

Moderating effect of inequality and average income

In the final sets of analyses, I tested whether the average level of income in egohoods moderates the relationship between income inequality and robbery or burglary. I present the results as figures in which I plot the values based on low, medium, and high values of average income and inequality (as the mean, and one standard deviation above and below the mean). The cross-sectional interaction robbery models are shown in Figure 1. Although there is no interaction effect in Chicago, there is a positive interaction in the other three cities. In Cincinnati and Atlanta we see that at low levels of inequality (the left side of these graphs) there are many more robberies in low income neighborhoods (the solid line) compared to higher income neighborhoods. However, the gap between low and high income neighborhoods narrows at high levels of inequality in Cincinnati, and evaporates entirely in Atlanta (the right side of these graphs). In Dallas, there is no difference in robbery rates among neighborhoods with low inequality, whereas robbery rates are highest in high income egohoods with high inequality.

<<<Figure 1 about here>>>

The pattern is slightly different for these interaction models for burglaries. In two of the cities—Cincinnati and Dallas—we again see a positive interaction effect. In Cincinnati, the level of inequality has little impact on burglaries in low income egohoods (the top, solid line), whereas there is a strong positive relationship between inequality and burglaries in high income egohoods (the bottom, dotted line). The story is similar in Dallas, as the positive relationship between inequality and burglaries is much stronger in high income neighborhoods (the green line). There is no interaction effect in Atlanta, and Chicago sees an unexpected, opposite, negative relationship. Thus, in Chicago egohoods with low inequality, the average level of income has little impact on the burglary rate. However, increasing inequality has a strong positive relationship on burglaries in low income egohoods in Chicago.

<<<Figure 2 about here>>>

In the change models, we observe consistent evidence of a positive interaction between inequality and average income for robbery. Thus, it appears that increasing inequality has the strongest effect on changes in robbery rates in increasing income egohoods (the dotted lines in these graphs). In Chicago and Dallas, the robbery rate is similar in egohoods with decreasing inequality regardless of how the income level is changing; however, robberies increase the most in egohoods with increasing inequality and increasing average income. In Cincinnati this effect is so strong that we see a cross-over effect: in egohoods with decreasing inequality robberies increase more if income is also falling, whereas the sharpest increases in robberies occur in egohoods with increasing inequality and increasing average income. The pattern is different in Atlanta: although changes in inequality have little impact on changing robberies in egohoods that are experiencing increasing income (the dotted line), increasing inequality actually is associated with falling robbery rates in egohoods with declining average income (the solid line).

<<<Figure 3 about here>>>

Finally, the models testing interaction effects in the change models for burglaries again find a positive interaction effect (except for Dallas). In all of the cities, the largest increase in burglaries occurs in egohoods with decreasing income and inequality (the solid lines on the left side of the graphs). In three of these cities, the effect of changing average income makes little difference for egohoods that are experiencing increasing inequality (the right side of the graphs).

<<<Figure 4 about here>>>

Discussion

This study has focused on the spatial scale of inequality and crime, using data across four different cities. I selected two cities representing the Rust Belt and two representing the Sun Belt to assess the robustness of the results. By measuring neighborhoods as ½ mile egohoods, and by accounting for inequality in the broader 2.5 mile area around each egohood, I have been able to explore these spatial patterns of inequality. I also assessed whether changing levels of inequality impact changes in robbery and burglary. So what have we learned in this study?

First, consistent with earlier research, it is indeed important to measure the local neighborhood environment as an egohood, rather than using some non-overlapping unit.[2] Egohoods more appropriately capture the level of income inequality existing across the spatial landscape, and therefore provide a better test of the possible relationship between local inequality and crime. Across these four cities, there was generally stronger evidence that higher levels of inequality were associated with higher robbery rates, but mixed evidence of a relationship with burglaries. Atlanta was the exception to these patterns, as egohoods with more inequality actually had lower robbery and burglary rates in this city. A similar counterintuitive negative relationship was found between changing inequality and crime in Atlanta egohoods. So what is different about Atlanta? Among these four cities, Atlanta has a higher level of inequality across egohoods as well as the lowest variance—indicating less of a gap in inequality across the landscape. Another notable feature is that Atlanta had the lowest population density of the four cities. One possible explanation for these anomalous results is that because of this lower population density, it would be more appropriate to measure inequality in larger egohoods in Atlanta. Indeed, in ancillary analyses I instead used ¾ mile egohoods and found no relationship between inequality and robbery or burglary, effectively eliminating this counterintuitive result. This suggests an important

[2] Although egohoods actually capture the spatial pattern of inequality and crime, one cannot simply sum them up to get a total of city-level crime. One could compute the average count of crimes across all egohoods that overlap with a block to get an estimate of crime for the block, and then sum those totals up to get a more accurate level of crime. Nonetheless, no bias is introduced by the egohood strategy.

direction for future research in considering inequality on flexible spatial scales across cities with different levels of population density.

A second key finding was the set of robust positive interaction effects between inequality and household income with crime. In nearly all cases, there was a positive interaction effect between these two measures. The implication is that inequality more strongly affected crime in *higher* income neighborhoods. Often, the highest crime was observed in low income neighborhoods that also had little inequality. The stronger impact of inequality in higher income neighborhoods may point to a social network effect in which this economic difference reduces social interaction and therefore reduces potential collective efficacy. This is speculative, but points to a direction for future work. In the change interaction models there were very different results across the two different crime types (despite the fact that the interaction term was almost always positive). On the one hand, the largest increases in robberies occurred in neighborhoods in which both inequality and average income were increasing. This combination of more targets (due to increasing income) along with more motivated offenders (due to increasing inequality) may explain this finding due to increased opportunities. However, the pattern was opposite for burglaries, as the largest increase in burglaries occurred in neighborhoods with decreasing inequality and falling average income, which may indicate increased offenders due to lower income levels.

Consistent with an earlier study in Los Angeles (Hipp and Kubrin 2017), there was quite strong evidence that the level of inequality in a broader 2.5 mile area around the egohood had a strong positive relationship with the level of crime, particularly robbery. Whereas neighborhood-level studies often only focus on the level of inequality in the specific neighborhood, or occasionally also consider the level of inequality compared to adjacent neighborhoods (Chamberlain and Hipp 2015), the results of the present study highlight that the level of inequality of a much broader spatial area has consequences for the level of crime, especially robbery. This broader scale may capture the broader spatial patterns of offenders, and therefore explain why this scale is particularly able to pick up important inequality effects for robbery. In fact, the effects of inequality in this broader scale were much stronger than those for the local egohood, highlighting the importance of this larger geographic scale. One other interesting finding related to spatial inequality was the fact that higher levels of average income in this larger buffer were far more protective for robbery in the Sun Belt cities. This may be related to the fact that we observed a much larger variance in average income across the egohoods within the Sun Belt cities compared to the two Rust Belt cities. If there is broader scale economic segregation in the Sun Belt cities, then these broader swaths of high income residents would potentially minimize the number of offenders nearby and therefore be protective for robbery, as we observed.

Finally, I also assessed whether the change in inequality impacts changes in crime levels. One general finding was that the results were weaker than the cross-sectional results, particularly for burglary. Although increasing inequality was associated with increasing robberies in three of the cities, the size of the effect was nonetheless smaller than in the cross-sectional models. I had hypothesized that changes in inequality might have a stronger impact on resident perceptions, but this was not the case. A counter viewpoint is that the causal impact of increasing inequality occurs more slowly than we might anticipate, which would explain why stable levels of inequality appear to have such a stronger effect on robbery than short-term changes. This suggests a need for future analyses that more carefully explore the temporality of these causal effects. On the other hand, I detected a very strong effect in which increasing average income in the broader spatial scale had a very strong negative relationship with changing levels of robbery and burglary. This effect was much stronger than for local egohoods. Why this might be is unclear: one explanation would be that it reduces the possible offenders within a broader area if the economic situation of households is improving. The fact that this effect was particularly strong in the two Rust Belt cities, which are often struggling economically is consistent with this possibility. But this is speculative, and suggests a needed direction for future research.

One goal of the present chapter was to compare two Sun Belt cities with two Rust Belt cities. In general, the results were somewhat equivocal, highlighting the need for a larger sample of cities. Nonetheless, there were a couple clear patterns. First, there was stronger evidence of a positive relationship between egohood inequality and robberies in the Rust Belt cities than in the Sun Belt cities. Likewise, there was a strong positive relationship between changes in inequality and changes in robberies in the Rust Belt cities. Second, in the more sprawling Sun Belt cities there was evidence that higher levels of inequality in the broader 2.5 mile area was associated with higher robbery rates, and some evidence that increasing inequality at this scale was related to increasing burglary levels. This is consistent with the evidence of a study in Los Angeles—yet another Sun Belt city—of such a positive relationship at the broader spatial scale (Hipp and Kubrin 2017). Likewise, whereas higher income in the broader 2.5 mile area had a protective effect for robbery in all cities, this effect was five times stronger in the Sub Belt cities, which also speaks to the geographic scale of economic segregation in these less dense cities.

The generally strong evidence that neighborhood-level inequality was associated with higher robbery rates (except in Atlanta) is consistent with the theories described earlier positing a relationship between neighborhood-level inequality and crime. However, given that possible mechanisms were not measured, it is not possible to say *why* this relationship existed. Nonetheless, the results highlight that egohoods are likely more appropriate for measuring inequality, given the sometimes mixed results for inequality and crime detected in prior studies using more traditional geographic units, as I described earlier. Nonetheless, the positive relationship between inequality in a broader spatial scale and robberies, especially in the Sun Belt cities, highlights that inequality can impact crime at multiple spatial scales. Whereas the social distance argument that inequality can impact guardianship in neighborhoods and result in more crime is not applicable for these larger scale patterns, this result could be consistent with an opportunity perspective in which potential offenders seek out targets on this larger scale. It could also be consistent with a conflict perspective, but played out between rather than within neighborhoods. Which is the case is uncertain.

It is difficult to make policy recommendations given the uncertainty regarding the mechanisms at work here. Nonetheless, one important takeaway point is the need to account for inequality on a larger geographic scale. It is not simply inequality within neighborhoods that matters, nor is it the case that it is inequality between adjacent neighborhoods, nor is it even the case that it is inequality measured at the level of the city that is only of importance. Instead, this chapter demonstrated that inequality on a relatively large spatial scale—based on a 2.5 mile radius—that is *within* city boundaries can strongly impact crime levels. There is a need to be aware of such inequality, which is often not a focus of most agencies. As to why it leads to more crime will need to be a focus of future research.

There are some limitations to acknowledge about this study. First, the fact that the results showed some differences across these cities highlights the need for studies to explore these patterns on larger samples of cities to assess the robustness of these results. Why differences might occur across cities is a useful direction for future research. Second, a challenge when comparing across different cities is that they can have different levels of population density, which then raises the question of what sized egohoods to use. It also raises the question of whether different sized egohoods should be used across different cities. This is an important direction for future research. Third, there was evidence of differences in the results across the two crime types used, despite the fact that they are each acquisitive crimes. This highlights the need for future research to consider other types of crime, and how the particular mechanisms involved may imply different inequality and crime relationships depending on the type of crime.

In conclusion, this chapter has demonstrated the importance of considering the spatial scale of inequality, and how this can be related to levels of crime. There was robust evidence across these four cities that higher levels of inequality across egohoods were associated with higher robbery rates. These results also highlighted the importance of using egohoods as a measure of neighborhood, rather than some non-overlapping units that are typically constructed based on a principle of similarity. Egohoods more accurately capture the inequality across the spatial landscape, and exhibited robust relationships for robbery. Likewise, there was strong evidence that the level of inequality in a broader 2.5 mile buffer around each egohood was positively related to robbery levels. This broader inequality is rarely considered in studies, but appears important to capture. Finally, these results across four different cities—two in the Rust Belt, and two in the Sun Belt—highlight the need for future work that explores the inequality and crime relationship across multiple cities that vary along key socio-demographic and built environment characteristics to better understand this relationship.

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Tables and Figures

Table 1. Summary statistics for variables used in analyses across four cities

	Chicago		Cincinnati		Atlanta		Dallas	
	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D
Robberies 2010	66.9	55.1	47.2	61.2	23.9	24.4	13.8	15.8
Change in robberies	-10.4	23.1	-6.1	28.9	-13.3	18.7	-7.8	14.0
Robbery rate per 1000	7.0	46.0	12.7	33.4	8.8	60.7	30.5	500.7
Burglaries 2010	113.1	72.8	82.5	59.5	66.6	47.5	45.8	39.1
Change in burglaries	3.1	41.3	-17.0	58.6	-4.8	33.3	-2.6	20.5
Burglary rate per 1000	12.0	62.9	31.9	103.6	25.6	68.5	25.0	183.4
1/2 mile egohoods								
Income inequality	0.96	0.11	1.02	0.10	1.04	0.09	0.91	0.10
Average household income, logged	11.04	0.38	10.85	0.43	11.11	0.64	11.07	0.77
2.5 mile egohood								
Income inequality	1.00	0.08	1.07	0.07	1.09	0.06	0.97	0.08
Average household income, logged	10.80	0.32	10.48	0.42	10.71	0.49	10.62	0.55
Change in 1/2 mile egohoods								
Income inequality	0.02	0.08	0.07	0.07	0.06	0.09	0.03	0.13
Average household income, logged	0.20	0.23	0.24	0.51	0.27	0.56	0.15	0.56
Change in 2.5 mile egohood								
Income inequality	3.37	3.37	8.05	1.79	5.54	3.36	3.29	4.53
Average household income, logged	0.23	0.14	0.20	0.06	0.16	0.19	-0.12	0.18
Population in 1/2 mile egohoods	11,065	5,742	3,740	2,369	3,195	2,013	3,726	2,346
Number of blocks	45,988		4,533		6,605		21,462	

Table 2. Robbery models in egohoods in 2010

	Robbery models in 1/2 mile egohoods								Robbery change models in 1/2 mile egohoods							
	Chicago		Cincinnati		Atlanta		Dallas		Chicago		Cincinnati		Atlanta		Dallas	
Egohood variables																
Income inequality	0.358	**	0.610	**	-0.696	**	0.682	**	22.381	**	16.894	**	-16.906	**	5.759	**
	(14.07)		(4.94)		-(6.01)		(13.54)		(16.81)		(4.18)		-(7.84)		(7.68)	
Average household income, logged	0.077	**	-0.397	**	-0.129	**	-0.029	**	0.607		-0.837		0.144		0.563	**
	(6.33)		-(11.00)		-(5.04)		-(3.29)		(1.13)		-(1.36)		(0.33)		(3.94)	
Variables in 2.5 mile buffer																
Income inequality	1.177	**	-0.083		2.805	**	2.136	**	1.331	**	-4.058	**	-0.360	**	0.130	**
	(28.10)		-(0.40)		(11.44)		(26.82)		(38.52)		-(20.07)		-(4.73)		(5.94)	
Average household income, logged	-0.085	**	-0.130	**	-0.696	**	-0.483	**	-45.0	**	-73.2	**	-16.7	**	-31.9	**
	-(8.61)		-(2.95)		-(20.50)		-(38.82)		-(42.29)		-(11.70)		-(10.78)		-(57.22)	
R-square	0.217		0.227		0.173		0.195		0.333		0.544		0.387		0.373	
N	45,988		4,533		6,605		21,462		45,955		4,524		6,596		21,151	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .10 (two-tail test). T-values in parentheses. All models include percent Black, percent Latino, percent Asian, racial/ethnic heterogeneity, percent immigrants, percent owners, percent vacant units, percent aged 16 to 29, logged population, racial/ethnic heterogeneity in a 2.5 mile buffer, and logged population in a 2.5 mile buffer.*

Table 3. Burglary models in egohoods in 2010

	Burglary models in 1/2 mile egohoods									Burglary change models in 1/2 mile egohoods							
	Chicago		Cincinnati		Atlanta		Dallas			Chicago		Cincinnati		Atlanta		Dallas	
Egohood variables																	
Income inequality	-0.065	**	0.730	**	-0.181	**	0.698	**		-2.607		10.202		-16.106	**	-1.244	
	-(2.75)		(9.61)		-(2.59)		(21.67)			-(1.29)		(1.42)		-(4.11)		-(1.03)	
Average household income, logged	-0.136	**	-0.361	**	-0.452	**	-0.068	**		-6.293	**	-3.666	**	-1.930	*	-0.479	*
	-(11.91)		-(16.67)		-(21.86)		-(10.05)			-(7.70)		-(3.36)		-(2.43)		-(2.07)	
Variables in 2.5 mile buffer																	
Income inequality	0.583	**	-3.278	**	3.176	**	-1.699	**		1.064	**	-10.528	**	0.421	**	0.045	
	(15.08)		-(24.59)		(21.77)		-(34.21)			(20.21)		-(29.29)		(3.04)		(1.27)	
Average household income, logged	0.270	**	0.170	**	-0.027		0.123	**		-170.0	**	-180.0	**	-79.5	**	-41.2	**
	(28.43)		(6.38)		-(1.31)		(14.78)			-(107.24)		-(15.78)		-(28.17)		-(45.58)	
R-square	0.154		0.191		0.170		0.168			0.515		0.650		0.365		0.234	
N	45,988		4,533		6,605		21,462			45,955		4,524		6,596		21,151	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .10 (two-tail test). T-values in parentheses. All models include percent Black, percent Latino, percent Asian, racial/ethnic heterogeneity, percent immigrants, percent owners, percent vacant units, percent aged 16 to 29, logged population, racial/ethnic heterogeneity in a 2.5 mile buffer, and logged population in a 2.5 mile buffer.*

Figures

Figure 1. Interaction of income and inequality in egohoods for robbery in four cities

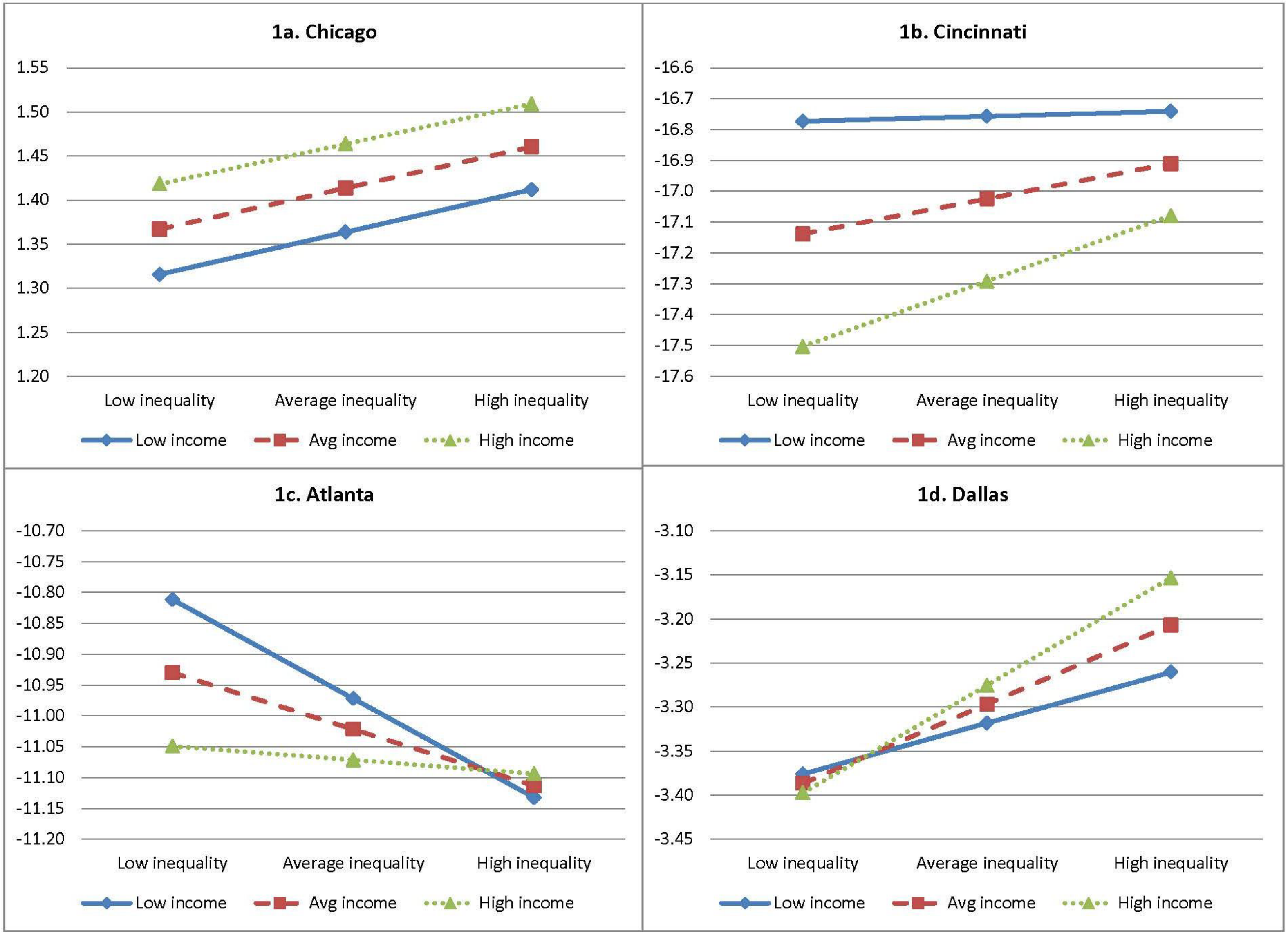

Figure 2. Interaction of income and inequality in egohoods for burglary in four cities

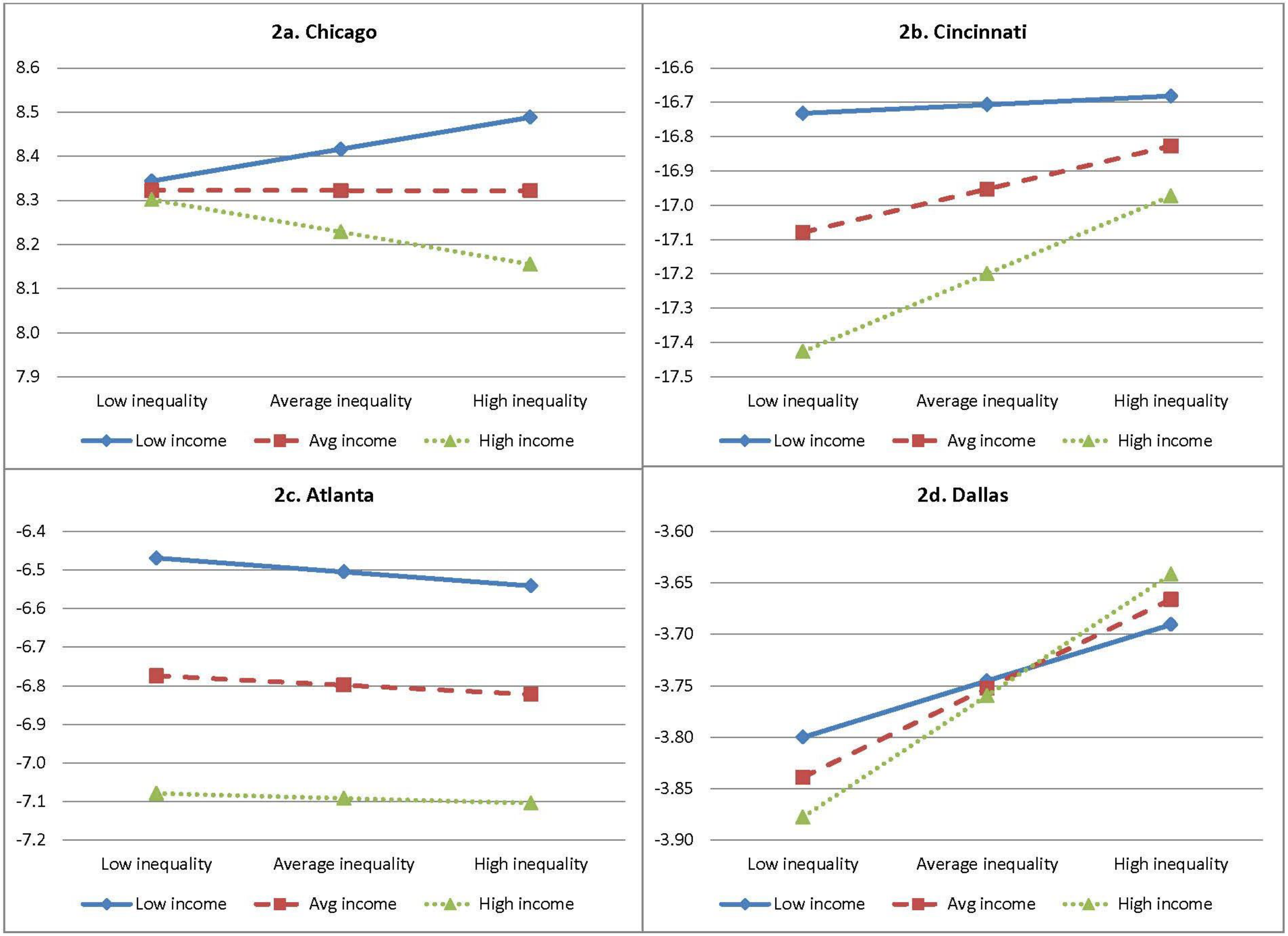

Figure 3. Interaction of income and inequality in egohoods for change in robbery in four cities

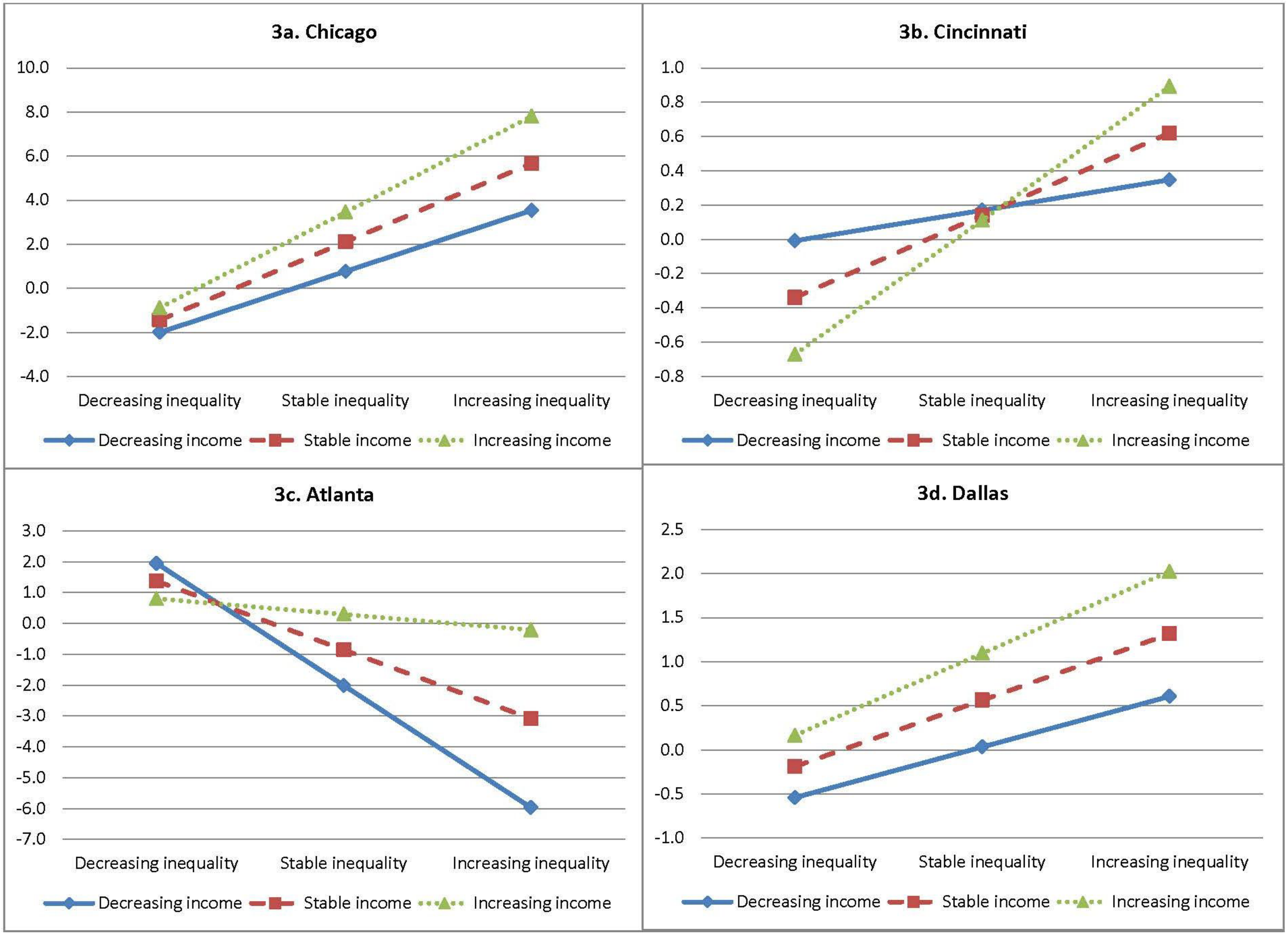

Figure 4. Interaction of income and inequality in egohoods for change in burglary in four cities