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Does concentrated poverty really have an accelerating increasing effect on crime?

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Ghettos, thresholds, and crime:

Does concentrated poverty really have a threshold effect on crime?

Abstract

Theories make varying predictions regarding the functional form of the relationship between neighborhood poverty and crime rates, ranging from a diminishing positive effect, to a linear positive effect, to an exponentially increasing or even threshold effect. Nonetheless, surprisingly little empirical evidence exists testing this functional form. The present study estimates the functional form of the relationship between poverty and various types of serious crime in a sample of census tracts for 25 cities, and finds that a diminishing positive effect most appropriately characterizes this relationship whether estimating the models nonparametrically or parametrically. Only for the crime of murder is there some evidence of an accelerating effect, although this occurs in the range of 20 to 40% in poverty, with a leveling effect on crime beyond this point of very high poverty. Thus, there is no evidence here in support of the postulate of scholars extending William Julius Wilson's insight that neighborhoods with very high levels of poverty will experience an exponentially higher rate of crime compared to other neighborhoods.

Keywords: neighborhoods, crime, poverty, spatial effects

Poverty and crime: threshold, linear, or diminishing relationship?

Bio
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Ghettos, thresholds, and crime:

Does concentrated poverty really have a threshold effect on crime?

Although there is much uncertainty regarding which characteristics of neighborhoods or communities create more crime, one bedrock conclusion is that the presence of more poverty is associated with more crime. Studies have observed this relationship when using data aggregated to large units of analysis such as cities (Chamlin and Cochran 1997; Land, McCall, and Cohen 1990; Liska and Bellair 1995; Messner 1983), counties (Kposowa, Breault, and Harrison 1995), or metropolitan areas (Bainbridge 1989; Crutchfield, Geerken, and Gove 1982; Messner and Blau 1987). Studies have also observed this relationship when using data aggregated to smaller units such as census tracts (Crutchfield, Glusker, and Bridges 1999; Hipp 2007; Warner and Pierce 1993; Warner and Rountree 1997).

One consequence of this robust relationship between poverty and crime are the numerous theories that have sprouted to explain this relationship. Although these theories all posit a positive relationship between poverty and crime at the micro-level of neighborhoods, some of them imply different a functional form for this relationship. These predictions range from a slowing increasing effect, to a simple linear effect, to a threshold effect in which crime increases at an exponential rate for neighborhoods with higher levels of poverty. For example, William Julius Wilson (1987) argued in one of the more influential ecological theories of the twentieth century that a recent emergence of extremely disadvantaged neighborhoods containing concentrated poverty are vulnerable to a spike in levels of crime and disorder due to the breakdown in social norms proscribing delinquent behavior. This theory posits a nonlinear relationship between poverty and crime as highly disadvantaged neighborhoods experience

sharply higher levels of crime. In contrast, some scholars have suggested that poverty and property crime exhibit a diminishing positive relationship due to two competing processes in which the increasing amount of disadvantage is countered by a diminishing number of potential targets (Hannon 2002). Walking the middle ground between these two perspectives are scholars in the social disorganization literature who generally posit a linear effect (Sampson and Groves 1989; Shaw and McKay 1942).

Although the precise functional form of the poverty/crime relationship in neighborhoods is important given that misspecification of it can bias the estimates of other predictors in the model we have surprisingly little evidence regarding this question. Existing research often assumes a particular form and tests for it. For instance, some neighborhood studies have simply estimated a linear relationship between poverty and crime, but failed to test for a possible nonlinear relationship (Alaniz, Cartmill, and Parker 1998; Crutchfield 1989; Messner and Tardiff 1986). Other studies have estimated a nonlinear relationship as an exponential increasing effect, but generally do not perform sensitivity analyses to determine if a different functional form more appropriately explains this relationship (Hannon 2002; Hipp 2007; Morenoff, Sampson, and Raudenbush 2001; Rountree and Warner 1999). These studies cannot rule out the possibility that other functional forms may in fact characterize the relationship. Likewise, few studies positing an accelerating increasing effect have rigorously tested if such an effect is in fact empirically present (Hannon 2005; Krivo and Peterson 1996). Whereas some have suggested that this threshold effect occurs at 40% in poverty, others have suggested that it occurs at 30%, or even at 20%. Clearly, if such a nonlinear threshold effect is present, there should not be such uncertainty about the actual point of the threshold. Nonetheless, tests do not exist of this.

Our goal in this manuscript is therefore to test the functional form of the relationship between poverty and crime using data for census tracts in 25 cities. This sample of tracts in many cities provides a more robust estimate of the shape of this functional form than studies of a single city. In addition, by carefully testing the form of this relationship with both nonparametric and parametric specifications, we are better able to assess this functional form than prior work.

Theories of the relationship between poverty and crime

The lack of empirical evidence regarding the functional form of the poverty and crime relationship is surprising given that there is no shortage of theoretical descriptions of this relationship. While the present study does not test each theory directly, we will suggest that many of these theories are not specific enough to be classified as positing only one functional form. The relationship posited by these theories can be classified into three basic functional forms: 1) an accelerating increasing relationship (sometimes referred to as a threshold effect, and sometimes as an exponential relationship); 2) a linear relationship; 3) a diminishing increasing relationship. We describe these theoretical models next.

Accelerating increasing effect of poverty on crime

The hypothesis that poverty and crime may exhibit an accelerating increasing effect builds on the theoretical perspective of William Julius Wilson (1987) and Massey and Denton (1993). This theoretical model notes that race and poverty in the U.S. are nearly indistinguishable, and focuses on how structural transformations can give rise to increased social isolation and the deterioration of "social buffers" in neighborhoods with particularly high levels of poverty. This macro theory describes a dynamic process in which middle-class black flight led to highly impoverished neighborhoods. As a consequence, these neighborhoods experienced

a general breakdown of the positive norms espoused by middle class residents that ameliorate the deleterious effects of disadvantage by exerting a level of social control that influences residents to refrain from undesirable behavior (Sampson and Wilson 1995). Thus, in this structural cultural model, the lack of middle class "role models" affects the norms of residents and brings about a cycle of disadvantage and higher rates of crime.

Of particular interest to us here is this model's key insight that such neighborhoods will be qualitatively different as they suffer a downward spiral. Wilson argued that "...inner-city neighborhoods today suffer from a severe lack of social organization" (Wilson 1987: 143). The ensuing disorganization creates a situation in which inhabitants of disadvantaged areas have limited opportunities, lack access to social institutions, and therefore have decreased interaction with members of mainstream society. These neighborhoods in turn become undesirable and are avoided by those who have the means to distance themselves from this type of environment. As a consequence, he argues that the steady out-migration of middle- and working-class families "...creates a ripple effect resulting in an *exponential increase* in related forms of social dislocation" (56-57, emphasis added). This implies that such neighborhoods will be qualitatively different as they suffer numerous deleterious consequences. The exact shape of the functional form between poverty and crime was never explicitly specified by Wilson, other than the assertion that such neighborhoods will experience a greater than linear increase in crime. Crane (1991) built upon this idea in specifying an epidemic model in which disadvantaged neighborhoods have a contagion effect leading to an explosive increase in numerous deleterious outcomes for juveniles, including dropping out of school or having a child out of wedlock.

This perspective has spawned a voluminous literature that distinguishes high poverty neighborhoods by some threshold under the assumption that such neighborhoods are

qualitatively different than those at lower levels of poverty (Jargowsky 1997; Jargowsky and

Bane 1991). Neighborhoods are often classified as high in poverty, very high, or extremely high,

with cutoffs placed at such values as 20%, 30%, or 40% in poverty (Danziger and Gottschalk

1987; Jargowsky 1997; Jargowsky and Bane 1991; Kasarda 1993; Krivo and Peterson 1996;

Massey and Denton 1993).[1] Some scholars label such tracts as "ghettoes" (Jargowsky 1997;

Jargowsky and Bane 1991), although we are agnostic on such terminology given arguments from

some that the term ghetto is more appropriately reserved to represent an institutional and

historical basis of racial exclusion (Wacquant 1997). Parker and Pruitt (2000) tested whether the

presence of such extremely high poverty tracts in a city increased the overall rate of crime.

Surprisingly, however, few studies have actually *tested* against competing hypotheses whether a

threshold effect indeed most appropriately captures the shape of this functional form in

neighborhoods. We contend that failing to test for such threshold effects leaves open the

question of the shape of the true functional form.

    If poverty in fact exhibits the accelerating increasing effect posited by Wilson, what

exactly is the functional form that we should expect to observe? We have little theoretical

guidance for answering this question. On the one hand, Wilson's suggestion of an exponential

relationship implies something akin to Figure 1a. Note that in this Figure, increasing levels of

poverty have an increasingly strong effect on the level of crime—indeed, this is an exponential

function. On the other hand, much existing research simply denotes a threshold point at which

the amount of crime jumps dramatically; such a model implies a relationship such as that shown

in Figure 1b. Here, crime shows a linear increase for lower levels of poverty, but then increases

dramatically at a distinct threshold point. It is then a question whether crime would continue to

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[1] We acknowledge that scholars employ categories for various reasons, including simply for convenience without specifically intending to hypothesize a threshold effect at a specific point. Nonetheless, the studies we focus on here are generally working in this nonlinear hypothesis paradigm.

increase as poverty increases beyond this threshold point. Of course, crime could continue to increase at higher levels of poverty, and Figure 1c illustrates what this relationship would look like. The lack of specificity in the literature theorizing such nonlinear effects from impoverished conditions leaves open the possibility that observing any of these effects would be consistent with the posited model. Furthermore, any of the virtually limitless additional functional forms characterizing something akin to an accelerating increasing effect that could be specified also would not be inconsistent with prior theorizing. Thus, there is little theoretical precision regarding the specific functional form that is expected, making it difficult to disconfirm the theory.

<<<Figures 1a to 1c about here>>>

Linear effect of poverty on crime

In contrast to theories describing a nonlinear accelerating increasing effect between poverty and crime, other theoretical models instead posit a simple linear relationship. Although numerous contextual theories describe a possible relationship between poverty and crime, a particularly prominent one is social disorganization theory, which posits that neighborhoods with higher rates of poverty have reduced cohesion and collective ability to petition for resources from the larger community to combat crime and delinquency in the neighborhood. Thus, increasing levels of poverty continually diminish the neighborhood's ability to secure resources, implying a linear relationship throughout the possible range of values of poverty rates.

There is a certain similarity between the logic of this model and Wilson's discussion of population flow out of neighborhoods, although social disorganization scholars focus particularly on how increased residential mobility can affect the level of community social control (Bursik and Grasmick 1993). While most proponents of social disorganization theory do not directly

advocate the existence of accelerating increasing effects, Quercia and Galster (2000) suggest that the ability of community members to act collectively to solve neighborhood problems, including crime, implies such an effect. Indeed, some scholars have suggested that social disorder may exhibit accelerating increasing effects on crime (Gladwell 2000; Wilson and Kelling 1982). Nonetheless, the vast majority of prior neighborhood research has simply specified the relationship between poverty and crime as a linear one, with less focus on the actual mechanisms explaining this relationship or possible nonlinearity.

Diminishing effect of poverty on crime

Other theories posit that although crime will increase with increasing levels of poverty, this relationship will weaken at higher levels of poverty. For instance, one perspective argues that the relationship between poverty and *property* crime will exhibit a diminishing positive relationship due to two countervailing factors posited by the routine activities theory (Hannon 2002). That is, at low levels of poverty, an increase in the poverty rate will increase the number of motivated offenders due to the increasing social disorganization and strain, but will likely have little effect on the number of suitable targets. However, at higher levels of poverty, increasing the poverty rate will still increase the number of motivated offenders but will actually begin to decrease the number of suitable targets due to the limited economic resources in the neighborhood. This implies a diminishing increasing effect on the rate of property crime. Although this model says little about the relationship between poverty and violent crime, recent work by Rosenfeld (2009) suggests that property crime can have a direct causal effect on violent crime in neighborhoods in which black markets exist for selling the stolen goods. In his model, in such neighborhoods a diminishing positive relationship between poverty and property crime would bring about a similar relationship for violent crime.

Poverty and crime: threshold, linear, or diminishing relationship?

The recent literature focusing on the differential effect of poverty for neighborhoods dominated by African Americans compared to those dominated by whites implicitly posits that poverty has a diminishing positive effect on *both* violent and property crime (Hannon and DeFina 2005; Sampson, Morenoff, and Raudenbush 2005). Such a nonlinear relationship might be due to a satiation effect: although increasing disadvantage will increase crime initially, at some point the level of disadvantage becomes such that further increases have little additional effect on crime rates (Hannon and DeFina 2005; Krivo and Peterson 2000). The precise mechanism underlying this posited relationship is not entirely clear. It could be that neighborhoods reach a level of disadvantage that cannot get any worse. In this scenario, social controls that guard against violent crime have already eroded to a minimal or nonexistent point such that they can no longer be reduced by further increases in disadvantage. As a consequence, given that most white neighborhoods are clustered at the low end of the poverty spectrum (where the slope is steepest) and most black neighborhoods are clustered at the high end of the poverty spectrum (where the slope is leveling off), linear estimates of the poverty/crime relationship in their neighborhoods will yield different slopes. Although this literature has documented the differing levels of poverty in black and white neighborhoods, it has provided little empirical evidence regarding the general functional form of the poverty and crime relationship at the level of neighborhoods.

The lack of specificity regarding the functional form of the poverty and crime relationship from these theories has created uncertainty regarding the actual form we should expect. Rather than accounting for the different possible functional forms, theories have been presented as deterministic of only one possible form. The lack of attention given by researchers in terms of the possibility that other forms of this relationship exist is even more evident when

reviewing empirical studies that have examined the functional form of the poverty and crime relationship, as we describe next.

Empirical studies

Few studies have carefully explored the functional form of the poverty/crime relationship. Most studies have simply estimated this as a linear relationship and have not tested for possible nonlinear effects. An observed positive effect could be consistent with a linear relationship, or an accelerating increasing effect, or even a diminishing positive effect. Such models therefore do not distinguish between these competing theories. For instance, a study of 26 New York neighborhoods found a significant positive linear effect of poverty (measured as persons below 75% of the poverty line) on homicide (Messner and Tardiff 1986). However, studies of aggravated assault and robbery in Seattle (Crutchfield 1989) and violent crime in a study of block groups across three California communities (Alaniz, Cartmill, and Parker 1998) found no effect for poverty when specifying this as a linear relationship. Of course, if the true relationship was a diminishing positive one, such studies might lack the statistical power to detect this given their linear specification.

Some studies have found evidence consistent with a diminishing positive effect, although this evidence is mixed. For instance, a study of census tracts in Austin and Seattle found a diminishing positive relationship between poverty and property crimes in Seattle and Austin (Hannon 2002). However, although McNulty (2001) claimed to find a diminishing positive relationship between a factor score of concentrated disadvantage and the *logged* rate of violent crime in Atlanta block groups, and for the percentage in poverty and *logged* black violent crime rates, Hannon and Knapp (2003) pointed out that the quadratic term was simply counteracting this nonlinear model specification. Correctly interpreting the results showed essentially a linear

relationship. Furthermore, the linear effect for white violent crime that McNulty detected actually provided evidence of an exponential increasing effect after correcting for the nonlinearity of the model specification.

Despite the importance of Wilson's theory for specifying an accelerating increasing effect of poverty rates on crime in neighborhoods, few studies have rigorously tested this. One study of census tracts in New York City specified a spline model by testing the slopes of the poverty and homicide relationship both above and below a specific threshold point (40%), finding a stronger relationship for the higher-poverty tracts (Hannon 2005). Krivo and Peterson (1996) studied Columbus, OH tracts, although the conclusions that can be drawn are limited given the analytic strategy adopted. That is, their approach simply created three indicators and compared whether tracts with more than 40% in poverty had a greater increase in the level of crime than tracts with 20 to 40% in poverty or tracts with 0 to 20% in poverty. This is a crude test of the functional form, and the results are dependent on the distribution of poverty in the tracts of the sample. To see this, consider a hypothetical instance in which the true effect is linear with a slope of β (a one percentage point increase in poverty increases the crime rate β units) and there is an equal probability of observing a tract with any particular poverty rate. In this case, the average effect of poverty on crime in their "low poverty" tracts will be $10*\beta$ (half the tracts will have more poverty, and half will have less). However, the average effect in a moderately high poverty tract will be $30*\beta$ (as the values range from 20 to 40). It appears that the effect of poverty on crime is three times larger in the moderate poverty tracts, even though it is in fact a linear relationship. Furthermore, the average effect of poverty on crime in a very high poverty tract will be $70*\beta$ (given this wider range from 40% to 100%). Thus, this gives the appearance of a stronger effect for high poverty tracts despite the fact that the relationship is

actually linear. Of course, this example has assumed that a tract with 99% in poverty is equally likely as one with 1% in poverty. To the extent that this is not the case, these parameter estimates will be further affected (though the underlying relationship remains linear). This particular parameterization is thus of limited utility to the question at hand. To complicate things further, as pointed out by Hannon and Knapp (2003), Krivo and Peterson log transformed the property crime outcome (but not the violent crime outcome), which biases their results against finding an accelerating increasing effect for property crime (indeed, they did not find such an effect), in contrast to their violent crime model which was biased *towards* finding an accelerating increasing effect given the above discussion.

Some research has implicitly tested the posited exponential increasing relationship between poverty and crime. Log transforming a crime rate measure creates an exponential relationship with any unlogged predictor variables, precisely that argued by such theories. Nonetheless, such studies have frequently failed to find a significant relationship. For example, a study of Seattle neighborhoods found no relationship for logged murder, rape, and violent crime (Crutchfield 1989), and another study of Seattle likewise found no effect for a logged combined measure of aggravated assault and robbery (Rountree and Warner 1999). And whereas a study of census tracts in 19 cities did find a positive effect for logged aggravated assault, it found no effect for logged burglary, motor vehicle thefts, robbery or murder (Hipp 2007). Although one study using victimization data found evidence consistent with an exponential effect of disadvantage on victimization with a national sample, this was only tested in bivariate analyses (Lauritsen and White 2001). Of course, such an effect could be confounded with central city location and metropolitan region effects, but their multivariate analyses only specified and tested a linear effect (Lauritsen and White 2001).

Poverty and crime: threshold, linear, or diminishing relationship?

Despite the numerous studies viewing the relationship between poverty and crime in neighborhoods, it is clear that few of these studies have rigorously explored the functional form of this relationship, leaving it unclear what this form actually does look like. Hence, in addition to the theoretical underpinnings, the methodological approaches used to test the effects of poverty on crime have also added to this confusion.

Data and Methods

Data

The present study utilizes crime data for census tracts in 25 cities (policing areas) in year 2000, as listed in Table A1 in the appendix.[2] These cities were not selected randomly, but rather are a convenience sample of cities with available crime data. Therefore, we are not generalizing to the population of cities, but rather are viewing the differences in tracts within particular cities by conditioning out the differences across cities, as described in the methods section. An advantage of using census tracts is that past studies have frequently used them to proxy for neighborhoods, they contain a mean of about 4,300 residents in 2000 (with 95% of the tracts containing between about 1,400 and 8,000 persons), and they were initially constructed by the Census Bureau to be relatively homogeneous neighborhoods (Green and Truesdell 1937; Lander 1954). Our sample size varies depending on the availability of the various crime types across cities, ranging from 3,458 to 4,392 tracts (see the note in Table 1 for the actual values).

Dependent Variables

The dependent variables in the analyses are the counts of the number of official crime events as reported to and coded by the police departments in the cities of the study, aggregated to

[2] In our study, 24 are city police departments, and one (San Diego County) is a county sheriff that patrols unincorporated areas of the county as well as certain smaller cities in the county.

census tracts, and also factor scores of property and violent crime rates. We computed three year averages (from 1999 to 2001) to smooth differences over years. For the count outcomes, we rounded these averages to the nearest integer value.

Although official crime reports suffer from underreporting, it is important for the present study to highlight that Baumer (2002) found no evidence that this underreporting for the serious violent crimes of aggravated assault and robbery is systematically related to the level of disadvantage in the neighborhood. We therefore feel comfortable using these two types of crime in the present study. Baumer did find evidence that reporting of simple assaults was more often underestimated in more disadvantaged neighborhoods, suggesting caution when using official rates of minor types of crime. Of course, the evidence that respondents are particularly prone to under-reporting simple assaults on victimization surveys suggests that we cannot be very certain about patterns in general for such minor crime types (Gove, Hughes, and Geerken 1985; Hindelang 1978). We also feel justified in using official homicide rates, given that they are considered to have minimal measurement error. For property crimes, the very high reporting rate for completed motor vehicle thefts—about 93% of such crimes were reported by victims in 1999-2001 (Rennison 2001)—suggests that there is little possibility for official rates to vary systematically by the level of disadvantage in the neighborhood. The outcome measures we use that should be treated with caution are burglary and the total property crime rate (which also includes the minor crimes of larcenies). Although we are aware of no studies testing whether burglary under-reporting in the U.S. is systematically related to the level of disadvantage in neighborhoods, the fact that the reporting rate for burglaries was about 50% in 2000 (Rennison 2001) implies that caution should be exercised in interpreting the results for this crime type. Furthermore, studies of the Netherlands for property crime events (Goudriaan, Wittebrood, and

Nieuwbeerta 2006) and China for burglary (Zhang, Messner, and Liu 2007) found a nonlinear effect in which the likelihood of reporting events dropped considerably in extremely high disadvantage neighborhoods (beyond the 80th percentile in disadvantage) (Goudriaan, Wittebrood, and Nieuwbeerta 2006). To the extent that we find a pattern for burglaries (or property crime) that is considerably different than the others would be cause for caution.

We estimated models using five types of crime separately: aggravated assault, murder, robbery, burglary, and motor vehicle theft. We also estimated models in which the outcome was a factor score from a principal components analysis (PCA) of three types of violent crime (aggravated assault, murder, and robbery), and a factor score from a PCA of three types of property crime (larceny, burglary, and motor vehicle theft). These factor scores weight crime based on the intercorrelations of the variables, rather than a simple sum, and are similar in spirit to an approach using confirmatory factor analysis (Parker and McDowall 1986), which is identical to an IRT approach (Bauer 2003; Kamata and Bauer 2008; Lee and Tsang 1999).

Independent Variables

Our key predictor variable is the percentage of tract households with income below the poverty level. In the initial models, we employed a non-parametric specification. We accomplished this by creating a set of indicator variables with five percentage point ranges, indicating whether or not the tract contains: 1) 0-5% in poverty; 2) 5-10% in poverty; 3) 10-15% in poverty, etc. up to 9) above 40% in poverty. We used the indicator of the lowest range as the reference category. Following that, we specified parametric models that included the percentage in poverty, the percentage in poverty squared, and (when necessary) the percentage in poverty cubed. In no instances was the quartic percentage in poverty significant in the models.

Poverty and crime: threshold, linear, or diminishing relationship?

The official poverty rate has known measurement error. Some have suggested using an index of concentrated disadvantage—combining measures such as the percent on welfare, single parent families, unemployed, out of the labor force, and non-professional workers—to capture this broader construct rather than just poverty (Krivo and Peterson 2000; Sampson, Morenoff, and Earls 1999; Sampson, Raudenbush, and Earls 1997). Others have suggested accounting for measurement error in official poverty rates with an instrumental variable approach (Loftin and Parker 1985). Sen (1976) proposed an interesting alternative approach that modifies the Gini coefficient to account for the distribution of persons relative to the poverty income level (rather than relative to the mean income level, which is how the Gini is usually constructed). We do not employ these other approaches here for several reasons. Constructing an index is not useful for our question given that the typical approach of creating an index through a factor reduction technique results in a standardized score for concentrated disadvantage, which does not allow comparisons to other locations and other points in time given that the standardization is specific to the particular sample. This is particularly problematic for testing a nonlinear relationship, as it precludes translating the nonlinearity to specific values of measured constructs; furthermore, given that the literature has provided specific values at which the percentage in poverty should exhibit threshold effects, using the poverty rate has more meaning than choosing arbitrary points on a factor score distribution. Nonetheless, we estimated ancillary models using a concentrated disadvantage index, and they were very similar to those presented in the text.[3] We suggest that Sen's approach is a useful direction for future research, but is not appropriate here given that

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[3] We constructed an index of concentrated disadvantage based on a factor analysis of four measures: the percent in poverty, the percent on welfare, the percent unemployed, and the percent single parent households. The ancillary models estimated with this index showed similar nonlinear effects. These results are presented in an online appendix [*give location*].

existing research makes explicit predictions about the relationship between a standard measure of poverty and crime rates.

Deciding which additional measures to include as control variables is not a trivial issue. It is important not to include measures that arguably are conceptually quite similar to our poverty measure, or arguably are *caused* by the percentage in poverty. We therefore do not include other measures of consolidated disadvantage such as the percentage of single parent households or the percentage on welfare, etc, as many have argued that they are measuring the same abstract construct (Sampson and Raudenbush 1999; Sampson, Raudenbush, and Earls 1997).

We accounted for the effect of economic resources beyond a simple poverty/non-poverty dichotomy by including the average family income in the tract. To capture the possible effect of inequality on crime rates, we computed the Gini coefficient for household income in the tract. Given that the economic investment of homeowners may make them particularly likely to intervene in times of neighborhood distress and therefore have a negative effect on crime, we included a measure of the percentage of households that own their residence.[4] As prior research suggests that young adults are most likely to commit crime, we included a measure of the percentage of residents between the ages of 16 and 29. A long literature suggests that the presence of African American residents in a neighborhood will increase the rate of crime, both with cultural explanations (Wolfgang and Ferracuti 1967) as well as structural-cultural ones (Sampson and Wilson 1995). We therefore account for this with a measure of the percentage African Americans in the tract. To account for the effect of racial/ethnic mixing on crime

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[4] We also created an index of residential instability by standardizing and combining the percent homeowners and the percent of residents who resided in their unit five years previously. The results of ancillary models using this index were extremely similar to those presented here. Given that the mobility of households can be affected by the crime rate and therefore may be endogenous (Bursik 1986; Hipp 2010a; Hipp 2010b; Hipp, Tita, and Greenbaum 2009; Schuerman and Kobrin 1986; South and Messner 2000; Xie and McDowall 2008), we chose to simply use the percent homeowner measure.

beyond any possible effect of African Americans, we constructed a measure of the racial/ethnic heterogeneity in the tract by using a Herfindahl index (Gibbs and Martin 1962: 670) of five racial/ethnic groupings (white, African-American, Latino, Asian, and other races) as follows:

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

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

Spatial effects

Given that these data come from tracts located in physical space, we accounted for the possibility that the structural characteristics of one neighborhood may affect nearby neighborhoods. Accounting for spatial effects requires considering how the spatial process might work. Although studies frequently adopt a model in which it is assumed that the outcome measure in adjacent tracts affects the outcome in the focal tract, recent scholars have called into question the wisdom of always employing such a default specification without more careful theoretical consideration (Elffers 2003; Morenoff 2003). We therefore follow the suggestion of Elffers (2003) and Anselin (2003: 161), among others, in specifying a model in which we test whether the spatial-lagged versions of our structural measures also impact neighborhood crime (Hipp 2010a).

Estimating spatial effects requires specifying what constitutes "close" neighborhoods. Given that past studies have suggested a distance decay function for offenders (Rengert, Piquero, and Jones 1999), with an average distance traveled between 1 to 2.5 miles (Pyle 1974), and that the median census tract in 2000 was about 1.4 miles across (1.95 square miles), we adopted a distance decay function with a cutoff at two miles (beyond which the neighborhoods have a value of zero in the W matrix) in measuring the distance of surrounding neighborhoods from the focal neighborhood. This weight matrix (W) was then row-standardized.

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We then multiplied the values of our predictor variables by this W matrix to create

spatially lagged measures of average family income, the percentage homeowners, racial/ethnic

heterogeneity, the percentage African American residents, and the percentage of residents below

the poverty rate, logged.[5] The summary statistics for the variables used in the analyses are

presented in Table 1.

<<<Table 1 about here>>>

Methodology

In the models in which the outcome measures were counts of crime events, we estimated

fixed effects negative binomial regression models. These models assume a Poisson process, with

an additional term allowing for overdispersion given the possible nonindependence of events.[6]

Our full model estimated for the counts is:

(2) $$E(Y \mid X) = \exp(X_i B)$$

where Y is the crime rate in tracts, and X is a vector of poverty measures (which can include

linear, quadratic, and cubic terms for poverty, or it can include our series of indicator variables in

the nonparametric specification), the other neighborhood measures, the various spatially lagged

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[5] We also estimated models that included a spatially lagged version of the unlogged poverty measure. In all models, the logged version of the spatially lagged measure always explained slightly more of the variance in the outcome, so we included this version of the measure in all models presented.

[6] An alternative estimation approach taken by Hannon and Knapp (2003) created an unlogged outcome measure of the crime rate per capita and employed a weighted least squares estimator to test for nonlinearities. However, we follow Osgood (2000) in accounting for the count nature of the crime data outcome by employing a negative binomial regression model. We account for the nonlinearity when interpreting the results by plotting the expected crime counts implied by the models. Nonetheless, we estimated OLS models on the log transformed outcome and WLS models, and obtained very similar results (shown in the online appendix). A limitation of WLS with population as the weight compared to Poisson estimation is that although WLS addresses heteroskedasticity, it does not address the problem of possible inappropriately predicted negative crime rates. Indeed, our WLS models had 11.5% predicted negative values for the aggravated assault models, 11.7% for robbery, 21.6% for murder, and 6.1% for motor vehicle theft, which emphasizes the preferability of the negative binomial regression models. Also, we followed the strategy of some prior research (Hannon 2005) and estimated bivariate spline models to assess whether the effect of poverty on murder is different for tracts below 40% in poverty compared to those above this value (Hannon 2005). These results also exhibited a diminishing effect for high poverty tracts, as the coefficient was five times as large for tracts below 40% in poverty compared to those above this value (49.48 versus 10.03) in weighted least squares models with the murder rate as the outcome.

variables, and *J*-1 indicator variables for *J* cities in the sample. Since we only have 25 cities, and they are not randomly sampled, we do not estimate a multilevel model but instead account for this clustering with the indicator variables for the cities. We included the tract-level logged population as an offset variable in these models with a coefficient constrained to one: thus, we are effectively modeling crime *rates* as the outcome. In all models presented, we assessed possible multicollinearity with variance inflation factors and detected no problems.

In the models in which the outcome measures were the factor scores of violent crime or property crime, we estimated linear city-level fixed effects models. This error term is assumed to have a Gaussian distribution given the approximately normal distribution of these factor scores.

It is important that we account for the nonlinearity introduced by the negative binomial estimator when interpreting the results, and we do so by creating predicted counts based on the parameters of our model to accurately capture the effect of poverty on the various crime types that we study. We provide graphs of these results, which allow for straightforward interpretation of the functional form of the relationship between poverty and various types of crime.

Given that there is some theoretical uncertainty regarding whether any nonlinear relationship between poverty and crime should be measured as a bivariate relationship or as a ceteris paribus partial correlation after taking into account other key predictors of crime, we specified four different models including increasing numbers of control variables. We estimated models with: 1) no control variables (the bivariate relationship of poverty and crime); 2) just two control variables (average family income and the percentage of African American residents); 3) the spatial lag versions of average family income, percent in poverty (logged), and percentage African Americans along with the variables in specification two; 4) a full model including all of

our measures. We also estimated one additional full model (#4) that includes the linear effect of

poverty (instead of the polynomials) to assess the magnitude of the difference between models

that take this naïve approach and our models accounting for this nonlinear effect. We tested for

influential cases, and only found potential candidates in the burglary and motor vehicle theft

models (due to tracts with smaller population values): we therefore dropped 4 tracts in these

models.

Results

Nonparametric estimates of the poverty/crime relationship

We begin by estimating our nonparametric models of the relationship between poverty

and crime in tracts. We present the results of these models by graphing the predicted count

within each of these 5% ranges (all other variables are at their mean values). In the model with

the violent crime factor as the outcome, we see in Figure 2 a distinctly nonlinear relationship.

Whether estimating the bivariate relationship, a model controlling for the average income and the

percentage African Americans, or a model also including the spatially lagged measures, the

pattern is distinctly nonlinear, with virtually no evidence of an accelerating increasing effect.

Instead, it appears that the effect of poverty on violent crime slows at higher levels, and actually

levels off when the neighborhood has 35% or more in poverty.[7]

<<<Figure 2 about here>>>

Turning to the models with the property crime factor score as the outcome, we again see

a diminishing positive effect of poverty on this type of crime. As seen in Figure 3 using the five-

percentage point ranges, higher levels of poverty increase property crime until the neighborhood

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[7] An ancillary model that included indicator variables for higher percentages in poverty (40-45%, 45-50%, 50-55%, 55-60%, and 60% and up) also showed no evidence that these neighborhoods with higher levels of poverty have any more violent crime than neighborhoods with 35 to 40% in poverty.

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achieves about 20-25% in poverty, and then levels off. In the model including the spatial lags, there is no evidence that increasing the poverty rate in a neighborhood beyond 25% has any effect on the property crime factor. Importantly, there is virtually no evidence of an accelerating increasing effect here for property crime.

<<<Figure 3 about here>>>

These factors of violent and property crime may mask the relationship for specific types of crime, so we next estimated nonparametric models for the various types of crime. The graphical results of these models are displayed in an online appendix. The pattern for aggravated assaults and robberies are similar, as they generally show a linear, or even diminishing increasing, effect of poverty on these types of crime (similar to violent crime in Figure 2). There is some evidence in the bivariate models that aggravated assault increases a little more sharply as the percentage in poverty in the tract goes from 25% to about 40%. However, this levels off beyond the 40% threshold. Likewise, robbery appears to bump up somewhat in the bivariate models as the percentage in poverty increases from about 35 to 40%. The general form of this relationship holds in the models adding covariates. Importantly, there is no evidence of an accelerating increasing effect in which these crime types increase dramatically in neighborhoods with high levels of poverty. In fact, the models including the spatial effects actually show a drop in the rate of crime for tracts above 40% in poverty.

The one type of crime that exhibits some evidence of an accelerating effect is murder. However, this escalation effect occurs at a lower range than some have hypothesized, and then levels off. In Figure 4, there appears to be evidence that the number of murders increases quite strongly for neighborhoods with between 25 and 40% in poverty, especially in the bivariate

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analyses. However, regardless of the model specification, the effect levels off for tracts above 40%--that is, the most disadvantaged.

<<<Figure 4 about here>>>

The property crimes of burglary and motor vehicle theft show a distinct slowing effect that parallels that of total property crime in Figure 3. This slowing effect is particularly pronounced for motor vehicle thefts, which appear to increase quite substantially as the level of poverty increases up to a point of about 15% in poverty, and then slow beyond that. In the model with spatial effects, there is no evidence that increasing poverty beyond the 20% level has any effect on motor vehicle thefts. Burglaries show a quite weak relationship, and it appears that increasing the poverty rate above 20% has little additional effect on this type of crime.

Parametric estimations of the poverty/crime relationship

We next estimated models specifying a parametric relationship between poverty and various types of crime. In these models we included the quadratic and cubic versions of the poverty measure in all models except for the models with murder as the outcome (the cubic term was not significant in these models). In the remainder of the models, the linear, quadratic, and cubic versions of the poverty measure were highly significant. We graph the predicted count when poverty ranges from 0% to 50%, given that only 3.4% of tracts have a higher poverty rate than this (all other variables are at their mean values).

In the models with the violent crime factor as the outcome, we see a pattern similar to that observed in the nonparametric models. Figure 5 shows strong nonlinear effects regardless of which control variables we include. In the model with no control variables, changes in poverty show stronger effects on violence for neighborhoods with lower levels of poverty, but weaker effects for neighborhoods with high levels of poverty. This parallels the results of the

nonparametric specification. The story is the same in the parsimonious model including just two control variables. Although poverty has a somewhat weaker effect on violent crime in the model including the spatial lags, and the full model including all of the control variables, the general shape of the nonlinear effect remains unchanged: a slowing increasing effect as neighborhoods approach 40% in poverty. Beyond this point, increases in poverty have no effect on violent crime.

<<<Figure 5 about here>>>

To demonstrate the consequences of ignoring the nonlinear effects of poverty on violent crime, we estimated a model in which poverty is specified linearly (with our full set of control variables). The effect graphed in Figure 6 is quite dramatic: in contrast to the estimated linear effect, correctly accounting for the nonlinearity results in a slowing effect of poverty on violent crime. As a consequence, a naïve approach ignoring the nonlinearity would predict more violence in the lowest and highest poverty tracts than actually occurs, and would predict less violence than actually occurs for tracts with between 15% and 50% in poverty. For instance, in a tract with 2% in poverty the linear specification predicts about .32 standard deviations more violent crime than does the nonlinear model, whereas it predicts about .15 standard deviations less than the nonlinear model for tracts with 30% in poverty.

<<<Figure 6 about here>>>

Turning to the parametric estimates for the total property crime factor, Figure 7 illustrates a pattern similar to that observed in the nonparametric models of a slowing increasing effect of poverty on property crime. In the bivariate model, the effect of increasing poverty on property crime weakens until it stops entirely at about 38% in poverty in the neighborhood. Additional poverty beyond this point has no effect on the level of property crime. When including the

spatial lags, this inflection point occurs with about 32% in poverty. And in the full models, this inflection point is about 22%, again demonstrating little evidence of an accelerating increasing effect for high poverty neighborhoods. This again has important implications for models that misspecify this relationship as a linear one: comparing this full-model cubic specification to the linear specification in Figure 8 highlights that the linear model would mistakenly imply a nonsignificant relationship between poverty and property crime, when in fact there is a quite pronounced nonlinear effect.

<<<Figure 7 about here>>>

<<<Figure 8 about here>>>

We next briefly consider the effect of poverty on the five specific types of crime with our parametric models. Poverty exhibits the distinctive logarithmic relationship with both aggravated assault and robbery. This pattern mirrors that of total violent crime, and there is some evidence that increasing levels of poverty in the ranges of about 15 to 35% have the strongest effect on aggravated assault and robbery. In the full models, increasing levels of poverty have almost no effect on the robbery rate beyond about 30% in poverty. On the other hand, the effect of poverty on murder in Figure 9 shows a very strong nonlinear effect: increasing levels of poverty have increasingly strong effects on the number of murders up until the neighborhood reaches about 30% in poverty in the full model; beyond that point, increasing levels of poverty have a diminishing positive effect on the number of murders. Again, murders are the one type of crime that show any evidence at all of an escalation effect, though this effect occurs at lower levels of poverty than some scholars have previously supposed, and it does not appear to increase monotonically for neighborhoods with the highest levels of concentrated poverty.

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<<<Figure 9 about here>>>

The patterns for the two property crimes of burglary and motor vehicle theft are somewhat similar. Burglary exhibits a distinctive slowing increasing effect in these models. Whereas increasing levels of poverty have the strongest effect in neighborhoods with very low levels of poverty, adding more impoverished households to neighborhoods with higher levels of poverty has a diminishing effect on the rate of burglaries. The pattern for motor vehicle thefts is strikingly nonlinear in the bivariate model, but in the full model the strongest effects occur in neighborhoods with very low levels of poverty. Beyond about 25% in poverty, increasing poverty actually decreases motor vehicle theft in the full model. In the bivariate analyses, this inflection point is about 40%. There is quite clearly no evidence of an accelerating increasing effect for these property crimes.

Effect of taking into account the nonlinear effect of poverty for other variables in the model

Finally, we briefly note the change in the effect of the other measures in the full model when properly taking into account the nonlinear effect of poverty on violent and property crime rates. The first two models in Table 2 present the coefficients for the model with the violent crime factor as the outcome when including a linear specification of poverty and the cubic specification, respectively. The third and fourth models show the parallel models with property crime as the outcome. A few of the variables are quite strongly impacted by accounting for this nonlinearity: for instance, the effects of average family income and inequality are reduced 35% to 40% in the violent crime model when accounting for this nonlinearity, and average family income is reduced 35% in the property crime model. The effect of owners is reduced 10 to 15% in these models. There is also evidence that the spatially lagged measure of poverty is,

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unsurprisingly, reduced 30% in these two models when properly accounting for the nonlinear effect of poverty in the focal tract.

<<<Table 2 about here>>>

Conclusion

Although numerous theories posit some particular functional form for the relationship between poverty and crime, few studies have rigorously explored the shape of this relationship. This is not a trivial issue, as a wealth of studies have followed the insight of William Julius Wilson (1987) in positing an accelerating increasing effect in which highly disadvantaged neighborhoods experience a general meltdown of norms and a subsequent exponential growth in crime rates. The lack of solid evidence regarding this hypothesis is surprising, and is of consequence given that nonlinearity between neighborhood poverty and crime implies that the *distribution* of poverty in the larger community might have implications for the overall level of crime. We explored this question by studying the functional form of the relationship between poverty and crime for five types of crime, as well as factor scores of violent and property crime in census tracts.

There was little evidence in this large sample of census tracts in 25 different cities that poverty exhibits an accelerating increasing effect on crime. For none of these types of crime was there any evidence of a sharp uptick in the amount of crime as poverty rates went above 40%--a value that numerous studies have used as an indicator of an extremely disadvantaged neighborhood. For example, the effect of poverty on the violent crime rate was a slowing increasing effect that was essentially flat beyond about 40% in poverty. Likewise, although the effect of poverty on property crime is particularly steep up until about 25% in poverty, it is also essentially flat beyond about 35% in poverty. We found similar results regardless whether we

specified a nonparametric form or a cubic functional form. Thus, there appears little justification

to assume that there is something qualitatively different about the amount of crime experienced

in neighborhoods once they exceed 40 percent in poverty.

Instead, the evidence appears stronger for a diminishing effect of poverty on various

types of crime, rather than an accelerating increasing effect. For the property crimes of burglary

and motor vehicle thefts this was particularly the case. The relationship between poverty and

burglary rates was clearly a slowing increasing effect up until about 40%, and although the

relationship between poverty and motor vehicle theft was particularly steep from 0 to 15%, it

was essentially flat beyond the 25% poverty rate. For the violent crimes of aggravated assault

and robbery, there was no evidence of accelerating effects in the models with control variables.

Although the bivariate relationship was particularly steep in the mid-ranges of poverty (from

about 15-35% for aggravated assault and from 5 to 30% for robbery), this mid-range effect

disappears when including control variables: although aggravated assault showed a steep

increase until about 15% in poverty, both robbery and aggravated assault generally show a

slowing increasing relationship with poverty. The property crime findings are consistent with

the hypothesis of a decreasing pool of suitable targets in these neighborhoods (Hannon 2002),

whereas the violent crime findings are consistent with Rosenfeld's (2009) argument that property

crime directly impacts the level of violent crime. The findings imply that problems in

neighborhoods begin to manifest themselves at much lower levels of poverty.

The only exception to this pattern were murder rates, which showed some evidence of an

increasing effect, though this occurred during the middle range of poverty values. In the model

with no control variables, this steep slope occurred from about 10 to 30% in poverty, with a

slowing increasing effect beyond this point. In the models with control variables the steep slope

occurred from about 20 to 40% in poverty. Nonetheless, even murders leveled off beyond about 40 or 50% in poverty. Thus, the notion of a threshold effect of poverty at 40% on violent or property crime clearly needs to be reconsidered.

We note that one might argue that the common strategy in the literature of using an indicator variable of high poverty neighborhoods is not unjustified given that there is little variation in the amount of crime among them. However, our findings highlighted that the bulk of the action is occurring among the neighborhoods *not* classified as high poverty. Thus, the heterogeneity in crime rates among neighborhoods with lower levels of poverty is clearly important to capture. The common scheme of simply classifying these as non-high-poverty and ignoring the variability among them is unjustified.

These strong nonlinear effects in the form of a diminishing positive relationship between poverty and crime in neighborhoods also imply that studies of neighborhood crime can obtain considerably mistaken predictions of the amount of crime in a neighborhood if inappropriately specifying poverty as a linear relationship rather than a nonlinear one. Scholars should be cognizant of, and test for, likely nonlinearity between poverty and crime. For neighborhoods with 2% in poverty, the level of aggravated assault or robbery was overestimated about 0.3 standard deviations by incorrectly specifying this as a linear relationship rather than a cubic one. We also showed that the parameter estimates of other measures included in the model can be affected by inappropriately specifying this relationship as a linear one. Of course, this is not terribly surprising, as any model misspecification can affect parameter estimates, but it is nonetheless the case that there can be important implications given the importance of poverty rates for explaining levels of crime.

Given the findings, it is not only important to consider how the relationship between poverty and crime is conceptualized and examined, but to also evaluate steps that can be taken to deal with crime in neighborhoods characterized by different levels of poverty. Given that many crime types appear to increase rapidly as the level of poverty begins to increase from very low levels, this may imply the need to provide resources to low poverty neighborhoods that are experiencing increases in poverty. Although we have tested a static model, it may be that the dynamic process of changing poverty levels implies something akin to a tipping point, but particularly so for neighborhoods with low levels of poverty.

It is an open question what implications our findings hold for city-level rates of crime given the distribution of poverty in the city's neighborhoods. For instance, Stretesky and Schuck (2004) found some evidence that poverty clustering in cities leads to higher homicide rates but has no impact on other types of crime. Our evidence that the poverty/homicide relationship in neighborhoods appears different than the relationship between poverty and other types of crime may in part explain such findings. We emphasize that our cross-sectional approach was not able to unpack the causal direction of this process. For example, some research has suggested that crime rates may disproportionately affect residential mobility patterns, affecting the level of poverty in a neighborhood (Bursik 1986; Schuerman and Kobrin 1986; Skogan 1990; Taylor 1995). It may even be that crime and poverty work in a reciprocal pattern in changing neighborhoods (Hipp 2010a; Hipp, Tita, and Greenbaum 2009). This suggests that the implications for city level crime rates will need to be explored carefully.

We acknowledge some limitations to this study. First, we were limited to studying the census tracts located in a non-random sample of 25 cities at one point in time. We emphasize that the generality of theories describing the poverty/crime relationship implies that our estimates

of this relationship would not be affected by the particular cities studied here or the time period of the study. Nonetheless, given the growth and contraction in high poverty neighborhoods over time, it would be useful to test whether these results do indeed generalize to other time points. If the poverty/crime relationship only exhibits an accelerating increasing effect in certain environments, theorists would need to make clear which these would be, and empirical studies using neighborhoods in a sample of cities could test such effects. A change in this relationship over time would also require theoretical explanation—especially given that we are aware of no claims in the literature that this relationship has changed in recent years. We leave such questions to future research. Second, our measures of burglary and general property crime quite possibly have measurement error that is related to the level of disadvantage in neighborhoods. This might explain some of their slowing effect; nonetheless, the fact that these two crime types exhibited similar relationships to poverty as the other crime types suggests that our findings may be reasonable representations of the general process.

It is also the case that we did not test any of the posited mechanisms here. Studies that fully measure the social transformations posited by Wilson could reveal key insights. Nonetheless, it is important to highlight that we did not observe the general pattern predicted by this theory of an accelerating increasing crime rate as poverty increases. In addition, testing the theoretical mechanisms of social disorganization and opportunity theory would be fruitful. While these theories do share some overlapping mechanisms, each perspective may be more advantageous in explaining the poverty and crime relationship especially with respect to their applicability to property and violent crimes. Thus, exactly why poverty might have such a nonlinear slowing effect on crime rates will need to be the focus of future work that teases out these processes.

In conclusion, we note two key findings. First, there are clearly strong nonlinear effects of poverty on crime rates. Although prior research has generally specified this as a linear relationship, our results point out that this is an unacceptable assumption. The robust nonlinear evidence here highlights the need for future work to build on this insight. Second, there is minimal evidence of an accelerating increasing effect of poverty on crime, but much stronger evidence of a diminishing positive effect. The lack of an accelerating increasing effect calls into question a key hypothesis of Wilson (1987)—and much research following in this tradition—that high rates of poverty will give rise to exponentially higher rates of crime. Nonetheless, why increasing poverty might affect crime more strongly in neighborhoods with the lowest levels of poverty—and presumably those with the lowest levels of social disorganization—needs to be the focus of future research.

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Poverty and crime: threshold, linear, or diminishing relationship?

Tables and Figures

Table 1. Summary statistics of variables used in analyses

	Mean	Standard Deviation
Violent crime factor score	0.000	0.898
Property crime factor score	0.000	0.960
Aggravated assaults	24.927	33.309
Robberies	14.870	25.021
Murders	0.177	0.576
Burglaries	38.493	34.710
Motor vehicle thefts	31.830	31.280
Proportion in poverty	0.195	0.143
Tract has 0 to 5% in poverty	0.116	0.321
Tract has 5 to 10% in poverty	0.199	0.399
Tract has 10 to 15% in poverty	0.160	0.366
Tract has 15 to 20% in poverty	0.123	0.329
Tract has 20 to 25% in poverty	0.099	0.299
Tract has 25 to 30% in poverty	0.081	0.272
Tract has 30 to 35% in poverty	0.074	0.262
Tract has 35 to 40% in poverty	0.051	0.221
Tract has 40% and above in poverty	0.096	0.295
Average family income ($10,000's)	5.897	3.671
Proportion owners	0.493	0.244
Proportion African American	0.206	0.284
Racial/ethnic heterogeneity	0.411	0.190
Spatial lags		
Percent in poverty, logged	2.834	0.571
Average family income ($10,000's)	5.635	2.549
Proportion owners	0.471	0.175
Proportion African American	0.219	0.242
Racial/ethnic heterogeneity	0.414	0.143

Sample sizes are: 4,392 tracts for violent crime, 4,392 tracts for property crime, 3,885 for aggravated assault, 3,784 tracts for robbery, 3,458 tracts for murder, 4,002 tracts for burglary, 3,815 tracts for motor vehicle theft
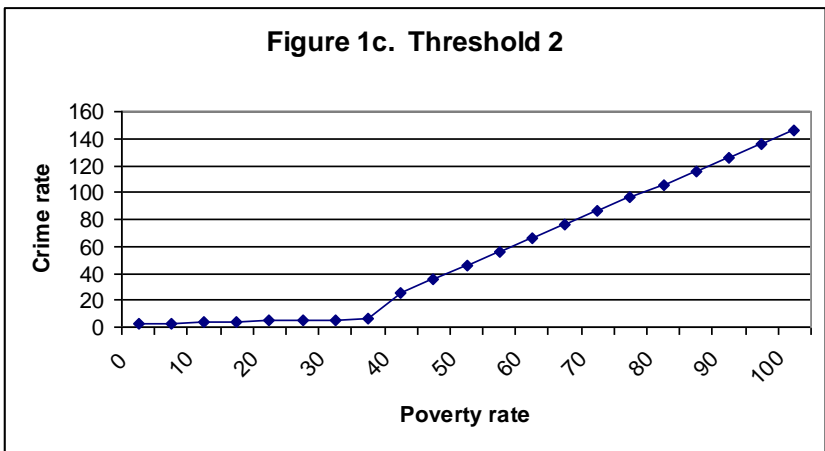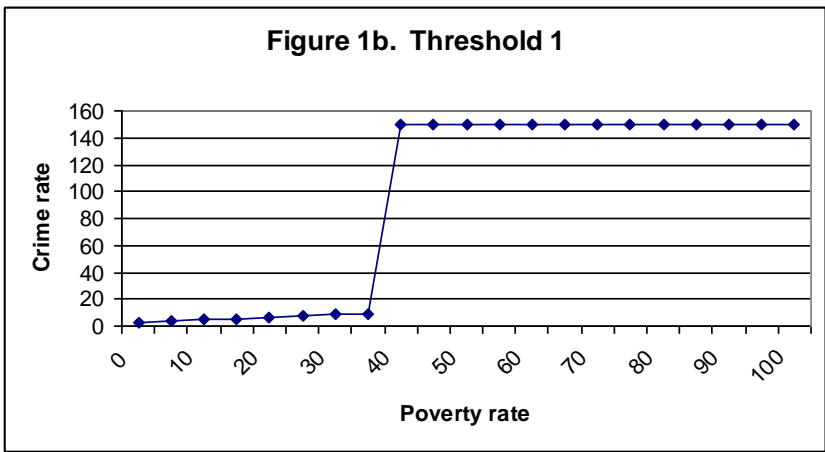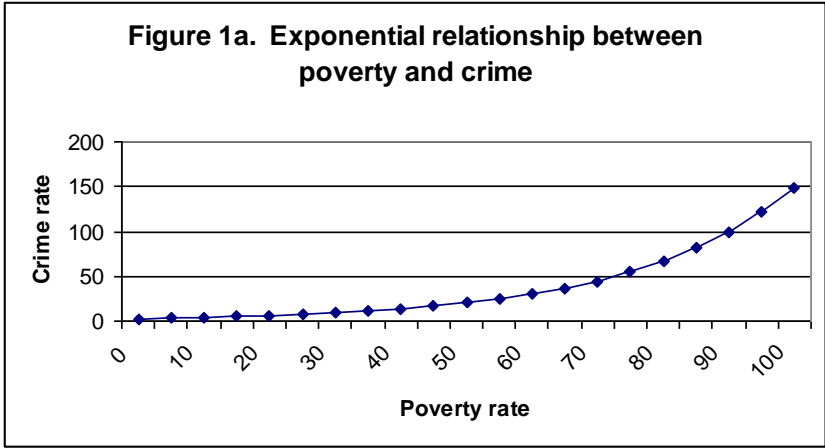
Poverty and crime: threshold, linear, or diminishing relationship?

Table 2. Predicting violent and property crime, comparing linear and nonlinear specifications of poverty

	Violent crime		Property crime	
	Linear specification	Cubic specification	Linear specification	Cubic specification
Proportion in poverty	0.782 **	5.501 **	0.224	4.291 **
	(5.30)	(10.31)	(1.25)	(6.11)
Proportion in poverty, squared		-11.213 **		-11.700 **
		-(7.92)		-(6.16)
Proportion in poverty, cubed		7.038 **		9.078 **
		(6.03)		(5.83)
Average family income ($10,000's)	-0.035 **	-0.021 **	-0.027 **	-0.018 *
	-(6.13)	-(3.55)	-(3.46)	-(2.23)
Inequality	1.398 **	0.911 **	1.762 **	1.608 **
	(6.76)	(4.21)	(6.56)	(5.76)
Proportion owners	-0.644 **	-0.548 **	-0.518 **	-0.461 **
	-(7.85)	-(6.68)	-(4.55)	-(4.04)
Proportion aged 16-29	-0.638 **	-0.640 **	-0.352 †	-0.421 *
	-(4.69)	-(4.71)	-(1.96)	-(2.34)
Proportion African American	0.639 **	0.618 **	0.033	0.033
	(7.33)	(6.98)	(0.28)	(0.29)
Racial/ethnic heterogeneity	0.046	-0.096	0.068	-0.043
	(0.48)	-(1.00)	(0.53)	-(0.32)
Spatial lags				
Percent in poverty, logged	0.376 **	0.262 **	0.222 **	0.157 **
	(7.59)	(5.06)	(3.89)	(2.61)
Average family income ($10,000's)	0.014	0.011	0.042 **	0.039 **
	(1.58)	(1.17)	(3.40)	(3.17)
Proportion owners	0.003 **	0.002	0.000	0.000
	(2.83)	(1.56)	(0.20)	-(0.28)
Proportion African American	-0.002 *	-0.002 †	0.000	0.000
	-(2.05)	-(1.65)	(0.07)	(0.18)
Racial/ethnic heterogeneity	0.006 **	0.006 **	0.006 **	0.006 **
	(4.14)	(4.57)	(2.91)	(3.06)

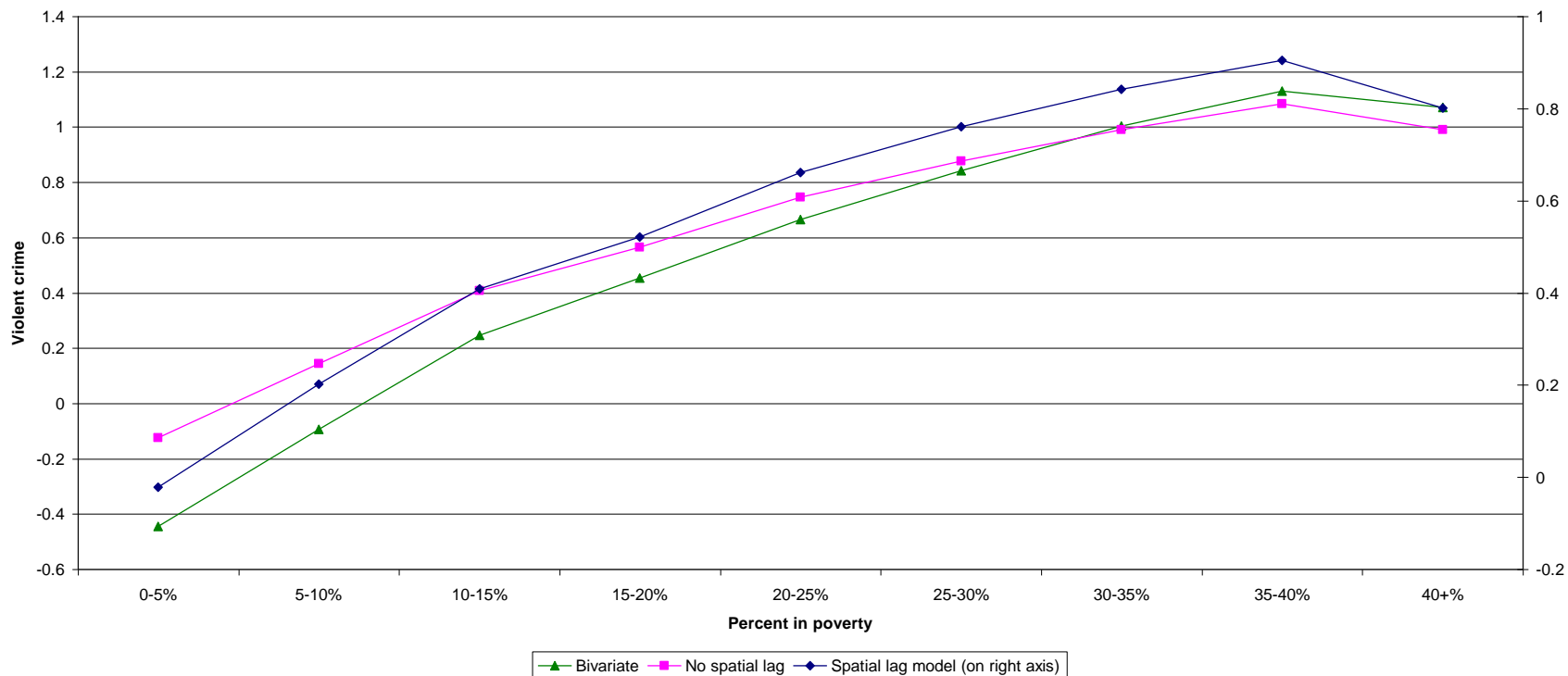*** $p < .01$ (two-tail test), * $p < .05$ (two-tail test), † $p < .05$ (one-tail test). T-values in parentheses. N = 4,392 tracts*

Poverty and crime: threshold, linear, or diminishing relationship?

Figure 1a. Exponential relationship between poverty and crime

Figure 1b. Threshold 1
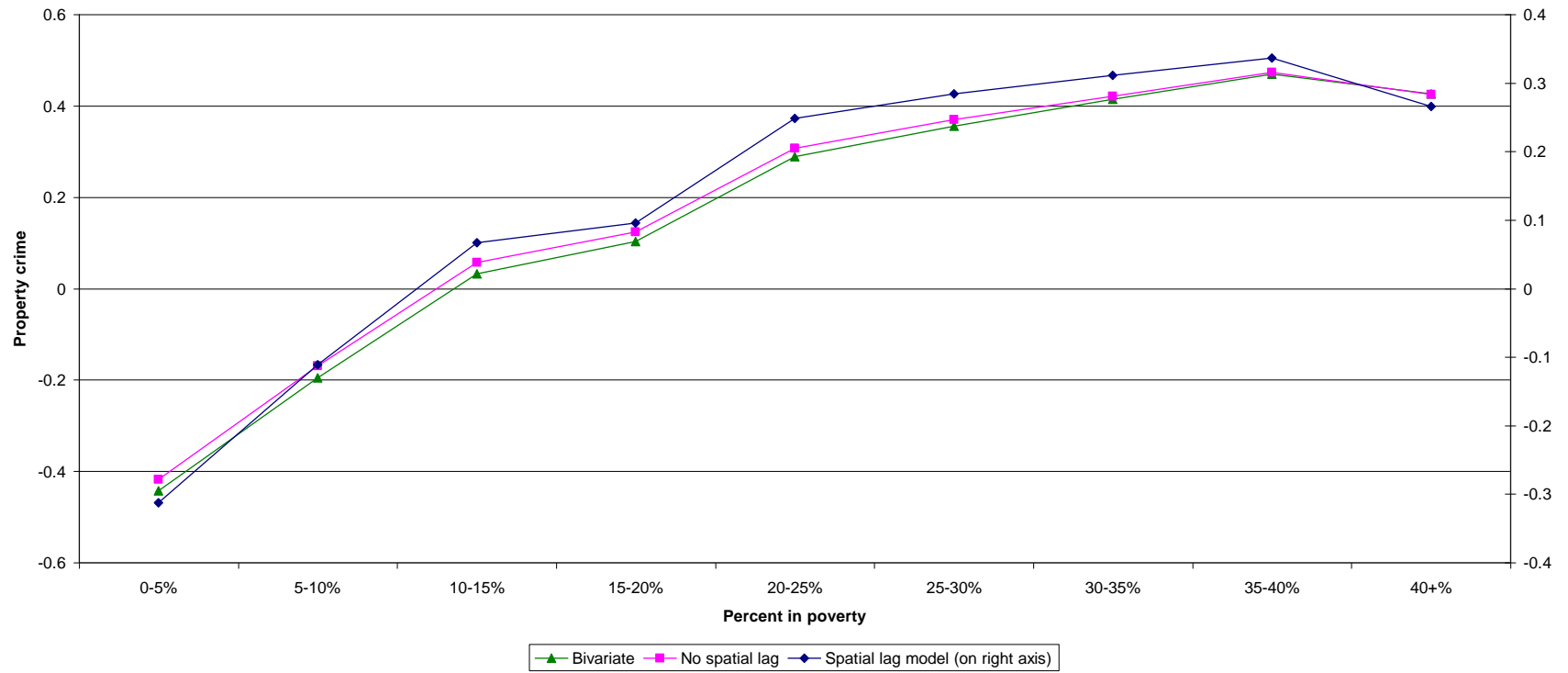
Figure 1c. Threshold 2

Poverty and crime: threshold, linear, or diminishing relationship?

Figure 2. Nonparametric estimate of the effect of poverty on violent crime factor score, various model specifications
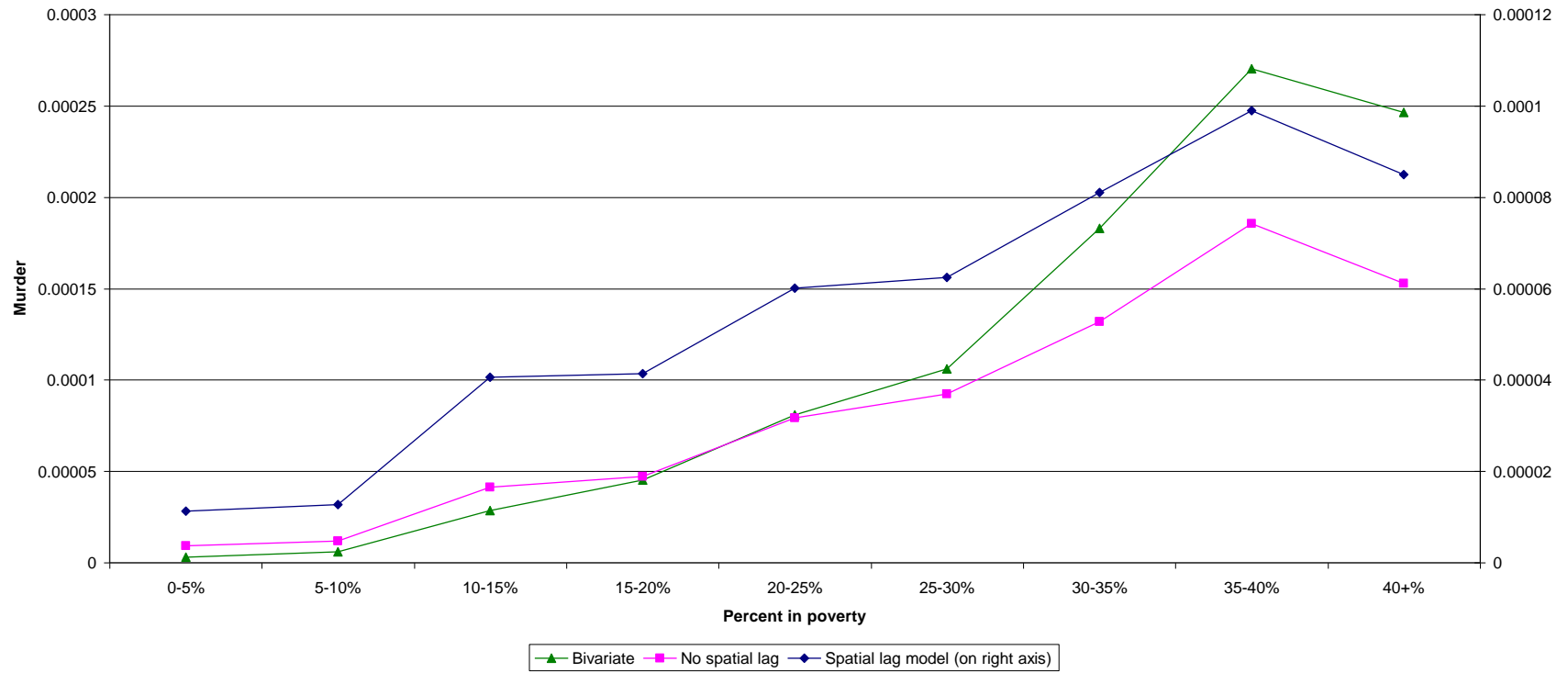
Poverty and crime: threshold, linear, or diminishing relationship?

Figure 3. Nonparametric estimate of the effect of poverty on property crime factor score, various model specifications
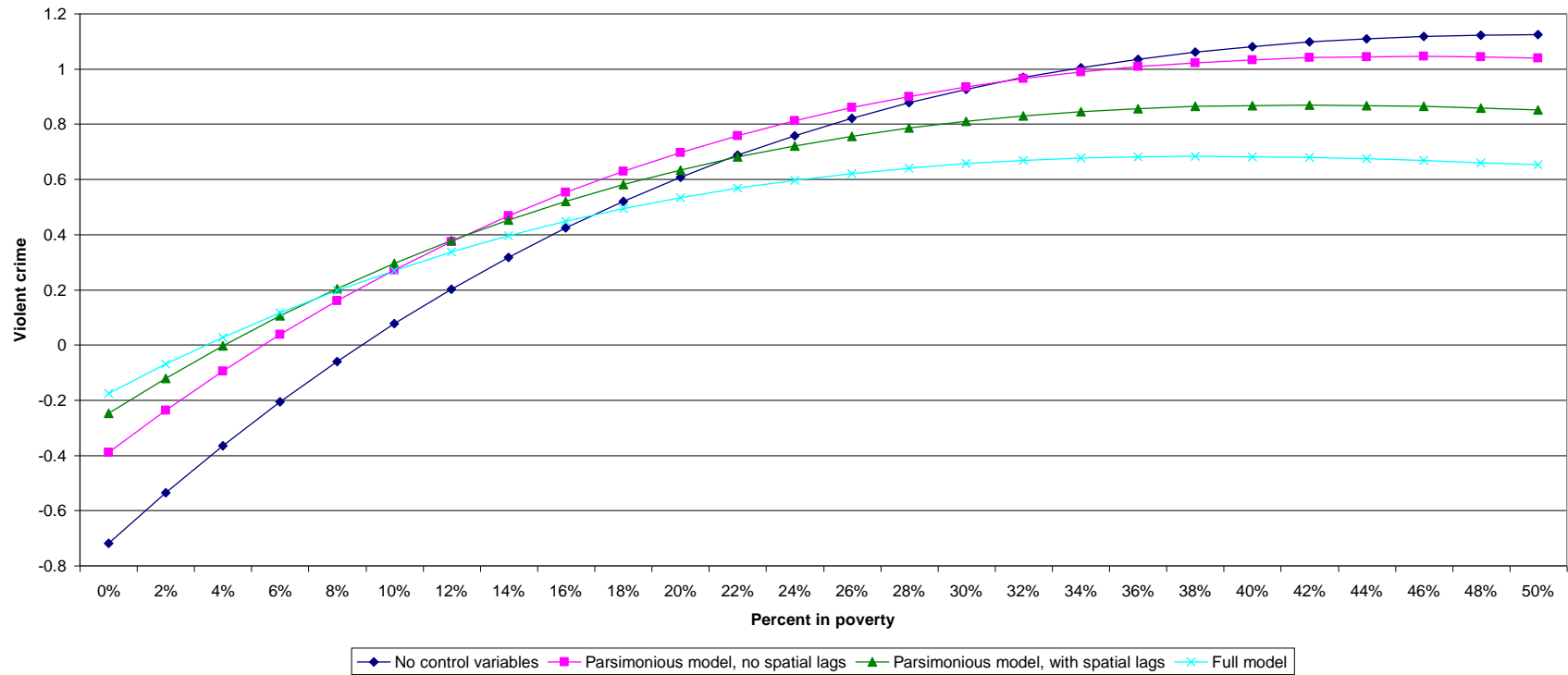
Poverty and crime: threshold, linear, or diminishing relationship?

Figure 4. Nonparametric estimate of the effect of poverty on murder, various model specifications
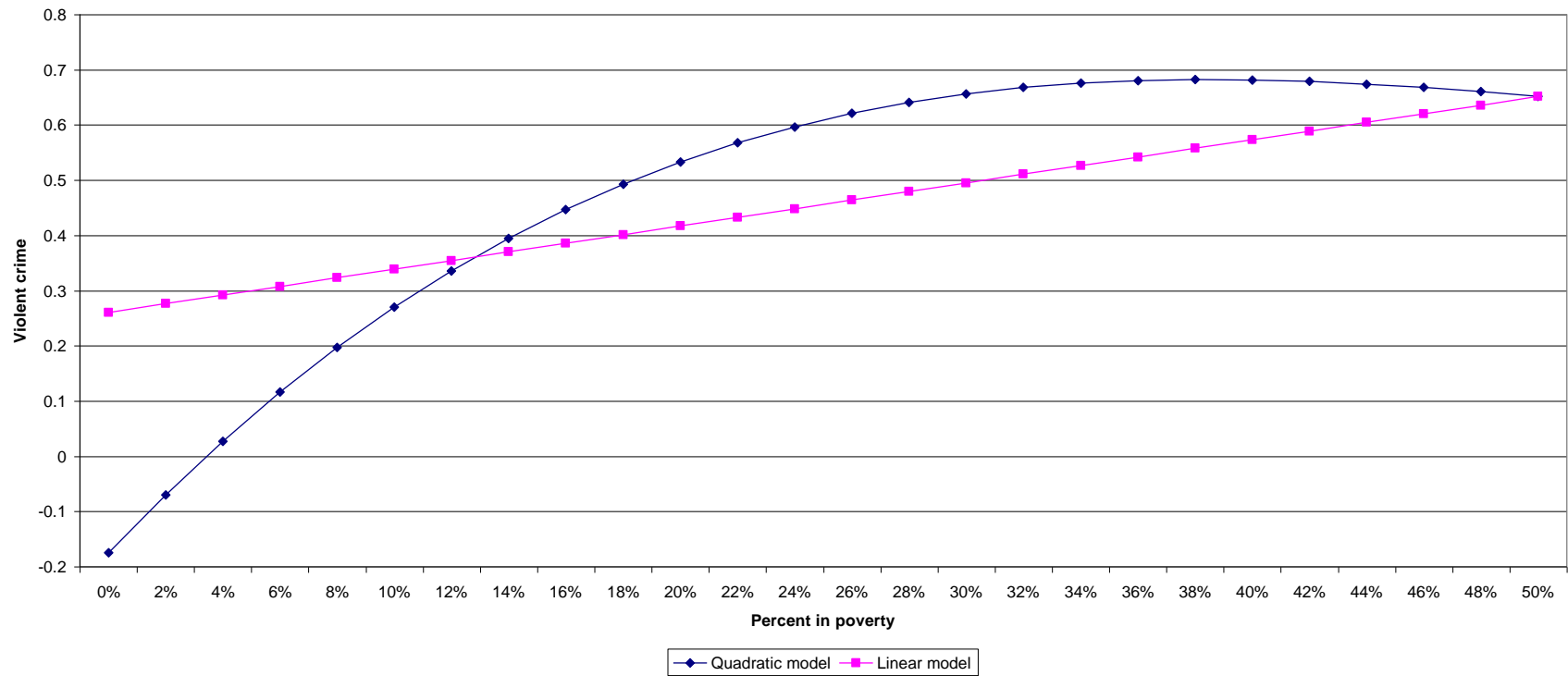
Poverty and crime: threshold, linear, or diminishing relationship?

Figure 5. Nonlinear (cubic) estimate of the effect of poverty on violent crime factor, various model specifications
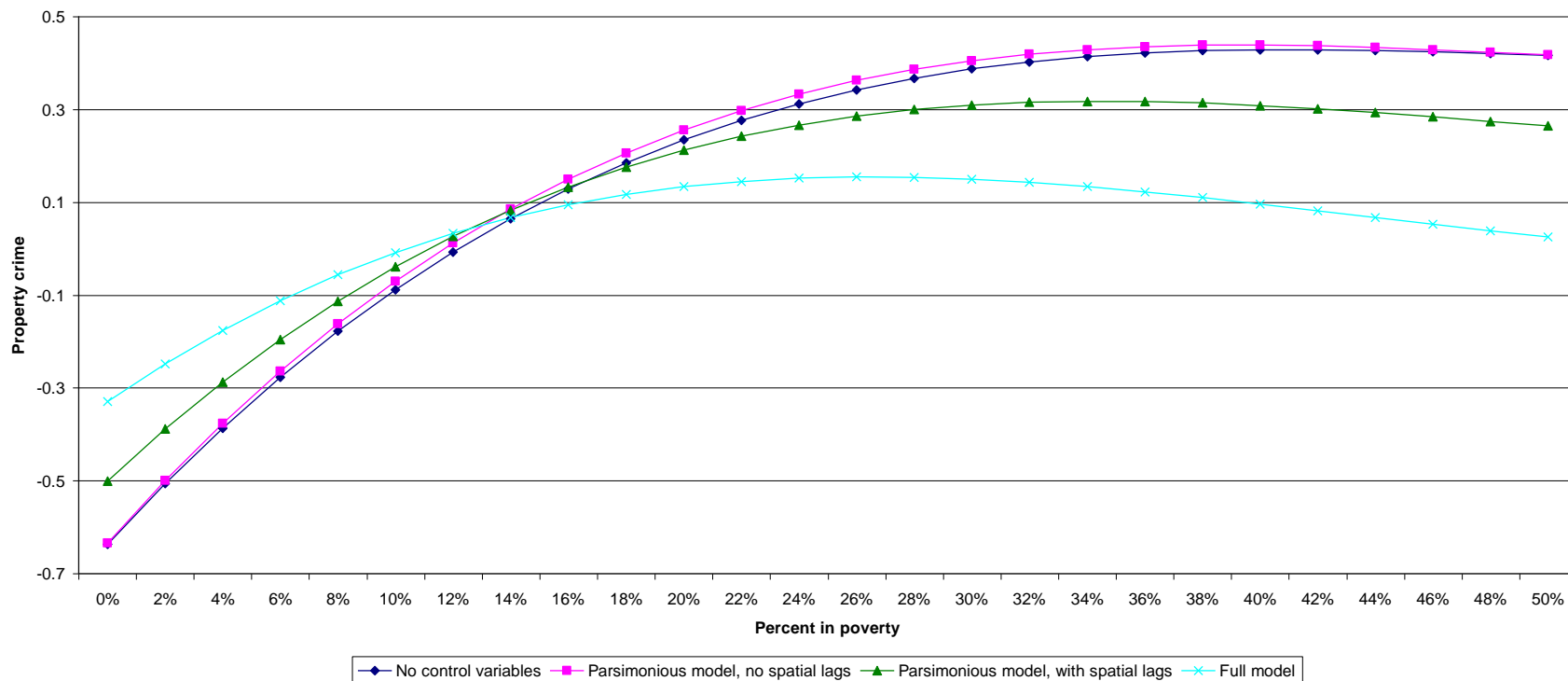
Poverty and crime: threshold, linear, or diminishing relationship?

Figure 6. Estimate of the effect of poverty on violent crime factor, comparing linear and nonlinear model specifications
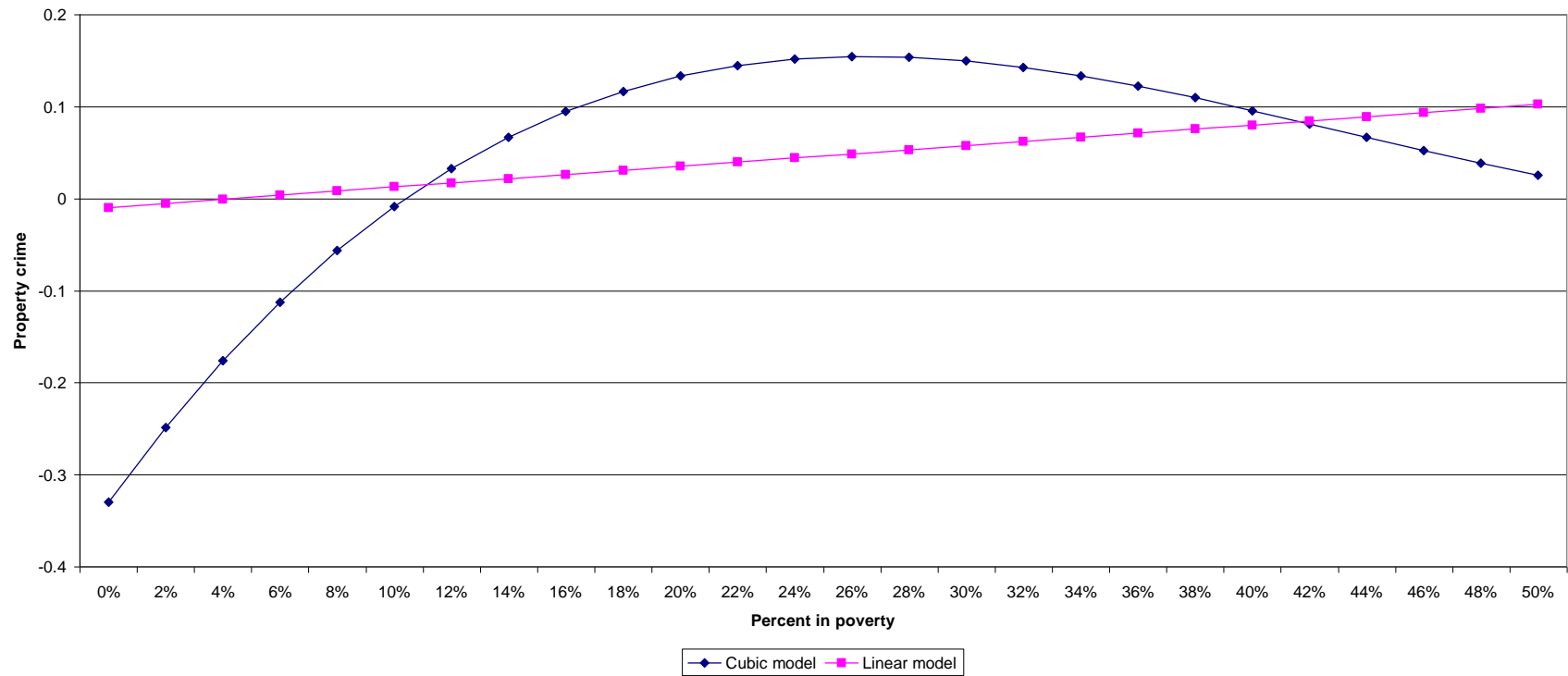
Poverty and crime: threshold, linear, or diminishing relationship?

Figure 7. Nonlinear (cubic) estimate of the effect of poverty on property crime factor, various model specifications
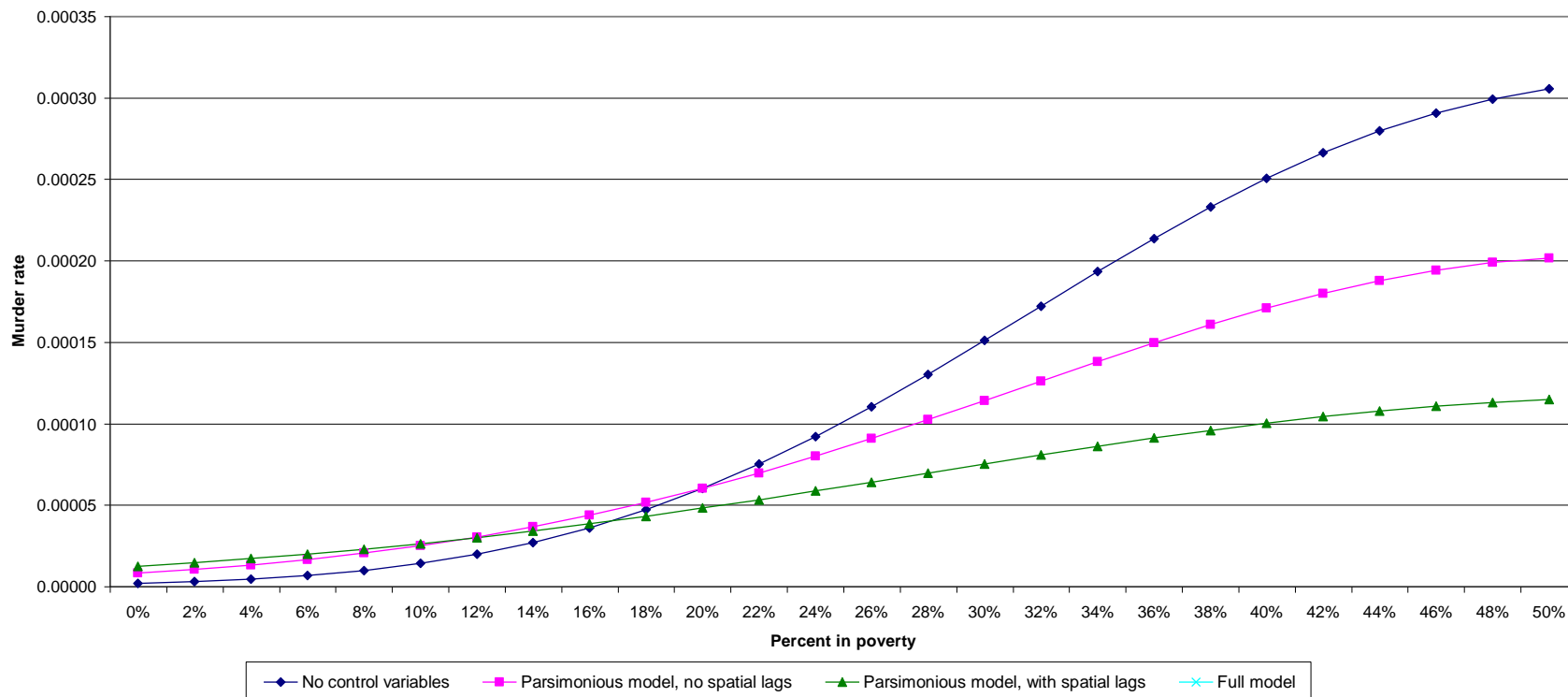
Poverty and crime: threshold, linear, or diminishing relationship?

Figure 8. Estimate of the effect of poverty on property crime factor, comparing linear and nonlinear model specifications

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Poverty and crime: threshold, linear, or diminishing relationship?

Figure 9. Nonlinear (quadratic) estimate of the effect of poverty on murder, various model specifications

Poverty and crime: threshold, linear, or diminishing relationship?

Appendix

Table A1. Cities with crime data for various types of crime

	Violent crime	Property crime	Aggravated assault	Robbery	Murder	Burglary	Motor vehicle theft	Tracts
Austin	X	X	X	X	X	X	X	165
Baltimore	X	X						202
Buffalo	X	X	X	X	X	X	X	93
Cincinnati	X	X	X	X	X	X	X	158
Cleveland	X	X	X	X	X	X	X	225
Denver	X	X				X		187
Indianapolis	X	X	X	X	X	X	X	146
Los Angeles	X	X	X	X	X	X	X	713
Miami			X	X				70
Milwaukee	X	X	X	X	X	X	X	235
Nashville	X	X	X	X	X	X	X	111
Philadelphia	X	X	X	X		X	X	365
Pittsburgh	X	X	X	X	X	X	X	175
Portland	X	X	X	X	X	X	X	157
Rochester	X	X	X	X	X	X	X	90
Sacramento	X	X	X	X	X	X	X	187
Salinas	X	X	X	X	X	X	X	27
San Antonio	X	X	X	X	X	X	X	219
San Diego	X	X	X	X	X	X	X	233
San Diego county	X	X	X	X	X	X	X	134
Seattle	X	X	X	X	X	X	X	126
St. Petersburg	X	X	X	X	X	X	X	66
Tampa	X	X	X	X	X	X	X	98
Tucson	X	X	X		X	X	X	101
Washington, D.C.	X	X						192

Note: 'X' indicates that this type of crime available for analyses