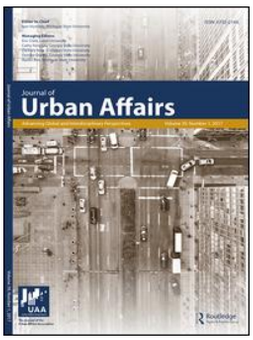

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NEIGHBORHOOD DISINVESTMENT, ABANDONMENT, AND CRIME DYNAMICS

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ABSTRACT: *This article develops a conceptual framework of neighborhood crime dynamics based on a synthesis of criminology and neighborhood change literatures which suggests that neighborhood decline can produce a nonlinear response in crime rates. The authors probe this relationship using a rich Detroit data set containing detailed, block-level information about housing, land, abandonment, population, schools, liquor outlets, and crime reports of various categories. Negative binomial models reveal that several neighborhood attributes are consistently associated with all types of crime (renter occupancy, population density, establishments with liquor licenses) while other attributes are only associated with particular types of crime. A simulation using estimated parameters suggests that processes of disinvestment and abandonment can generate a nonlinear pattern in the rate of growth in neighborhood crimes that vary in intensity by crime type. The authors explore the implications of their findings for anticrime strategies focusing on demolishing abandoned housing, "right-sizing" urban footprints, and regulating liquor-selling establishments.*

Many neighborhoods in declining U.S. cities continue to empty out and decay (Mallach, 2012). The consequences of such urban depopulation, disinvestment, and abandonment have been of long-standing and paramount interest to scholars, policymakers, and citizens alike. As demand for a neighborhood wanes, owners of homes and apartments face intensified incentives to defer maintenance and mortgage and property tax payments and, ultimately, may abandon their properties if no buyers can be identified. Increasingly, the remnant population in such neighborhoods is comprised of those who cannot afford to move. Eventually, empty, dilapidated properties blight the environs until they can be demolished, ultimately creating swaths of vacant territory where once a vibrant community stood. The full social and economic costs of this process are incalculable, but the erosion of residents' quality of life, property owners' equity, and jurisdictions' tax base is palpable.

The housing and household dimensions of this urban disinvestment and abandonment process have been thoroughly studied (e.g., Grigsby, Maclennan, Baratz, & Galster, 1987; Mallach, 2012). What is not well-understood is how this process influences crime dynamics in the vicinity. Filling this gap will be the goal of our article, because crime not only abets the neighborhood decline process itself but has severe effects upon residents' satisfaction and physical and mental health (Ross, 2000; Ross & Mirowsky, 2001).

Perhaps no other American city has been more often portrayed by the news media as the national symbol of depopulation, disinvestment, and crime than the Detroit. These stereotypes unfortunately have a grim foundation in reality. A 2009 parcel survey revealed that roughly a third of the city's

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land area consisted of vacant land or abandoned buildings (Detroit Residential Parcel Survey, 2010). The city lost a quarter of its population in the last decade, and nearly 26,000 housing units were demolished. Despite this 6.9% decrease in the number of housing units, the number of vacant housing units increased by over 100%, from 38,668 in 2000 to 79,725 in 2010 (U.S. Bureau of the Census, 2010). In 2010, Detroit had the highest violent crime rate among cities with a population of 100,000 or more, and the eleventh highest property crime rate in the same bracket (Federal Bureau of Investigation, 2012). Small wonder that a recent poll of Detroit residents (Elrick, 2012) found that the two most frequently expressed concerns were crime (43%) and abandoned properties (19%). The editor and publisher of the *Detroit Free Press* was recently quoted exhorting citizens, "Every house boarded up ... will make children safer as they go to school" (Dawsey & Lawrence, 2012). Volunteers in this effort were recruited by being told, "vacant homes are dangerous threats ... [they] can become dens of criminal activity ... the lairs of rapists" (Damron, 2012). It is thus highly appropriate that we will use a unique data set recently produced in Detroit—the "poster child" of neighborhood decline, vacancies, abandonment, and crime–to investigate these interrelated phenomena.

Though it is tempting to assume that the process of depopulation, disinvestment, and abandonment progressively causes a higher crime rate in affected neighborhoods, a deeper probe reveals the connections are less obvious and more nuanced. In the early stages of neighborhood decline, downward income succession of residents and falling rates of owner occupancy may indeed lead to increasing rates of both property and violent crime as collective efficacy falls in concert with the rising financial needs of the populace. As decline progresses, however, the impact on crime rates becomes more difficult to predict. More abandoned buildings open to trespass may provide more venues for certain types of violent criminal activity but at the same time may provide less desirable loci for property crime because all items of potential value have previously disappeared. By the time the neighborhood has considerable swaths of vacant land, crime rates may be reduced because of the dearth of targets and the exposed environs that offer no cover for illegal activities. As a final complication, even if the absolute number of crimes declines, resident population may decline disproportionately, potentially yielding unexpected changes in crime *rates*.

No prior theoretical or empirical scholarship has probed these nuances holistically from an interdisciplinary perspective; this is the task of our article. In particular we ask the following research question: To what extent do block-level indicators of neighborhood decline (rates of poverty, renter occupancy, vacant housing, abandoned buildings, vacant land, and population density) predict different types of crime during the subsequent quarter? We employ 2009–2010 data for Detroit, assembled from several sources, and analyze their interrelationships using negative binomial regression techniques. We find several strong relationships suggesting that the neighborhood disinvestment process produces nonlinear crime responses, though the precise nature of the response depends on the particular type of crime.

Our study contributes to the scholarship on urban neighborhoods and crime in at least five ways. First, we forward a conceptual framework for understanding why the neighborhood decline process could produce a cyclical, type-specific pattern of crime responses as it evolves. This framework unites two balkanized literatures regarding urban crime and neighborhood change, demonstrating their mutually causal interrelationships. Second, we analyze an unusually comprehensive set of block-level indicators of the demographic, socioeconomic, and physical environment. In particular, we have unprecedented citywide information about the occupancy and physical conditions of residential structures and vacant land and presence of establishments holding liquor licenses. Third, we employ a rich set of neighborhood population characteristics as controls, so that we have confidence that relationships between neighborhood physical characteristics and crime are not unduly influenced by omitted variable bias. Fourth, we analyze a variety of crime types to obtain a nuanced portrait of the dynamics of neighborhood decline and crime. Fifth, we employ our econometric results to conduct a simulation demonstrating how the neighborhood decline process could yield a nonlinear pattern of crime rate dynamics.

Our article is organized as follows. The next section reviews the relevant theory and evidence from the disparate neighborhood dynamics and urban criminology literatures. Following that, we

develop our conceptual framework of neighborhood decline and crime cycles, which draws upon and synthesizes this extant literature. We then introduce our empirical approach, describe the data we have assembled for Detroit, provide an overview of neighborhood physical conditions and crime in the city, and then present our negative binomial model for analyzing their interrelationships. We present our empirical findings in the following section and then employ the parameter estimates in a simulation of a stylized Detroit neighborhood to illustrate the changes of crime associated with neighborhood decline dynamics. Finally, we conclude, discuss policy implications of our findings, and offer caveats and suggestions for next steps.

THE LITERATURE ON NEIGHBORHOODS AND CRIME

Past scholarship relevant for our article may be categorized into three groups. One focuses on the process of neighborhood changes in population and housing and the forces driving them; in this set the explanatory role of crime is almost never considered. The second focuses on the population and physical environment correlates of urban crime in a static, cross-sectional context; in this set the dynamics of these correlates are not considered. The third, and by far smallest, focuses on how the changes in population, physical environment, and crime may mutually interact intertemporally within a neighborhood.

Neighborhood Change Processes and their Determinants

Describing how neighborhoods change demographically or economically has a longstanding tradition, dating back at least to the "Chicago School" sociologists of the 1920s, who described neighborhood transitions as *invasion and succession* processes occurring at the borders of neighborhoods organized according to concentric rings. Postwar descriptive efforts included *neighborhood life cycle* and *stages of decline* conceptualizations (e.g., Downs, 1981). Most recently, the increased availability of annual data collected at small geographic scales has permitted several rich empirical descriptions of how neighborhood indicators evolve over time (e.g., Galster, Cutsinger, & Lim, 2007). Unfortunately, with rare exceptions (e.g., Lim & Galster, 2009), this descriptive empirical literature has not traced the intertemporal patterns of neighborhood crime, likely due to lack of appropriate crime data.

Contemporary models attempting to explain neighborhood change typically have been based on theoretical perspectives drawn from economics on why households choose particular residences and why property owners choose to buy, repair, maintain, downgrade, or abandon particular residences (Galster, 2001; Grigsby et al., 1987; Rothenberg, Galster, Butler, & Pitkin, 1991, ch. 9). Even after supplementation with noneconomic considerations (Temkin & Rohe, 1996), minimal consideration has been given in these models to the role of crime or perceptions of public safety in these neighborhood dynamic processes.

This analytical framework has spawned numerous multivariate statistical studies, each addressing a specific aspect of neighborhood change. Outcomes investigated include housing prices (Galster & Tatian, 2009; Li & Rosenblatt, 1997), population density (Guest, 1972, 1973), income or social class (Carter, Schill, & Wachter, 1998; Dewar, Basmajian, Alter, & Law, 2005; Galster & Mincy, 1993; Galster, Mincy, & Tobin, 1997; Galster & Peacock, 1985; Guest, 1974; Wyly & Hammel, 1999, 2000), home ownership rates (Baxter & Lauria, 2000), female headship rates (Krivo, Peterson, Rizzo, & Reynolds, 1998), dwelling vacancy rates (Dewar et al., 2005), and racial composition (Baxter & Lauria, 2000; Crowder, 2000; Ellen, 2000; Denton & Massey, 1991; Galster, 1990a, 1990b; Lauria & Baxter, 1999; Lee & Wood, 1991; Ottensmann & Gleeson, 1992; Ottensmann, Good, & Gleeson, 1990; Schwab & Marsh, 1980). Unfortunately, measures of crime have not been employed as a predictor in the aforementioned neighborhood change empirical literature. This is especially ironic, given that the earliest theoretical formulations of changing neighborhood ecologies (Park & Burgess, 1921; Shaw & McKay, 1942) posited that households would choose to reside in the "most desirable" (i.e., safest) neighborhoods they could afford (Hipp, Tita, & Greenbaum, 2009).

Fortunately, a few empirical studies have supplied hints of how crime may shape neighborhood change processes. Residential dissatisfaction and, in turn, desires and actions to leave the neighborhood have appeared more prevalent in neighborhoods with higher crime rates (Skogan, 1990). Morenoff and Sampson (1997) have found that neighborhoods lost more population and increased their percentage of minority residents over the decade if they had higher violent crime rates at the start of the period. Finally, it has often been observed that higher crime rates become capitalized into lower property values (Buck & Hakim, 1989; Schwartz, Susin, & Voicu, 2003; Thaler, 1978) and lower rates of appreciation (Tita, Petras, & Greenbaum, 2006), implying that succession of lower income groups and disincentives for property maintenance may follow crime upsurges.

Neighborhood Conditions as Causes of Crime

The second strand of literature examines why some neighborhoods have higher crime rates than others. The theoretical frameworks exploring the causes of crime tend to fall into one of the following categories: (1) the criminal perspective, focusing on the motivations urging offenders to commit crimes; (2) the victim perspective, exploring the activities and choices that expose people to criminal offenses; and (3) the context perspective, examining the social and environmental conditions which give rise to crime (Miethe & Meier, 1994).

Theories taking the criminal perspective focus on the ways in which society and a person's immediate social network influence the development of, and learning by, an offender. Through a variety of proposed mechanisms, the peers, family members, or social institutions surrounding individuals influence their potential for becoming an offender.[1] One prominent example of this perspective, the rational choice theory, explains the decision making of offenders as a choice based upon the weighing of the costs and the benefits of committing a criminal act (Cornish & Clarke, 1987; Felson & Boba, 2010). When applied to neighborhoods, this view implies that contexts where potential offenders are presented with perceptibly greater benefits and/or lesser costs will generate more crime.

Victimization theories focus on the characteristics of potential victims that may put them at an increased risk of experiencing crime. For example, the routine activity approach posits that "most criminal acts require convergence in space and time of *likely offenders, suitable targets,* and the *absence of capable guardians* against crime" (Cohen & Felson, 1979, p. 588). Another prominent perspective is the lifestyle exposure theory, which suggests that demographic differences in the likelihood of victimization can be attributed to variations in lifestyles that produce differential exposure to dangerous places, times, and others. Applying such frameworks to neighborhoods means that different contexts will provide different "proximity to motivated offenders, exposure to high-risk environments, target attractiveness, and the absence of guardianship" (Miethe & Meier, 1994, p. 40).

The context perspective provides a way in which one can view neighborhood effects on crime more holistically, and thus is of most use in the current research. Here the social and physical environment plays multiple roles, providing signals to likely offenders and space and time patterns through which potential victims pass. Considerable scholarship in this vein has investigated cross-sectional differences in social processes across neighborhoods, including social disorganization, place attachment, informal social control and collective action, and collective efficacy (Brown, Perkins, & Brown, 2003, 2004; Harcourt & Ludwig, 2006; Sampson, 1989; Sampson, Raudenbush, & Earls, 1997; Skogan, 1989). Informal social control has been identified consistently as a key inhibitor of neighborhood crime, and appears strongly correlated with community social cohesion (Bellair & Browning, 2010), residential stability (Bellair, 1997; Hipp, 2007a; McNulty & Holloway, 2000; Sampson & Groves, 1989), and home ownership rates (Dietz & Haurin, 2003; Herbert & Belsky, 2008; Lindblad, Manturuk, & Quercia, 2012; Rohe, Van Zandt, & McCarthy, 2000; Spelman, 1993).

Another strand of the context perspective has focused on the physical environment's effect on crime. There has been some urban design theorizing and supportive evidence about whether buildings and neighborhoods providing *defensible spaces* deter crime (Newman, 1972; Poyner, 1983; Taylor, Gottfredson, & Browner, 1984). Probing the *signaling effect* of physical disorder hypothesized by Wilson and Kelling (1983), several studies have identified relationships between reported crimes

and neighborhood physical incivilities (litter, graffiti, etc.), though relationships varied substantially across types of crime (cf. Brown et al., 2004; Kurtz, Koons, & Taylor, 1998; Perkins, Wandersmann, Rich, & Taylor, 1993; Sampson & Raudenbush, 1999; Taylor, 2001; Taylor, Shumaker, & Gottfredson, 1985). Recent evidence indicates the importance of concentrations of housing choice voucher holders (Ellen, Lens, & O'Regan, 2011; Mast & Wilson, 2013; Popkin, Rich, Hendey, Parilla, & Galster, 2012) in predicting crime rates nearby. Finally, the evidence examining the impact of housing stock characteristics suggests that violent and property crime rates are higher in neighborhoods with higher housing vacancy rates (Krivo & Peterson, 1996; Roncek, 1981), foreclosed homes (Cui, 2010; Ellen, Lacoe, & Sharygin, 2012; Goodstein & Lee, 2010; Immergluck & Smith, 2006; Katz, Wallace, & Hedberg, 2011; Williams, Galster, & Verma, 2013) and more abandoned, unsecured buildings (Spelman, 1993), although with one exception (Plerhoples, 2012).

Neighborhood Change–Crime Mutual Interrelationship

The third segment of the relevant scholarly literature focuses on how changes in population, physical environment, and crime may mutually interact intertemporally within a neighborhood. A few scholars have conceptualized the relationship between crime and neighborhood population composition and instability as reciprocal (Bursik, 1988; Felson, 2002; Miethe & Meier, 1994; Skogan, 1990). But in this view, reciprocity manifests itself only in crime-shaped selective in- and out-migration from a neighborhood, yielding changes in the aggregate population characteristics, stability, and (presumably, though unmeasured) informal social controls in that neighborhood, in turn affecting crime rates there subsequently. What this view overlooks is changes in the physical environs and housing market during these processes. The one exception is Taub, Taylor, and Dunham (1984), who argued that perceptions of safety (strongly influenced by stable racial homogeneity) contributed to owners' willingness to reinvest in their residential properties, and both in turn contributed to the relative competitiveness of that neighborhood within the metropolitan area-wide hierarchy of neighborhoods, thereby shaping who moves in and property values alike.

Recently, three studies have probed aspects of these mutually causal relationships statistically. Hipp, Tita, and Greenbaum (2009) found that increased property and violent crime rates predicted increased housing turnover (and, in the case of violent crime, lower home values) in the neighborhood during the subsequent year, but not *vice versa,* suggesting that crime was more a driver of neighborhood change than a response to it. A similar but more nuanced implication follows from the work of Hipp (2010), who found that higher violent or property crime rates in a neighborhood led to more concentrated disadvantage, more residential turnover, a weaker retail sector, and a higher share of black population ten years later, but not *vice versa*. However, for concentrated disadvantage there also was a reciprocal positive relationship with crime rates a decade later, suggesting that crime does respond to endogenously produced changes in neighborhood population composition. Williams, Galster, and Verma (forthcoming) explored a different set of neighborhood indicators and identified evidence of strong mutual causality in year-to-year neighborhood changes among violent and property crime, lending for home mortgages and small businesses, and property values. This suggests that crime contributes to the neighborhood investment climate, which, in turn, shapes the physical environment in ways (such as visible disorder and decay) that may feed back to affect crime. Unfortunately, none of these three provocative studies employed any indicators of the neighborhood's physical environment (housing stock conditions, land uses, vacant land, etc.).

The Literature on Neighborhoods and Crime: Conclusion

Instead of offering a holistic portrait of the intertwined dynamics of neighborhoods and crime, the extant social scientific literature is balkanized. On the one hand, the dominant theories and empirical studies of neighborhood population and housing (tenure, value, and physical condition) change have typically overlooked the role played by crime. On the other hand, the scholarship on neighborhood conditions as predictors of crime has emphasized population profiles and social

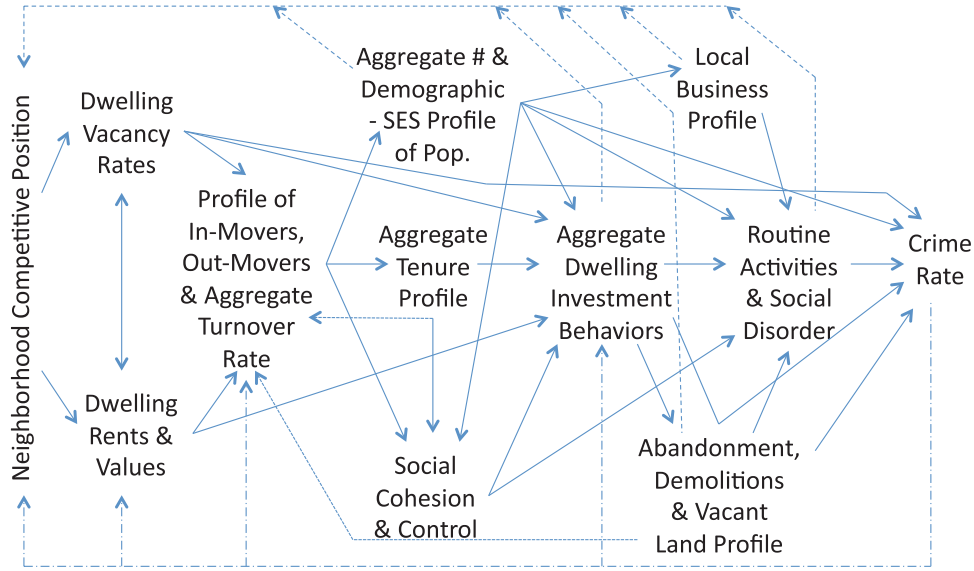

FIGURE 1

Neighborhood and Crime Dynamics: A Holistic Conceptual Framework

Note: With solid arrows time is presumed to flow from left to right; vice versa for dashed arrows.

processes, typically overlooking housing and other physical conditions. These shortcomings appear in bold relief in light of the handful of empirical studies that indicate that crime both shapes and is subsequently shaped by flows of households and economic resources into and out of neighborhoods. Unfortunately, many measures of the physical and housing conditions have not yet been investigated due to unavailability of data. Our article responds to these weaknesses in the literature by (1) developing a conceptual framework that makes explicit the mutual causal relationships among crime and various neighborhood characteristics, and (2) offering an empirical exploration of part of this framework employing unusually comprehensive measures of neighborhood physical and housing conditions.

A CONCEPTUAL FRAMEWORK FOR NEIGHBORHOOD DECLINE AND CRIME

In this section we develop a holistic conceptual framework that attempts to integrate the disparate theoretical and empirical literatures on neighborhood and crime dynamics. Carefully considering the time sequence of changing aspects of the neighborhood's demographic, socioeconomic, housing, and physical condition profile raises the intriguing possibility that neighborhood decline may be associated with a nonlinear crime response.

Our framework is portrayed diagrammatically in Figure 1. Let us begin by analyzing the neighborhood change process and how this may be expected to produce changes in crime rates observed there; that is, consider the solid arrows moving from left to right in Figure 1. From the economics literature we know that the nature and intensity of demand for a particular neighborhood will rest on its relative position in the quality hierarchy as assessed by the metropolitan area housing market actors. Based on its competitive strength, properties in the illustrative neighborhood will command particular rents and sales prices, inversely associated with a corresponding vacancy rate. Given these market conditions, certain households will select (or be financially constrained) for occupancy in this neighborhood, and will dominate the profile of in-movers. If there has been a recent and sizable shift in these market conditions, prior residents may choose (or be forced) to move out, potentially producing distinct differences in the in- and out-mobility profiles and altering thereby the aggregate composition of the

neighborhood in terms of demographic and/or socioeconomic characteristics and, potentially, rates of owner occupancy. As noted above, the sociological literature suggests that residential turnover itself, especially coupled with a change in the population composition and homeownership rates, will affect the degree of social cohesion and place attachment and the intensity of informal social controls that the neighborhood can apply. These changes in the neighborhood's aggregate demographic, financial, and tenure character will modify the profile of owner decision makers controlling the nature of reinvestments in residential properties. Moreover, new revenue projections shaped by evolving rents, values, and vacancy rates can alter these reinvestment behaviors, as can local social cohesion and control, at least in the case of owner-occupants (Galster, 1987). Of course, the aggregate demographic and socioeconomic profile of the neighborhood will shape the sorts of business that are located there and the physical standards to which their establishments are maintained. In concert, the characteristics of residents, local businesses, and the residential structures (especially if they are dilapidated, abandoned, and open for trespass, or demolished to be replaced by vacant land) will affect the spatial pattern of routine activities. Analogously, these same characteristics will influence the visible signs of disorder in the neighborhood, subject of course to the potential mediating effects of collective social control. Finally, the criminological literature indicates that resident financial and psychological stressors and family composition (related to their socioeconomic and demographic profiles[2]), routine activity patterns, collective social control, and physical features of the built environs (vacant and abandoned buildings, empty lots, defensible space dimensions) will ultimately determine the crime rate manifested in the neighborhood.

We posit that the interactive dynamics do not stop at this point. Consider next patterns of causation emanating from crime and influencing other elements of the structure just delineated, that is, the dashed-dotted arrows running from right to left along the bottom of Figure 1. Consistent with the evidence presented above, crime can discourage property owners from maintaining or improving their residences, weaken place attachment, generate residential dissatisfaction and out-migration by those households with the greatest financial capacity to move, reduce property values and rents, and stigmatize a place as "unsafe," eroding thereby its competitive position.

Our framework is completed by the specification of some additional feedback effects not involving crime; see the dashed arrows from right to left along the top of Figure 1. The neighborhood's competitiveness in the view of potential demanders will be shaped by the panoply of its current population characteristics, dwelling upkeep levels, abandoned buildings, vacant land, other signs of visible disorder, and local retail profile. Finally, the turnover rates observed in a neighborhood will be affected by its housing tenure rates and the degree to which owners have allowed their buildings to become uninhabitable through dilapidation and abandonment.

Consider next how this framework can be applied to the process of long-term neighborhood disinvestment and decline that has plagued so many deindustrialized cities like Detroit over the last half-century. For decades, scholars have employed a typology of neighborhoods that are distinguished according to their stage in the *life cycle* (cf. Downs, 1981; Galster, 1987; Grigsby et al., 1987). We employ the classic terminology associated with this typology in describing the archetypical decline process and focus on the consequences for crime in each stage using our framework portrayed in Figure 1. As a *healthy* neighborhood moves into the initial stage of *incipient decline*, two changes transpire that our framework suggests will adversely affect public safety in the area: (1) the profile of in-movers begins to differ from that of current residents (and out-movers) in terms of various markers of status (more stressors, fewer resources available for crime prevention); and (2) more dwellings shift from owner to renter occupancy (less collective efficacy). In the next life-cycle stage of *clearly declining*, the aforementioned two changes become intensified and are supplemented by four other forces that our framework suggests will augment crime: (3) more female-headed families (fewer resources for supervision of youth and guardianship of public spaces); (4) widespread minor deficiencies and spot major deficiencies in home repair (visible disorder); (5) increasing commercial vacancies (potential loss of local employment and change in routine activity patterns); and (6) *lack of pride in the neighborhood* (which we translate as reduction in collective efficacy). In the next stage of *accelerating decline*, the life-cycle typology suggests that the prior forces grow yet more powerful and are supplemented by (7) growing residential vacancies (because rents can fall no

further without creating negative cash flow); (8) absolute loss of population; (9) incompatible land uses allowed (which indicates transformation of the local business profile); and (10) the start of spot residential abandonment. The life-cycle typology labels the final stage of decline *abandoned*. At this point the only remaining residents are of the lowest socioeconomic status, the rental market has collapsed (extreme vacancy and rent collection problems), and the physical environs are characterized by generalized dilapidation, widespread abandonment, and a new element: (11) vacant lots where structures have been demolished.

We have no reason to challenge the notion that crime rates will rise as a neighborhood evolves from *healthy* to *clearly declining* stages. Both downward income succession (1) and increasing rates of rental occupancy (2) would be predicted by criminological theory to produce upsurges in crime rates.

In the stage of *accelerating decline* predictions are less certain, however. The life-cycle stage approach suggests that the aforementioned crime-generating forces (2), (4), (5) and (6) grow still more powerful. Yet, indicators of resident socioeconomic status (1) and (3) may have fallen nearly as far as they can go. If so, this would imply that the *rate of increase* in the crime rate is less than for the prior stage transition. Further, consider the four new forces the life-cycle perspective suggests arise during this stage: (7) growing residential vacancies; (8) absolute loss of population; (9) incompatible land uses; and (10) spot residential abandonment. Factors (7) and (10) would be predicted to increase crime rates inasmuch as these structures constitute more vulnerable targets for property crime and serve as venues in which violent crimes can be more readily committed without detection. However, abandoned structures may produce a reduction in property crime to the extent that they contain nothing more of value to steal. The transformation of the local business profile also has less predictable consequences for changes in crime, since it could alter routine activity patterns and signals of social order in ways that cannot be specified *a priori*. As illustration, the closure of local retail stores could reduce crime by removing potential victims from the area, but the opening of a bar would be expected to have the opposite effect. The loss of population has similarly ambiguous influences. The *number* of crimes in a neighborhood will be mathematically related to the resident population of potential offenders and victims; so long as this function is linearly related to population the crime *rate* will be unaffected by declines in population. But the function may be nonlinear: offending may fall less than proportionately to population (perhaps due to nonlinear declines in collective efficacy), in which case population loss will increase the crime rate. On the other hand, offending may fall more than proportionately to population (perhaps due to nonlinear declines in offenders' perceptions of valuable targets of opportunity), in which case population loss will lower the crime rate (Hannon, 2002). In sum, the foregoing raises the possibility that a neighborhood in *accelerating decline* may exhibit only a modestly higher crime rate than it did in its prior stage. Put differently, the *rate of increase* in the crime rate may well be low when a neighborhood transitions into the stage of *accelerating decline*.

Predictions become even murkier when the *abandoned* neighborhood stage is analyzed. To the extent that vestigial populations living in these neighborhoods may be a selected group based either on their proclivity to commit crimes and/or their vulnerability to be victimized (such as the elderly), observed crime rates would skyrocket. However, other characteristics of such neighborhoods might suggest only a modest increase in crime compared to the prior life-cycle stage. Signs of physical disorder are likely rampant in this stage, but there may well be diminishing returns in terms of the new information provided to offenders by this indicator compared to the prior stage. Analogously, there may be diminishing returns from vacant and abandoned structures; if criminal activity is drawn to these venues because of the reduced chances of detection these structural remnants may provide, their value in this regard becomes diminished the more they cluster in space. Finally, the new element to be considered in this stage is the appearance of vacant lots, which may provide the opposite sort of environmental context as vacant and abandoned structures: places where it is *more* difficult to avoid detection while perpetrating and/or fleeing from an illegal act. Of course, a final complication here relates to the aforementioned point about relative changes in population and crime. Even if the absolute number of crimes declines, resident population may decline disproportionately, potentially yielding unexpected changes in crime rates. In sum, it is theoretically possible that as neighborhoods

move into the last, *abandoned* stage of decline their crime rates may grow rapidly or, on the other hand, might fall compared to the prior stage.

In sum, our theoretical analysis raises the distinct possibility that as a neighborhood passes through stages of decline it will demonstrate *nonlinear* changes in crime rates. Considerations of the crime-influencing characteristics commonly associated with the classical neighborhood life-cycle stages suggest a rapidly increasing crime rate will be associated with the onset of decline. Transitions into subsequent stages do not yield similarly clear predictions, however. We now turn to our empirical model that will shed more light on these ambiguous dynamics.

EMPIRICAL MODEL AND DATA

Empirical Strategy and Statistical Model

Unfortunately, the detailed, longitudinal, small geographic scale data needed to estimate holistically the conceptual framework summarized in Figure 1 were unavailable to us. In this research we therefore operationalize and estimate the parameters of a reduced-form statistical model based on a distillation of Figure 1:

$$\text{Crimes}_{ijt} = \text{f}([\text{Abandoned/Vacant}_{it-1}]; [\text{Housing}_{it}]; [\text{Population}_{it}]; [\text{Business}_{it}]), \quad (1)$$

where, using the terminology of Figure 1,

Crimes_{ijt} = Number of crimes of a particular type j reported as committed on block i during quarter t,

$[\text{Abandoned/Vacant}_{it-1}]$; = abandoned building, vacant building and land profile on block i during quarter $t - 1$,

$[\text{Housing}_{it}]$ = dwelling vacancy rates and aggregate tenure profile on block i during quarter t,

$[\text{Population}_{it}]$ = aggregate number and socioeconomic profile of residents on block i during quarter t, and

$[\text{Business}_{it}]$ = local business profile on block i during quarter t.

Following recent convention in criminological research, we employ a negative binomial specification for function f in (1) (Hipp & Yates, 2009; Osgood, 2000; Popkin et al., 2012). This specification uses counts of crime instead of crime rates as the dependent variable, but includes population as a separate explanatory variable with its coefficient constrained to one. This constraint on the coefficient for population allows the model parameters to be interpreted as relationships with crime rates per capita instead of counts. The coefficients in this model can be interpreted as the proportional change in crime rates associated with a change of one in the given predictor.

A negative binomial estimation is preferable to standard ordinary least squares regression here because it accounts for skewed distribution of crime rates (see the appendix and below), particularly in areas with small populations (like blocks, which we employ), where small increases in crime counts can produce dramatic changes in the crime rates (Osgood, 2000). This estimation uses the Poisson distribution for counts and includes an error term with a gamma distribution, the latter to allow for overdispersion caused by dependence among crime events.

Our spatial unit of analysis is the census block. Prior research has definitively established the substantial inter-block variation in crime rates within a given neighborhood (Hipp, 2007a; Perkins & Taylor, 1996; Taub, Taylor, & Dunham, 1984; Taylor, 1997), validating its appropriateness as a scale for modeling crime.

Operationalization of Variables and Data Sources

Crime

Criminal offense data recorded by the Detroit Police Department (DPD) were provided to us at point level, with address, latitude and longitude coordinates, offense date, DPD offense category (a two-digit code used for summary reporting), and DPD offense code (a four-digit code indicating type of offense). Offense codes align directly with the Michigan Incident Crime Reporting (MICR) system, allowing for translation from MICR coding to the two main federal coding systems, Uniform Crime Reporting (UCR) and the National Incident-Based Reporting System (NIBRS). Both federal systems have established methodology for aggregating criminal offenses to meaningful categories, which we employ here.

All crime variables we used are 2010 census block level aggregations of these point data reported in the first 3 months (quarter one) of 2010. We employed as alternative dependent variables a selection of NIBRS Group A offenses for which a substantial number observations were reported in the first quarter (>1,000). These included assault (7,062), burglary/breaking and entering (4,401), destruction/damage/vandalism of property (3,174), larceny/theft (4,279), and robbery (1,311). We also included as two summary crime measures UCR Part I categories constituting violent crimes (murder/non-negligent manslaughter, negligent manslaughter, forcible rape, robbery, and aggravated assault) and property crimes (burglary/breaking and entering, larceny/theft, motor vehicle theft, and arson).

The spatial distribution of violent and property crime during the first quarter of 2010 across Detroit blocks is portrayed in Figures 2 and 3. Three features are immediately apparent: (1) there are distinctive geographic "hot spots" of crime; (2) patterns for violent and property crime are distinctive; and (3) many blocks have no reports of crime during the quarter. The implications for our empirical investigations are that crime types should be disaggregated and that our negative binomial model is indeed justified because of the extreme positive skew in the crime reports: many block groups with zero crimes and a few with a large number of crimes. Frequency distributions of property and violent crime counts by block are presented in the appendix.

Housing and Land Vacancy and Condition

Data on vacant lots and structure condition derive from the Detroit Residential Parcel Survey (DRPS, 2010). DRPS was conducted by the Detroit Data Collaborative, a partnership between the Detroit Office of Foreclosure Prevention and Response, Community Legal Resources, the Ginsberg Center of the University of Michigan, and Data Driven Detroit (an independent, nonprofit data center). DRPS involved a windshield survey of all residential parcels with up to four-unit structures in the City of Detroit (nearly 350,000 parcels) in August and September of 2009. The data collected on each parcel included presence of residential structure, structure type, condition, occupancy, fire damage, vacant/open/dangerous status, and vacant lot type (improved or unimproved).

For the current study, parcel level DRPS data were aggregated to 2010 census block data. Several constructions of a blight variable were tested in preliminary runs of the model, and were found to demonstrate fairly consistent results. As a representation of residential abandonment, blight, and/or signals of disorder, we use the proportion of residential structures surveyed that are in "to-demolish (poorest) condition, or fire-damaged, or vacant/open/dangerous;" we will abbreviate this composite condition hereafter as DFV. Also deriving from this data set is the proportion of parcels surveyed that are vacant lots.[3]

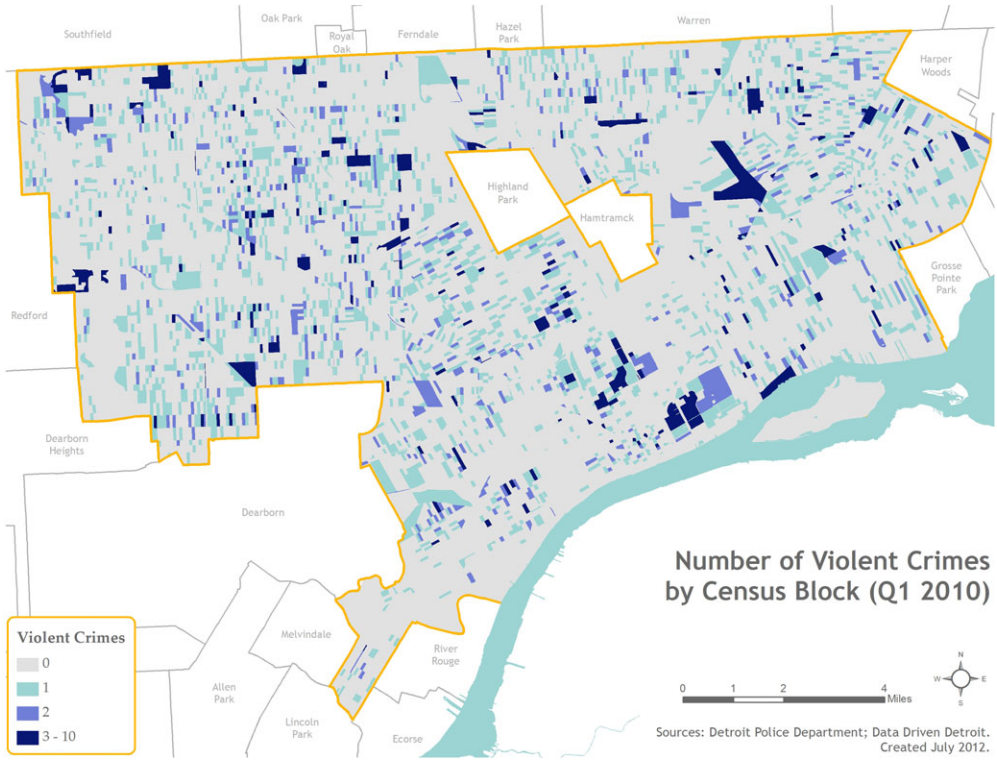

FIGURE 2

Violent Crimes by Detroit Block, First Quarter 2010

Source: Authors' tabulations of Detroit Police Department data.

We also utilize data from the 2010 census, conducted in April 2010, which are reported at the census block level. As a counterpoint to the DFV variable described above, census data are used to determine the proportion of housing units that are vacant. It is critical to distinguish between the U.S. Census Bureau's definition of vacant housing units and the DFV definition used for the DRPS. According to the Bureau, "Vacant units are *excluded* if they are exposed to the elements, that is, if the roof, walls, windows, or doors no longer protect the interior from the elements, or if there is positive evidence (such as a sign on the house or block) that the unit is to be demolished or is condemned." Therefore, we assume the census-derived vacancy measure represents unoccupied housing that is in fairly good condition and available for purchase or rent, as opposed to the DRPS-derived DFV measure that represents housing in blighted condition that is no longer a functional component of the housing market. Also note that DFV refers to structures and Census vacancies refer to dwelling units.

Our final housing market characteristic is the proportion of occupied housing stock that is occupied by renters. This information is also derived from the 2010 census.

Population Characteristics

We used the 2010 census to measure several features of the block's age, gender, ethnic, and household composition profile that have proven predictive in prior empirical studies of crime. These included a Herfindahl index of ethnic heterogeneity,[4] proportion of children living in single-parent families, ratio of the population age 18 and older to the population under age 18, proportion of the population that is male and age 15 to 24, proportion of the population living

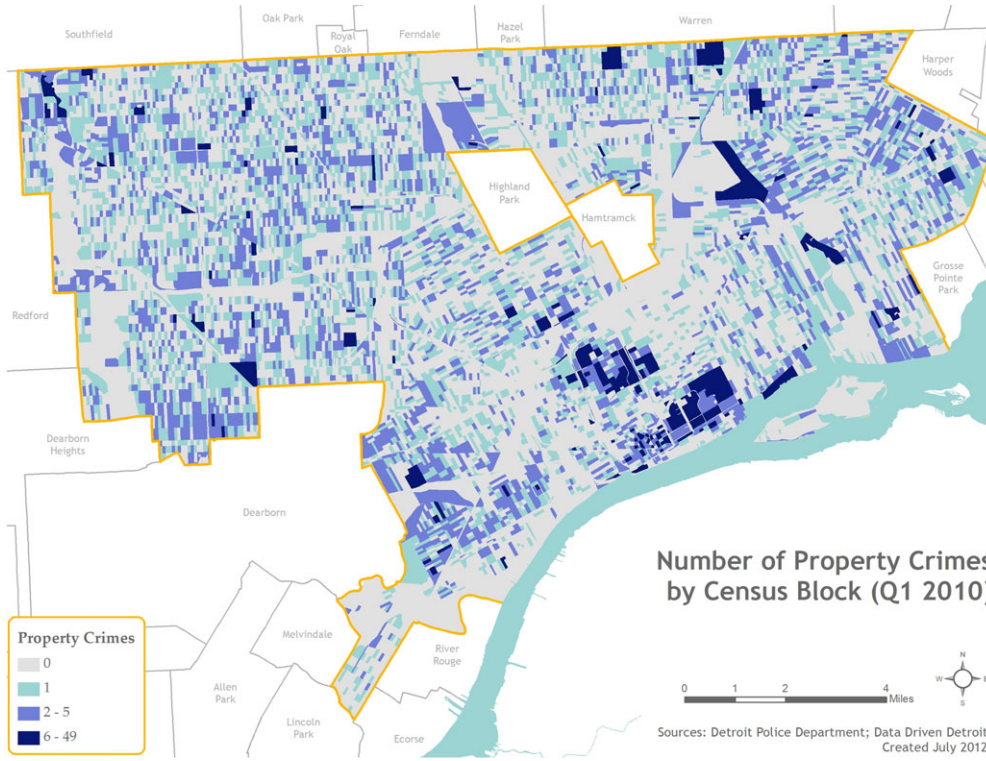

FIGURE 3

Property Crimes by Detroit Block, First Quarter 2010

Source: Authors' tabulations of Detroit Police Department data.

alone, and population density per square mile (which excludes institutionalized group quarters population).

We also employed block group–level data from the American Community Survey (ACS) to fill in gaps created by the limited scope of the 2010 census. Data from ACS at this small scale are only available with 5-year averages; the 2007–2011 data are used for this study. ACS values at the block group–level were applied to the census blocks comprising each block group. Variables from this source included proportion of the population age 25 and older without a high school diploma or equivalent; proportion of the civilian employed population age 16 and older in management, business, science, and arts occupations; and median family income.

Finally, we obtained additional information about the economic characteristics of the population through the Local Employment Dynamics OnTheMap (OTM) 2010 data. Population variables we specified from this source included proportion of employed residents earning less than $1,250 per month (the "working poor"),[5] a Herfindahl index of earning heterogeneity among employed residents,[6] and the ratio of employed residents to the population age 18 and older (denominator from 2010 census).

Local Business Characteristics

Criminological theory suggests that the prevalence and types of nonresidential land uses in a neighborhood can be important, so we attempted to measure this in several ways. We used Local Employment Dynamics OnTheMap (OTM) 2010 data for information on the location of employment. From this source we were able to measure the density of neighborhood employment by computing

the ratio of employees (employment located in the block) to the total block population (from 2010 census).

The Michigan Liquor Control Commission (MLCC) provided information on the location of licensed establishments. We calculated the density of licensed alcohol vendors by aggregating the number of licenses to sell alcohol to 2010 census block data. In addition, we measured proximity to alcohol vendors by two dummy variables indicating whether the census block was within a quarter mile of an on-premises licensed establishment (licensed to sell alcoholic beverages for consumption on the premises), and whether the census block was within a quarter mile of an off-premises licensed establishment (licensed to sell alcoholic beverages for consumption outside of the premises).

Finally, the Educational Entity Master file of the Michigan Department of Education provided information on the location and types of high schools. For this analysis, a school was considered a high school if the grades served included the tenth grade. We measured proximity to a high school by a dummy variable indicating whether the census block was within a half mile of a high school.

Spatial Lag Variables

We account for likely inter-neighborhood spillover effects of blight, housing vacancy, and vacant lots by including in our model spatially lagged versions of these crime predictors corresponding to their counterparts measured at the block scale.[7] We also include the spatial lag of the crime dependent variable to minimize potential bias from spatial autocorrelation. We constructed three variations of spatially lagged terms for each type of crime. Preliminary econometric estimates indicated that the model was not sensitive to the particular construction employed, so we only report results for the versions yielding the highest statistical significance.[8]

Blocks Employed in Analysis

Many of the foregoing variables are standardized by dividing by the 2010 resident population on the block. To avoid undefined or invalid standardized variables, we limited our analytical data set to only those blocks with a noninstitutionalized resident population of more than two people. This constituted 11,289 of the 15,965 census blocks in Detroit. Descriptive statistics of all the aforementioned variables for these data sets are presented in Table 1.

RESULTS

Overview

Our negative binomial models estimated with STATA's NBREG procedure performed well in relating the cross-block variation in numbers of crimes by type to our explanatory variables (see the likelihood ratio tests and Chi-bar squared tests in Tables 2 and 3). Results are presented for overall violent crime and its components in Table 2 and for overall property crime and its components in Table 3. Most of our variables measuring aspects of the neighborhood's population, housing–land market, and local economy proved significant predictors of one or more types of crime, providing strong support for our model summarized in Figure 1. Several variables proved strongly predictive of all crime types analyzed: proportion of occupied housing units that are renter occupied, number of licenses to sell alcohol, population density, and the spatial lag of the dependent crime variable. However, the magnitude of these associations varied across crime types for a given predictor and across predictors for a given crime type. Moreover, several measures of the physical environment unique to this study—proportion of parcels that are vacant lots and proportion of vacant dwellings—were strongly predictive of particular types of crime. These results suggest the possibility of nonlinear impacts on crime as neighborhoods decline, an implication we will explore in the next section.

TABLE 1

Descriptive Statistics for Sampled Blocks in Detroit

	Mean	Median	Std. Dev.	Minimum	Maximum
Crime (Dependent)					
# assault offenses	0.57	0.00	1.04	0.00	17.00
# burglary/breaking and entering offenses	0.34	0.00	0.69	0.00	11.00
# destruction/damage/vandalism offenses	0.25	0.00	0.59	0.00	9.00
# drug/narcotic offenses	0.09	0.00	0.39	0.00	7.00
# larceny/theft offenses	0.29	0.00	0.92	0.00	36.00
# motor vehicle theft offenses	0.21	0.00	0.53	0.00	10.00
# robbery offenses	0.10	0.00	0.37	0.00	7.00
# violent offenses	0.29	0.00	0.68	0.00	10.00
# property offenses	0.86	0.00	1.52	0.00	49.00
Assault offense rate per 10,000 residents	122.48	0.00	595.64	0.00	50,000.00
Burglary offense rate per 10,000 residents	67.80	0.00	229.65	0.00	10,000.00
Destruction offense rate per 10,000 residents	58.68	0.00	344.85	0.00	17,500.00
Drug offense rate per 10,000 residents	21.73	0.00	139.15	0.00	3,333.33
Larceny offense rate per 10,000 residents	90.66	0.00	1,008.45	0.00	76,666.67
Motor vehicle theft rate per 10,000 residents	48.53	0.00	381.43	0.00	23,333.33
Robbery offense rate per 10,000 residents	25.97	0.00	181.50	0.00	10,000.00
Violent crime rate per 10,000 residents	67.37	0.00	291.71	0.00	10,000.00
Property crime rate per 10,000 residents	212.01	0.00	1,413.35	0.00	100,000.00
Housing and Land Vacancy and Condition					
Proportion of structures DFV	0.05	0.00	0.10	0.00	1.00
Proportion of housing units vacant for rent/sale	0.22	0.20	0.16	0.00	1.00
Proportion of lots that are vacant	0.25	0.15	0.26	0.00	1.00
Proportion of dwellings renter occupied	0.43	0.40	0.24	0.00	1.00
Population Characteristics					
Herfindahl index of race/ethnicity	0.16	0.10	0.18	0.00	0.80
Proportion of children in single-parent families	0.69	0.75	0.29	0.00	1.00
Ratio of adults to children	3.87	2.72	7.01	0.13	303.00
Proportion of population male age 15-24	0.08	0.08	0.06	0.00	0.67
Proportion of households living alone	0.29	0.28	0.17	0.00	1.00
Population density (pop./square mile)	7.27	6.82	6.97	0.04	360.19
Proportion of pop. age 25+ without high school diploma	0.24	0.21	0.14	0.00	0.82
Proportion of employees in prof./managerial occup.	0.21	0.18	0.16	0.00	1.00
Median family income	35.37	31.66	19.50	0.00	171.35
Proportion of earners who are low-income	0.31	0.30	0.18	0.00	1.00
Herfindahl index of earnings	0.61	0.62	0.09	0.20	0.75
Ratio of employed residents to pop. 18+	0.38	0.32	0.34	0.00	9.00
Local Business Characteristics					
Ratio of jobs to resident population	0.26	0.00	3.71	0.00	247.00
# licenses to sell alcohol	0.08	0.00	0.33	0.00	9.00
Within 1/4 mi. on-premises liquor vendor (1=yes)	0.43	0.00	0.50	0.00	1.00
Within 1/4 mi. off-premises liquor vendor (1=yes)	0.79	1.00	0.41	0.00	1.00
Within 1/2 mile of high school (1=yes)	0.39	0.00	0.49	0.00	1.00
Spatial Lag Variables					
Spatial lag of assault rate	87.55	84.95	32.78	0.99	259.10
Spatial lag of burglary rate	55.92	38.86	72.65	0.00	1,666.67
Spatial lag of destruction rate	43.03	35.48	39.07	0.00	626.64
Spatial lag of drug rate	18.54	0.00	48.28	0.00	870.54
Spatial lag of larceny rate	54.25	44.52	45.56	0.00	520.74
Spatial lag of motor vehicle theft rate	31.15	29.66	17.01	0.18	255.59
Spatial lag of robbery rate	20.16	14.51	21.16	0.00	156.71
Spatial lag of violent crime rate	50.05	46.49	21.75	0.54	127.63
Spatial lag of property crime rate	144.10	128.01	129.57	0.00	2,944.13
Spatial lag of proportion DFV	0.04	0.03	0.04	0.00	0.27
Spatial lag of proportion vacant housing	0.18	0.18	0.07	0.00	0.40
Spatial lag of proportion vacant lots	0.21	0.17	0.17	0.00	0.79

Sources: Multiple; see text for details; $N = 10{,}021$.

TABLE 2

Results of Negative Binomial Models of Predictors of Violent Crime and its Components

Variable	Dependent: Assault				Dependent: Robbery				Dependent: Violent			
	Coef.	Std. Err.	z	P>|z|	Coef.	Std. Err.	z	P>|z|	Coef.	Std. Err.	z	P>|z|
Housing												
Proportion DFV (of structures)	0.347	0.250	1.390	0.165	0.462	0.570	0.810	0.418	0.158	0.342	0.460	0.644
Proportion vacant housing units	0.085	0.141	0.610	0.545	0.041	0.316	0.130	0.897	0.317	0.189	1.670	0.094
Proportion vacant lots	−0.071	0.132	−0.530	0.593	−0.399	0.305	−1.310	0.191	−0.114	0.180	−0.640	0.525
Proportion renter occupied	0.954	0.094	10.110	0.000	0.886	0.219	4.040	0.000	0.871	0.129	6.730	0.000
Population												
Herfindahl index of race/ethnicity	−0.132	0.104	−1.270	0.204	−0.067	0.245	−0.270	0.784	−0.240	0.148	−1.620	0.105
Proportion of children in single-parent families	0.362	0.070	5.160	0.000	0.038	0.157	0.240	0.809	0.170	0.094	1.810	0.071
Ratio of adults to children	0.002	0.005	0.330	0.742	0.027	0.011	2.510	0.012	0.014	0.006	2.230	0.026
Proportion male age 15–24	−0.846	0.366	−2.310	0.021	−0.793	0.849	−0.930	0.351	−0.384	0.500	−0.770	0.442
Proportion of households living alone	−0.159	0.130	−1.230	0.219	0.059	0.297	0.200	0.843	−0.085	0.175	−0.480	0.628
Population density	−0.049	0.005	−9.880	0.000	−0.114	0.013	−8.960	0.000	−0.072	0.007	−10.110	0.000
Proportion without high school diploma	0.040	0.142	0.280	0.779	−0.037	0.337	−0.110	0.914	0.071	0.196	0.360	0.718
Proportion prof.l/managerial occupations	−0.199	0.121	−1.640	0.102	−0.004	0.286	−0.010	0.990	−0.059	0.167	−0.350	0.725
Median family income	−0.004	0.001	−3.780	0.000	0.000	0.003	−0.120	0.908	−0.003	0.002	−2.250	0.025
Proportion low-income earners	0.091	0.105	0.860	0.388	−0.279	0.251	−1.110	0.265	−0.178	0.146	−1.220	0.222
Herfindahl index of earnings	−0.044	0.200	−0.220	0.825	−0.381	0.472	−0.810	0.420	−0.020	0.278	−0.070	0.944
Ratio of employed residents to pop. 18+	0.208	0.077	2.700	0.007	0.435	0.140	3.100	0.002	0.348	0.094	3.710	0.000
Business												
Ratio of jobs to resident population	0.038	0.015	2.600	0.009	0.030	0.032	0.940	0.349	0.018	0.022	0.830	0.407
# licenses to sell alcohol	0.237	0.049	4.850	0.000	0.609	0.095	6.400	0.000	0.476	0.061	7.830	0.000
Within 1/4 mile on-premises vendor	0.101	0.034	2.980	0.003	0.100	0.080	1.240	0.215	0.077	0.047	1.630	0.102
Within 1/4 mile off-premises vendor	0.113	0.045	2.520	0.012	0.635	0.128	4.950	0.000	0.363	0.067	5.420	0.000
Within 1/2 mile of high school	0.030	0.034	0.900	0.366	0.201	0.079	2.540	0.011	0.077	0.046	1.660	0.097
Spatial Lag												
Spatial lag of proportion DFV	0.436	0.732	0.600	0.551	−1.448	1.674	−0.860	0.387	−0.370	1.015	−0.370	0.715
Spatial lag of proportion vacant housing units	0.510	0.377	1.350	0.176	2.603	0.882	2.950	0.003	1.339	0.524	2.560	0.011
Spatial lag of proportion vacant lots	−0.556	0.195	−2.840	0.004	−0.906	0.467	−1.940	0.052	−0.514	0.269	−1.910	0.056
Spatial lag of dependent crime variable	0.001	0.001	2.160	0.031	0.008	0.002	4.490	0.000	0.003	0.001	2.290	0.022
_constant	−5.061	0.182	−27.780	0.000	−7.017	0.430	−16.310	0.000	−5.979	0.253	−23.640	0.000
/lnalpha	−0.622	0.069			0.743	0.131			−0.115	0.086		
alpha	0.537	0.037			2.102	0.276			0.891	0.076		
	Likelihood-ratio test of alpha = 0: chibar2(01) = 415.10 Prob> = chibar2 = 0.000 Number of obs = 10,021				Likelihood-ratio test of alpha = 0: chibar2(01) = 153.58 Prob> = chibar2 = 0.000 Number of obs = 10,021				Likelihood-ratio test of alpha = 0: chibar2(01) = 288.78 Prob> = chibar2 = 0.000 Number of obs = 10,021			

TABLE 3

Results of Negative Binomial Models of Predictors of Drug and Property Crime and its Components

	Dependent: Burglary				Dependent: Destruction/Vandalism				Dependent:Drug/Narcotic			
Variable	Coef.	Std. Err.	z	P>|z|	Coef.	Std. Err.	z	P>|z|	Coef.	Std. Err.	z	P>|z|
Housing												
Proportion DFV (of structures)	−0.335	0.337	−0.990	0.320	0.310	0.364	0.850	0.395	1.176	0.626	1.880	0.060
Proportion vacant housing units	0.798	0.175	4.570	0.000	0.263	0.200	1.320	0.188	1.053	0.376	2.800	0.005
Proportion vacant lots	−0.489	0.168	−2.910	0.004	−0.323	0.191	−1.690	0.091	0.085	0.360	0.240	0.814
Proportion renter occupied	0.384	0.115	3.330	0.001	0.661	0.134	4.940	0.000	0.722	0.260	2.780	0.005
Population												
Herfindahl index of race/ethnicity	0.225	0.118	1.900	0.057	0.006	0.145	0.040	0.967	−0.713	0.290	−2.460	0.014
Proportion of children in single-parent families	0.035	0.082	0.430	0.667	0.231	0.098	2.360	0.018	0.050	0.178	0.280	0.777
Ratio of adults to children	−0.008	0.007	−1.150	0.252	0.004	0.007	0.620	0.538	−0.002	0.016	−0.140	0.892
Proportion male age 15–24	0.483	0.442	1.090	0.274	−0.126	0.521	−0.240	0.808	−0.216	0.956	−0.230	0.821
Proportion of households living alone	0.025	0.160	0.160	0.874	0.113	0.185	0.610	0.541	0.573	0.352	1.630	0.104
Population density	−0.047	0.006	−7.830	0.000	−0.049	0.007	−6.790	0.000	−0.112	0.016	−7.190	0.000
Proportion without high school diploma	0.411	0.168	2.450	0.014	0.042	0.202	0.210	0.835	−0.127	0.399	−0.320	0.750
Proportion prof./managerial occupations	0.088	0.144	0.610	0.542	−0.099	0.170	−0.580	0.562	−0.061	0.321	−0.190	0.849
Median family income	−0.002	0.001	−1.730	0.084	0.000	0.002	−0.140	0.888	−0.008	0.003	−2.590	0.009
Proportion low-income earners	−0.084	0.130	−0.640	0.520	−0.276	0.155	−1.780	0.075	−0.205	0.279	−0.730	0.464
Herfindahl index of earnings	0.161	0.246	0.650	0.513	−0.576	0.284	−2.030	0.043	−0.260	0.556	−0.470	0.640
Ratio of employed residents to pop. 18+	0.260	0.100	2.590	0.009	0.471	0.086	5.470	0.000	−0.261	0.236	−1.110	0.269
Business												
Ratio of jobs to resident population	0.026	0.017	1.520	0.129	0.048	0.017	2.800	0.005	0.019	0.046	0.410	0.683
# licenses to sell alcohol	0.277	0.055	5.000	0.000	0.388	0.064	6.100	0.000	0.579	0.131	4.410	0.000
Within 1/4 mile on-premises vendor	0.012	0.040	0.310	0.758	0.043	0.048	0.900	0.367	−0.053	0.095	−0.560	0.572
Within 1/4 mile off-premises vendor	0.172	0.053	3.250	0.001	0.060	0.062	0.960	0.339	0.643	0.140	4.600	0.000
Within 1/2 mile of high school	−0.033	0.040	−0.830	0.406	0.000	0.048	0.000	0.998	−0.076	0.095	−0.800	0.421
Spatial Lag												
Spatial lag of proportion DFV	0.176	0.927	0.190	0.849	1.341	1.042	1.290	0.198	1.649	1.927	0.860	0.392
Spatial lag of proportion vacant housing units	−1.097	0.451	−2.440	0.015	0.021	0.529	0.040	0.968	0.440	1.044	0.420	0.674
Spatial lag of proportion vacant lots	−0.358	0.247	−1.450	0.147	−0.617	0.284	−2.180	0.030	−0.673	0.546	−1.230	0.218
Spatial lag of dependent crime variable	0.001	0.000	5.320	0.000	0.002	0.001	3.460	0.001	0.003	0.001	3.140	0.002
_constant	−5.314	0.219	−24.260	0.000	−5.514	0.256	−21.520	0.000	−6.400	0.506	−12.660	0.000
/lnalpha	−0.823	0.113			−0.571	0.136			1.814	0.093		
alpha	0.439	0.050			0.565	0.077			6.136	0.568		
	Likelihood-ratio test of alpha = 0: chibar2(01) = 129.08 Prob>=chibar2 = 0.000 Number of obs = 10,021				Likelihood-ratio test of alpha = 0: chibar2(01) = 85.96 Prob>=chibar2 = 0.000 Number of obs = 10,021				Likelihood-ratio test of alpha = 0: chibar2(01) = 518.77 Prob>=chibar2 = 0.000 Number of obs = 10,021			

Continued

TABLE 3

Continued

Variable	Dependent: Larceny				Dependent: Motor Vehicle Theft				Dependent: Property			
	Coef.	Std. Err.	z	P>|z|	Coef.	Std. Err.	z	P>|z|	Coef.	Std. Err.	z	P>|z|
Housing												
Proportion DFV (of structures)	−0.553	0.404	−1.370	0.171	−0.397	0.435	−0.910	0.361	−0.223	0.226	−0.990	0.324
Proportion vacant housing units	−0.548	0.208	−2.640	0.008	0.180	0.219	0.820	0.410	0.184	0.118	1.550	0.121
Proportion vacant lots	−0.519	0.189	−2.740	0.006	0.051	0.202	0.250	0.800	−0.339	0.111	−3.060	0.002
Proportion renter occupied	0.730	0.136	5.350	0.000	0.441	0.141	3.130	0.002	0.537	0.078	6.880	0.000
Population												
Herfindahl index of race/ethnicity	0.232	0.144	1.610	0.107	−0.185	0.151	−1.220	0.221	0.154	0.082	1.880	0.060
Proportion of children in single-parent families	0.031	0.095	0.330	0.744	0.028	0.101	0.280	0.778	0.030	0.055	0.540	0.587
Ratio of adults to children	0.010	0.007	1.450	0.147	0.004	0.007	0.640	0.524	0.001	0.004	0.330	0.738
Proportion male age 15–24	0.393	0.522	0.750	0.452	−0.279	0.559	−0.500	0.617	0.268	0.299	0.900	0.371
Proportion of households living alone	0.478	0.185	2.580	0.010	0.038	0.193	0.200	0.844	0.172	0.107	1.600	0.109
Population density	−0.104	0.007	−13.950	0.000	−0.038	0.007	−5.200	0.000	−0.063	0.004	−15.130	0.000
Proportion without high school diploma	0.181	0.205	0.880	0.379	0.109	0.210	0.520	0.603	0.230	0.116	1.990	0.047
Proportion prof./managerial occupations	−0.033	0.177	−0.180	0.853	0.021	0.177	0.120	0.907	0.015	0.099	0.160	0.876
Median family income	0.000	0.002	−0.230	0.818	−0.001	0.002	−0.890	0.371	−0.002	0.001	−1.760	0.079
Proportion low-income earners	−0.063	0.151	−0.410	0.678	0.004	0.161	0.020	0.981	−0.069	0.087	−0.790	0.429
Herfindahl index of earnings	−0.358	0.295	−1.220	0.224	−0.409	0.300	−1.370	0.172	−0.108	0.168	−0.640	0.521
Ratio of employed residents to pop. 18+	0.242	0.121	2.010	0.045	0.083	0.140	0.590	0.557	0.242	0.067	3.600	0.000
Business												
Ratio of jobs to resident population	0.083	0.018	4.550	0.000	0.054	0.016	3.460	0.001	0.055	0.011	5.160	0.000
# licenses to sell alcohol	0.429	0.062	6.890	0.000	0.213	0.069	3.110	0.002	0.335	0.038	8.940	0.000
Within 1/4 mile on-premises vendor	0.151	0.049	3.060	0.002	0.006	0.050	0.110	0.911	0.043	0.028	1.530	0.125
Within 1/4 mile off-premises vendor	0.220	0.066	3.340	0.001	0.091	0.064	1.430	0.153	0.169	0.036	4.650	0.000
Within 1/2 mile of high school	0.052	0.049	1.060	0.290	0.011	0.049	0.220	0.824	0.002	0.028	0.060	0.951
Spatial Lag												
Spatial lag of proportion DFV	−1.632	1.132	−1.440	0.149	0.188	1.182	0.160	0.874	−0.513	0.632	−0.810	0.417
Spatial lag of proportion vacant housing units	0.422	0.546	0.770	0.439	−0.909	0.555	−1.640	0.102	−0.707	0.310	−2.280	0.023
Spatial lag of proportion vacant lots	−0.047	0.280	−0.170	0.867	−0.799	0.303	−2.630	0.008	−0.321	0.163	−1.970	0.049
Spatial lag of dependent crime variable	0.003	0.001	3.590	0.000	0.007	0.002	3.410	0.001	0.001	0.000	5.980	0.000
_constant	−5.308	0.260	−20.400	0.000	−5.390	0.266	−20.250	0.000	−4.253	0.149	−28.510	0.000
/lnalpha	0.027	0.082			−1.290	0.258			−1.032	0.064		
alpha	1.028	0.084			0.275	0.071			0.356	0.023		
	Likelihood-ratio test of alpha = 0: chibar2(01) = 370.56 Prob>=chibar2 = 0.000 Number of obs = 10,021				Likelihood-ratio test of alpha = 0: chibar2(01) = 20.04 Prob>=chibar2 = 0.000 Number of obs = 10,021				Likelihood-ratio test of alpha = 0: chibar2(01) = 495.73 Prob>=chibar2 = 0.000 Number of obs = 10,021			

Housing Characteristics

The characteristics of the occupied and vacant dwellings and land in the block offered by far the greatest explanatory power in our model compared to any other categories of contextual characteristics. The tenure composition of the block's housing stock proved to be the most consistent predictor of every type of crime we analyzed. Higher rates of rental occupancy were associated with higher rates of both violent crime and property crime, as well as their respective components; a block with a 10-percentage-point higher renter occupancy rate would be predicted to have 8.7% and 5.4% higher violent and property crime rates, respectively, all else equal. The two types of violent crime we were able to analyze exhibited the strongest connections to rental occupancy rates: blocks with a 10 percentage-point higher rental rate would be predicted to have 9.5% and 8.9% higher assault and robbery rates. We think this result primarily reflected the lower collective efficacy and higher visible disorder typically associated with renter-dominant blocks (Sampson & Groves, 1989; Sampson, Raudenbush, & Earls, 1997).

The proportion of housing units that were vacant (for sale or rent) on the block displayed strong relationships with several sorts of crime. The measure was (predictably) significantly positively associated ($p < 0.01$) with both burglary and drug crimes, but significantly negatively associated with larceny ($p < 0.01$). Blocks with a 10-percentage-point higher housing vacancy rate would be expected to have an 8.0% higher burglary rate, 10.5% higher drug crime rate, and 5.5% lower larceny rate. Burglary may have been positively associated with vacant housing units because they may have had items of value remaining inside (appliances, lighting fixtures, copper pipes, etc.), yet were not as likely to be well-defended as occupied dwellings. On the other hand, a vacant dwelling is unlikely to have items of value left outside the home, and thus be a less likely target for larceny. The association with drug crimes may have been the result of offender illegal occupancy of vacant structures that were more habitable than those captured in the DFV measure, and their appropriation as "drug houses." Our results are consistent with a large body of literature identifying a positive association between property crime rates and proximity to a particular type of vacant property undoubtedly well-represented in our Detroit sample: foreclosures (Cui, 2010; Ellen et al., 2012; Goodstein & Lee, 2010; Immergluck & Smith, 2006; Katz et al., 2011; Williams et al., 2013).

Crime was also related to vacant dwellings nearby the given block, but not in a consistent fashion. Blocks with a 10-percentage-point higher vacancy rate on blocks within 2,232 feet would be predicted to have a 26% higher robbery rate and 13.4% higher violent crime rate overall; but they also would be predicted to have a 11.0% lower burglary rate and a 7.1% lower property crime rate overall. These positive spatial spillover effects might indicate that violent offenders used vacant dwellings nearby as a base from which to seek victims and/or to hide after such crimes. The negative spatial correlation with property crime may imply, however, that increased options for such crime in vacant dwellings nearby may divert criminals away from the given block, thereby serving as a protective factor.

Several property crime types analyzed were significantly negatively associated with the proportion of parcels that were vacant lots (while controlling for housing vacancy rate and population density). Blocks with a 10-percentage-point higher vacant lot rate would be predicted to have 4.9% lower burglary, 5.2% lower larceny, and 3.4% lower property crime rates. These results suggest that areas with a higher proportion of empty lots may offer less opportunity and/or greater costs to commit property crimes—fewer potential targets and less physical cover with which to mask an illegal act or escape undetected from same.

Several types of (mainly property) crime were also significantly negatively associated with the proportion of vacant parcels in nearby blocks. Blocks with a 10-percentage-point higher vacant lot rate on blocks within 2,232 feet would be predicted to have a lower rates of vandalism (6.2%), motor vehicle theft (8.0%), property crimes overall (3.2%), and assaults (5.6%). Unlike the case of negative spatial lag effects for vacant dwellings on property crimes, however, this result is unlikely to be explained as diversion of criminals to nearby targets because vacant lots offer no such attractive alternative targets. We think that more vacant lots (controlling for housing vacancy rate and population density) both on and nearby a block might discourage would-be property criminals by both reducing the density of potential targets while raising the visibility of perpetrators operating on foot.

Finally, consider the results for the prevalence of abandoned, blighted, dangerous (DFV) properties. The only crime type even marginally significantly (positively) associated ($p < 0.06$) with the DFV measure was drugs.[9] Blocks with a 10-percentage-point higher rate of DFV dwellings would be predicted to have an 11.8% higher rate of drug crimes. One potential explanation for this relationship is that DFVs served as attractive venues for the sale and/or consumption of illegal substances. The spatially lagged measure of DFVs was not correlated with any crime type. We caution that DFVs are not that prevalent (even in Detroit)[10] and statistically significant relationships are difficult to detect between rare predictors and rare outcomes (like violent crime). Nevertheless, our limited set of relationships suggests that DFVs may not (contrary to common belief) serve as loci for violent criminal offenses or indicators of social disorder that might signal a general lack of collective efficacy promoting all sorts of criminality. Analogous to the situation with vacant lots, fewer potential victims of assaults or robberies may be found in and around blocks with more DFVs, and there may be little of value to steal from such dilapidated structures, thus limiting the numbers of burglaries or larcenies. By the time a few structures fall into DFV status it is plausible that collective efficacy has already disappeared, so DFVs might then offer no new "signaling effect" on the margin.

Population Characteristics

In contrast to characteristics of houses and lots in the neighborhood, most demographic and economic characteristics of the block's residents provided little explanatory power. Many such variables—proportion of low-income earners, index of racial diversity, proportion in professional/managerial occupations—did not prove statistically significant predictors of any type of crime. Many others only predicted one type of crime, including proportion without a high school diploma, proportion of the population that is male and age 15–24, index of income inequality, proportion of children in one-parent families, ratio of adults to children, and proportion living alone. A few demographic and economic characteristics of the block were important correlates of violent and property crime, however.

Population density of the block demonstrated a consistent and significant negative correlation with all crime types. This result should be interpreted carefully in light of the fact that population is implicitly controlled in our model (via the NBREG offset option). At least three explanations are possible. First, higher density might translate into a greater intensity of "eyes on the street" informal surveillance that could deter crime. Second, because our model also holds proportion of vacant dwellings and proportion of vacant lots constant, higher density blocks are likely those with larger shares of multi-unit structures constituting their occupied stock. Such building types may alter routine activity patterns nearby and/or the degree of "defensible spaces" in a way that is distinctive from neighborhoods comprised of single-family, detached dwellings. Third, higher-density blocks may be those with smaller shares of land devoted to nonresidential land uses, venues that may be more likely loci for crime.

Blocks with higher median family incomes had lower rates of assaults and violent crime overall. This finding is consistent with a large literature identifying a positive association between deprived places and rates of violent crime (e.g., Crutchfield, Glusker, & Bridges, 1999; Hannon, 2002, 2005; Hipp, 2007b; Hipp & Yates, 2011; Krivo & Peterson, 1996; Warner & Pierce, 1993; Warner & Rountree, 1997).

Unexpectedly, blocks with higher rates of employment among adult residents were significantly associated with higher rates of almost every category of crime. A block with a 10-percentage-point higher employment rate would be predicted to have 2.1% to 4.4% higher rates of violent crime in all categories analyzed, and 2.4% to 4.7% higher rates of all categories of property crime except drug and motor vehicle theft. Recalling that we are controlling for median family incomes and education, we believe that this finding may relate to absence of adults from the premises. Working adults are less likely to be at home to protect property or to supervise youth who otherwise might perpetrate and/or be victimized by crime.

Local Business Characteristics

One of our most dramatic results was the strong correlation between many crime types and proximity to on- and off-premises vendors of alcohol. Having any type of liquor vendor on the block was associated with more incidents of all types of crime. Compared to an otherwise-identical block with no establishments with a license to sell liquor (to be consumed either on or off premises), a block having such an establishment was predicted to have a 34% higher property crime rate and a 48% higher violent crime rate. Proximity within one-quarter mile to an on-premises liquor vendor was significantly correlated with higher rates of assault (10%) and larceny (15%). Proximity to an off-premises vendor was an even more powerful predictor. It was significantly correlated with nearly all crime types: assault (11%), burglary (17%), larceny (22%), drugs (64%), property crimes overall (17%), robbery (64%), and violent crimes overall (36%). We recognize that there may be a degree of endogeneity here, with declining, crime-ridden neighborhoods being more likely places for liquor establishments to seek and be granted licenses to operate. Nevertheless, there are compelling reasons to believe that these establishments can cause more crime to occur in the vicinity. Liquor establishments may create hot spots for a wide variety of criminal activity, either because they sharply define activity spaces in ways that bring potential victims and offenders into close contact and/or are associated with the consumption of more alcohol by either group in a fashion that makes a criminal act more likely (e.g., by rendering a potential victim more vulnerable and/or a perpetrator more aggressive).

Finally, proximity to a high school and the associated routine activities generated thereby was positively associated with more robberies. Compared to an otherwise identical block, one within a half-mile of a high school would be predicted to have a 20% higher rate of robbery. There is also a less precise estimate that violent crimes are higher near high schools. We cannot be sure, of course, but these findings are consistent with the notion that children walking to school may be victimized at higher rates, perhaps by student offenders.

Spatial Spillovers of Crime

As expected, there were strong patterns of spatial associations for all the various crime types, demonstrated by the large and statistically significant coefficients on the spatial lag versions of the dependent variables. For the overall indices, violent crime exerted its spatial spillovers over a longer distance and with greater strength than did property crime. An additional violent crime up to 4,680 feet away would be predicted to increase the probability of a violent crime on a given block at roughly three times the effect of an additional property crime up to 2,232 feet away.

NEIGHBORHOOD DECLINE AND CRIME DYNAMICS: A SIMULATION OF A STYLIZED DETROIT NEIGHBORHOOD

At the beginning of this article we advanced some plausible reasons why the relationship between neighborhood decline and crime rates might assume a nonlinear pattern. In the previous section we saw how individual attributes of Detroit neighborhoods predicted various types of crime in a *ceteris paribus* context. Here we explore more holistically how these attributes in combination produce aggregate crime rates for neighborhoods and indeed whether nonlinearity is suggested. We utilize a thought experiment involving a stylized Detroit census tract that transitions through five stages of decline, each characterized by an archetypical set of housing, land and demographic conditions.

Specifically, we simulate a hypothetical Detroit census tract as it experiences a representative pattern of income and tenure succession, physical decay and, eventually, residential abandonment and vacant land. For values of these attributes at each of five stages we assign our stylized neighborhood with values of selected variables corresponding to the 10th, 30th, 50th, 70th and 90th percentiles of their distributions in our sample, that is, the midpoints of each quintile.[11] The percentiles were ordered consistently so that all variables' values were associated with decline as the neighborhood evolved from Stage 1 to Stage 5 (i.e., more vacant land, vacant housing units, and renters; lower median

TABLE 4

Values of Variables Used in Simulation of Neighborhood Decline and Crime Dynamics

	% Housing Units Vacant	% Lots Vacant	Employed/ Population aged 18+	Median Family Income ($1,000s)	% Units Renter-Occupied	Population/ Square Mile (thousands)
10th Percentile (Stage 1)	3.70%	0.00%	0.42	63.93	13.30%	11.71
30th Percentile (Stage 2)	12.50%	4.30%	0.35	43.67	28.60%	8.74
50th Percentile (Stage 3)	20.00%	14.80%	0.32	33.4	40.00%	6.82
70th Percentile (Stage 4)	28.60%	35.70%	0.29	25.83	52.50%	4.75
90th Percentile (Stage 5)	43.30%	66.70%	0.24	14.86	75.00%	2.14

incomes and employment rates; less density). The variables we used to simulate the dimensions of neighborhood decline and their respective values at each stage are presented in Table 4.[12]

We then calculated the absolute change in each variable associated with a progression from one stage of decline to the next (i.e., the differences in the interstage values shown in Table 4), and then applied the coefficients of our models (shown in Tables 2 and 3) to generate the predicted proportional change in crime associated with this neighborhood change.[13] Finally, we accumulated the proportional changes attributable to each variable shown in Table 4 to get the full proportional change in crime predicted in total by the model.

We emphasize that even though this is a thought experiment simulation of decline, it reflects the norm for actual neighborhood trajectories in Detroit during the last decade. We conducted an exploratory factor analysis of 2000 census tract indicators in our model related to neighborhood change for which comparable estimates were available in 2010. This yielded one factor with an eigenvalue greater than one, which heuristically corresponded to a summary "disinvestment factor" measured for all Detroit tracts in 2000. We then computed values of this disinvestment factor using the same 2000 weights (factor coefficients) and normalized values of the comparable component variables in 2010. By comparing the values of these indices we found that fully 95% of all tracts in Detroit had higher disinvestment scores in 2010 than in 2000, indicating that the typical dynamic was indeed one of decline, as we simulate.

The results for the aggregate violent and property crime indexes are presented in Figure 4. The results for the various component crime categories closely parallel those of the aggregate indexes, so for simplicity we focus only on the latter. Their outstanding feature is that, though our model predicts that the *level* of violent and property crimes (and all their component crimes) will steadily rise as a neighborhood declines from Stage 1 to Stage 5, the *rate* of this increase will not be constant. On the contrary, as a neighborhood declines we estimate that crime changes in a clearly nonlinear fashion. Specifically, it rises first at a decreasing rate but then, finally, at an increasing rate as the neighborhood enters its most deteriorated, vacated stage. If a neighborhood were to decline from Stage 1 to 2, we estimate that violent crime would rise 39% and property crime would rise 24%. By contrast, decline from Stage 3 to 4 generates a considerably smaller (though still substantial) estimated increase of 27% in violent crime and 12% in property crime. However, the final transition from Stage 4 to Stage 5 is associated with an upsurge in the growth rate of crime: 40% and 17% for violent and property crimes, respectively. Although our simulation is not definitive, we think the results are sufficiently provocative to warrant advancing nonlinear crime dynamics associated with neighborhood decline as a hypothesis justifying future investigation.

These nonlinear dynamics of crime are driven quantitatively in our simulation primarily by changes in renter occupancy and population density. The U-shaped rate of change in crime functions portrayed in Figure 4 mimics the change trajectory of population density: more sizable proportionate declines both between Stages 1–2 and 4–5 than between the intermediate stages (see Table 4). The growth in renter occupancy rates across the stages is relatively constant until the exceptionally large increase associated with the transition into Stage 5 (see Table 4). For both violent and property crime rates this translates into a disproportionate increase associated with this transition. This nonlinear pattern is blunted somewhat by the countervailing pattern of increasing land vacancies, which works to

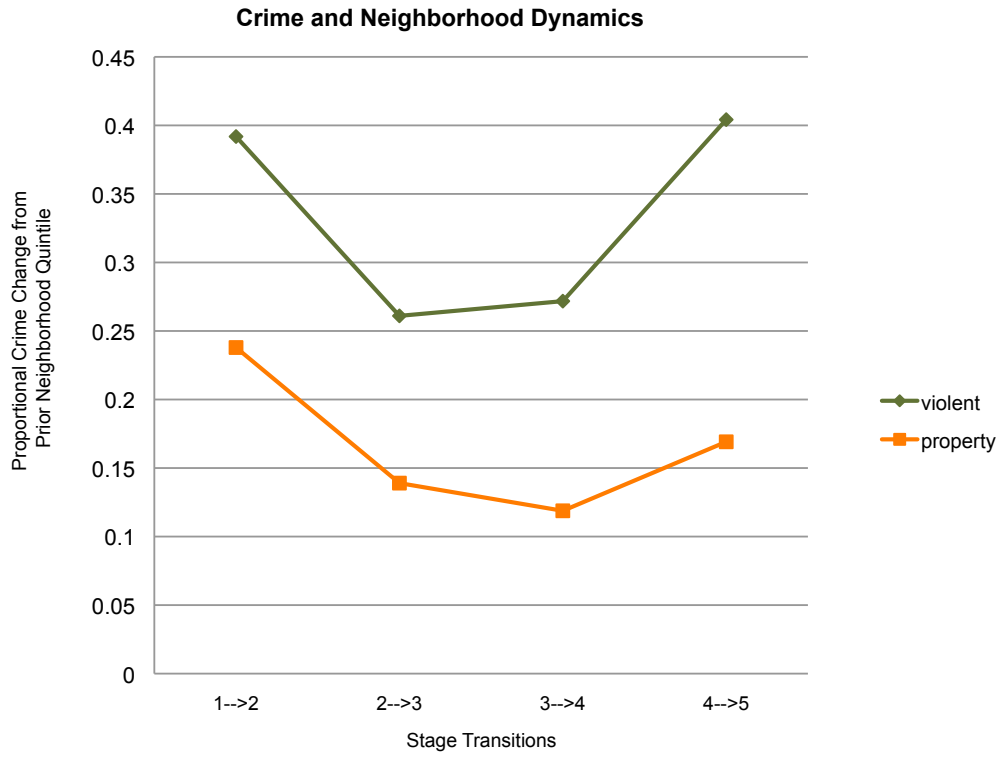

FIGURE 4

Proportional Changes in Crime Across Simulated Stages of Neighborhood Decline

Note: Horizontal axis values are changes between values of predictor variables measured at their respective midpoints of quintiles shown, i.e., between 10th, 30th, 50th, 70th, and 90th percentiles.
Source: Author's calculations based on estimated parameters in Tables 2 and 3 and changes in variable values shown in Table 4; baseline number of crimes in Stage 1 assumed to be 10th percentile.

reduce property crime (see Table 3). Land vacancy rates grow disproportionately as our stylized neighborhood evolves across the stages of decline, skyrocketing especially in Stage 5 in a way that attenuates the upturn in the U-shape for property crime (see Figure 4). By contrast, simulated variations in median family incomes and employment rates hold far less quantitative importance in shaping crime dynamics associated with neighborhood decline.

CONCLUSIONS, IMPLICATIONS, AND CAVEATS

Our article contributes to the literature by (1) developing a conceptual framework that synthesizes views of several scholarly disciplines and makes explicit the mutual causal relationships among crime and various neighborhood characteristics, (2) offering an empirical exploration of part of this framework that employs a negative binomial crime model with exceptionally rich measures of neighborhood physical and housing conditions in Detroit, and (3) using estimated parameters to demonstrate how neighborhood decline may be associated with nonlinear crime responses. Our negative binomial model estimates reveal several neighborhood attributes that are consistently associated with all types of crime: renter occupancy, vacant land, population density, and proximate establishments with liquor licenses; other attributes are associated with particular types of crime. Our simulation using estimated parameters suggests that processes of disinvestment and abandonment may generate a distinctly nonlinear pattern in the rate of growth in neighborhood crime rates:

increasing rapidly during the initial stages of decline, then slowing and, in the final stage of low-density rental occupancy, increasing rapidly again (especially in the case of violent crime).

The causal mechanisms through which these nonlinear dynamics seem to be produced can only be inferred with extreme caution, of course. We recognize that our simulation drew longitudinal inferences from cross-sectional estimates and that causal claims cannot be made, especially given the endogenous processes we have posited in Figure 1. Nevertheless, we would tentatively offer the following as a plausible causal scenario for interpreting our results. Crime-spawning processes associated with neighborhood decline appear to be driven by changes in both resident population characteristics and housing–land characteristics. Increasing neighborhood shares of renter households, diminished median family incomes, and falling population densities yield higher rates of violent crime (and, to a lesser degree, property crime), conceivably by eroding collective efficacy, increasing household economic and social stress profiles, and generating more vulnerable routine activity patterns. If during this decline process the proximate number of liquor-selling establishments grows, these increasing crime rates will be augmented significantly, arguably by altering routine activity patterns, vulnerability of potential victims, and/or aggressiveness of potential offenders. However, these crime-enhancing forces appear to be offset somewhat by two countervailing forces. As neighborhoods become increasingly occupied by households who have no employees there may be augmented supervision of property and youth as well as more "eyes on the street." If neighborhoods become so abandoned that they begin to sprout vacant lots, property crime should be discouraged, plausibly due to elimination of potential targets and camouflage for illegal activities.

It is striking that our scenario paid no attention to an aspect of neighborhood disinvestment that has captured the public's imagination as a catalyst for violent crime: abandoned, blighted dwellings in need of demolition (what we have labeled DFV structures). Contrary to conventional wisdom, the only category of crime for which we observed even a modestly statistically significant (and quantitatively small) link with DFV was drugs.

Policy Implications

If the relationships we have observed are indeed reflective of causal relationships, they would hold provocative implications for anticrime strategies focusing on (1) demolishing abandoned housing, (2) "right-sizing" urban footprints, and (3) regulating liquor-selling establishments. First, it has long been conventional for Detroit mayors to promise accelerated efforts to demolish DFV structures. While this strategy might be applauded for many reasons (Mallach, 2012), its expected impact on crime must be interpreted carefully in light of our findings. Recall we found that, *compared to an otherwise identical block with 100% occupied dwellings and parcels*, one with more vacant (for rent or sale) dwellings will have substantially more burglaries and drug crimes; vacant parcels will have fewer burglaries and property crimes overall; and DFV-occupied parcels will have no large differences in crime (with the possible exception of drugs). This suggests that it is *vacant* dwellings, not abandoned ones, which are the scourge of neighborhood safety. It is difficult to imagine how Detroit can substantially reduce its vacancy rate (Neighborhood Stabilization Program funds notwithstanding), given the excess speculative housing supply perpetually being created in the suburban ring (Galster, 2012). Of course, there nevertheless may be a crime reduction rationale for demolition of DFVs, given our finding that the vacant lot produced thereby will likely reduce property crime.

Detroit Mayor Dave Bing took office in 2010 advocating a "right-sizing" plan for shrinking the city's functional footprint. This proposed scheme would have moved out vestigial households from nearly vacated neighborhoods and demolished their dwellings, relocated them to vacant units in higher density areas, and withdrawn city services from the now completely vacant areas. Though the Mayor has since backpedaled on this proposal in the face of strong community opposition, the recently released Detroit Future City strategic framework advises a functionally similar strategy over the next ten to fifty years (Detroit Works Project Long Term Planning, 2013). Our estimates imply that it will have a crime-reducing effect if it is pursued. The reduction in dwelling vacancy rates and increasing population densities in the destination neighborhoods will reduce crime there, while

replacing occupied dwellings with vacant land will also reduce crime in the origin neighborhoods from which population was relocated.

The last policy issue relates to the issuing of liquor licenses. Recall that the magnitudes of association between proximity to either on- or off-premises liquor establishments and all types of crime were nothing short of staggering. Of course, causation is ambiguous here; licenses may have been granted in the past to locales already deemed sufficiently crime-ridden and "too far gone" to make any difference. To the extent that the opposite causal relationship exists, however, our findings suggest that liquor licenses issued for establishments in or near residential areas be considered circumspectly for their potential impact on public safety and, ultimately, neighborhood stability.

Caveats and Directions for Future Research

In closing, we note several caveats and limitations associated with our study as a foundation for future research. The first set relates to the measurement of crime. We recognize the likelihood of underreporting criminal offenses, especially for the less serious types of crime. In particular, if there were systematic geographic variations in the extent of underreporting it would potentially bias results for the associated neighborhood characteristics that we employ in our model. Moreover, our crime data omit some potentially important details. For example, we now only can examine NIBRS assault rollup and violent rollup data; aggravated assault could be the portion of violent rollup producing the observed relationship with vacant housing. We are unable to match crime reports to the times at which particular dwellings were vacated or abandoned, and thus we cannot measure any discontinuous upsurges in crime associated with such events, as contrasted with longer term crime levels associated with the persistence of such neighborhood conditions. Last, we only can measure crime patterns during the winter quarter, given available data. Relationships among crime and neighborhood attributes may appear different with altered routine activity patterns during warmer weather.

Our second caveat relates to generality of findings. Admittedly, Detroit represents an extreme case of widespread neighborhood decline and abandonment, as our aforementioned factor analysis confirmed. We would hasten to note, however, that similar processes are prevalent in a wide array of older, depopulating, former industrial cities in the North East and North Central regions, notably Buffalo, Cincinnati, Cleveland, and St. Louis. Even cities with stable populations and obvious economic strengths, such as Chicago, have vast swaths of declining neighborhoods associated with well-publicized crime epidemics. Nevertheless, we recognize that the relationship between crime and neighborhood dynamics may be considerably different in neighborhoods that are improving (Taub et al., 1984), so the specific predictors econometrically estimated here may not necessarily be generalized.

Our last set of caveats relate to econometric issues. We were unable to measure several theoretically important predictors of crime: place attachment, collective efficacy, litter, graffiti, and home foreclosures. To the extent that these omitted control variables are correlated with our observed physical conditions in the neighborhood (Brown et al., 2003, 2004), the potential of biased coefficients of these conditions is magnified. Last, our data are cross-sectional, and thus we can make no claims of causality. Indeed, both our own theorizing summarized in Figure 1 and prior scholarship (Hipp, 2010; Hipp et al., 2009; Skogan, 1990; Taub et al., 1984) make a compelling case that causation likely runs in both directions between neighborhood and crime dynamics. This simultaneous equations bias would operate to reduce the measured size of coefficients on crime predictors measuring the extent of neighborhood physical decline. Moreover, we assumed our parameters estimated from a cross-section could be applied in a hypothetical longitudinal simulation and that these parameters appertained to ranges of predictor values that were considerably different from the mean. Clearly, future work will require more longitudinal information on physical conditions in neighborhoods related to property maintenance, vacancies and abandonment, coupled with more sophisticated econometric strategies involving instrumental variables, fixed effects, or difference models. Only then will we gain a more robust, confident understanding of the complex interrelationships between the dynamics

of neighborhood disinvestment, abandonment, and crime, and be able to offer more compelling recommendations to urban policymakers on this vital issue.

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APPENDIX A: DISTRIBUTION OF PROPERTY AND VIOLENT CRIME OFFENSES BY BLOCK, DETROIT, 2010 QUARTER

Recorded Property Offenses	Count of Blocks	Recorded Violent Offenses	Count of Blocks
0	5890	0	8936
1	3202	1	1794
2	1262	2	386
3	510	3	109
4	212	4	29
5	93	5	15
6	38	6	12
7	23	7	4
8	18	8	2
9	6	9	1
10	8	10	1
11	5	Total	11289
12	4		
13	1		
14	3		
15	1		
16	1		
17	1		
18	2		
19	1		
21	2		
24	2		
25	1		
30	1		
35	1		
49	1		
Total	11289		

Source: Detroit Police Department.

ENDNOTES

1 For additional references, see Miethe and Meier (1994).

2 One of the few consensual findings in the criminological literature is the positive correlation between neighborhood poverty rates and crime rates (Crutchfield, Glusker, and Bridges, 1999; Hannon, 2002, 2005; Hipp, 2007; Warner & Pierce, 1993; Warner & Rountree, 1997), although recently Hipp and Yates (2011) found that crime rates were highest in tracts with 35% poverty rates and lower in tracts with even greater poverty concentrations.

3 The vacant lot designation used for this study includes both "unimproved" (74%) and "improved" (24%) vacant lots ($n = 91{,}488$) as recorded by the Detroit Residential Parcel Survey. Both types are defined as parcels without residential structures, and "improved" parcels are those with some visible improvement, such as a paved lot, accessory structure, fence, or park.

4 The Herfindahl index of ethnic heterogeneity is expressed as $1 - \sum_{j=1}^{J} G_j^2$, where G represents the proportion of the population of race/ethnic group j out of J groups. In this instance, the index includes Hispanic or Latino, non-Hispanic white alone, non-Hispanic black or African American alone, non- Hispanic American Indian and Alaska Native alone, non-Hispanic Asian alone, non-Hispanic Native Hawaiian and Other Pacific Islander alone, non-Hispanic some other race alone, and non-Hispanic two or more races. The index takes on a value of zero with a homogenous composition and a limiting value of one with many groups identically represented.

5 Alternatively, we employed the conventional poverty rate available from ACS but found it less predictive.

6 Our Herfindahl index of earning heterogeneity uses four groups: residents who have not worked in the past 12 months and are assumed to have zero earnings (from ACS), employed residents earning $1,250 per month or less, employed residents earning $1,251 to $3,333 per month, and employed residents earning $3,333 per month or more. The inclusion of ACS data for this measure required aggregation of OTM data to block group–level, and application of the calculated values to blocks comprising each block group.

7 All these lags employ a distance-to-block centroid within cutoff threshold of 2,232 feet. These spatial lags assume that the relationship between crime in the focal block and vacancy/blighting influences in proximate blocks is linear and symmetric regardless of whether nearby blocks are more or less blighted than the focal block.

8 The spatial lag for burglary and drug crime was based on queen's-based contiguity; for vandalism, robbery, and all property crime it used distance within a threshold of 2,232 feet; for all other crimes it used distance within threshold of 4,680 feet.

9 This variable was positively associated with rates of violent crime in all three categories analyzed, but in no case did the relationship approach statistical significance.

10 Of 11,289 blocks in the sample, 4,673 (41.4%) have at least one DFV, and 2,574 (22.8%) have two or more DFVs.

11 For the simulation we are forced to switch to the census tract scale because the variable distributions at the block scale were so positively skewed that distinct quintile breaks often could not be identified. Note all the zero medians for crime in Table 1 and appendix table.

12 For tractability we excluded spatial interactions in this simulation, both endogenously among blocks within our hypothetical tract and from other blocks nearby.

13 The first proportional change was based on the number of crimes at the 10th percentile of the distribution, assuming this would appertain to the neighborhood in Stage 1; thereafter in the simulation the proportional change was based on the prior stage's simulated level of crime. In the simulation we assumed that all blocks within the stylized census tract changed uniformly, since our coefficients are based on underlying block, not tract, data. We also assume that the negative binomial regression parameters estimated cross-sectionally appertain to this implicitly longitudinal process being simulated.

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