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Predicting Decade-Long Changes in Community Motor Vehicle Theft Rates

Impacts of Structure and Surround

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Motor vehicle theft (MVT) is arguably the most underresearched Part I crime. This work predicts long-term changes in community MVT rates, extrapolating from earlier work in community fabric and changing personal crime and delinquency rates and cross-sectional work on MVT. Police data on MVTs generated MVT rates in one Midwestern city in 1990-1991 and 2000-2001 that were linked with census block group data. MVT rates went up later in communities more racially mixed initially and in those surrounded by initially higher MVT rates, suggesting extant community structure and surrounding crime generate subsequently unfolding impacts on MVT. A second series of models links changing MVT rates with contemporaneously increasing racial heterogeneity, decreasing community instability, and increasing surrounding MVT rates. Some associations between community structure and changing delinquency or crime appear relevant to shifting MVT rates. Resident-based, target-linked, and offender-dependent processes to be investigated are outlined.

Keywords: *motor vehicle theft; communities and crime; ecology; spatial dependence*

In the past three decades, research on communities and crime and on delinquency and crime has moved from cross-sectional to longitudinal investigations, considering how community fabric may cause later crime rate or delinquency rate changes or may shift as these crime and delinquency rates do (see Bursik 1986a, 1986b; Bursik and Webb 1982; Scheurman and Kobrin 1986; Taylor and Covington 1988). The current work brings the insights from those works to bear on arguably the most underresearched Part I crime: motor vehicle theft (MVT).

Recent interest in MVT has resulted in an edited volume by Maxfield and Clarke (2004) and in work focusing on thieves' motivation and decision-making (Cherbonneau and Copes 2005; Copes 2003b; Jacobs, Topalli, and Wright 2003), target hardening and security (Brown 2004; Mayhew and Braun 2004; Webb, Smith, and Laycock 2004), and offender travel patterns (Lu 2003). There is still, however, a very limited literature addressing the relationship between MVT and community structure (see Copes 1999; Rice and Smith 2002) and seemingly no work looking at this relationship longitudinally.

MVT, some might say, has been historically underresearched for a good reason. Its impacts on the victim and community may be weaker than the impacts of personal crimes or of other property crimes such as burglary, with its sense of violation (Waller and Okihiro 1978). Nonetheless, MVT's psychological, social, and economic impacts can be profound and substantial (see account by Berkson 2004). Furthermore, it can engender considerable inconvenience (Harlow 1989; Hough and Mayhew 1985). In addition to these personal and interpersonal impacts, there are substantial economic impacts. The value of the 1.24 million stolen motor vehicles in the United States in 2004 was estimated at $7.6 billion (Federal Bureau of Investigation 2005). Victims of MVT collectively lost an estimated $8.6 billion, or an average of $6,797 per offense (Federal Bureau of Investigation 2004). This was more than double the $3.3 billion in losses estimated from burglary (Copes 2003a). In short, for a host of reasons, although they are a far less riveting topic than serial killers, community MVT rates deserve close examination.

This work investigates changing MVT rates during a decade, community structural fabric, changes in that fabric, and MVT rates in adjoining communities. It considers two types of questions. First, how are long-term unexpected changes in community MVT rates linked to the initial demographic community features and to initial surrounding MVT theft rates?[1] These questions ask about impacts on MVT unfolding over time. Second, as community MVT rates shift, how do those shifts connect to co-occurring structural shifts and/or to co-occurring exogenous shifts in crime patterns? These questions ask how different threads of change weave together. The current

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research advances earlier work on community MVT rates by examining long-term, longitudinal shifts and by fully incorporating spatial lag effects.

Community, Crime, and Delinquency

Community Structure

Core aspects of community demographic structure include status, stability, and race. Though the specific form of each of these dimensions may shift somewhat over time and place (e.g., the labels for stability), extensive work in social area analysis and factorial ecology has confirmed the consistency of these three components in both American cities and abroad (Berry and Kasarda 1977; Berry and Rees 1969; Hunter 1971, 1974a, 1974b; Schevky and Bell 1955; Schevky and Williams 1949; Sweetser 1965; Van Arsdol, Camilleri, and Schmid 1958).[2]

Communities and Crime or Delinquency

Studying the reciprocal and lagged relationships between community structure and changing delinquency or crime is a relatively recent undertaking by scholars of communities and crime. Even though the publication of Amos Hawley's (1950) book *Human Ecology* "posed the central problem of ecology as the analysis of community adaptation to change" (Bursik 1986b:40), the empirical work up until the 1980s was dominated by cross-sectional studies, even when the referenced models posited dynamics linked to community instability and change (Bursik 1986b; Kornhauser 1978:429; Kubrin and Weitzer 2003; Taylor 2000:477).

Looking at changes in delinquency rates in the middle portion of the twentieth century, Bursik and colleagues (Bursik 1984, 1986a, 1986b; Bursik and Webb 1982; Heitgard and Bursik 1987) found community-delinquency links contingent on historical decade, simultaneous community structure-delinquency rate shifts, and impacts of nearby neighborhood composition changes on delinquency. Works on changing arrests (e.g., Chilton 1986) proved complementary, finding "for many central cities the change which has had the greatest impact on arrest counts has been the changing racial composition of the cities" (Chilton 1986:113). Looking specifically at multidecade shifts in crime rates, Schuerman and Kobrin (1986) found that changes in household and family composition and in racial makeup of locale preceded rising crime rates. They suggested high-speed structural changes facilitated the transition of neighborhoods from low- to high-crime locales.

Furthermore, rapid ecological changes, even when they were in a presumably good direction, such as increasing status relative to other neighborhoods, can elevate some crime rates (Covington and Taylor 1989).

Considerable cross-sectional work has confirmed that local social climate and related dynamics such as collective efficacy or informal social control mediate impacts of structure on outcomes such as victimization and offender rates (Elliott et al. 1996; Sampson 1987; Sampson and Groves 1989; Sampson and Lauritsen 1994; Sampson, Raudenbush, and Earls 1997; Veysey and Messner 1999). This work has further confirmed the impacts of adjacent community dynamics (Morenoff and Sampson 1997; Sampson, Morenoff, and Earls 1999).

Given past work, the following broad points appear warranted. Enduring components of community demographic structure, including status, stability, and aspects of racial composition, link cross-sectionally to offender and delinquency rates, and crime or victimization rates, in part and perhaps substantially through links to mediating dynamics. These dynamics include local social network features and related processes such as collective efficacy or informal social control.[3] Composition of and demographic changes in adjoining communities can affect these mediating dynamics and crime and related outcomes (e.g., Heitgard and Bursik 1987; Morenoff 2003; Sampson et al. 1999). Structural and demographic community changes link to crime and delinquency changes (Bursik 1986a, 1986b; Taylor and Covington 1988) and also can be conditioned by features of and changes in surrounding locales (Morenoff and Sampson 1997). Crime change and community change link bidirectionally (Taylor 1995). “Just as we find that neighborhood structure influences crime, there is mounting evidence that crime and violence shape neighborhood conditions themselves” (Kubrin and Weitzer 2003:389). Of course, numerous outstanding questions remain about neighborhood effects generally (Sampson, Morenoff, and Gannon-Rowley 2002) and about community-crime links.

Despite considerable work on community violent crime and delinquency rates and some work on community burglary (e.g., Rountree and Land 1996) or larceny (e.g., Taylor and Covington 1988) rates, there has been far less work on community MVT rates. The work that has been done (which is reviewed below) is exclusively cross-sectional. Before turning to the MVT work, however, some lessons from the communities-crime work generally might be incorporated. The latter has suggested specific communities hold a position or niche relative to other communities on major attributes such as status (Park and Burgess 1925), and these connect to relative position on specific crimes and delinquency (Bursik 1986b). These same relative positions or niches also might link to MVT. The structural correlates of MVT might be similar to those from the communities and crime literature if the same dynamics and dysfunctional controls responsible for diminished collective efficacy and self-protection, emerging from the community's relative position in the local ecology, are also relevant to MVT.

Of course, one might argue the reverse. The correlates of community MVT rates might be substantially different from correlates of community delinquency or violent crime rates for two reasons. First, variations in local land use and subsequent opportunity structures may have such a strong effect on MVT rates that they supersede impacts of community demographic structure (e.g., appeal of a target-rich unsupervised parking lot may overshadow community impacts). If this is correct, then the predictors examined here will not prove significant. Second, the favored-group hypothesis suggests that MVT is concentrated among the socially advantaged, who have greater exposure and familiarity with vehicles (McCaghy, Giordano, and Henson 1977). It argues for a demographic impact exactly opposite what we would expect based on the communities and crime literature. If this is correct, status will not be significant in the direction hypothesized.

Empirical Links between Community Structure and MVT

Socioeconomic status (SES). SES has emerged as one of the sturdier correlates of delinquency, victimization, crime, and offending rates (Bursik and Grasmick 1993). The same low SES–high crime link has emerged with MVT rates as well (Copes 1999; Hope and Hough 1988; Miethe and McCorkle 2001). Controlling for exogenous spatial autocorrelation and other aspects of community structure, Walsh and Taylor (in press) found such a link in two separate decades in one city. The suggested dynamics mediating the impacts of SES may have been variations in informal social control and/or vehicle protection devices, and/or community permeability to criminal invasion, and/or availability and abundance of vehicle targets. It is expected here that low SES can lead to subsequent increases in MVT rates because impacts of a community's ecological niche in the urban or suburban fabric unfold over time (Bursik 1986b). Self-reinforcing or amplifying endogenous dynamics and the external spreading reputations among potential offenders both might be involved. Declining status and increasing MVT may occur simultaneously as well, again through endogenous (control linked) or exogenous (reputation linked) dynamics.

Stability. Bellair (1997) found that more stable neighborhoods had lower rates of MVT. Similarly, a review of the literature by Miethe and McCorkle

(2001) found higher MVT rates linked with mobility and household composition (e.g., prevalence of single-parent families), as did work by Rice and Smith (2002). Impacts of instability on MVT rates, however, may be decade dependent (Walsh and Taylor, in press). Prevalence of multiple-household units, a component of instability, links to higher rates (Copes 1999). Following the systemic model of attachment, the presumed mediating dynamics may involve sense of community, local involvement, attachment, and related individual and collective prevention activities (Bursik and Grasmick 1993; Kasarda and Janowitz 1974).

Consequences of stability or instability also can self-reinforce over time (Bursik and Grasmick 1993; Shaw and McKay 1942), leading to the expectation that less stable locales will experience subsequently increasing MVT rates. Furthermore, given dynamic contextualism (Sampson 1993) and the systemic model more generally (Bursik and Grasmick 1993), one would expect MVT rates to rise as community stability declines.

Racial heterogeneity and composition. Work to date on race presents an unclear picture. Clarke and Harris (1992) found MVT rates greater in areas characterized by increased racial and ethnic diversity. Walsh and Taylor (in press) found heterogeneity was a significant predictor of MVT rates, though only in one decade. Research by Davison (1995) and Rice and Smith (2002), however, found that MVT was actually lower in heterogeneous communities but greater in primarily African American communities.

This unclear picture with respect to heterogeneity and MVT rates stands in contrast to the communities and crime literature, which links greater heterogeneity to higher offending and victimization rates (Bursik and Grasmick 1993; Sampson and Groves 1989; Warner and Pierce 1993). According to Kornhauser (1978; see also Merry 1981), heterogeneous communities have difficulty solving common problems because of conflicts between diverse ethnically or racially based subcultural values and norms.

The current model expects heterogeneity to link to subsequently increasing MVT rates. The underlying rationale is that more heterogeneous locales are more permeable to in-migrating potential offenders and that these opportunities get communicated more broadly among potential offenders over time. Increasing heterogeneity may link contemporaneously with rising MVT rates because the compositional shift further weakens local cohesiveness, surveillance, and prevention efforts.

Young males. Young males are involved and arrested in disproportionate numbers to their representation in the population. This appears to hold true for the crime of MVT as well (McCaghy et al. 1977; Saville and Murdie 1988). One study, however, found no link between MVT rates and young males (Walsh and Taylor, in press). The current study controls for presence of young males given their strong involvement in MVT (Rice and Smith 2002:317).

Framework

The current work builds on previous literature, described above, to specify expected associations between community demographic structure at the beginning of a decade and changes in MVT rates apparent by the end of the decade. The core idea is that structural attributes set in motion processes whose consequences subsequently unfold. The outcome focus is explicitly on changing community MVT rates.

In addition, the model describes (see above) how structural changes may accompany MVT rate changes during this time frame. In the course of a decade, it is likely that there are several feedback cycles of reciprocating influence between crime changes and community changes (Miller 1981), but these individual cycles cannot be captured here. With a decade between the two demographic census snapshots, all that can be said is that the structural and crime changes may covary.

The proposed model also seeks to satisfactorily resolve the problem of spatial dependence. Although communities are surrounded by and affected by adjoining communities and community crime rates often are spatially autocorrelated, (Anselin et al. 2000; Kubrin and Weitzer 2003:393), this has been generally ignored in the MVT work. Studies with inadequate controls for spatial dependency may overestimate impacts of endogenous community factors. Nearly all of the previous cross-sectional studies on MVT have either neglected to control spatially autocorrelated MVT rates or have done so inadequately. This work uses a comprehensive and clean two-stage technique (Land and Deane 1992) to ensure that the error component in the spatial lag variable is not connecting to error component in the outcome. No works to date of which these authors are aware have faithfully implemented Land and Deane's (1992) recommended procedure for constructing a spatially lagged MVT rate variable.[4]

Spatially lagged crime variables not only are important as controls for correct specification of endogenous impacts but also are of inherent theoretical interest over time as well. If initial surrounding MVT rates link to subsequent rate increases in the target community, that might be indicative of growing criminal subcultures and differential social organization (Akers

1993; Sutherland, Cressey, and Luckenbill 1992:90) and/or contagion-related processes (Crane 1991).

Data Sets and Indicators

MVT

Reported MVTs from a police department in a Midwestern city (January 1, 1990 to December 31, 2001; N = 10,439) are the outcome.[5] The period coincides with a 200 percent rate increase in the city during the decade. Incidents were geocoded with a 95 percent hit rate or better, exceeding the suggested minimum threshold of 85 percent (Ratcliffe 2004).

Decennial Census Data: 1990-2000

Community sociodemographic data are from the 1990 and 2000 census. Descriptive information appears in Table 1. Dramatic changes occurred during the decade in median owner-occupied property value (up 64 percent), median income (up 24 percent), and percentage African American population (up 18 percent).

Unit of Analysis

Areal units used in studies of MVT have varied in size from countries (Webb 1994) to cities (Krimmel and Mele 1998) to census tracts (Copes 1999) to face blocks (Rice and Smith 2002), and even small units such as parking lots and shopping centers (Hollinger and Dabney 1999; Plouffe and Sampson 2004). Census block groups (n = 90) are the unit of analysis here in part because of their alignment with many of the mediating interpersonal and control-related community dynamics (Bursik and Grasmick 1993) and to the possibility of standardizing boundaries across the two time points using a GeoLytics (2006) product and thus averting one variety of the modifiable areal unit problem (Openshaw 1984; Ratcliffe and McCullagh 1999).[6]

Dependent Variable

MVT counts were averaged over 2 years (1990-1991; 2000-2001 for beginning and end of decade). The 2-year averages were converted to rates per 1,000 households and natural logged after adding 1 to reduce skewness.[7]

Table 1
1990 and 2000 Census Demographic Variables and Change over a Decade

Predictor	1990	Percentage	2000	Percentage	Increase or Decrease	Percentage
Total population	113,504		112,936		–568	–.005
Median household income	$29,363		$36,397		$7,034	24
Median property value owner occupied	$51,114		$84,000		$32,886	64
Total number of persons living below poverty level	20,258	18.0	20,220	19.0	–38	–.20
Housing units occupied by renters	19,291	40.0	18,091	37.0	–1,200	–6.2
Single-person housing units	31,768	66.0	33,370	68.0	1,602	5.0
Population living in different house 5 years prior	59,373	52.0	54,373	48.0	–5,000	–8.4
Percentage of multiple unit housing	15,632	32.0	15,166	31.0	–466	–3.0
Percentage of owner-occupied housing units	25,625	53.0	26,996	60.0	1,371	5.4
Percentage of population unemployed 16 years old and older	3,711	4.2	3,982	4.6	271	7.0
Percentage Black alone in the population	23,469	21.0	27,601	24.0	4,132	18.0
Percentage White alone in the population	87,478	77.0	78,111	69.0	–9,367	–11.0
Percentage of males in the population	53,444	47.0	53,267	47.0	–177	–.003
Males age 14-17	3,179	6.0	3,226	6.0	47	1.5
Males age 18-24	6,828	13.0	6,353	12.0	–475	–7.0
Vehicles available	66,308		68,161		1,853	3.0

Population-Weighted Percentiles

Ecological changes in an urban mosaic over time reflect shifts in community relative position (Bursik 1986a, 1986b; Choldin, Hanson, and Bohrer 1980; Covington and Taylor 1989; Taylor and Covington 1988). This contextualizing is accomplished by converting indicators at each point to population-weighted percentiles (pwp; Choldin et al. 1980).[8]

Measuring Changes in MVT Rates and Community Structure

Disagreements on how to operationalize ecological changes abound (Taylor 2001). The approach taken here was to construct residual change scores (Bohrnstedt 1969; see Bursik 1986b; Taylor 2001; Taylor and Covington 1988).[9]

Outliers

Bivariate scatterplots show one case repeatedly exceeded recommended Leverage and Cook's *D* diagnostic thresholds.[10] The data were analyzed after removing this case.

Sociodemographic Predictors

The descriptive statistics for each structural variable used in the creation of the time 1 and time 2 indexes and their components appear in Tables 2 and 3.

SES. A status index was created by summing the *z* scores for median property value logged, median income logged, and * – 1 × the percentage of people living below the poverty line (Cronbach's $\alpha = .896$ at time 1, .888 at time 2). Given the strong correlation between SES and the MVT spatial lag variable, only the portion of SES unrelated to MVT at each point in time was retained. The analyses, therefore, provide a conservative but fully endogenous estimate of SES impacts.[11]

Instability. The instability index summed the *z* scores for percentage of housing units occupied by renters, percentage of housing units occupied by one person, percentage of multiple housing units, and percentage of people age 5 and older not residing in the same house 5 years prior (Cronbach's $\alpha = .841$ at time 1, .762 at time 2).

Table 2
1990 Descriptives of All Census Predictors Before and After Indexing Socioeconomic Status (SES) and Instability

	N	Min	Max	*M*	*SD*
Total population 1990	89	399.0	5551.0	1374.0	886.0
Median household income logged	89	9.0	11.0	10.0	.52
Median property value logged	88	9.0	12.0	11.0	.55
Percentage of the population with income below poverty level (* – 1)	89	9.0	0.0	19.0	18.0
Percentage of housing units occupied by renters	89	4.0	100.0	42.0	21.0
Percentage of 1-person housing units	89	1.0	71.0	30.0	12.0
Multiple unit housing as a percentage of total housing units	89	0.0	95.0	28.0	23.0
Percentage of population living in a different house 5 years prior	89	21.0	84.0	51.0	11.0
Percentage of males in the population age 14-17	89	0.0	8.0	3.0	2.0
Percentage of males in the population age 18-24	89	1.0	43.0	6.0	7.0
Heterogeneity	89	0.0	.25	.11	.08
African American	89	0.0	99.0	22.0	23.0
Spatial autocorrelation	89	2722.0	18352.0	10332.0	3508.0
Contiguous boundary	89	0.0	1.0	.12	.331
Straddle boundary	89	0.0	1.0	.14	.355
SES index	89	–6.64	5.97	.0746	2.70
Instability index	89	–4.50	4.4	–.0603	1.71

Table 3
2000 Descriptives of All Census Predictors before and after Indexing Socioeconomic Status (SES) and Instability

	N	Min	Max	*M*	*SD*
Total population	89	395.0	6164.0	1382.0	1002.0
Median household income logged	89	9.0	12.0	10.0	.51
Median property value logged	88	10.0	12.0	11.0	.56
Percentage of the population with income below poverty level (* – 1)	89	62.0	0.0	22.0	18.0
Percentage of housing units occupied by renters	89	2.0	99.0	37.0	18.0
Percentage of 1-person housing units	89	12.0	72.0	32.0	11.0
Multiple unit housing as a percentage of total housing units	89	0.0	100.0	25.0	24.0
Percentage of population living in a different house 5 years prior	89	26.0	85.0	49.0	13.0
Percentage of males in the population age 14-17	89	0.0	8.0	3.0	2.0
Percentage of males in the population age 18-24	89	0.0	39.0	5.0	6.0
Heterogeneity	89	0.0	.25	.12	.07
African American	89	0.0	95.0	28.0	25.0
Spatial autocorrelation	89	7472.0	53871.0	31286.0	12250.0
Contiguous boundary	89	0.0	1.0	.12	.331
Straddle boundary	89	0.0	1.0	.15	.355
SES index	89	–5.52	5.33	.005	2.7
Instability index	89	–4.87	10.25	.0013	3.07

Racial heterogeneity. Racial heterogeneity was captured using the ratio of White to Black persons in each block group's population, at each point in time (White ÷ total population) × (Black ÷ total population) (Miethe and McDowall 1993; Rice and Smith 2002).[12]

Age structure. Two predictors were used: percentage 14 to 17 and percentage 18 to 24.

MVT spatial lag. Following a two-stage least squares procedure (Land and Deane 1992; Roncek and Montgomery 1995), an instrumental variable capturing MVT potential was created (see note 3).

Spatial boundary controls. Two dummy variables control for edge effects and the modifiable areal unit problem. The first captured census block groups within the city but touching a city boundary (contiguous boundary = 1, otherwise = 0). The second represented census block groups partially outside the city limits (straddle boundary = 1, otherwise = 0).[13] For the analysis of 1990 features on later MVT changes, moderate correlations between the two boundary control variables and the other variables suggested partialling the entire matrix (predictors and outcome) for these two variables and completing this analysis using just these partialled data. Removing the boundary variables was not necessary for the analysis of changing structure and changing crime.

Correlations between 1990 community fabric and subsequent changes in MVT rates show subsequently increasing rates in locations with initially lower SES, with initially higher racial heterogeneity, and surrounded initially by higher MVT rate locales.[14]

Correlations between changing community structure and simultaneously changing MVT rates show that communities with high heterogeneity and surrounded by high-theft locales were more likely to experience subsequently increasing MVT rates. The two control variables also linked to changing MVT rates (see note 17).

Analysis Plan

The first ordinary least squares regression analysis series assesses impacts of surrounding MVT rates at the beginning of the decade and community structure on subsequent changes in MVT rates during the following decade.[15] The spatially lagged MVT rate was entered first to learn (a) how much of the later changes it accounted for and (b) what the net contributions were of initial endogenous community conditions. Finally, an alternate model that substituted racial composition, in the form of percent African American, rather than racial heterogeneity was completed.

A second series of analyses tests the relationships between contemporaneously changing community structure and MVT rates. Again, as in the previous series, spatially lagged crime was entered first. An alternate model was again completed substituting percentage African American for racial heterogeneity. For both sets of analyses, variables are in population-weighted percentile format.

Results

Initial Structure and Surround and Subsequent MVT Rate Changes

Model A in Table 4 shows that higher MVT rates in surrounding communities at the beginning of the decade strongly elevated subsequent MVT rates (b = .912, p < .001), explaining 18 percent of the variance in these later changes. Controlling for these adjoining impacts, the initial community fabric explained an additional 8.9 percent of the outcome (p < .05 by F test of R^2 change). Heterogeneity (b = .002, p < .05) and surrounding MVT rates (b = .685, p < .01) both significantly elevated later MVT rates.

Substituting the heterogeneity predictor with percentage African American (model C, Table 4) suggested that less variance was explained (22 percent vs. 29 percent). The take-away lesson is simply this: Stronger ethnic heterogeneity and higher surrounding MVT rates at the beginning of the decade caused later increases in MVT rates.

Changes in Structure, Surround, and Co-Occurring MVT Rates

Model D (Table 5) shows that those communities partially outside the city have more slowly increasing MVT rates (b = –.160, p < .01). Adding changing surrounding crime to the two boundary variables (model E) adds a significant (p < .01) additional 19 percent in explained variance (total = 26 percent). The coefficient for changing surrounding MVT rates is significant (b = .000743, p < .001). Controlling for boundary conditions, MVT rates go up faster in locations where the rates are going up faster nearby.

Table 4
Impacts of 1990 Community Structure and Surrounding Motor Vehicle Theft (MVT) Rates on Subsequently Changing MVT Rates

	Model A		Model B		Model C	
Variables Entered	*B*	*SE*	*B*	*SE*	*B*	*SE*
Socioeconomic status (SES)	—	—	–.001	(.001)	–.001	(.001)
Instability	—	—	–.103	(.072)	–.088	(.074)
Heterogeneity	—	—	.002*	(.001)	—	—
Males age 14-17	—	—	–.001	(.001)	–.001	(.001)
Males age 18-24	—	—	.001	(.001)	.001	(.001)
Spatially lagged MVT	.912***	(.072)	.685**	(.247)	.767**	(.255)
African American	—	—	—	—	–.030	(.155)
R^2	.18		.27		.22	
R^2 change (from A)	—		.089*		.04	

Note: $N = 89$. The dependent variable is unexpected change, from 1990-1991 to 2000-2001, in population weighted percentile form, based on logged motor vehicle theft rates. Predictors are population-weighted percentiles from 1990 census or, for the spatially lagged MVT rate, from 1990-1991 MVT rates. Coefficients shown are unstandardized. SES has been partialled to remove portion linked to spatially lagged MVT rates. Entire matrix of predictors and outcome was partialled for two edge effect control variables so $df = 86$ even though $N = 89$.
*$p < .05$. **$p < .01$. ***$p < .001$.

Model F adds in structural changes and increases explained variance by 14 percent ($p < .01$ by F test of the R^2 change; total $R^2 = .40$). As a community's MVT rate increases, so too does its racial heterogeneity ($b = .003$, $p < .01$). But its instability ($b = –.002$, $p < .002$) declines, confounding expectations. Spatially lagged crime changes remain influential ($b = .000392$, $p < .05$).

Substituting changing relative racial composition for changing racial heterogeneity (model G) results in a less powerful model (total $R^2 = .29$). It also reduces the impact of changing instability to nonsignificance. Changes in surrounding MVT rates continue to be significant ($p < .05$).

The analysis of co-occurring changes tells a somewhat predictable, but also somewhat unpredictable, story. Communities simultaneously getting more heterogeneous and more stable and surrounded by increasingly high-MVT-rate locations also are simultaneously experiencing rising relative MVT rates.[16] The increasing heterogeneity may prove relevant because it links to weakening endogenous surveillance or protection dynamics. The impact of nearby crime shifts suggests smaller communities can be caught up in broader crime dynamics affecting an entire segment of a jurisdiction.

Table 5
Structural Changes, and Changes in Surrounding MVT Rates, Accompanying Changing Community Motor Vehicle Theft (MVT) Rates

	Model D		Model E		Model F		Model G	
Variables Entered	*B*	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*
Socioeconomic status (SES)	—	—	—	—	.0003	(.002)	.001	(.002)
Instability	—	—	—	—	–.002**	(.001)	–.001	(.001)
Heterogeneity	—	—	—	—	.003***	(.001)	—	—
Males age 14-17	—	—	—	—	–.001	(.001)	–.001	(.001)
Males age 18-24	—	—	—	—	.0007	(.001)	.0004	(.001)
Changing surrounding MVT	—	—	.0007***	(.0002)	.0004*	(.0002)	.0006*	(.0003)
Contiguous boundary	–.033	(.058)	.043	(.055)	.050	(.053)	.038	(.058)
Straddle boundary	–.160**	(.054)	–.026	(.057)	–.055	(.054)	–.034	(.059)
R^2	.09		.26		.40		.29	
R^2 change			.17***		.14**		.027	

Note: $N = 89$. The dependent variable is unexpected change from 1990-1991 to 2000-2001, in population weighted percentile form, based on logged motor vehicle theft rates. Predictors are population-weighted percentiles representing co-occurring changes in structure over the decade. Coefficients shown are unstandardized. SES has been partialled to remove a portion linked to co-occurring changes in MVT rates.
$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

In sum, an examination across all models shows some hypotheses supported by the findings. Initial and contemporaneously changing heterogeneity, and initial and contemporaneously changing surrounding MVT rates, affect changes in target community MVT rates. Furthermore, a surprising positive contemporaneous link emerges between changing instability and changing MVT rates.

Discussion

In a medium-sized Midwestern city, community MVT rates prove moderately stable from about 1990-1991 to 2000-2001. Slightly more than half of the latter rate (R^2 = .55) is predictable from the earlier one. This moderate stability across time attests to relatively enduring geographies of crime in an urban locale, even when the targets in question are automobiles. The analyses reported here concentrate on the changes in the community MVT rates not predictable from initial rates.

Hypotheses from the past communities and crime work suggests that lower SES, lower stability, and more racial mixing all might link to increasing MVT rates. The ecological work specific to MVT rates has uncovered similar links, except for a decidedly mixed picture on heterogeneity. The work specific to MVT rates further suggested the relevance of young males.

Turning attention first to the temporally lagged models where initial conditions predict later shifts and results can be interpreted as causal, the results tell a simpler story. MVT rates increase later in locations with higher initial levels of racial mixing or surrounded by higher MVT rate locations initially. These two features, one endogenous, one exogenous, probably set in motion processes, early in the decade, that facilitated rising MVT rates later in the decade. The racial mixing impact probably speaks to subsequent weakening of social climate (Merry 1981) or surveillance or collective efficacy processes over time in initially more mixed locales.

Turning to the impacts of initial surrounding MVT rates, recall that MVT, with few exceptions, relies to some extent on social learning processes. Ecological patterns of differential social organization (Sutherland et al. 1992:90) around MVT may expand over time. Put differently, criminal subcultures involved in MVT may expand their target territories and/or recruits over time. The expansion may be driven by any number of factors including, among others, hardening of targets or declining target densities in previously high-rate areas. Figuring out what is behind this longitudinal and causal impact of surrounding MVT rates probably requires collecting a wide variety of geographical and behavioral information on crime sites, offender locations, offender networks, offender search patterns, and incident and target characteristics. The behavioral geography of individual MVT thieves, and groups of thieves, needs clarification.[17]

It is often the case that switching from a static to a changing outcome results in findings not fully confirming cross-sectional links (e.g., Bursik and Webb 1982). That seems to be the case here, underscoring how important it is to investigate changing crime and delinquency rates.

The results of the contemporaneous endogenous change analyses are strikingly similar to the lagged analyses in two ways: The changing surround links positively with changes in MVT rates, as do changes in heterogeneity. Undoubtedly nested within this decade-long frame and driving both these latter two associations are processes of reciprocal causal influence (Kubrin and Weitzer 2003), perhaps involving a host of mediating interpersonal and localized dynamics involving offenders or residents or both. MVT rates going up nearby may be having an impact on the target neighborhoods' rates because of broader ecological processes linked to aspects of target density. The potential dynamics related to increasing mixing in the target neighborhood have been well described elsewhere (Merry 1981; Wilcox, Land, and Hunt 2003).

One result, unforeseen given the communities and crime literature, is the connection between rising MVT rates and increasing stability. Though unforeseen, it is not without precedent. Covington and Taylor (1989) found rapidly increasing status and stability, such as occurs in gentrifying neighborhoods, linking strongly to increasing robbery rates and more subtly to increasing larceny rates. Several indicators in the instability index could have gone up in locations where lower income, larger households were replaced by single, higher income households moving in. This kind of population shift may have driven increases in attractive target densities. Alternatively, putting race and target properties aside, this kind of population shift may have created localized divergences in income and lifestyle, resulting in more spatially restricted surveillance patterns or less surveillance generally.

The discrepancies seen between the current results and past work could have many sources, including, among others, switching from a cross-sectional to a longitudinal outcome; the more complete control for spatial patterning used here; the conversion of predictors and outcomes to relativized (population-weighted percentile) form in keeping with an ecological framework; the specific city and decade used; the size of the city; or level of spatial aggregation used here compared to those used in other studies.

Although the model used here relies on the communities and crime or delinquency literature, the pattern of results raises a question: Do community MVT rates need their own alternative theoretical approach? Heterogeneity's impacts suggest underlying micro-level processes at work in the target neighborhoods, whereas impacts of surrounding MVT rates suggest processes and spatial patterning organized or playing out at a larger spatial level, such as a sector of the city. Work by Jacobs et al. (2003), Cherbonneau and Copes (2005), and Copes (2003a, 2003b) examining micro-level offender behavioral processes provides a promising bridge for this next phase of research. These two dynamics, in the community and around it, can be folded together into a multilevel criminal circumstance model (Wilcox et al. 2003). Within that framework, relevant resident-based processes such as routine activities (Cohen and Felson 1979) and collective efficacy (Sampson et al. 1997) and relevant offender-based processes such as behavioral geographies (Brantingham and Brantingham 1981) and social organization and learning patterns (Sutherland et al. 1992:90) can be elaborated.

Turning for a moment to more pragmatically minded considerations of target-specific crime-prevention devices such as keyless entry and kill switches, some might point out, correctly, that these were likely to be more prevalent in the residents' collective vehicle fleet at the end of the decade rather than the beginning. Furthermore, and also correctly, they might point out that these shifts in prevalence of harder-to-steal vehicles were probably spatially nonuniform. The failure to include variables along those lines, however, does not diminish these findings. It is likely that better theft-proofed vehicles showed up sooner and in larger numbers in the higher SES neighborhoods. If so, then initial status, or increasing status, should have, respectively, caused or linked to dropping rates. But it did not. Furthermore, despite increased availability of better theft-proofed vehicles, the rate of MVT citywide went up 200 percent during the decade. So either changing community-level prevalence of harder-to-steal cars were resident-status driven but had no net impact, or they were driven by other as yet unmodeled effects, and, when modeled, they will further increase explained variance beyond the levels seen here.

In considering the potential for differential MVT patterns based on different types of theft (e.g., joyriding vs. professional theft rings), it has been suggested that a comparison of recovered and nonrecovered vehicles would help contextualize community-level findings. We agree. The recovery data necessary for this comparison, unfortunately, were not available because of inconsistent follow-up and record keeping.

The findings perhaps warrant some attention from policymakers. First, given the importance of the surround for later changes, micro-level prevention or deterrence strategies such as citizen or police patrolling would not necessarily be more effective than patrols targeting a broader section of the city. The good news here is that future MVT rate shifts are somewhat predictable, and this information can be used to craft long-term risk-reduction efforts (Taylor and Covington 1990).

Like all other studies, this one has its limits. Beyond being essentially a case study, a second limitation is that the current study did not incorporate land-use indicators for residential, commercial, and mixed-use areas. Lessening this concern, however, is the fact that households were used as the rate denominator. This partially controlled for some land-use and opportunity variations, given that the majority of MVTs occur in the vicinity of the victim's residence (Kinshott 2001). Finally, official records generated the outcome variable, not victims. Perhaps mitigating this concern, however, are the tremendously high MVT reporting rates. Furthermore, an advantage of these data is that locations where the vehicles were stolen were geocoded and were not simply the owners' residential addresses.[18] Given these limits, developing any type of specific policy recommendations awaits either multiple replications or work with samples of communities from representative samples of cities. As always, external validity remains an open empirical question and is not a study limitation (Taylor 1995).

In sum, the current work examined the impacts in one typical Midwestern city of community demographic structure, and surrounding MVT rates, on later, decade-long changes in community MVT rates. Those later changes were driven in part by initial racial mixing and by adjoining levels of the crime. Furthermore, the changing MVT rates intertwined with nearby crime changes and increased racial mixing. The determinants of changing community MVT rates look somewhat similar to, but also simpler than, the determinants of changing neighborhood violence and property crime rates.

Notes

1. The changes examined are unexpected in that they were completely uncorrelated with the initial level of the variable.

2. These dimensions may serve as setting conditions for but should not be confused with local processes relevant to motor vehicle theft (MVT) rates such as routine activities and/or social disorganization and/or collective efficacy.

3. There is a strong relationship between local network features and dynamics such as collective efficacy; questions persist about how it should be modeled (Taylor 2002).

4. A generalized MVT potential variable, following the logic for population density potential models, takes into account all other locations "to calculate the population potential for a set of *n* location, each place is treated successively as the point of reference" (Land and Deane

1992:227). The crime-potential variable measures the cumulative proximity of MVT of all the areas surrounding a particular place. The formula for calculating the current crime potential variables according to Land and Deane (1992) is as follows (with minor modification):

$$\mathrm{CP}i = \Sigma\ (\mathrm{P}j/\mathrm{D}ij);\ j \neq i;\ i = 1, \ldots, n,$$

where:

CPi = the crime potential for location i (i = the target census block group, CBG)
Pj = the number of MVTs for CBGj in the environment of CBGi
Dij = the distance of CBGj from CBGi, a summation is taken over all locations j other than i.

Next, the MVT potential variables for time 1 and time 2 must be cleaned up to avoid correlation between the MVT potential variable and the error term. Using a two-stage process (Land and Deane 1992), instrumental variables that were predictors of the MVT potential variables were identified. Although one other recent MVT rate study (Rice and Smith 2002) did intend to follow the recommended Land and Deane (1992) procedure, a close reading of their methods suggest that they did not do so. For example, rather than include all street blocks in the spatially lagged variable, they included just blocks running in the same vector, up to a distance of 10 blocks.

5. Research shows a high concordance between experienced and reported MVT (Karmen 2004; Maxfield and Clarke 2004).

MVTs that occurred within the city limits but were erroneously reported to state- or county-level law enforcement were included. For accuracy, a statewide crime reporting program was used to sort incidents that had occurred within city limits for inclusion.

6. A block group is a cluster of census blocks containing between 250 and 550 housing units. The block group is an appropriate spatial aggregation given the theoretical model used here. Large units obscure local structural change impacts and provide little insight into community-based meso-level crimes and prevention strategies. Extremely small spatial units, the face block, make the calculation of MVT rates difficult (Copes 1999) and result in a large number of units with zero events making skewness a greater concern. The block group though is generally spatially homogeneous given what is known about residential settlement patterns and geodemographic segmentation. People generally select to live near others similar to themselves across a variety of structural dimensions, including age, income, education, ethnicity, family structure, and housing, resulting in relative spatial homogeneity (Nelson and Wake 2005). However, block groups do suffer from limitations. Although they are spatially homogenous, large block groups may have different opportunity structures present throughout the block group.

The "normalizing" function created identical units of analysis over time. GeoLytics documentation provides the following national-level explanation:

> 1990 to 2000 Block relations were determined from Tiger Files 2000. 85 percent of Blocks had a 1:1 relationship, 10 percent had a 2:1, and 5 percent had a greater than 2:1 relationship. Block splits between 1990 and 2000 were weighted by an analysis of the 1990 streets. The assumption is that roads indicate where people reside. 1990 streets were determined using Tiger Files 1992 which facilitated correspondence between 1990 and 2000 Blocks. A weighting value was then used to help split Block demographics for those Blocks that had been split or merged between the two decennial Censuses'. The file produced by this process is the 1990 to 2000 Block Weighting File (BWF). From this BWF the 1990 data can be associated to any 2000 geography (tract, zip code, county, etc.). (GeoLytics 2006).

7. Skewness for 1990/1991 = –.312 for the logged rate; skewness for 2000/2001 = –.425 for the logged rate.

Two alternative denominators were explored, including the number of registered vehicles and aggregate population age 16 and older. Kendall tau B correlations for all three rates, the one used two alternatives, were strong at both points in time (.83 and .91).

8. The MVT population weighting percentile score was computed following a formula, with slight modification, previously used by Covington and Taylor (1989):

$$\text{Percentile}_M = 100 \times \frac{[\text{Sum } (\text{i} = \text{i} - \text{M}) \text{ Household}_\text{i}] \text{ Motor Vehicle Theft}}{[\text{Sum } (\text{j} = \text{j} - \text{n}) \text{ Households}^\text{j}]}$$

$\text{Household}_\text{i}$ is the number of households in the *i*th lowest CBG, $\text{Household}_\text{j}$ is the total number of households in all CBG in the city, *M* = the CBG of interest, and *n* = the total number of CBGs examined. Thus, a CBG with the lowest MVT rate in the city would have a MVT percentile score of 0; the CBG with the highest rate would have a score approaching 100. Also, a CBG with a MVT score of 50 is a CBG in which the MVT rate is equal to or greater than the CBG MVT rate experienced by 50 percent of the households in the city's CBGs. Stated differently, 50 percent of the households are in CBGs where the rate of MVT is equal to or less than the rate experienced by the CBG with a MVT score of 50.

9. "To create such a measure, one regresses the level of a variable at time *t* on its level at time *t*-1" (Bursik 1986b:43). "[This] residual represents, conceptually, unexpected change over the period, i.e., redefinition of a neighborhood's role on that parameter vis a vis other neighborhoods" (Taylor and Covington 1988:564). To measure change over the decade in the MVT rate, the time 1 logged population weighted MVT rate outcome variable was regressed against the time 2 logged population weighted MVT rate outcome variable. The resulting residuals were saved. The residualized (contemporaneous unexpected change) portion of the outcome is the MVT rate outcome variable not explained by the time 1 MVT rate and correlates 0 with the time 1 MVT rate. It is also the portion of time 2 MVT rate in each CBG not predicted given, overall, how all CBG MVT rates changed from time 1 to time 2 (Taylor 1999). For the structural predictors, the time 1 population weighted percentile values for each were regressed against the time 2 predictor values. Again, the resulting residuals (reflecting unexpected change) were saved as new variables.

10. According to the 1990 normalized census data, this CBG had a population of 818 residents and only 4 in 2000. The mean number of MVTs for 1990-1991 was 11. The mean number of for 2000-2001 was 2, half as many thefts as residents.

11. Time 1 and time 2 spatial autocorrelation was used to predict time 1 and time 2 socioeconomic status (SES). The resulting residuals were saved. This portion of the SES predictor does not correlate with spatial autocorrelation and became the new SES index for time 1 and time 2.

12. Prior to creating the racial heterogeneity index a race variable, percentage of the population that is Black, was converted to component parts (lagged and contemporaneous) and entered into the analysis. Inclusion of this predictor in the lagged and unexpected change analyses was not significant and resulted in high multicollinearity with SES, as indicated by the variance inflation factor and tolerance. Given that more prior work has used heterogeneity than percentage African American, and because the former presented fewer multicollinearity problems, only heterogeneity was retained.

13. MVTs taking place in CBGs partially outside city limits were not included in the data.

14. Correlation matrixes can be obtained by contacting the first author.

15. Variance of this outcome was 45 percent of the variance of initial 1990-1991 MVT rates.

16. Indicators are expressed in relative terms. So a neighborhood can become more stable, relative to all other neighborhoods in the city, and more heterogeneous, relative to all other neighborhoods in the city, and both of these can happen at the same time.

17. Some may be surprised by the nonsignificance of initial SES and should recall that only that portion of SES independent of surrounding rates was used (i.e., the fully endogenous component of SES).

18. One reviewer suggested that small sample size may be a limitation. Power analyses indicated otherwise. With 90 cases, an initial R^2 of .25 produced by 7 predictors and alpha (two-tailed) of .05, the statistical power was .76 for an additional variable explaining an additional 6 percent of the outcome. This is very close to the suggested cutoff of .80. If the initial R^2 was .30, the power for the same sized increment goes up to .79. Therefore, it is unlikely that weak statistical power, because of the low *n*, contributed substantially to the effects found to be nonsignificant here.

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