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Can We Predict Long-term Community Crime Problems? The Estimation of Ecological Continuity to Model Risk Heterogeneity

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Abstract

Objectives: In small-scale, intra-urban communities, do fundamental demographic correlates of crime, proven important in community criminology, link to *next* year's crime levels, even after controlling for this year's crime levels? If they do, it would imply that shifting ecologies of crime apparent after a year are driven in part by dynamics emerging from structural differentials. To the best of the authors' knowledge, this question has not yet been addressed. *Methods:* For Philadelphia (PA) census block groups, 2005 to 2009 data from the American Community Survey and 2009 crime counts were used to predict spatially smoothed 2010 crime counts in three different models: crime only, demographics only, and crime plus demographics. Models are

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tested for major personal (murder, rape-aggravated assault, and robbery) and property (burglary and motor vehicle theft) crimes. *Results:* For all crime types investigated except rape and homicide, crime plus demographics resulted in the best combination of prediction/simplicity based on the Bayesian Information Criterion. Socioeconomic status (SES) and racial composition linked as expected theoretically to crime changes. *Conclusions:* Intercommunity structural differences in power relationships, as reflected in SES and racial composition, link to later crime shifts at the same time that ongoing crime continuities link current and future crime levels. The main practical implication is that crime analysts tasked with long-term, one-year-look-ahead forecasting may benefit by considering demographic structure as well as current crime.

Keywords
community criminology, structural criminology, small area, crime prediction

Crime prediction generally refers to two types of crime risk: short term and long term. Evidence for the existence of increased short-term risk, over a look-ahead period of days to weeks, has foundations in the literature on repeat victimization (Pease 1998; Polvi et al. 1991; Ratcliffe and McCullagh 1998) and near-repeat victimization (Bowers and Johnson 2004; S. D. Johnson et al. 2007; Ratcliffe and Rengert 2008; Townsley, Homel, and Chaseling 2003). Long-term crime patterns can persist for years or even decades (Bursik and Grasmick 1993; Weisburd et al. 2004; Weisburd, Groff, and Yang 2012). Both long- and short-term crime risk models have theoretical and operational value (S. D. Johnson 2010). The prediction work for long-term year-to-year crime risk heterogeneity models links conceptually to extensive work in community criminology and the geography of crime; that work has identified the cultural, structural, and physical correlates of high-crime communities at different spatial scales (Harries 1980; Pratt and Cullen 2005; Taylor 2015). The current investigation, focusing on this long-term risk heterogeneity, asks the following question: Using the only two annual data sources likely to be readily available to crime analysts interested in small-scale community crime predictions, census data and crime data, do models based on both current crime and demographic structure do better than commonly used models that are based only on crime data? Furthermore, how do models using only demographic structure fare in comparison?

More specifically, three conceptually distinct models can be contrasted. A stable crime niche model, derivable from a Hawley-esque (1950) ecological frame, assumes that communities occupy crime niches in a broader jurisdiction, that those roles are largely stable from year to year (crime only model), and that those roles have self-maintaining properties. The focus in this model is on ecological continuity, within a broader system assumed-to-be stable, with causal priority assigned to the crime levels (niches) themselves.

A structural model derivable from work on urban sociology (Logan and Molotch 1987), structuration (Molotch, Freudenburg, and Paulsen 2000), and structural criminology (Hagan 1989; Peterson and Krivo 2010) assumes that key current demographic setting conditions, especially socioeconomic status (SES) and racial composition, generally shape crime levels (demographics only model). Causal priority is now assigned to broad demographic setting conditions reflecting structural inequalities.

Finally, a dynamic ecological and structural model posits an even stronger version of the latter model. This last model assumes, net of the connections between current crime and demographic structure, that current structural conditions influence future long-term *changes* in crime for a year in the future. The focus here is on ecological crime *dis*continuities, with priority assigned to demographic factors shaping such crime shifts over time. At the same time, ecological crime continuities also are present to a degree, linking current and future crime levels.

The current work seeks to learn which of these three model types does a better job. Because the intent is to craft generally applicable models, the theoretical frame is limited to components of demographic structure generating theoretically consistent connections with future crime across *all* the crime types considered. It turns out that the demographic components meriting inclusion are also the two sturdiest demographic structural covariates of community crime rates generally (Pratt and Cullen 2005).

The remainder of the introduction outlines theoretical frames behind each of these three models, explains the choice of structural elements explored, and closes with a statement of different model expectations.

Theoretical Foundations

The Ecological Frame and Crime Niches

Two key ideas in the human ecological framework are as follows. Different communities in a broader ecosystem like a city or a metropolitan area are interdependent. Further, these communities serve different functional niches relative to one another. In effect, different communities play different roles for populations throughout the region. "Ecological organization pertains to the total fabric of dependences that exist within a population" (Hawley 1950:179). These niches can be stable from year to year or even decade to decade under some conditions. For example, with regard to delinquency "Shaw and McKay concluded that the local community areas of a city maintained an ongoing, consistent role in the dynamics of the urban system" (Bursik 1986:39). This is acceptable "if the ecological structure of an urban system is in a state of equilibrium" (Bursik 1986:41). Of course, research has shown that over a longer period, such as a decade, ecological structures, crime and delinquency, and perhaps the connections between structure and crime or delinquency can shift (Bursik 1986; Taylor and Covington 1988; Velez, Lyons, and Boursaw 2012). But for the look-ahead period of interest here, one year, if a large urban system is not afflicted with a major natural or man-made event like a Hurricane Katrina or 9/11 attacks, "local community areas" *generally* should be expected to maintain "an ongoing consistent role" to some degree.

One set of roles concerns crimes taking place within those communities. "Illicit or criminal occupations," and perhaps the patterns of their targets, can be part of those differentiated ecological functions (Hawley 1950:217). This is perhaps most readily grasped for crime functions like open air drug markets (L. Johnson, Taylor, and Ratcliffe 2013), but may apply to other major property and personal crimes as well. Therefore, next year's community crime levels may be largely shaped by this year's levels. Weisburd et al. (2012) powerfully demonstrated this for many of the streetblock trajectories they followed in Seattle. If this is largely true, then the only long-term risk factor needed to reliably estimate next year's crime risk level is this year's crime level. Ecological continuity of community crime niches will dominate, assuming stability in the broader ecosystem.

The Structural Frame

The key premise of structural criminology is that "the meaning and explanation of crime is to be found in its structural foundations" (Hagan and Palloni 1986:432). Further, "structural relations organized along vertical, hierarchical lines of power are of greatest interest to criminologists ... Structural criminology is distinguished by its attention to power relations and by the priority it assigns them in addressing criminological issues" (*op cit*). For community criminology in the United States, when considering communities at the intra-urban scale, the two dimensions of community fabric most clearly reflecting "lines of power" are SES and racial—or, depending on the region of the country, ethnic—composition. Although in many cities these two threads correlate negatively and substantially (Peterson and Krivo 2010:58), creating a racial spatial divide, the two are conceptually distinct and associated with distinct covariates and impacts (Massey 1998).

If models with just structural conditions outperform prediction models with only current crime, this would suggest two points. First, the structural setting conditions prove broadly applicable, shaping future crime more strongly than current crime. These setting conditions may better reflect current and future power differentials than does observed crime. (As an aside, what observed community crime rates reflect may be far more tangled than current scholarship has acknowledged (Taylor 2015:25-68).) Second, numerous crime niches at the community level, that is, relative crime levels, may be shifting over time and thus demonstrating ecological discontinuities. Such shifts may reflect responses to changing intercommunity power relations. The latter may be connected to temporal instability in the broader urban system.

Relatively small community units are examined here. Since smaller ecological units have greater potential for sizable change in shorter time frames (Abbott 2001), the crime functions that communities serve relative to one another may shift substantially in short time frames.

Structure and Crime Predict Continuities and Discontinuities

The third prediction possibility combines Hawley's consideration of ecological continuity with the structural idea that power differentials shape ecological discontinuities. This frame expects that next year's community crime levels represent a mix of ecological crime continuities *and* discontinuities. If this is the case, next year's levels would be best predicted by this year's crime levels *and* structurally driven crime discontinuities. If a model controls for current crime, the only portion of future crime remaining in the outcome reflects crime shifts *unrelated* to current crime levels (Bohrnstedt 1969; Bursik and Webb 1982). This portion reflects temporal discontinuities in the crime niches occupied by communities. If any noncrime predictors have a significant effect on future crime, it is these discontinuities that structural factors are forecasting. Thus, these ecological crime discontinuities are *emerging from* current structural conditions. These conditions link not only to current crime, they also have generative impacts, unfolding over time, on crime. The current crime/future crime link is building on ecological continuities of crime niches over time, and the current demographics/ future crime link is building on structurally driven, temporally lagged ecological discontinuities in those same crime niches. Current structural relations are shaping elements of next year's crime, elements not detectable given this year's crime levels. If this mix of ecological continuity and discontinuity is the perspective that applies to year-ahead crime-level predictions at the community level, then both current crime and current community structural data are needed.

Model Contrasts

Which model outperforms which other models carries important theoretical implications. If the crime functions, or *niches*, which communities hold relative to one another and are reflected in their crime levels, (a) remain largely static from one year to the next, that is, are operating within a largely stable urban system; and (b) are functionally more important than ongoing structural setting conditions, the crime-only model would offer the simplest, most accurate model for next year's crime levels. By contrast, if the crime niches are (a) largely static from one year to the next but (b) are trumped in empirical importance by current setting conditions reflecting power relations, then the demographic model will offer the simplest, most accurate model for next year's crime levels. Finally, if the crime plus demographics model offers the simplest, most accurate model for the coming year's crime, this suggests that crime niches are changing substantially from year to year and in ways not entirely predictable from their current crime levels. Additional implications follow if this last model proves preferable. Specific implications will depend on specific findings. (1) Should current demographic conditions significantly shape future crime, *after controlling* for current crime, this means that these current structural features play a role in generating forthcoming ecological crime discontinuities. The forthcoming shifts represent discontinuities because they are *unrelated* to current crime levels, since the latter are controlled. Structural consequences continue to unfold over time in ways not predictable given current crime. (2) Should current crime also significantly link to later crime after controlling for structure, it means that next year's crime levels reflect a mix of ecological crime continuities, captured with the link to current crime, as well as ecological crime discontinuities, captured with the link between current structure and future crime after controlling for current crime.

Demographic Structural Dimensions of Communities

Historically, in older cities like Philadelphia where this study takes place, the geographic position of a community in a city, and consequently its location relative to major city features—the downtown, major institutions, major employers, amenities such as large parks, and important large-scale land uses like manufacturing facilities, ports, docks, and rail hubs—shaped the type and value of residential options available (Hawley 1950). These features and histories created structural and cultural differentials across communities, differentials which over time continued to build on preexisting differentials. This is Molotch et al. (2000) idea of structuration.

The most foundational structural dimensions differentiating intra-urban communities are "socioeconomic status, family status [familism/stability], and ethnic [/racial] status [which] are necessary to describe the social differentiation that occurs in urban ecological systems" (Golledge and Stimson 1997:138).[1] The basic systemic model of crime (Bursik and Grasmick 1993:39) highlights ways the first two of these contribute to local crime and delinquency levels. One of the most comprehensive recent multicity studies in community criminology has highlighted the relevance of racial composition, specifically the extent to which a community is African American, to both violent and property crime community outcomes (Peterson and Krivo 2010:77, 85).

Most Relevant to Crime

Pratt and Cullen's (2005:378) meta-analysis and review of ecological crime correlates found that "the strongest and most stable macro-level predictors of crime" included racial composition and poverty. Among the demographic *structural* crime correlates, their meta-analysis (p. 399, table 1) found the following rank ordering based on overall effect size estimates: (1) SES (unemployment), (2) racial composition (percentage non-White), and (3) racial composition (percentage Black). Clearly, research points to SES and racial composition as the two sturdiest structural correlates of community crime levels. If this is so, it would be these two features of community structure which we would expect to link most strongly and most consistently with upcoming crime levels. We also explore the relevance of the third structural component included in the basic systemic model of crime, residential stability (see subsequently).

Focus

In the preceding sections, three models with the potential to forecast crime have been outlined. These will be examined here. One model links to an ecological frame and expects that communities operating in a largely stable urban system possess largely time-stable crime niches; thus, prior crime is

Table 1. Descriptive Statistics.

Crime	2009	Mean	*SD*	Minimum	Maximum	Sum
	Homicide	0.2	0.48	0	4	356
	Rape	0.45	0.80	0	6	804
	Robbery	4.76	5.07	0	62	8,433
	Aggravated assault	4.63	4.65	0	41	8,201
	Burglary	5.83	5.25	0	110	10,320
	MVT	3.72	3.12	0	26	6,587
	2010	Mean	*SD*	Minimum	Maximum	Sum
	Homicide	0.2	0.49	0	4	346
	Rape	0.47	0.83	0	6	834
	Robbery	4.42	4.93	0	49	7,820
	Aggravated assault	4.70	4.75	0	43	8,201
	Burglary	5.75	4.66	0	34	10,189
	MVT	5.83	5.25	0	24	6,607
City block group community structure		Mean	*SD*	Minimum	Maximum	
	SES index	−0.06	0.89	−2.91	2.60	
	Percentage WNH	35.13	36.03	0	100	
	Population	864.55	583.95	4	4,548	

Note: N = 1,771 block groups. Census block group data for Philadelphia. The analysis excluded census block groups with no reported population. Structural variables based on the 2005 to 2009 American Community Survey estimates. MVT = motor vehicle theft; *SD* = standard deviation. SES = socioeconomic status; WNH = White non-Hispanic.

the only needed predictor of future crime. A second model grounded in structural criminology expects that if an urban system is not completely stable, and crime niches are shifting over time, future crime will prove largely structurally driven. This view anticipates instability in the ecosystem due to ongoing conflicts (Logan 1978; Logan and Molotch 1987). In this model, community demographic features reflecting power differentials—SES and race—are the only needed predictors of future crime. A third model combines ecological and structural perspectives and expects a mix of ecological continuities and discontinuities in crime. The component of future crime levels reflecting ecological continuities over time will link to current crime levels, and the component reflecting ecological discontinuities over time will link to current structural conditions. What follows is an analysis of these three models to learn which ones provide the best combination of fit and parsimony.

Data, Methodology, and Analytical Approach

Data Overview

This study uses 2009 crime frequencies, demographic data reflecting these locations during the period 2005 to 2009, or both, as predictors of 2010 crime counts. The study location is Philadelphia, PA. Philadelphia is the fifth largest city in the country with a population of about 1.5 million people. In 2012, about 15 percent of Americans were living below the poverty line, but in Philadelphia 25 percent of residents were living below the poverty line (American Community Survey [ACS] 2012). From 2009 to 2010, there were modest increases in the number of reported rapes, aggravated assaults, and motor vehicle thefts (MVTs) while burglary, robbery, and homicide incidents all decreased slightly (see Table 1).

Unit of Analysis. As S. D. Johnson et al. (2009) explain, it is important that the unit of analysis in a study matches the social processes under investigation. The spatial unit in this study is the census block group. Numerous studies on crime, drugs, and reactions to crime using census block groups can be found in the literature (Gorman et al. 2001; Harries 1995; Jennings et al. 2012; McCord and Ratcliffe 2007). It seems a reasonable approximation of a community although, of course, community exists at smaller and larger scales than this (Suttles 1972). In a developed city, a census block group usually includes four contiguous census blocks, with each census block having four sides. In all, 1,771 census block groups in the city of Philadelphia were included in the analysis.[2]

Structural Data

This study uses demographic variables collected through the ACS. The ACS is administered every year by the U.S. Census Bureau. ACS data are published every year for counties with populations of 65,000 people or more, every three years for populations of 20,000 people or more and every five years at the census block group level. The data that are used in this article are from the 2005 to 2009 five-year data release. These data were downloaded with the Alchemist tool (Azavea 2012). Our operationalization of these variables is described in the following section.[3]

SES index. The SES index included four variables: percentage households reporting income less than US$20,000 in 2009 (reversed); percentage households reporting income greater than US$50,000 in the same year; median house value (natural logged after adding 1, in 2009 dollars); and median household income (natural logged after adding 1, in 2009 dollars). Each variable was z-scored and then averaged to create the SES index; higher scores indicate higher SES (Cronbach's $\alpha = .90$). Descriptive statistics appear in Table 1.

Race. In the current study, a variable measuring the percentage of residents in a neighborhood who identified themselves as White non-Hispanic indicated racial composition. This variable ranged from 0 to 100 percent, with a mean value of 35 percent (median = 20 percent; see Table 1).

Population. The population variable summed the number of males and the number of females. This variable was natural log transformed and entered as a predictor. This is a recommended approach for a generalized count model (King 1988:857; Maddala 1983:51, 53) and does *not* assume marginal impacts.

Geographically Smoothed Outcome Counts

Predictions were generated using negative binomial regression models with a spatially smoothed outcome variable.[4] Generating a spatially smoothed outcome variable also helped to correct for potential geocoding imprecision in the data set.[5] The spatial smoothing reduced the number of census block groups that experienced no crime over the outcome period (calendar year 2010).[6] Using a lagged outcome variable also helped to reduce potential modifiable areal unit problems (Openshaw 1984), a useful trait given that one goal of this analysis is to generate a model that accurately and simply predicts crime counts in a general area.

Model Sequence

Three different negative binomial models were generated for each crime type. Throughout, each model was used for all six crime types. Model 1 represented the crime-only model which used prior crime counts to generate predicted counts for the following year. Model 2 included the two consistently linked, theoretically most central, and empirically most important demographic predictors, the SES index and racial composition, and the population variable (natural logged). Model 3 contained both demographic variables, population, and 2009 crime counts.

Identifying the Best Model

When assessing forecast quality, no one statistic can determine which model performs the best. Whether the model is used to predict the weather, flu outbreaks, future sales or crime, multiple measures are needed to assess various aspects of the model performance (Ebert 2003). In the current study, models were assessed relative to one another based primarily on a measure that considers both model fit to the data and model simplicity. This is the Bayesian Information Criterion (BIC). Standard forecast indicators of accuracy and bias are reported as well.

Goodness of Fit and Parsimony. The BIC "has become quite popular for model selection in sociology" especially for generalized models (Raftery 1995:112). BIC values take into account both model fit to the data and model parsimony.

When comparing across models, the strength of the evidence is determined by the difference of the BIC values: The model with a lower BIC value is preferred. If the absolute difference between the two BIC values is greater than 10, this is interpreted as "very strong" evidence that one model is preferred over another. Differences of 6 to 10 provide "strong" evidence to prefer one model over another, and differences of 2 to 6 provide "positive" evidence that one model is preferred. Differences less than 2 are interpreted as "weak" evidence for preferring one model (Raftery 1995:138-41).

Model Accuracy. Model accuracy was measured with two statistics commonly applied in forecasting models (Pepper 2008). Mean absolute error (MAE) measures the magnitude of the error values without considering whether errors in prediction arise from over- or underprediction. The absolute value of the error term was calculated for each census block group. These values were then averaged together across the data set. The root mean square error (RMSE) is more sensitive to substantial prediction errors (Pepper 2008). Residual values (observed − predicted) for each census block group were squared. The squared residuals were averaged over the data set and then the square root of that average was calculated to produce the RMSE.

Given that each crime outcome was modeled three times, for individual predictors a Bonferroni-adjusted α level of $p < .01$ was adopted.

Results

Three prediction models were generated for each crime type resulting in a total of 18 regression models. The output generated by these models can be seen in Table 2.

Preferred Models

For four outcomes—robbery, aggravated assault, burglary, and motor vehicle theft—model 3 with demographic structure and earlier crime provided by far the strongest combination of accuracy and parsimony. In all four of these cases, the BIC value was at least 10 lower than the next closest model, providing "very strong" evidence that this was the preferred model for these outcomes.

Results proved different for homicide and rape. For rape, model 3 (crime plus demographics) did not do appreciably better than model 2 (demographics). For homicide, model 2 (demographics) was preferred, generating a BIC value six units smaller than the next best model, model 3 (crime plus demographics). This represents "positive" evidence that model 2 was preferred.

These conflicting results about preferred model type, model 2 (demographics) or 3 (crime plus demographics) for rape and model 2 (demographics) for homicide versus model 3 (crime plus demographics) for the other four crimes, may have arisen in part from the relatively infrequent nature of homicide and rape. In 2009 and 2010, there were less than 400 homicides and less than 850 rapes reported citywide in each calendar year. For other crime types, at least 6,000 incidents were reported yearly. Those lower yearly totals for homicide and rape, when disaggregated to the census block group level, may have affected the strength of the connection between 2009 and 2010 crime counts at this level.

Model Accuracy Differences

Turning to the accuracy measures, model 3 (crime plus demographics) generated the lowest MAE for all crimes save homicide. For the latter, model 3 and model 2 (demographics) proved equally accurate.

We gain a closer idea of what this means for model performance if we compare MAE to observed values, and fitted counts to observed counts, for a crime like robbery. An MAE for model 3 (crime plus demographics) of 2.777 compares to a mean observed count of 4.42 suggesting on average predicted counts were off by about 63 percent. Although this is a sizable

Table 2. Model Comparisons by Crime Type.

	Homicide			Rape			Robbery		
	Crime	Demog.	Both	Crime	Demog.	Both	Crime	Demog.	Both
2009 crime	0.278**		0.113	0.189**		0.121**	0.042**		0.034**
Population		0.186	0.162		0.096	.047		0.141*	0.052
SES index		−0.346**	−0.341**		−0.234**	−0.217**		−0.176**	−0.136**
Percentage WNH		−0.009**	−0.009**		−0.006**	−0.006**		−0.004**	−0.003**
BIC	−11,628	−11,687	−11,681	−10,522	−10,581	−10,583	−5,289	−5,289	−5,481
MAE	0.323	0.310	0.310	0.615	0.600	0.592	2.782	3.178	2.777
RMSE	0.491	0.481	0.480	0.808	0.804	0.794	3.909	4.759	4.001
	Aggravated assault			**Burglary**			**MVT**		
	Crime	Demog.	Both	Crime	Demog.	Both	Crime	Demog.	Both
2009 Crime	0.055**		0.032**	0.020**		0.017**	0.058**		0.055**
Population		0.196**	0.042		0.232**	0.165**		0.198**	0.045
SES index		−0.237**	−0.176**		−0.095**	−0.078**		−0.143**	−0.116**
Percentage WNH		−0.006**	−0.005**		0.000147	0.0000659		0.000659	0.0009501
BIC	−5,137	−5,417	−5,556	−5,206	−5,134	−5,239	−6,429	−6,238	−6,451
MAE	2.822	3.034	2.770	3.239	3.315	3.163	2.076	2.288	2.060
RMSE	3.765	4.259	3.810	4.395	4.506	4.286	2.762	3.058	2.742

Note: N = 1,771 block groups. Negative binomial regressions. Outcomes are spatially smoothed 2010 crimes (six nearest neighbors). BIC = Bayesian Information Criterion. Demog. = demographics model; MAE = mean absolute error; MVT = motor vehicle theft; RMSE = root mean square error; SES = socioeconomic status; WNH = White non-Hispanic.
$^*p < .01$. $^{**}p < .001$.

number, it should be borne in mind that these were crime counts for *very small areas*, and thus the average yearly count per area was also quite small.

If we turn to the absolute difference in robbery relative frequencies, results were more encouraging. The mean absolute relative frequency differences in (observed − predicted relative frequencies) was .0168 for counts of 0; for counts of 1, it was .0163; for counts of 2, it was .0183; and for counts of 3 or more, it was .0148. Inspection of these same absolute difference patterns across counts for other outcomes suggested similarly sized differences in observed minus predicted relative frequencies.

Individual Predictors

Looking just at model 3 (crime plus demographics), SES was significant ($p < .01$) in the expected direction for all six crimes. This aligns with Pratt and Cullen's (2005) conclusions about the primacy of SES for community crime.

Racial composition was significant in the expected direction ($p < .01$) for all four personal crimes, but not the two property crimes. This discrepancy for race aligns to some extent with Peterson and Krivo's (2010) finding of more complicated links between racial composition and property crime than between race and violent crime. Earlier crime linked significantly ($p < .01$) to later crime for all crimes save homicide.

The relative impacts of crime, racial composition, and SES can be brought into closer focus by examining the impacts associated with standard deviation shifts in each of these predictors while holding other predictors constant.[7] We use robbery as an example. Communities one standard deviation higher ($SD = .89$) on SES had an expected robbery count that was lower by a factor of .89, that is, an expected robbery count 11 percent lower. Locales one standard deviation ($SD = .36$) higher on percentage of White non-Hispanic had expected robbery counts that were also lower by a factor of .89, that is, 11 percent lower. So, for this crime, racial composition and socioeconomics proved comparably influential. Earlier crime, however, proved somewhat more potent. Places one standard deviation ($SD = 5.07$) higher on robbery in 2009 had an expected robbery count a year later that was 19 percent higher.

Discussion

This study compared the relative abilities of three theoretically grounded, risk heterogeneity models to predict one-year, look-ahead future crime counts at the community level. Two practical considerations intentionally limited the scope of inquiry. Models relied only on data routinely and freely available to crime analysts in local police departments. Second, since general models applicable across a *range* of crime outcomes were of interest, only predictors that consistently worked as theoretically expected across those crimes were included.[8]

The three different model types examined here made different theoretical assumptions about community crime levels in the broader urban system. The crime only model can be derived from an ecological perspective. Crime levels reflect ecological niches (Hawley 1950), functional roles served by communities relative to other communities in the ecological system. If the broader urban system is in a relatively stable state from one year to the next, communities will not shift crime roles relative to one another, ecological crime continuity will predominate, and this year's crime should do the best job of predicting next year's crime. The demographics-only model can be derived from structural criminology and the focus on power relations (Hagan and Palloni 1986; Logan 1978; Logan and Molotch 1987). Communities are constantly in conflict with one another, and thus are continually sorting and re-sorting. Power differentials arise in part from different structural conditions at the community level, most notably SES and racial composition. These differentials shape future crime levels, especially if the broader urban system is in flux and community crime niches are shifting. Finally, a demographics-plus-crime model suggests that future crime levels in part reflect ongoing ecological crime continuities, leading to current crime significantly shaping future crime, and in part reflect ecological crime discontinuities over time, crime shifts unrelated to current crime but related to current ecological power differentials.

For all crimes save homicide and rape, current work supported the mixing of ecological crime continuities and discontinuities. Crime plus demographics (model 3) generated the best combination of parsimony and accuracy as reflected in markedly lower BIC scores. To some extent, future community crime levels represent a continuation of current crime levels; current crime connected significantly to future crime in all versions of model 3 save the model for homicide. Crime levels from one year to the next reflect significant ecological continuity. But there are discontinuities as well. *After controlling for current crime*, current demographic structure linked significantly to next year's crime levels in all six crime-plus-demographic models. Because current crime was already factored in, demographics were linking to emerging crime changes that were *unpredictable and unrelated to* current crime levels. It is in this sense that these demographic–crime shift links reflect ecological crime discontinuities. In strong support of the structural perspective broadly, and the basic systemic model of crime (Bursik and Grasmick 1993) and work on the racial spatial divide in particular (Peterson and Krivo 2010), these emerging discontinuities link to community SES and racial composition.

The relatively poor performance of the models that only used demographic data (model 2) would indicate that future crime counts cannot be predicted with structurally driven factors alone. While these models were generally accurate in generating 2010 crime predictions, they consistently underperformed relative to crime-only (model 1) and crime-plus-demographics models (model 3).

Particularly small counts seem to shift the picture. The demographics-only models did best for homicide and rape. This may simply reflect the weakness of the current crime indicators for these two variables, given their low counts. Results based on small numbers are analogous to results based on small samples. The latter are more variable from sample to sample than is commonly believed (Tversky and Kahneman 1971). Analogously, small numbers like yearly murder or rape counts in small areas like communities are also highly variable from year to year, even after spatial smoothing, compromising the predictive impact of current crime.

But for the four most frequently occurring serious crimes, the main take-away lesson at the community level tells a two-part story about place distinctiveness in terms of crime levels (Molotch et al. 2000:792), while at the same time raising questions. One part of the story is what Hawley (1950) and Bursik (1986) would see as ongoing ecological continuity, or what Molotch et al. (2000:792) would see as "tradition." Current crime shapes future crime. But a key question is "how the continuity works" (Molotch et al. 2000:793). In community criminology broadly, work has concentrated more on understanding community determinants of crime levels than on understanding impacts of community crime levels. More insight is needed into the dynamics, whether those are within the community or nearby, that maintain either high or low crime levels from year to year. The second part of the story is ecological discontinuity in a Hawley/Bursik frame. Molotch et al. (2000:792) would call these impacts of place "character" while structural criminologists would see these as reflections of ongoing power differentials and related conflicts (Hagan and Palloni 1986). As we think about how structural setting conditions shape cultural dynamics, including social and political processes, the basic systemic model of community crime rates (Bursik and Grasmick 1993) presents one set of possibilities about how all this might work. Other models offer different suggestions. There are numerous challenges to figuring all this out.

Another future challenge, and one where there may be less theoretical guidance, is determining whether sub-city, regional discrepancies are at work, shaping the dynamics described here differently in different places. For example, Graif and Sampson (2009) found language diversity and foreign-born composition had differently signed significant impacts on homicide in different parts of Chicago. There are tools for considering such dynamics (Anselin 1988; Fotheringham, Brunsdon, and Charlton 2002). But whether geographically weighted regression or a spatial Chow test (or equivalent) is used, the key questions are (1) how much can accuracy be improved? (2) where is our theoretical guidance on how these extra-community influences operate (Taylor 2015:117-19)?; and, from the policy-oriented perspective of crime analysts, (3) are the model accuracies gained significant enough and durable enough to justify the additional modeling complexities?

The most significant limitation of the current work is the inability of these models to remove spatial autocorrelation from the outcomes. Because the outcome already was spatially smoothed, a further spatially smoothed crime predictor was too diffuse theoretically. Further, such a predictor sometimes created "beta bounce" problems (Gordon 1968) in the rest of the model. We cannot simultaneously test the net impact of current structure and crime while also introducing a doubly spatially lagged crime outcome as a predictor.

One thing that might seem to be a significant limitation but, we would argue, is not, is the sparseness of the predictor space. This does not mean that we have created a mis-specified model. Tests with additional predictors such as residential stability did not alter the significance pattern of the predictors reported here or the patterns of (observed − predicted) relative frequencies for different counts.

Study limits are perhaps partially counterbalanced by study strengths which include a focus on the theoretically most relevant and empirically most supported community crime demographic correlates, tests of model robustness by repeating models using different amounts of spatial smoothing for the outcome,[9] a focus on predictors that worked as expected across six serious crimes, and constraining the predictor space to items readily available *at no cost* to crime analysts.

Practical/Policy Concerns

Fortunately in the United States, demographic data are freely available to all law enforcement agencies through the U.S. Census Bureau and they are accessible with the development of the Alchemist extraction tool. The use of structural predictor variables will enhance analysts' abilities to inform police executives about which areas in their jurisdiction are most likely to foster criminal activity in the medium to long-term future. Indirectly, the research also suggests some practical value to the yearly estimates from the ACS.

Conclusion

For urban, small-scale communities, crime *and* structural predictors together generate the best crime prediction model for four out of six serious crimes. This performance suggests ecological crime continuities are operative over time while, at the same time, ecological crime discontinuities, linked to current structural conditions, also unfold over time. SES and racial composition prove sturdy crime predictors over all six crimes, as would be expected by structural criminologists. Serious work remains ahead identifying the processes maintaining these ecological crime continuities, and the processes that generate the unfolding ecological discontinuities. Crime analysts would benefit from the use of demographic predictor variables for strategic estimates of future crime concentration. The generation of improved maps depicting future long-term crime potential within jurisdictions will assist with the strategic planning operations of police departments and other agencies concerned with community harm. If such tools are developed and routinely used to guide law enforcement strategic planning, agencies should be alert to how tools with demographic variables might impair police-community dynamics even while they boost the accuracy of crime predictions. The current article predicts crime incident locations not offender rates.

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Notes

1. Of course, different researchers have highlighted different facets of these three main constructs or of closely related ideas. For example (Sampson and Lauritsen

1994), household structure or racial heterogeneity (Bellair et al. 2010) has proven important in different models. Nevertheless, to the best of current authors' knowledge, no study has demonstrated the *consistent* theoretical relevance of additional community factors, net of the three examined here, to all six of the crime types examined here, at a comparable spatial scale.

2. This excluded 45 census block groups in the city because these areas had no residential population, and therefore no demographic data were associated with them. There were no crimes geocoded to these areas in 2010, and therefore no crime data were eliminated from the analysis by this exclusion.
3. Details on the construction of the demographic indices can be found in an online appendix located at http://www.rbtaylor.net/crime_continuity_online_appendix.pdf. It provides names of specific ACS variables used and how each variable was modified to construct each index.
4. The spatially lagged outcome variable was generated using OpenGeoda (v. 1.0.1). Crime counts for each census block group were averaged with the six nearest neighbors to that block group. Alternate versions of the outcome, using seven, eight, or nine neighbors also were created and analyzed. These alternate analyses showed similar results. Further, models were also run after rounding the outcome variable to a whole number. The pattern of significant differences across models was unchanged.
5. The data used in this study may have slight inaccuracies for street segments that cross census block group boundaries because the specific location on one side of the street segment is approximated.
6. After spatial smoothing, the number and percentage of census block groups with crime counts of zero in the outcome year were as follows: burglary 0 (0 percent), motor vehicle theft 0 (0 percent), aggravated assault 1 (.06 percent), robbery 4 (0.23 percent), rape 271 (15.3 percent), and homicide 729 (41.2 percent). Comparisons with theoretical expectations showed these distributions matched a *non*zero inflated count model.
7. These can be generated by hand, or automatically using the sppost command listcoef (Long and Freeze 2006:360).
8. It did not appear that these limitations on structural variables resulted in more poorly mis-specified models. Comparisons of observed relative frequencies to predicted relative frequencies showed *no improvement* when additional predictors (e.g., residential stability) were included in models.
9. Models with spatially smoothed outcomes based on seven to nine nearest neighbors provided closely comparable results.

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