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Communities, Crime, and Reactions to Crime Multilevel Models: Accomplishments and Meta-Challenges

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Introduction

This essay offers a few reflections on cross-sectional criminological research about people in places where community-level causes are considered, and victimization or reactions to crime are the outcome. It is by design not only selective but also Janus-faced. On the one hand it notes accomplishments in this research area facilitated by increasing use of multilevel models. On the other hand it notes meta-theoretical challenges currently preventing work in this arena from advancing theoretically. Some of these concerns have been voiced by scholars in other disciplines (Entwisle 2007; Roux 2001, 2002, 2004).

The discussion is pitched at a meta-theoretical level. That is, the focus is not on evaluating the specific merits of one theory versus another. Rather, comments center on concerns that cut across any number of theories. Using a Boudon-Coleman metamodel, relations between individuals and societal structure are highlighted (Boudon 1986: 29–31; Coleman 1990: 1–23). Because a significant impact of a community predictor in a multilevel model with an individual-level outcome is targeting ecological variation in the outcome, community-level variation in outcomes enters the discussion.

Definitions and an Orienting Metamodel

Of interest here are theories about the impacts of both community and individual features on individual-level outcomes like victimization, reactions to crime like fear or avoidance, or related perceptions of features of local context such as perceived risk. Relevant community features could be almost anything, depending on the theory: demographic structural dimensions, land use features, reported crime rates, removal or return rates, or features of local social, cultural or political climate. Communities are areas where people live which are smaller than cities and larger than individual address parcels or land uses (Hunter

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1979). Spatial communities exist at multiple levels, such as streetblocks within neighborhoods. (Taylor 1997). Crime refers to reported crime rates and self-reported victimization. Reactions to crime include concerns for personal safety such as fear of crime and worries for personal property, and more cognitively-weighted reactions such as perceptions of risk or assessments of crime severities in the locale (Dubow et al. 1979).

A modified Boudon-Coleman "boat" diagram can be used as a metamodel for organizing our understanding of the types of links in theories about crime impacts or reactions to crime. See Fig. 1 (Boudon 1986: 29–31; Bunge 2006; Coleman 1990: 10). Although community attributes and changes are conditioned by broader societal and geographic factors such as de-industrialization (Kasarda 1992; Lane 1997) and suburban expansion (Marshall 1979) for example, the primary conceptual focus is on community-level features and individual-level features and dynamics. The Boudon-Coleman metamodel suggests two links are operative when individual-level outcomes are of interest: context effects of community features (macro-level inputs) on individual attributes (micro-level inputs) (Ma-I → Mi-I), and impacts of individual-level attributes on individual-level outcomes (micro-level outputs) (Mi-I → Mi-O). Of course, if spatially aggregated outcomes are of interest then the final link between individual-level outcomes and community-level outcomes (macro-level outcomes) (Mi-O → Ma-O) becomes relevant as well. This perspective assumes methodological individualism—the behaviors of individuals are key building blocks for social change—but is not tautological when considering aggregated outcomes (Boudon 1986: 53).

In such a theoretical frame the macro-to-micro and micro-to-macro links hold considerable theoretical interest (Liska 1990). The first tells us about how context shapes individual-level dynamics. The second tells us how agency operates. Methodological individualism is avoided when interpreting the second link since local social processes such as norm formation also shape such dynamics (Boudon 1986: 53; Coleman 1990: 22, 30, 265, 273,599). Even if attention is limited to aggregated individual actions without

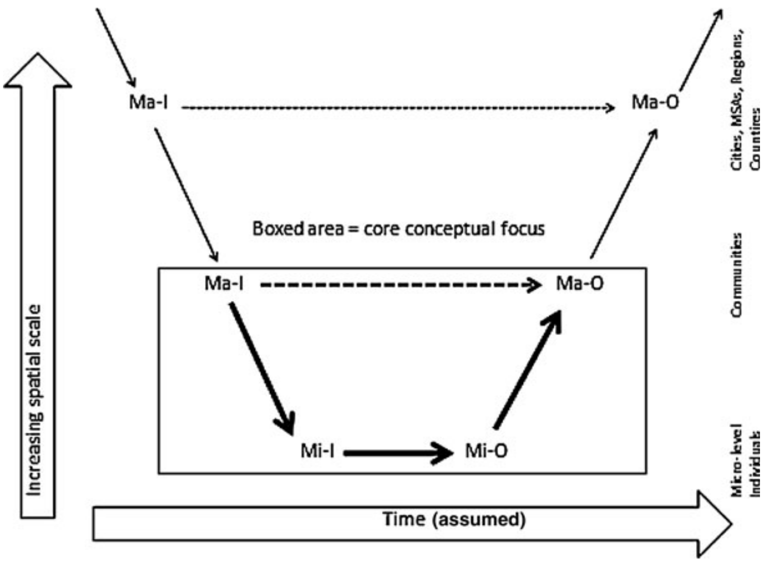

Fig. 1 Meta-model orientation to crime, people, and places

the concept of interdependencies, non-intuitive collective outcomes can arise (Boudon 1986: 57).

The most central idea in this metatheoretical approach, given the current focus, is as follows: although ecological relationships between macro-level inputs and macro-level outputs can be modeled, understanding such macro-level dynamics (Ma-I → Ma-O) hinges on gaining insight into the constituent links in the chain: Ma-I → Mi-I → Mi-O → Ma-O. The ecological connection depends on the underlying macro → micro → micro → macro processes.

How Have Multilevel Models (MLMs) Helped?

MLMs (Gelman and Hill 2007; Raudenbush and Bryk 2002; Snijders and Bosker 1999) have contributed to our modeling of impacts of community crime, or community determinants of reactions to crime, perceived disorder or victimization, in numerous ways. For a typical cross-sectional data design where data are collected about communities from individual surveys and other sources, and data about individuals within those communities are available from surveys, on-site assessments, archival records, or other sources, MLMs provide several advantages.

The more routine benefits of MLMing include: Empirical Bayesian adjustments to community-level means on the outcome; separation of outcome variation into between- versus within-community portions; when slopes of individual-level predictors are allowed to vary across communities, several features of the data structures in the different communities condition the estimated slopes for each; and finally, reporting whether the remaining between-community outcome variation on the outcome is more than sampling error.

Somewhat more conceptually significant are two additional advantages. What started as an individual-level predictor can be separated into two parts: (1) the pooled within-community portion via group mean centering, and (2) community means. This permits simultaneously investigating a predictor as a frog pond effect (Shinn 1989; Shinn and Toohey 2003) and as a community attribute, and thus the estimation of multilevel impacts. In a model predicting fear of crime, for example, the researcher might separate perception of risk into the community average and the discrepancy between the respondent and his/her average neighbor (Wyant 2008). It is of course incumbent on the researcher to develop appropriate theoretical statements about causes and causal processes to justify such separate estimations.

Two additional advantages with cross-sectional people-in-community MLMs are notable. Both assist in theory development and testing. First is the ability to examine cross-level interactions. These have a specific structure within these analyses. If an individual-level predictor is allowed to have varying impacts across communities, the researcher can hypothesize and test what community attributes significantly affect these slopes. An individual-level dynamic—the b weight associated with the individual-level predictor in a particular community—is conditioned on a community attribute. The work of Rountree and colleagues (1996a, b, 1994) on both reactions to crime and victimization, and of Tseloni (2000, 2006; Tseloni et al. 2001) on victimization has examined a number of such cross-level links. Tseloni (2000) has suggested the patterns observed have significant policy as well as theoretical implications.

Second is the ability to examine patterns of covariation, across community contexts, of the parameters (slopes and intercepts) estimated for each community context. Here is an example. Tseloni (2006) analyzed property victimization counts using the 2000 British Crime Survey and grouped respondents by small areas, for which she had 1991 census data. Previous research on repeat victimization had suggested either event dependence or unobserved heterogeneity as "two possible explanations of repeat victimization" (206). She hoped to learn more about the latter by examining some random effects, specifically, "between areas covariance of the random part of the model" (207). Her work aimed "to improve our understanding of the processes which lead to repeat property victimization, by estimating and interpreting any random effects of known individual and/or contextual crime covariates beyond household, area, and their interactions' fixed effects" (207). Here is an example: the impact on property victimization of being a household participating in a neighborhood watch program interacted with the impact of single parent household status. In general: being a single parent household significantly increased the expected count of burglaries and thefts combined, and belonging to neighborhood watch on average significantly decreased the same expected count. But strengths of these two impacts proved mutually dependent. A significant and positive covariance between these two varying slopes indicated that in areas where the risk increasing impact of being a single parent household was higher than the average risk created by this factor, the protective impact associated with participating in neighborhood watch was stronger than the average protective impact. This contingent relationship may have reflected within-area target displacement on the part of potential burglars. Generally, "random covariances between household characteristics' shed some light on conflicting or collaborating effects, which operate in certain areas of England and Wales rather than nationally" (229). This kind of finding requires an MLM approach.

One other advantage which is perhaps more methodologically than conceptually notable is the ability to model error structures within MLMs. For example, in a people-in-places model the first level can be a measurement model, and the parameters estimated at that first level become latent true scores of indicators after correction for measurement error (Sampson et al. 1997). More generally, a case can be made for several significant parallels between MLMs and structural equation models (Mehta and Neale 2005; Raykov and Mels 2007).

Of course, significant conceptual developments in MLMs continue and these include multiple membership models or cross-classified models (e.g., separating school from neighborhood effects) (Browne et al. 2001), Full Bayesian estimation via Monte Carlo Markov Chain models for rare outcomes (Gelman et al. 2003, 2007), and separation of upper-level and lower-level mediation effects (Bauer et al. 2006; Kenny et al. 2003), among others.

Multilevel Modeling to Date in a Metatheoretical Context

Figure 2 places the accomplishments of MLMs for people-in-place criminological research on victimization or reaction to crime outcomes within a modified Boudon-Coleman metatheoretical diagram. Compared to the original diagram, some portions have been addressed, some portions are missing, there have been some additions, and one portion has been mis-interpreted.

With regard to portions addressed, MLMs permit specifying the contribution of individual-level predictors to individual-level outcomes (Mi-I → Mi-O) while controlling for areal context. A properly configured analysis of covariance with attention to clustered error

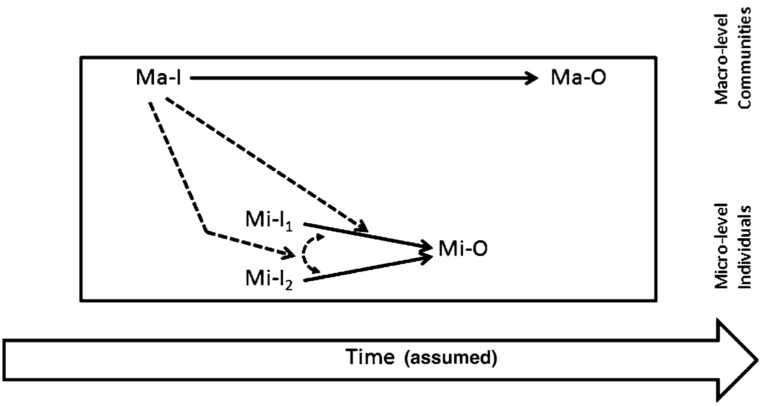

Fig. 2 Links examined by multilevel models

terms could accomplish almost the same result, but MLMs add Empirical Bayes estimation.

Further, MLMS specify contributions of community-level attributes to the community-level portion of an outcome (Ma-I → Ma-O), while controlling for compositional differences across communities in individual-level predictors (Mi-$I_{1,2}$). Again, a properly configured ANCOVA with appropriate treatment of errors could successfully accomplish most of this. This ecological dynamic (Ma-I → Ma-O), however, also can be viewed as a misinterpretation of the depicted meta-model.

It is a misinterpretation because a fundamental assumption of the Boudon-Coleman meta-model is that ecological or macro-level relationships do not exist in a freestanding way, but rather reflect underlying (macro → micro → macro) dynamics which have taken place over time. Rooted in the works of Weber, Simmel, Pareto and Merton is a "fundamental principle in action sociologies … that social change has to be analyzed as a result of a set of individual actions" (Boudon 1986: 29). This contrasts with a Durkheimian "argument of scale, maintain[ing] that it would not be possible to take explicit account of individual actions except in the case of small scale processes" (Boudon 1986: 31) These ecological relationships are implied whenever an areal predictor significantly shapes an individual level outcome, because that predictor is addressing only the ecological variation in that outcome. According to the Boudon-Coleman metamodel, these ecological relationships do not exist in a free-standing way (Wikstrom 2007).

With regard to portions added, various MLM studies have contributed to capturing macro-to-micro links in two ways not anticipated by the Boudon-Coleman diagram. The right-most dashed line shows impacts (slopes) of individual-level predictors being shaped by specific macro-level predictors. Individual-level dynamics (Mi-I → Mi-O) are moderated by macro-level factors (Ma-I). Such findings of cross-level moderating impacts are intriguing and tantalizing (Rountree and Land 1996b; Rountree et al. 1994).

In addition, the curved, double-arrowed dashed line shows that there is a community-level relationship between slopes of two individual-level predictors (Mi-I_1, Mi-I_2), and the left-most dashed line with the elbow suggests that community context, not specific community features, shapes that relationship between slopes (Tseloni 2006). A MLM appears to be required for demonstrating both of these types of cross-level relationships. But there are two conceptual concerns.

First, on what theoretical basis does one anticipate that a community attribute might condition an individual-level dynamic in the ways shown here? Both the cross-level dynamics examined through MLMs seem reasonable: (a) a community variable altering an individual-level slope, or (b) community context shaping the relationship between multiple individual-level slopes. But with (a), which predictors are *theoretically* relevant based on existing theory? Simply allowing all predictors relevant to the intercepts to also moderate the individual-level slopes seems sensible at one level, but at another level suggests theoretical under-specification. And with (b), should the *theoretical* focus be on *any* significantly covarying pairs of slopes for individual level predictors? A cross-level theory can, potentially, offer *specific* suggestions about how both of these dynamics (a and b) might work. For a dated but clear example on the context-dependency of age impacts on fear, see Maxfield (1984). Until theories are at the point of being able to point out which cross-level effects should work which way, and suggest why, a prudent stance might be to consider most of these cross-level patterns as inputs to grounded theorizing (Glaser and Strauss 1967).

Further supporting such a stance is another feature of work in this arena. Although multilevel predictors of intercepts in models for outcomes like burglary victimization risk have been replicated (Rountree and Land 2000), there has been far less attention to replicating cross-level interactions. Such replications are of course difficult. But in line with the grounded theorizing idea, it might make sense for researchers in an area to focus on what they think are the most theoretically significant cross-level patterns, whether those are of type (a) or (b) above, and seek to replicate those.

Turning to the portions of the diagram which are missing, Fig. 2 contrasted with Fig. 1 suggests three gaps which could be interpreted as broader limitations of MLMs for people-in-place research. First, work has not yet clarified how community conditions shape individual-level *determinants* of victimization risk or reactions to crime (Ma-I → Mi-I). For criminological research about people in communities, we do not yet understand the causes, and causal dynamics, whereby places get into people's heads and shape their attitudes, cognitions, sentiments, and behaviors that in turn lead to outcomes like victimization or fear. Testing these meditational models (Ma-I → Mi-I → Mi-O) is extremely demanding for a number of reasons (Cook et al. 1997).

In addition, also on the input side of the diagram, there is the related challenge of interpreting neighborhood effects (Sampson et al. 2002) and being sure that these are separate from selection effects (Fu et al. 2004; Tienda 1991). Sampson and Sharkey (2008) have recently clarified the sociological contribution of selection dynamics to maintaining and deepening structural inequalities (Ma-O), but that leaves in place the original selection vs. neighborhood effects question.

Third, agency (Sampson 1993) remains elusive. As noted above, impacts of ecological factors on individual-level outcomes are really examining macro-level relationships (Ma-I → Ma-O), and according to the Boudon-Coleman metamodel these relationships do not "really" exist. As shown in Fig. 2, this link is detached. How do individual-level outcomes shape community-level outcomes (Mi-O → Ma-O)? Understanding how localized differences in action, sentiments, or cognitions shape areal-level outcomes either through local interdependencies (Coleman 1990) or unanticipated consequences of aggregation (Boudon 1986) has not been advanced by MLM work to date. MLMs may not be the best approach for these questions.

Entwisle (2007: 687) stated concisely what was needed in her discussion about understanding people and place differences in health:

> A more dynamic conceptualization is needed that fully incorporates human agency, integrates multiple dimensions of local social and spatial context, develops the necessary longitudinal data, and implements appropriate tools. Diverse approaches with complementary strengths will help surmount the many analytic challenges to studying the dynamics of neighborhoods … including agent-based microsimulation models.

Sampson's (1993) earlier comments about advancing our understanding of impacts of context on individuals sounded similar concerns.

Moving Ahead: Some Pointers

As researchers move ahead in their quest to understand the full sequence of dynamics represented in the Boudon-Coleman diagram (Fig. 1), some metatheoretical pointers may be helpful. These address spatial or temporal scaling, issues too frequently overlooked in this area of research.

Spatial Scaling Concerns

As suggested above, MLM studies have not yet told us much about the Ma-I → Mi-I link in the Boudon-Coleman metamodel, or about the Mi-O → Ma-O link. Learning more about these links will require careful attention to spatial scaling.

Several researchers have sought to make the case that the level of community is irrelevant to communities and crime research (Land et al. 1990; McCall and Nieuwbeerta 2007; Parker and McCall 1999); that it does not matter if census tracts, cities, MSAs or streetblocks are investigated as the relevant contextual units. This endorsement of the homology-across-spatial-scales assumption, however, is not warranted. Rather, the discontinuity thesis is (Hannan 1991: 3). For a range of analytic and theoretical reasons, *different types of processes* are likely to be involved at different spatial scales. Thus, for example, understanding the Ma-I → Mi-I link will depend on the spatial scale of the macro-level inputs. Of course, the more aggregate the contextual unit, the harder it becomes to portray the dynamics involved in these contextual impacts. Stated differently, more insight can probably be gained by examining impacts of smaller-scale contexts like streetblocks (Taylor 1997).

An important corollary follows. Expecting discontinuity means "expect[ing] to find large and important differences in analogous models estimated at different levels of aggregation," differences that to those assuming homology would be "quite disturbing." (Hannan, 1991: 3) Say a researcher is looking at the impact of a neighborhood predictor I, and a group-mean centered individual-level predictor I, on an individual level outcome O. In essence two relationships are being investigated simultaneously: Ma-I → Ma-O and Mi-I → Mi-O. What is to be made of the differences observed in the two relationships?

Answering such a question is not a trivial exercise if discontinuity is assumed. One does *not* just wave one hands and talk about aggregation bias or disaggregation effects. If one assumes continuity, yes, one admits aggregation bias and then goes looking into the statistical components of one's model for its source (Hannan 1991). *But if discontinuity rather than continuity is assumed, understanding the different relationships across levels is a key activity in one's theory development.* Potentially theoretical, meta-theoretical, or analytic reasons, or a mix, are relevant to the discrepant relationships at different levels, and all might deserve attention.

In short, if one assumes discontinuity: one is also likely to assume those discrepant relationships at different spatial scales occur for theoretical, meta-theoretical or analytic reasons; further, one needs to explain why those differences arise. Consequently, it is incumbent upon the researcher to learn about the causes of the discrepancies seen in relationships at different spatial scales. For many theories about community and victimization or reactions to crime, considerable theoretical specification is needed. In short, one needs to have a metatheory about

> how the criterion for aggregation (here, proximity) fits into this theory. Without such a theory, one will have no way of deciding whether the micro-theory is better specified than the macro-, or vice versa, or whether [the mean of] X belongs in the correctly specified micro-equation for Y. (Blalock 1982: 258).

How do we get to such a theory about spatial scale, key variables, and key outside variables? This is something also that is not answered with statistical modeling, but rather with theorizing and empirical examination of localized data patterns.

Spatial scaling is about more than just clustering and aggregation bias. It also is about avoiding fallacies of the wrong level. In recent years, this idea has been associated with Johan Galtung.

> In general the fallacy of the wrong level consists not in making inferences from one level of analysis to another, but in making direct translation of properties or relations from one level to another, i.e., making too simple inferences. The fallacy can be committed working downwards, by projecting from groups or categories to individuals, or upwards, to higher units. (Galtung 1967: 45)

Variations on this fallacy include the group fallacy (Allport 1924), the ecological and individualistic fallacies (Subramanian et al. 2009) and the contextual fallacy (Hauser 1970, 1974). Again, this is an area deserving careful conceptual consideration.

Recently, some scholars have promoted replacing individuals as the fundamental units in communities and crime research with small scale places (Weisburd et al. 2009). This tendency is perfectly acceptable for crime control purposes, but depending on the specific place unit used, may not be if the goal is to understand community-crime or community-reaction to crime dynamics. Some proposed units—places, situations, or opportunities—should be resisted as fundamental units because the proposed spatial basic units are not free-standing socio-spatial, ecologically valid units in the everyday environment (Taylor 2009). Further, some units may spatially export important consequences, meaning that no overall conceptual simplification is achieved.

Temporal Scaling Concerns

In the simplest terms, temporal units, like spatial units, are modifiable. (Yule and Kendall 1950: 312) There is a temporal modifiable temporal unit problem (MTUP) that is as troublesome as the modifiable area unit problem (MAUP) (Openshaw and Taylor 1979).

Therefore, "temporal spuriousness" might cause relationships between "non-corresponding micro- and macro-variables" (Hannan 1991: 86). Studies of the same spatial units using different sized temporal windows either for static or changing attributes can generate discrepant results. Further, if the assumption about homogeneity is wrong, then the logical mis-steps that one can make when thinking across spatial scales also can be made when thinking across temporal scales. Very generally, the fallacy of the wrong level applies to time as well as space. In communities and crime research it seems this issue has drawn serious attention only in two areas: ecological deterrence (Cousineau 1973) and routine activities (Eck 1995).

Studying impacts of changing community attributes on changing individual characteristics or actions is critical to understanding how contextual dynamics operate. Given Lieberson's (1985: 180–182) critique of causal dynamics, only longitudinal analyses, hopefully capturing changes in both predictors and outcomes, will come close to providing insight into causal dynamics. Further, his points about asymmetric cause are particularly appropriate given that communities and crime theorizing concerns itself with places which have a local history, and where past and current conditions constrain current and future dynamics (Lieberson 1985: 175).

Studying change is complicated because different dynamics in a model might have different time horizons. When a theorist, policy maker or program evaluator asks "How long," she wants to know how long it will take for a change in a theoretically relevant predictor, policy, or intervention, to have a demonstrable impact. Underlying any answer provided are one or more assumptions about the time horizon. "The time horizon of a variable or phenomenon is that period which must elapse before we can measure a meaningful change in it (a change distinguishable from noise) … time horizons of aggregates are usually longer than those of their micro constituents." (Abbott 2001: 286) There is a significant gap in many communities and crime theories. They provide little guidance on the time horizons for dynamics described within the model. They often assume a unity of time horizons for different processes in the model, and this may not be correct.

A response to these issues can only be framed if one fully understands the local context. How much time things take, and whether certain neighborhood conditions, once they appear, are reversible, depend on what is happening nationally, regionally, and locally. Putting the point more broadly, the intersection of temporal scaling with contingency and spatial dependency dictates elaborating current popular theories about community-crime connections so that they take into account theories of city, neighborhood, and service changes. Few of our current theories are sufficiently contextualized; rather, most are startlingly detached from the disciplines of urban studies and political economy. This isolation is problematic.

The connections called for here are not new. The work of Bursik and colleagues has emphasized linkages between historical context and community processes with crime and delinquency processes (Bursik 1984, 1986; Bursik and Webb 1982; Bursik and Grasmick 1993: 263) Given that so much current work ignores such context dependency, however, the call must be repeated and emphasized.

Closing Comment

This article considered multilevel modeling of community + individual impacts on victimization and reactions to crime through a Boudon-Coleman metamodel. MLMs have added two new dynamics to the framework: impacts of community variables on the slopes of individual predictors, and areally-dependent covariation of individual slopes. In these two areas, however, the models appear to be running ahead of relevant theories, and further theoretical specifications are needed. Studies using MLMs also disagree with a key assumption of this metamodel—macro-level relationships cannot exist independent of micro-level dynamics—and have yet to address key agency and context issues. Closer *theoretical* attention to temporal and spatial scaling concerns was urged.

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