CRIMINOLOGY

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# TOWARD AN ANALYTICAL CRIMINOLOGY: THE MICRO–MACRO PROBLEM, CAUSAL MECHANISMS, AND PUBLIC POLICY*

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*In this address, I revisit the micro–macro problem in criminology, arguing for an "analytical criminology" that takes an integrated approach to the micro–macro problem. I begin by contrasting an integrated methodological-individualist approach with traditional holist and individualist approaches. An integrated approach considers the concept of emergence and tackles the difficult problem of specifying causal mechanisms by which interactions among individuals produce social organizational outcomes. After presenting a few examples of micro–macro transitions relevant to criminology, I discuss research programs in sociology and economics that focus on these issues. I then discuss the implications of social interaction effects for making causal inferences about crime and for making crime policy recommendations.*

The micro–macro problem—sometimes called the "levels of explanation problem"—has a long history in criminology. With reference to the problem, quoting Longfellow, Short (1998: 3), observed that scholarship sometimes takes on the appearance of "ships that pass in the night." The problem is that scholars often address questions at the macro-level, seeking to explain crime rates of a macro-entity, such as groups or spatial aggregates, and ignore the micro-level. Conversely, scholars working at the micro-level seek to explain the genesis of individual criminal acts but often at the expense of considering the role of social organization and social context. By contrast, if we address the relationship between micro- and macro-processes, we encounter several important and challenging puzzles and questions: How are the purposive acts of individuals constrained by extant social structure and organization? How do individual social interactions produce and reproduce social structures and organizations—that is, what are the specific generating mechanisms? What implications—if any—do answers to these

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questions have for our ability to make valid causal inferences and to generate policy recommendations?

In this address, I wish to revisit the micro–macro problem and to discuss the prospects for what can be termed, "analytical criminology," which is focused on the relationship between micro- and macro-levels of explanation. I begin by describing three traditional approaches in the social sciences: methodological holism, methodological individualism, and an integration of micro–macro levels. I then describe Coleman's (1990) analytical approach to the latter position, as well as his attempt to address the difficult question of specifying how individual interactions produce socially organized (macro) outcomes. To illustrate the micro–macro transition, I describe a few examples from criminology, sociology, and economics on specific mechanisms by which individuals produce macro-outcomes. Thereafter, I describe research programs in sociology and economics that provide theoretical and methodological advances that can inform analytical criminology. Sociological models identify the specific causal mechanisms by which individuals generate macro-outcomes. Economic models of endogenous social interactions provide utility models of individual decisions and econometric models of social interactions. Finally, I discuss the implications of complex micro–macro relations (social interaction effect) for research and policy. First, social interactions complicate causal inference by producing what statisticians call "interference," in which treatment assignment of one individual affects the outcome of another. Second, social interactions can produce what economists call "social multiplier effects," which can alter the effects of policy interventions.

## THE MICRO–MACRO PROBLEM

### METHODOLOGICAL HOLISM

Methodological holists assume that causality operates at the macro-level of groups and societies. This position is often attributed to pure structuralists, such as Durkheim (1964 [1893]), Blau (1977), and Black (1993). Some extreme holists argue that causality lies exclusively at the macro-level as structures produce aggregate outcomes, and therefore, they believe that individuals can be safely ignored (e.g., Blau, 1977; Black, 1993). Others argue that the whole is greater than the sum of its parts because of emergence, the notion that "collective phenomena are collaboratively created by individuals yet are not reducible to individual action" (Sawyer, 2001: 552). According to this argument, the study of individuals misses the emergent properties of the group, and therefore, the group as a whole should be studied to reveal macro-level causality. This is exemplified by Durkheim's (1982 [1895]: 59) treatment of a "social fact" as "having an existence of its own, independent of its individual manifestations," and "capable of exerting over the individual an external constraint."

In criminology, researchers in the holist tradition have tested Blau's theory of heterogeneity and violence (e.g., Blau and Blau, 1982), Durkheim's theory of anomie and crime (Messner and Rosenfeld, 2007), and Shaw and McKay's (1969 [1942]) theory of social disorganization and delinquency (Bursik and Webb, 1982; Sampson and Groves, 1989). Assuming that causality lies in macro-level processes, these researchers examined the effects of structural variables on rates of crime using metropolitan areas, cities, and neighborhoods as the unit of analysis. Data on individuals, if used at all by researchers, are typically aggregated to the corresponding macro-level.

## METHODOLOGICAL INDIVIDUALISM

The primary alternative to holism, methodological individualism, has a long history in the social sciences, which includes philosophers such as Karl Popper, classical microeconomists such as Adam Smith and Friedrich Hayek, and sociologists such as Max Weber and George Homans (see Udehn, 2001). In the extreme case, methodological individualists argue that causality operates solely at the individual level and, therefore groups, collectivities, and societies are simple aggregations of individual-level causal mechanisms. Here, methodological individualism rules out macro-level causality, contextual effects, and emergence—the possibility that the group contains properties that are not reducible to its constituent individuals. This position has important implications for empirical research, which can be focused entirely on the collection and analysis of data on individuals as the units of analysis. Long ago, advocates of methodological individualism cautioned scholars from using aggregate data to draw inferences about individual-level theories, a problem termed "the ecological fallacy" by Robinson (1950) and "aggregation bias" by Theil (1954).

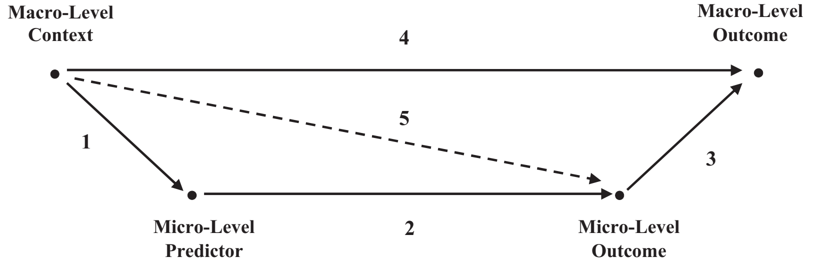
In developing his theory of crime, Sutherland (1947) took the position of methodological individualism. He specified his theory of differential association at the individual level: Crime is the result of a learned excess of definitions favorable to crime versus definitions unfavorable to crime. He then specified differential social organization to explain aggregate rates of crime: The crime rate of a group or society is the result of the extent to which the group or society is organized in favor of crime versus organized against crime. Sutherland (1973 [1942]) argued that, because crime rates are aggregations of individual acts of crime, the individual and group levels must be consistent. Thus, he specified that differential social organization identified those aspects of groups that differentially exposed individual members of the group to an excess of definitions favorable and unfavorable to crime (Matsueda, 1988). In other words, Sutherland adopted a version of methodological individualism that ruled out emergent properties. Other criminological theories that adopt methodological individualism include social learning theories (Akers, 1998), social control theories (Hirschi, 1969; Sampson and Laub, 1993), self-control theories (Gottfredson and Hirschi, 1990), and rational choice theories (e.g., Clarke and Cornish, 1985).

Individual-level theories of crime can be tested by using individual-level survey data. The development of self-report measures of crime (Nye and Short, 1957) has stimulated a wealth of individual-level quantitative research into the causes of crime using survey data, but it is not without its critics (Cullen, 2011). Since Hirschi's (1969) landmark self-report study, criminologists have refined the self-report method (e.g., Hindelang, Hirschi, and Weis, 1981) and have capitalized on statistical innovation (e.g., Nagin, 2005) to produce a steady stream of research on the causes of individual crimes. Researchers using these methods have examined the causal role of group membership, social structure, or social organization by including individual-level measures of group membership. Recently, criminologists have turned to nested designs, in which individuals are nested within groups or neighborhoods to disentangle contextual effects from individual effects.

## INTEGRATING MICRO- AND MACRO-LEVELS

A third position on the micro–macro problem attempts to specify a macro-level process as well as a micro-level process, and then it attempts to link the two levels theoretically.

**Figure 1. Links Between Micro-and Macro-Level Mechanisms**




*SOURCE*: Adapted from Coleman (1990).

James Coleman (1983, 1990) argued persuasively for a complex solution to the micro–macro problem that integrated levels of explanation and allowed for emergence from individuals to collectivities. His position is illustrated with his diagram in figure 1, colloquially termed, "the Coleman boat."[1] This diagram has been used in criminology recently to illustrate several points. Wikström (2012) used it to conceptualize the role of social interaction, person-emergence, and area crime rates in linking a situational model of crime to social contexts. Sampson (2012) used it to conceptualize the problem of individual selection into neighborhoods as a social process producing neighborhood outcomes. I used it to conceptualize how an individual-level model of investment in neighborhood social capital produces neighborhood collective efficacy through positive externalities and informal norms and sanctions (Matsueda, 2013).

Here, I use the Coleman boat to conceptualize the problem of integrating micro- and macro-levels of explanation. Figure 1 explicitly specifies twin explanatory mechanisms: The top horizontal arrow depicts a macro-process (link 4) in which a macro-level variable produces a macro-level outcome. This is a system-level explanation, the focus of methodological holism.[2] The bottom horizontal arrow depicts a micro-level process (link 2), in which a micro-level variable produces an individual-level outcome, characteristic of methodological individualism. This link captures individual-level theories of crime, such as social learning, social control, general strain, and rational choice. The downward-sloping arrow (link 1) links a macro-level variable with a micro-level endogenous predictor, such as a predisposition, goal, or attribute. Links 1 and 2 are commonly studied empirically in criminology and other social sciences by using survey data on individuals nested within a broader group or context and by examining the effects of the group characteristic on the attribute of the individual.

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1. This diagram, and the example of Weber's analysis of the spirit of capitalism and the protestant work ethic, was originally introduced by McClelland (1961).
2. In his useful discussion of the micro–macro problem using the Coleman boat, Opp (2011) took a reductionist position of methodological individualism and argued that the macro–macro mechanism (link 4) is not a causal link but only a correlation. I take an agnostic view of this effect, treating its causal status as an empirical question. Thus, in some substantive contexts, it is conceivable that when controlling for the appropriate individual-level causal mechanism, there remains a residual effect of macro-predictor on macro-outcome.

The novel contribution of Coleman's conceptualization is link 3, the upward-slanting arrow that links a micro-level outcome to a macro-level outcome. This arrow depicts how individual action produces a group or an organizational outcome: What are the rules by which individuals combine to produce a group outcome? These rules can be elementary. Perhaps the simplest rule would be an aggregation process: The sum of individual actions produces a group rate. For example, *independent* acts of crimes committed by members of a group or neighborhood, when summed, produce the aggregate crime count for the group or neighborhood. By contrast, when individual purposive actions are *dependent*, the rules for aggregation can become much more complex. Here, Wikström (2012) specified a situational model of the emergence of crime that involved a micro–macro transition, and Sampson (2012) specified a selection model of residential choice in which neighborhoods were reproduced.

I have drawn a dotted line from macro-context to individual outcomes to depict the empirical possibility that context has a direct effect. That is, it is possible that, even when individual-level causal mechanisms are controlled, social context may still have an effect on individual outcomes. For example, routine activities and criminal opportunity theories posit that net of individual criminal motivations, the objective opportunity for offending will affect individual crime as a result of the distribution of suitable targets and capable guardians facing the individual (Cohen and Felson, 1979).

Coleman (1990) presented a useful illustration of the micro–macro problem by analyzing Weber's (2002 [1920]) theory of religious values and the emergence of capitalism. On the surface, Weber's analysis seems straightforward: During the Reformation, certain ascetic values found in Calvinism, and other Protestant denominations, facilitated the development of capitalism as an economic system. This is a system-level proposition: Societal values produce capitalism. Noting that Weber invoked evidence on individual cases to illustrate the causal mechanisms, Coleman suggested that Weber included individual purposive actors in the theory, making the explanation consistent with figure 1. Thus, Protestant religious doctrine produces capitalism by inculcating individuals with ascetic values, which in turn, facilitates individual economic behavior that somehow creates the system of capitalism. This latter relation, a micro–macro transition, raises additional difficult questions. How do individual values produce an economic system? Are the Protestant values equally shared by entrepreneurs and laborers? How do such values create structures of positions, including class distinctions? How do persons come to occupy such positions? How is the incentive system sustained, and how are markets created? Coleman (1990: 9) maintained that Weber failed to answer these questions.[3]

Coleman (1990) not only conceptualized the micro–macro problem in terms of figure 1 but also developed his version of social capital theory that specifies an individual-level mechanism and identifies some micro–macro transitions. At the individual level, Coleman specified a "wide" rational choice model, in which purposive action is only approximated by utility maximization subject to constraints, as decisions are often based on rules of

3. The importance of this example is not the veracity of Coleman's (1990) critique of Weber but the way in which it illustrates the problem of specifying micro–macro transitions. For an argument that Weber provided a satisfactory answer to this question, not in *The Protestant Ethic and the Spirit of Capitalism*, but spread across the entire corpus of his substantive writings, see Cherkaoui (2005).

thumb and satisficing rather than optimality, information is often imperfect, and rationality is typically bounded (e.g., Hechter and Kanazawa, 1997). The rational choice model describes individual investments in social capital (as well as in financial, physical, and human capital). Moreover, Coleman used social capital theory as way of identifying specific rules that combine individual purposive acts into macro-level outcomes. A defining feature of social capital is that it inheres in the structure of social relations and facilitates purposive action. Thus, social capital is a resource in which individuals can invest to realize a return. Moreover, the creation of social capital tends to produce multiplier effects, resulting in the creation of more social capital. For example, the most elementary form of social capital consists of obligations and expectations that develop from exchange relationships as individuals do favors for one another. On the one hand, doing favors requires a certain amount of trust in the social system—one is more likely to do a favor when that favor will be reciprocated. On the other hand, trust in the system is increased when favors are returned, facilitating more exchange. By contrast, trust is undermined when favors are not reciprocated, diminishing future exchange. This situation likely characterizes disorganized and disadvantaged neighborhoods with high residential turnover, little commitment to community, and high rates of crime.

Furthermore, for Coleman (1990), social capital has a public goods aspect: When a member of a group invests in social capital for instrumental reasons—for example, doing a favor today knowing that the favor will be reciprocated at a time of one's choosing in the future—he or she contributes to the stock of social capital for the group as a whole. For example, when residents of a neighborhood exchange favors, they produce social capital in the neighborhood, which in turn, becomes a resource for the neighborhood by creating the possibility of individual actions to address problems such as crime (Matsueda, 2013). This is the collective process of informal social control or collective efficacy (Sampson, 2012). A group or community rich in social ties produced by exchange relationships has the potential to create more complex forms of social capital, including norms and effective sanctions, as well as authority relations. For example, informal norms may obligate adults to watch for strangers, and community leaders may be empowered to bring resources into the neighborhood. Coleman (1990) provided several mathematical equilibrium models based on expected utility theory and game theory, in which he showed how social interactions produce macro-level outcomes, beginning with bilateral exchange, multilateral exchange, and corporate actions. The growing body of empirical research on social capital and crime (e.g., Morenoff, Sampson, and Raudenbush, 2001; Rosenfeld, Baumer, and Messner, 2001) would be enriched from exploring these micro–macro relations.

## MICRO–MACRO TRANSITIONS: ILLUSTRATIVE EXAMPLES

As emphasized by Coleman (1990), a difficult but important question involves specifying how individual purposive actions together create group-level outcomes. Theory and research on this topic have resulted in several exciting lines of research that have relevance for criminology. I will here provide a few illustrative examples and relate them to the study of crime. The most obvious example is social interaction that produces criminal behavior. For example, Mesquita and Cohen (1995) began with a utility maximization model of criminal decision-making, including the returns to crime, costs of punishment, opportunity costs of conventional employment, and provision of welfare. They then introduced the concept of "fairness in society," in which unjust societies contain unfair social institutions, which, for example, will not guarantee that more qualified persons will get jobs. Then using game theory to model society and individual, they used simulations to show the importance of social justice and how it interacts with other rational choice parameters of the model.[4]

In the volume, *When Crime Appears: The Role of Emergence*, several criminologists theorized about the emergence of crime from social interactions (McGloin, Sullivan, and Kennedy, 2012). For example, Griffiths, Grosholz, and Watson (2012) conceived of predatory crime as a game and they used game theory to explain the emergence of predatory acts of violence. Brantingham and Short (2012) developed a routine activities theory of the emergence of crime, and Brantingham et al. (2012) showed how simulation models can help clarify theories of the routine activities and the emergence of crime.

An understudied area in criminology is the dynamics of collective acts of crime. Why do some individuals engage in collective behaviors, such as riots, gang fights (Short and Strodtbeck, 1965), and genocidal acts (Hagan and Rymond-Richmond, 2009)? By drawing on Schelling's (1978) seminal work on threshold models, Granovetter (1978) developed a theory of collective action that is relevant for collective acts of crime. Suppose that a group of $N$ potential rioters on the street each has a personal threshold for joining the action. The distribution of thresholds follows a uniform distribution, beginning with 0 and increasing by increments of 1 ($0, 1, 2, \ldots, N - 1$). A zero threshold means the individual is a rabble rouser and will riot even if he or she is the only rioter. A one-unit threshold means the individual will riot if at least one other person has rioted, and so on, until reaching $N - 1$. High thresholds reflect something like a belief of safety in numbers. Following Schelling's logic, Granovetter pointed out that, given the uniform distribution of thresholds, all individuals will riot. If, however, we make a minute change in the distribution and eliminate the person with a threshold of 1, the result will be that only one person will riot. In the first example, if $N$ is 2,000, the headline in the paper reads, "thousands of rioters wreak havoc on city street," whereas in the second, the headline reads, "lone individual makes a scene on the street." This model can be applied to collective acts of crime by developing an individual-level threshold theory of crime propensity and then using agent-based simulation models to examine the macro-level outcomes of different distributions of thresholds.

McGloin and Rowan (2015) applied Granovetter's (1978) threshold model to collective acts of student vandalism, using a vignette study to estimate individual thresholds, and then predict variation in the thresholds. McGloin and Thomas (2016) used a vignette study of student vandalism and found that group size interacted with perceptions of sanction risk, informal social costs, and informal social rewards. Matsueda, Robbins, and Pfaff (2016) used a vignette study of student protest to test Olson's (1965) theory of group size and selective incentives for collective action, and found support for both group size and selective incentives.

Important research in criminology has been aimed at explaining the spatial distribution of crime across urban neighborhoods and, in particular, why disadvantaged inner-city neighborhoods have such high rates of criminal violence. Theories of social

4. For other examples of game theory and crime, see McCarthy (2002).

disorganization, collective efficacy, and routine activities have explained much of the spatial variation in neighborhood crime. Behind these studies lies an important question: How does the sorting process, which creates neighborhood compositions of residents, operate? For example, Sampson and Sharkey (2008) examined individual residential mobility patterns in Chicago to address how disadvantaged neighborhoods are reproduced. They found that disadvantaged residents are likely to move to disadvantaged neighborhoods and that affluent residents are likely to move to advantaged neighborhoods, resulting in the reproduction of neighborhood inequality. From this work, Sampson (2012) concluded that selection bias in models of neighborhoods is not as big a problem as once feared and that the process is best characterized by neighborhoods selecting residents rather than by residents selecting neighborhoods.

An important model of the dynamics of individual choices that produce aggregate neighborhood compositions of residents is Schelling's (1971) classic tipping-point model of residential segregation. He showed that residential in-migration and out-migration could produce extreme residential segregation even though all residents in a community preferred to live in a racially mixed neighborhood. We can see this in a simple example of a neighborhood composed of 52 percent Whites and 48 percent Blacks. In a hypothetical larger population of Whites and Blacks, each prefers to live in a mixed-race neighborhood, but each also prefers not to be the minority, with a varying tolerance level. Suppose that Whites move in, replacing some Blacks who had a low tolerance for being the minority, shifting the race split to 64–36. The split is acceptable to the White residents but unacceptable to Black residents with a very low tolerance level of 35 percent minority. They move out, are replaced by Whites, altering the split further, which is unacceptable to Black residents with a tolerance of 30 percent. This continues until the entire neighborhood is White. Thus, despite all residents preferring to live in a mixed-race neighborhood, all end up in completely segregated neighborhoods—which no one wanted. Schelling (1971) then varied the initial preferences of the population, as well as other parameters; simulated various distributions; and identified equilibria, distinct macro-outcome patterns of segregation, and tipping points, which occur "when a recognizable new minority enters a new neighborhood in sufficient numbers to cause the earlier residents to begin evacuating" (Schelling, 1971: 181). Research within Schelling's framework in which survey research on residential preferences and agent-based simulations are combined provides a basis for understanding extreme residential segregation by race and income (e.g., Bruch and Mare, 2006).

These are just a few examples of micro–macro transitions relevant to criminology. A couple of other notable examples are worth naming. First, studies of the effect of work and crime would benefit from considering matching models of labor markets, in which employment is conceived of as a match between firms (including vacancy chains and employer preferences) and job applicants (including human and social capital and job preferences; see Sørenson and Kalleberg, 1981; White, 1970). Second, studies on the effect of marriage and cohabitation on crime would benefit from considering marriage markets and models of assortative mating, in which homogamy by education, religion, income, and crime vary over generations. Third, rational choice and criminal opportunity models may benefit from considering models of information cascades, in which otherwise rational individuals may abandon their privately held information and preferences when they observe the behavior of others (Bikhchandani, Hirschleifer, and Welch, 1992).

## RESEARCH PROGRAMS IN SOCIOLOGY AND ECONOMICS

Two research programs have developed independently in sociology and economics that provide promising frameworks for examining an integrated micro–macro perspective. In sociology, Peter Hedström (2005), among others, formalized Coleman's (1983, 1990) framework into an "analytical sociology." In economics, Brock and Durlauf (2001) have developed a set of economic models of "social interaction effects" (see also Manski, 1993). I briefly describe each in turn.

### ANALYTICAL SOCIOLOGY: HEDSTRÖM

Building on the work of Coleman (1990), Schelling (1978), and Elster (1978, 1999), Hedström (2005) laid out a programmatic framework for what he terms "analytical sociology." Hedström began with the conceptual framework of the Coleman boat, emphasizing the importance of deductive theory in identifying social mechanisms by which individuals act and interact to produce and reproduce social interactions. He maintained that, rather than relying solely on statistical analyses of phenomena to identify empirical associations, we should be identifying the generating mechanisms that brought about such statistical associations (Elster, 1989). For example, analytical sociology would explain change in organizations by "referring to a constellation of actors and their actions that typically bring about such changes in organizational structures, and then would use statistical and other types of empirical analyses to test the assumptions of the theory" (Hedström, 2005: 32). This echoes Sutherland (1973 [1942]), who expressed dissatisfaction with multiple factor explanations of crime and argued for constructing a theory that identified the social psychological processes that accounted for those statistical associations.[5]

For Hedström (2005), the search for generating mechanisms implies a move away from statistical models of causality, as well as from causal models and potential outcomes models of causality. He drew on Goldthorpe's (2000) critique of "robust dependence" (i.e., structural equation models) and "consequential manipulation" (i.e., potential outcomes models), in which Goldthorphe argued that causal models and the typical data sets used are unsuited to model social mechanisms. Hedström argued that, instead, the focus should be on developing theoretical generating mechanisms and then using simulations to test whether the generative model approximates social regularities observed in the real world. I argue in this article that a potential outcomes framework for examining causality and causal mechanisms is compatible with an analytical criminology and is separate from the process of developing generative theories of causal mechanisms.

At the micro-level, Hedström (2005) followed Elster (1989) in expanding a rational choice model to include endogenous preferences shaped by three concepts from the standpoint of the actor: 1) *desires*, which are goals or wants; 2) *beliefs*, which are propositions about the world believed to be true; and 3) *opportunities*, which are a set of objective alternatives available to the actor to satisfy desires. The mechanistic approach would specify how desires, beliefs, and opportunities of actors interact to explain individual action and social interaction. In some ways, this is a different way of slicing concepts

5. Sutherland's (1973 [1942]) search for mechanisms, however, assumed determinism, in which analytical induction would identify necessary and sufficient conditions of crime (see Matsueda, 1988). By contrast, Hedström (2005: 32) assumed a probabilistic model in which social mechanisms identify "probabilities of different outcomes conditional upon general ceteris paribus assumptions."

from rational choice theories, in which preferences are endogenous, opportunities are conceptualized as constraints and opportunity costs, and beliefs are restricted to expectations about utility. Relative to utility maximization, the model has the strength of linking concepts to research literatures in social psychology but the weakness of offering less-precise a priori predictions and propositions. It is easy to see that when applied to social transactions between two or more individuals, the interactions among the three concepts can become highly complex. To address this complexity, Hedström rightly recommended using agent-based modeling to simulate the macro-level outcomes from interactions among actors with various combinations of desires, beliefs, and opportunities.

## ECONOMIC MODELS OF SOCIAL INTERACTION EFFECTS

Within a rapidly growing research literature in economics, economists interested in the micro–macro problem have applied standard economic theory and models to examine social interaction effects beyond those solely imposed by a market. Social interaction effects are defined as the "interdependencies among individuals in which the preferences, beliefs, and constraints faced by one person are directly influenced by the characteristics and choices of others" (Durlauf and Ioannides, 2010: 452). They include effects of conformity, in which utility increases when others make the same choice, and effects of the diffusion of information across social networks. Consistent with Coleman (1990), these researchers assume methodological individualism, specify a rational expectations individual-level model, and then seek to disentangle various processes that produce within-group similarities (dependencies). Thus, the approach is consistent with game theory, in which strategic interactions among rational actors produce group-level outcomes (Durlauf, 2001). The social interaction effects are a form of emergence, which creates group properties that are not reducible to the sum of its individual members. Social interaction effects can arise from a variety of sources—exchange, role-modeling, normative controls, and social network effects. Much of the early work on social interactions was focused on the problem of disentangling social interaction effects from other mechanisms that produce correlated outcomes among individuals.

Following Moffitt (2001), we can get a flavor for this approach with a simple simultaneous equation model for two members of a group $g$, person 1 and person 2, who engage in purposive actions (criminal acts) $Y_{1g}$ and $Y_{2g}$, respectively. This models a bilateral interaction:

$$Y_{1g} = \beta Y_{2g} + \eta Z_{2g} + \gamma X_{1g} + \varepsilon_{1g} \tag{1}$$

$$Y_{2g} = \beta Y_{1g} + \eta Z_{1g} + \gamma X_{2g} + \varepsilon_{2g} \tag{2}$$

Here, $\beta$ is the endogenous social interaction effect of person 2's crime $Y_{2g}$ on person 1's crime $Y_{1g}$ (and, analogously, for person 2). $Z_{2g}$ is a characterstic of person 2 in group $g$ that has an exogenous social interaction (or contextual) effect $\eta$ on the criminal acts $Y_{1g}$ of person 1 (and vice versa for person 2), and $X_{1g}$ is a characteristic of person 1 in group $g$ that has an effect $\gamma$ on her own criminal acts $Y_{1g}$ (and by analogy for person 2), which would be a nonsocial effect. The unobserved error terms are represented by $\varepsilon_{1g}$ and $\varepsilon_{2g}$.

The model allows us to define specific effects. If $\beta \neq 0$, we have a simultaneous endogenous social interaction effect of each person's crime on the other's crime. This produces a social multiplier effect as $Y_{2g}$ affects $Y_{1g}$, which in turn feeds back to affect $Y_{2g}$, and so on, until convergence is reached. Note that if the relationship between $Y_{2g}$ and $Y_{1g}$ is unidirectional (i.e., recursive) and the crime of one person affects the crime on a second person, but not vice versa, we have a social effect—sometimes called a "spillover"—without a multiplier. This could reflect an asymmetric relationship, in which a leader affects a follower but not the reverse. Furthermore, if asymmetries induce a positive effect of one person on a second, and a negative effect of the second on the first, we have effects toward conformity as well as deviance coexisting in the population (Durlauf, 2001). This would describe, for example, a situation of differential social organization, as described by Sutherland and Cressey (1978) and by Matsueda (2006).

If $\eta \neq 0$, we have an exogenous social interaction effect of an exogenous characteristic of one person affecting the behavior of another and vice versa. This effect contains no social multiplier. If $\gamma \neq 0$, then an individual characteristic of one person affects her own crime. When aggregated to the group level, this implies correlated individual effects, a nonsocial effect (Manski, 1993). Each effect induces correlated outcomes between individuals within a group. An important task of models of social interaction is to disentangle different causal effects underlying these correlations. This raises the identification problem.

The identification issue for social interaction models gets complicated quickly. Here I will just highlight some key issues (for details, see Brock and Durlauf, 2007; Manski, 1993). Begin by noting that the simultaneous endogenous effects $\beta$ are underidentified without additional assumptions. If one can assume unidirectionality—that is, the crime of person 1 affects that of person 2 but not vice versa, the relationship would be recursive and identified.

In the absence of such assumptions, the nonrecursive relationship requires an exclusionary restriction in which an instrumental variable (IV) that affects person 1's decisions to commit crime can be excluded from the crime equation of person 2 and vice versa. That is, the IV for $Y_{1g}$ will affect person 2's crime $Y_{2g}$ only indirectly through her own crime $Y_{1g}$.

Moffitt (2001) showed that, in the presence of endogenous social interactions and the absence of exclusion restrictions, the parameters $\beta$, $\eta$, and $\gamma$ are not separately identified.[6] Nevertheless, perhaps the most important identification result, from Manski (1993), is that, even though it is difficult to identify the $\beta$'s and $\eta$'s separately, the composite of the parameters is identified from the reduced form (Moffitt, 2001). This means that the hypothesis of no social interaction effect $\beta = \eta = 0$ can be tested, as well as the hypothesis of no nonsocial effect $\gamma = 0$. Thus, one can test whether there are social interaction effects versus nonsocial effects. See Moffitt (2001) for a discussion of identification using nonlinearities (multiple equilibria) and Manski (1993) for a discussion of this identification problem applied to reference group effects. Finally, note that this assumes that reference groups are known a priori; when the selection of reference groups is endogenous, identification becomes more complicated. Here, social network data would be useful for distinguishing reference groups.

6. Moffitt (2001) also discussed other identifying possibilities, such as making the assumption that the disturbances $\varepsilon_{1g}$ and $\varepsilon_{2g}$ are uncorrelated, making the assumption that either $\beta = 0$ or $\eta = 0$, or running an intervention in which group membership is randomly assigned.

Brock and Durlauf (2001) specified a rational expectations binary choice model with social interactions (Durlauf, 2001). In this case, a model for discrete choice expresses a payoff function that consists of private utility, social utility, and random utility. If there are no social interaction effects, social utility drops out, and the model reduces to a familiar binary choice (private) utility model. The key to the social interaction model is a social utility function, which includes a parameter representing bilateral interaction (endogenous social interactions) between two members of a reference group. A positive sign implies that an individual derives higher utility from making the same choice as another individual in the population, whereas a negative sign implies lower utility from such a choice. This allows the model to incorporate a wide range of social interaction effects. If conflicting signs coexist, the population contains incentives for conformity and deviation (Durlauf, 2001). If the signs vary by reference group, the population would consist of subcultures, which might explain higher crime rates in disadvantaged neighborhoods (e.g., Anderson, 1999). Moreover, such models contain spillover and multiplier effects, and when the individual-level model is nonlinear, it includes the possibility of multiple equilibria and allows identification from nonlinearities. These models are highly complicated but show great promise for addressing the micro–macro problem. (For an overview of these models, see Durlauf, 2001; Durlauf and Ioannides, 2010.)

Social interaction models have been applied to criminal behavior. For example, Glaeser, Sacerdote, and Sheinkman (1996) examined cross-sectional data on crime rates across cities. They argued that if individual decisions to commit crimes were independent, the crime rate of a city could be approximated by the city average, controlling for local economic conditions. Finding that economic conditions explain less than one third of the variance in crime across cities, they suggested the existence of social interaction effects. In an exemplary study of social interaction effects and crime, Sirakaya (2006) used a hazard model with social interaction to examine recidivism among probationers. Using data on probationers within 32 jurisdictions (counties and/or cities), she attempted to disentangle endogenous social interaction effects from exogenous social (contextual) effects, as well as from nonsocial effects. Sirakaya (2006) noted the key policy implication of endogenous social interaction effects versus exogenous social (contextual) effects: A crime prevention program without social interactions reduces crime for the individual, producing correlated individual effects in a group; a program with social interactions—for example through social learning—will create a social multiplier effect as the treatment of one individual in the group affects the treatment of another group member. By specifying a nonlinear Cox model of recidivism over time, she is able to identify the nonlinear social interaction effects relative to the linear group effects, even though the group and individual effects are correlated. Using Bayesian model averaging to select models, Sirakaya found strong support for social interaction effects even in the face of exogenous contextual effects.

## CAUSALITY, INTERFERENCE, AND CAUSAL MECHANISMS

The micro–macro transition has important implications for making causal inferences from social science data. Specifically, social interaction effects will produce interference, a violation of a key assumption for making causal inferences from a counterfactual perspective. To explain how interference works, permit me to review the basics of a potential outcomes perspective on causal inference.

## POTENTIAL OUTCOMES AND IGNORABILITY

In the literature on causal inference, important advances have been made by scholars using an interventionist, potential outcomes (or counterfactual) framework in philosophy (Woodward, 2003), statistics (Rubin, 1974, 1990), and economics (Imbens, 2004; Imbens and Wooldridge, 2009) (see morgan and Winship [2015] for an introduction to causal inference). This work follows from the Neyman–Rubin framework, in which causality is defined in terms of potential outcomes. If $Y_i^1$ is the potential outcome of individual $i$ in the treatment state and $Y_i^0$ is the potential outcome of individual $i$ in the control group, then it follows that the individual (or unit) causal effect is:

$$\Delta_i = Y_i^1 - Y_i^0 \tag{3}$$

This definition of unit causal effects makes the stable treatment value assumption (SUTVA), a term coined by Rubin (1986: 961):

> SUTVA is simply the a priori assumption that the value of $Y$ for unit $u$ when exposed to treatment $t$ will be the same no matter what mechanism is used to assign treatment $t$ to unit $u$ and no matter what treatments the other units receive.

We will return to the SUTVA assumption later. The fundamental problem of causal inference is that, for those in the treatment group, we cannot observe their outcome in the control group; conversely, for those in the control group, we cannot observe their outcome in the treatment group (Holland, 1986). Therefore, we cannot compute individual (unit-level) causal effects. Under additional assumptions, we can estimate average causal effects. For example, we can assume, in a randomized experiment with a treatment and a control group, treatment assignment is ignorable:

$$\left(Y^0,\ Y^1\right) \perp T \tag{4}$$

where $T = 0, 1$ denotes treatment assignment, and $\perp$ denotes statistical independence. It follows that $E\,(Y|T = t\,) = E\,(Y^t|T = t) = E(Y^t)$. That is, the conditional expectation equals $E(Y^t)$, and an unbiased and consistent estimate of $E(Y^t)$ is the sample mean for subjects in treatment group $T = t$. Therefore, the difference in the sample means for assignments $T = 1$ and $T = 0$ estimates $\mathrm{E}(Y^0 - Y^1)$.

In an observational study, equation (4) is unlikely to hold, but treatment assignment may be ignorable after conditioning on covariates $Z$:

$$\left(Y^0,\ Y^1\right) \perp T \mid Z,\ 0 < \Pr\,(T = t|Z) < 1 \tag{5}$$

Equation (5) includes the additional identification condition that at each level of the covariates, there is a positive probability of receiving either treatment. The conditions described in equation (5) are known as strong ignorability given covariates (Rosenbaum and Rubin, 1983).

Equation (5) suggests three general ways of estimating treatment effects. First, because $E\,(Y|T = t,\ Z = z) = E\,(Y^t|T = t,\ Z = z) = E(Y^t|Z = z)$, it follows that the conditional average treatment effect $E(Y^1 - Y^0|Z = z)$ is identifiable from the observable conditional expectations. These can be used to estimate some form of regression. Recently, researchers have used nonparametric regression or adaptations of methods in machine learning for this purpose. Second, $\Pr(T = 1|Z,\ Y^0,\ Y^1) = \Pr(\mathrm{T} = \mathrm{t}|Z) = \pi$. This is the propensity score. To estimate average treatment effects, one could regress the outcome on the propensity score $\pi$ to create a balanced sample of treated and controls, use subclassification on the propensity score, or use the propensity score to weight the treatment and control observations appropriately. Third, a class of doubly robust models combines model-based predictions for $Y$ with inverse probability weights. Such models begin with a regression of $Y$ on $Z$, which yields residuals for only the sampled observations, and then uses the $\pi$ weights to estimate mean residuals for the entire population. The latter is then used to correct for bias in the regression estimate (Kang and Schafer, 2007).

Given ignorability, one can use these methods to estimate various conditional average treatment effects, such as the overall conditional average treatment effect $E(Y^1 - Y^0|Z = z)$, the conditional average treatment effect on the treated $E(Y^1 - Y^0|Z,\ T = 1)$, and the conditional average treatment effect on the untreated $E(Y^1 - Y^0|Z,\ T = 0)$.

VIOLATIONS OF SUTVA: INTERFERENCE

Although most attention in the causal inference literature has been aimed at addressing conditional ignorability (or exchangeability), an additional important question concerns interference: What happens when SUTVA is violated and potential outcomes are dependent on treatment assignment? Interference forces us to consider different patterns of treatment assignment for each individual. Our treatment effect would be more complicated:

$$\Delta_i\,(\boldsymbol{T}) = Y_i^1\,(\boldsymbol{T}) - Y_i^0\,(\boldsymbol{T}) \tag{6}$$

where $\boldsymbol{T}$ is an $(N-1) \times 1$ vector of treatment assignments for the $N$ individuals in the sample except for the $i$th individual. Here, the potential outcome for a given individual is dependent on his or her own treatment assignment, as well as on that of all other individuals. Under SUTVA, we can assume that $Y_i^1(\boldsymbol{T}) = Y_i^1$ and $Y_i^0(\boldsymbol{T}) = Y_i^0$, which simplifies the unit-causal effect to be $\Delta_i$.

Rubin's (1986) definition of SUTVA implies two overlapping components. The first, often termed "consistency," requires that the potential outcomes will be the same for the possible treatment assignment mechanisms (Cole and Frangakis, 2009), for example, if treatments are compound (consisting of multiple components) or if the potential outcome differed when assigned in the real world versus in a randomized experiment. Of more importance for our purpose is the second component, termed "interference" or "spillover," which occurs when the potential outcome of one individual is affected by the treatment of other individuals (Cox, 1958; Hudgens and Halloran, 2008; Sobel, 2006).

Interference would occur, for example, if the treatment of person A in the treatment group affects the outcome of person B in the treatment group. This complicates the treatment status of person B, who now has two sources of treatment: 1) the direct effect of her own treatment plus 2) the spillover effect through the treatment of person A (Hudgens and Halloran, 2008). Depending on the substantive context, researchers may be interested in either treatment effect or the sum of the two. For example, one may be interested in the sum of the two effects if spillover is conceived as a part of the treatment program of interest. Such estimates, of course, would not generalize to populations in which the spillover process is different or absent. In other contexts, one may be interested in the direct treatment effect and view spillover as contamination of the pure treatment of interest. Here, the total treatment effect would be a compound treatment, which violates the assumption of consistency.

Interference also occurs when the treatment of person A in the treatment group affects the outcome of person C in the control group. This complicates the treatment status of person C, who experiences a spillover treatment effect, while remaining in the control group. In the general case, if all experimental subjects affect all other subjects, there will be an exponential number of treatment possibilities, with a potential outcome associated with each, which violates SUTVA. Thus, interference can create complications to causal inference that are virtually intractable.

The solution to interference lies in theorizing about the sources of interference and spillover that reduces the number of treatment possibilities to a manageable quantity amenable to modeling. It is important to note that interference affects causal inferences made when ignorability is addressed by randomization of treatment. That is, randomizing does not buy you out of the problem. Moreover, our discussion of the micro–macro question suggests several ways that spillover is likely to occur.

## MICRO–MACRO TRANSITIONS AND SPILLOVER EFFECTS

A clear example of a spillover effect recognized in criminology is the phenomenon of crime displacement in studies of the deterrent effect of hot-spots policing (e.g., Ratcliffe et al., 2011; Sherman and Weisburd, 1995). Here, when policing interventions target high-crime, "hot-spot" (treatment) neighborhoods, criminals may simply move their criminal activity to adjacent (control) neighborhoods. This is an example of interference as the outcomes of control neighborhoods are contaminated by application of treatment in experimental neighborhoods, complicating estimation. Spillover can also be positive as the treatment effect spills over or diffuses into adjacent neighborhoods (Guerette and Bowers, 2009). More generally, spillover effects are likely to occur in neighborhood models of crime as crime in a focal neighborhood affects crime in adjacent neighborhoods (Morenoff, Sampson, and Raudenbush, 2001).

Our discussion of the transition from micro- to macro-levels implies that social interaction and social capital are likely to produce spillover effects. Indeed, social capital theory suggests multiplier effects as a result of positive externalities of individual investments in social capital for the larger group as a whole, and from social capital building on itself, as social exchange creates trust, which fosters more exchange and, in turn, provides the basis for norms and sanctions, as well as for authority relations. Thus, research on neighborhood social capital has been aimed at examining spillover effects from adjacent neighborhoods (Sampson, Morenoff, and Earls, 1999) and multiplier effects across individuals (Glaeser, Laibson, and Sacerdote, 2002).

The threshold and cascade models also imply nonlinear spillover effects that may produce interference in randomized experiments. For example, a randomized experiment of policies to reduce residential segregation by altering, through selective incentives, the preferences of residents will be subject to interference as the treatment assignment of experimentals will affect the potential outcomes of controls. Furthermore, the moving to opportunity experiment attempted to ameliorate neighborhood effects by giving families vouchers to move from high-poverty to low-poverty neighborhoods. Evaluations of the experiment, using instrumental variable methods to control for noncompliance, found modest short-term effects on outcomes such as crime (e.g., Kling, Ludwig, and Katz, 2005) but stronger long-term effects, particularly for children younger than 13 years of age when they moved (Chetty, Hendren, and Katz, 2016). Sobel (2006), however, argued that the no-interference assumption may be violated by social interaction effects: Families given vouchers may be reluctant to move unless most of their neighborhood friends also move, and families given vouchers may be unable to find suitable housing in a tight housing market when many other families are given vouchers. Such interference means that estimates of the average treatment effect and average treatment effect on the treated are contaminated by spillover effects (see Sobel, 2006).

## MODELING SPILLOVER EFFECTS

The problem of interference often requires separating out the direct effects of treatment from the indirect effects via spillover. As noted, in the absence of a theory of spillover, the number of treatment combinations increases exponentially with the number of observations. This underscores the importance of a theory of micro–macro transitions, which can help identify the structure of spillover and thereby simplify the treatment regimes. I follow Halloran and Struchiner (1995) in conceptualizing the problem of separating direct and spillover effects in terms of hypothetical study designs. Let's assume that criminal behavior is transmittable across persons whereby criminals transmit crime—either through a learning process such as differential association or the transmission of criminal opportunities by a person creating crime opportunities for another—at a given rate of transmission. Imagine two hypothetical groups, A and B, which are independent, with no possibility of cross-group social interaction or interference. Now consider a randomized intervention in group A so that some but not all members receive a treatment seeking to prevent individuals from committing crimes as well as from transmitting crimes to others. Study design I compares treatment units with untreated units in group A to evaluate the direct effect of treatment. Under randomization, each person is assigned an equal probability of receiving the treatment. Here, randomization ensures equal exposure to the intervention but does not rule out interference. Nevertheless, design I lacks a comparison group in which no one has been treated. Therefore, without additional assumptions, this design cannot estimate spillover effects or the overall effect of the intervention program. In study design II, we can make three comparisons. First, we can compare crime outcomes of control units in group A (that did not receive the intervention) with control units in group B (in which no intervention occurred). This estimates the indirect effect of the intervention. Second, we can compare crime outcomes of treatment units in group A with those of control units in group B (in which no intervention program occurred). This comparison of outcomes evaluates combined direct effects of the intervention plus the spillover effects of the intervention program. Finally, we can compare the weighted average of crime outcomes for treatment and control units of group A with crime outcomes of group B. This evaluates the overall crime-reduction effect of the intervention program.

Statisticians working on the problem of causal inference with interference have attempted to use research designs and statistical models to identify, estimate, and control for spillover effects (e.g., Hudgens and Halloran, 2008; Manski, 2013; Sobel, 2006;

Tchetgen Tchetgen and VanderWeele, 2010). When the structure of spillover is known to be localized—such as contiguous units in space—treatment units can be compared with contiguous control units before and after an intervention. For example, in evaluating hot-spots policing, Ratcliffe et al. (2011) compared treatment, control, and buffer neighborhoods before and after treatment to estimate potential crime displacement and found treatment effects for neighborhoods exceeding a baseline threshold of violent crime. More generally, in regression models of neighborhood crime, contiguous spillover effects can be estimated as a spatial lag variable, assuming they form, for example, a first-order autoregressive process (e.g., Morenoff, Sampson, and Raudenbush, 2001).

When spillover effects among individuals are known to occur within a given aggregated unit, such as households, neighborhoods, or classrooms, estimation becomes tractable. For example, Sinclair, McConnell, and Green (2012) conducted a randomized multilevel experiment to estimate the spillover effect of get-out-the-vote flyers within households and neighborhoods. They sent a flyer to a randomly selected member within a household and randomized households receiving the flyer across neighborhoods varying in neighborhood saturation of households receiving flyers (high, medium, and low saturation). They found significant spillover effects within households but not across households within neighborhoods. Using a multilevel model of the effects of retention in kindergarten (versus graduation to first grade) on student learning, Hong and Raudenbush (2006) examined interference as a result of peer effects: What effect does retention have on learning when more peers are retained? With data on students nested within classrooms and within schools, they assumed no interference across schools and reduced peer effects to a scalar: high versus low retention rate of the school. They found negative effects of retention and no evidence of peer effects.

Economic models of social interaction effects model spillover effects, and therefore, estimates of treatment effects with interference fall out as a feature of the model, as effects of exogenous variables (Manski, 2013). Such models can be expressed in terms of models for potential outcomes (see Imbens and Wooldridge, 2009). Other more complicated estimates can be found in Sobel's (2006) treatment of spillover effects in moving to opportunity experiments, in which he found that the usual estimate of causal effects does not estimate the average treatment effect of interest; Hudgens and Halloran's (2008) estimates of direct and indirect effects of vaccines on infectious disease; and Bowers, Fredrickson, and Panagopoulos's (2013), exploration of using social network information to model interference

I raise this issue of interference in causal inference for three reasons. First, the micro–macro transition consists of social interactions, which suggest that interference is likely to be omnipresent in criminological data as well as in social science data in general. Second, recent advances in causal inference have identified tractable ways of estimating interference by relying on social science theory to reduce the number of treatment effects. It follows that research on social interaction effects inherent in the micro–macro transition can help refine our understanding of spillover effects and thereby help make causal models with interference increasingly tractable.

Third, interference presents complications for making causal inferences, even when ignorability is assured with randomized experiments (or well-specified statistical models). Criminologists interested in making causal statements would do well to consider implications of the assumption of no interference.

## CAUSAL MECHANISMS AND CAUSAL MEDIATION

As noted earlier, in his writings on analytical sociology, Hedström (2005) argued against a causal modeling, counterfactual, and potential outcomes approach to causality in favor of an approach that emphasizes causal mechanisms and generative theory (see also Hedström and Swedberg, 1998). I will argue here that a potential outcomes or interventionist approach to causality shows promise for an analytical criminology, as well as for estimating and testing causal mechanisms (see Woodward, 2003, for an excellent discussion of this position within philosophy). I agree with Hedström (2005: 33) when he concluded that:

> We need to use the most appropriate statistical techniques when testing our theories, and we need to be as precise in formulating our theories as are the best sociologists in the statistical tradition when they specify and diagnose their statistical models.

Statistical models, including potential outcomes models, are useful for testing hypotheses derived from social science theories, including theories about micro–macro transitions. In his critique of counterfactual causal models, Hedström (2005) at times confused the inherent properties of a statistical model with the veracity of the social process assumed to underlie the model in a specific application. For example, he criticized the Blau–Duncan status attainment model for ignoring the crucial role of social interactions in the attainment process. Such models, in fact, assume that a myriad of social interactions generate strongly patterned actions ("structures") that are modeled as paths in the structural model. At other times, Hedström seemed to conflate the process of generating theory about specific social interactions "theory development" with the process of testing propositions derived from extant theory (2005: 113).

There is no contradiction between using observational methods—or simulation models—to generate theories about concrete social interactions, and then using counterfactual models not to generate theory but to test hypotheses from theories already generated. Counterfactual reasoning would ask what would happen if the social interactions did not occur? The trick is to specify the generative theory and then to translate implications of the theory into testable propositions about variables representing important features of the theory. Indeed, as we discussed, economic models of social interaction effects seek to identify social interaction effects from nested data after partialing out competing hypothesized individual- and group-level covariates.

The embracement of the concept of causal mechanism does not require a rejection of counterfactual approaches to causality, but instead, the two can be viewed as compatible. A key feature of structural equation models has been "mediation analysis"—the examination of whether an intervening variable M mediates the relationship between X and Y. For example, does education mediate the effect of father's occupation on son's occupation, as predicted by meritocratic theories of stratification? The results of recent research on causal mediation from a counterfactual approach have shed important light on the assumptions needed to interpret the direct and indirect effects as causal effects. In short, causal mediation requires the assumption of sequential ignorability (Robins and Greenland, 1992). That is, if we treat X and M as treatments, the ignorability discussion can be applied to X and M sequentially. This makes mediation analysis enormously complicated and difficult but not impossible (see Emsley, Dunn, and White, 2010; Imai et al., 2010; Sobel, 2008).

## IMPLICATIONS FOR PUBLIC POLICY

This discussion of the micro–macro problem has important policy implications. I will give a few illustrative examples. Generally speaking, taking the position of integrating micro- and macro-levels suggests multiple points of intervention, including the macro-level, micro-level, and possibly the mechanisms producing the micro–macro transition. With respect to macro-interventions, the obvious implication is that, unless causality truly operates at the macro-level, as argued by methodological holists, social policies targeting social structure and groups to alter macro-level outcomes will benefit from a microfoundation. Such a foundation would specify an individual-level causal mechanism, a link between the macro-policy and individual mechanisms, and a link between individual outcomes at macro-outcomes.

An example of a macro-policy, randomized experiments of hot-spots policing in randomly assigned neighborhoods, has benefited from individual-level theories of routine activities and criminal opportunities in specifying the conditions under which criminal acts would be displaced from targeted neighborhoods into a contiguous control neighborhood. Similarly, policies of policing interventions benefit from individual-level theories of deterrence. For example, using the concept of ambiguity aversion, in which criminals avoid situations in which risk is uncertain, Nagin (1998) speculated that hot-spots policing will likely have a decaying effect as criminals adjust to the new higher likelihood of arrest (Sherman, 1990). Therefore, varying the targeted neighborhoods over time would be an efficient use of police resources.

Ratcliffe et al. (2011) attempted to model crime displacement and diffusion effects in experiments of hot-spots policing (see also Bowers and Johnson, 2003). Recently Nagin, Solow, and Lum (2015) developed an integrated rational choice theory that specifies the distribution of criminal opportunities and offender decision-making from which to devise efficient police deployment strategies, including hot-spots policing, problem-oriented policing, and random patrol. After specifying a mathematical model of the distribution of criminal opportunities, they identified where police could intervene to change opportunities. They noted that police could prevent crime in two ways: acting as "apprehension agents," in which they arrest criminals after a crime is committed, and as "sentinels," in which they deter crime by serving as capable guardians as specified by routine activities theory (see Nagin, 2013). Based on their model, they described the conditions under which police can reduce crime in their roles as sentinels and apprehension agents, demonstrated why the clearance rate is a poor measure of police performance (it ignores the sentinel role), and explained how programs for increasing legal opportunities, such as the Chicago Safe Neighborhoods program (e.g., Papachristos, Meares, and Fagan, 2007), would be expected to reduce crime.

An integrated micro–macro framework would also be informative for individual-level policy interventions by specifying micro–macro transitions in which interventions of individuals produce aggregate crime rates. For example, as noted by Sirakaya (2006), an intervention program that reduces the criminality of individuals may create positive endogenous social interaction effects—through role-modeling, social learning, or dissemination of information—producing a social multiplier that enhances the program's effect. Knowledge of the form and magnitude of the social interaction effects for a given population would refine our expectations of the program's effectiveness. When endogenous social interaction effects are both positive and negative, and their distribution varies by subgroups within a population, a more complicated pattern of consequences may result—possibly entailing subcultures.

As another example, social policies that seek to intervene in neighborhood effects, such as Moving to Opportunity, would benefit from a theory of micro–macro transitions with feedback. For example, a mover–stayer model of local residential moves would help explain the conditions under which residents will use vouchers to move to better neighborhoods. Is there a threshold effect in which residents in disadvantaged neighborhoods will not use vouchers to move unless more than some proportion of their neighborhood friends move away or some proportion of their friends move to a destination neighborhood? Housing market models would help identify potential saturation effects on destination neighborhoods as a result of the program, as pointed out by Sobel (2006).

Another example concerns the use of job training programs to increase the employment chances of inner-city disadvantaged young men and thereby reduce crime rates. Coleman (1983) pointed out that a job training program that targets young Black disadvantaged men may succeed at the individual level but, depending on the form of the micro–macro relation, may produce different aggregate results, such as inequality or crime rates. Let's assume that the targeted youth are at high risk of crime. A successful job training program would result in targeted program participants getting jobs. The overall result, however, depends on how those jobs come about. If the participants obtain jobs that were previously held by other young Black disadvantaged men at risk of crime, neither the macro-level social inequality nor the macro-level crime rate would change. If the participants displace young Black disadvantaged men that are not at risk of crime, the program will reduce crime but not inequality. Finally, if the success of the program in creating new skilled workers causes firms to create new jobs to capitalize on the new skilled workers, both crime *and* inequality may be reduced.

Finally, attention to social interaction effects and micro–macro transitions may suggest more efficient points of intervention to prevent crime. For example, social networks within neighborhoods or schools typically reveal a mixture of a few social isolates who have few social connections, a few social hubs who have a large number of social ties, and everyone else. Assuming that social ties help transmit crime (and anti-crime) from person to person, knowledge of the social network may suggest that interventions targeting social hubs may capitalize on social multiplier effects, and result in greater efficiency. Thus, the results of research on social networks and crime may have indirect policy implications (e.g., Kreager et al., 2016; Papachristos, 2009).

## CONCLUSIONS

In this address, I have advocated for an analytical criminology that incorporates an integrated approach to the micro–macro problem. Toward this end, I have described several micro–macro transitions, or social interaction effects, that have relevance for the study of crime. The study of those mechanisms has generated exciting new ways of thinking about traditional social science topics, such as collective behavior, residential choice and segregation, reference groups, and collective choice. I have also tried to sketch out research programs in sociology, economics, and applied statistics that may be helpful for addressing these issues in the study of crime.

Although I have discussed the central role of using statistical models in assessing social interaction effects, I should emphasize that a variety of forms of data and methodological approaches have important roles to play. Ethnographic studies of crime, such as Anderson's (1999) study of the code of the street, can be a rich source of hypotheses about micro–macro transitions. For example, street confrontations may be conceived as a repeated game of hawk and dove in which actors project a tough image to overcome asymmetries of information and avoid negative outcomes in the payoff matrix. Repeated games produce a status system and social norms as part of the code. Specific theoretical mechanisms by which actors generate group outcomes can be tested in controlled laboratory experiments used in, for example, behavioral economics and social psychology (e.g., Lawler, Ridgeway, and Markovsky, 1993). Such complex mechanisms can be further explored using agent-based simulation models, and if parameters are rooted in empirical research, they can be used to predict out-of-sample cases. Economists working on social interaction effects have made substantial progress in modeling micro–macro relations with econometric models, including finding ways of identifying key parameters under reasonably weak assumptions. This important research program is rapidly expanding, and I have only been able to give a flavor for this approach. For reviews, see Brock and Durlauf (2001) and Durlauf and Ioannides (2010).

An analytical criminology addressing the micro–macro problem opens up new puzzles and can shed new light on theoretical, methodological, and policy questions in criminology. It deepens our theoretical understanding of criminal behavior within broader groups and social contexts by specifying how individuals generate those groups and contexts, which in turn, constrain individual purposive action. Moreover, ignoring social interaction effects and complex micro–macro linkages when they are in fact present will have negative consequences for individual-level research. Theories will miss important causal mechanisms and have less explanatory power. Estimates of parameters of empirical models will be misleading because they fail to consider feedback loops, social multipliers, and interference generated from social interactions. In closing, I hope I have outlined several issues that criminological researchers will consider in their own work, including emergence and social interaction effects, identification issues, the problem of interference in making causal inferences, and the role of social interaction and spillover in studies of crime policies.

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