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Social Interactions

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Contents

Abstract

The concept of social interactions in economics allows economists to explore applications that are as rich as the social fabric. It also introduces numerous definitional, econometric and measurement issues. The paper aims at introducing the classes of models that accommodate estimation of social interactions and at examining the key areas where significant advances have been made in the identification of social effects. It surveys linear and nonlinear models and their applications, including results regarding partial identification. The paper also examines conceptual and methodological links with the spatial econometrics and the social networks literatures and applications.

`Keywords:` social interactions, neighborhood effects, peer effects, quantal response, statistical mechanics, social interaction empirics, endogenous social effects, partial identification, self selection, sorting, nonlinear models, social multipliers, social networks, spatial econometrics, variance contrasts.

Journal of Economic Literature `classification codes: C00, C31, C35, C45, C73, C81, D01, R22, Z13`

"Most people are other people. Their thoughts are some one else's opinions, their lives a mimicry, their passions a quotation." Oscar Wilde, *de Profundis.*

1 Introduction

Within economics, the study of social interactions has expanded the domain of inquiry to incorporate many ideas that are traditionally associated with sociology. Social interaction analysis also extends the methodological individualism of economics in new directions due to its focus on the feedbacks between individual behaviors and aggregate outcomes. By social interactions we refer to interdependencies among individuals in which the preferences, beliefs and constraints faced by one socioeconomic actor are directly influenced by the characteristics and choices of others. We emphasize the word "directly" since these interactions do not occur because individuals are affected through the effects of the choices of others on prices, as occurs in an Arrow-Debreu world. In fact, these effects typically have features that render them forms of externalities. Canonical examples include conformity effects which mean that the utility from a given behavior increases when others make the same choice and social network effects in which information diffuses according to who is in contact with whom. Social interactions have been used to help explain phenomena ranging from cigarette smoking to the persistence of ghettos and inner city poverty.[2]

While social interactions models take sociological ideas seriously, they fully preserve the purposive, choice-based formulation of individual decisionmaking. The theoretical work is different from "standard" economics only in that it expands the domain of factors that determine individual decisions. It is thus no surprise that a precursor to the modern literature

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[2] It is interesting to note that many of the ideas concerning persistent poverty in Wilson (2009) have been formalized and studied in the social interactions literature.

is Becker (1974). Further, it is also no surprise that social interactions models have close parallels in game theory, e.g. global games [Morris and Shin (2003)] and especially quantal response equilibria [McKelvey and Palfrey (1995)].

While still relatively new, the social interactions literature is already sufficiently large and wide-ranging that a complete survey is beyond the scope of a single article.[3] We therefore focus on providing a framework that can function as a template for understanding the broader literature. To do this, we outline a general theoretical framework for social interactions and then describe the econometric implementation of variations of this framework, specifically focusing on identification issues. Various empirical papers are discussed as examples of the particular models and econometric strategies. In addition, we describe some of the implications of the social networks and spatial economics literatures for the study of social interactions.

Section 2 outlines a basic model of social interactions. We focus on a discrete choice model of social interactions which has direct econometric analogs and so is in principle estimable. Section 3 describes the baseline econometric models that have been used in the study of social interactions and focuses on what we call "classical" identification problems which involve the disentanglement of endogenous and exogenous social effects. Some major empirical studies using the baseline models are also described. Section 4 describes contemporary identification problems, by which we refer to environments in which the error structures are affected by self-selection and unobserved group variables. Empirical studies that address these problems, including those that use experimental data, are reviewed. Section 5 discusses spatial and network approaches to social interactions. Section 6 concludes.

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[3] See Durlauf (2004) and Ioannides and Loury (2004) for related surveys in economics and Sampson, Morenoff, Gannon-Rowley (2002) for a survey from the sociology perspective. Manski (2000) is a conceptual overview.

2 A Discrete Choice Model of Social Interactions

A basic model of social interactions, one that captures many of the interesting implications of integrating social factors into individual behavior, can be developed in the context of decisions over a discrete set of choices. We generalize the multinomial choice model of Brock and Durlauf (2002, 2007) to allow for social interactions structures, following Durlauf (1997) and Ioannides (2006). We develop this framework for a population of I individuals each of whom chooses between L different alternatives; individual choices are denoted by ω_i. The choice set is: $S = \{0, 1, \ldots, L-1\}$. Each agent i is associated with a group $g(i)$, which is defined as those members of the population whose behaviors and characteristics enter as direct arguments in i's decision problem. The analysis of this section will assume that each actor is a member of the same group, as our goal is describing how social interactions affect individual and aggregate outcomes. Econometric analyses of the model typically presuppose sampling of individuals across groups.

Each of the possible choices ℓ produces utility $V_{i,\ell}$ for individual i. We conceptualize choice-specific utility as having three distinct components. The first is $h_{i,\ell}$, which we think of as private deterministic utility. It is private in that it does not exhibit direct dependence on the choices of others and is deterministic as it is treated as known to the modeler; in econometric work this is operationalized by assuming it is known modulo some set of unknowns that are estimable. The second component is deterministic social utility and captures dependence of the utility of a given choice on others' choices. If individual i chooses ℓ and j chooses s, then individual i receives $J_{i,j,\ell,s}$. This is quite general as each pair of individuals and pair of choices is assigned a separate payoff; we will restrict the payoffs in order to produce tractable results. We further assume that the payoffs to the choices of others are additive. A final component is a random utility term, $\epsilon_{i,\ell}$. These are assumed to be independent across choices and individuals; relaxation of this assumption is straightforward and not additionally insightful. Together, these components are summed so that $V_{i,\ell} = \mathcal{E}\{V_{i,\ell}\} + \epsilon_{i,\ell}$, with the expected utility taking the form:

$$\mathcal{E}\{V_{i,\ell}\} = h_{i,\ell} + \sum_{s=0}^{L-1} \sum_{j \neq i} J_{i,j,\ell,s} p^e_{j,s|i}, \tag{1}$$

where $p^e_{j,s|i}$ denotes the probability i assigns to choice s on the part of j. For later use, we define $\mathbf{J}$ as the array of interaction coefficients, a $I \times I \times L \times L$ array with element $J_{i,j,\ell,s}$, and $\mathbf{I}$ as the $I \times I$ identity matrix.

This expected utility function allows for an explicit characterization of the equilibrium choice probabilities once the probability distributions for the random utility terms is specified. We assume that the $\epsilon_{i,\ell}$'s are distributed according to the multinomial logit model with dispersion parameter ς, so that individual i's choice probabilities are given by:

$$\text{Prob}(\omega_i = \ell) = p_{i,\ell} = \frac{\exp\left[\varsigma\left(h_{i,\ell} + \sum_{s=0}^{L-1}\sum_{j\neq i} J_{i,j,\ell,s} p^e_{j,s|i}\right)\right]}{\sum_{\ell'=0}^{L-1}\exp\left[\varsigma\left(h_{i,\ell'} + \sum_{s=0}^{L-1}\sum_{j\neq i} J_{i,j,\ell',s} p^e_{j,s|i}\right)\right]}, \ell \in S, i = 1, \ldots, I. \quad (2)$$

Higher ς implies lower variance. The case of $\varsigma = 0$ implies purely random choice, where all outcomes are equally likely because the private random utility density is so diffused that the maximum of the random utility shocks will control the choice. In contrast $\varsigma = \infty$ means that choices are deterministic in the sense that the private random utility terms are all equal to 0 with probability 1.

Self-consistency of beliefs for this model requires that

$$\text{Prob}(\omega_i = \ell) = p_{i,\ell} = \frac{\exp\left[\varsigma\left(h_{i,\ell} + \sum_{s=0}^{L-1}\sum_{j\neq i} J_{i,j,\ell,s} p_{j,s}\right)\right]}{\sum_{\ell'=0}^{L-1}\exp\left[\varsigma\left(h_{i,\ell'} + \sum_{s=0}^{L-1}\sum_{j\neq i} J_{i,j,\ell',s} p_{j,s}\right)\right]}, \quad \ell \in S \; i = 1, \ldots, I. \quad (3)$$

It is straightforward to verify that under the Brouwer fixed point theorem, at least one such fixed point exists for each of individual i's choice probabilities.

It is common in the social interactions literature to simplify the interaction structure by restricting social utility so that individuals only care about the fraction of the population making the same choice he does. This renders the agent indifferent as to who makes the choices and means that if others do not coincide with the choice, what they choose instead is irrelevant. Under this simplification, the object of interest is not the matrix with elements $p_{i,\ell}$, the individual choice probabilities, but rather the aggregate choice probabilities, $p_\ell = I^{-1}\sum_i p_{i,\ell}$. This leads to:

$$p^e_\ell = p_\ell = \frac{1}{I}\sum_i \frac{\exp\left[\varsigma\left(h_{i,\ell} + J_{i,\ell} p_\ell\right)\right]}{\sum_{s=0}^{L-1}\exp\left[\varsigma\left(h_{i,s} + J_{i,s} p_s\right)\right]}, \quad \ell \in S, \quad (4)$$

where $J_{i,\ell}$ is the social utility weight i assigns to the share among the population of others making the choice ℓ.

A leading case in the theoretical literature focuses on binary choices with the decision space $\{1, -1\}$. These models typically treat social utility as a function of the expected average choice of others, i.e., where $m^e_{i,j} = p^e_{j,1|i} - p^e_{j,-1|i}$. Under the assumption of self-consistency of beliefs, $m_j = m^e_{i,j}$. Let $\mathbf{m}$ denote the $I-$vector with the m_j's as elements. In this case, it is convenient to use the hyperbolic tangent function, $\tanh(x) \equiv \frac{\exp(x)-\exp(-x)}{\exp(x)+\exp(-x)}$, $-\infty < x < \infty$, and have:

$$m_i = \tanh\left[\varsigma h_i + \varsigma \mathbf{J}_i \mathbf{m}\right], \ i = 1, \ldots, I, \tag{5}$$

where $h_i = h_{i,1} - h_{i,-1}$, and $\mathbf{J}_i$ denotes the ith row of the array, now a matrix, of interaction coefficients J_{ij}.[4] Brouwer's fixed point theorem guarantees that the system of social interactions with an interactions matrix $\mathbf{J}$ admits an equilibrium that satisfies (5) [Ioannides (2006)].

To understand the properties of the binary choice model, we consider the case where all heterogeneity across agents is due to random utility, i.e. we assume that $h_{i,\ell}$, and $J_{i,\ell}$, are constant across agents. This implies $\mathcal{E}_i\{\omega_j\} = m$, for all individuals, so that the Nash equilibria associated with (5) simplify to

$$m = \tanh(\varsigma h + \varsigma J m). \tag{6}$$

The properties of this special case are straightforward to describe. If $\varsigma J > 1$, and $h = 0$, then the function $\tanh(\varsigma h + \varsigma J m)$ is centered at $m = 0$, and equation (6) has three roots: a positive one ("upper"), (m^*_+), zero ("middle"), and a negative one ("lower"), (m^*_-), where $m^*_+ = |m^*_-|$. If $h \neq 0$ and $J > 0$, then there exists a threshold H^*, which depends on ς and J, such that if $\varsigma h < H^*$, equation (6) has a unique root, which agrees with h in sign.

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[4] It is easy to see this as a specification of $\mathbf{J}$ in (1) above. That is, by going back to the original notation of equation (1) and setting $J_{i,j,\ell,1} = J_{ij}$, $J_{i,j,\ell,-1} = -J_{ij}$, then

$$\sum_{j \neq i} J_{i,j,\ell,s} p_{j,s|i} = \sum_j J_{ij} m_j.$$

In other words, given a private utility difference h, if the dispersion of the random utility component is sufficiently large, the random component dominates choice. If, on the other hand, $\varsigma h > H^*$, then equation (6) has three roots: one with the same sign as h, and the others of the opposite sign. That is, given a private utility difference, if the dispersion of the random utility component is small, then the social component dominates choice and is capable of producing multiplicity in conformist behavior. If $J < 0$, then there is a unique equilibrium that agrees with h in sign.

The relationship between the number of equilibria and the parameters J, h, and ς can be given some intuition. Holding ς constant, it is not surprising that multiple equilibria emerge when the strength of conformity effects, measured by J, is large relative to the strength of private incentives, measured by h. What is less obvious is the role of ς. The parameter ς measures the degree of heterogeneity in payoffs across individuals in the population. Higher ς means greater heterogeneity. The degree of heterogeneity, in turn, determines how private and social incentives interact to produce equilibria. When ς is small, which means that ςJ is small, then relatively large fractions of the population will experience draws such that either $\epsilon_{i,\ell} - \epsilon_{i,\ell'}$ or $\epsilon_{i,\ell'} - \epsilon_{i,\ell}$ is large. This means in turn that a relatively high fraction will have their decisions "controlled" by their idiosyncratic payoffs in the sense that the realization of the idiosyncratic part of the payoffs is large enough that it dominates the common private and social incentives. By symmetry of the density for $\epsilon_{i,\ell} - \epsilon_{i,\ell'}$, equal percentages of the population, in expectation, will make choices 1 and -1 because their payoffs are dominated by the idiosyncratic terms. But this means that a relatively small percentage of the population remains that can engage in self-consistent bunching because of social utility effects. Put differently, when enough agents make choices driven by symmetrically distributed payoff differences, this implicitly delimits the magnitude of the social utility terms since it delimits the m term in Jm.

The existence of a mapping between parameters characterizing the strength of social influences, deterministic private incentives, and heterogeneity in random private incentives is not unique to the binary choice model. For example, Brock and Durlauf (2002, 2007) show that for the multinomial choice model, when $h_{i,\ell} = h, \ \forall i, \ell$, then if $\frac{\varsigma J}{L} > 1$, then at least three equilibria exist, whereas if $\frac{\varsigma J}{L} < 1$, the equilibrium aggregate choice probabilities are unique. The dependence of the threshold for multiplicity on the number of choices L occurs because when the $\epsilon_{i,\ell}$'s are independent across i, the probability that the idiosyncratic draw for one of the possible choices will dominate the agent's decision is increasing in the number of choices. To give another example, we consider local interaction models such as Blume (1993), which conceptualize agents as located on an integer lattice. Applying this assumption to our model amounts to replacing our social utility formulation with $J \sum_{|j-i|=1} \mathcal{E}\{\omega_j\}$ so that agent utility is only affected by the choices of so-called nearest neighbors. It is straightforward to see that the mean choice level is characterized by equation (6). These examples illustrate a general principle about discrete choice models of social interactions, namely that their qualitative properties are often independent of the specifics of the interaction structure. This property, called universality in the physics literature, helps justify the analysis of particular interactions structures, since their properties are not tied to their detailed specification.

The property of universality provides a segue between social interactions models and statistical mechanics models in physics (which is the context in which the property was originally conceptualized.) Statistical mechanics models study the macroscopic properties of large number of interaction objects (e.g. atoms). Interestingly, the Brock-Durlauf model with $h_{i,j} = h$, and $J_{i,j} = J$ corresponds to the mean field approximation of the Curie-Weiss model of ferromagnetism. The Curie-Weiss model is designed to explain the magnetization of iron, in which magnetization is created when the majority of atoms are spinning in one direction (atoms spin either up or down.) Curie and Weiss hypothesized that ferromagnets occurred in nature because the probability of a given atom's spin depends on the overall spin of the system. The mean field approximation refers to the use of the expected rather than realized average spin; this is done because the model is too complicated for analytical work otherwise. We explain this analogy because we believe the mathematics of statistical mechanics systems has yet to be fully exploited by social scientists. That said, interesting examples do exist, including Topa (2001), who employs so-called contact processes to study local interactions in unemployment.

Despite universality, it is of course still essential to be careful in translating statistical mechanics models into social science contexts. One basic reason is that statistical mechanics models take as primitives the conditional probabilities that relate objects in a system, whereas socioeconomic contexts require that these conditional probabilities derive from primitives with respect to preferences, constraints, and information sets. One important demonstration of the importance of making this distinction is due to Horst and Scheinkman (2006) who show that in a social interactions model in which the individual payoff structure has one set of nonzero versus zero values for $J_{i,j,\ell,s}$, the equilibrium conditional probabilities that relate the choices will have a different distribution of zero and nonzero values when agents know the choices of others when making their own. Therefore, the conditional probability structure for a given statistical mechanics model does not immediately reveal the payoff interdependencies needed to generate it. Another basic reason is that exact versus approximate statistical mechanics models can have substantively different interpretations in social science contexts even though the approximation has not intrinsic interest in a physical context and is useful to simplify calculations and provide analytical tractability. Brock and Durlauf (2001a) show that the exact solution to the Curie-Weiss model without approximation corresponds to a social planner's problem whereas the mean field approximation represents an exact (to social scientists) noncooperative model of binary choice.

Our treatment of social interactions models does not address the microfoundations of the interactions. Our canonical social interactions model treats $J_{i,j,\ell,s}$ as a primitive. One can identify models which produce different types of social interactions as equilibrium outcomes, e.g. Bernheim (1994) for a general theory of conformity in choices, Streufert (2000) on the mapping from group educational characteristics on individual educational choices induced by the use of local information to infer the payoffs to education, and Akerlof and Kranton (2002) on the interaction of personal identity and behavior. This type of work, however, has not been directly integrated into the abstract theoretical structures we have outlined.

3 Econometric Models of Social Interactions: Classical Identification Issues

In this section we consider the problem of identifying social interactions when individual unobservables are i.i.d. within and across groups. This leads to variations of the classical identification problem of simultaneous equations systems that reflect the specific structure of social interactions models. These statistical models are designed both to allow for the estimation of a role for some type of social influence on behavior as well as for the determination of what types of social influences are empirically relevant.[5]

The distinction between types of social interactions did not arise in our baseline theoretical model of social interactions because effects other than those associated with the J_{ij}'s are subsumed in the private deterministic utility term, since we were considering individuals within a common group. Manski (1993) is the first to emphasize the importance of distinguishing types of social interactions when one moves from analysis of equilibria within one group to analysis of data drawn across groups, and develops an important dichotomy. One type of interactions he refers to as endogenous effects, which capture the case where social interactions occur between one agent's own decisions and those of others; an essential feature of this type of interaction is that the choices are simultaneously determined. A canonical example is peer effects in classroom effort; one student works hard based on whether others do so (or are expected to do so) because the effort of others either renders his effort more productive or less psychologically costly. Of course, one can equally well imagine that individuals are affected by the personal characteristics of others. The educational level of parents of classmates matters if these parents, for example, help form the aspirations of the student (which for us means affects their net utility from effort). Manski calls these contextual effects.

In discussing the econometrics of social interactions, we will first consider the case where the unobserved heterogeneity is independent across agents and unpredictable given individual

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[5] For reasons of space we ignore issues of estimation of social interactions models, e.g. Aradillas-Lopez (2007), de Paula (2009), Krauth (2006), and Conley and Topa (2007).

and group characteristics. We will relax these assumptions in the next section.

Our analysis of identification focuses on the two main classes of econometric models that have been employed. We start with the linear in means models, which represents the linear regression version of social interactions models. Next, we study identification problems as apply to discrete choice models of social interactions. It will be evident that the connections between the first class of models and any underlying economic theory are at best tenuous; Brock and Durlauf (2001b) show that one can reverse engineer a linear in means model to represent an agent's optimal behavior, but this type of analysis is tautological. Discrete choice models of course, provide a tighter link between theory and econometrics, but even here the empirical literature has typically eschewed the explorations of these links. In our view, the social interactions literature would benefit from a more structural approach to econometric analysis.

3.1 Linear Models of Social Interactions

The most common econometric model of social interaction describes outcomes a linear functions of individual and group level determinants. The data are conceptualized as observations of individuals across groups. Letting $g(i)$ denote i's group, let $\mathbf{x}_i$ denote individual level characteristics, $\mathbf{z}_g$ denote group level characteristics, $m_{g(i)}$ the expected average choice in the group and ϵ_i as unobserved individual heterogeneity. The linear in means model expresses outcome y_i as:

$$y_i = \alpha_0 + \alpha \mathbf{x}_i + \theta \mathbf{z}_{g(i)} + \beta m_{g(i)} + \epsilon_i. \tag{7}$$

Applying an expectations operator to both sides of (7) provides an expression for $m_{g(i)}$ in terms of observables. Substituting this back into (7) produces a reduced form description of individual behavior:

$$y_i = \frac{\alpha_0}{1-\beta} + \alpha \mathbf{x}_i + \frac{\beta}{1-\beta} \alpha \mathbf{x}_{g(i)} + \frac{\theta}{1-\beta} \mathbf{z}_{g(i)} + \epsilon_i. \tag{8}$$

Some of the literature often does not differentiate between contextual and endogenous effects, in the sense that $\mathbf{x}_{g(i)}$, the average value of $\mathbf{x}_i$ in $g(i)$, and $m_{g(i)}$ are not distinguished; any variable that is common to all agents within $g(i)$ is treated as a source of social interactions.

Regressions of the form (7) and especially (8) have been used in many contexts to study social interactions. Datcher (1982) deserves credit for pioneering the empirical approach along the lines of equation (8). Durlauf (2004) provides an overview of the many studies that have estimated regressions of this type and surveys the sorts of variables that have been purported to represent evidence of social interactions. Prominent examples include Brooks-Gunn, Duncan, Klebanov and Sealand (1993), who relate IQ and behavioral problems at 36 months, high school dropout rates, and non-marital fertility, Aizer and Currie (2004) and Bertrand, Luttmer, Mullainathan (2000) who argue that individual use of social services/public assistance is affected by the usage rates of others with whom one interacts, Weinberg, Reagan and Yankow (2004) and Bayer, Ross and Topa (2008) who argue that individual market outcomes are influenced contemporaneously by the labor market status of neighbors (see also Ioannides and Loury (2004) for a review of the literature), Corcoran, Gordon, Laren, and Solon (1992) who argue that individual labor market outcomes are influenced by growing up in a poor neighborhood, Burke, Fournier and Prasad (2003) who argue that physicians' following each others' practices produces geographical variations in medical care practices, Young and Burke (2001) who establish that competitive forces versus social interactions in the form of custom in crop-sharing contracts lead to patterns in contract terms that are spatially uniform separated by boundaries where the terms shift abruptly, and Gaviria and Raphael (2001) who explore endogenous peer effects in drinking and smoking among teens. An especially interesting example of this type of regression is Mas and Moretti (2009) who employ a data set which measures supermarket employee productivity in 10 minute intervals; the data set is also impressive because the set of peers for a given worker rapidly shifts due to differences in shift composition and because the spatial orientation of workers in a store is known. This allows for analyses of such questions as whether frequent interactions induces stronger social effects and whether physical proximity to others matters.

One topic that has received particular attention concerns the effects of school and classroom peers. Examples of studies on this subject include Hoxby (2000) who examines peer effects in the classroom, Hanushek, Kain, Markman, and Rivkin (2003) who find that growth in academic achievement is associated with average achievement of school peers, Hoxby and Weingarth (2006) who find that once the effects of peers' achievement are properly accounted for, peers' race, ethnicity, income, and parental education have no or very weak effects, Henry and Rickman (2007) who study peer academic achievement and learning for preschoolers, and Lavy, Paserman and Schlosser (2008) who find that the proportion of low achieving peers has a negative effect on the performance of regular students.

To be clear, there have also appeared numerous studies that have failed to find evidence of social interactions. Among recent studies, Oreopoulos (2003) fails to find evidence that differences in neighborhood quality affect longer run labor market outcomes, which contrasts with findings such as Corcoran, Gordon, Laren, and Solon. Guryan, Kroft, and Notowidigdo (2007), employing methods similar to Moretti and Mas, find little evidence of workplace effects in the context of golf tournaments. We do not attempt to adjudicate the disparate results in the extant literature, which may be due to factors ranging from different data sets to different model specifications, but rather wish to emphasize that, taken on face value, the empirical evidence for social interactions is not decisive.

The regression literature on social interactions suffers from serious measurement problems. One difficulty with empirical studies based on (8) (and for that matter, nonlinear analogs of this equation) is that the relevant economic theory does not dictate the appropriate empirical measures of contextual variables that a researcher ought to use. As a result, one finds Bertrand, Luttmer, and Mullainathan (2000) using the product of welfare usage and own-ethnic group intensity to explain individual welfare usage whereas Aizer and Currie (2004) use the utilization rate of an individual's language group to measure social effects on public prenatal care utilization. Related to the absence of guidance on qualitative measures of social interactions, the empirical literature does not typically consider how social variables should interact with individual decisions. If the reason why utilization of social services depends on the usage of others is due to information transmission, as argued by Bertrand *et al.*, then it is unclear why the percentage of users is the appropriate variable, as opposed to some nonlinear transformation, since presumably one only needs one neighbor to provide the information.

Cooley (2009) analyzes this measurement problem from a different vantage point, namely the discrepancy between observable measures and causal ones. She argues that from the vantage point of theory causal sources of peer effects between students in a classroom involve the unobservable endogenous effort and the unobservable contextual ability whereas work on classroom peer effects typically uses classroom achievement as the measure of outcomes and various ad hoc measures of student characteristics for contextual efforts. Cooley demonstrates that absence of attention to the link between unobserved causal factors and observable proxies can render regression coefficients uninterpretable. Cooley's arguments ultimately highlight the importance of rich observable measures for the identification of social interactions if one is to uncover behavioral mechanisms; this is one reason why the results in Mas and Moretti (2009) are especially compelling.

A distinct measurement problem arises because theory does not provide guidance as to the appropriate measure of groups. Hence one finds the use of zipcodes to determine neighborhoods in Corcoran *et al.* and census tracts and blocks in Weinberg, Reagan and Yankow (2004). Akerlof (1997) argues that social interactions are best understood as occurring in a social space which may have many dimensions; this follows naturally when one considers the overlapping effects of physical proximity, ethnicity, gender, education and the like on ways in which individuals interact. Conley and Topa (2002) are unusual in seeking to identify the appropriate axes for social space, arguing that ethnicity is of particular importance in defining social interactions.

Statistical models of social interactions in sociology typically are different from the specification of equations (7) and (8). One reason is that the role of endogenous effects, m_i, is typically ignored. A second reason is that sociologists typically prefer hierarchical models in which contextual effects mediate individual effects, i.e.

$$y_i = \alpha_{0,i} + \alpha_{1,i}\mathbf{x}_i + \epsilon_i, \tag{9}$$

where

$$\alpha_{0,i} = \gamma_0 + \gamma\mathbf{z}_{g(i)} + \eta_{0,i}, \tag{10}$$

$$\alpha_{1,i} = \lambda_0 + \lambda\mathbf{z}_{g(i)} + \eta_{1,i}. \tag{11}$$

The terms $\eta_{0,i}$ and $\eta_{1,i}$ are random variables that allow for unpredictable parameter heterogeneity. Modulo the complications these terms introduce into the error structure, the hierarchical model in essence adds additional regressors to (7) which consist of the products of elements of $\mathbf{x}_i$ and $\mathbf{z}_{g(i)}$. These models are thoroughly discussed in Bryk and Raudenbush (2001); see Raudenbush and Sampson (1999) for an elaborate treatment of these models for social interactions contexts.

As is true for most of econometric literature on social interactions, much of the attention devoted to the linear in means model has involved the study of identification. In fact, the linear in means model exhibits a variant of the classical identification problem of simultaneous equations; this was first recognized by in a seminal paper by Manski (1993) and dubbed the reflection problem. To understand the problem, assume that the within group averages of the individual characteristics map one to one to the contextual effects, $\mathbf{x}_{g(i)} = \mathbf{z}_{g(i)}$, where both are $r-$vectors. In this case, the reduced form expression for outcomes is

$$y_i = \frac{\alpha_0}{1-\beta} + \alpha \mathbf{x}_i + \frac{\beta\alpha + \theta}{1-\beta}\mathbf{x}_{g(i)} + \epsilon_i. \tag{12}$$

In this case, there are $2r + 1$ coefficients corresponding to $2r + 2$ structural parameters. Identification thus fails. In contrast, a necessary condition for identification is that there exists at least one individual characteristic whose group level average is not a contextual effect, shown originally in Brock and Durlauf (2001b); this corresponds to the classical row condition for instrumental variables estimation. Durlauf and Tanaka (2008) give the sufficient conditions for identification, which corresponds to the rank condition in simultaneous equations estimation. These conditions, of course, require prior knowledge on the part of the researcher and as such fall prey to the problem that social interactions models are typically open-ended,[6] which means that the presence of particular group level determinants of behavior are logically independent of the presence or absence of various individual level determinants.

Once one moves away from a linear cross-section structure, the reflection problem may not hold even if there is a one to one correspondence between individual and contextual

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[6] Brock and Durlauf (2001b) introduce the idea of model openendedness in the context of economic growth models, but the idea is implicit in earlier critiques of econometric practice such as Sims (1980).

effects. For example, nonlinear in means variants do not exhibit it. Brock and Durlauf (2001b) show that the reflection problem does not apply to

$$y_i = \alpha_0 + \alpha \mathbf{x}_i + \theta \mathbf{z}_{g(i)} + \beta\mu(m_{g(i)}) + \epsilon_i, \tag{13}$$

for $\frac{\partial^2 \mu(m_{g(i)})}{\partial m^2_{g(i)}} \neq 0$, relative to the space of twice differentiable functions, outside of nongeneric cases. The intuition is straightforward; the reflection problem requires linear dependence between group outcomes and certain group level aggregates, which is ruled out by the nonlinearity in (13). Similarly, shown in Blume and Durlauf (2005), when one introduces endogenous effects into a hierarchical model nonlinearities that are produced because of cross product terms between m and $\mathbf{x}_i$ also break the reflection problem.[7] Further, the reflection problem does not arise in linear models with dynamic forms of interactions, e.g.

$$y_{it} = \alpha_0 + \alpha \mathbf{x}_{i,t} + \theta \mathbf{z}_{g(i),t} + \beta m_{g(i),t-1} + \epsilon_{i,t}. \tag{14}$$

However, the logic of the reflection problem, which derives from co-movement of contextual and endogenous effects, carries over when one considers the precision of parameter estimates. As such, it is a fundamental problem in empirical work. Further, the examples we have given where the problem does not arise rely on parametric modeling assumptions. Manski (1993), for cross section data, in fact provides a nonidentification result for nonparametric contexts that parallels the reflection problem in linear models.

The fact that endogenous social interactions help amplify differences in the average group behavior across groups can itself serve as basis for identification. Glaeser *et al.* (2003) use patterns in the data to estimate a social multiplier. For a change in a particular fundamental determinant of an outcome, this is defined as the ratio of a total effect, which includes a

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[7] Drewianka (2003) draws attention to the fact that nonlinearities that are inherent in a particular phenomenon may further aid identification. In his study of social effects in marriage markets, Drewianka argues that a higher marriage rate in a community may induce the propensity of unmarried people to marry (an endogenous social effect), *cet. par.* But by also leaving fewer people unmatched it hampers search and reduces marriage prospects of others and thus causes additional variation. He finds that an increase in the share of the population that is unmarried reduces the marriage rate of never-married men by the same amount and that of never-married women by less.

direct effect to an individual outcome plus the sum total of the indirect effects through the feedback from the effects on others in the social group, to the direct effect.

Glaeser, Sacerdote and Scheinkman suggest measuring the social multiplier by comparing the coefficient vector produced by a within-group regression across individuals,

$$y_{ig} = \kappa + \pi \mathbf{x}_i + \eta_{ig}, \tag{15}$$

with the coefficient produced by a regression across group level averages,

$$\bar{y}_{g(i)} = \kappa' + \pi' \bar{\mathbf{x}}_{g(i)} + \bar{\eta}_{g(i)}. \tag{16}$$

Social multipliers are defined as the ratios of the coefficients in π' to their respective ones in π.[8] This approach, of course, requires the existence of at least one contextual effect, x_i. The social multiplier approach has also proven useful in uncovering β, even when no individual or contextual effects are present. We will return to this approach in the next section.

The social multiplier approach is particularly useful in delivering a range of estimates for the endogenous social effect when individual data are hard to obtain, as in the case of crime data. Glaeser, Sacerdote and Scheinkman (1996) motivate their study of crime and social interactions by the extraordinary variation in the incidence of crime across US metropolitan areas over and above differences in fundamentals. If social interactions in criminal behavior are present, variations in observed outcomes are larger than what would be expected from variations in underlying fundamentals, precisely because of the social multiplier. [9]

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[8] For example, suppose that the true data generating process is $y_{ig} = \alpha_0 + \alpha \mathbf{x}_i + \sum_{j \neq i} y_{ij} + \eta_{ig}$, where α is scalar. Then, one can show that $\frac{\pi'}{\pi} = \frac{1}{(1-\beta)(1+\sigma\beta)}$, which Glaeser *et al.* refer to as the social multiplier, where $\sigma = \frac{\mathrm{Var}(\bar{x}_g)}{\mathrm{Var}(x_i)}$.

[9] While the literature on the social multiplier has so far rested on linear models in static settings and emphasizes measuring the strength of social interactions, the concept may be extended fruitfully to dynamic and nonlinear settings, to complete versus incomplete information, and to more complex interaction topologies [Brock and Durlauf (2001a); Bisin *et al.* (2006); Ioannides (2006)]. The nature of social multipliers and their use to measure social interactions will differ in these contexts. Bisin *et al.* (2006) show that incomplete information has the effect of dampening the aggregate effects of the agents' preferences for conformity and thus reducing the social multiplier relative to the complete information. And of course, the equilibrium aggregate effects of a marginal change in private incentives will generally no longer be constant in nonlinear contexts.

3.2 Discrete Choice Models of Social Interactions

Discrete choice models of social interactions have been applied in a wide range of contexts, although the model is used more frequently than its linear in mean analog. Early examples include Crane (1991) Evans, Oates and Schwab (1992) on teenage behaviors; more recent examples range from cigarette smoking [Krauth (2005), Nakajima (2007)] to medical practices [Burke *et al.* (2003)]. As in the case of linear models, one finds conflicting results in the literature. For example, Crane, focusing on residential neighborhoods, finds strong social effects whereas Evans Oates and Schwab do not, focusing on schools, does not; similarly, Nakajima concludes that peer effects play a larger role in smoking than does Krauth.

The econometrics of discrete choice models with social interactions is studied in Brock and Durlauf (2001a,b; 2006, 2007). These papers show that the reflection problem does not, with relatively weak assumptions, hold in multinomial choice models when the analyst knows the distribution of the unobserved error terms; the standard assumption in theoretical models that the errors are logit is inessential. Intuitively, identification holds so long as the individual and contextual effects exhibit sufficient variation so as to imply that choice probabilities are nonlinearly related to them. Further, Brock and Durlauf show that for the binary choice case identification holds even if the error distribution is unknown, following Manski (1988).

A number of interesting variations of our baseline discrete choice model have been studied. Soetevent and Kooreman (2007) use Brock and Durlauf (2001a) as a building block for their empirical discrete-choice social interactions model with a finite number of agents, which is roughly along the lines of equation (5) above, but adapted to a probit model (shocks are normally distributed). They characterize its equilibrium properties — in particular, the correspondence between interaction strength, number of agents, and the set of equilibria. There is an interesting conceptual difference between this model and the binary Brock and Durlauf formulation [Brock and Durlauf (2001a)]. In the latter, equilibrium in a group of interacting agents is derived by imposing a rational expectations condition on the subjective choice probabilities of the agents and by assuming that the number of agents is sufficiently large that each agent ignores the effect of his own choice on the average choice level. In contrast, Soetevent and Kooreman's model involves interactions in relatively small groups of given sizes in which choices of other individuals are assumed to be fully observed and therefore an individual's pay-off depends on the actual choice of others in her group — interactions are eponymous. In such a classic non-cooperative game setting, Soetevent and Kooreman focus on its one-shot pure Nash equilibria with binary outcomes, $\omega_i = 1, -1$, and estimate the model in effect as a system of simultaneous equations by means of simulation methods.[10] That is, the likelihood of a choice pattern $\widetilde{\omega} = (\omega_1, \ldots, \omega_I)$ is the product of the individual likelihoods for all individuals:

$$\epsilon_i > \alpha x_i + \theta \mathbf{z}_{g(i)} - \frac{\beta}{I-1} \sum_{j, j \neq i}^{I} \omega_j, \text{if } \omega_i = 1;\ \epsilon_i \leq \alpha x_i + \theta \mathbf{z}_{g(i)} - \frac{\beta}{I-1} \sum_{j, j \neq i}^{I} \omega_j, \text{if } \omega_i = -1. \quad (17)$$

Their empirical application examines individual behavior of high school teenagers in almost 500 school classes from 70 different schools using data from National School Youth Survey (NSYS) of the Netherlands. In their baseline model endogenous social interaction effects are strong for behavior closely related to school (truancy), somewhat weaker for behavior partly related to school (smoking, cell phone ownership, and moped ownership) and absent for behavior far away from school (asking parents permission for purchases). Intra-gender interactions are generally much stronger than cross-gender interactions. When school-specific fixed effects are allowed, social interaction effects are insignificant, with the exception of intra-gender interactions for truancy. The fact that they do find significant social interaction effects for a type of behavior closely related to school-based interactions (truancy), and do not find such effects for behaviors that might not be school-based, suggests that their model measures genuine endogenous social interaction effects rather than unobserved social group effects. This work is also significant because its simulation-based estimation method allows the authors to account for the potential multiplicity of non-cooperative Nash equilibria and the identification problems it poses.

Another interesting variation of our baseline discrete choice model is developed in Aradillas-Lopez (2008, 2009) and considers the question of identification of social effects when agents'

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[10] With many agents, the two formulations are equivalent, but the finite-agent case raises issues of identification which are common in models of systems of simultaneous outcomes. See Tamer (2003).

expectations are not necessarily correct. Aradillas-Lopez (2008) focuses on the empirical implications when beliefs are only required to be consistent with the iterated elimination of dominant strategies. Probability bounds are established for social interactions parameters which depend on the number of iterations. Aradillas-Lopez (2009) extends this type of reasoning to consider environments in which agents' behavior is required to obey a criterion known as weakly consistent equilibrium, which amounts to requiring that the choices of other agents always lies in the support over which an agent forms beliefs about these behaviors. These approaches provide a link between the social interactions literature and developments in behavioral economics.

In terms of empirical work, our baseline discrete choice model has been extended to consider dynamic contexts and in turn been applied to duration and optimal stopping problems. Sirakaya (2006) uses a national US sample to identify the risk factors for recidivism among female, male, black, white and Hispanic felony probationers. She assumes that the individual hazard function, the probability that a probationer will recidivate depends on individual and neighborhood characteristics as well as social interactions among probationers, that is: the hazard function for probationer i is assumed to depend on individual i's characteristics, $\mathbf{x}_i$, characteristics of i's neighborhood, $\mathbf{z}_{g(i)}$, and i's expectation of the proportion of probationers who recidivate by some duration in i's neighborhood, $m_{g(i)}(t)$, and the mean time to recidivate among them, $r_{g(i)}$, where time t varies continuously. That is:

$$m_i\left(t, \mathbf{x}_i, \mathbf{z}_{g(i)}, m_{g(i)}(t), r_{g(i)}\right) = \epsilon_0(t) \exp\left[\alpha_0 + \alpha \mathbf{x}_i + \theta \mathbf{z}_{g(i)} + \beta_m m_{g(i)}(t) + \beta_{time} r_{g(i)}\right], \quad (18)$$

where $\epsilon_0(t)$ denotes the baseline hazard function. Since, a probationer is required to live in the jurisdiction that passed the probation sentence, the neighborhood of probationer i, $g(i)$, is assumed to be the jurisdiction. That is, probationers do not endogenously sort into neighborhoods. Sirakaya's results point to social interactions as one of the most significant factors affecting recidivism within all gender, ethnicity and race groups with unobserved neighborhood-level heterogeneity being negligible. Other significant factors are being male, being young, unemployed, having a drug abuse history and prior felony convictions, and living in neighborhoods with high serious violent crime per capita for Blacks.

A number of other studies are closely related to Sirakaya's methodological framework.

Irwin and Bockstael (2002) argue that the development of adjacent parcels of land in exurbia may confer benefits, if proximity is desired, but also costs, if congestion and environmental degradation arise. They estimate net social interaction effects in exurban land use development that are negative. A second is Costa and Kahn (2007), who use a longitudinal data set of Union Army soldiers and a cross-sectional data set of the population of Andersonville to examine the role of social networks in ensuring survival of Union Army soldiers in captivity. They use the panel data to estimate hazard functions for individual survival probabilities as functions of the number of friends, individual characteristics, and camp conditions, and the cross-sectional data to estimate a probit model of the probability of survival as a function of the number of friends and of demographic characteristics. They find that friends had a statistically significant positive effect on survival probabilities (which theoretical considerations make it ambiguous) and that the closer the ties between friends as measured by such identifiers as ethnicity, kinship, and the same hometown the bigger the impact of friends on survival probabilities. De Paula (2009) uses the same data and finds evidence of bunching in desertions that is consistent with social interactions. His analysis is based on a sophisticated optimal stopping problem with endogenous social interactions whose econometric properties are carefully examined.

4 Identification: Contemporary Perspectives

In our discussion of social interactions, we made what is conventionally regarded as the "best case" assumption on the error structure, namely that individual unobservables are exchangeable across individuals and groups. In other words, there is no basis on which to differentiate the errors according to the observable information on the individuals and the associated groups of which they are members. Much of modern econometric practice has, of course, developed in a systematic effort to avoid such assumptions [*cf.* Heckman (2001)]. In this section, we explore the implications of two deviations from these assumptions: self-selection into groups and the presence of group level unobservables.

4.1 Identification of Social Interactions with Self Selection to Groups and Sorting

For many contexts, most notably residential neighborhoods, it is natural to assume that economic agents choose their group memberships and that these choices are influenced by social interaction effects. Endogenous group formation of this type naturally affects the distribution of the unobserved heterogeneity within groups which depends on both endogenous and contextual effects, as well as individual specific characteristics., i.e. in equation (7), $\mathcal{E}\{\epsilon_i|\mathbf{x}_i, \mathbf{z}_{g(i)}; m_{g(i)}; i \in g(i)\} \neq 0$. This means that data taken from environments with endogenous group choice suffer from the standard self-selection problem. Since self-selection into a group means that each member of the group has been influenced by a common set of social factors, this leads to dependence in the conditional expectations across individuals; Manski (1993) refers to this as correlated effects. It is easy to see that the failure to account for correlated effects can produce spurious evidence of social interactions.

The social interactions literature has followed the broader econometric literature in developing strategies to address self-selection. A number of studies have employed instrumental variables methods; see Evans, Oates and Schwab (1992). Instrumental variables approaches can be problematic. The basic problem is that empirical social interactions models tend to be open-ended [Brock and Durlauf (2001b)], in the sense that the underlying behavioral model for the phenomenon under question does not naturally generate valid instruments, i.e. there is typically no reason outside of "intuition" why an instrument may be used. This contrasts with the case in the estimation of Euler equations, in which a theory of interest is used to produce a forecast error, which naturally generates instruments via the information set that was used to construct the implied forecasts.

A second, in our view, more promising strategy, follows the control function approach pioneered in Heckman (1979). From this vantage point, self-selection is addressed in a way that respects the fact that it constitutes an additional behavior on the part of individuals. Following Heckman, suppose that evaluation of the attractiveness of a group g may be expressed in terms of an unobservable "latent" quality variable $Q^*_{i,g(i)}$. That is, individual i

evaluates group g by means of observable attributes $W_{i,g(i)}$ which enter with weights ζ, and unobservable component $\vartheta_{i,g(i)}$:

$$Q^*_{i,g(i)} = \zeta W_{i,g(i)} + \vartheta_{i,g(i)}. \tag{19}$$

Random shocks ϵ_i and $\vartheta_{i,g(i)}$ are assumed to have zero means, conditional on (are orthogonal to) regressors $(\mathbf{x}_i, \mathbf{z}_{g(i)}, W_{i,g(i)})$, across the population. If individual i were to choose the group which affords her the highest possible evaluation, then the respective shocks no longer have zero means. For various classes of parametric and semiparametric assumptions on the joint distribution of $(\epsilon_i, \vartheta_{i,g(i)})$, conditional on choosing group $g(i)$, an expression for $\mathcal{E}\{\epsilon_i|\mathbf{x}_i, \mathbf{z}_{g(i)}; i \in g(i)\}$ may be obtained as proportional to a function $\delta(\zeta, W_{i,g(i)}; W_{i,-g(i)})$, so that (7) may be rewritten as:

$$y_i = \alpha_0 + \alpha \mathbf{x}_i + \theta \mathbf{z}_{g(i)} + \beta m_{g(i)} + \kappa \delta(\hat{\zeta}, W_{i,g(i)}; W_{i,-g(i)}) + \xi_i. \tag{20}$$

Note that the selection correction term depends on the attributes of all groups in the opportunity set, not only the one that is chosen. This model is estimable.[11]

Equation (20) integrates information about the group selection process into the behavioral equation for outcomes and in fact does so in a way that provides additional information on social interactions. The additional regressor $\delta(\hat{\zeta}; W_{i,g(i)}, W_{i,-g(i)})$, affects the structure of the linear in means model relative to the reflection problem. To see why, consider two possibilities. First, suppose that groups are chosen according to the individuals' characteristics $\mathbf{x}_i$ and the group's characteristics $\mathbf{z}_{g(i)}$. If so, then the additional regressor will take the form $\delta(\hat{\zeta}; \mathbf{x}_i; \mathbf{z}_{g(i)}, \mathbf{z}_{-g(i)})$. As such it constitutes an individual specific random variable whose group level average does not appear in the equation. Second, suppose that groups are chosen according to expected average behavior in the group. In this case δ will functionally depend on $m_{g(i)}$, i.e. $\delta(\hat{\zeta}; m_{g(i)}, m_{-g(i)})$, where $m_{-g(i)}$ refers to groups other than $g(i)$. Since δ is almost always a nonlinear function, its introduction transforms the linear in means model to a nonlinear one. Both of these changes are sufficient to produce identification even if the model were not identified under random assignment. The ability of self-selection to facilitate

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[11] Brock and Durlauf (2001b; 2006) provide more details on the econometric properties of the estimation process.

identification is, at one level, not a surprise. Since group choice is a behavior, it naturally contains information about the determinants of the choice. What is perhaps more surprising is that this is a case where randomization works to the detriment of identification.

Ioannides and Zabel (2008) exploit the first of the above possibilities in an application of housing demand with neighborhood effects. Individuals choose neighborhoods and the quantity of housing. By working with the neighborhood clusters subsample of the National American Housing Survey (NAHS) and the confidential version of the NAHS, Ioannides and Zabel identify the neighborhood in which each dwelling unit is located and thus link with rich contextual information. Their results for the neighborhood choice model suggest, roughly speaking, that individuals prefer to live near others like themselves. Their estimation of the demand equation for housing structure allows for contextual effects, defined in terms of demographic characteristics in the census tract of residence, and for endogenous social effects, defined as the mean housing demand among neighbors. Their estimation results confirm that the endogenous neighborhood effect is significant and stronger (at 0.8504 instead of 0.7254) when endogeneity of neighborhood choice is accounted for. Endogenous effects are smaller when cluster-specific random effects are included.

A third route to addressing self-selection in estimating social interactions follows from consideration of prices for group membership. It is natural to expect that self-selection into residential neighborhoods will be reflected in housing prices, making them prices of admission into neighborhoods. Such prices may be thought of as hedonic prices and are often estimated as arbitrary functions of neighborhood amenities. Not surprisingly in view of Brock and Durlauf's results on the role of self-selection, Nesheim (2002) shows that preferences and the technology of social interactions, measured as children's schooling as a function of the mean parental education in the neighborhood and of parental characteristics,[12] may be identified,

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[12] This is often posited and the associated sorting bias emphasized. See Brooks–Gunn *et al.* (1993), Kremer (1997), who estimates schooling as a function of parental schooling and neighborhood schooling and assesses the implied role of sorting in inequality, and Ioannides (2003), who shows by means of non-parametric estimation techniques with the same data as those used by Kremer that non-linearities in the general relationship, whose special case is estimated by Kremer, may alter his key results. Educational outcomes for children are sigmoid functions of parental schooling and neighborhood schooling, allowing for

in principle, provided that the endogeneity of the hedonic price is acknowledged. This allows one to control for dependence between equilibrium marginal price and neighborhood quality. It is facilitated by an explicit solution for the hedonic price in terms of the mean parental education in the neighborhood [Nesheim (2002); Ioannides (2008)].[13]

A fourth strategy for integrating group choice with social interactions has involved estimation of equilibrium models of neighborhood formation in which social interactions play a role in locational decisions. Bayer, Ferreira, and McMillan (2007) employ a discrete choice model to estimate preferences over neighborhood composition with respect to housing choices. Calabrese, Epple, Romer and Sieg (2006) estimate a sophisticated structural model which explicitly addresses the political economy of local educational expenditure in which neighborhood composition is shown to affect neighborhood choice.

4.2 Group-level Unobservables

The second basic problem facing econometric analyses of social interactions is the presence of unobserved group effects. In considering a classroom, for example, it is evident that differences in teacher quality will simultaneously affect all students in a classroom. Manski (1993) refers to this as the problem of correlated unobservables. From the perspective of our basic social interactions models in sections 3.1 and 3.2, these may be understood as replacing the initial error assumptions with $\alpha_{g(i)} + \epsilon_i$, where $\alpha_{g(i)}$ is a common group-specific shock. Of course, one can imagine more elaborate changes in the error structure so that, for example, group effects have differential impact across agents, but this has not been the focus of the econometric literature.

In our view, unobserved group effects represent the most difficult hurdle to the construction of compelling evidence of social interactions. The reason for this is that, unlike the case of self-selection, there is typically no economic reasoning that can be brought to bear to

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multiple equilibria.

[13] Bayer, Ferreira, and McMillan (2007) report some nonstructural hedonic regressions of housing prices on neighborhood characteristics. See also Bayer and Ross (2009) who propose using neighborhood prices to construct a control function to proxy for unobserved neighborhood characteristics.

model unobserved group influences. Hence there is no natural solution to group effects that is analogous to the joint modeling of group formation and behaviors within groups. The methods that exist for overcoming their presence are thus essentially statistical.

One approach, unsurprisingly, involves the use of panels to difference out the group effects. This approach is put to good use in Hoxby (2000). Intuitively, variation in $\mathbf{z}_{g(i)}$ over time induces variation in $m_{g(i)}$ overtime and so produces identification in the differenced model. For Hoxby's model, $\mathbf{z}_{g(i)}$, is the percentage of a student's own ethnic group in a classroom. Brock and Durlauf (2007) show that this argument can be readily applied in panels with discrete data, using ideas due to Chamberlain (1984). This justifies the approach taken in Arcidiacono and Nicholson (2005) in evaluating the effects of peers on specialty choice in medical school. This approach, of course, requires that the assumption that $\alpha_{g(i)}$ is itself not time varying. Further, this treats the individual fixed effects as a nuisance parameter. Arcidiacono, Foster, Goodpaster, and Kinsler (2007) consider a linear model in which the spillover effects operate through the fixed effects of a student's peers making fixed effects for one agent influence others. They provide conditions under which these effects can, in a panel, be exploited to facilitate identification of social interactions.

This class of strategies for dealing with group level unobservables can be problematic when errors do not enter the model additively. Cooley (2008) shows how social interactions may be identified for a class of models with nonadditive group effects, exploiting results in Imbens and Newey (2009). This allows for interesting differences in social interaction effects across quantiles of observable characteristics. Cooley applies the strategy to school data in North Carolina, finding strong evidence of intra-ethnic group social interactions in achievement. Cooley's approach does require the use of instrumental variables, which of course constitutes a second general strategy for dealing with unobserved group effects, albeit one that can be hard to justify because of theory openendedness. Given the fact that unobserved group effects are often undertheorized, openendeness is especially hard to overcome in finding plausibly valid instruments. On the other hand, as the careful discussion in Cooley shows, it is not impossible given a specific context.

4.2.1 Variance Based Approaches

An alternative strategy for uncovering social interactions in the presence of unobserved group effects is based on the variance covariance structure of outcomes. One approach is due to Graham (2008) and extends the variance comparisons of the type initially suggested by Glaeser, Sacerdote, and Scheinkman (2003). To understand the method, we follow Graham and make two substantive modifications of the linear-in-means model. First, any observable individual and contextual controls are ruled out. Second, behaviors depend on the realized rather than expected choice of others, that is on $\bar{y}_{g(i)}$ rather than on $m_{g(i)}$. This leads to the model

$$y_{i,g(i)} = k + \beta \bar{y}_{g(i)} + \epsilon_{i,g(i)} = k + \beta m_{g(i)} + \beta [\bar{y}_{g(i)} - m_{g(i)}] + \epsilon_{i,g(i)}. \tag{21}$$

It is easy to see that the regression approach cannot uncover the presence of endogenous social interactions if averages of the individual-level determinants are used to instrument for $m_{g(i)}$. However, Graham shows that identification can still be achieved if one places some structure on (21). In doing this, he employs an approach that echoes the classical literature on identification in simultaneous equations models, in which the structure of the variance covariance matrix of the reduced-form system augments identification via exclusion restrictions. The key to this approach is assuming that the unobserved group effects are random rather than fixed effects, which imposes structure on the variance covariance of outcomes. The random effects assumption can be unappealing in contexts where groups are endogenously formed, but is more appealing in Graham's case since teachers are randomly assigned to classrooms.

To see how a random effects assumption facilitates identification, suppose that the residuals in (21) can be decomposed as

$$\epsilon_{i,g} = \vartheta_g + \eta_{i,g}, \tag{22}$$

where ϑ_g is a group level unobservable and $\eta_{i,g}$ is an individual level unobservable; each has mean 0 and constant variance across i and g; further the two variables are uncorrelated with each other. These assumptions imply that for a group of size n, the variance covariance matrix of the vector of $\epsilon_{i,g}$'s will equal

$$\mathbf{V}_n = \sigma_\vartheta^2 \mathbf{1}_n + \sigma_\eta^2 \mathbf{I}_n,$$

where $\sigma_\vartheta^2 = \mathrm{Var}(\vartheta_g), \sigma_\eta^2 = \mathrm{Var}(\eta_{i,g}), \mathbf{1}_n$ is an $n \times n$ matrix of 1's and $\mathbf{I}_n$ the $n \times n$ identity matrix, so that the variance of average outcomes in groups of size n equals

$$\mathrm{Var}[\bar{y}_g] = \left[\mathbf{I}_n - \frac{\beta}{n}\mathbf{1}_n\right]^{-1} \mathbf{V}_n \left[\mathbf{I}_n - \frac{\beta}{n}\mathbf{1}_n\right]^{-1}.$$

This last expression indicates how the parameters $\beta, \sigma_\vartheta^2, \sigma_\eta^2$ can be recovered from size-specific group variances. Graham (2008) and Durlauf and Tanaka (2008) discuss ways to modify Graham's baseline assumptions and preserve identification. For example, the latter paper shows that identification is preserved when independence of within classrooms is replaced by exchangeability. An especially valuable study is Davezies *et al.* (2006) which provides a systematic discussion of the use of the variance covariance matrix of residuals for the linear in means model to facilitate identification; they also provide results for binary choice models. A nice feature of their work is the clarification of when homoskedasticity assumptions are needed.

Graham's approach decomposes the unconditional between-group variance of outcomes into the variance of group-level heterogeneity (here, due to teacher quality), the between-group variance of any individual-level heterogeneity (here due to variance of average student ability across classrooms), and a third term that reflects the strength of any social interactions. Graham uses data from Project STAR, a class-size reduction experiment in Tennessee. In that experiment, kindergarten students and teachers were randomly assigned to large and small classrooms. Whereas in large classrooms, performance of talented students is typically offset by that of below average students, resulting in little variation in mean student ability, in small classrooms groups being composed of mostly above or below average students are more frequently observed, thus generating greater variation in mean ability. As a result, the variance of peer quality is greater across the set of small classrooms than it is across the set of large classrooms, while random assignment of teachers ensures that the distribution of their characteristics is similar across the two types of classrooms. Graham (2008) reports differences in peer group quality which constitute evidence of social interactions.

4.2.2 Variance Components and Social Interactions

The use of variance information has been exploited in a different way by Solon, Page and Duncan (2000). The analysis focuses on the case where one cannot observe either family-specific or group-specific effects. Solon, Page and Duncan propose a variance decomposition of individual outcomes to bound the contribution of group effects. One can formulate their analysis in terms of a variance components decomposition [Searle, Casella and McCullough (2006)]:

$$y_{i,f,n} = \mu_f + \nu_n + o_{f,n} + \epsilon_{i,f,n}, \tag{23}$$

where μ_f denotes a family effect, ν_n denotes a group effect, $o_{f,n}$ denotes an interactive effect between family and group and $\epsilon_{i,f,n}$ denotes an idiosyncratic effect. Assuming that these components are orthogonal (and such a decomposition of $y_{i,f,n}$ always exists), one can calculate the variance contribution of $o_{f,n} + \epsilon_{i,f,n}$ to the overall variance of $y_{i,f,n}$. Solon, Page and Duncan do not use this decomposition directly, instead they use sibling versus neighbor covariances to bound the variance of ν_n, finding little evidence that neighborhoods affect education.

One limitation of this approach is that it reduces the vector of social interactions defined by $\mathbf{z}_g$ into a scalar corresponding to $\frac{\beta\alpha+\theta}{1-\beta}z_g$; as such one cannot tell whether the lack of aggregate influence of neighborhoods is due to social influences of others nor can one tell whether the individual components are canceling each other out. Another limitation is that the presence of $o_{f,n}$ can make interpretations problematic, although Solon, Page and Duncan argue that one can assume the term is positive due sorting across neighborhoods. For these reasons, Oreopoulos (2003) is a particularly interesting application of the correlation method. This paper uses data from Toronto that allow one to trace the adult labor market outcomes of children who grew up in different public housing projects; these projects differ in terms of neighborhood characteristics such as crime. The restriction to public housing project differences simplifies the interpretation of variance decompositions in terms of social interactions since one can more easily conceptualize reasons for public housing neighborhoods to differ than neighborhoods in general. Further, since assignment was random across public housing projects, this eliminates correlations between individual and neighborhood characteristics. That said, Oreopoulos also finds that social interactions fail to play a large role in explaining differences in adult economic outcomes.

4.2.3 Partial Identification with Nonlinear Models

A final approach to unobserved group effects is due to Brock and Durlauf (2007), who develop partial identification results for binary choice models under what they argue are weak assumptions about the distribution of the unobserved group effect. The basic idea of this work is to exploit an essential difference between endogenous effects and unobserved group effects: only endogenous effects can produce multiple equilibria. Hence, if evidence of multiple equilibria can be generated, it represents evidence of social interactions.

Brock and Durlauf operationalize this in several ways. First, they consider the use of "pattern reversals" in group level outcomes. A pattern reversal occurs when the rank order of average outcomes between two groups is the reverse of what one would predict given the observed individual and contextual effects for the groups. Brock and Durlauf then demonstrate that under various shape restrictions on the probability density of the unobservables, pattern reversals can only occur because of social interactions. For example, if the distribution of unobservables shifts monotonically in observables, then pattern reversals cannot occur without social interactions. A second approach involves the bimodality of linear combinations of contextual effects. Here Brock and Durlauf show that, conditioning on a common average outcome, the cross section distribution of certain linear combinations of contextual variables must be unimodal. This last result corrects a misconception that multiple equilibria induce multimodality of average outcomes conditional on contextual effects; while multiple equilibria do induce a mixture density of outcomes, not all mixtures are multimodal.

Brock and Durlauf (2009) extends this idea to the study of social effects in technology adoption. In this analysis, individuals are motivated to adopt a new technology by both individual observable and unobservable characteristics (which may be correlated across individuals) as well as by the percentage of the population that has adopted, which defines the social interactions effect. They provide conditions under which a higher adoption rate by individuals whose observable fundamentals predict a lower adoption rate than another group can only occur because of social effects. This pattern reversal does not occur due to multiple equilibria but rather due to the potential for social effects to lead agents with different private incentives to bunch and adopt simultaneously. As such the analysis complements the more structural one of de Paula (2009) as well as a subtle investigation by Young (2008) on the observational differences between learning and conformity models in dynamic environments.

While partial identification arguments of the Brock-Durlauf type have not been used empirically, one does find analyses that may be interpreted in this way. For example, Card, Mas, Rothstein (2008) evaluate Schelling's classic tipping model of segregation by a search for discontinuities in the relationship between changes in neighborhood racial composition and initial racial composition. We conjecture that this achieves partial identification of the effect of neighborhood composition on individual utility so long as one imposes a continuity assumption on the density of unobservables, which is what Brock and Durlauf (2009) call a shape assumption.

For many forms of social interactions, endogenous group formation can produce assortative matching. One intuition follows from the Becker (1973) marriage model and can be generalized in a number of ways [Durlauf and Seshadri (2003)]: social interactions can represent complementarities and mean that stratification is efficient. One example for this is human capital complementarity across workers. In other contexts, such as neighborhoods, social interactions can produce incentives to stratify regardless of whether the stratification is efficient; Becker and Murphy (2000) give a nice exposition of this property for residential neighborhoods. These theoretical results suggest that another strategy for uncovering social interactions could involve the evaluation of degrees of stratification across groups. While there does exist a literature on the identification of complementarities via stratification patterns, see Eeckhout and Kircher (2009), Fox (2009), and Siow (2009) for recent studies, this method has yet to be used to uncover social interactions per se. The closest example of this strategy is Card, Mas and Rothstein (2008) discussed above as it uses changes in the degree of segregation as the basis for inferences. It should be noted that methods for estimating neighborhood choices as exemplified in Epple and Sieg (1999) are explicitly designed to explain the intragroup distributions of characteristics, so our suggestion should be understood as complementary to this structural style of work.

While we have focused on partial identification in social interactions contexts, it is important to note that there is a broader literature on partial identification in games, much of which is driven by multiple equilibrium issues; Tamer (2003) is a seminal contribution and Berry and Tamer (2006) and Pakes (2008), are valuable overviews of this approach in the context of industrial organization. Most recently, work has been done to address the construction of sharp bounds in such games, see Beresteanau, Molchanov, and Molinari (2008), and Galichon and Henry (2008).[14]

4.3 Experiments

As is true for much of economics, concerns over the assumptions needed to achieve identification with observational data have led to substantial interest in experiments and quasi-experiments as ways to uncover social interactions. Experimental approaches have been applied to a wide range of scales and contexts. The experimental approach has seen little direct work on econometric issues, relying on the existing treatment effect methods to study social interactions. One exception is Hirano and Hahn (2009) who study design issues for social interactions experiments. Another is Graham, Imbens and Ridder (2008) who formulate measures of changes in group composition on group outcomes that generalizes standard treatment effect calculations to explicitly consider social interactions.

At one end of the scale, interest in the effects of residential neighborhoods led the Department of Housing and Urban Development in 1994 to implement the Moving to Opportunity (MTO) demonstration in Baltimore, Boston, Chicago, Los Angeles and New York.[15] The

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[14] We thank Andres Aradillas-Lopez for suggesting the importance of this literature to social interactions analysis.

[15] MTO was at least partially motivated by a previous intervention known as the Gautreaux program, which involved moving some public housing families in Chicago to other parts of the city and other families to nearby suburbs. As a means of evaluating social interactions, the Gautreaux data suffer from the absence

program provides housing vouchers to a randomly selected group of families from among residents of high-poverty public housing projects. Within this subsidized group, families in turn were randomly allocated between two subgroups: one which received unrestricted vouchers; and another which received vouchers that could only be used in census tracts with poverty rates below 10% (these users are termed the experimental group). Members of the experimental group also received relocation counseling.

The data from the MTO program have been used by a number of researchers to evaluate social interactions; Kling, Liebman and Katz (2007) is the state of the art study both in terms of methodology and coverage across all study sites; earlier analyses include Ludwig, Duncan and Hirschfeld (2001) and Kling, Ludwig and Katz (2005). Following Kling, Liebman and Katz, social interactions are inferred when evidence is found that movement to low poverty neighborhood affects socioeconomic outcomes. In doing this, the authors calculate both intent to treat and treatment on the treated effects, corresponding to the effects of receipt of the voucher and use of the voucher respectively.

Overall, Kling, Liebman and Katz (2007) find at best mixed evidence on the effects of movement to lower poverty communities, even though the housing voucher lottery caused otherwise similar groups of families to reside in very different neighborhoods. For adults, their analysis revealed little evidence that movement to low poverty neighborhoods affected economic self-sufficiency although some improvements occurred in mental health. In terms of the children, they find that beneficial effects for teenage girls with respect to education, risky behavior and physical health. On the other hand, for teenage boys, relocation to lower poverty neighborhoods was associated with deterioration of a number of socioeconomic outcomes, in particular with respect to criminal behavior. The evidence that effects of housing vouchers appear to accrue from changes in neighborhood characteristics rather than from moves per se suggests that interventions which substantially improve distressed neighborhoods could have effects as least as large as those observed from moving to lower-poverty

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of information about families that moved to suburbs and then returned as well as from substantial screening of eligible families. For example, eligibility required a track record of good treatment of public housing units. Rosenbaum (1995) is a good overview of Gautreaux findings.

neighborhoods.

While the MTO program is a unique evidence source, there are a number of limitations to the use of existing findings of program effects to either draw policy implications or even to infer the empirical salience of social interactions. One general problem is that only one quarter of eligible families signed up for MTO, which also suggests that decisions are influenced by unobservables. These statistics also suggest that the respective populations are not representative. In terms of policy, one criticism is due to Sobel (2006) who argues that different respondents' outcomes are correlated, which is known as interference among respondents. Using the MTO demonstration as a concrete context, Sobel provides a causal framework for policy evaluation when interference is present. He characterizes the properties of the usual estimators of treatment effects, which are unbiased and/or consistent in randomized studies without interference. When interference is present, the difference between a treatment group mean and a control group mean does not estimate an average treatment effect, but rather the difference between two effects defined on two distinct sub-populations. This result means that a researcher who fails to recognize it could infer that a treatment is beneficial when in fact it is not. Kling *et al.* (2007) reject the argument of interference by pointing to the fact that 55% of household heads who signed up for MTO had no friends, and 65% no family in their baseline neighborhoods. However, to the extent that interference did not occur, then it is unclear how to extrapolate the program to larger policy interventions. In particular, Durlauf (2004) argues that moving large numbers of poor families to more affluent communities will induce general equilibrium effects in terms of the location decisions of other families, the ability of schools in these neighborhoods to provide needed services, etc. One can additionally imagine that the commitment of affluent families to public schools would be strained by a massive influx of poor families into their communities.

In terms of the question of the empirical salience of social interactions, MTO studies suffer from the lack of attention to mapping between treatment parameters and the underlying social interactions. A range of neighborhood characteristics generate social interaction effects; the role model effects of affluent neighbors are quite distinct from the support mechanisms that are generated by proximity to friends and relatives. MTO families who moved to low poverty neighborhoods did not simply move from worse to better neighborhoods, rather they traded off one vector of neighborhood attributes for another. This also renders the interpretation of positive evidence of voucher effects problematic. One example is discussed by Kling, Liebman and Katz: the reduction in asthma among children who move to low poverty neighborhoods. One reason this may occur is due to stress reduction; to the extent this is generated by neighborhood characteristics this is reasonably a social interaction effect. Another reason for lower asthma rates, however, could be reduced exposure to vermin infestations, which in turn could be a consequence of changes in housing quality induced by the requirement that the vouchers were used in low poverty neighborhoods. This is not a social interactions effect.

Another study in this class is due to Angrist and Lang (2004) and focuses on Boston's Metropolitan Council for Educational Opportunities (METCO). This is a voluntary desegregation program that involves enrolling underprivileged inner city children in suburban public schools. Angrist and Lang (2004) show that the receiving school districts, which have higher mean academic performance than the sending ones, do experience a mean decrease due to the program. However, they also show that the effects are merely compositional in that there is little evidence of statistically significant effects of METCO students on their non-METCO classmates. Their analysis with micro data from one receiving district (Brookline, Massachusetts) generally confirms this finding, but also produces some evidence of negative effects on minority students in the receiving district. Since METCO is a voluntary program for both sides and thus involves self-selection both at the individual and at the receiving end, at best it can be thought of as uncovering treatment on the treated, which does not translate naturally into claims about social interactions per se for reasons analogous to the limitations of the MTO studies.

A second class of experimental studies have been conducted in laboratories, such as Falk and Ichino (2006). Their experiment involves workers who are assigned in pairs to stuff envelopes, with control being provided by subjects working alone in a room. These authors find that standard deviations of output are significantly smaller within pairs than between pairs and average output per person is greater when subjects work in pairs. They also predict theoretically that peer effects are asymmetric: low productivity workers are more sensitive to the behavior of high productivity workers as peers. They cannot confirm this claim directly but do so indirectly.[16] While the findings of the effects of working in pairs versus singly are quite clean, they do not reveal why the effects are occurring and cannot even differentiate between endogenous and contextual effects.

Another interesting study is Falk, Fischbacker, and Gächter (2009) who test endogenous social interactions in a laboratory experiment where each subject simultaneously is a member of two randomly assigned and economically identical groups with only "neighbors" being different.[17] In each group the subjects decides how much to contribute to a public good. Social interactions are said to be present if a subject's contribution in a given group depend on the contribution by the subject's respective neighbors' at the same time. Most of the subjects' contributions proved to be strongly influenced by the contributions of their respective neighbors. Still, about 10% of the subjects were not influenced by the behavior of their neighbors. And, once again, it is not clear what these effects say about behavioral primitives.

A third class of studies involve natural experiments, in which assignment of individuals to groups has occurred in a way that facilitates identification of social effects. Sacerdote (2001) exploits the effects of randomly assigned freshman year room and dormmates at Dartmouth College. Sacerdote estimates equation (7) with an individual's grade point average as a dependent variable, as a function of an individual's own academic ability prior to college

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[16] That is so, because with the data at their disposal for each subject they observe the output level only in the treatment he or she is assigned to but not the output level in the counterfactual treatment. However, the comparison of the quantiles of the distributions for the single and the pair treatment provide evidence that is consistent with the claim [*ibid.*, p. 53, columns 1 and 2, Table 1]. At low productivity levels, peer effects determine large differences in output between the pair treatment and the single treatment, while at high productivity levels the differences are small.

[17] The ideal data set would observe the same individual at the same time in different groups or neighborhoods. Obviously, it is very difficult for something like this to occur naturally. By contrast, it is possible to come very close to such a "counterfactual state" in the lab, where decisions are observed by the same subject at the same time in two otherwise economically identical environments, except for the fact that a person is systematically and differentially affected by the behavior of his neighbors in the two environments.

entrance, of his/her social habits, and of the academic ability and grade point average of roommates, finding that peers have an impact on each others' grade point average and on decisions to join social groups such as fraternities. He does not, however, find residential peer effects in other major decisions by college students, such as choice of college major. Interestingly, peer effects are smaller the more directly a decision is related to labor market activities. This illustrates an important limitation to many experimental studies, namely whether results in one context extrapolate to others in which the consequences of choices are larger.

Laschever (2008) exploits the random assignment of young American men to the military during World War I to define exogenously constructed peer groups. He then measures the impact of a group's unemployment rate from the 1930 Census on a veteran's own likelihood of being employed. The magnitude of the effect is quite large: a one percentage point increase in his peers' unemployment rate is associated with a half percentage point decrease in one's own expected employment. He further decomposes this effect into endogenous and contextual components and finds that the endogenous effect is at least four times as large as the contextual one. This lends some support to the hypothesis that the estimated social effect is due to referrals or informal job contacts.

A final class of studies follows the spirit of natural experiments but does not rely on identifying contexts where random assignment holds, but rather on other data features. Young and Burke (2001) uses differences in the terms of tenant/landowner agriculture contracts across Illinois to evaluate the importance of social norms on contract terms. They find that contract terms tend to focus on simple crop sharing rules that cannot be explained by standard contract theory. Frey *et al.* (2009) use an extraordinarily detailed data set on passengers from the 1912 sinking of the Titanic and argue that there exist evidence that social norms mattered in determining survival. While studies of this type cannot illuminate the sources of social forces, as they in essence identify similarities in intra-group behavior that do not appear to be plausibly explained by individual characteristics, they are an important source of evidence in favor of the general view that social interactions are meaningful determinants of behavior.

While we have emphasized some of the limitations of experimental studies, we should be clear that this does not imply either that the studies are uninformative or that their utility is lower than observational studies of social interactions. Rather, we seek to combat the presumption that experimental studies trump observational ones and that randomization should be regarded as the gold standard for empirical work. Each has a key role.

5 Social Interactions in Social Networks

Our discussion of empirical work so far has focused on social interactions models in which group influences are generated by relatively crude aggregates, normally the average characteristics or behaviors of others. In contrast, social network models provide a primary focus on the microstructure of interactions emphasizing heterogeneity in these interactions across individual pairs. Goyal (2007) and Jackson (2008) provide broad overviews of the new theories. Our objective here is to focus on the ways that social interactions analysis has been enriched by network thinking.

5.1 Models

Methodologically, social networks matter in social interactions contexts because they facilitate identification by breaking the reflection problem. This was originally recognized in Cohen-Cole (2006) and is systematically explored in Bramoullé, Djebbari, and Fortin (2009). These authors modify equation (7) so that in a linear-in-means model each individual has her own specific reference group within a social network with an arbitrary adjacency matrix $\mathbf{J}$ and the endogenous social effect is in terms of actual instead of expected actions of others. Using $\mathbf{Y}$ to represent the $I-$column vector with individual actions as its entries, we may generalize the linear in means model (7) to allow for an arbitrary set of pairwise interactions. In a linear setting, this could be accomplished by using an arbitrary $I \times I$ matrix $\mathbf{J}$. The literature has specified interactions more narrowly by defining $J_{ik} = 1$, if i is influenced by k, and $J_{ik} = 0$, otherwise. In graph theory, this is known as an adjacency matrix. In addition, the endogenous effect is defined as $\beta \mathbf{JY}$. In other words, each pairwise interaction has a endogenous interaction weight β or a weight zero and every contextual effect has a θ or zero, depending on whether or not the agents are directly linked. Given these assumptions, the vector counterpart of (7) is:

$$\mathbf{Y} = \alpha_0 \iota + \alpha \mathbf{X} + \theta \mathbf{JX} + \beta \mathbf{JY} + \varepsilon. \tag{24}$$

This system of equations retains a single parameter β for the endogenous social effect but allows for more complicated interactions among individuals.

If $|\beta| < 1$ then the properties of the adjacency matrix $\mathbf{J}$ ensure that $\mathbf{I} - \beta \mathbf{J}$ is invertible.[18] Solving (24) yields the reduced form:

$$\mathbf{Y} = \frac{1}{1-\beta} \alpha_0 \iota + \alpha \mathbf{X} + (\alpha\beta + \theta) \sum_{k=0}^{\infty} \beta^k \mathbf{J}^{k+1} \mathbf{X} + \sum_{k=0}^{\infty} \beta^k \mathbf{J}^k \varepsilon. \tag{25}$$

Assuming $\mathcal{E}\{\varepsilon | \mathbf{X}\} = 0$ and that for each i $J_{ij} \neq 0$ for at least one j, (individual i is socially connected with at least one other individual), equation (25) leads to:

$$\mathcal{E}\left\{\mathbf{JY} | \mathbf{X}\right\} = \frac{1}{1-\beta} \alpha_0 \iota + \alpha \mathbf{JX} + (\alpha\beta + \theta) \sum_{k=0}^{\infty} \beta^k \mathbf{J}^{k+2} \mathbf{X}. \tag{26}$$

Bramoullé *et al.*, Proposition 1 states that identification of social effects in equation (24) requires both $\alpha\theta + \beta \neq 0$, and matrices $\mathbf{I}, \mathbf{J}, \mathbf{J}^2$ be linearly independent. Moreover, in Appendix B they prove, when no individual is isolated, that the matrices $\mathbf{I}, \mathbf{J}, \mathbf{J}^2$ are linearly dependent if and only if $\mathcal{E}\left\{\mathbf{JY} | \mathbf{X}\right\}$ is perfectly collinear with regressors $(\iota, \mathbf{X}, \mathbf{JX})$. Otherwise, the network structure is rich enough to make the variables $(\iota, \mathbf{X}, \mathbf{JX}, \mathbf{J}^2\mathbf{X}, \mathbf{J}^3\mathbf{X}, \ldots,)$ serve as appropriate instruments that allow endogenous and exogenous effects to be identified. Of course, identification may fail for some particular structures, but generally it is network interactions that ensure identification.

Why does this condition allow for identification? Intuitively, accounting for network structure means that each individual i's behavior is associated with a set $\mathcal{E}\{\mathbf{Y}_{g(i)}\} = \mathbf{J}\mathcal{E}\{\mathbf{Y}\}$

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[18] If $\mathbf{J}$, a non-negative matrix, is indecomposable, then Debreu and Herstein (1953), Theorem III., p. 601, ensures that $\mathbf{I} - \beta \mathbf{J}$ is invertible, provided that β times the maximal eigenvalue of $\mathbf{J}$ is less than 1. This also holds under less stringent conditions. I.e., $\mathbf{J}$ is typically row-normalized and thus may be treated as a stochastic matrix for which $\mathbf{I} - \beta \mathbf{J}$ is invertible for less stringent conditions than indecomposability of $\mathbf{J}$.

of variables that need to be instrumented. Consider two other agents, j and k such that $J_{ij} = 0$, (i and j are not socially connected) is imposed a priori. When $J_{ik} = 0$ has not been imposed a priori, one can use the individual characteristics for j to instrument for $\mathcal{E}\{\mathbf{Y}_{g(k)}\}$ so long as j does directly affect k. In other words, network structure, by setting certain coefficients equal to 0, produces exclusion restrictions that are analogous to the rank and order condition in simultaneous equations analysis.

There exists a close relationship between social interactions and spatial econometrics models that only recently was recognized by researchers. Consider the canonical version of the linear social interactions model, in vector form, as in (24) above. This coincides with the classic Cliff-Ord model of spatial autocorrelation (SAR) with one spatial lag, $\mathbf{JY}$, but no spatial error structure [see Cliff and Ord (1981)]. Spatial autocorrelation of the error structure may be introduced and dealt with for estimation purposes. Since matrix $\mathbf{J}$ is row normalized, then the matrix $[\mathbf{I} - \beta\mathbf{J}]$ is invertible, and the above system may be rewritten in reduced form. Harry Kelejian and Ivar Prucha, and Lung-fei Lee have helped advance the frontier on asymptotic properties of spatial econometric models. Kelejian and Prucha (2008) offer a modern treatment of spatial models of econometrics. Bramoullé *et al.* (2009), as we discuss above, and Lee (2007) and Lee *et al.* (2008) emphasize that identification of peer effects in social interactions models may in fact be facilitated by network structure.

Lee *et al.* (2008) and Lin (2008) study the econometric properties and estimate a more general version of the social interactions problem with a network structure, which is specified in terms of groups $g = 1, \ldots, G$:

$$\mathbf{Y}_g = \beta\mathbf{J}_g\mathbf{Y}_g + \alpha\mathbf{X} + \theta\mathbf{J}_g\mathbf{Z} + \alpha_{0g}\iota_g + \varepsilon_g, \tag{27}$$

where $\mathbf{Y}_g$ is the column n_g-vector of outcomes for each member of group g and n_g the group's size, $\mathbf{J}_g$ the group g specified adjacency matrix, ι_g a column n_g-vector of ones, and ε_g, column n_g-vector of shocks, and α_{0g} is a group specific fixed effect. The adjacency matrices are row-normalized. This is a generalization of the typical SAR model. The shocks ε_g's may have a general variance-covariance matrix. However, the spatial econometrics literature has typically assumed that

$$\varepsilon_g = \rho\bar{\mathbf{J}}_g\varepsilon_g + \epsilon_g, \tag{28}$$

where $\bar{\mathbf{J}}_g$ is the group g specified error adjacency matrix, which may or may not be the same as $\mathbf{J}_g$, ϵ_g and denotes a n_g-column of i.i.d. shocks. This may be thought of as a generalization of variance based approaches with a more general interactions pattern.

A comparison of (24) and (27)–(28) indicates how network and spatial models are interrelated. Each assumes prior knowledge of the members of each agents group. Each assumes that interactions within a group are homogeneous, i.e. the same weight is assigned to each member of the group. The key differences lie in the introduction of an error structure corresponding to the network structure in the spatial econometrics case.

5.2 Empirics of Social Interactions in Social Networks

As we have emphasized, network models requires prior knowledge of the network structure. Relatively few data sets have this feature.[19] For this reason, economists have been especially interested in the Add Health data set. Add Health[20] is a US-based study that is designed to facilitate exploration of the causes of health-related behaviors of adolescents in grades 7 through 12, the structure of adolescent friendship networks, and individual outcomes in young adulthood. Add Health seeks to examine how social contexts (families, friends, peers, schools, neighborhoods, and communities) influence adolescents' health and risk-taking behaviors. It has become a major resource for social network analysis. In the remainder of this section we describe some of the most valuable studies using this data set.

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[19] Interesting exceptions may be found in the development literature, e.g. Conley and Udry (2009), who are able to study diffusion of technology across farmers, and the medical literature, in which Christakis and Fowler (2007,2008a, 2008b) use a remarkable data set, the Framingham Heart Study, which was originally constructed to study cardiac disease, to argue that obesity, smoking and happiness are all socially determined. Other studies involve the creative use of more standard data sets. One example is Head and Meyer (2008), who employ French birth data to study spatial patterns in names and identify social influences on name choices. Of course, remarkable data do not by themselves reveal social interactions; Cohen-Cole and Fletcher (2008a,b) strongly critique the Christakis and Fowler claims, based on the self-selection and unobserved group effects problems we have mentioned: Christakis and Fowler (2008c) is a response.

[20] The National Longitudinal Study of Adolescent Health (Add Health) `http://www.cpc.unc.edu/addhealth`.

Fryer and Torelli (2006) use academic achievement as a definition of “acting white” by nonwhite students to examine its relationship to popularity. They measure popularity in terms of a network-specific spectral popularity measure, which identifies popularity of the members of a group with the intensity of the social connections among the members of that group. It is derived from the eigenvector associated with the maximal positive eigenvalue of the adjacency matrix of each social group. Their data allows construction of the full adjacency matrix for school-based social groups. Specifically, this study can be seen as a simplified version of (24), where instead of the full system of simultaneous equations, achievement as an outcome is related to popularity, a statistic based on $\mathbf{J}$ in equation (24). They demonstrate that there are large racial differences in the relationship between popularity and academic achievement.

Weinberg (2007) reports on patterns on a broader set of behaviors. He finds that behavior for one’s associates are above the mean for own behaviors, and so are their grades and the educational accomplishments of their parents. A large part of the variation in friends’ grades, television watching, and family background arises within school grades. Regressing individuals’ characteristics against their own other characteristics and those of their friends produces strong positive associations, which may be due to residential sorting. In examining how endogenous association affects behavior, Weinberg predicts that hump-shaped difference in associations and behaviors between people with high and low predicted behaviors with respect to the share of the group with high predicted level of behavior is evidence of assortative matching. The empirical results confirm the hump shape. That is as the share of a social group with high (predicted) behavior increases, the mean behavior among their friends who have a high (predicted) behavior increases relative to others initially, and then declines as most of the macro-group has a high (predicted) level of that behavior.

Calvó-Armengol, Patacchini and Zenou (2009) estimate individual school performance as a function of the topology of their friendship networks, while controlling for individual characteristics, such as family background controls, residential group variables, contextual effects and school fixed effects. Specifically, they assume that the part of observed individual educational outcomes that are not explained for by individual characteristics are made up of network-component fixed effects, denoted by the vector η_g, and spatially autocorrelated errors, ε. This may be expressed in terms of the system (27)–(28), where $\mathbf{Y}$ are educational attainments, with the following modifications: $\beta = 0$, and the error structure in (28) allows for component-specific fixed effects:

$$\varepsilon = a\mathbf{J}_g\iota + \phi\mathbf{J}_g\varepsilon + \epsilon. \tag{29}$$

Since the error structure represents individual outcomes that are not explained for by individual characteristics, $\mathbf{X}$, and contextual effects, $\mathbf{JX}$, it reflects correlated effects and peer effects. So, their estimation of the stochastic structure of of (27) with (29) subsumes endogenous social effects into the estimation of (a, ϕ) above. Their results suggest that a one-standard deviation increase in their proxy for the Bonacich centrality index [Bonacich (1987)][21] translates into roughly 7 percent of a standard deviation in education outcomes. Interestingly, these authors' estimates of (a, ϕ), the effect on a school performance index of the number of each individual's friends and of the peer effect that is subsumed in the error structure change little if social interactions are allowed to be directional [*ibid.*, Table 3]. Testing alternative measures of network connectedness, that is centrality as measured by each individual's network degree, closeness, and betweenness shows that only degree centrality is significant.

Lee, Liu and Lin (2008) report results using the Lee *et al.* techniques. This application involves 74,300 observations belonging to 488 groups, defined as school-grades. The average group size is 119. Friendship networks within each school-grade group are modeled as components of the social network. These authors obtain significant positive estimates of β in equation (27), using study effort as an outcome, and negative ones for ρ, both for undirected and directed networks. Lin (2008) explores a variety of alternative network specifications, allows for spatial autocorrelation in the residuals, obtaining significant negative estimates of ρ in (27) and confirms that presence of spatial autocorrelation in the residuals makes a big

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[21] This concept teases out of the spectral properties of the normalized adjacency matrix the social importance of each individual, measured in terms of their social connectedness. The centrality of each individual in the social structure reflects the weighted sum of paths along the interaction structure of all different possible lengths.

difference in that it raises the estimates of the endogenous social effect.

6 Conclusions

Scholarly interest in social interactions has rapidly expanded in many areas of economics and led to numerous methodological and empirical advances. For theorists, key challenges include the development of analytically tractable frameworks that allow for the analysis for social interactions contexts in ways which accommodate increasingly rich forms of intertemporal as well as cross-section heterogeneity; in parallel to this theoretical work needs to find a more constructive role for simulations when analytical tractability is impossible.[22] For econometricians, key challenges include social interactions effects on market outcomes coexisting with feedbacks from the characteristics of individual market participants via their impacts on prices, consequences of self-selection and the attendant role of presence of individual and group unobservables. In the light of ever improving data availability, social interactions empirics will rely increasingly critically on careful theorizing that involves precise definitions of social interactions, possibly by calling on psychology and sociology to define appropriate social boundaries, and their scope, and must facilitate use of data from different sources. The likely payoff is enormous: better understanding of social forces in the modern economy, with individuals' sharing information while self-selecting into social groups and living and working in close proximity to one another as in firms and cities encapsulate much of what constitutes modern economic life..

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[22] So called agent-based models do involve the simulation of interaction populations of agents, but this work, in our view, has yet to embody interesting microeconomic foundations of the type found in the social interactions literature.

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