Identifying Social Interactions: A Review

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…political economy…does credit to thought because it finds the laws underlying a mass of contingent occurrences. It is an interesting spectacle to observe here how all the interconnections have repercussions on others, how the particular spheres fall into groups, influence others and are helped or hindered by these. This interaction, which seems at first sight incredible since everything seems to depend on the arbitrary will of the individual…bears a resemblance to the planetary system, which presents only irregular movements to the eye, yet whose laws can nevertheless be recognized.

G.W. F. Hegel, *Elements of the Philosophy of Right*[2]

1. Introduction

While economics has long focused on how individual decisions are interconnected via markets, there has for the last decade or so developed growing interest in understanding how social factors beyond the marketplace affect individual decisions and outcomes. Economic analysis now incorporates a range of dimensions in which individuals interact directly with one another, rather than indirectly via the effects of individuals on market prices. As noted by Manski (2000), the emergence of the social interactions literature parallels the rise of game theory, in which the key primitive assumptions are based on modeling how the behaviors of others affect an individual relative to general equilibrium theory, which focuses on the analysis of conditions under which markets can coordinate many individual decisions via a price system. Such direct interdependences in behaviors and outcomes are known in the economics literature as social interactions.

Economic research on social interactions has proceeded along theoretical as well as empirical lines.[3] In terms of abstract theory, the social interactions research has

[2] Allen Wood translation, Cambridge University Press, 1991, pg. 228.

[3] Surveys of different aspects of the economic approach to social interactions include Becker and Murphy (2000), Brock and Durlauf (2001b), Durlauf (2004) and Manski (2000). See also Sampson, Morenoff, and Gannon-Rowley (2004) for a sociological perspective.

followed two main directions. A first direction is the description of how interdependent decisions produce different aggregate configurations. Early examples of this work include Blume (1993,1995), Brock (1993), and Durlauf (1993); more recent research includes Brock and Durlauf (2001a,b,2004,2005), Bisin, Horst, and Ozgur (2004) and Horst and Scheinkman (2004). This sort of research investigates the appropriate specification of individual decisionmaking in the presence of social influences and the consequent implications of these influences for the behavior of population aggregates. One important message from this work is that the incorporation of social interactions into economic models is fully compatible with standard economic reasoning, in which individuals make purposeful decisions subject to constraints. A second direction evaluates the role of social interactions in determining how groups form. Research of this type includes Bénabou (1996), Durlauf (1996) and Hoff and Sen (2004). Perhaps unsurprisingly, the canonical example of endogenous group formation is residential neighborhoods; in fact, in economics, social interaction effects and neighborhood effects are used interchangeably.[4] These general structures have been used to develop theoretical descriptions of phenomena ranging from spatial unemployment patterns (Oomes (2003)) to welfare dependence ((Lindbeck, Nyberg and Weibull (1999)) to economic development and the transition from underdeveloped to modern economies (Kelly (1997)). These "applied theory" studies have typically been motivated by various empirical claims that seem hard to understand using other types of economic models. The sources of social interactions in various types of theoretical models are themselves varied. Some models assume that there are primitive psychological reasons why individuals wish to conform to the behavior of others while others focus on the information transmission that occurs when one person observes what others choose to do.

In parallel to this theoretical work, many empirical studies of social interactions now exist. Among the conventional economic phenomena that have been studied are public assistance use (Aizer and Currie (2004), Bertrand, Luttmer, and Mullainathan (2000)), labor market behavior (Conley and Topa (2002), Topa (2001), Weinberg,

[4]Following Akerlof (1997), individuals may be conceptualized as located in a general social space in which groups of commonly interacting individuals constitute a neighborhood.

Reagan, and Yankow, (2004)), agricultural contract specification (Young and Burke (2001)) and urban economics (Ioannides and Zabel (2003a,b), Irwin and Brockstaed (2002)). In addition, interest in social interactions has led economists to study phenomena that are traditionally in the domain of other social sciences such as crime (Glaeser, Sacerdote, and Scheinkman (1996), Sirakaya (2004)), choice of medical techniques by physicians (Burke, Fournier, and Prasad (2004)) and smoking (Krauth (2003,2004), Soetevent and Kooreman (2004)).

A third component of the new social interactions research program has been the systematic investigation of econometric issues. This econometric work primarily focuses on the determination of conditions under which various types of social interactions may be econometrically identified.[5] Identification arguments in this context amount to asking under what conditions on data and model can the role of social interactions effects be distinguished from other influences on behavior. Thus, identification analysis represents a key link between theory and empirics.

The econometric research program on the identifiability of social interactions was initiated in Manski (1993), a seminal paper that still warrants careful study; recent contributions include Brock and Durlauf (2001a,b,2004,2005), Glaeser, Sacerdote, and Scheinkman (1996), Graham (2005), Graham and Hahn (2004), Moffitt (2001) and Soetevent and Kooreman (2004). While the general econometrics of social interactions has not developed to the same extent as the theoretical and empirical literatures, there now exists a fairly wide range of results on identification.

In this chapter, we review some of the identification results that have been developed in the econometrics literature on social interactions. We will focus on two statistical frameworks in which social interactions have been embedded: linear models and binary choice models. The discussion avoids formal proofs in order to highlight major conceptual issues. The results we describe are not specific to economic contexts and so presumably may be useful for social epidemiologists as well.

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[5]There is also some work on estimation and computation issues, cf. Bisin, Moro and Topa (2002).

Section 2 describes the two statistical social interactions models which we will analyze. Section 3 describes the identification problems that arise when model errors are independent and identically distributed. This is a useful baseline for understanding how identification problems arise that are intrinsic to the structure of the behavioral process. Section 4 discusses how self-selection of individuals into groups affects identification. Section 5 analyzes identification in the presence of unobserved group effects. Section 6 relates the econometrics literature on social interactions to some aspects of the social epidemiology literature. Hierarchical models and models which incorporate social capital are studied. Section 7 provides summary and conclusions.

2. Basic models

To understand the main identification problems that arise in empirical studies of social interactions, we start with some notation and baseline models. These models, while not exhaustive, cover much of the economic social interactions literature and illustrate the main identification problems faced by a researcher attempting to adduce evidence that social interactions matter.

Individuals are denoted by i and groups are denoted by g. Each individual is a member of a single group; the composition of these groups is known to the researcher. In other words, prior to the statistical exercise, a researcher has determined the relevant environment in which social interactions are present. This is a standard assumption in social interactions analyses. For example, a researcher investigating the role of residential neighborhoods typically makes an ex ante decision on how neighborhoods are measured, i.e. via census tracts, etc. The analysis of social interactions when there is uncertainty about the correct specification of the relevant social groups has not been pursued, to our knowledge, although work such as Conley and Topa (2002) has attempted to compare the predictive power of different conceptions of neighborhoods defined in a general social space. In principle, one can incorporate model uncertainty about the correct social group for individuals into the econometric analysis of social interactions, cf. Brock, Durlauf and West (2003) for one way to proceed, but the implications for identification have not been explored; this seems an important area for future research.

Each individual makes a choice ω_i. These choices are assumed to depend on a combination of individual-specific and group-specific factors. The individual-specific factors come in two types: X_i, deterministic (to the modeler) characteristics associated with individual i, and ε_i, random and unobservable (to the modeler) characteristics associated with i. In the econometric analog to the theoretical model of choice under social interactions, ε_i corresponds to the random error in a regression. We assume in both the theoretical and econometric discussion that these random terms are independent and identically distributed across individuals. This means that the within-group distribution of ε_i does not depend on the individual's characteristics or the identity of the group of which he is a member

$$F_{\varepsilon_i|X_i,Y_g} = F_\varepsilon. \tag{1}$$

The assumption of i.i.d. errors will be relaxed in some directions when we discuss econometrics.

Group-specific factors are partitioned into Y_g, predetermined (with respect to decisions by individuals concerning ω) group-level characteristics, and $m_{i,g}^e$, the expected average choice in the group. In the economics social interactions literature, the role of Y_g in affecting individuals is known as a contextual effect whereas the role of $m_{i,g}^e$ is known as an endogenous effect and plays a central role in the discussion below. Contextual effects thus describe how the characteristics of others affect an individual's decisions whereas endogenous effects describe how the behaviors of others affect an individual's decision or choice. The importance of this distinction is that endogenous effects are usually understood to be reciprocal and thus create feedbacks between individual decisions. While behavioral endogeneity is rarely considered in other social sciences, from the economics perspective, social interactions have not been modeled at a deeper level than the endogenous/contextual effect distinction. An important open research question is whether attention to particular generative mechanisms, such as social interactions as a mechanism for information transmission, could facilitate identification.

The use of expected average choice rather than the realized average choice is made for analytical convenience. The assumption makes most sense for larger groups where the behaviors of the rest of group are not directly observable. The assumption that individuals react to expected rather than actual behaviors is not critical for the bulk of the identification analysis we describe; we will indicate where the assumption matters. See Graham (2005) and Soetevent and Kooreman (2004) for analysis of social interactions in small groups where all behaviors are observed.

To make this abstract description concrete, we follow discussion in Durlauf (2005) and consider the example of modeling the determinants of schooling outcomes among children. One class of explanations may focus on how parental characteristics affect these outcomes, as more successful parents are able to provide more educational resources to their children, provide role models that enhance their children's aspirations, etc. These sorts of determinants are captured by the vector X_i. In contrast, other theories might focus on the role of contextual influences, such as how the sorts of occupations observed across adults within a residential neighborhood affect student aspirations or how the distribution of incomes across families within the community affects decisions on the level of expenditures on education. These sorts of factors are captured by the vector Y_g. A final set of explanations may derive from direct interdependence between the educational outcomes of children; for example, high outcomes by one student may be induced by the desire of the student to perform as well as his peers. This type of explanation is captured by $m^e_{i.g}$.

How do these different factors combine to determine individual choices? We consider two formal frameworks. The first is a basic linear model with social interactions, originally studied in Manski (1993), in which outcomes are described by a linear model:

$$\omega_i = k + cX_i + dY_g + Jm^e_{i,g} + \varepsilon_i . \tag{2}$$

Note that k and J are scalars whereas c and d are vectors[6]. This model is typically not derived from a fully articulated decision problem for individual agents, but this can in principle be done. The model has the important virtue that it is easily interpreted as a regression and so may be directly taken to data, where the goal of the analysis is to estimate the parameters k, c, d, and J. Claims about social interactions are, from the econometric perspective, equivalent to statements about the values of d and J. The statement that social interactions matter is equivalent to the statement that at least some element of the union of the parameters in d and J is nonzero. The statement that contextual social interactions are present means that at least one element of d is nonzero. The statement that endogenous social interactions matter requires that J is nonzero.

A second useful model is the binary choice model with social interactions studied in detail by Brock and Durlauf (2001a,b). Following Brock and Durlauf (2001a,b), choices are coded so that they lie in the set $\{-1,1\}$. For example, -1 can denote *had a child while a teenager* while 1 denotes *did not have a child while a teenager*, if one is studying teenage fertility. This model is directly derived from an individual decision problem. Each choice is associated with a payoff level $V_i(\omega_i)$. The difference between the payoffs for the two choices is assumed to be additive in the different factors that have been defined, i.e.

$$V_i(1) - V_i(-1) = k + cX_i + dY_g + Jm_{i,g}^e - \varepsilon_i \, . \tag{3}$$

Individual i chooses 1 if and only if $V_i(1) - V_i(-1) > 0$, which is to say that an individual acts rationally in the sense that he makes the choice that makes him best off. Since

$$\begin{aligned} \Pr\left(V_i(1) - V_i(-1) \geq 0\right) = \Pr\left(\varepsilon_i \leq k + cX_i + dY_g + Jm_{i,g}^e\right) = \\ F_\varepsilon\left(k + cX_i + dY_g + Jm_{i,g}^e\right), \end{aligned} \tag{4}$$

[6]Throughout, coefficient vectors such as c are row vectors whereas variable vectors such as X_i are column vectors.

$\Pr\left(\omega_i = 1 \middle| X_i, Y_g, g\right)$, the probability that *i* chooses 1, is defined by

$$\Pr\left(\omega_i = 1 \middle| X_i, Y_g, g\right) = F_\varepsilon\left(k + cX_i + dY_g + Jm_{i,g}^e\right). \tag{5}$$

Neither the linear model nor the binary choice model has any empirical content without restricting how individuals form expectations about the average behavior of others. Otherwise, any set of observed behaviors could be reconciled with any set of model parameters by appropriate choices of $m_{i,g}^e$. In economics, the standard approach to closing the social interactions model is the requirement that expectations are consistent with the structure of the choices in the model. This property, known as self-consistency, means that the subjective expectation of the average choice in one's group corresponds to the mathematical conditional expectation of the average choice, m_g, given the information set of each agent. We assume these information sets include the values of X_i for other agents within *i*'s group, the value of Y_g, as well as the equilibrium expected choice level that occurs for his group. Agents are assumed to be unable to observe the choices of others or their random payoff terms ε_i. Alternative information assumptions will not affect the qualitative properties of the model. For the linear in means model, self-consistency means that

$$m_{i,g}^e = m_g = \frac{k + cX_g + dY_g}{1-J} = \frac{k + dY_g}{1-J} + \frac{cX_g}{1-J} \tag{6}$$

where X_g is the average of X_i within *g*. In simple terms, the mathematical expectation of average behavior in a group depends linearly on the average of the individual determinants of behavior, X_g, and the contextual effects that each member experiences in common, Y_g.

For the binary choice model, self-consistency means that

$$m_{i,g}^{e} = m_g = 2\int F_{\varepsilon}\left(k + cX + dY_g + Jm_g\right) dF_{X|g} - 1 \qquad (7)$$

where recall that $F_{X|g}$ is the empirical within-group distribution of X. The description of a process for individual choices combined with its associated self-consistency condition fully specifies a model.

From the perspective of economic theory, there is an important difference between the linear and binary choice models of social interactions: multiple equilibria can exist for the latter but not the former. A model exhibits multiple equilibria if its microeconomic structure is compatible with more than one aggregate outcome. For the models we have described, the only aggregate outcome of interest is the expected average choice level m_g. It is evident for the linear model that once one knows the individual and group characteristics within a group, there is only one expected average choice level that is consistent; eq. (6) maps these characteristics into a single m_g. In contrast, eq. (7) can produce more than one solution for m_g. In general, as shown in Brock and Durlauf (2004), for each value of Y_g and $F_{X,g}$ for a given group, there will exist a threshold H (which depends on these values) such that if $J > H$, then there are at least three solutions to (7) whereas if $J < H$ then the solution to (7) is unique.[7]

More precise results may be obtained if one specifies the functional forms for $F_{X,g}$ and F_{ε}, these different cases are analyzed in Brock and Durlauf (2001a,b,2004). For example, suppose that

$$F_{\varepsilon}(z) = \frac{1}{1 + \exp(-z)} \qquad (8)$$

[7] The knife edge case $J = H$ is conventionally ignored in theoretical studies since it is presumably a probability 0 possibility.

so that the model errors are negative exponentially distributed, and that $k + cX_i + dY_g = h$, so that this component of the payoff differential between the two choices is constant across group members. For this special case,

$$\Pr\left(\omega_i = 1 \middle| X_i, Y_g, g\right) = \frac{\exp\left(h + Jm_{i,g}^e\right)}{\exp\left(h + Jm_{i,g}^e\right) + \exp\left(-h - Jm_{i,g}^e\right)}. \tag{9}$$

Under self-consistency, the expected average choice level m_g within a group must obey

$$m_g = \tanh\left(h + Jm_g\right). \tag{10}$$

In (10), $\tanh\left(x\right) = \frac{\exp\left(x\right) - \exp\left(-x\right)}{\exp\left(x\right) + \exp\left(-x\right)}$. For this case, one can show formally that if $J < H$, then the equilibria is unique whereas if $J > H$ there are three equilibria, of which only the two extremal equilibria (in terms of the magnitude of m_g) are stable under dynamic analogs of the model. This special case is of interest since the assumption (8) corresponds to the logit regression model for binary choice.

Blume and Durlauf (2003) extend this work by considering a dynamic analog of the binary choice model with social interactions. This paper studies the stability of the self-consistent equilibria in the static model and finds that over time, a dynamic analog of this model will have the property that the population spends most of its time in the vicinity of the equilibrium that maximizes average utility, i.e. the equilibrium whose mean choice has the same sign as h. One question that has not been examined is whether the far-from-steady state behavior of the model can provide additional information on social interactions that is not present in a steady state. This is intuitively plausible since far-from-steady state behavior will obey a different probability process from steady state behavior, even though it derives from the same microeconomic foundations.

The assumption that each agent reacts to the mean behavior of the population is restrictive. Within the economic theory literature, there has been considerable attention to models in which interactions are local. In such models, agents are located in some sort of social space and interact only with those agents that, according to some metric, are near the agent. This type of work was pioneered in Föllmer (1974). Blume (1993,1995) provides a rigorous analysis of models of this type, employing formal game theoretic arguments; Kirman (1997) is a valuable survey. As far as we know empirical analogs of such models have not been formally investigated with respect to identification.

3. Identification and the reflection problem

In this section, we consider how the various determinants of individual behavior may be revealed empirically. We focus on a cross-section of data where individuals are sampled across a set of groups. The objective of a statistical exercise is to estimate the parameters *k*, *c*, *d*, and *J*; identification arguments will focus on whether more than one set of values for these parameters generate identical probability statements about ω_i. When discussing binary choice models, it is understood that identification means identification up to scale, i.e. to say that the parameters *k*, *c*, *d*, and *J* are identified means that any alternative set of parameters that produces the same probability statements about ω_i must be a multiple of the initial parameter set. The reason for this is that if one were to multiply all the parameters in (3) by a nonzero constant, individual behavior would be unchanged, since the choice is based on the comparison of the utility levels for each of the choices, not their absolute values.

The available data to a researcher are assumed to be ω_i, X_i and Y_g, the individual choices and associated individual-specific contextual effects, as well as $F_{X|g}$ and $F_{\omega|g}$, the empirical distribution functions for the individual characteristics and individual outcomes within each group of which the individuals are members. We do not consider whether other data can facilitate identification. One obvious candidate is price data on group memberships (e.g. housing or rental prices for different neighborhoods.) Work by

Ekeland, Heckman and Nesheim (2002,2004) and Nesheim (2002) suggests that such data may be very valuable from the perspective of hedonic pricing models Blume and Durlauf (2005) consider the information content of prices in the context of structural estimation.

The first problem which arises in the study of social interactions is the classic identification problem: under what conditions on the data, if any, can the different parameters in the linear model (2) and/or the binary choice model (5) be distinguished from an alternative set of parameters? Intuitively, the reason why identification may not hold is that the distinct roles of the endogenous effects and the contextual effects may be difficult to disentangle because the two types of effects move together. This comovement occurs because, when beliefs are self-consistent, the contextual variables Y_g help to determine the endogenous variable m_g as indicated by the self-consistency conditions (6) and (7). Thus the identification problem for social interactions bears much resemblance to the elementary identification problem that occurs in linear regressions when the regressors are not linearly independent.

Does the fact that endogenous and contextual social interaction effects are, by the logic of social interaction models, correlated, lead to a failure of identification? In the case of the linear regression model, the answer is yes. Specifically, without prior information about the relationship between the individual-specific characteristics X_i and the group-level characteristics Y_g, the linear model of social interactions is not identified. The possibility for nonidentification was first recognized by Manski (1993). To see why identification may fail for this model, assume, following Manski's original argument, that $Y_g = X_g$. This means that every contextual effect is the average of a corresponding individual characteristic. In this case, eq. (6) reduces to

$$m_g = \frac{k + \left(c + d\right) Y_g}{1 - J} \qquad (11)$$

which means the regressor m_g in (2) is linearly dependent on the other regressors, i.e. the constant and Y_g. This linear dependence means that identification fails: the comovements of m_g and Y_g are such that one cannot disentangle their respective influences on individuals. Manski (1993) named this failure the reflection problem; metaphorically, if one observes that ω_i is correlated with the expected average behavior in a neighborhood, (11) indicates it may be possible that this correlation is due to the fact that m_g may simply reflect the role of Y_g in influencing individuals.

Are there versions of the linear model where the reflection problem does not hold? The answer is yes. To see why it is possible for some linear models with social interactions to be identified, suppose that we relax the assumption that $X_g = Y_g$. In this case, as indicated by eq. (6), it is possible that m_g is not linearly dependent on the constant and Y_g. The reason for this is the presence of the term $\frac{cX_g}{1-J}$ in (6). This term can break the reflection problem. This will happen if the $\frac{cX_g}{1-J}$ term is such that it is not linearly dependent on a constant and Y_g; when this is so, m_g cannot be linearly dependent on the other regressors in (6). A necessary condition for this to happen is that there exists at least one regressor in X_i whose group-level average does not appear in Y_g. For example, identification can be achieved if an individual's age affects educational outcomes, but we are willing to rule out in advance that the average age of his peers influences him, once we have controlled for other characteristics of the peers. Formal conditions for identification in the linear model with social interactions are given in Brock and Durlauf (2001a,b).

While the reflection problem arises naturally in the linear model, it does not necessarily generalize to alternative data structures such as the binary choice model we have described. For the binary choice model, formal statements of conditions for identification appear in Brock and Durlauf (2001a,b) for the case when the random terms ε_i are logistically distributed and in Brock and Durlauf (2004) for general distribution functions. The logic of the reflection problem as it emerges in the linear model indicates why identification will not fail for the binary choice model. Eq. (7) indicates that for the binary choice model, m_g cannot be a linear function of the other regressors in (5). This is intrinsic to the model when there is sufficient variation in X_i and Y_g; since probabilities are bounded between 0 and 1, m_g (which is a weighted average of the individual-specific choice probabilities) *cannot* be linearly dependent on X_i and Y_g when these vectors have sufficiently wide supports. This finding does not depend on the fact that the error distribution is known, see Brock and Durlauf (2005) for a proof. Further, identification will generally hold for other nonlinear models, such as nonlinear regressions and duration data models; Brock and Durlauf (2001b) discuss these cases.

Of course, identification will even fail even for nonlinear models if the elements that comprise X_i and Y_g are themselves linearly dependent. However, this source of nonidentification does not seem natural in most contexts. One example where this would happen is a world where 1) $Y_g = X_g$ and 2) individuals are perfectly segregated by X_i (so that each person in a group has the same value of X_i). Perfect segregation means that, $X_g = X_i$ which in turn implies that $Y_g = X_i$.

Therefore, the two key messages for identification of social interactions with iid errors are 1) for linear models, identification requires that there exist individual specific characteristics and 2) identification will hold under standard conditions for nonlinear models.

4. Social interactions and self-selection

For contexts such as residential neighborhoods, it is natural to believe that assumption (1), which states that individuals are randomly assigned to groups, is not tenable. The natural reason for this is that in many contexts, group membership is itself a choice variable. One does not think of families as being randomly allocated across neighborhoods; rather, families choose neighborhoods subject to constraints such as rent levels and personal income. For environments in which self-selection is present, the consistency of various statistical methods for estimating social interactions may be affected. Specifically, the presence of self-selection can mean that the expected value of the random term ε_i, conditional on the individual's characteristics and group memberships, may no longer be zero. If one observes a poor family living in a rich neighborhood, one would reasonably infer that the level of parental investment in children is higher than other families. If this investment contains an unobservable component, then it will be part of the ε_i term. Following this logic, for a model of educational attainment, the conditional value of ε_i for a child who is part of a poor family in a rich neighborhood is positive.

If one ignores self-selection in estimation, then one may produce spurious evidence of social interactions. For example, if poorer neighborhoods tend to contain relatively less ambitious parents than affluent neighborhoods, and if lack of ambition on the part of parents leads to lower educational performance by children, then the failure to account for this self-selection could lead to the false conclusion that poor neighborhoods causally affect education. Generally, if neighborhoods are (partially) stratified according to unobservable individual-level characteristics that affect outcomes, then the danger of finding spurious evidence of social interactions will be present.

There is a vast literature in economics on accounting for self-selection in statistical exercises and it is covered in virtually any graduate microeconometrics textbook; see Cameron and Trivedi (2005) for a recent example. One solution to self-selection is the use of instrumental variables. In this approach, the problem of self-selection is interpreted as the presence of correlation between the regression errors in a model and the model regressors; the example of parental ambition given above produces such a correlation. Evans, Oates, and Schwab (1992) is a well known example of the use of instrumental variables to account for self-selection; this study concluded that controlling for self-selection eliminated the statistical significance of neighborhood effects for the data that were analyzed. Of course, there is no reason why this must be the case; in a similar exercise, Rivkin (2001) finds estimates of social interactions increase in magnitude when instrumental variables are used. One important point to note here is that the identification of valid instruments is often quite hard, see Heckman (1997) for discussion in the context of treatment effects analysis and Brock and Durlauf (2001c) for discussion using aggregate data to study economic growth. Intuitively, one often finds that asserted instruments, while predetermined with respect to a behavioral equation, nevertheless are likely to violate the requirement of uncorrelatedness with the equation error, once one considers a complete description of the behavioral decisions of the agents under study.

Within econometrics, the deepest analyses of self-selection are based on explicitly modeling the self-selection and including it as part of the statistical analysis. Unlike the instrumental variables approach, this has interesting implications for identification, at least for the linear model; Brock and Durlauf (2001b), first recognized this possibility. To understand their argument, rewrite the regression error in the linear model as

$$\omega_i = cX_i + dY_g + Jm_g + E\left(\varepsilon_i \middle| X_i, Y_g, F_{X|g}\right) + \xi_i . \tag{12}$$

This expression exploits Heckman's (1979) idea that in the presence of self-selection, the regression residual ε_i no longer has a conditional mean of zero. Following the logic behind Heckman's classic selection correction, eq. (12) can be consistently estimated if one adds a term proportional to $E\left(\varepsilon_i \middle| X_i, Y_g, F_{X|g}\right)$ to (12) prior to estimation; denote this estimate as $\widehat{\kappa E\left(\varepsilon_i \middle| X_i, Y_g, F_{X|g}\right)}$. Heckman's great insight was that one can construct such a term. Hence, from this perspective, controlling for self-selection amounts to estimating

$$\omega_i = cX_i + dY_g + Jm_g + \rho\widehat{\kappa E\left(\varepsilon_i \middle| X_i, Y_g, F_{X|g}\right)} + \xi_i . \tag{13}$$

Thus, accounting for self-selection necessitates considering identification for this regression, as opposed to (2).

The property of interest for the identification of social interactions is that the term $\widehat{\kappa E\left(\varepsilon_i \middle| X_i, Y_g, F_{X|g}\right)}$ can help facilitate identification. To see this, consider two possibilities for the underlying conditional expectation $E\left(\varepsilon_i \middle| X_i, Y_g, F_{X|g}\right)$. One possibility is that

$$E\left(\varepsilon_i \middle| X_i, Y_g, F_{X|g}\right) = \phi\left(m_g\right) \tag{14}$$

In this case, the presence of the regressor $\kappa\widehat{E\left(\varepsilon_i \middle| X_i, Y_g, F_{X|g}\right)}$ in (13) means that the model is no longer linear in m_g. Assuming $\phi(\cdot)$ is invertible, then the self-consistent solution for m_g is

$$m_g = \psi\left(k + \left(c + d\right) Y_g\right) \tag{15}$$

where $\psi(\cdot)$ is the inverse of $1 - \phi(\cdot)$. Eq. (15) illustrates that for this case, self-selection converts a linear model that is not identified into a nonlinear (in m_g) model in which m_g cannot be linearly dependent on a constant term and Y_g. The key point is that self-selection induces an intrinsic nonlinearity into the determinants of individual behavior and so converts the linear model into a nonlinear one.

Alternatively, suppose that

$$E\left(\varepsilon_i \middle| X_i, Y_g, F_{X|g}\right) = \phi\left(X_i, Y_g\right) \tag{16}$$

In this case, $\phi\left(X_i, Y_g\right)$ functions as an additional individual-specific regressor whose group level average does not appear in (13). Hence, following the argument about identification in linear models that was developed in the previous section, the presence of the regressor with a nonzero coefficient can allow for identification to occur. This approach to identification has been successfully used in Ioannides and Zabel (2003b) to identify social interaction effects in housing.[8]

The incorporation of self-selection into social epidemiology analyses seems, from the vantage point of econometrics, of first order significance. Self-selection issues have proven to be of enormous importance in understanding a range of issues involving questions of policy evaluation. A major component of James Heckman's profound contributions to economics revolves around developing ways to draw inferences when self-selection is present. See Heckman (2001) for an extraordinary survey.

In accounting for self-selection, it is important to recognize that self-selection can occur with respect to *unobservable* variables. In the context of job training programs, for example, program participation and completion is likely to be associated with the abilities and ambitions of an individual. This contrasts with the sort of analysis that is associated with causal inference in which selection is assumed to occur with respect to observables. The latter does not necessarily affect inferences; for example in the linear model selection on observables does not affect analysis of the linear model (2) so long as $E\left(\varepsilon_i \middle| X_i, Y_g, F_{X|g}\right) = 0$. Much of the statistical literature on causal effects focuses on self-selection on observables, as Heckman (1996) makes clear, such an approach is often inadequate as it is typical that "persons making decisions have more information about the outcomes than the statisticians studying them" (p. 461). This is clearly the case for group memberships.

It appears that there has been some confusion in the social epidemiology literature on the implications for self-selection in empirical analysis when selection occurs on unobservables. Subramanian (2004), in criticizing arguments of Oakes (2004) who

[8] An important unanswered research question is how one can employ semiparametric estimates of $\widehat{\kappa E\left(\varepsilon_i \middle| X_i, Y_g, F_{X|g}\right)}$ to help identify social interactions models; existing theoretical results on identification (Brock and Durlauf (2001b,2004), Ioannides and Zabel (2003b)) construct estimates based on parameter assumptions about the distribution of the error ε_i in (2) as well as the selection question that is combined with (2) to produce the estimated $\widehat{\kappa E\left(\varepsilon_i \middle| X_i, Y_g, F_{X|g}\right)}$.

argues that self-selection invalidates many claims in the social epidemiology literature, suggests that self-selection issues "are partially tractable and one potential strategy is through applying creative multilevel structures" (p. 1963). His example seems to suggest that movements across neighborhoods can provide information on the presence of social interactions. Such a claim is untenable unless one models the decision to change neighborhoods. The value of the self-selection correction $E\left(\varepsilon_i \middle| X_i, Y_g, F_{X|g}\right)$ will depend on the characteristics of a neighborhood and so will differ for a given individual when he is observed in different neighborhoods. Perhaps this is reading too much into the discussion in Subramanian (2004). However, what is known from the econometrics literature is that one cannot make arguments about what is or is not identified without formal analysis; terms such as "partially tractable" are only meaningful in the context of a fully articulated model.

We also disagree with Oakes (2004) to the extent that he advocates randomized experiments as clearly superior to other data sets in uncovering social interactions. His argument that such data sets can overcome self-selection problems is of course correct. However, as illustrated in the discussion of eqs. (12)-(16), self-selection can, when correctly modeled, facilitate identification. This should not be surprising. Self-selection describes another behavior by individuals beyond the behavioral choice ω_i-the choice of group membership. This second choice has implicit information about the social interactions the group produces. While exploration of how this additional information may be exploited has only just begun, it seems potentially important.

5. Unobserved group effects

The second major deviation from the baseline social interactions model concerns the possibility that unobserved group effects exist. This case has received attention in the linear case in Brock and Durlauf (2001b), Graham and Hahn (2004) and Graham (2005) and in the binary choice case in Brock and Durlauf (2005). To be concrete, if one is interested in whether residential neighborhoods produce social interactions that affect offspring educational performance, a natural candidate for an unobservable is the average quality of schools, at least some component of which is unobservable to the econometrician.

Similar to the case of self-selection, the presence of the unobservable group effects can, if not accounted for, lead to spurious conclusions concerning the presence of social interactions. Why? Suppose that more affluent parents choose neighborhoods with higher school quality. If one then calculates the correlation between student outcomes and average neighborhood income, this correlation will be positive not because of any influence of the incomes of others on a given student, but because average parental income is itself correlated with school quality. Notice one would not necessarily regard these effects as unobserved types of social interactions. For example, variations in school quality may derive from variation in the quality of teachers, which is driven by community attributes such as the opportunities for spousal employment that have nothing to do with social influences on children.

Algebraically, the introduction of unobserved group effects is simple. Denoting the fixed effect as α_g, the original linear model is modified to

$$\omega_i = k + cX_i + dY_g + Jm_g + \alpha_g + \xi_i . \tag{17}$$

In parallel, the payoff comparison in the original binary choice model is modified to

$$V_i(1) - V_i(-1) = k + cX_i + dY_g + Jm^e_{i,g} + \alpha_g - \varepsilon_i . \tag{18}$$

So that the conditional probability that 1 is chosen is modified from (3) to

$$\Pr\left(\omega_i = 1 \middle| X_i, Y_g, \alpha_g\right) = F_\varepsilon\left(k + cX_i + dY_g + Jm^e_{i,g} + \alpha_g\right) \tag{19}$$

with the new self-consistency condition

$$m_g = 2\int F_\varepsilon\left(k + cX + dY_g + Jm_g + \alpha_g\right) dF_{X|g} - 1. \tag{20}$$

Unobserved group effects are usually best regarded as fixed effects, since there is typically no plausible reason to believe the effects are orthogonal to observable group characteristics. In contrast, suppose that group memberships are generated endogenously and individuals observe α_g when groups are formed. If so, then there will presumably be some relation between α_g and those characteristics of individuals and the associated groups that are observed by the econometrician. Returning to our neighborhoods and education example, since families will presumably care about teacher quality when selecting neighborhoods this will induce correlations between unobserved (to the econometrician) school quality and variables such as average income of parents. In our view, the problem of unobserved group characteristics is the most serious impediment to developing persuasive evidence of social interactions.

For linear models, identification in cross-sections is impossible when fixed effects are present. Any pattern of outcomes in the linear model without unobserved fixed effects can be replicated one for one by an identical model with no social interactions and unobserved group effects. One simply sets $\alpha_g = dY_g + Jm_g$. Identification of social interactions in linear models with unobserved group effects can occur for alternative data structures and models.

One way to achieve identification with unobserved fixed effects involves using panel data. In this approach, the assumption is that the unobservable group effects are time invariant whereas other determinants of behavior are not. The basic idea in the panel approach is to consider a time indexed analog to (17), i.e.

$$\omega_{i,t} = k + cX_{i,t} + dY_{g,t} + Jm_{g,t} + \alpha_g + \xi_{i,t} \tag{21}$$

and construct differences of the form

$$\omega_{i,t} - \omega_{i,t-1} = c\left(X_{i,t} - X_{i,t-1}\right) + d\left(Y_{g,t} - Y_{g,t-1}\right) + J\left(m_{g,t} - m_{g,t-1}\right) + \xi_{i,t} - \xi_{i,t-1} \tag{22}$$

As (22) illustrates, taking first differences of $\omega_{i,t}$ can eliminate the unobserved fixed effect α_g. This approach is employed, for example, in Hoxby (2000a,b). The validity of this approach, of course, depends on the validity of the assumption that α_g does not vary over time. For this reason, differencing generally cannot be used to account for self-selection in panels; the time-indexed version of the self-selection correction analyzed in Section 4 will normally vary across time as it is a function of $X_{i,t}$ and $Y_{g,t}$.

Alternatively, one can follow Graham (2005) and assume that α_g is a random effect rather than a fixed effect. Of course, to do this, one needs to be able to defend the random effect assumption; for Graham the assumption is tenable because the data he studies involves random assignments of students to classrooms. This approach also necessitates restricting the analysis to the effort to identify some social interactions, i.e. conducting the analysis without distinguishing between endogenous and contextual effects. A variant of Graham's approach, which corresponds to the framework we have been using, is the following.[9] Consider the regression

$$\omega_i = k + dY_g + \alpha_g + \varepsilon_i , \tag{23}$$

we assume that Y_g is a scalar for convenience. If there are no social interactions present, i.e. $d = 0$, then

$$\operatorname{var}(\omega_i) = \operatorname{var}(\varepsilon_i) + \operatorname{var}(\alpha_g) \tag{24}$$

Note that the random effect assumption means that $\operatorname{cov}(Y_g, \alpha_g) = 0$. In contrast, if social interactions are present, then

[9] Graham (2005) considers the model $\omega_i = k + J\bar{\omega}_g + \alpha_g + \varepsilon_i$ and exploits data from an experiment in which students were assigned to classrooms of different sizes, leading to differences in the variance of $\bar{\omega}_g$ which is partially determined, of course, by the number

$$\text{var}\left(\omega_i\right) = \text{var}\left(\varepsilon_i\right) + \text{var}\left(dY_g\right) + \text{var}\left(\alpha_g\right). \tag{25}$$

Now suppose that groups come in two types: those such that Y_g is drawn from a distribution with variance $\overline{h}$ and those such that Y_g is drawn from a distribution with variance $\underline{h}$; by assumption $\overline{h} > \underline{h}$, one can construct an estimate of the social interactions parameter *d*.

$$\begin{gathered}\text{var}\left(\omega_i \middle| \text{var}\, Y_g = \overline{h}\right) - \text{var}\left(\omega_i \middle| \text{var}\, Y_g = \underline{h}\right) = d^2\left(\overline{h} - \underline{h}\right) \Rightarrow \\ d = \sqrt{\frac{\text{var}\left(\omega_i \middle| \text{var}\, Y_g = \overline{h}\right) - \text{var}\left(\omega_i \middle| \text{var}\, Y_g = \underline{h}\right)}{\overline{h} - \underline{h}}}\end{gathered} \tag{26}$$

The idea of using variance differences to identify social interactions is also employed in Glaeser, Sacerdote, and Scheinkman (1996); this analysis focuses on what may be learned about social interactions from aggregated data.

In using tests of this type, it is important that a researcher is able to justify the assumption that the distribution of α_g does not vary across groups. It is not clear that this is so, even if group memberships are randomly assigned. For example, in Graham's analysis, in which students are observed in classrooms with different numbers of classmates, the assumption implicitly means that the variance of teacher quality does not depend on the number students who are being taught.

In moving from linear models to binary choice models, some new results emerge. For binary choice models, one can develop evidence of social interactions for cross-section data even in the presence of group-level fixed effects. Panel methods can help with identification as well; these are discussed in Brock and Durlauf (2005). Unlike the linear model case, Brock and Durlauf (2005) show that it is also possible to learn something about social interactions from cross-section data.

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of members of g. Computation of the value of *J* is more elaborate than the calculation of

The reason why cross-section data on binary choices may produce evidence in support or against social interactions is that the binary choice model can produce multiple equilibria only if endogenous social interaction effects are present. If the available data require the existence of multiple equilibria, this in turn implies the existence of endogenous social interactions. To develop this argument, we assume that there is random assignment of individuals across groups

$$F_{X|g} = F_X . \quad (27)$$

Brock and Durlauf (2005) consider various relaxations of this assumption, but the bulk of the analysis in that paper is conducted under (27), as may be seen when one examines the formal proofs underlying the subsequent discussion.

The translation of multiple equilibria into data restrictions is somewhat complicated. A major intuition as to why multiple equilibria are associated with endogenous social interactions is that the multiple equilibria can produce what Brock and Durlauf refer to as pattern reversals. Assume that $d > 0$ so that increasing any element in Y_g increases, other things equal, the probability that an individual in g chooses 1. One can always measure the elements of Y_g this way, so long as one knows the direction of the effects of its elements. A pattern reversal occurs for groups g and g' if

$$Y_g < Y_{g'} \text{ and } m_g > m_{g'} . \quad (28)$$

Recall that m_g can be computed, since it is the conditional expectation of the same average of within-group choices $\bar{\omega}_g$, so pattern reversals represent restrictions on data. For the identification of social interactions, pattern reversals are important because they may derive from the presence of endogenous social interactions producing multiple equilibria. Why? Intuitively, multiple equilibria can produce a pattern reversal because

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d which we illustrate, but the idea is the same.

group g can coordinate on a high m_g equilibrium whereas group g' does not so that the effect of the higher value of Y on the average outcome in the group is negated.

The difficulty with using this heuristic argument is that without any restrictions on α_g, pattern reversals can occur without multiple equilibria being present. Brock and Durlauf (2005) thus attempt to identify weak restrictions associated with α_g such that pattern reversals imply the existence of multiple equilibria and hence endogenous social interactions. This type of argument does not identify the value of the endogenous social interactions parameter J, rather it shows that the value is nonzero and large enough to produce multiple equilibria. As such, it is a form of partial identification, cf. Manski (2003).

What sorts of assumptions allow for partial identification of J via pattern reversals? One potentially appealing assumption is a stochastic monotonicity restriction on the group level unobservables. Suppose that if $Y_g > Y_{g'}$, then the conditional distribution of unobservables in g', $F_{\alpha_{g'}|Y_{g'}}$, is first order stochastically dominated by $F_{\alpha_g|Y_g}$. In this case, subject to various technical conditions described in Brock and Durlauf (2005), the pattern reversal defined by (28) will imply that endogenous social interactions exist.

Another route towards partial identification of social interactions is via unimodality versus multimodality comparisons. Suppose that Y_g is constant across groups, X_i is constant across all individuals within and across groups and that $\alpha_g = 0$. In this case, it is easy to see that m_g will take on a single value when there are no endogenous social interactions and will take on one of a finite set of values when there are multiple equilibria due to social interactions. Suppose that $dF_{\alpha_g|Y_g}$ is unimodal for all Y_g. In this case, m_g will be multimodal, with each equilibrium representing a possible value. This leads to the intuition that multiple equilibria may occur when one relaxes the assumption that Y_g and X_i are constant.

The translation of this intuition into data restrictions turns out to be fairly hard.

One reason for this is straightforward: if α_g exhibits multimodality, then there is no link between multiple equilibria and unimodality of the other variables. Hence it is necessary to assume that $dF_{\alpha_g|Y_g}$ is unimodal for all Y_g. However, even in this case, it turns out that multimodality of m_g conditional on Y_g is neither a necessary nor a sufficient condition for the existence of multiple equilibria. The reason for this is that the relationship between m_g and Y_g is nonlinear as indicated by eq. (20), and this nonlinearity can induce multimodality. Brock and Durlauf (2005) overcome this problem by considering $dF_{Y_g|m_g}$ rather than $dF_{m_g|Y_g}$. Specifically, they show that unimodality of $dF_{\alpha_g|Y_g}$ implies that there must exist a vector π such that $dF_{\pi Y_g|m_g}$ is unimodal if there are no endogenous social interactions. This is the correct way to think about pattern reversals and multimodality. When social interactions are present, a given m_g may be associated with more than one value of Y_g.

In our judgment, the identification of social interactions effects in the presence of unobserved group effects represents the major existing impediment to developing evidence of the role of social influences. The reason for this is that in the contexts in which social interactions are usually studied, there are typically many unobserved group characteristics that can be argued to plausibly affect individual outcomes. One example was given for the relationship between educational outcomes and neighborhoods. For another example, the ability to infer a relationship between social factors and crime rates requires careful attention to the possibility of differential police resources across neighborhoods. Further work on identification for the case of unobserved group effects is thus of great importance.

6. Some implications for social epidemiology

In this section, we relate some of our analysis to the treatment of social interactions in the social epidemiology literature.

i. the reflection problem and endogenous social interactions

As far as we know, with the exception of Oakes (2004) there has been no attention to the reflection problem in the social epidemiology literature. The reason for this appears to derive from differences between the economic and epidemiological concepts of individual outcomes. In the economics contexts, choices are purposeful and so it is natural to attempt to identify direct interdependences in decisions, whether they are due to a primitive psychological preference for conformity or information transmission that occurs via the behaviors of others. In contexts such as health outcomes, e.g. coronary heart disease, such factors do not directly occur. That being said, it does appear that consideration of endogenous social interactions would augment epidemiological studies. In the context of health outcomes, endogenous social interactions can affect behaviors that in turn affect health. So, to the extent that exercise levels are influenced by social interactions, if exercise affects health, one has an endogenous influence.

Does the explicit evaluation of endogenous versus contextual effects matter? If one is interested in understanding causal mechanisms, the answer is clearly yes. However, there are certain dimensions along which the answer is no. Suppose that one is interested in changing the value of an element in X_i for each of the members of a group. The effect of this in the linear model is fully characterized by the reduced form for individual behavior, i.e. the combination of (2) with (6)

$$\omega_i = \frac{k}{1-J} + cX_i + \frac{d}{1-J} Y_g + \frac{Jc}{1-J} X_g + \varepsilon_i \tag{29}$$

The regression is known in the econometrics literature as a reduced form as it relates ω_i to a set of predetermined variables. The coefficients in this regression are, as analyzed in Manski (1993), all identified under standard linear independence conditions on the regressors X_i and Y_g, even if one cannot identify the distinct roles of contextual and endogenous effects. So, if all one wants to do is generate predictions of the effect of a change in some predetermined variable (i.e. an element of X_i or Y_g) on an individual[10], this regression is sufficient. For example, if one is interested in the effects on student outcomes from redistricting schools, and if school district define the groups through which social interactions occur, then the effects of the policy change on students may be determined without distinguishing between the respective roles of contextual effects and endogenous effects; the effects can be determined via (29); the reduced form is thus sufficient for prediction of policy effects.

In contrast, the distinction between contextual effects and endogenous effects must be accounted for in order to understand the implications of changing elements of X_i and/or Y_g. In the binary choice model, if one omits the endogenous effect in estimating (5), then the estimates of the remaining parameters will not be consistent and cannot be interpreted as a reduced form. If one considers the effects of redistricting on binary choices such as graduation, one potentially important effect may derive through the effect of the redistricting on the number of equilibria.

ii. hierarchical models

Unlike economics, social interactions are generally modeled in the social epidemiology literature using hierarchical models, i.e. models in which contextual effects alter the coefficients that link individual characteristics to outcomes. The reason for this again appears to be a different conceptualization of the meaning of social interactions in economics in comparison to other social sciences. Hierarchical models appear, in our reading, to be motivated by a view of social groups as defining ecologies in which decisions are made and matter because different ecologies induce different mappings from the individual determinants of these behaviors and choices, cf. Raudenbush and Sampson (1999). Economics, in contrast, regards the elements that comprise endogenous and contextual social interactions as directly affecting the preferences, constraints, and beliefs of agents and so treats them as additional determinants to individual specific

[10]By predetermined variables, we refer to variables that are determined at the time the choices ω_i are made.

characteristics, X_i. The specific modeling choices in terms of either allowing for coefficients to linearly depend on group characteristics as occurs in hierarchical models, or the direct embedding of group characteristics in decision rules as suggested by the role they are hypothesized to play, as occurs in economics, follow from these different conceptions of why group memberships matter.

For hierarchical models, there has been little attention to identification problems of the sort that have been analyzed in the social interactions literature, although these arguments are clearly germane. This subsection explores identification of hierarchical models. One formulation that seems consistent with the logic of hierarchical models is

$$\omega_i = k_i + c_i X_i + J_i m_g + \varepsilon_i \tag{30}$$

where self-consistency of beliefs has been imposed, and

$$k_i = k + dY_g,\ c_i = c + Y_g'\Pi_c,\ J_i = J + \pi_J Y_g\,. \tag{31}$$

In (31), Π_c is a matrix. We omit any random terms in (31) for simplicity. This formulation assumes that the endogenous effect directly affects outcomes whereas the contextual effect works via the individual behavioral coefficients. This model can easily be translated into the original linear framework we have analyzed. The hierarchical model described by (30) and (31) is thus equivalent to the linear model

$$\omega_i = k + cX_i + dY_g + Jm_{i,g}^e + Y_g'\Pi_c X_i + \pi_J Y_g m_{i,g}^e + \varepsilon_i\,. \tag{32}$$

Hence, the difference between the linear model used in economics and the hierarchical structure is the addition of the terms $Y_g'\Pi_c X_i$ and $Y_g m_{i,g}^e$.

Can this model exhibit the reflection problem? The self-consistent solution to eq. (32) is

$$m_g = \frac{k + cX_g + dY_g + Y_g'\Pi_c X_g}{1 - J - \pi_J Y_g} \tag{33}$$

where, as before, X_g is the within group average of X_i. The reflection problem originally emerged when the Y_g vector equalled the within-group averages of X_i. If we impose this, then (33) becomes

$$m_g = \frac{k + cX_g + dY_g + Y_g'\Pi_c Y_g}{1 - J - \pi_J Y_g}. \tag{34}$$

Eq. (34) makes clear that the relationship between m_g and the other regressors is nonlinear; further, the presence of $Y_g'\Pi_c Y_g$ in the numerator and $-\pi_J Y_g$ in the denominator ensures that linear dependence will not hold, except for hairline cases, so long as there is sufficient variation in X_i and Y_g. In other words, the hierarchical model will be identified under standard conditions on X_i and Y_g.

This hierarchical model with contextual and endogenous social interactions will not exhibit multiple equilibria even though the model contains nonlinearities. However, the nonlinear structure of the model distinguishes it from the linear model in that the reflection problem can be overcome without prior information about the relationship between X_g and Y_g. And equally important, because hierarchical models are nonlinear, this means that the failure to account for the possibility of endogenous effects will lead to inconsistent estimates so that the misspecified model cannot be used to evaluate the effects of changes in different variables, or the effects on individual outcomes of altering group memberships, e.g. by changing school district boundaries.

This is apparent from eq. (34). The equilibrium effect of a change in Y_g on m_g is nonlinear when endogenous effects are present, i.e. when the vector π_J is nonzero. This means that the effect of a change in contextual effects on the expected average behavior of the system will differ according to the initial value of Y_g. If the system defined by eqs.

(30) and (31) is estimated under the assumption that $\pi_J = 0$, then the resultant estimates will not provide a model in which counterfactuals may be accurately evaluated. Predictions based on the erroneous assumption of no endogenous effects can be highly misleading, although the extent to which this is true will depend on context.

iii. social capital

A large number of social epidemiology papers study the role of social capital in determining various health related outcomes. These studies often use aggregated data at levels ranging from residential neighborhoods to larger units; see Lochner et al (2003) and Kawachi et al (1997) for examples in which social capital is used to understand mortality. In this approach, average group outcomes are regressed against various group level controls and a measure of social capital. The general social capital literature has been subjected to criticism due to the lack of conceptual precision in defining, let alone measuring, social capital (see Durlauf (2002a,b) and Portes (1998,2000)), but our purpose here is to evaluate identification.

To do this, we consider the case where social capital is endogenous. What this means is that each individual chooses a level of social capital SC_i in addition to the outcome of interest ω_i. Notice that even for outcomes such as mortality, which are not themselves choice variables, behaviors that contribute to the outcome such as exercise, diet, and willingness to take risks, are endogenous, so the identification analysis we have employed seems relevant. Further, the notion that social capital is endogenous does not necessarily imply that the individual choices that produce social capital are conscious ones. One may adopt a level of personal honesty in dealing with others based on norms of honesty in a community without being consciously aware that one has done so.

Our discussion will focus only on the linear model, in order to use results in Durlauf (2002a). The introduction of social capital thus leads to a two equation linear model that generalizes (2)

$$\omega_i = k + cX_i + dY_g + J_1 m_g + J_2 s_g + \varepsilon_i \quad (35)$$

and

$$SC_i = \bar{k} + \bar{c}X_i + \bar{d}Y_g + \bar{J}_1 m_g + \bar{J}_2 s_g + \eta_i. \tag{36}$$

These two equations describe the joint determination of the outcome of interest and social capital. In these equations, SC_i denotes the level of social capital associated with individual *i* and s_g denotes the expected average level of social capital in his group. The terms $\bar{k}$, $\bar{c}$, $\bar{d}$, $\bar{J}_1$, are $\bar{J}_2$ are all coefficients in the social capital equation; regressors in the two equations are assumed to be the same. As before, we employ expected rather than realized levels for aggregate outcome variables for simplicity.

Durlauf (2002a) provides conditions for identification of this model. The main findings are that this joint social interactions/social capital model suffers from an analogous reflection problem to the original social interactions model. Identification requires prior information to restrict the presence of particular terms in the equations. In particular, to identify the parameters of (35) it is necessary that there exist *two* elements of X_i whose group level analogs are not elements of Y_g.

In many contexts in which social capital is analyzed, individual level data are not available. If one only has group level data available, then the equations that may be studied are parallel to the individual model, i.e.

$$\omega_g = k + dY_g + J_1 m_g + J_2 s_g + \varepsilon_g \tag{37}$$

where ω_g is the sample average within group *g* of ω_i and

$$SC_g = \bar{k} + \bar{d}Y_g + \bar{J}_1 m_g + \bar{J}_2 s_g + \eta_g. \tag{38}$$

In order to identify the social capital effect, i.e. the coefficient J_2, with aggregate data, it is necessary to distinguish it from the contextual effects Y_g as well as the endogenous effect m_g. Formal conditions for identification are given in Durlauf (2002a). One requirement for identification is that one must be able to identify two elements of Y_g that appear in the social interaction equation (38) but do not appear in the outcome equation (37); i.e. the coefficients in (37) are a priori known to equal 0. Unless these two elements exist, *SC* cannot be linearly independent of both Y_g and m_g.

Durlauf (2002a) argues that such prior information is generally implausible. One reason for this relates to the definitional ambiguities for social capital. Without a clear definition, it is hard to see how one can argue that an aggregate variable affects its aggregate level without directly affecting the aggregate outcome ω_g. If one is willing to assume that $J_1 = 0$, then one still needs at least one element of Y_g to affect social capital without affecting the aggregate outcome, which again requires justification. We are not aware of any empirical application where this defense is actually made.

This discussion illustrates some reasons why empirical claims on the role of social capital in influencing individuals and especially for groups are, in our judgment, often very weak. Empirical studies of social capital rely on implicit assumptions about which variables influence individuals and groups that are not stated and, in our view, can be highly unappealing. This negative conclusion should not be interpreted as a dismissal of the social capital concept; weaknesses in current empirical practice in no way imply social capital is uninteresting or unimportant. Durlauf and Fafchamps (2004) discuss routes by which social capital inferences may be strengthened.

7. Conclusions

While the econometrics literature on social interactions is still quite new, progress has been made in understanding important aspects of identification. Much remains to be done, in particular with respect to comprehensive studies of dynamic versus cross-section environments. Still, considerable progress has been made in understanding when social interactions can or cannot be identified in various data sets.

In conclusion, we note that terms such as “propensity score” and “causality” did not earlier appear anywhere in this essay. This omission is not inadvertent. From the perspective of the social interactions, the causality research program pioneered in the statistics literature has had little impact. The reason for this is that social interactions models in economics have been conceptualized as fully articulated descriptions on individual behavior, as opposed to efforts to identify the effects of changing certain factors, as occurs in the analysis of treatment effects; as such, social interactions econometrics reflects standard economic reasoning. From the social interactions perspective, one does not naturally think of a group as a treatment, but rather as a constrained choice by the individual. When one worries about selection on unobservables, one moves away from the sorts of assumptions such as strong ignorability that are important in the causality literature. Perhaps the most important message of this chapter is that there are perspectives on the inference of social interactions that are not well captured from the perspective of purely statistical literatures and may be addressed only by careful consideration of the behavioral foundations that underlie a statistical model specification.

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