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ABSTRACT

An endogenous social effect exists if the propensity of an individual to behave in some way varies with the prevalence of that behavior in some reference group containing the individual. This paper investigates aspects of the problem of identifying endogenous effects from data on actual behavior. Empirical researchers have long been sensitive to the problem of distinguishing social effects from reference-group fixed effects. The present analysis reveals that the identification of endogenous effects is tenuous even in the absence of reference-group fixed effects. There are two main findings. First, a researcher who does not a priori know how individuals form their reference groups cannot infer this from data on actual behavior and cannot determine whether social effects really are present. Second, suppose that individual behavior is known to be affected directly by specified variables z and that an individual's reference group is known to be the sub-population having specified attributes x. Then the effect of reference-group behavior on individual behavior is not identified if x and z are either functionally dependent or statistically independent.

1. Introduction

ENDOGENOUS SOCIAL EFFECTS: A variety of terms in common use connote endogenous social effects, wherein the propensity of an individual to behave in some way varies with the prevalence of that behavior in some reference group containing the individual. These effects may, depending on the context, be called "social norms," "peer influences," "neighborhood effects," "conformity," "imitation," "contagion," "epidemics," "bandwagons," "herd behavior," "social interactions," or "interdependent preferences."

Endogenous social effects have long been central to sociology and social psychology; see, for example, Asch (1952), Merton (1957), and Bandura (1986). Mainstream economics has always been fundamentally concerned with a particular endogenous effect: an individual's demand for a product varies with price, which is partly determined by aggregate demand in the relevant market. Economists have also studied other types of endogenous effects. Models of oligopoly posit reaction functions, wherein the output chosen by each firm is a function of aggregate industry output. Schelling (1972) analyzed the residential patterns that emerge when individuals choose not to live in neighborhoods where the percentage of residents of their own race is below some threshold. Conlisk (1980) showed that, if decision making is costly, it may be optimal for individuals to imitate the behavior of other persons who are better informed. Akerlof (1980), Jones (1984), and Bernheim (1991) studied the equilibria of noncooperative games in which individuals are punished for deviation from group norms.

Gaertner (1974), Pollak (1976), Alessie and Kapteyn (1991), and Case (1991) analyzed consumer demand models in which, holding price fixed, individual demand increases with the mean demand of a reference group.

Endogenous social effects are to be distinguished from exogenous effects, wherein the propensity of an individual to behave in some way varies with the distribution of exogenous characteristics in the reference group. (Exogenous effects are referred to by sociologists as contextual effects; see, for example, Sewell and Armer, 1966; and Hauser, 1970). An example may help to clarify the distinction. Consider the high school dropout decision faced by a teenage youth. An endogenous effect exists if, all else equal, the decision to drop out varies with the rate of dropout in the youth's high school, ethnic group, or other reference group. An exogenous effect exists if, all else equal, the decision to drop out varies with, say, the socioeconomic composition of the reference group.

IDENTIFICATION: Broadly speaking, empirical evidence on endogenous social effects derives from three sources. There are controlled experiments in which individuals are randomly assigned to groups of different compositions and their behavior observed. There are the statements people make, in structured surveys and open-ended interviews, about why they behave as they do. And there are data on actual patterns of behavior.

This paper investigates aspects of the problem of identifying endogenous effects from data on actual behavior. Empirical researchers have long been sensitive to the problem of distinguishing social effects from reference-group fixed effects; Hauser (1970), working with an exogenous-effects model, offers an informative and entertaining case study. The present analysis reveals that the identification of endogenous effects is tenuous even in the absence of reference-group fixed effects.

There are two main findings, both negative, the first more so than the second. First, a researcher who does not a priori know how individuals form their reference groups cannot infer this from data on actual behavior and cannot determine whether social effects really are present. Suppose a researcher hypothesizes that individual behavior is affected directly by a vector of observed exogenous variables z and that an individual's reference group is a sub-population having observed attributes x. (For example, in a study of high school dropout, z might be hypothesized to be a youth's ability and ethnicity and x to be youth in the same ethnic group.) Proposition 1 of Section 3 shows that an endogenous-effects model holds tautologically if x is a function of z, if z is a function of x, or if behavior does not actually vary with z. Data on actual behavior are not capable of distinguishing among a host of alternative specifications of (x,z).

The second finding concerns identification conditional on a maintained hypothesis for (x,z). Suppose that individual behavior really is affected directly by the specified variables z and that an individual's reference group really is the sub-population having the specified attributes x. Propositions 2 and 3 of Section 4 shows that the effect of reference-group behavior on individual behavior is not identified if x and z are either functionally dependent or statistically independent. Identification is possible only if x and z are "moderately" related random variables.

The foregoing pair of identification problems constitute the "reflection problem" studied in this paper. The rationale for this term will be given in Section 2, which lays the formal groundwork for the analysis. The analysis is carried out in Sections 3 and 4. The empirical literature estimating social effects models is surveyed and interpreted in Section 5. Conclusions are drawn in Section 6.

Before proceeding, it is important to make clear that this paper takes no stand on the empirical existence and nature of social effects. Many social scientists hold strong, sometimes visceral beliefs on this subject. Numerous economists regard purported instances of social effects, the demand-price relationship aside, as spurious phenomena to be explained by processes operating entirely at the level of the individual. The Friedman (1957) criticism of Duesenberry (1949) is an apt example. Sociologists and social psychologists typically view social effects as fundamental determinants of human behavior. As I see it, these drastically different perspectives are able to persist, with no convergence, because the available data on behavior cannot readily distinguish among alternative hypotheses.

2. Reflection Regressions

A LINEAR ENDOGENOUS-EFFECTS MODEL: I shall introduce the basic ideas through a linear model, which will then be generalized. Let each member of a population be characterized by a realization of (y,x,z,u), a random column vector taking values in a real vector space $Y \times X \times Z \times U = R^1 \times R^J \times R^K \times R^1$. Here y is a scalar behavioral response and (x,z,u) are attributes of a person, the first component of z being an intercept.

A researcher observes a random sample of N realizations of (y,x,z); realizations of u are not observed. The researcher hypothesizes that, for some value of the parameters (β,γ),

$$(1) \quad y = \beta E(y|x) + z'\gamma + u, \qquad E(u|x,z) = 0,$$

so that

$$(2) \quad E(y|x,z) = \beta E(y|x) + z'\gamma.$$

If $\beta \neq 0$, the linear regression (2) expresses an endogenous social effect. Holding z fixed, a person's expected response y varies with E(y|x), the mean of y among those members of the population having attributes x. The sub-population with attributes x is the person's hypothesized reference group.[1]

Model (1) is a relatively benign starting point for our analysis. Observing x, the researcher knows the composition of reference groups and need not model the process by which individuals select their reference groups. The assumption that $E(u|x,z) = 0$ implies that there are no unobserved reference-group fixed effects. The social effect operates through $E(y|x)$, which is a function of x. So there is no "simultaneity problem" of the type that would occur if a function of y were to appear as a regressor in (1). The regressions $E(y|x,z)$ and $E(y|x)$ are identified by the random sampling process, almost everywhere on $X \times Z$, and may be estimated consistently even in the absence of prior functional form restrictions; see, for example, Hardle (1990). Hence, in analyzing the identifiability of social effects, we can treat $E(y|x,z)$ and $E(y|x)$ as known and focus attention on (β,γ).

Nevertheless, inference on social effects remains problematic. The reason is that the regressor $E(y|x)$ is not just any function of x. If (2) holds, then integrating both sides of this equation with respect to z reveals that $E(y|x)$ solves the equation

$$(3) \quad E(y|x) = \beta E(y|x) + E(z|x)'\gamma .$$

And, whether or not (2) holds, $E(y|x)$ satisfies the identity

$$(4) \quad E(y|x) \equiv \int E(y|x,z)dP(z|x),$$

where $P(z|x)$ denotes the distribution of z conditional on x. These restrictions on $E(y|x)$ generate the identification problems studied in this paper.

GENERAL REFLECTION REGRESSIONS: Linearity is not fundamental to the idea of endogenous social effects. Model (2) is the linear member of the class of regression models in which $E(y|x,z)$ varies with x only through $E(y|x)$. That is,

$$(5) \quad E(y|x,z) \quad = \quad f[E(y|x),z],$$

$f(.,.)$ being a member of some family F of functions on $Y \times Z$. Whereas (2) implies that $E(y|x)$ solves (3), (5) implies that $E(y|x)$ solves

$$(6) \quad E(y|x) \quad = \quad \int f[E(y|x),z]dP(z|x).$$

I shall refer to models satisfying (5) and (6) as "reflection regressions." This term seems appropriate because $E(y|x,z)$ provides a higher-resolution image of the random variable y than does $E(y|x)$. So (5) can be interpreted as saying that a higher-resolution image varies with its reflection in a lower-resolution mirror.

Equations (5) and (6) formalize the idea that the propensity of an individual to behave in some way varies with the prevalence of that behavior in a group containing the individual. It seems appropriate to say that a social equilibrium exists if there is a value of $E(y|x)$ solving (6). If no social equilibrium exists, the reflection regression model is not coherent.

FURTHER GENERALIZATIONS: Reflection regression models more general than (5) will not be examined in this paper but warrant attention. It may be that social norms are conveyed not just through the mean behavior $E(y|x)$ of the reference group but through other features of the distribution $P(y|x)$. For example, dispersion may matter; the more homogeneous is reference-group behavior, the stronger the norm. If so, then we should replace (5) with

$$(5') \quad P(y|x,z) = f[P(y|x),z],$$

where $f(.,z)$ now maps probability distributions on Y into probability distributions on Y. Note, however, that if y is a binary random variable, then $E(y|x) = P(y=1|x)$ and $E(y|x,z) = P(y=1|x,z)$. So (5') reduces to (5) in this case.

Another possibility is that individuals are influenced by multiple reference groups, giving more weight to the behavior of some groups than to others. Then (5) might be generalized to

$$(5'') \quad E(y|x_1,\ldots.x_M,z) = f[E(y|x_1),\ldots.,E(y|x_M),z].$$

Here x_m is the attribute characterizing the m^{th} reference group.

3. Tautological Models

Proposition 1 shows that the reflection regression model holds tautologically for many specifications of (x,z).

Proposition 1: Let F be the family of measurable functions on $Y \times Z$.

A. Suppose that y is mean-independent of z, conditional on x. Then equations (5) and (6) hold with $E(y|x,z) = E(y|x)$.

B. Suppose that z is a function of x. Then equations (5) and (6) hold with $E(y|x,z) = E(y|x)$.

C. Suppose that x is a function of z. Then equations (5) and (6) hold with $E(y|x,z) = E(y|z)$.

D. Suppose that $E(y|x)$ is a one-to-one function of x. Then equations (5) and (6) hold. ∎

PROOF:

A. Conditional mean independence is defined by $E(y|x,z) = E(y|x)$. Hence (5) holds by definition. Equation (6) reduces to the identity $E(y|x) = \int E(y|x)dP(z|x)$.

B. If z is a function of x, then $E[y|x,z(x)] = E(y|x)$. So this is a special case of part A.

C. If x is a function of z, then $E[y|x(z),z] = E(y|z)$ is a function of z alone. Hence (5) holds. Equation (6) reduces to the identity $E[y|x(z)] = \int E(y|z)dP[z|x(z)]$.

D. If the mapping from x to $E(y|x)$ is one-to-one, then $E(y|x,z) = E[y|E(y|x),z]$. Hence (5) holds. Equation (6) reduces to the identity (4).

Q.E.D.

Proposition 1 is technically trivial but has strong implications for the empirical study of endogenous social effects. Suppose a researcher hypothesizes a reflection regression model (5) and that either condition A or B holds. If the family F of feasible models includes $f[E(y|x),z] = E(y|x)$, the researcher's hypothesis cannot be falsified. In particular, the linear model (2) cannot be falsified; setting $(\beta,\gamma) = (1,0)$ yields $f[E(y|x),z] = E(y|x)$. Suppose alternatively that condition C holds. If F includes $f[E(y|x),z] = E(y|z)$, then again the researcher's hypothesis cannot be falsified. For example, a linear model hypothesis cannot be falsified if $E(y|z)$ happens to be a linear function of z, say $z'\delta$; setting $(\beta,\gamma) = (0,\delta)$ yields $f[E(y|x),z] = E(y|z)$. Finally, suppose that x is either a discrete random variable or a scalar continuous random variable. In these cases condition D will typically hold and it will not be possible to falsify a hypothesis in which $E[y|E(y|x),z]$ happens to be a member of F.

The foregoing implies that a researcher who does not a priori know how individuals form reference groups cannot infer this from data on actual behavior and, moreover, cannot determine whether social effects really are present. For example, consider a researcher studying student achievement. Suppose that the researcher observes each student's ability and ethnicity. If the researcher specifies x to be (ability,ethnicity) and z to be (ability), he will find that the data are consistent with the hypothesis that individuals do condition on (ability,ethnicity) to form their reference groups, that individual achievement mirrors reference-group achievement, and that ability has no direct effect on achievement. (Part B). If the researcher specifies x to be (ethnicity) and z to be (ability,ethnicity), he will find that the data are consistent with the hypothesis that reference-group achievement does not affect individual achievement (Part C).

4. Non-Tautological Models

This section concerns identification of non-tautological reflection regression models. Proposition 1 does not apply if (x,z) satisfies an exclusion restriction, wherein x contains a component not in z, and z contains a component that is not in x and that moves the mean of y, conditional on x. The Proposition also does not apply if the specification of F omits tautological models. The present analysis examines identification in these situations.

Section 4.1 continues the examination of the linear model begun earlier and Section 4.2 considers general reflection regressions with unique social equilibria. Some of the findings reported below are closely related to those reported in Proposition 1. The main new finding is that an exclusion restriction in (x,z) and omission of tautological models from F are not enough to identify a social-effects model. Part D of Proposition 2 shows that, if the linear model (2) holds and equation (3) has a unique solution, then β is unidentified when z is mean-independent of x. Part D of Proposition 3 shows that, if (5) holds and (6) has a unique solution, then the effect of reference-group behavior on individual behavior is not identified when z is statistically independent of x.

4.1. LINEAR MODELS

Assume that the linear model (2) correctly describes behavior and that equation (3) has a unique solution $E(y|x)$. Given (2), equation (3) has a unique solution if and only if $\beta \neq 1$. If $\beta = 1$ and $\gamma = 0$, then $E(y|x,z) = E(y|x)$ and (3) is the identity $E(y|x) = E(y|x)$. If $\beta = 1$ and $\gamma \neq 0$, then (3) has no solution except in the uninteresting case where $\text{Prob}(z'\gamma=0) = 1$.

Given that $\beta \neq 1$, the solution to (3) is

(7) $$E(y|x) = E(z|x)'\gamma/(1-\beta).$$

Hence, equation (2) may be rewritten as

(8) $$E(y|x,z) = [\beta/(1-\beta)]E(z|x)'\gamma + z'\gamma.$$

The parameter β, which measures the effect of reference-group behavior on individual behavior, is identified if and only if there is a unique value of β such that (8) holds almost everywhere on $X \times Z$. Proposition 2 shows that β is not identified in each of four situations.

<u>Proposition 2</u>: Assume that (2) holds for some $\beta \neq 1$.

A. Suppose that the slope components of γ equal 0. Then $E(y|x)$ is constant on X and β is not identified.

B. Suppose that z is a function of x. Then $E(y|x)$ is a linear function of $z(x)$ and β is not identified.

C. Suppose that x is a function of z and $E[z|x(z)]$ is a linear function of z. Then $E[y|x(z)]$ is a linear function of z and β is not identified.

D. Suppose that z is mean independent of x. Then $E(y|x)$ is constant on X and β is not identified. ■

Proof:

A. If $\gamma = (\gamma_1, 0, \ldots, 0)$, then $E(z|x)'\gamma = \gamma_1$ and (8) reduces to $E(y|x,z) = [\beta/(1-\beta)]\gamma_1 + \gamma_1 = \gamma_1/(1-\beta)$. So β is not identified relative to γ_1.

B. If $z = z(x)$, then $E(z|x) = z(x)$ and (8) reduces to $E(y|x,z) = [\beta/(1-\beta)]z(x)'\gamma + z(x)'\gamma = z(x)'\gamma/(1-\beta)$. So β is not identified relative to γ.

C. If $x = x(z)$ and $E[z|x(z)] = Az$ for some $(K \times K)$-matrix A, then (8) reduces to $E(y|x,z) = [\beta/(1-\beta)]z'A'\gamma + z'\gamma = z'\lambda$, where $\lambda \equiv \{[\beta/(1-\beta)]A'+I\}\gamma$ and where I is the $(K \times K)$-identity matrix. So β is not identified relative to γ.

D. If $E(z|x) = E(z)$, then (8) reduces to $E(y|x,z) = [\beta/(1-\beta)]E(z)'\gamma + z'\gamma = \{[\beta/(1-\beta)]E(z)'\gamma+\gamma_1\} + z_{-1}'\gamma_{-1}$, where $z_{-1} \equiv (z_2,\ldots,z_K)$ and $\gamma_{-1} \equiv (\gamma_2,\ldots,\gamma_K)$. So β is not identified relative to γ_1.

Q.E.D.

Conditions A, B, and C of Proposition 2 imply the corresponding parts of Proposition 1. Condition A of Proposition 2 implies not only that $E(y|x,.)$ is constant on Z but that $E(y|.,.)$ is constant on $X \times Z$. Thus, when the linear model holds, the mean reference-group behavior $E(y|x)$ cannot vary with x unless there exist exogenous variables z which directly affect the behavior y.

Condition B is the same in Propositions 1 and 2. Part B of Proposition 1 showed that a linear model with $(\beta,\gamma) = (1,0)$ always holds. Part B here shows that, if a linear model holds for some $\beta \neq 1$, then a linear model holds for all $\beta \in R^1$.

Condition C of Proposition 2 is stronger than condition C of Proposition 1.[2] If x is a function of z and the linear model holds, then $E(y|x,z) = [\beta/(1-\beta)]E\{z|x(z)\}'\gamma + z'\gamma$. Provided that $E(y|x,z) \neq 0$ a.e. on $X \times Z$, the parameters (β,γ) are identified if the distribution of $\{E[z|x(z)],z\}$ is not concentrated on a proper linear subspace of $Z \times Z$. Thus, Condition C of Proposition 1 does not by itself imply that β is unidentified. On the other hand, that condition plus the assumption that $E[z|x(z)]$ is linear in z do imply that β is unidentified.

Condition D of Proposition 2 does not have a counterpart in Proposition 1. We find that, if the linear model holds and z is mean-independent of x, then y is mean-independent of x. Because the mean reference-group behavior $E(y|x)$ does not vary with x, β is unidentified.

It is important to observe that, even when β is unidentified, the linear model has testable implications. If the model holds and $\beta \neq 1$, then $E(y|x)$ is a linear function of $E(z|x)$. The quantities $E(y|x)$ and $E(z|x)$, which are identified by the sampling process, can be estimated without prior functional form restrictions. This done, the linear-model hypothesis can be tested.

It is also important to observe that, even when β is unidentified, features of γ may be identified. Part D of Proposition 2 shows that, if z is mean independent of x, then β cannot be distinguished from the intercept component of γ. The slope components of γ remain identifiable.

4.2. MODELS WITH A UNIQUE SOCIAL EQUILIBRIUM

Assume now that the general model (5) correctly describes behavior and let the family F of feasible reflection regressions include all measurable functions yielding a unique social equilibrium (6). This nonparametric specification substantially generalizes the linear model examined above.

In this nonparametric setting, the effect of reference-group behavior on individual behavior is measured by the way $f[E(y|x),z]$

varies with $E(y|x)$, conditional on z. Social effects cannot be identified if $E(y|x)$ has a degenerate distribution conditional on z; in particular, they cannot be identified if $E(y|x)$ is functionally dependent on z. Proposition 2 gave conditions implying that $E(y|x)$ is a linear function of z. Proposition 3, which is a nonparametric version of Proposition 2, gives conditions implying that $E(y|x)$ is a function of z.

Proposition 3: Assume that (5) holds for some $f(.,.)$ such that (6) has a unique solution.

A. Suppose that, for each $\eta \in Y$, $f(\eta,.)$ is constant on Z. Then $E(y|x)$ is constant on X.

B. Suppose that z is a function of x. Then $E(y|x)$ is a function of $z(x)$.

C. Suppose that x is a function of z. Then $E[y|x(z)]$ is a function of z.

D. Suppose that z is statistically independent of x. Then $E(y|x)$ is constant on X. ■

Proof:

A. Let $g(\eta)$ denote the constant value of $f(\eta,.)$. Then (6) reduces to $E(y|x) = \int g[E(y|x)]dP(z|x) = g[E(y|x)]$. So $E(y|x)$ solves the same equation for each value of x. The assumed uniqueness of the solution to (6) then implies that $E(y|x)$ is constant on X.

B. Let $\varsigma \in Z$. The distribution of x conditional on the event $[z = \varsigma]$ is concentrated on the set $X(\varsigma) \equiv [x \in X: z(x)=\varsigma]$; hence, the distribution of $E(y|x)$ conditional on the event $[z=\varsigma]$ is concentrated on $[E(y|x), x \in X(\varsigma)]$. For $x \in X(\varsigma)$, $P(z|x)$ has all its mass at the point ς. Hence, for $x \in X(\varsigma)$, equation (6) reduces to $E(y|x) = f[E(y|x),\varsigma]$. So $E(y|x)$ solves the same equation for each x in $X(\varsigma)$. The uniqueness assumption then implies that $E(y|x)$ is constant on $X(\varsigma)$.

C. This holds by assumption.

D. Statistical independence means that $P(z|x) = P(z)$. Hence (6) reduces to $E(y|x) = \int f[E(y|x),z]dP(z)$. So $E(y|x)$ solves the same equation for each value of x. The uniqueness assumption then implies that $E(y|x)$ is constant on X.

Q.E.D.

Each of the four parts of Proposition 3 is a nonparametric version of the corresponding part of Proposition 2. Conditions A and D imply that $E(y|x)$ does not vary with x. Individuals may have different reference groups but all reference groups have the same mean behavior. So inference on social effects is impossible.

Conditions B and C imply that $E(y|x)$ is a function of z but do not imply that $E(y|x)$ is constant. These conditions eliminate the possibility of nonparametric identification of social effects but leave open the possibility of identification if one possesses suitable prior knowledge of the form of the function $f(.,.)$.

Parts A, B, and D of Proposition 3 do not necessarily extend to models with multiple equilibria. Suppose that (5) holds for a function f(.,.) implying multiple solutions to (6). Then conditions A and D do not imply that $E(y|x)$ is constant and condition B does not imply that $E(y|x)$ is constant conditional on z. Multiple equilibria make possible variation in $E(y|x)$ that enhances the possibilities for identification.

5. The Empirical Literature

A diverse empirical literature is concerned with social-effects models of various types. Five bodies of work are discussed here. These estimate linear spatial correlation models, linear dynamic linear models, linear exogenous-effects models, binary response models, and demand-price models.

5. 1. LINEAR SPATIAL CORRELATION MODELS

Spatial correlation models have the form

$$(9) \quad y_i = \beta W_{iN} Y + z_i \gamma + u_i, \qquad i = 1,\ldots,N.$$

Here $Y = (y_i, i=1,\ldots,N)$ is the $N\times 1$ vector of sample realizations of y and W_{iN} is a specified 1xN weighting vector; that is, the components of W_{iN} are non-negative and sum to one. The disturbances u are assumed to be normally distributed, independent of x, and the model is estimated by maximum likelihood. See, for example, Cliff and Ord (1981), Andreoni and Scholz (1990), or Case (1991).

Equation (9) states that the behavior of each person in the sample varies with a weighted average of the behaviors of the other sample members. Thus, the spatial correlation model assumes that a social effect is generated within the researcher's sample rather than within the population from which that sample was drawn. This makes sense in studies of small-group interactions, where the sample is composed of clusters of friends, co-workers, or household members; see, for example, Duncan, Haller, and Portes (1968). But it does not make sense in studies of neighborhood and other large-group social effects, where the sample members are randomly chosen individuals. Taken at face value, equation (9) implies that the sample members know who each other are and choose their outcomes only after having been selected into the sample.

The spatial correlation model does make sense in studies of large-group interactions if interpreted as a two-stage method for estimating model (2): In the first stage, one uses the sample data on (y,x) to estimate $E(y|x)$ nonparametrically, and in the second stage, one estimates (β,γ) by finding the least squares fit of y to $[E_N(y|x),z]$, where $E_N(y|x)$ is the first-stage estimate of $E(y|x)$. Many nonparametric estimates of $E(y|x_i)$, including kernel and nearest-neighbor estimates, are weighted averages of the form $E_N(y|x_i) = W_{iN}Y$, with W_{in} determining the specific estimate (see

Hardle,1990). Hence, estimates of (β,γ) reported in the spatial correlation literature can be interpreted as estimates of (2).

5.2. LINEAR DYNAMIC MODELS

Some authors, such as Alessie and Kapteyn (1991) and Borjas (1991), use a two-stage method of the type just described to estimate a dynamic version of (2). Here

$$(10) \quad E_t(y|x,z) = \beta E_{t-1}(y|x) + z'\gamma,$$

where E_t and E_{t-1} denote expectations taken at periods t and t-1. The idea is that an individual is influenced not by the behavior of his contemporaries but by the behavior of an earlier cohort.

If $E(z|x)$ is time-invariant and $-1 < \beta < 1$, the dynamic process (10) has a unique stable temporal equilibrium in which (8) holds and Proposition 2 applies. The Proposition does not apply if one observes the dynamic process out of equilibrium. In this case, the recursive structure of (10) opens possibilities for identification that are not available when the process is in equilibrium.

One should not, however, casually conclude that dynamic social effects models "solve" the reflection problem. To exploit the recursive structure of (10), a researcher must maintain the hypothesis that the transmission of social effects really follows the assumed temporal pattern. But empirical studies typically provide no evidence for any particular timing. Some authors assume that individuals are influenced by the behavior of their contemporaries, some assume a time lag of a few years, while others assume that social effects operate across generations.

5.3. LINEAR EXOGENOUS-EFFECT MODELS

Numerous empirical studies have reported two-stage estimates of linear models of the form

$$(11)\quad E(y|x,z) = E[g(z)|x]'\alpha + z'\gamma,$$

with g(z) a specified function of z and α a parameter vector. As in the endogenous-effects case, one first uses the sample data on (z,x) to estimate E[g(z)|x] nonparametrically and then estimates (α,γ) by finding the least squares fit of y to $[E_N[g(z|x),z]$. See, for example, Coleman et al. (1966), Sewell and Armer (1966), Hauser (1970), Crane (1991) or Mayer (1991).

Models (2) and (11) express conceptually distinct social effects. The effect in (2) is generated by the reference-group mean of the endogenous variable y. That in (11) is generated by the reference-group mean of the exogenous variables g(z). The empirical literature has not, however, clearly differentiated between endogenous and exogenous social effects.

Studies of school integration, typified by Coleman et al. (1966), often seem to have in mind an endogenous social effect, wherein the achievement of each student is affected by the mean achievement of the students in the same school. But these studies generally estimate exogenous-effects models, wherein the achievement of each student is affected by the racial composition of his school. The same tension appears in analyses of neighborhood effects. The theoretical section of Crane (1991) poses an "epidemic" model of endogenous neighborhood effects, wherein a teenager's school dropout and childbearing behavior is influenced by the neighborhood frequency of dropout and childbearing. But Crane estimates an exogenous-effects model, wherein a teenager's behavior depends on the occupational composition of her neighborhood. This juxtaposition of endogenous-effect theorizing and exogenous-effect empirical analysis also appears in Jencks and Mayer (1989).

The common confusion between endogenous and exogenous social effects may, perhaps, be traceable to the fact that endogenous-effects models with unique social equilibria have reduced-form representations as exogenous-effects models. Recall that if (2) holds and $\beta \neq 1$, then $E(y|x)$ is the linear function of $E(z|x)$ given in (7). So (2) is observationally indistinguishable from the special case of (11) with $g(z) = z$ and $\alpha = [\beta/(1-\beta)]\gamma$. More generally, when (5) holds and (6) has a unique solution, then $E(y|x)$ is a function of $P(z|x)$. So (5) is observationally indistinguishable from an exogenous-effects model in which $E(y|x,z)$ is a function of $[P(z|x),z]$.

The fact that endogenous-effects models have reduced-form representations as exogenous-effects models does not imply that the distinction between the two types of social effects is inconsequential. Here, as elsewhere, the difference between the structural and reduced form of a model is critical when one wishes to predict outcomes following a structural change. Suppose, for example, that a linear endogenous-effects model explains student achievement in school. Let z measure a student's human capital upon entering school, so that γ is the coefficient of the educational production function transforming pre-school into post-school human capital, ceteris paribus. Now suppose that an educational innovation changes γ to some other value c. Then the exogenous-effects model with $g(z) = z$ incorrectly predicts that student achievement following the innovation is $E(z|x)'\alpha + z'c$, where $\alpha = [\beta/(1-\beta)]\gamma$. The endogenous-effects model correctly predicts that achievement becomes $[\beta/(1-\beta)]E(z|x)'c + z'c$.

5.4. BINARY RESPONSE MODELS

Empirical studies of endogenous effects have not always assumed linear models. Perhaps the most common non-linear reflection regressions to be estimated are binary response models. Let y be a binary random variable, so that $E(y|x,z) = P(y=1|x,z)$ and $E(y|x) = P(y=1|x)$. Assume that, for some continuous and strictly increasing distribution function H(.) on the real line,

$$(12) \quad E(y|x,z) = H[\beta E(y|x)+z'\gamma],$$

where (β,γ) are parameters. This nonlinear reflection regression model has a social equilibrium if $E(y|x)$ solves the equation

$$(13)\quad E(y|x) = \int H[\beta E(y|x)+z'\gamma]dP(z|x).$$

Models of the form (12) have been estimated by two-stage methods. One estimates $E(y|x)$ nonparametrically and then estimates (β,γ) by maximizing the quasi-likelihood in which $E_N(y|x)$ takes the place of $E(y|x)$. Examples include Case and Katz (1991) and Gamoran and Mare (1989). A multinomial response model was estimated in this manner by Manski and Wise (1983), Chapter 6.

It is of interest to ask whether binary response reflection regresions do have social equilibria. If $\beta \leq 0$, then equation (13) has a unique solution. If $\beta = 0$, $E(y|x) = \int H(z'\gamma)dP(z|x)$. If $\beta < 0$, the right-hand-side of (13) decreases strictly and continuously from $\int H(z'\gamma)dP(z|x)$ to $\int H(\beta+z'\gamma)dP(z|x)$ as $E(y|x)$ rises from 0 to 1. Meanwhile, the left-hand-side increases strictly and continuously from 0 to 1. Hence the left and right hand sides cross at a unique value of $E(y|x)$.

If $\beta > 0$, equation (13) has at least one solution. A solution exists because the right-hand-side of (13) increases strictly and continuously from $\int H(z'\gamma)dP(z|x)$ to $\int H(\beta+z'\gamma)dP(z|x)$ as $E(y|x)$ rises from 0 to 1. Meanwhile, the left-hand-side traverses the larger interval [0,1]. Hence, the left-hand-side must cross the right-hand-side from below at some value of $E(y|x)$.

5.5. DEMAND-PRICE MODELS

In the Introduction, it was noted that mainstream economic demand models embody an endogenous social effect: individual demand for a product varies with price, which is partly determined by aggregate demand in the relevant market. This section elaborates.

Let y denote a consumer's demand for a given product. Let x denote the market in which the consumer operates; different values of x may, for example, refer to different geographic areas or to different time periods. Let p(x) be the market equilibrium price in market x. Then a conventional model of consumer demand assumes that, conditioning on consumer attributes, the market in which a consumer operates affects demand only through the price prevailing in that market. A common empirical formulation is

$$(14) \quad E(y|x,z) = D[p(x),z],$$

where z are consumer attributes observed by the researcher and where D(.,.) is expected demand, conditional on (x,z).

A conventional market equilibrium model assumes that the price p(x) is determined by aggregate demand in market x and by supply conditions in this market. Let the population of consumers living in market x have size m(x). Then E(y|x) is per capita demand in market x and E(y|x)m(x) is aggregate demand. Let h(x) denote the relevant supply conditions. Then

(15) $p(x) = \pi[E(y|x)m(x),h(x)]$

expresses the determination of price by demand and supply.

Equations (14) and (15) imply that

(16) $E(y|x,z) = D\{\pi[E(y|x)m(x),h(x)],z\}.$

This is a reflection regression model of a type distinct from (5). Given z, y varied with x only through $E(y|x)$ in (5) but varies with x through $E(y|x)$, $m(x)$, and $h(x)$ in (16). Equation (16) reduces to (5) if $m(.)$ and $h(.)$ are constant on X; that is, if the population of consumers has the same size in all markets and if supply conditions are homogeneous across markets. In this case, the variation of price across markets derives entirely from variation in the distribution $P(z|x)$ of consumer attributes. Propositions 1 through 3 apply to the problem of identifying the consumer demand function.

5.6. A NOTE ON SAMPLING INFERENCE

While the concern of this paper is with identification, it is necessary to point out that studies reporting two-stage estimates of social-effects models have routinely misreported the sampling distribution of their estimates. The literature on spatial correlation models has presumed that equation (9) holds as stated and has not specified how the weights W_{iN} should change with N. The practice in two-stage estimation of exogenous-effects models has been to treat the first-stage estimate $E_N[g(z)|x]$ as if it were $E[g(z)|x]$ rather than an estimate thereof. The same remark applies to the estimation of dynamic models and discrete response models.

Two-stage estimation of social-effects models is similar to other semiparametric two-stage estimators whose asymptotic properties have been studied recently. Ahn and Manski (1991), Andrews (1989), Ichimura and Lee (1991), and others have analyzed the asymptotic behavior of various estimators whose first stage is nonparametric regression and whose second stage is parametric estimation conditional on the first-stage estimate. It is typically found that the second-stage estimate is $\sqrt{N}$-consistent with a limiting normal distribution if the first-stage estimator is chosen appropriately. The variance of the limiting distribution is typically larger than that which would prevail if the first-stage regression were known rather than estimated. It seems likely that this result holds here as well.

6. Conclusion

Empirical researchers have long been aware of the problem of distinguishing social effects from reference-group fixed effects. The analysis of this paper reveals that the identification of endogenous social effects is even more tenuous than previously recognized.

The findings in Propositions 1 through 3 raise troubling questions about the interpretation of empirical estimates of endogenous-effects models. Suppose that one specifies a linear model and reports a two-stage estimate of (β,γ). Because the first-stage estimate $E_N(y|x)$ measures $E(y|x)$ with error, the second stage may produce a point estimate of (β,γ) even if the model is unidentified. An unaware researcher may estimate a tautological linear model following from Condition A or B of Proposition 1, obtain an estimate of (β,γ) close to (1,0), and improperly conclude that individual behavior reflects reference-group behavior.

Particularly worrisome is the fact that empirical researchers typically cannot justify the assumptions they make about the variables x on which individuals condition their reference groups. They rarely cite any evidence justifying their specifications of x; an exception is Woittiez and Kapteyn (1991), who use individuals' responses to questions about their "social environments" as evidence on their reference groups. In fact, the empirical literature never questions whether individuals actually observe the behavior of their supposed reference-groups. But individual behavior cannot depend on $E(y|x)$ if individuals do not know this quantity.[3]

Yet other problems compound the difficulty of identifying social effects. We have found that endogenous-effects models have reduced-form representations as exogenous-effects models (Section 5.3). And we have called attention to the absence of empirical evidence on the temporal transmission of social effects (Section 5.2).

If the identification of social effects is so tenuous, then why is there such a widespread perception (at least among non-economists), that mean reference-group behavior affects individual behavior? It may be that this common perception is poorly grounded, fed by a flawed interpretation of actual behavior. But actual behavior is not the only source of evidence on social effects. Prevailing views on social effects also rest on evidence from controlled experiments and on subjective data, the statements people make about why they behave as they do.[4] The findings of this paper suggest that experimental and subjective data must continue to play an important role in efforts to learn about social effects. The evidence in actual behavior alone is too weak to support strong conclusions.

Notes

1. Beginning with Hyman (1942), reference-group theory has sought to operationalize the idea that individuals learn from or are otherwise influenced by the behavior and attitudes of some reference group. Bank et al. (1990) give an historical account. Sociological writing on reference groups has remained predominately verbal but economists have formalized the term in the manner of the present paper. See Alessie and Kapteyn (1991) and Manski (1991a).

2. Condition C of Proposition 2, albeit a strong assumption, is satisfied in various familiar settings. It holds if z is normally distributed and x is a linear function of z. It also holds if z = (x,w) and w is mean-independent of x.

3. The same problem arises in empirical studies of decision making under uncertainty. Researchers generally assume they know the information on which individuals condition their expectations but cite no evidence justifying their assumptions. I have recently criticized this practice in the context of studies of schooling choice. See Manski (1991b).

4. Some of the experimental literature is surveyed by Jones (1984).

References

Ahn, H. and C. Manski(1991), "Distribution Theory for the Analysis of Binary Choice Under Uncertainty with Nonparametric Estimation of Expectations," Journal of Econometrics, forthcoming.

Akerlof, George (1980), "A Theory of Social Custom, of Which Unemployment may be One Consequence," Quarterly Journal of Economics, 94: 749-775.

Alessie, R. and A. Kapteyn(1991), "Habit Formation, Interdependent Preferences and Demographic Effects in the Almost Ideal Demand System," The Economic Journal, 101: 404-419.

Andreoni, J. and K. Scholz(1990), "An Econometric Analysis of Charitable Giving With Interdependent Preferences," Department of Economics, University of Wisconsin-Madison.

Andrews, D.(1989), "Semiparametric Econometric Models: I. Estimation", Cowles Foundation for Research in Economics, Yale University.

Asch, Solomon E. (1952), Social Psychology, Englewood Cliffs, N.J: Prentice-Hall.

Bandura, A.(1986), Social Foundations of Thought and Action, Englewood Cliffs, N.J.: Prentice-Hall.

Bank, B., R. Slavings, and B. Biddle(1990), "Effects of Peer, Faculty, and Parental Influences on Students' Persistence," Sociology of Education, 63, 208-225.

Bernheim, B. (1991), "A Theory of Conformity," Department of Economics, Princeton University.

Borjas, G.(1991), "Ethnic Capital and Intergenerational Mobility," Department of Economics, University of California at San Diego.

Case, A.(1991), "Spatial Patterns in Household Demand," Econometrica, 59: 953-965.

Case, A. and L. Katz (1991), "The Company You Keep: The Effects of Family and Neighborhood on Disadvantaged Youth," Working Paper No. 3705, National Bureau of Economic Research, Cambridge, Mass.

Cliff, A. and J. Ord(1981), Spatial Processes, London: Pion.

Coleman, J., E. Campbell, C. Hobson, J. McPartland, A. Mood, F. Weinfeld, and R. York(1966), Equality of Educational Opportunity, Washington D.C.: U.S. Government Printing Office.

Conlisk, J.(1980), "Costly Optimizers Versus Cheap Imitators," Journal of Economic Behavior and Organization, 1:275-293.

Crane, J.(1991), "The Epidemic Theory of Ghettos and Neighborhood Effects on Dropping Out and Teenage Childbearing," American Journal of Sociology, 96: 1226-1259.

Duesenberry, J.(1949), Income, Savings, and the Theory of Consumption, Cambridge: Harvard University Press.

Duncan, O., A. Haller, and A. Portes(1968), "Peer Influences on Aspirations: A Reinterpretation," American Journal of Sociology, 74: 119-137.

Friedman, M.(1957), A Theory of the Consumption Function, Princeton: Princeton University Press.

Gaertner, W.(1974), "A Dynamic Model of Interdependent Consumer Behavior," Zeitschrift fur Nationalokonomie, 70: 312-326.

Gamoran, A. and R. Mare(1989), "Secondary School Tracking and Educational Inequality: Compensation, Reinforcement, or Neutrality?" American Journal of Sociology, 94: 1146-1183.

Hardle, W.(1990), Applied Nonparametric Regression, New York: Cambridge University Press.

Hauser, R.(1970), "Context and Consex: A Cautionary Tale," American Journal of Sociology, 75: 645-664.

Hyman, H.(1942), "The Psychology of Status," Archives of Psychology," No. 269.

Ichimura, H. and Lee, L.(1991), "Semiparametric Estimation of Multiple Indices Models: Single Equation Estimation," in W. Barnett, J. Powell, and G. Tauchen (editors), Nonparametric and Semiparametric Methods in Econometrics and Statistics, New York: Cambridge University Press.

Jencks, C. and S. Mayer(1989), "Growing Up in Poor Neighborhoods: How Much Does it Matter?" Science, 243: 1441-1445.

Jones, S.(1984), The Economics of Conformism, Oxford: Basil Blackwell.

Manski, C.(1991a), "Dynamic Choice in a Social Setting: Learning from the Experiences of Others," Journal of Econometrics, forthcoming.

Manski, C.(1991b), "Adolescent Econometricians: How Do Youth Infer the Returns to Schooling?" in C. Clotfelter and M. Rothschild (editors), The Economics of Higher Education, Chicago: University of Chicago Press, forthcoming.

Manski, C. and D. Wise(1983), College Choice in America, Cambridge: Harvard University Press.

Mayer, S.(1991), "How Much Does a High School's Racial and Socioeconomic Mix Affect Graduation and Teenage Fertility Rates?" in C. Jencks and P. Peterson (editors) The Urban Underclass, Washington, D.C.: The Brookings Institution.

Merton, R.(1957), Social Theory and Social Structure, Glencoe: The Free Press.

Pollak, R.(1976), "Interdependent Preferences," American Economic Review, 78: 745-763.

Schelling, Thomas (1971), "Dynamic Models of Segregation," Journal of Mathematical Sociology, 1: 143-186.

Sewell, W. and J. Armer(1966), "Neighborhood Context and College Plans," American Sociological Review, 31: 159-168.

Woittiez, I. and A. Kapteyn(1991), "Social Interactions and Habit Formation in a Labor Supply Model," Department of Economics, University of Leiden.

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