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identification

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Abstract

The problem of identification is defined in terms of the possibility of characterizing parameters of interest from observable data. This problem occurs in many fields, such as automatic control, biomedical engineering, psychology, systems science, the design of experiments, and econometrics. This article focuses on identification in econometric models, which typically involve random variables. Identification in general parametric statistical models is defined, and its meaning in a number of specific econometric models is considered: regression (collinearity), simultaneous equations, dynamic models, and nonlinear models. Identification in nonparametric models, weak identification, and the statistical implications of identification failure are also discussed.

Keywords

Bayes' th; collinearity; endogeneity and exogeneity; identification; instrumental variable; linear models; multivariate regression models; nonparametric estimation; nonparametric models; probability; random variables; returns to schooling; separability; serial correlation; simultaneous equations models; treatment effect; weak identification; weak instruments

Article

In economic analysis, we often assume that there exists an underlying structure which has generated the observations of real-world data. However, statistical inference can relate only to characteristics of the distribution of the observed variables. Statistical models which are used to explain the behaviour of observed data typically involve parameters, and statistical inference aims at making statements about these parameters. For that purpose, it is important that different values of a parameter of interest can be characterized in terms of the data distribution. Otherwise, the problem of drawing inferences about this parameter is plagued by a fundamental indeterminacy and can be viewed as 'ill-posed'.

To illustrate, consider X as being normally distributed with mean $E(X) = \mu_1 - \mu_2$. Then $\mu_1 - \mu_2$ can be estimated using observed X. But the parameters μ_1 and μ_2 are not uniquely estimable. In fact, one can think of an infinite number of pairs (μ_i, μ_j), $i, j = 1, 2, \ldots (i \neq j)$ such that $\mu_i - \mu_j = \mu_1 - \mu_2$. In order to determine μ_1 and μ_2 uniquely, we need additional prior information, such as $\mu_2 = 3\mu_1$ or some other assumption. Note, however, that inference about the variance of X remains feasible without extra assumptions.

More generally, *identification failures* – or situations that are close to it – complicate considerably the statistical analysis of models, so that tracking such failures and formulating restrictions to avoid them is an important problem of econometric modelling.

The problem of whether it is possible to draw inferences from the probability distribution of the observed variables to an underlying theoretical structure is the concern of econometric literature on identification. The first economists to raise this issue were Working (1925; 1927) and Wright (1915; 1928). The general formulations of the identification problems were made by Frisch (1934), Marschak (1942), Haavelmo (1944), Hurwicz (1950), Koopmans and Reiersøl (1950), Koopmans, Rubin and Leipnik (1950), Wald (1950), and many others. An extensive treatment of the theory of identification in simultaneous equation systems was provided by Fisher (1976). Surveys of the subject can be found in Hsiao (1983), Prakasa Rao (1992), Bekker and Wansbeek (2001), Manski (2003), and Matzkin (2007); see also Morgan (1990) and Stock and Trebbi (2003) on the early development of the subject.

In this article, we first define the notion of identification in general parametric models (Sections 1 and 2) and discuss its meaning in a number of specific statistical models used in econometrics, such as regression models (collinearity), simultaneous equations, dynamic models, and nonlinear models (Section 3). Identification in nonparametric models (Sections 4 and 5), weak identification (Section 6), and the statistical implications of identification failure (Section 7) are also considered.

1 Definition of parametric identification

It is generally assumed in econometrics that economic variables whose formation an economic theory is designed to explain have the characteristics of random variables. Let y be a set of such observations. A structure S is a complete specification of the probability distribution function of y. The set of all a priori possible structures, T, is called a model. In most applications, y is assumed to be generated by a parametric probability distribution function $F(y, \theta)$, where the probability distribution function F is assumed known, but the $q \times 1$ parameter vector θ is unknown. Hence, a structure is described by a parametric point θ, and a model is a set of points $A \subseteq R^q$.

Definition 1: Two structures, $S^0 = F(y, \theta^0)$ and $S^* = F(y, \theta^*)$ are said to be observationally equivalent *if $F(y, \theta^0) = F(y, \theta^*)$ for ('almost') all possible y. A model is identifiable if A contains no two distinct structures which are observationally equivalent. A function of θ, $g(\theta)$, is identifiable if all observationally equivalent structures have the same value for $g(\theta)$.*

Sometimes a weaker concept of identifiability is useful.

Definition 2: A structure with parameter value θ^0 is said to be locally identified if there exists an open neighborhood of θ^0, W, such that no other θ in W is observationally equivalent to θ^0.

2 General results for identification in parametric models

Lack of identification reflects the fact that a random variable has the same distribution for some if not all values of the parameter. R.A. Fisher's information matrix provides a sensitivity measure of the distribution of a random variable due to small changes in the value of the parameter point (Rao, 1962). It can therefore be shown that, subject to regularity conditions, q^0 is locally identified if and only if the information matrix evaluated at q^0 is nonsingular (Rothenberg, 1971).
It is clear that unidentified parameters cannot be consistently estimated. There are also pathological cases where identified models fail to possess consistent estimators (for example, Gabrielson, 1978). However, in most practical cases, we may treat identifiability and the existence of a consistent estimator as equivalent; for precise conditions, see Le Cam (1956) and Deistler and Seifert (1978).

3 Some specific parametric models

The choice of model structure is one of the basic ingredients in the formulation of the identification problem. In this section we briefly discuss some identification conditions for different types of models in order to demonstrate the kind of prior restrictions required.

3.1 Linear regression with collinearity

One of the most common models where an identification problem does occur is the linear regression model:

$$\mathbf{y} = X\beta + \mathbf{u} \tag{1}$$

where $\mathbf{y}$ is an $n\times1$vector of dependent observable variables, X is an $n\times k$ fixed matrix of observable variables, β a $k\times1$ unknown coefficient vector, and $\mathbf{u}$ is an $n\times1$ vector of disturbances whose components are (say) independent and identically distributed according to a normal distribution $N(0, \sigma^2)$ with unknown positive variance σ^2.
In this model, the value of β must be determined from the expected value of $\mathbf{y}$: $E(\mathbf{y}) = X\beta$. If the latter equation has a solution for β (that is, if the model is correct), the solution is unique if and only the regressor matrix X has rank k. If X has rank zero (which entails X=0), all values of β are equivalent (β is completely *unidentifiable*). If $1 \leq \text{rank}(X) < k$, then not all the components can be determined, but some linear combinations of the components of β (say $c'\beta$) can be determined (that is, they are *identifiable*). A necessary and sufficient condition for $c'\beta$ to be estimable (identifiable) is that $c = (X^0X)d$ for some vector d. Linear combinations that do not satisfy this condition are not identifiable. The typical way out of such collinearity problems consists in imposing restrictions on β (identifying restrictions) which set the values of the unidentifiable linear combinations (or components) of β.
Correspondingly, when X does not have full rank, the equation $(X^0X)\hat{\beta} = X^0\mathbf{y}$, which defines the least squares estimator $\hat{\beta}$, does not have a unique solution. But all solutions of the least squares problem can be determined by considering $\hat{\beta} = (X^0X)^-X^0\mathbf{y}$ where $(X^0X)^-$ is any generalized inverse of (X^0X). Different generalized inverses then correspond to different identifying restrictions on β. For further discussion, see Rao (1973, ch. 4).

3.2 Linear simultaneous equations models

Consider a theory which predicts a relationship among the variables as

$$B\mathbf{y}_t + \Gamma\mathbf{x}_t = \mathbf{u}_t,\ t = 1, \ldots, n, \tag{2}$$

where $\mathbf{y}_t$ and $\mathbf{u}_t$ are $G\times1$ vectors of observed and unobserved random variables, respectively, $\mathbf{x}_t$ is a $K\times1$ vector of observed non-stochastic variables, B and Γ are $G\times G$ and $G\times K$ matrices of coefficients, with B nonsingular. We assume that the $\mathbf{u}_t$ are independently normally distributed with mean 0 and variance-covariance matrix Σ. Equations (2) are called structural equations. Solving for the endogenous variables, $\mathbf{y}$, as a function of the exogenous variables, $\mathbf{x}$, and the disturbance u, we obtain:

$$\mathbf{y}_t = -B^{-1}\Gamma\mathbf{x}_t + B^{-1}\mathbf{u}_t = \Pi\mathbf{x}_t + \mathbf{v}_t, \tag{3}$$

where $\Pi = -B^{-1}\Gamma$, $E\mathbf{v}_t = 0$, $E\mathbf{v}_t\mathbf{v}_t^0 = V = B^{-1}\Sigma(B^{-1})^0$. Equations (3) are called the *reduced form* equations derived from (2) and give the conditional likelihood of $\mathbf{y}_t$ for given $\mathbf{x}_t$ that summaries the information provided by the observed ($\mathbf{y}_t$, $\mathbf{x}_t$). The variables in $\mathbf{x}_t$ are often also called 'instruments'.
From (3), we see that the simultaneous equations model can be viewed as a special case of a multivariate regression model (MLR), such that the regression coefficient matrix Π satisfies the equation:

$$B\Pi = -\Gamma. \tag{4}$$

Provided the matrix X=[x_1,…,x_n]$'$ has full rank K (no collinearity), the regression coefficient matrix Π is uniquely determined by the distribution of Y=[y_1,…,y_n]$'$ (it is *identifiable*). The problem is then whether B and Γ can be uniquely derived from eq. (4). Premultiplying (2) by a $G\times G$ nonsingular matrix D, we get a second structural equation:

$$B^*\mathbf{y}_t + \Gamma^*\mathbf{x}_t = \mathbf{u}_t^*, \tag{5}$$

where $B^*=DB$, $\Gamma^*=D\Gamma$, and $\mathbf{u}_t^* = D\mathbf{u}$. It is readily seen that the reduced form of (5) is also (3). So eq. (4) cannot be uniquely solved for B and Γ,

given •. Therefore, the two structures are observationally equivalent and the model is *non-identifiable*.
To make the model identifiable, additional prior restrictions have to be imposed on the matrices B, • and/or •. Consider the problem of estimating the parameters of the first equation in (2), out of a system of G equations. If the parameters cannot be estimated, the first equation is called *unidentified* or *underidentified*. If given the prior information, there is a unique way of estimating the unknown parameters, the equation is called *just identified*. If the prior information allows the parameters to be estimated in two or more linearly independent ways, it is called *overidentified*.
A necessary condition for the first equation to be identified is that the number of restrictions on this equation be no less than G•1 (order condition).
A necessary and sufficient condition is that a specified submatrix of B, • and • be of rank G•1(rank condition) (see Fisher, 1976; Hausman and Taylor, 1983). For instance, suppose the restrictions on the first equation are in the form that certain variables do not appear. Then this rank condition says that the first equation is identified if and only if the submatrix obtained by taking the columns of B and • with prescribed zeros in the first row is of rank G•1 (Koopmans and Reiersøl, 1950).

3.3 Dynamic models

When both lagged endogenous variables and serial correlation in the disturbance term appear, we need to impose additional conditions to identify a model. For instance, consider the following two equation system (Koopmans, Rubin and Leipnik, 1950):

$$y_{1t} + \beta_{11} y_{1,t-1} + \beta_{12} y_{2,t-1} = u_{1t}, \beta_{12} y_{1t} + y_{2t} = u_{2t}. \tag{6}$$

If (u_{1t}, u_{2t}) are serially uncorrelated, (6) is identified. If serial correlation in (u_{1t}, u_{2t}) is allowed, then

$$y_{1t} + \beta^*_{11} y_{1,t-1} + \beta^*_{12} y_{2,t-1} = u^*_{1t}, \beta_{12} y_{1t} + y_{2t} = u_{2t}, \tag{7}$$

is observationally equivalent to (6), where $\beta^*_{11} = \beta_{11} + d\beta_{21}$, $\beta^*_{12} = \beta_{12} + d$, and $u^*_{1t} = u_{1t} + du_{2t}$.
Hannan (1971) derives generalized rank conditions for the identification of this type of model by first assuming that the maximum orders of lagged endogenous and exogenous variables are known, then imposing restrictions to eliminate redundancy in the specification and to exclude transformations of the equations that involve shifts in time. Hatanaka (1975), on the other hand, assumes that the prior information takes only the form of excluding certain variables from an equation, and derives a rank condition which allows common roots to appear in each equation.

3.4 Nonlinear models

For linear models, we have either global identification or else an infinite number of observationally equivalent structures. For models that are linear in parameters, but nonlinear in variables, there is a broad class of models whose members can commonly achieve identification (Brown, 1983; McManus, 1992). For models linear in the variables but nonlinear in the parameters, the state of the mathematical art is such that we only talk about local properties. That is, we cannot tell the true structure from any other substitute; however, we may be able to distinguish it from other structures which are close to it. A sufficient condition for local identification is that the Jacobian matrix formed by taking the first partial derivatives of

$$\omega_i = \bullet_i(\theta), \quad i = 1, \ldots, n, 0 = \jmath_j(\theta), \quad j = 1, \ldots, R, \tag{8}$$

with respect to • be of full column rank, where the $\bullet_i$ are n population moments of y and the $\jmath_j$ are the R a priori restrictions on • (Fisher, 1976).
When the Jacobian matrix of (8) has less than full column rank, the model may still be locally identifiable via conditions implied by the higher-order derivatives. However, the estimator of a model suffering from first-order lack of identification will in finite samples behave in a way which is difficult to distinguish from the behaviour of an unidentified model (Sargan, 1983).

3.5 Bayesian analysis

In Bayesian analysis all quantities, including the parameters, are random variables. Thus, a model is said to be identified in probability if the posterior distribution for • is proper. When the prior distribution for • is proper, so is the posterior, regardless of the likelihood function of y. In this sense unidentifiability causes no real difficulty in the Bayesian approach. However, basic to the Bayesian argument is that all probability statements are conditional, that is, they consist essentially in revising the probability of a fixed event in the light of various conditioning events, the revision being accomplished by Bayes' theorem. Therefore, in order for an experiment to be informative with regard to unknown parameters (that is, for the posterior to be different from the prior), the parameter must be identified or estimable in the classical sense and identification remains as a property of the likelihood function (Kadane, 1975).
Drèze (1975) has commented that exact restrictions are unlikely to hold with probability 1 and has suggested using probabilistic prior information. In order to incorporate a stochastic prior, he has derived necessary rank conditions for the identification of a linear simultaneous equation model.

4 Definition of identification in nonparametric models

When the restrictions of an economic model specify all functions and distributions up to the value of a finite dimensional vector, the model is said to be parametric. When some functions or distributions are left parametrically unspecified, the model is said to be semiparametric. The model is nonparametric if none of the functions and distributions are specified parametrically. The previous discussion is based on parametric specification. We now turn to the issue of whether economic restrictions such as concavity, continuity and monotonicity of functions, equilibrium conditions, the implications of optimization, and so on, may be used to guarantee the identification of some nonparametric models and the consistency of some nonparametric estimators (see Matzkin 1994).
Formally, an econometric model is specified by a vector of observable dependent and independent variables, a vector of unobservable variables, and a set of known functional relationships among the variables. When such functional relationships are unspecified, the nonparametric identification

studies what functions or features of function can be recovered from the joint distribution of the observable variables.
The set of restrictions on the unknown functions and distributions in an econometric model defines the set of functions and distributions to which these belong. Let the model T denote the set of all a priori possible unknown functions and distributions. Let m denote a vector of the unknown functions and distributions in T and $P(m)$ denote the joint distribution of the observable variables under m. Then the identification of m can be defined as follows.

Definition 3: The vector of functions m is identified in T if for any other vector, $m^* \bullet T$ *such that* $m \bullet m^*$, $P(m) \bullet P(m^*)$.

Let $C(m)$ denote some feature of m, such as the sign of some coordinate of m.

Definition 4: The feature $C(m)$ *of m is identified if* $C(m)=C(m^*)$ *for all m,* $m^* \bullet T$ *such that* $P(m)=P(m^*)$.

5 Examples of nonparametric identification

Contrary to the parametric model, there is no general result for nonparametric identification. We shall therefore give some examples of how restrictions can be used to identify nonparametric functions.

5.1 Generalized regression models

Economists often consider a model of the form

$$y = g(\mathbf{x}) + u.$$

(9)

When $E(u|\mathbf{x})=0$ and $g(\cdot)$ is a continuous function $g : \mathbf{x}$! R, then $g(\cdot)$ can be recovered from the joint distribution of $(y, \mathbf{x})$ because $E(y|\mathbf{x})=g(\mathbf{x})$.
In some cases, the object of interest is not a conditional mean function $g(\cdot)$, but some 'deeper' function, such as a utility function generating the distribution of demand for commodities by a consumer. For example, $\mathbf{x}$ in (9) can be a price vector for K commodities and the income of a consumer. Mas-Colell (1977) has shown that we can recover the underlying utility function from the distribution of demand if we restrict $g(\cdot)$ to be monotone increasing, continuous, concave and strictly quasi-concave functions.

5.2 Simultaneous equations models

Suppose $(\mathbf{y}, \mathbf{x})$ satisfies the structural equations

$$\mathbf{r}(\mathbf{x}, \mathbf{y}) = \mathbf{u},$$

(10)

where $\mathbf{y}$ and $\mathbf{u}$ denote $G\times1$ vectors of observable endogenous and unobservable variables, respectively, $\mathbf{x}$ is a $K\times1$ vector of observable exogenous variables, $\mathbf{r}$ denotes the G unknown functions, and let $p(\mathbf{r})$ and $p(\mathbf{r}^*)$ represent the joint distributions of the observables under $\mathbf{r}$ and $\mathbf{r}^*$ respectively. Assume also that: (i) $\bullet(\mathbf{x}, \mathbf{y})$, $\bullet\mathbf{r}/\bullet\mathbf{y}$ has full rank, (ii) there exists a function $\bullet(\cdot)$ such that $y=\bullet(\mathbf{x}, \mathbf{u})$ (for conditions ensuring this, see Benkard and Berry, 2006), and (iii) $\mathbf{u}$ is distributed independently of $\mathbf{x}$. Then a necessary and sufficient condition guaranteeing that $p(\mathbf{r}^*)=p(\mathbf{r})$ is that

$$\operatorname{rank} \begin{bmatrix} \dfrac{\bullet \mathbf{r}_i^*}{\bullet(\mathbf{x}, \mathbf{y})} \\ \dfrac{\bullet \mathbf{r}}{\bullet(\mathbf{x}, \mathbf{y})} \end{bmatrix} < G+1,$$

(11)

for all $(\mathbf{x}, \mathbf{y})$ and $i=1,\ldots,G$, and all, where $\mathbf{r}_i^*$ denotes the i-th coordinate function of $\mathbf{r}^* \bullet T$ (see Roehrig, 1988; Matzkin, 2007).

5.3 Latent variable models and the measurement of treatment effects

For each person i, let (y_{0i}^*, y_{1i}^*) denote the potential outcomes in the untreated and treated states, respectively. Then the treatment effect for individual i is

$$\bullet_i = y_{1i}^* - y_{0i}^*$$

and the average treatment effect (ATE) is defined as

$$E(\bullet_i) = E(y_{1i}^* - y_{0i}^*);$$

(12)

see Heckman and Vytlacil (2001).
Let the treatment status be denoted by the dummy variable d_i where $d_i=1$ denotes the receipt of treatment and $d_i=0$ denotes nonreceipt. The observed data are often in the form

$$y_i = d_i y_{1i}^* + (1-d_i) y_{0i}^*.$$

(13)

Suppose $y_{1i}^* = \mathrm{m}_1(\mathbf{x}_i, u_{1i})$, $y_{0i}^* = \mathrm{m}_0(\mathbf{x}_i, u_{0i})$, and $d_i^* = \mathrm{m}_D(\mathbf{z}_i) - u_{di}$, where $d_i=1$ if $d_i^* \geq 0$ and 0 otherwise, $\mathbf{x}_i$ and $\mathbf{z}_i$ are vectors of observable exogenous variables and (u_{1i}, u_{0i}, u_{di}) are unobserved random variables. The average treatment effect and the complete structural econometric

model can be identified with parametric specifications of $(\bullet_1(\cdot), \bullet_0(\cdot), \bullet_D(\cdot))$ and the joint distributions of (u_{1i}, u_{0i}, u_{di}) even though we do not simultaneously observe y^*_{1i} and y^*_{0i}. In the case that neither $(\bullet_1(\cdot), \bullet_0(\cdot), \bullet_D(\cdot))$ nor the joint distribution of (u_1, u_0, u_d) are specified, certain treatment effects may still be nonparametrically identified under weaker assumptions. For instance, under the assumption that d_i is orthogonal to (y^*_{1i}, y^*_{0i}) conditional on a set of confounders (x, z) (conditional independence or ignorable selection), the ATE is identifiable and estimable by comparing the difference of the average outcomes from the treatment group and from the untreated (control) group (Heckman and Robb, 1985; Rosenbaum and Rubin, 1985). If the focus is on the average treatment effect for someone who would not participate if $p(\mathbf{z}) \le p(\mathbf{z}_0)$ and would participate if $p(\mathbf{z})>p(\mathbf{z}_0)$ (the local average treatment effect (LATE)), where $p(\mathbf{z})=\text{Prob}(d=1|\mathbf{z})$ (propensity score), Imbens and Angrist (1994) show that under the assumptions of separability of the effects of observable factors and unobservable factors and independence between observed factors and unobserved factors, they can be estimated by the sample analogue of

$$\bullet_{LATE}(\mathbf{x},\ p(\mathbf{z}),\ p(\mathbf{z}_0)) \equiv \frac{E(y|\mathbf{x},\ p(\mathbf{z})) - E(y|\mathbf{x},\ p(\mathbf{z}_0))}{p(\mathbf{z}) - p(\mathbf{z}_0)}$$

(14)

where, without loss of generality, we assume $p(\mathbf{z})>p(\mathbf{z}_0)$. The limit of LATE provides the local instrumental variable (LIV) estimand (Heckman and Vytlacil, 1999):

$$\bullet_{LIV}(\mathbf{x},\ p(\mathbf{z})) \equiv \frac{\bullet E(y|\mathbf{x},\ p(\mathbf{z}))}{\bullet p(\mathbf{z})}.$$

(15)

Heckman and Vytlacil (2001) give conditions that suitably weighted versions of LIV identify the ATE.

6 Weak instruments and weak identification

The most common way of trying to achieve identification consists in imposing exclusion restrictions on the variables of a structural equation. In model (2), suppose that $\mathbf{y}_t$ and $\mathbf{x}_t$ are partitioned as $\mathbf{y}_t = (y_{1t}, \mathbf{y}'_{2t}, \mathbf{y}'_{3t})'$ and $\mathbf{x}_t = (\mathbf{x}'_{1t}, \mathbf{x}'_{2t})'$ where y_{1t} is a scalar, $\mathbf{y}_{it}$ has dimension $G_i(i=2, 3)$ and $\mathbf{x}_{it}$ has dimension $K_i(i=1, 2)$. If $\mathbf{y}_{3t}$ and $\mathbf{x}_{2t}$ are excluded from the first equation and the coefficient of y_{1t} is normalized to one, this yields an equation of the form:

$$y_{1t} - \mathbf{y}'_{2t}\beta_1 = \mathbf{x}'_{1t}\gamma_1 + u_{1t},\ t = 1,\ \ldots,\ n.$$

(16)

Let us also rewrite the reduced equation for $\mathbf{y}_{2t}$ in terms of $\mathbf{x}_{1t}$ and $\mathbf{x}_{2t}$:

$$\mathbf{y}_{2t} = \bullet_{21}\mathbf{x}_{1t} + \bullet_{22}\mathbf{x}_{2t} + \mathbf{v}_{2t}.$$

(17)

Then, substituting (17) into (16), we see that the reduced form for y_{1t} is:

$$y_{1t} = \bullet_{11}\mathbf{x}_{1t} + \bullet_{12}\mathbf{x}_{2t} + \mathbf{v}_{1t},$$

(18)

where $\mathbf{v}_{1t} = u_{1t} + \mathbf{v}'_{2t}\beta_1$, $\bullet_{11} = \gamma'_1 + \beta'_1\bullet_{21}$ and

$$\bullet'_{12} = \bullet'_{22}\beta_1.$$

(19)

Since $\bullet_1$ is free, $\bullet_{11}$ is not restricted, but eq. (19) determines the identifiability of $\bullet_1$, hence also of $\bullet_1$. Provided eq. (19) has a solution (that is, if eq. (16) is consistent with the data), the solution is unique if and only if the rank of the $G_2 \times K_2$ matrix $\bullet_{22}$ is equal to G_2, the dimension of $\bullet_1$:

$$\text{rank}(\bullet_{22}) = G_2.$$

(20)

If $\text{rank}(\bullet_{22})<G_2$, the vector $\bullet_1$ is not identifiable. However, it is completely unidentifiable only if $\text{rank}(\bullet_{22})=0$, or equivalently if $\bullet_{22}=0$. If $1<\text{rank}(\bullet_{22})<G_2$, some linear combinations $c'\bullet_1$ are identifiable, but not all of them. Failure of the identification condition means that the regressors (or the 'instruments') $\mathbf{x}_{2t}$ do not move enough to separate the effects of the different variables in $\mathbf{y}_{2t}$. Condition (20) underscores two important things: first, exclusion and normalization restrictions – which are easy to check – are not sufficient to ensure identification; second, identification depends on the way the exogenous variables $\mathbf{x}_{2t}$ *excluded* from the structural equation of interest (16) are related to endogenous variables $\mathbf{y}_{2t}$ included in the equation. The latter feature is determined by the matrix $\bullet_{22}$ whose rows should be linearly independent. Since $\bullet_{22}$ is not observable, this may be difficult to determine in practice.

A situation that can lead to identification difficulties is the one where the identification condition (20) indeed holds, but, in some sense, $\bullet_{22}$ is 'close' not to have sufficient rank. In such situations, we say that we have *weak instruments*. In view of the fact that the distributions of most statistics move continuously as functions of $\bullet_{22}$, the practical consequences of being close to identification failure are essentially the same. Assessing the closeness to non-identification may be done in various ways, for example by considering the eigenvalues of the matrices which measure the 'size' of $\bullet_{22}$, such as $\bullet_{22}\bullet'_{22}$, $\bullet_{22}X'_2M(X_1)X_2\bullet'_{22}$ or a *concentration matrix* $\bullet^{-1/2}_{22}\bullet_{22}X'_2M(X_1)X_2\bullet'_{22}\bullet^{-1/2}_{22}$ where $X_1=[\mathbf{x}_{11},\ldots,\mathbf{x}_{1n}]'$, $X_2=[\mathbf{x}_{21},\ldots,\mathbf{x}_{2n}]'$, $\bullet_{22}$ is the covariance matrix of $\mathbf{v}_{2t}$, $\bullet^{-1/2}_{22}$ is its square root, and $M(X_1) = I_n - X_1(X'_1X_1)^{-1}X'_1$. More generally, any situation where a parameter may be difficult to determine because we are close to a case where a parameter ceases to be identifiable

may be called *weak identification*. Weak identification was highlighted as a problem of practical interest by Nelson and Startz (1990), Bound, Jaeger and Baker (1995), Dufour (1997), and Staiger and Stock (1997); for reviews, see Stock, Wright and Yogo (2002) and Dufour (2003).

7 Statistical consequences of identification failure

Identification failure has several detrimental consequences for statistical analysis:

1. 1. Parameter estimates, tests and confidence sets computed for unidentified parameters have no clear inpt; this situation may be especially misleading if the statistical instruments used do not reveal the presence of the problem.
2. 2. Consistent estimation is not possible unless additional information is supplied.
3. 3. Many standard distributional results used for inference on such models are not anymore valid, even with a large sample size (see Phillips, 1983; 1989; Rothenberg, 1984).
4. 4. Numerical problems also easily appear, due for example to the need to invert (quasi) singular matrices.

Weak identification problems lead to similar difficulties, but may be more treacherous in the sense that standard asymptotic distributional may remain valid, but they constitute very bad approximations to what happens in finite samples:

1. 1. Standard consistent estimators of structural parameters can be heavily biased and follow distributions whose form is far from the limiting Gaussian distribution, such as bimodal distributions, even with fairly large samples (Nelson and Startz, 1990; Hillier, 1990; Buse, 1992).
2. 2. Standard tests and confidence sets, such as Wald-type procedures based on estimated standard errors, become highly unreliable or completely invalid (Dufour, 1997).

A striking illustration of these problems appears in the reconsideration by Bound, Jaeger and Baker (1995) of a study on returns to education by Angrist and Krueger (1991). Using 329,000 observations, these authors found that replacing the instruments used by Angrist and Krueger (1991) with randomly generated (totally irrelevant) instruments produced very similar point estimates and standard errors. This result indicates that the original instruments were weak. Recent work in this area is reviewed in Stock, Wright and Yogo (2002) and Dufour (2003).

8 Concluding remarks

The study of identifiability is undertaken in order to explore the limitations of statistical inference (when working with economic data) or to specify what sort of a priori information is needed to make a model estimable. It is a fundamental problem concomitant with the existence of a structure. Logically it precedes all problems of estimation or of testing hypotheses.
An important point that arises in the study of identification is that without a priori restrictions imposed by economic theory it would be almost impossible to estimate economic relationships. In fact, Liu (1960) and Sims (1980) have argued that economic relations are not identifiable because the world is so interdependent as to have almost all variables appearing in every equation, thus violating the necessary condition for identification. However, almost all the models we discuss in econometrics are only approximate. We use convenient formulations which behave in a general way that corresponds to our economic theories and intuitions, and which cannot be rejected by the available data. In this sense, identification is a property of the model but not necessarily of the real world. It is also important to be careful about situations where identification almost does not hold (weak identification), since these are in practice as damaging for statistical analysis as identification failure itself.
The problem of identification arises in a number of different fields such as automatic control, biomedical engineering, psychology, systems science, and so on, where the underlying physical structure may be deterministic (for example, see Aström and Eykhoff, 1971). It is also aptly linked to the design of experiments (for example, Kempthorne, 1947; Bailey, Gilchrist and Patterson, 1977). Here, we restrict our discussion to economic applications of statistical identifiability involving random variables.

See Also

- econometrics
- endogeneity and exogeneity
- simultaneous equations models
- treatment effect

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