

**IDENTIFICATION OF NONPARAMETRIC SIMULTANEOUS
EQUATIONS MODELS WITH A RESIDUAL INDEX STRUCTURE**

By

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Identification of Nonparametric Simultaneous Equations Models with a Residual Index Structure*

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Abstract

We present new results on the identifiability of a class of nonseparable nonparametric simultaneous equations models introduced by Matzkin (2008). These models combine exclusion restrictions with a requirement that each structural error enter through a “residual index.” Our identification results encompass a variety of special cases allowing tradeoffs between the exogenous variation required of instruments and restrictions on the joint density of structural errors. Among these special cases are results avoiding any density restriction and results allowing instruments with arbitrarily small support.

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1 Introduction

Economic theory typically produces systems of equations characterizing the outcomes observable to empirical researchers. The classical supply and demand model is a canonical example, but systems of simultaneous equations arise in a wide range of economic settings in which multiple agents interact or a single agent makes multiple interrelated choices. The identifiability of simultaneous equations models is therefore an important question for a wide range of topics in empirical economics. Here we consider nonparametric identification in a class of nonseparable simultaneous equations models with a “residual index” structure introduced by Matzkin (2008). Our results generalize those obtained previously for this and related models in Matzkin (2008, 2015) and in Berry and Haile (2011, 2014a). Special cases of our results reveal a variety of available tradeoffs between requirements on the support of instruments and restrictions on the joint density of structural errors.

Early work on (parametric) identification treated systems of simultaneous equations as a primary focus. Prominent examples include many contributions to Koopmans (1950) and Hood and Koopmans (1953), as well as Fisher’s (1966) monograph.¹ Nonparametric identification, on the other hand, has remained a significant challenge. Despite substantial recent interest in identification of nonparametric economic models with endogenous regressors and nonseparable errors, there remain remarkably few such results for fully simultaneous systems.

A general representation of a nonparametric simultaneous equations model (more general than we will allow) is given by

$$m_j(Y, Z, U) = 0 \quad j = 1, \dots, J \tag{1}$$

where $J \geq 2$, $Y = (Y_1, \dots, Y_J) \in \mathbb{R}^J$ are the endogenous variables, $U = (U_1, \dots, U_J) \in \mathbb{R}^J$ are the structural errors, and Z is a set of exogenous conditioning variables. Assuming m is invertible in U ,² this system of equations can be written in “residual” form

$$U_j = \rho_j(Y, Z) \quad j = 1, \dots, J. \tag{2}$$

Identification of such models was considered by Brown (1983), Roehrig (1988), Brown and Matzkin (1998), and Brown and Wegkamp (2002). However, a

¹With the title, *The Identification Problem in Econometrics*, Fisher focused exclusively on simultaneous models, explaining (p. *vii*) “Because the simultaneous equation context is by far the most important one in which the identification problem is encountered, the treatment is restricted to that context.”

²See, e.g., Palais (1959), Gale and Nikaido (1965), and Berry, Gandhi, and Haile (2013) for conditions that can be used to show invertibility in different contexts.

claim made in Brown (1983) and relied upon by the others implied that traditional exclusion restrictions would identify the model when U is independent of Z . Benkard and Berry (2006) showed that this claim is incorrect, leaving uncertain the nonparametric identifiability of fully simultaneous models.

Completeness conditions (Lehmann and Scheffe (1950, 1955)) offer one possible approach, and in Berry and Haile (2014a) we showed how identification arguments in Newey and Powell (2003) or Chernozhukov and Hansen (2005) can be adapted to an example of the class of models considered below.³ However, independent of general concerns one might have with the interpretability of completeness conditions, this approach may be particularly unsatisfactory in a simultaneous equations setting. A simultaneous equations model already specifies the structure generating the joint distribution of the endogenous variables, exogenous variables, and structural errors. A high-level assumption like completeness implicitly places further restrictions on the model, although the nature of these restrictions is typically unclear.⁴

Much recent work has focused on systems of equations with a triangular (recursive) structure (see, e.g., Chesher (2003), Imbens and Newey (2009), and Torgovitzky (2015)). A two-equation version of the triangular model takes the form

$$\begin{aligned} Y_1 &= m_1(Y_2, Z, U_1) \\ Y_2 &= m_2(Z, X, U_2) \end{aligned}$$

where U_2 is a scalar error entering m_2 monotonically and X is an exogenous observable excluded from the first equation. This structure often arises in a program evaluation setting, where Y_2 might denote a non-random treatment and Y_1 an outcome of interest. To contrast this model with a fully simultaneous system, suppose Y_1 represents the quantity sold of a good and that Y_2 is its price. If the first equation is the structural demand equation, the second equation would be the reduced form for price, with X as a supply shifter excluded from demand. However, in a supply and demand context (as in many other simultaneous equations settings) the triangular structure is difficult to reconcile with economic theory: typically both the demand error and the supply error will enter the reduced form for price. One obtains the triangular model only when the two structural errors monotonically enter the reduced form for price through a single index.⁵ This is an index assumption quite different from the

³Identification results for nonparametric regression models are not directly applicable because the structural functions m_j take multiple structural errors as arguments. Nonetheless, the extensions are straightforward. See also Chiappori and Komunjer (2009b), which shows identification in a related model by combining completeness conditions with arguments that exploit the classic change of variables approach.

⁴Recent work on this issue includes D'Haultfoeuille (2011) and Andrews (2011).

⁵Examples of simultaneous models that do reduce to a triangular system can be found

residual index structure we consider. Blundell and Matzkin (2014) provide a necessary and sufficient condition for a simultaneous model to reduce to the triangular model, pointing out that this condition is quite restrictive.

An important breakthrough in this literature came in Matzkin (2008), which considered a model of the form

$$m_j(Y, Z, \delta) = 0 \quad j = 1, \dots, J$$

where $\delta = (\delta_1(Z, X_1, U_1), \dots, \delta_J(Z, X_J, U_J))'$ is a vector of indices

$$\delta_j(Z, X_j, U_j) = g_j(Z, X_j) + U_j. \quad (3)$$

Here $X = (X_1, \dots, X_J) \in \mathbb{R}^J$ are observed exogenous observables (instruments) specific to each equation, and each $g_j(Z, X_j)$ is strictly increasing in X_j . This formulation respects traditional exclusion restrictions in that X_j is excluded from equations $k \neq j$ (e.g., there is a “demand shifter” that enters only the demand equation). However, it restricts the more general model (1) by requiring X_j and U_j to enter the nonparametric function m_j through a “residual index” $\delta_j(Z, X_j, U_j)$. Given invertibility of m (now in δ), the analog of (2) is $\delta_j(Z, X_j, U_j) = r_j(Y, Z)$, $j = 1, \dots, J$, or equivalently,⁶

$$r_j(Y, Z) = g_j(Z, X_j) + U_j \quad j = 1, \dots, J. \quad (4)$$

In Berry and Haile (2014b) we show how this structure arises in a variety of important economic applications, including the classic simultaneous equations framework (e.g., classical supply and demand or macro models, models of peer effects), models of imperfectly competitive differentiated products markets, and models of input choices by a profit-maximizing firm faced with factor-specific productivity shocks. Matzkin (2008) showed that this model is identified when U is independent of X , $(g_1(X_1, Z), \dots, g_J(X_J, Z))$ has large support conditional on Z , and the joint density of U satisfies certain global restrictions.⁷ This was, to our knowledge, the first result demonstrating identification in a fully simultaneous nonparametric model with nonseparable errors.

in Benkard and Berry (2006), Blundell and Matzkin (2014), and Torgovitzky (2010).

⁶This model can be interpreted as a generalization of the transformation model to a simultaneous system. The usual (single-equation) semiparametric transformation model (e.g., Horowitz (1996)) takes the form $t(Y) = Z\beta + U$, where $Y \in \mathbb{R}$, $U \in \mathbb{R}$, and the unknown transformation function t is strictly increasing. Besides replacing $Z\beta$ with $g(Z, X)$, (4) generalizes this model by dropping the requirement of a monotonic transformation function and, more fundamental, allowing a vector of outcomes Y to enter each unknown transformation function. Chiappori and Komunjer (2009a) considers a nonparametric version of the single-equation transformation model. See also Berry and Haile (2009).

⁷Matzkin (2008) applied a new characterization of observational equivalence to prove identification in several special cases, including a linear simultaneous equations model, a single equation model, a triangular (recursive) model, and a fully simultaneous nonparametric model (her “supply and demand” example) of the form (4).

Matzkin (2015) provides additional results and estimation strategies for a version of the model in which each residual index function $g_j(Z, X_j)$ is linear conditional on Z (see also Matzkin (2010); Berry and Haile (2011, 2014a)).

We provide new identification results for the model (4) and discuss special cases with varying demands on the instruments and the joint density of structural errors. A key result provides a general sufficient condition for identification of the functions g_j . A special case demonstrates that such identification holds under a mild local density restriction, even when the instruments X have arbitrarily small support. Once each $g_j(Z, X_j)$ is known, identification of the model follows as in the special case of a linear residual index function. To exploit this fact, we review and extend identification results for the model with a linear residual index. We show that under Matzkin’s (2008) large support condition, identification of the linear index model holds without any restriction on the joint density. At an opposite extreme, we show that even when the instruments have arbitrarily small support, *failure* of identification requires strong restrictions on the joint density. Combined with our results on the identification of the index functions $g_j(Z, X_j)$, these results then demonstrate identification of the full nonlinear index model (4) under a wide variety of support and density conditions. Importantly, these results include the first identification conditions for the nonlinear index model that do not require large support for X .

We begin by completing the model setup in section 2. A brief preview of results follows in section 3. In section 4 we provide conditions for identification of the index functions g_j . Section 5 then considers alternative sets of sufficient conditions for identification of the linear index model. Finally, these results are combined in section 6 to yield identification of the full nonlinear index model. Along the way we point out that our primary sufficient conditions for identification are *verifiable*—i.e., their satisfaction or failure is identified—and that the maintained assumptions defining the model are falsifiable.

2 The Model

2.1 Setup

The observables are (Y, X, Z) , with $X \in \mathbb{R}^J$, $Y \in \mathbb{R}^J$, and $J \geq 2$. The exogenous observables Z are important in applications but add no complications to the analysis of identification. Thus, from now on we condition on an arbitrary value of Z and drop it from the notation. As usual, this treats Z in a fully flexible way, and all assumptions should be interpreted to hold conditional on Z . Stacking the equations in (4), we then consider the model

$$r(Y) = g(X) + U \tag{5}$$

where $r(Y) = (r_1(Y), \dots, r_J(Y))'$, $g(X) = (g_1(X_1), \dots, g_J(X_J))'$, and r maps a set $\mathbb{Y} \subset \mathbb{R}^J$ onto the support of $(g(X) + U)$. We let $\mathbb{X} = \text{int}(\text{supp}(X))$.

Assumption 1. (i) \mathbb{X} is nonempty; (ii) g is continuously differentiable, with $\partial g_j(x_j) / \partial x_j > 0$ for all j, x_j ; (iii) U is independent of X and has continuously differentiable joint density f that is positive on \mathbb{R}^J ; (iv) r is injective, twice differentiable, and for all $y \in \mathbb{Y}$ has nonsingular Jacobian matrix $J(y) = \frac{\partial r(y)}{\partial y}$.

Part (i) rules out discrete instruments. Part (ii) combines an important monotonicity restriction with a differentiability requirement imposed for convenience. The primary role of parts (iii) and (iv) is to allow us to attack the identification problem using a standard change of variables approach (see, e.g., Koopmans, Rubin, and Leipnik (1950)), relating the joint density of observables to that of the structural errors. In particular, letting $\phi(\cdot|X)$ denote the joint density of Y conditional on X , we have

$$\phi(y|x) = f(r(y) - g(x)) |J(y)|. \quad (6)$$

In addition, we have the following lemma.

Lemma 1. *Under Assumption 1, (a) $\forall y \in \mathbb{Y}$, $\text{supp}(X|Y = y) = \text{supp}(X)$; (b) $\forall x \in \mathbb{X}$, $\text{supp}(Y|X = x) = \text{supp}(Y)$; and (c) \mathbb{Y} is open and connected.*

Proof. See Appendix B.

With this result, below we treat $\phi(y|x)$ as known for all $x \in \mathbb{X}$ and $y \in \mathbb{Y}$.

2.2 Normalizations

We impose three standard normalizations.⁸ First, observe that all relationships between (Y, X, U) would be unchanged if for some constant κ_j , $g_j(X_j)$ were replaced by $g_j(X_j) + \kappa_j$ while $r_j(Y)$ were replaced by $r_j(Y) + \kappa_j$. Thus, without loss, for an arbitrary point $\dot{y} \in \mathbb{Y}$ and an arbitrary vector $\tau = (\tau_1, \dots, \tau_J)$ we set

$$r_j(\dot{y}) = \tau_j \quad \forall j. \quad (7)$$

Similarly since, even with (7), (5) would be unchanged if, for every j , $g_j(X_j)$ were replaced by $g_j(X_j) + \kappa_j$ for some constant κ_j while U_j were replaced by $U_j - \kappa_j$, we set

$$g_j(\dot{x}_j) = \dot{x}_j \quad \forall j. \quad (8)$$

⁸We follow Horowitz (2009, pp. 215–216), who makes equivalent normalizations in his semiparametric single-equation version of our model. His exclusion of an intercept is the implicit analog of our location normalization (8). Alternatively we could follow Matzkin (2008), who makes no normalizations in her supply and demand example and shows only that the derivatives of r and g are identified up to scale.

This fixes the location of each U_j , but we must still choose its scale.⁹ In particular, since (5) would continue to hold if both sides were multiplied by a nonzero constant, we normalize the scale of each U_j by taking an arbitrary $\hat{x} \in \mathbb{X}$ and setting

$$\frac{\partial g_j(\hat{x}_j)}{\partial x_j} = 1 \quad \forall j. \quad (9)$$

Finally, given (8), we will find a convenient choice of τ (recall (7)) to be $\tau_j = \hat{x}$, so that

$$r_j(\hat{y}) - g_j(\hat{x}_j) = 0 \quad \forall j. \quad (10)$$

2.3 Identifiability, Verifiability, and Falsifiability

Before proceeding, we must define some key terminology. Following Hurwicz (1950) and Koopmans and Reiersol (1950), a *structure* S is a data generating process, i.e., a set of probabilistic or functional relationships between the observable and latent variables that implies (generates) a joint distribution of the observables. Let \mathfrak{S} denote the set of all structures. The true structure is denoted $S_0 \in \mathfrak{S}$. A *hypothesis* is any nonempty subset of \mathfrak{S} . We say that a hypothesis \mathcal{H} is true if $S_0 \in \mathcal{H}$.¹⁰

A *structural feature* $\theta(S_0)$ is a functional of the true structure S_0 . As usual, we say that $\theta(S_0)$ is *identified* (or *identifiable*) under the hypothesis \mathcal{H} if $\theta(S_0)$ is uniquely determined within the set $\{\theta(S) : S \in \mathcal{H}\}$ by the joint distribution of observables. The primary structural features of interest in our setting are the functions r , f , and g . However, we will also be interested in binary features indicating whether key hypotheses hold. Given a maintained hypothesis \mathcal{M} , we will say that a hypothesis $\mathcal{H} \subset \mathcal{M}$ is *verifiable* if the indicator $1\{S_0 \in \mathcal{H}\}$ is identified under \mathcal{M} . Thus, when a hypothesis is verifiable, its satisfaction or failure is an identified feature.¹¹ We show below that our primary sufficient conditions for identification—those beyond the model setup and maintained regularity conditions—are verifiable.

We also consider the weaker and more familiar notion of falsifiability. Let $\mathcal{P}_{\mathcal{H}}$ denote the set of probability distributions (for the observables) generated

⁹Typically the location and scale of the unobservables can be set arbitrarily without loss. However, there may be applications in which the location or scale of U_j has economic meaning. With this caveat, we follow the longstanding convention in the literature and refer to these restrictions as normalizations.

¹⁰Hurwicz (1950) and Koopmans and Reiersol (1950) call any strict subset of \mathfrak{S} a *model*, although some authors will make distinctions between the notions of “model,” “identifying assumptions,” or “overidentifying assumptions.” All of these notions are nested by our term hypothesis.

¹¹We are not aware of prior formal use of the notion of verifiability in the econometrics literature although, as our definition makes clear, this is merely a particular case of identifiability.

by structures in \mathcal{H} . Given a maintained hypothesis \mathcal{M} , we say that $\mathcal{H} \subset \mathcal{M}$ is *falsifiable* if $\mathcal{P}_{\mathcal{H}} \neq \mathcal{P}_{\mathcal{M}}$. Thus, as usual, a hypothesis is falsifiable when it implies a restriction on the observables. We show below that important maintained hypotheses of our model are falsifiable. A model that is falsifiable is sometimes said to be *testable* or to imply *testable restrictions*. We avoid this terminology because, just as identification does not imply existence of a consistent estimator, falsifiability (or verifiability) does not imply existence of a satisfactory statistical test. We leave all matters of estimation and hypothesis testing for future work.

3 Preview of Results

We begin by previewing important special cases of the results developed below. One is the result given in the pathbreaking work of Matzkin (2008), obtained below as Corollary 4.

Proposition 1. *Let $g(\mathbb{X}) = \mathbb{R}^J$ and suppose that there exists $u^0 \in \mathbb{R}^J$ such that $\frac{\partial f(u^0)}{\partial u_j} = 0$ for all j . Suppose further that for each j and every $u_j \in \mathbb{R}$ there exists $\hat{u}(u_j) \in \mathbb{R}^J$ satisfying $\hat{u}_j(u_j) = u_j$ and such that $\frac{\partial f(\hat{u}(u_j))}{\partial u_j} = 0$ while $\left| \frac{\partial f(\hat{u}(u_j))}{\partial u_k} \right| > 0$ for all $k \neq j$. Then g is identified on \mathbb{X} , and r and f are identified.*

Neither the large support condition nor density restriction of Proposition 1 is required, however. We illustrate this with two alternative results. Both utilize a mild regularity condition on the joint density f , requiring that it have an isolated local minimum or maximum. To make this precise (taking the case of a local max for simplicity), for $c \in \mathbb{R}$ and $\Sigma \subset \mathbb{R}^J$ we define the upper contour sets of the restriction of f to Σ :

$$\mathcal{A}(c; \Sigma) = \{u \in \Sigma : f(u) \geq c\}. \quad (11)$$

Condition 1. *For some compact connected set $S \subset \mathbb{R}^J$ with nonempty interior, there exists $\underline{c} \in \mathbb{R}$ such that (i) $\mathcal{A}(\underline{c}; S) \subset \text{int}(S)$, and (ii) the restriction of f to $\mathcal{A}(\underline{c}; S)$ attains a maximum $\bar{c} > \underline{c}$ at its unique critical value.*

Condition 1 requires that if we “zoom in” to a sufficiently small neighborhood of a local max (first to S , then further to an upper contour set of f on the restricted domain S), the local max is the only local critical value. Using this mild restriction, we obtain the following results.

Proposition 2. *Let Assumption 1 and Condition 1 hold, and suppose that $g(\mathbb{X}) = \mathbb{R}^J$. Then g is identified on \mathbb{X} , and r and f are identified.*

Proposition 3. *Let Assumption 1 and Condition 1 hold and suppose that \mathbb{X} is connected. Then if $\partial^2 \ln f(u) / \partial u \partial u'$ is nonsingular almost everywhere, g is identified on \mathbb{X} , and r and f are identified.*

Proposition 2 shows that Matzkin’s global density restriction can be replaced with Condition 1. Proposition 3 shows that identification can be obtained even with arbitrarily small support for X under relatively mild density restrictions.¹² Further, Condition 1 is (like Matzkin’s assumptions) merely an example of a sufficient condition for the “rectangle regularity” condition on f developed below. We show that when rectangle regularity holds, failure of identification requires strong restrictions on the joint density f .

4 Identification of the Index Functions

We begin by considering identification of the index functions g_j . Differentiating (6) yields

$$\frac{\partial \ln \phi(y|x)}{\partial x_j} = - \frac{\partial \ln f(r(y) - g(x))}{\partial u_j} \frac{\partial g_j(x_j)}{\partial x_j} \quad (12)$$

and

$$\frac{\partial \ln \phi(y|x)}{\partial y_k} = \sum_j \frac{\partial \ln f(r(y) - g(x))}{\partial u_j} \frac{\partial r_j(y)}{\partial y_k} + \frac{\partial \ln |J(y)|}{\partial y_k}. \quad (13)$$

Together (12) and (13) imply

$$\frac{\partial \ln \phi(y|x)}{\partial y_k} = - \sum_j \frac{\partial \ln \phi(y|x)}{\partial x_j} \frac{\partial r_j(y) / \partial y_k}{\partial g_j(x_j) / \partial x_j} + \frac{\partial \ln |J(y)|}{\partial y_k}. \quad (14)$$

Our approach builds on an insight in Matzkin (2008), exploiting critical values of f and “tangencies” to its level sets to isolate the unknowns in (14). We first introduce a general sufficient condition that we call “rectangle regularity.” This is followed by discussion of special cases that are more easily interpretable. Finally, we demonstrate identification of each function g_j under rectangle regularity.

4.1 Rectangle Regularity

We begin with some definitions.

Definition 1. A J -dimensional rectangle is a Cartesian product of J nonempty open intervals.

¹²These two results are special cases of, respectively, Corollaries 5 and 6 in section 6 below.

Definition 2. Let $\mathcal{M} \equiv \times_{j=1}^J (\underline{m}_j, \overline{m}_j)$ and $\mathcal{N} \equiv \times_{j=1}^J (\underline{n}_j, \overline{n}_j)$ denote two J -dimensional rectangles. \mathcal{M} is *smaller than* \mathcal{N} if $\overline{m}_j - \underline{m}_j \leq \overline{n}_j - \underline{n}_j$ for all j .

Definition 3. Given a J -dimensional rectangle $\mathcal{U} \equiv \times_{j=1}^J (\underline{u}_j, \overline{u}_j)$, the joint density f is *regular on* \mathcal{U} if (i) there exists $u^* \in \mathcal{U}$ such that $\frac{\partial f(u^*)}{\partial u_j} = 0$ for all j ; and (ii) for all j and almost all $u'_j \in (\underline{u}_j, \overline{u}_j)$, there exists $\hat{u}(u'_j) \in \mathcal{U}$ satisfying

$$\begin{aligned} \hat{u}_j(u'_j) &= u'_j \\ \frac{\partial f(\hat{u}(u'_j))}{\partial u_j} &\neq 0 \quad \text{and} \\ \frac{\partial f(\hat{u}(u'_j))}{\partial u_k} &= 0 \quad \forall k \neq j. \end{aligned}$$

Definitions 1 and 2 are standard and provided here only to avoid ambiguity. Definition 3 introduces a particular notion of regularity for the density f . It requires that f have a critical value u^* in a rectangular neighborhood \mathcal{U} in which the level sets of f are “nice” in a sense defined by part (ii). There, $\hat{u}(u'_j)$ has a geometric interpretation as a point of tangency between a level set of f and the $(J - 1)$ -dimensional plane $\{u \in \mathbb{R}^J : u_j = u'_j\}$. Part (ii) of Definition 3 requires such a tangency within the rectangle \mathcal{U} in each dimension j .

Figure 1 illustrates an example in which $J = 2$ and u^* is a local extremum. There, within a neighborhood of u^* the level sets of f (or $\ln f$) are connected, smooth, and strictly increasing toward u^* . Therefore, each level set is horizontal at (at least) one point above u^* and one point below u^* . Similarly, each level set is vertical at least once each to the right and to the left of u^* . There are many J -dimensional rectangles on which the illustrated density is regular. One such rectangle is defined in the figure using a single level set. The upper limit \overline{u}_2 is defined by the topmost horizontal tangency to this level set, while \overline{u}_1 is defined by the rightmost vertical tangency, and so forth. For each $u'_1 \in (\underline{u}_1, \overline{u}_1)$, the point $\hat{u}_2(u'_1)$ is the value of U_2 at a tangency between the vertical line $U_1 = u'_1$ and a level set of f closer to u^* than that defining \mathcal{U} . Since level sets within \mathcal{U} are smooth, the tangency cannot be at a corner of the rectangle \mathcal{U} ; therefore, $\underline{u}_2 < \hat{u}_2(u'_1) < \overline{u}_2$, implying $(u'_1, \hat{u}_2(u'_1)) \in \mathcal{U}$.

Figure 1: The solid curves are the level sets of a bivariate density (or log-density) with a “regular” hill leading up to a local maximum at u^* , but with a less useful shape in other areas. For each $u'_1 \in (\underline{u}_1, \bar{u}_1)$ the point $\hat{u}_2(u'_1)$ is the value of U_2 at a tangency between the vertical line $U_1 = u'_1$ and a level set.

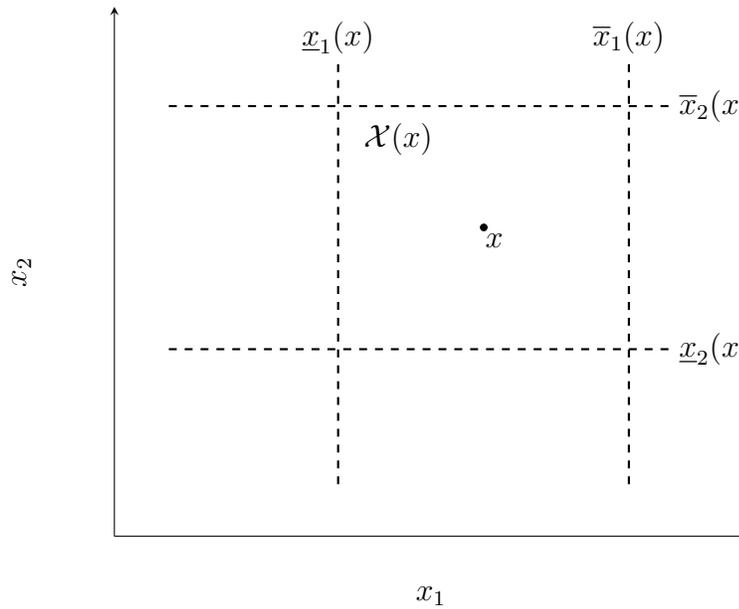
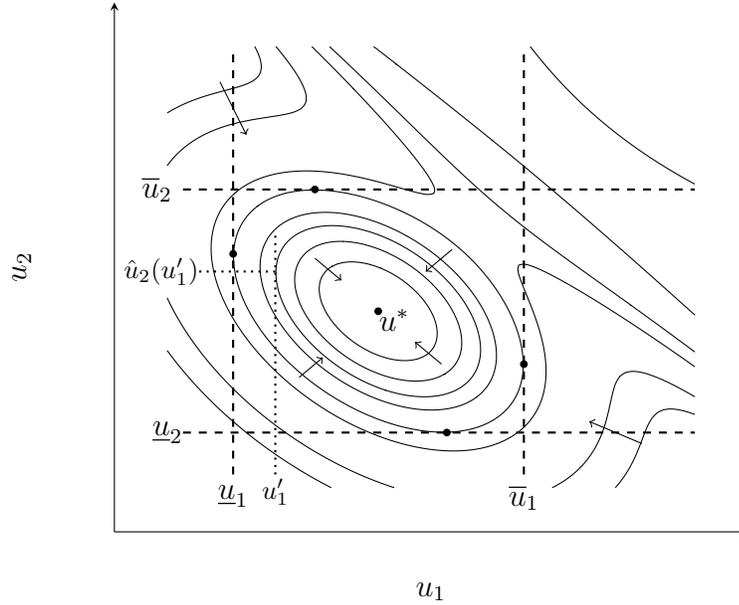


Figure 2: For arbitrary $x \in \mathcal{X}$, the rectangle $\mathcal{U} \equiv (\underline{u}_1, \bar{u}_1) \times (\underline{u}_2, \bar{u}_2)$ in Figure 2 is mapped to a rectangle $\mathcal{X}(x)$ by first defining y^* to satisfy $r_j(y^*) = g_j(x_j) + u_j^*$ for all j , then defining $\underline{x}(x)$ and $\bar{x}(x)$ by $r_j(y^*) = g_j(\underline{x}_j(x)) + \bar{u}_j = g_j(\bar{x}_j(x)) + \underline{u}_j$, thereby satisfying (15).

The following is our primary condition allowing identification of the index functions g_j .

Assumption 2 (“Rectangle Regularity”). For all $x \in \mathbb{X}$ there is a J -dimensional rectangle $\mathcal{X}(x) = \times_j (\underline{x}_j(x), \bar{x}_j(x)) \subset \mathbb{X}$ containing x such that for (i) some u^* such that $\partial f(u^*)/\partial u_j = 0$ for all j and (ii) $\underline{u}_j(x)$ and $\bar{u}_j(x)$ defined by

$$\begin{aligned}\underline{u}_j(x) &= u_j^* + g_j(x_j) - g_j(\bar{x}_j(x)) \\ \bar{u}_j(x) &= u_j^* + g_j(x_j) - g_j(\underline{x}_j(x)),\end{aligned}\tag{15}$$

f is regular on $\mathcal{U}(x) = \times_j (\underline{u}_j(x), \bar{u}_j(x))$.

Assumption 2 requires, for each x , that f be regular on a rectangular neighborhood around a critical point u^* that maps through (5) to a rectangular neighborhood in \mathbb{X} around x . Because \mathbb{X} is open, there exists a rectangle in \mathbb{X} around every point $x \in \mathbb{X}$. Further, when \mathbb{X} includes any rectangle \mathcal{M} , it also includes all smaller rectangles $\mathcal{X} \subset \mathcal{M}$. Thus, since $g(\mathcal{X})$ is a rectangle whenever \mathcal{X} is, as long as f is regular on some rectangle that is not too big relative to the support of X around x , the set $\mathcal{X}(x)$ required by Assumption 2 is guaranteed to exist. Figure 2 illustrates, taking an arbitrary point x and the rectangle $\mathcal{U} = (\underline{u}_1, \bar{u}_1) \times (\underline{u}_2, \bar{u}_2)$ in Figure 1 and mapping them to the rectangle $\mathcal{X}(x)$.

Observe that although we write $\underline{u}_j(x)$ and $\bar{u}_j(x)$ in (15), the same rectangle $\times_j (\underline{u}_j, \bar{u}_j)$ may be used to construct $\mathcal{X}(x)$ for many (even all) values of x . This is because for every $x \in \mathbb{X}$ there must exist $y^*(x) \in \mathbb{Y}$ such that

$$r(y^*(x)) = g(x) + u^*,\tag{16}$$

allowing construction of the rectangle $\times_j (\underline{x}_j(x), \bar{x}_j(x))$ from (15) with a single critical value u^* and with $\underline{u}_j(x) = \underline{u}_j$ and $\bar{u}_j(x) = \bar{u}_j$ for all x and j (see Figure 2). Thus, Assumption 2 can be satisfied with limited variation in X , even if f has a single critical value.

Although Assumption 2 involves a condition on the joint distribution of latent variables, the following result (proved in Appendix B) shows that it is equivalent to a condition on observables.

Remark 1. *Assumption 2 is verifiable.*

4.2 Sufficient Conditions for Rectangle Regularity

Here we provide two alternative sufficient conditions for Assumption 2 that are more easily interpreted. The first combines large support for X with regularity of f on \mathbb{R}^J . This corresponds to the combination of conditions used

by Matzkin (2008).¹³ The second allows arbitrarily small support for X and requires regularity only in sufficiently small rectangular neighborhoods around a critical point u^* . Outside such neighborhoods, f is unrestricted.

Remark 2. *Suppose that $g(\mathbb{X}) = \mathbb{R}^J$ and that f is regular on \mathbb{R}^J . Then Assumption 2 holds.*

Proof. Let $\mathcal{X}(x) = \times_j (g_j^{-1}(-\infty), g_j^{-1}(\infty))$ for all x . Then by (15), $\mathcal{U}(x) = \mathbb{R}^J$, yielding the result. \square

Definition 4. f satisfies *local rectangle regularity* if for every J -dimensional rectangle \mathcal{M} , there exists a smaller J -dimensional rectangle \mathcal{N} on which f is regular.

Remark 3. *Suppose that f satisfies local rectangle regularity. Then Assumption 2 holds.*

Proof. Take arbitrary $x \in \mathbb{X}$. Because \mathbb{X} is open, it must contain a rectangle $\tilde{\mathcal{X}}(x) \ni x$. Taking one such $\tilde{\mathcal{X}}(x)$ let $\mathcal{M} = g(\tilde{\mathcal{X}}(x))$ and let \mathcal{N} be a smaller rectangle $\times_j (\underline{u}_j, \bar{u}_j)$ on which f is regular (guaranteed to exist by local rectangle regularity). Because f is regular on \mathcal{N} , it has a critical point $u^* \in \mathcal{N}$. Taking such a point u^* , define $y^*(x)$ by (16). Now define $\underline{x}_j(x)$ and $\bar{x}_j(x)$ for all j by

$$r_j(y^*(x)) = g_j(\underline{x}_j(x)) + \bar{u}_j \quad (17)$$

$$r_j(y^*(x)) = g_j(\bar{x}_j(x)) + \underline{u}_j. \quad (18)$$

Let $\mathcal{X}(x) = \times_j (\underline{x}_j(x), \bar{x}_j(x))$. Then by (15), (16), (17), and (18), $\mathcal{U}(x) = \mathcal{N}$. Thus f is regular on $\mathcal{U}(x)$. \square

Neither of these sufficient condition implies the other. If $\mathbb{X} = \mathbb{R}^J$, regularity on \mathbb{R}^J holds when f is one of many standard densities, including the multivariate normal. Local rectangle regularity places no requirement on the support of X and holds for essentially any smooth density f with an isolated local minimum or maximum (recall Condition 1 from section 3):

Remark 4. *Suppose Condition 1 holds. Then f satisfies local rectangle regularity.*

¹³The assumption stated in Matzkin (2008) is actually stronger, equivalent to assuming regularity of f on \mathbb{R}^J but replacing “almost all $u'_j \in (\underline{u}_j, \bar{u}_j)$ ” in the definition of regularity with “all $u'_j \in (\underline{u}_j, \bar{u}_j)$.” The latter is unnecessarily strong and rules out many standard densities, including the multivariate normal. Throughout we interpret the weaker condition as that intended by Matzkin (2008).

Proof. See Appendix A.

The proof requires several steps. However, for the case $J = 2$, Figure 3 shows level sets of a joint density in a small neighborhood of a critical value u^* and suggests how the mild requirements of Condition 1 ensure local rectangle regularity.

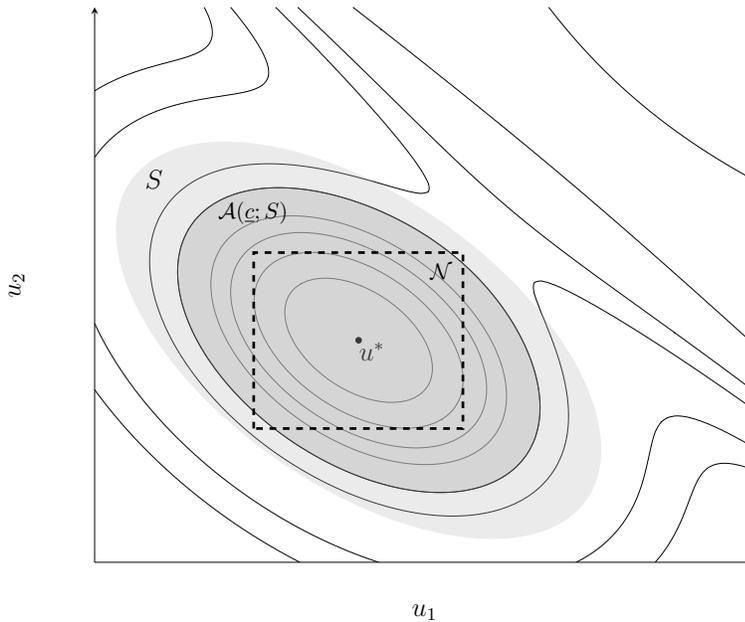


Figure 3: The shaded area is a connected compact set S . The darker subset of S is an upper contour set $\mathcal{A}(\underline{c}; S)$ of the restriction of f to S . The point u^* is a local max and the only critical value of f in $\mathcal{A}(\underline{c}; S)$. For any J -dimensional rectangle \mathcal{M} there will exist $c^0 \geq \underline{c}$ such that (i) the rectangle $\mathcal{N} = \times_j \left(\min_{u^- \in \mathcal{A}(c^0; S)} u_j^-, \max_{u^+ \in \mathcal{A}(c^0; S)} u_j^+ \right)$ (see (A.2) in Appendix A) is smaller than \mathcal{M} and (ii) f is regular on \mathcal{N} .

4.3 Identification of the Index Functions

Under rectangle regularity, identification of the index functions g_j follows in three steps. The first exploits a critical value u^* to pin down derivatives of the Jacobian determinant at a point $y^*(x)$ for any x . The second uses tangencies to identify the ratios $\frac{\partial g_j(x'_j)/\partial x_j}{\partial g_j(x^0_j)/\partial x_j}$ for all pairs of points (x^0, x') in a sequence of overlapping rectangular subsets of \mathbb{X} . The final step links these rectangular neighborhoods so that, using the normalization (9), we can integrate up to the functions g_j , using (8) as boundary conditions.

The first step is straightforward. For any $x \in \mathbb{X}$, if u^* is a critical value of f and $y^*(x)$ is defined by (16), equation (13) yields

$$\frac{\partial \ln |J(y^*(x))|}{\partial y_k} = \frac{\partial \ln \phi(y^*(x)|x)}{\partial y_k} \quad \forall k. \quad (19)$$

For arbitrary x and x' , this allows us to rewrite (14) as

$$\sum_j \frac{\partial \ln \phi(y^*(x)|x')}{\partial x_j} \frac{\partial r_j(y^*(x))/\partial y_k}{\partial g_j(x'_j)/\partial x_j} = \frac{\partial \ln \phi(y^*(x)|x)}{\partial y_k} - \frac{\partial \ln \phi(y^*(x)|x')}{\partial y_k} \quad (20)$$

where the only unknowns are the ratios $\frac{\partial r_j(y^*(x))/\partial y_k}{\partial g_j(x'_j)/\partial x_j}$. Using this result, the second step is demonstrated in Lemma 2 below. Here we exploit the fact that, under Assumption 2, as \hat{x} varies around the arbitrary point x , $r(y^*(x)) - \hat{x}$ takes on all values in a rectangular neighborhood of u^* on which f is regular.

Lemma 2. *Let Assumptions 1 and 2 hold. Then for every $x \in \mathbb{X}$ there exists a J -dimensional rectangle $\mathcal{X}(x) \ni x$ such that for all $x^0 \in \mathcal{X}(x) \setminus x$ and $x' \in \mathcal{X}(x) \setminus x$, the ratio*

$$\frac{\partial g_j(x'_j)/\partial x_j}{\partial g_j(x^0_j)/\partial x_j}$$

is identified for all $j = 1, \dots, J$.

Proof. For arbitrary $x \in \mathbb{X}$, let u^* and $\mathcal{U}(x) = \times_j (\underline{u}_j, \bar{u}_j)$ be as defined in Assumption 2.¹⁴ Define y^* by (16). By Assumption 2 there exists $\mathcal{X} = \times_i (\underline{x}_i, \bar{x}_i) \subset \mathbb{X}$ (with $x \in \mathcal{X}$) such that

$$r_j(y^*) = g_j(\bar{x}_j) + \underline{u}_j, \quad j = 1, \dots, J \quad (21)$$

$$r_j(y^*) = g_j(\underline{x}_j) + \bar{u}_j, \quad j = 1, \dots, J \quad (22)$$

and (recalling (12)) such that for each j and almost every $x'_j \in (\underline{x}_j, \bar{x}_j)$ there is a J -vector $\hat{x}(x'_j) \in \mathcal{X}$ satisfying

$$\hat{x}_j(x'_j) = x'_j$$

$$\frac{\partial \ln \phi(y^*|\hat{x}(x'_j))}{\partial x_j} \neq 0 \quad \text{and} \quad (23)$$

$$\frac{\partial \ln \phi(y^*|\hat{x}(x'_j))}{\partial x_k} = 0 \quad \forall k \neq j. \quad (24)$$

¹⁴To simplify notation, we will suppress dependence of y^* , \underline{x}_j , \bar{x}_j , \underline{u}_j , and \bar{u}_j on the arbitrary point x .

Since $\phi(y|x)$ and its derivatives are observed for all $y \in \mathbb{Y}, x \in \mathbb{X}$, the point y^* is identified, as are the pairs $(\underline{x}_j, \bar{x}_j)$ and the point $\hat{x}(x'_j)$ for any j and $x'_j \in (\underline{x}_j, \bar{x}_j)$.¹⁵ Taking arbitrary j , arbitrary $x'_j \in (\underline{x}_j, \bar{x}_j)$ and the known vector $\hat{x}(x'_j)$ defined above, (20) becomes

$$\frac{\partial \ln \phi(y^*|\hat{x}(x'_j))}{\partial x_j} \frac{\partial r_j(y^*)/\partial y_k}{\partial g_j(x'_j)/\partial x_j} = \frac{\partial \ln \phi(y^*|x)}{\partial y_k} - \frac{\partial \ln \phi(y^*|\hat{x}(x'_j))}{\partial y_k}.$$

By (23), we may rewrite this as

$$\frac{\partial r_j(y^*)/\partial y_k}{\partial g_j(x'_j)/\partial x_j} = \frac{\frac{\partial \ln \phi(y^*|x)}{\partial y_k} - \frac{\partial \ln \phi(y^*|\hat{x}(x'_j))}{\partial y_k}}{\frac{\partial \ln \phi(y^*|\hat{x}(x'_j))}{\partial x_j}}. \quad (25)$$

Since the right-hand side is known, $\frac{\partial r_j(y^*)/\partial y_k}{\partial g_j(x'_j)/\partial x_j}$ is identified for almost all (and, by continuity, all) $x'_j \in (\underline{x}_j, \bar{x}_j)$. By the same arguments leading up to (25), but with x_j^0 taking the role of x'_j , we obtain

$$\frac{\partial r_j(y^*)/\partial y_k}{\partial g_j(x_j^0)/\partial x_j} = \frac{\frac{\partial \ln \phi(y^*|x)}{\partial y_k} - \frac{\partial \ln \phi(y^*|\hat{x}(x_j^0))}{\partial y_k}}{\frac{\partial \ln \phi(y^*|\hat{x}(x_j^0))}{\partial x_j}} \quad (26)$$

yielding identification of $\frac{\partial r_j(y^*)/\partial y_k}{\partial g_j(x_j^0)/\partial x_j}$ for all $x_j^0 \in (\underline{x}_j, \bar{x}_j)$. Because the Jacobian determinant $|J(y^*)|$ is nonzero, $\partial r_j(y^*)/\partial y_k$ cannot be zero for all k . Thus for each j there is some k such that the ratio $\frac{\partial r_j(y^*)/\partial y_k}{\partial g_j(x_j^0)/\partial x_j} / \frac{\partial r_j(y^*)/\partial y_k}{\partial g_j(x'_j)/\partial x_j}$ is well defined. This establishes the result.¹⁶ \square

The final step of the argument will yield the following result.

Theorem 1. *Let Assumptions 1 and 2 hold and suppose that \mathbb{X} is connected. Then g is identified on \mathbb{X} .*

Proof. We first claim that Lemma 2 implies identification of the ratios $\frac{\partial g_j(x'_j)/\partial x_j}{\partial g_j(x_j^0)/\partial x_j}$ for all j and any two points x^0 and x' in \mathbb{X} . This follows immediately if there is some x such that $\mathcal{X}(x) = \mathbb{X}$. Otherwise, observe that because each rectangle $\mathcal{X}(x)$ guaranteed to exist by Lemma 2 is open, $\{\mathcal{X}(x)\}_{x \in \mathbb{X}}$ is an open cover of

¹⁵We do not require uniqueness of u^* or the set \mathcal{U} . Rather, we use only the fact that for a given x there exist both a value y^* mapping through (27) to a critical point u^* and a rectangle around x mapping through (21) and (22) to a rectangle around u^* on which f is regular. Through (12), such a y^* and a rectangle around x are both identified.

¹⁶Since the argument can be repeated for any k such that $\partial r_j(y^*)/\partial y_k \neq 0$, the ratios of interest in the lemma may typically be overidentified.

\mathbb{X} . Since \mathbb{X} is connected, for any x^0 and x' in \mathbb{X} there exists a simple chain from x^0 to x^1 consisting of elements (rectangles) from $\{\mathcal{X}(x)\}_{x \in \mathbb{X}}$.¹⁷ Since the ratios $\frac{\partial g_j(x_j^1)/\partial x_j}{\partial g_j(x_j^2)/\partial x_j}$ are known for all points (x_j^1, x_j^2) in each of these rectangles, it follows that the ratios $\frac{\partial g_j(x_j')/\partial x_j}{\partial g_j(x_j^0)/\partial x_j}$ are known for all j . The claim then follows. Finally, observe that because \mathbb{X} is a connected open subset of \mathbb{R}^J , \mathbb{X} is path-connected. Taking $x_j^0 = \dot{x}_j$ for all j , the conclusion of the Theorem then follows from the normalization (9) and boundary condition (8). \square

5 Identification with a Linear Index

When the functions g_j are known, the model (5) reduces to that with a linear index:¹⁸ i.e.,

$$r_j(Y) = X_j + U_j \quad j = 1, \dots, J. \quad (27)$$

We use the “linear index model” in (27) primarily to consider identification of each $r_j(Y)$ conditional on knowledge of the functions g_j . The model is of independent interest as well and has been studied previously in Matzkin (2015) and, in the context of a differentiated products model, Berry and Haile (2014a). Below we discuss several alternative sufficient conditions for identification of the linear index model, including one given previously by Matzkin (2015). Note that in the linear index model, the change of variables (6) becomes

$$\phi(y|x) = f(r(y) - x) |J(y)|. \quad (28)$$

5.1 Identification without Density Restrictions

Our first result shows that when the instruments X have large support (e.g., Matzkin (2008, 2010)) there is no need to restrict the joint density f .^{19 20}

Theorem 2. *Let Assumption 1 hold and suppose $\mathbb{X} = \mathbb{R}^J$. Then in the linear index model, r and f are identified.*

¹⁷See, e.g., van Mill (2002), Lemma 1.5.21.

¹⁸ Formally, redefine $X_j = g_j(X_j)$ and note that the properties of $\mathbb{X} = \text{int}(\text{supp}(X))$ required by Assumption 1 are preserved.

¹⁹Theorem 2 holds under slightly weaker smoothness conditions on f and r than those requires by Assumption 1.

²⁰The argument used to show Theorem 2 was first used by Berry and Haile (2014a) in combination with additional assumptions and arguments to demonstrate identification in a model of differentiated products demand and supply.

Proof. Since $\int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} f(r(y) - x) dx = 1$, (28) implies

$$|J(y)| = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} \phi(y|x) dx$$

so that (again from (28)) we obtain

$$f(r(y) - x) = \frac{\phi(y|x)}{\int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} \phi(y|t) dt}.$$

Thus the value of $f(r(y) - x)$ is uniquely determined by the observables for all $x \in \mathbb{R}^J$ and $y \in \mathbb{Y}$. Let F_j denote the marginal CDF of U_j . Since

$$\int_{\hat{x}_j \geq x_j, \hat{x}_{-j}} f(r(y) - \hat{x}) d\hat{x} = F_j(r_j(y) - x_j) \quad (29)$$

the value of $F_j(r_j(y) - x_j)$ is identified for all $x_j \in \mathbb{R}$ and $y \in \mathbb{Y}$. By (10), $F_j(r_j(\hat{y}) - \hat{x}_j) = F_j(0)$. For every $y \in \mathbb{Y}$ we can then find the value $\hat{x}^{\circ}(y)$ such that $F_j(r_j(y) - \hat{x}^{\circ}(y)) = F_j(0)$, which reveals $r_j(y) = \hat{x}^{\circ}(y)$. This identifies each function r_j on \mathbb{Y} . Identification of f then follows from (27). \square

Thus, given the maintained Assumption 1, large support for X is sufficient for identification of the model. Because X is observable, this condition is verifiable.

Remark 5. *The condition $\mathbb{X} = \mathbb{R}^J$ is verifiable.*

In addition, although the Jacobian determinant is a functional of r , the relationship between $|J(y)|$ and r was not imposed in our proof; rather, the Jacobian determinant was treated as a nuisance parameter to be identified separately. Thus, the requirement $|J(y)| = \left| \frac{\partial r(y)}{\partial y} \right|$ provides a falsifiable restriction.

Remark 6. *Suppose $\mathbb{X} = \mathbb{R}^J$. Then the model defined by (27) and Assumption 1 is falsifiable.*

5.2 Identification Using First Derivatives

We now explore an alternative approach that exploits restrictions on f . In the linear index model (12) and (14) become, respectively,

$$\frac{\partial \ln \phi(y|x)}{\partial x_j} = - \frac{\partial \ln f(r(y) - x)}{\partial u_j} \quad (30)$$

and

$$\frac{\partial \ln \phi(y|x)}{\partial y_k} = \frac{\partial \ln |J(y)|}{\partial y_k} - \sum_j \frac{\partial \ln \phi(y|x)}{\partial x_j} \frac{\partial r_j(y)}{\partial y_k}. \quad (31)$$

We rewrite (31) as

$$a_k(x, y) = d(x, y)' b_k(y) \quad (32)$$

where we define $a_k(x, y) = \frac{\partial \ln \phi(y|x)}{\partial y_k}$, $d(x, y)' = \left(1, -\frac{\partial \ln \phi(y|x)}{\partial x_1}, \dots, -\frac{\partial \ln \phi(y|x)}{\partial x_J}\right)$, and $b_k(y) = \left(\frac{\partial \ln |J(y)|}{\partial y_k}, \frac{\partial r_1(y)}{\partial y_k}, \dots, \frac{\partial r_J(y)}{\partial y_k}\right)'$. Here $a_k(x, y)$ and $d(x, y)$ are observable whereas $b_k(y)$ involves unknown derivatives of the functions r_j . From (32) it is clear that $b_k(y)$ is identified if there exist points $\tilde{\mathbf{x}} = (\tilde{x}^0, \dots, \tilde{x}^J)$, with each $\tilde{x}^j \in \mathbb{X}$, such that the $(J+1) \times (J+1)$ matrix

$$D(\tilde{\mathbf{x}}, y) \equiv \begin{pmatrix} d(\tilde{x}^0, y)' \\ \vdots \\ d(\tilde{x}^J, y)' \end{pmatrix} \quad (33)$$

has full rank.²¹ This yields the following observation, given previously in Matzkin (2015).²²

Lemma 3. *Let Assumption 1 hold. For a given $y \in \mathbb{Y}$, suppose there exists no nonzero vector $c = (c_0, c_1, \dots, c_J)'$ such that $d(x, y)'c = 0 \forall x \in \mathbb{X}$. Then in the linear index model, $\partial r(y)/\partial y_k$ is identified for all k .*

Lemma 3 provides a sufficient condition for identification of $\partial r(y)/\partial y_k$ at a point. Using (30), Assumption 3 then documents the rank condition ensuring identification at all points. As shown in Theorem 3, identification of the model then follows easily.

Assumption 3. For almost all $y \in \mathbb{Y}$ there is no $c = (c_0, c_1, \dots, c_J)' \neq 0$ such that

$$\left(1, \frac{\partial \ln f(r(y) - x)}{\partial x_1}, \dots, \frac{\partial \ln f(r(y) - x)}{\partial x_J}\right) c = 0 \quad \forall x \in \mathbb{X}.$$

Theorem 3. *Let Assumptions 1 and 3 hold. Then in the linear index model, r and f are identified.*

Proof. By Lemma 3 and continuity of the derivatives of r , $\partial r_j(y)/\partial y_k$ is identified for all j, k , and $y \in \mathbb{Y}$. Since \mathbb{Y} is an open connected subset of \mathbb{R}^J , every pair of points in \mathbb{Y} can be joined by a piecewise smooth (\mathcal{C}^1) path in \mathbb{Y} .²³ With the boundary condition (7) and Lemma 1 (part (c)), identification of $r_j(y)$ for all y and j then follows from the fundamental theorem of calculus for line integrals. Identification of f then follows from (5). \square

²¹In particular, let $A_k(\tilde{\mathbf{x}}, y) = (a_k(\tilde{x}^0, y) \cdots a_k(\tilde{x}^J, y))'$ and stack the equations obtained from (32) at each of the points $\tilde{x}^{(0)}, \dots, \tilde{x}^{(J)}$, yielding $A_k(\tilde{\mathbf{x}}, y) = D(\tilde{\mathbf{x}}, y) b_k(y)$. When $D(\tilde{\mathbf{x}}, y)$ is invertible we obtain the closed-form solution $b_k(y) = D(\tilde{\mathbf{x}}, y)^{-1} A_k(\tilde{\mathbf{x}}, y)$.

²²Although we obtained and presented this result independently, we learned later that Matzkin had obtained the result earlier in a previously uncirculated draft.

²³See, e.g., Giaquinta and Modica (2007), Theorem 6.63.

5.2.1 Special Cases: Critical Points and Tangencies

Assumption 3 is a verifiable sufficient condition for identification of the linear index model.²⁴ However, the interpretation of this joint restriction on \mathbb{X} and f is not transparent, leaving the scope of Theorem 3's applicability unclear. Here we discuss one approach to obtaining more easily interpretable sufficient conditions, building (for a second time) on insights in Matzkin (2008, 2010) involving critical points and tangencies.

Begin with the case $J = 2$ and suppose that for almost all $y \in \mathbb{Y}$ there exist points $(x^0(y), x^1(y), x^2(y))$, each in \mathbb{X} , such that $\frac{\partial \ln f(r(y) - x^0(y))}{\partial u_j} = 0$ for all j while

$$\begin{aligned} \frac{\partial \ln f(r(y) - x^1(y))}{\partial u_1} &\neq 0 = \frac{\partial \ln f(r(y) - x^1(y))}{\partial u_2} \\ \frac{\partial \ln f(r(y) - x^2(y))}{\partial u_2} &\neq 0. \end{aligned}$$

The point $u^0(y) = r(y) - x^0(y)$ is a critical value of f . The point $u^1(y) = r(y) - x^1(y)$ is a point of tangency between a level set of f (or $\ln f$) and some vertical line. Finally $u^2(y) = r(y) - x^2(y)$ is any point such that the derivative of $f(u^2)$ with respect to u_2 is nonzero (i.e., not also a point of vertical tangency).

Letting $\tilde{\mathbf{x}} = (x^0(y), x^1(y), x^2(y))$ and recalling (30), (33) becomes a triangular matrix

$$D(\tilde{\mathbf{x}}, y) = \begin{pmatrix} 1 & 0 & 0 \\ 1 & \frac{\partial \ln f(r(y) - x^1(y))}{\partial u_1} & 0 \\ 1 & \frac{\partial \ln f(r(y) - x^2(y))}{\partial u_1} & \frac{\partial \ln(r(y) - x^2(y))}{\partial u_2} \end{pmatrix}$$

with nonzero diagonal terms, ensuring that Assumption 3 holds. There is, of course, an analogous construction using a horizontal tangency to a level set of f instead of a vertical tangency. Generalizing to $J \geq 2$ is straightforward and yields the following result.

Corollary 1. *Let Assumption 1 hold and suppose that for almost all $y \in \mathbb{Y}$ there exist points $(x^0(y), x^1(y), \dots, x^J(y))$ in \mathbb{X} such that (a) $\partial \ln f(r(y) - x^0(y))/\partial u_j = 0$ for all j , (b) $\partial \ln f(r(y) - x^j(y))/\partial u_j \neq 0$ for all j , and (c)*

²⁴Verifiability follows from the fact that $\frac{\partial \ln f(r(y) - x)}{\partial u_j} = -\frac{\partial \ln \phi(y|x)}{\partial x_j}$ and $\frac{\partial \ln \phi(y|x)}{\partial x_j}$ is observable. In addition, the model defined by (27) and Assumption 1 is falsifiable under Assumption 3 (see Appendix B).

the matrix

$$\begin{pmatrix} \frac{\partial \ln f(r(y)-x^1(y))}{\partial u_1} & \dots & \frac{\partial \ln f(r(y)-x^1(y))}{\partial u_J} \\ \vdots & \ddots & \vdots \\ \frac{\partial \ln f(r(y)-x^J(y))}{\partial u_1} & \dots & \frac{\partial \ln f(r(y)-x^J(y))}{\partial u_J} \end{pmatrix}$$

can be placed in triangular form through simultaneous permutation of rows and columns. Then in the linear index model, r and f are identified.

Existence of the points $(x^0(y), x^1(y), \dots, x^J(y))$ required by Corollary 1 still involves a joint requirement on the density f and the support of X . However, because critical values and tangencies are natural properties of a density, sufficient conditions in terms of explicit support and density restrictions are more easily seen. Corollary 1 requires f to have both a critical value and a suitable set of tangencies somewhere in the set $\{r(y) - \mathbb{X}\}$ for every $y \in \mathbb{Y}$. When X has large support, Corollary 1 requires existence of only a single set of points (u^0, u^1, \dots, u^J) such that $\frac{\partial \ln f(u^0)}{\partial u_j} = 0$ for all j while $\frac{\partial}{\partial u} (\ln f(u^1), \dots, \ln f(u^J))'$ is triangular.²⁵ In principle, more limited support for X can also allow identification through Corollary 1, although densities with the required critical values and tangencies in the set $\{r(y) - \mathbb{X}\}$ for every y would then be quite special.²⁶

5.3 Identification Using Second Derivatives

The preceding discussion may suggest an overly pessimistic view of identification when the instruments X have limited support. By considering conditions on the second derivatives of $f(\cdot)$, however, we can show that a fairly mild restriction on the density f ensures identification of the linear index model even when X has arbitrarily small support.

²⁵If f has at least one critical point and at least one point of tangency in *each* dimension, $\frac{\partial}{\partial u} (\ln f(u^1), \dots, \ln f(u^J))'$ will be diagonal (with nonzero diagonal terms). Combining this property with a large support condition yields the special case of Corollary 1 given by Matzkin (2010, Theorem 3.1).

²⁶This contrasts with our use of critical values and tangencies for the rectangle regularity condition, where a single small neighborhood with an isolated critical value can suffice.

5.3.1 A General Hessian Condition

Supposing that f is twice differentiable,²⁷ define the second-derivative matrix

$$H_\phi(x, y) = \frac{\partial^2 \ln \phi(y|x)}{\partial x \partial x'} = \begin{pmatrix} \frac{\partial^2 \ln \phi(y|x)}{\partial x_1^2} & \cdots & \frac{\partial^2 \ln \phi(y|x)}{\partial x_J \partial x_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 \ln \phi(y|x)}{\partial x_1 \partial x_J} & \cdots & \frac{\partial^2 \ln \phi(y|x)}{\partial x_J^2} \end{pmatrix}. \quad (34)$$

Lemma 4. *Let f be twice differentiable. For a nonzero vector $c = (c_0, c_1, \dots, c_J)'$,*

$$d(x, y)' c = 0 \quad \forall x \in \mathbb{X} \quad (35)$$

if and only if for the nonzero vector $\tilde{c} = (c_1, \dots, c_J)'$

$$H_\phi(x, y) \tilde{c} = 0 \quad \forall x \in \mathbb{X}. \quad (36)$$

Proof. Recall that $d(x, y)' = \left(1, -\frac{\partial \ln \phi(y|x)}{\partial x_1}, \dots, -\frac{\partial \ln \phi(y|x)}{\partial x_J}\right)$. Suppose first that (35) holds for nonzero $c = (c_0, c_1, \dots, c_J)$. Differentiating (35) with respect to x yields (36), with $\tilde{c} = (c_1, \dots, c_J)'$. If $c_0 = 0$ then the fact that $c \neq 0$ implies $c_j \neq 0$ for some $j > 0$. If $c_0 \neq 0$, then because the first component of $d(x, y)$ is nonzero and $d(x, y)' c = 0$, we must have $c_j \neq 0$ for some $j > 0$. Thus (36) must hold for some nonzero \tilde{c} . Now suppose (36) holds for nonzero $\tilde{c} = (c_1, \dots, c_J)'$. Take an arbitrary point x^0 and let $c_0 = \sum_{j=1}^J \frac{\partial \ln \phi(y|x^0)}{\partial x_j} c_j$ so that, for $c = (c_0, c_1, \dots, c_J)'$, $d(x^0, y)' c = 0$ by construction. Since the first component of $d(x, y)$ equals 1 for all (x, y) , (36) implies that $\frac{\partial}{\partial x_j} [d(x, y)' c] = 0$ for all j and every $x \in \mathbb{X}$. Thus (35) holds for some nonzero c . \square

Lemma 4 allows us to provide a sufficient condition for identification in terms of the Hessian matrices $\frac{\partial^2 \ln f(r(y)-x)}{\partial u \partial u'}$.

Theorem 4. *Let Assumption 1 hold and assume that f is twice differentiable. Suppose that, for almost all $y \in \mathbb{Y}$, there is no nonzero J -vector \tilde{c} such that*

$$\frac{\partial^2 \ln f(r(y)-x)}{\partial u \partial u'} \tilde{c} = 0 \quad \forall x \in \mathbb{X}.$$

Then in the linear index model r and f are identified.

Proof. From (30), $\frac{\partial^2 \ln \phi(y|x)}{\partial x_j \partial x_k} = \frac{\partial^2 \ln f(r(y)-x)}{\partial u_j \partial u_k}$. The result then follows from the definition (34), Lemma 4, and Theorem 3. \square

²⁷Similar arguments apply without this additional differentiability. See Appendix D.

5.3.2 Special Cases: Nonsingular Hessian

Given Assumption 1, a sufficient condition for application of Theorem 4 is that for almost all y , $\ln f(u)$ have nonsingular Hessian matrix at a point $u \in \{r(y) - \mathbb{X}\}$. At one extreme, if $\mathbb{X} = \mathbb{R}^J$ it is sufficient that $\frac{\partial^2 \ln f(u)}{\partial u \partial u'}$ be invertible at a single point. At an opposite extreme, if $\frac{\partial^2 \ln f(u)}{\partial u \partial u'}$ be nonsingular almost everywhere, the support of X can be arbitrarily small. We state this second special case in the following result.

Corollary 2. *Let Assumption 1 hold and assume that f is twice differentiable. If $\frac{\partial^2 \ln f(u)}{\partial u \partial u'}$ is nonsingular almost everywhere, then in the linear index model r and f are identified.*

Nonsingularity of $\frac{\partial^2 \ln f(u)}{\partial u \partial u'}$ almost everywhere holds for many standard joint probability distributions. A strong sufficient condition is that $\frac{\partial^2 \ln f(u)}{\partial u \partial u'}$ be negative definite almost everywhere—a property of the multivariate normal and many other log-concave densities (see, e.g., Bagnoli and Bergstrom (2005) and Cule, Samworth, and Stewart (2010)). Examples of densities that violate the requirement of Corollary 2 are those that are flat (uniform) or log-linear (exponential) on an open set.

In some applications, it may be reasonable to assume that U_j and U_k are independent for all $k \neq j$. For example, when estimating a production function based on observed outputs and (cost-minimizing) inputs, shocks to the productivity of labor might reasonably be assumed independent of Hicks-neutral productivity shocks. Under independence, $\frac{\partial^2 \ln f(u)}{\partial u \partial u'}$ is diagonal. The following result, whose proof is immediate from Theorem 4, shows that this can allow identification with arbitrarily small \mathbb{X} under a relatively mild restriction on the marginal densities f_j .

Corollary 3. *Let Assumption 1 hold. Suppose that $f(u) = \prod_j f_j(u_j)$ for all u and that, for all j , $\frac{\partial^2 \ln f_j(u_j)}{\partial u_j^2}$ exists and is nonzero almost surely. Then in the linear index model r and f are identified.*

5.3.3 Failure of Identification Requires Strong Restrictions

We pause to emphasize that although Corollaries 2 and 3 provide sufficient conditions involving nonsingularity of $\frac{\partial^2 \ln f(u)}{\partial u \partial u'}$, this is not required by Theorem 4. For a given pair (x, y) , $\frac{\partial^2 \ln f(r(y)-x)}{\partial u \partial u'}$ is singular if and only if there exists a nonzero vector c such that $\frac{\partial^2 \ln f(r(y)-x)}{\partial u \partial u'} c = 0$. However, the sufficient condition for identification in Theorem 4 fails only when (for values of y with positive measure) the *same* vector c solves this equation *for every* $x \in \mathbb{X}$. When this happens, the columns of $\frac{\partial^2 \ln f(r(y)-x)}{\partial u \partial u'}$ do not merely exhibit linear dependence at each x : they exhibit the *same* linear dependence for *all* x . Thus, even with

limited support for X , *failure* of identification requires a strong restriction on the joint density f .

6 Identification of the Nonlinear Index Model

Together, the results in sections 4 and 5 allow many combinations of sufficient conditions for identification of (r, f, g) in the full nonlinear index model. We give three examples, beginning with the identification result for nonparametric fully simultaneous models given (with different proof) in Matzkin (2008).²⁸

Corollary 4. *Let Assumption 1 hold. Suppose that $g(\mathbb{X}) = \mathbb{R}^J$ and that f is regular on \mathbb{R}^J . Then g is identified on \mathbb{X} , and r and f are identified.*

Proof. Since $g(\mathbb{X}) = \mathbb{R}^J$ and each g_j has everywhere strictly positive derivative, g has a continuous inverse g^{-1} on \mathbb{R}^J . Since the image of a path-connected set under a continuous mapping is path-connected, $\mathbb{X} = g^{-1}(\mathbb{R}^J)$ is path-connected. Thus by Lemma 2 and Theorem 1, g is identified on \mathbb{X} . Redefining $X = g(X)$ (recall footnote 18) we then obtain a linear index model, for which regularity of f on \mathbb{R}^J implies the conditions of Corollary 1. \square

The next result shows that if the large support assumption of Corollary 4 is retained, it also suffices that f satisfy local rectangle regularity.

Corollary 5. *Let Assumption 1 hold. Suppose that $g(\mathbb{X}) = \mathbb{R}^J$ and that f satisfies local rectangle regularity. Then g is identified on \mathbb{X} , and r and f are identified.*

Proof. Identification of g on \mathbb{X} follows as in the proof of Corollary 4. The result then follows from Theorem 2. \square

Finally, we provide one of the many possible results demonstrating identification with only limited support for X .

Corollary 6. *Let Assumption 1 hold. Suppose that \mathbb{X} is connected, f satisfies local rectangle regularity, and that $\partial^2 \ln f(u) / \partial u \partial u'$ is nonsingular almost everywhere. Then g is identified on \mathbb{X} , and r and f are identified.*

Proof. By Lemma 3 and Theorem 1, g is identified on \mathbb{X} . The result then follows from Corollary 2. \square

In each case above, we proved identification of the model by showing that, once g is known, all is as if we are in the case of a linear residual index. By the same logic, given identification of g , the falsifiable restrictions derived in Remarks 6, 8 and 9 imply falsifiable restrictions of the more general model. The proof of the following remark (given in Appendix B) provides additional falsifiable restrictions.

²⁸Berry and Haile (2011) also provides a simple constructive proof.

Remark 7. *Under Assumptions 1 and 2, the model defined by (5) is falsifiable.*

7 Conclusion

Building on Matzkin's (2008, 2015) work, we consider identification in a class of nonparametric simultaneous equations models that make use of traditional exclusion restrictions together with a residual index structure. We establish identification of the nonlinear residual index model under considerably more general conditions than previously recognized. Special cases of these conditions admit a range of tradeoffs between the support of the instruments and shape restrictions on the joint density of unobservables. These include cases in which the instruments have arbitrarily small support. Our conditions on the support of instruments and on the shape of the density of unobservables are verifiable, while the other maintained assumptions of the model are falsifiable.

Together these results demonstrate the robust identifiability that holds in models with Matzkin's residual index structure. These results are relevant to a wide range of applications of simultaneous equations models in economics. Although we have focused exclusively on identification, our results provide a more robust foundation for existing estimators and may suggest strategies for new estimation and testing approaches.

Appendices

A Proof of Remark 4

Below we let $\mathcal{B}(u, \epsilon)$ denote an ϵ -ball around a point $u \in \mathbb{R}^J$. To prove Remark 4 we rely on three lemmas.

Lemma 5. *Let S be a connected compact subset of \mathbb{R}^J with nonempty interior, and let $h : S \rightarrow \mathbb{R}$ be a continuous function with upper contour sets $\mathcal{A}(c) = \{u \in S : h(u) \geq c\}$. Suppose that for some $\underline{c} < c_{\max} \equiv \max_{u \in S} h(u)$, $\mathcal{A}(\underline{c}) \subset \text{int}(S)$. Then $\mathcal{A}(c)$ has nonempty interior for all $c < c_{\max}$.*

Proof. Since $\mathcal{A}(\underline{c}) \subset \text{int}(S)$, we must have $h(\tilde{u}) < c_{\max}$ for some $\tilde{u} \in S$. Therefore, since the continuous image of a connected set is connected, $h(S)$ is a nonempty interval. For any $c < c_{\max}$ there must then exist $u \in S$ such that $\max\{\underline{c}, c\} < h(u) < c_{\max}$. Since $\mathcal{A}(\underline{c}) \subset \text{int}(S)$, such u lies in $\{\mathcal{A}(c) \cap \mathcal{A}(\underline{c})\} \subset \text{int}(S)$. Thus, for sufficiently small $\epsilon > 0$, we have both $\mathcal{B}(u, \epsilon) \subset S$ and (by continuity of h) $h(\hat{u}) > c \forall \hat{u} \in \mathcal{B}(u, \epsilon)$. Thus $\mathcal{A}(c)$ contains an open subset of \mathbb{R}^J . \square

Lemma 6. *Let S be a connected compact subset of \mathbb{R}^J with nonempty interior, and let $h : S \rightarrow \mathbb{R}$ be a continuous function with upper contour sets $\mathcal{A}(c) = \{u \in S : h(u) \geq c\}$. Suppose that for some $\underline{c} \in \mathbb{R}$, (i) $\mathcal{A}(\underline{c}) \subset \text{int}(S)$ and (ii) the restriction of h to $\mathcal{A}(\underline{c})$ attains a maximum $\bar{c} > \underline{c}$ at its unique critical value u^* . Then \mathcal{A} is a continuous correspondence on $(\underline{c}, \bar{c}]$.*

Proof. For all $c \in (\underline{c}, \bar{c}]$, $\mathcal{A}(c)$ contains u^* and is therefore nonempty. Since S is compact and h is continuous, \mathcal{A} is compact-valued. Suppose upper hemi-continuity of \mathcal{A} fails at some point $\hat{c} \in (\underline{c}, \bar{c}]$. Then there must exist sequences $c^n \rightarrow \hat{c}$ and $u^n \rightarrow u$ such that $u^n \in \mathcal{A}(c^n)$ for all n but $u \notin \mathcal{A}(\hat{c})$. The latter requires $h(u) < \hat{c}$, since $\lim_{n \rightarrow \infty} u^n$ must lie in S . But by continuity of h this would imply $h(u^n) < c^n$ for sufficiently large n —a contradiction. To show lower hemi-continuity,²⁹ take arbitrary $\hat{c} \in (\underline{c}, \bar{c}]$, $\hat{u} \in \mathcal{A}(\hat{c})$, and $c^n \rightarrow \hat{c}$. If $\hat{u} = u^*$ then $\hat{u} \in \mathcal{A}(c)$ for all $c \leq \bar{c}$, so with the constant sequence $u^n = \hat{u}$ we have $u^n \in \mathcal{A}(c^n)$ for all n and $u^n \rightarrow \hat{u}$. So now suppose that $\hat{u} \neq u^*$. Define a sequence u^n by

$$u^n = \arg \min_{u \in \mathcal{A}(c^n)} \|u - \hat{u}\| \quad (\text{A.1})$$

so that $u^n \in \mathcal{A}(c^n)$ by construction. We now show $u^n \rightarrow \hat{u}$. Take arbitrary $\epsilon > 0$. Since h is continuous and $h(\hat{u}) > \underline{c}$ by construction, for sufficiently small $\delta > 0$ we have $\mathcal{B}(\hat{u}, \delta) \subset \mathcal{A}(\underline{c})$. Thus, $\{\mathcal{B}(\hat{u}, \epsilon) \cap \mathcal{A}(c)\}$ contains an

²⁹This argument is similar to that used to prove Proposition 2 in Honkapohja (1987).

open set. If $h(u) \leq h(\hat{u})$ for all u in that set, \hat{u} would be a critical value of the restriction of h to $\mathcal{A}(\underline{c})$. Since \hat{u} is not a critical value, there must exist $u^\epsilon \in \{\mathcal{B}(\hat{u}, \epsilon) \cap \mathcal{A}(\underline{c})\}$ such that $h(u^\epsilon) > h(\hat{u})$. Since $h(\hat{u}) \geq \hat{c}$, this implies $h(u^\epsilon) > \hat{c}$. Recalling that $c^n \rightarrow \hat{c}$, for n sufficiently large we then have (by continuity of h) $h(u^\epsilon) > c^n$ and, therefore, $u^\epsilon \in \mathcal{A}(c^n)$. So, recalling (A.1), for n sufficiently large we have $\|u^n - \hat{u}\| \leq \|u^\epsilon - \hat{u}\| < \epsilon$. \square

Lemma 7. *Let S be a connected compact subset of \mathbb{R}^J with nonempty interior, and let $h : S \rightarrow \mathbb{R}$ be a continuous function with upper contour sets $\mathcal{A}(c) = \{u \in S : h(u) \geq c\}$. Suppose that for some \underline{c} , (a) $\mathcal{A}(\underline{c}) \in \text{int}(S)$ and (b) the restriction of h to $\mathcal{A}(\underline{c})$ attains a maximum $\bar{c} > \underline{c}$ at its unique critical value u^* . Then $\mathcal{A}(c)$ is a connected set for all $c \in (\underline{c}, \bar{c})$.*

Proof. Proceeding by contradiction, suppose that for some $c \in (\underline{c}, \bar{c})$ the upper contour set $\mathcal{A}(c)$ is the union of disjoint nonempty open (relative to $\mathcal{A}(c)$) sets \mathcal{A}^1 and \mathcal{A}^2 . Without loss let u^* lie in \mathcal{A}^1 . Because $\mathcal{A}(\underline{c}) \in \text{int}(S)$, and h is continuous, \mathcal{A}^2 must be a compact subset of \mathbb{R}^J . The restriction of h to \mathcal{A}^2 must therefore attain a maximum u^{**} . But since u^{**} must lie in the interior of $\mathcal{A}(\underline{c})$, u^{**} must be a critical value of h on $\mathcal{A}(\underline{c})$. \square

With these preliminary results, we can now prove Remark 4, restated below for convenience. Recall that for $c \in \mathbb{R}$ and $\Sigma \subset \mathbb{R}^J$ we let $\mathcal{A}(c; \Sigma)$ denote the upper contour set of the restriction of f to Σ .

Remark 4. Suppose that Condition 1 holds. Then f satisfies local rectangle regularity.

Proof. We first show that, for any J -dimensional rectangle \mathcal{M} , there exists $c^0 \in (\underline{c}, \bar{c})$ such that $\mathcal{A}(c^0; S)$ is contained in a J -dimensional rectangle \mathcal{N} that is smaller than \mathcal{M} . Because S is compact and f is continuous, $\mathcal{A}(c; S)$ is compact for all c . Further, by Lemma 6, $\mathcal{A}(c; S)$ is a continuous correspondence on $(\underline{c}, \bar{c}]$.³⁰ Thus $\max_{u \in \mathcal{A}(c; S)} u_j$ and $\min_{u \in \mathcal{A}(c; S)} u_j$ are continuous in $c \in (\underline{c}, \bar{c}]$, implying that the function $H : (\underline{c}, \bar{c}] \rightarrow \mathbb{R}$ defined by

$$H(c) = \max_j \max_{\substack{u^+ \in \mathcal{A}(c; S) \\ u^- \in \mathcal{A}(c; S)}} u_j^+ - u_j^-$$

is continuous. Thus, since $H(\bar{c}) = 0$, for some $c^0 \in (\underline{c}, \bar{c})$ the J -dimensional rectangle (Lemma 5 ensures that each interval is nonempty)

$$\mathcal{N} = \times_j \left(\min_{u^- \in \mathcal{A}(c^0; S)} u_j^-, \max_{u^+ \in \mathcal{A}(c^0; S)} u_j^+ \right) \quad (\text{A.2})$$

is smaller than \mathcal{M} . To complete the proof, we show that f is regular on \mathcal{N} . By construction $u^* \in \mathcal{A}(c^0; S) \subset \mathcal{N}$. Now take arbitrary j and any $u_j \neq u_j^*$

³⁰In Lemmas 5–7, let $\mathcal{A}(c) = \mathcal{A}(c; S)$ and let h be the restriction of f to S .

such that $(u_j, u_{-j}) \in \mathcal{N}$ for some u_{-j} . By Lemma 7 and the definition of \mathcal{N} , there must also exist \tilde{u}_{-j} such that $(u_j, \tilde{u}_{-j}) \in \mathcal{A}(c^0; S)$. Let $\hat{u}(u_j)$ solve

$$\max_{\hat{u} \in \mathcal{A}(c; S): \hat{u}_j = u_j} f(\hat{u}).$$

This solution must lie in $\mathcal{A}(c^0; S) \subset \mathcal{N}$ and satisfy the first-order conditions

$$\frac{\partial f(\hat{u}(u_j))}{\partial u_k} = 0 \quad \forall k \neq j.$$

Since $u_j \neq u_j^*$, we have $\frac{\partial f(\hat{u}(u_j))}{\partial u_j} \neq 0$. \square

B Other Proofs Omitted from the Text

Proof of Lemma 1. With (5), part (iii) of Assumption 1 immediately implies (a) and (b). Parts (iii) and (iv) then imply that r has a continuous inverse $r^{-1} : \mathbb{R}^J \rightarrow \mathbb{R}^J$. Connectedness of \mathbb{Y} follows from the fact that the continuous image of a connected set (here \mathbb{R}^J) is connected. Since r^{-1} is continuous and injective and $r^{-1}(\mathbb{R}^J) = \mathbb{Y}$, Brouwer's invariance of domain theorem implies that \mathbb{Y} is an open subset of \mathbb{R}^J . \square

Proof of Remark 1. Fix an arbitrary $x \in \mathbb{X}$. By (12),

$$\frac{\partial \phi(y^*(x) | x)}{\partial x_j} = 0 \tag{B.1}$$

if and only if, for $u^* = r(y^*(x)) - g(x)$, $\frac{\partial f(u^*)}{\partial u_j} = 0 \forall j$. Thus, the existence of the point u^* in part (i) is equivalent to existence of $y^*(x) \in \mathbb{Y}$ such that (B.1) holds. This is verifiable. Now observe that for $\mathcal{X}(x)$ and $\mathcal{U}(x)$ as defined in Assumption 2,

$$x \in \mathcal{X}(x) \iff (r(y^*(x)) - g(x)) \in \mathcal{U}(x).$$

Thus, part (ii) holds if and only if there exists a rectangle $\mathcal{X}(x) = \times_j (\underline{x}_j(x), \bar{x}_j(x)) \subset \mathbb{X}$, with $x \in \mathcal{X}(x)$ such that for all j and almost all $x_j \in (\underline{x}_j(x), \bar{x}_j(x))$ there exists $\hat{x}(x_j) \in \mathcal{X}(x)$ satisfying

$$\begin{aligned} \hat{x}_j(x_j) &= x_j \\ \frac{\partial \phi(y^*(x) | \hat{x}(x_j))}{\partial x_j} &\neq 0 \\ \frac{\partial \phi(y^*(x) | \hat{x}(x_j))}{\partial x_k} &= 0 \quad \forall k \neq j. \end{aligned}$$

Satisfaction of this condition is determined by the observables, implying that part (ii) is verifiable. \square

Proof of Remark 7. The proof of Lemma 2 began with an arbitrary $x \in \mathbb{X}$ and the associated $y^*(x)$ defined by (16). It was then demonstrated that for some open rectangle $\mathcal{X}(x) \ni x$ the ratios

$$\frac{\partial g_j(x'_j)/\partial x_j}{\partial g_j(x_j^0)/\partial x_j}$$

are identified for all $j = 1, \dots, J$, all $x^0 \in \mathcal{X}(x) \setminus x$ and all $x' \in \mathcal{X}(x) \setminus x$. Let

$$\frac{\partial g_j(x'_j)/\partial x_j}{\partial g_j(x_j^0)/\partial x_j} [x]$$

denote the identified value of $\frac{\partial g_j(x'_j)/\partial x_j}{\partial g_j(x_j^0)/\partial x_j}$. Now take any point $\tilde{x} \in \mathcal{X}(x) \setminus x$ and repeat the argument, replacing $y^*(x)$ with the point $y^{**}(\tilde{x})$ such that (assuming the model is correctly specified) $r(y^{**}(\tilde{x})) = g(\tilde{x}) + u^{**}$ where $\partial f(u^{**})/\partial u_j = 0 \forall j$ and f is regular on a rectangle around u^{**} (u^{**} may equal u^* , but this is not required). For some open rectangle $\mathcal{X}(\tilde{x})$, this again leads to identification of the ratios

$$\frac{\partial g_j(x'_j)/\partial x_j}{\partial g_j(x_j^0)/\partial x_j}$$

for all $j = 1, \dots, J$, all $x^0 \in \mathcal{X}(\tilde{x}) \setminus \tilde{x}$ and all $x' \in \mathcal{X}(\tilde{x}) \setminus \tilde{x}$. Let

$$\frac{\partial g_j(x'_j)/\partial x_j}{\partial g_j(x_j^0)/\partial x_j} [\tilde{x}]$$

denote the identified value of $\frac{\partial g_j(x'_j)/\partial x_j}{\partial g_j(x_j^0)/\partial x_j}$. Because both x^* and \tilde{x} are in the open set $\mathcal{X}(x)$, $\{\mathcal{X}(x) \cap \mathcal{X}(\tilde{x})\} \neq \emptyset$. Thus we obtain the verifiable restriction

$$\frac{\partial g_j(x'_j)/\partial x_j}{\partial g_j(x_j^0)/\partial x_j} [x] = \frac{\partial g_j(x'_j)/\partial x_j}{\partial g_j(x_j^0)/\partial x_j} [\tilde{x}]$$

for all j and all pairs $(x^0, x') \in \{\mathcal{X}(x) \cap \mathcal{X}(\tilde{x})\}$. \square

C Falsifiability of the Linear Index Model

Here we provide two additional results on falsifiability of the linear index model when Assumption 3 (or the equivalent Hessian condition given in Lemma 4) holds. First we point out that Theorem 3 proves separate identification of

the derivatives $\{\partial r(y)/\partial y_k\}_{k=1,\dots,J}$ at all y and the derivatives $\frac{\partial \ln |J(y)|}{\partial y_k}$ for all k . Since knowledge of the former implies knowledge of the latter, under the assumptions of Theorem 3 we have the falsifiable restrictions

$$\frac{\partial}{\partial y_k} \left| \begin{pmatrix} \frac{\partial r_1(y)}{\partial y_1} & \cdots & \frac{\partial r_1(y)}{\partial y_J} \\ \vdots & \ddots & \vdots \\ \frac{\partial r_J(y)}{\partial y_1} & \cdots & \frac{\partial r_J(y)}{\partial y_J} \end{pmatrix} \right| = \frac{\partial \ln |J(y)|}{\partial y_k} \quad \forall k. \quad (\text{C.1})$$

Remark 8. Under Assumption 3, the model defined by (27) and Assumption 1 is falsifiable.

Under another verifiable condition—that there exist two sets of points satisfying the rank condition of Assumption 3—the maintained assumptions of the model are falsifiable.

Remark 9. Suppose that, for some $y \in \mathbb{Y}$, \mathbb{X} contains two sets of points $\tilde{\mathbf{x}} = (\tilde{x}^0, \dots, \tilde{x}^J)$ and $\tilde{\tilde{\mathbf{x}}} = (\tilde{\tilde{x}}^0, \dots, \tilde{\tilde{x}}^J)$ such that (i) $\tilde{\mathbf{x}} \neq \tilde{\tilde{\mathbf{x}}}$ and (ii) $D(\tilde{\mathbf{x}}, y)$ and $D(\tilde{\tilde{\mathbf{x}}}, y)$ have full rank. Then the model defined by (27) and Assumption 1 is falsifiable.

Proof. By Lemma 3, $\partial r(y)/\partial y_k$ is identified for all k using only $\tilde{\mathbf{x}}$ or only $\tilde{\tilde{\mathbf{x}}}$. Letting $\partial r(y)/\partial y_k[\tilde{\mathbf{x}}]$ and $\partial r(y)/\partial y_k[\tilde{\tilde{\mathbf{x}}}]$ denote the implied values of $\partial r(y)/\partial y_k$, we obtain the verifiable restrictions $\partial r(y)/\partial y_k[\tilde{\mathbf{x}}] = \partial r(y)/\partial y_k[\tilde{\tilde{\mathbf{x}}}]$ for all k . \square

D Differenced Derivatives

In section 5.3 we exploited the assumed twice-differentiability of f . It is straightforward to extend our arguments to cases without this additional differentiability by replacing the matrix of second derivatives with differences of the first derivatives. To see this, suppose that (35) holds for some nonzero c . This implies that $d(y, x)'c$ is constant across all $x \in \mathbb{X}$; i.e., for any x and x' in \mathbb{X} ,

$$[d(y, x) - d(y, x')]c = 0.$$

Since the first component of $d(y, x) - d(y, x')$ is zero, this is equivalent to the condition

$$\begin{bmatrix} \frac{\partial \ln \phi(y|x)}{\partial x_1} - \frac{\partial \ln \phi(y|x')}{\partial x_1} \\ \vdots \\ \frac{\partial \ln \phi(y|x)}{\partial x_J} - \frac{\partial \ln \phi(y|x')}{\partial x_J} \end{bmatrix}' \tilde{c} = 0 \quad \forall x \in \mathbb{X}, x' \in \mathbb{X}. \quad (\text{D.1})$$

Thus, for identification to (possibly) fail there must exist a nonzero vector \tilde{c} satisfying (D.1).

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