



# INSTRUMENTAL VALUES

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# Instrumental Values

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**ABSTRACT.** This paper studies the identification of partial differences of nonseparable structural functions. The paper considers triangular structures with no more stochastic unobservables than observable outcomes, that exhibit a degree of monotonicity with respect to variation in certain stochastic unobservables. It is shown that, the existence of a set of instrumental values of covariates, over which the stochastic unobservables exhibit local quantile invariance and over which a local order condition holds, defines a model which identifies certain partial differences of structural functions. This result is useful when covariates exhibit discrete variation. The paper also considers the identification of partial derivatives in smooth structures when covariates exhibit continuous variation.

## 1. INTRODUCTION

**1.1. Nonseparable structures.** Structures in which stochastic unobservables are nonseparable are of interest because they are capable of representing a very wide class of social and economic processes. Further, they allow responses to changes in conditioning variables<sup>1</sup> to exhibit stochastic variation which may be significant in the analysis of the social and economic behaviour of individuals.

Economic theory rarely tells us where the sources of stochastic variation appear in economic models, so conservative analysis of the econometric issues that arise when models are brought to data allows for the possibility that structures are nonseparable.

This paper explores the limits of identification of characteristics of nonseparable structures<sup>2</sup> using a construction which allows for the possibility that covariates and outcomes may exhibit discrete variation. One aim of this paper is to understand the limitations that discrete variation may place on the class of structural characteristics that can be identified by a model.

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<sup>†</sup>This revision corrects an error in previous versions in which it was stated that the results of the Theorem of the paper apply when outcomes have discrete distributions of general form conditional on covariate values. In fact the Theorem allows for only rather special types of discrete distributions for outcomes which appear as arguments of structural functions if partial differences of structural functions are to be identifiable under the weak conditions considered in this paper. Section 5.3 contains a discussion of this issue. This revision also corrects the discussion of large structural systems in Section 5.10.

<sup>1</sup>By “conditioning variables”, which I shall refer to as “covariates”, I mean variables whose values may determine the distribution of a random variable - a distribution I will refer to as a “conditional distribution”. The covariates discussed in this paper may not be random variables in the sense that they may not have well defined probability distributions - for example they may be values selected by an experimenter. A consequence of this is that the “distribution” of covariates will convey no information about structures. Of course values taken by covariates may contain information.

<sup>2</sup>Structures, characteristics of structures, models and identification of structural characteristics are defined as in Hurwicz (1950) and Koopmans and Reiersol (1950). Definitions are given in Section 3.

**1.2. Discrete variation.** Covariates frequently show discrete variation. Covariates may be realisations of discrete random variables such as binary indicators, for example measuring labour force participation, or of integer valued random variables, for example years of schooling, or, because of the granularity of the observation process, show discrete variation in practice, even though continuous variation is possible in principle.

This paper focuses on identification of members of a particular class of structural characteristics, namely values of partial *differences* of structural functions, that is differences obtained when all arguments but one are held constant and the remaining argument takes two distinct values. These structural characteristics are, unlike say derivatives of structural equations, characteristics which could feasibly be identified in the absence of parametric restrictions when covariates exhibit discrete variation. The analysis of this paper permits discrete variation in covariates but the results also apply when there is continuous variation and limiting arguments allow the study of identifiability of partial *derivatives* of structural functions and so a link to the results in Chesher (2001a, 2001b, 2001c, 2002).

Of course conditions must be placed on structures if a structural characteristic is to be identified. The strategy taken in this paper is to seek *weak* identifying conditions. Since the interpretation of all econometric analysis is contingent upon identifiability and identifiability necessarily rests on some untestable restrictions, it is prudent to base identifiability on the weakest possible restrictions.

Weak restrictions may lead to identifiability of only a limited class of structural characteristics and it may be that none of its members is of interest in practice. In this circumstance one may wish to impose further restrictions which lead to identification of interesting characteristics. The impact of additional (for example parametric) restrictions can be examined using the construction developed here.

**1.3. Local identification.** This paper studies the identifiability of *local* characteristics of structures and there is no attempt to develop conditions under which, say, a complete structural function is identified. This approach is taken because, when there is discrete variation in covariates, and in the absence of parametric restrictions, data may only be informative about local characteristics of structures, for example, the partial difference of a structural function when its arguments are set to particular values.

If parametric restrictions are imposed then the value of a local characteristic (for example the slope of a chord of a structural function over some interval) may be equal to the value of a global characteristic (for example the slope of a parametric linear structural function). Then the force of the parametric restriction is to allow identification of the value of the global characteristic from information provided by just local discrete variation in covariates.

A significant advantage of a focus on identification of local characteristics of structures is that, as shown in Chesher (2001b), restrictions placed on structures to achieve local identification need only be locally valid. For example, to identify a partial difference of a nonseparable function over some interval one need not restrict attention to structures in which stochastic unobservables and covariates are statistically independent<sup>3</sup>. Identification can be achieved if there is dependence but it is limited in extent *at the values of arguments* of the structural function at which knowledge of the value of the structural feature is desired.

Global validity of local identification restrictions may lead to identification of global characteristics of structures, a possibility that can be examined using the construction developed in this paper.

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<sup>3</sup>A restriction commonly imposed in the study of identification when structures may be nonseparable.

**1.4. Partial differences.** Classical identification conditions impose a degree of independence<sup>4</sup> on the variations in stochastic unobservables and covariates and an “order” condition<sup>5</sup> which limits the covariate driven variation in structural functions.

The focus of this paper on the restrictions on structures required to identify *partial differences* of structural functions allows the role played by these conditions to be seen rather clearly.

Under very weak conditions, which do *not* include these classical identification conditions, differences of structural functions *are* identifiable.

The classical identification conditions just described ensure that certain identifiable differences of structural functions are *partial* differences, that is differences obtained by varying just one argument of a structural function.

The classical “rank” condition, when viewed entirely in the context of the study of identification ensures that an identifiable partial difference is non-zero.

**1.5. Quantiles.** A key to progress in the study of identification when structures may be nonseparable is understanding that an analysis that proceeds in terms of *conditional quantile functions* is extremely well suited to the nature of the problem considered.

For  $\tau \in (0, 1)$  the  $\tau$ -quantile of a scalar random variable,  $A$ , with distribution function  $F_A$  is defined as follows<sup>6</sup>,

$$Q_A(\tau) = \inf\{q \in \mathfrak{R} | F_A(q) \geq \tau\}$$

and note that such quantiles are equivariant with respect to monotone transformations, that is, if  $h$  is a non-decreasing function on  $\mathfrak{R}$  then

$$Q_{h(A)}(\tau) = h(Q_A(\tau)).$$

This  $\tau$ -quantile is well defined whenever  $A$  has a proper distribution function, including cases in which  $A$  is a discrete random variable and the equivariance property applies in such cases.

The conditional  $\tau$ -quantile of  $A$  given a vector of covariates  $B = b$  is analogously defined as

$$Q_{A|B}(\tau, b) = \inf\{q \in \mathfrak{R} | F_{A|B}(q, b) \geq \tau\}$$

where  $F_{A|B}$  is the conditional distribution function<sup>7</sup> of  $A$  given  $B = b$ , and the equivariance property

$$Q_{h(A,B)|B}(\tau, b) = h(Q_{A|B}(\tau, b), b)$$

applies for all  $b$  for which  $h(a, b)$  is a nondecreasing function of  $a$ .

Because of this equivariance property, restrictions imposed on the covariate driven variation of conditional quantiles of a stochastic unobservable given covariates can be “passed through” a structural function as long as the function is restricted to exhibit a degree of monotonic variation with respect to the unobservable.

That sort of monotonicity restriction is an essential element in the restrictions that define the identifying models of this paper.

**1.6. Multiplicity of stochastic unobservables.** Another essential element in the restrictions considered in this paper is that the number of unobservables ( $R$ ) should be *no greater than* the number of observable outcomes ( $M$ ). This does allow the possibility that a structure involves more than  $M$  unobservables, but for the purpose of this paper

<sup>4</sup>For example, conditional mean independence, full independence, or, as considered in this paper, conditional quantile invariance.

<sup>5</sup>In the language of Koopmans, Rubin and Leipnik (1950).

<sup>6</sup>The distribution function is defined as:  $F_A(a) = P[A \leq a]$ .

<sup>7</sup>That is  $F_{A|B}(a, b) = P[A \leq a | B = b]$ .

a model contains only such structures in which unobservables coalesce to produce  $M$  or fewer unobservables, no more than the number of observable outcomes.

In a nonparametric attack under weak restrictions, imposing this condition is essential, a point easily seen when we consider that otherwise one would be seeking knowledge of characteristics of a structure generated by  $R > M$  stochastic unobservables from information contained in a  $M < R$  dimensional distribution function for outcomes given covariates.

There are of course many econometric models used in practice that do not embody such a restriction, for example the mixed proportionate hazard models popular in the analysis of durations, measurement error models and models for panel data that incorporate “individual effects”. It is notable that in all cases models of this sort gain identifying power from strong restrictions, which usually require additivity (in some specified metric) at key points in admissible structural functions<sup>8</sup>.

**1.7. Restrictions and instrumental values.** Two types of restrictions define the models considered in this paper.

First there are restrictions on admissible structural equations, specifically that they have a triangular structure, that they exhibit monotonic variation with respect to certain unobservables and that there is a specific sort of variation in the values delivered by the structural functions as covariate values vary.

A two equation example of the sort of triangular structure considered here is the following<sup>9</sup>.

$$\begin{aligned} Y_1 &= h_1(Y_2, X, \varepsilon_1, \varepsilon_2) \\ Y_2 &= h_2(X, \varepsilon_2) \end{aligned}$$

The monotonicity requirement is that  $h_1$  be non-increasing or non-decreasing in  $\varepsilon_1$  and  $h_2$  be strictly increasing or strictly decreasing in  $\varepsilon_2$ . These conditions can be weakened, for example to “single crossing” conditions as set out in Chesher (2002). The functions  $h_1$  and  $h_2$  are normalised to be respectively non-decreasing and strictly increasing<sup>10</sup>.

The second type of restriction limits the variation in the conditional distribution of the unobservables ( $\varepsilon_1$  and  $\varepsilon_2$ ) as covariate values ( $X$ ) vary. Specifically if identification of a structural feature at  $\tau_1$ - and  $\tau_2$ - quantiles of respectively  $\varepsilon_1$  and  $\varepsilon_2$  is required then restrictions are placed on the dependence of those conditional quantiles given  $X = x$  as  $x$  varies.

The restrictions on  $X$ -driven variation in conditional quantiles of unobservables and on  $X$ -driven variation in structural functions are both required to hold for variations in  $X$  confined to a set of *instrumental values*. This set may be non-denumerable, but in cases in which there is discrete variation it may be denumerable.

In Section 4 a theorem is stated and proved which defines a model such that, for two equation admissible structures as set out above, if  $x'$  and  $x''$  belong to a set of instrumental values,  $V^* \subseteq \mathfrak{R}^K$ , then the partial difference:

$$h_1(y'_2, x^*, e_1^*, e_2^*) - h_1(y''_2, x^*, e_1^*, e_2^*) \quad (1)$$

<sup>8</sup>For example measurement error models typically have measurement error additive in some specified metric, mixed proportionate hazard models typically have the unobserved heterogeneity term additive in the log hazard function, panel data models typically have individual effects additive with the other unobservables.

<sup>9</sup>Note that  $\varepsilon_2$  need not be present in  $h_1$  and that  $\varepsilon_1$  and  $\varepsilon_2$  can be jointly dependent and dependent upon  $X$ .

<sup>10</sup>The requirement that  $h_2$  be *strictly* monotonic with respect to variation in  $\varepsilon_2$  is significant, restricting the stochastic variation in  $Y_2$  (which note appears in the function  $h_1$ ) to take place across a support which has a one-to-one correspondence with the support of  $\varepsilon_2$ . The issue is addressed further in Section 5.3.

is identifiable. Here  $e_2^*$  is the  $\tau_2^*$ -quantile of the conditional distribution of  $\varepsilon_2$  given  $X$ ,  $e_1^*$  is the  $\tau_1^*$ -quantile of the conditional distribution of  $\varepsilon_1$  given  $\varepsilon_2$  and  $X$ ,  $y_2'$  and  $y_2''$  are respectively  $h_2(x', \varepsilon_2^*)$  and  $h_2(x'', \varepsilon_2^*)$  and  $x^*$  is any value of  $X$  in the set of instrumental values.

The set of instrumental values is required to be such that:

1. the  $\tau_2^*$ -quantile of the conditional distribution of  $\varepsilon_2$  given  $X = x$ ,  $e_2^*$ , and the  $\tau_1^*$ -quantile of the conditional distribution of  $\varepsilon_1$  given  $\varepsilon_2 = e_2^*$  and  $X = x$ ,  $e_1^*$ , are invariant with respect to variation in  $x$  within the set of instrumental values, and,
2. for any  $x'$  and  $x''$  in the set of instrumental values,

$$h_1(y_2', x', e_1^*, e_2^*) = h_1(y_2'', x'', e_1^*, e_2^*)$$

which is in the nature of an order condition.

The membership of the set of instrumental values may depend upon the probabilities,  $\tau_1^*$  and  $\tau_2^*$ , which define the conditional quantiles of  $\varepsilon_1$  and  $\varepsilon_2$ . The “\*” in “V\*” is intended to indicate this dependence. A more expansive, but cumbersome, notation would write a set of instrumental values associated with  $\tau_1^*$  and  $\tau_2^*$  as  $V(\tau_1^*, \tau_2^*)$ . The membership of the set of instrumental values may also depend upon the partial difference whose identification is sought.

It is shown in Section 4 that in this two equation problem:

1. the partial difference (1) is uniformly identified<sup>11</sup> by a model embodying restrictions as set out above, restrictions made precise in the statement of a Theorem set out in Section 4, and,
2. all structures in which the partial difference (1) takes a particular value, say  $a$ , generate conditional distributions for  $Y$  given  $X$  such that the difference in conditional quantiles:

$$Q_{Y_1|Y_2X}(\tau_1^*, Q_{Y_2|X}(\tau_2^*, x'), x') - Q_{Y_1|Y_2X}(\tau_1^*, Q_{Y_2|X}(\tau_2^*, x''), x'') \quad (2)$$

takes the same value,  $a$ . Here  $Q_{Y_1|Y_2X}$  and  $Q_{Y_2|X}$  are conditional quantile functions of respectively  $Y_1$  given  $Y_2$  and  $X$ , and of  $Y_2$  given  $X$ .

The analog principle<sup>12</sup> suggests an estimator of the value of the partial difference, namely the expression (2) applied to estimates of these conditional quantile functions.

**1.8. Plan of this paper.** Section 2 briefly reviews the related literature. Section 3 defines concepts used in the paper and states and proves a Lemma which is helpful in determining whether a model identifies a structural characteristic.

Section 4 states and proves a Theorem which defines a model that identifies values of, and partial differences of, structural functions in two equation systems. The model embodies restrictions of the sort described above.

The ten sub-sections of Section 5 consider the following issues.

1. The requirement that a rank condition hold (that is  $y_2' \neq y_2''$  in the example above) if the identification result is to be useful, the impact that discrete variation in covariates has on the information that data can provide about differences of structural functions, and the utility of parametric restrictions when covariates show discrete variation.

<sup>11</sup>In the sense of Koopmans and Reiersol (1950), see Section 3.

<sup>12</sup>Manski (1988).

2. The impact of weak instruments on the ability to identify interesting partial differences.
3. Discrete variation in outcomes.
4. Analog estimation of partial differences.
5. The way in which a classical analysis *via* instrumental variables is subsumed in the analysis of this paper.
6. The concept of overidentification in this analysis *via* instrumental values and the use of overidentifying restrictions in analog estimation.
7. Smooth structures and the identification of partial *derivatives* of structural functions.
8. Identification of partial differences with respect to *covariates*.
9. Identification of partial differences with respect to *stochastic unobservables*.
10. Identification of partial differences in  $M$  equation structures.

Section 6 concludes.

## 2. RELATED LITERATURE

The study of identification has a long history with early contributions by Working (1925, 1927), and Frisch (1934, 1938) and with notable developments by, among others, Haavelmo (1944), Hurwicz (1950), Koopmans and Reiersol (1950), Koopmans, Rubin and Leipnik (1950), Wald (1950), Fisher (1959, 1961, 1966), Wegge (1965) and Rothenberg (1971). One product of this research was the order and rank conditions in linear models, local versions of which feature in the results of this paper.

Most of this work was cast in the context of *parametric* models although Koopmans and Reiersol (1950) understood that identification could be achieved with less restricted models and the definitions provided by Hurwicz (1950), adopted by Koopmans and Reiersol (1950), and used in this paper, were designed to apply in the consideration of identification in the absence of parametric restrictions.

Until the early 1970's much econometric analysis dealt with aggregate market or national data. One would not expect such data to be generated by highly nonlinear structures and so the focus of the study of identification on simple parametric models and indeed on linear models was apposite.

The microeconometrics revolution of the 1970's wrought a major change, bringing new interest in the study of the behaviour of individual economic agents who may face wide variations in conditions under which choices are made, leading to consideration of structures in which nonlinearity is an essential and an interesting element. Economic theory provides little guidance concerning the precise forms of nonlinear structural equations and so interest in *nonparametric* identification, that is identification of structural characteristics in the absence of parametric restrictions, was rekindled.

Charles Roehrig (1988), extending the work of Brown (1983), re-stimulated interest in *nonparametric* identification. Roehrig (1988) is concerned with global identification of structural functions for models in which stochastic unobservables are restricted to be statistically independent of covariates. Most of the discussion in Roehrig (1988) is for the case in which the stochastic unobservables are separable, appearing additively in the structural equations of the model. Newey and Powell (1988), Newey, Powell and Vella (1999), Pinkse (2000), Darolles, Florens and Renault (2000) study identification using

such models with stochastic unobservables which satisfy mean independence conditions of various types.

There has been recent interest in determining when global identification can be achieved in structures with *nonseparable* disturbances. Brown and Matzkin (1996) consider the identification of nonparametric primitive nonseparable structural functions (for example production or utility functions) under the restriction that stochastic unobservables and covariates are independently distributed. Altonji and Matzkin (2001) study panel data structures restricted by conditional exchangeability conditions. Imbens and Newey (2001) study triangular, nonseparable structures similar to those addressed in this paper<sup>13</sup>. They determine conditions under which there is global identification of structural functions when stochastic unobservables are restricted to be statistically independent of covariates, and they develop an ingenious estimator of a structural function and provide conditions under which it is consistent.

Statistical independence of stochastic unobservable and covariates is a very strong condition which we might not expect to hold in practice, particularly when working with microdata, which may exhibit heteroskedastic variation.

One of the aims of this paper is to develop identification conditions which do not require full statistical independence of unobservables and covariates while still allowing identification of pertinent structural characteristics. This is achieved by placing restrictions on the covariate-driven variation of conditional *quantiles* of the unobservables. Such restrictions can be tailored to suit the case under study. For example where heteroskedastic variation is considered likely one might only be prepared to place restrictions on covariate-driven variation in conditional *medians*, allowing other conditional quantiles to depend upon the values of covariates.

One of the few papers to consider identification from a conditional quantile perspective is Matzkin (1999) which considers a model in which a structural function takes the form  $Y = m(X, \varepsilon)$  with  $\varepsilon$  distributed independently of  $X$  and  $m(X, \varepsilon)$  strictly monotonic in  $\varepsilon$ . Conditions under which the function  $m(\cdot, \cdot)$  and the distribution function of  $\varepsilon$  are identifiable are obtained. The value of  $m(\cdot, \cdot)$  at a point  $(x, e)$  is shown, under suitable conditions, to be identifiable as the value of the conditional  $\tau$ -quantile of  $Y$  given  $X = x$  where  $\tau$  is such that  $e$  is the  $\tau$ -quantile of the marginal distribution of  $\varepsilon$ .

There is a large recent literature concerning the identifying power of treatment effect models<sup>14</sup>. The structures admitted in these models have two potential outcomes only one of which is observed depending on whether a treatment is assigned or not. These structures contain more sources of stochastic variation than observable stochastic outcomes and so the analysis of this paper is not applicable.

The identification conditions of this paper include local quantile independence restrictions. A number of papers have used quantile independence restrictions as the basis for developing estimators including Amemiya (1982), Powell (1983), Newey and Powell (1990), Chaudhuri, Doksum and Samarov (1997), Kahn (2001) and Chernozhukov and Hansen (2001).

This paper extends the research reported in Chesher (2001a, 2001b, 2001c, 2002) to problems in which there is discrete variation in covariates or outcomes. The results of this paper can be specialised to yield those given in the earlier papers, as indicated in Section 5.7. As is often the case, viewing a problem, as here, from a more general standpoint creates great simplification, so the results of this paper shed light on the results contained

<sup>13</sup>In the Imbens-Newey model each structural equation contains exactly one stochastic unobservable. In the model of this paper more than one stochastic unobservable may appear in a structural equation as long as the unobservables appear in triangular form.

<sup>14</sup>See for example many contributions by James Heckman including Heckman (1990) and Heckman, Smith and Clements (1997), and Heckman and Vytlačil (2001) and the papers referenced therein, and Imbens and Angrist (1994), Das (2000), Chernozhukov and Hansen (2001), Abadie, Angrist and Imbens (2002), and Vytlačil (2002).



in these earlier papers, and more generally on a number of results in the extensive literature on identification of structures and their characteristics.

### 3. STRUCTURES, MODELS AND IDENTIFICATION

This Section makes precise the definitions of various concepts used in this paper and states and proves a Lemma which is helpful in determining whether a model identifies a structural characteristic.

Following Hurwicz (1950), a *structure* is defined as:

1. a system of equations delivering a value of a vector outcome,  $Y = \{Y_m\}_{m=1}^M$  given a value of a vector covariate,  $X = \{X_k\}_{k=1}^K$  and a value of a vector of unobservable random variables,  $\varepsilon = \{\varepsilon_r\}_{r=1}^R$ , and,
2. a conditional distribution function,  $F_{\varepsilon|X}$  for the unobservables given the covariates,
3. such that, the conditional distribution function of outcomes given covariates,  $F_{Y|X}$  is well defined.

Note that the definition of a particular structure requires a complete (i.e. numerical) specification of a system of equations and a conditional distribution  $F_{\varepsilon|X}$ .

A *structural characteristic*<sup>15</sup> is a functional  $\theta(S)$  of a structure,  $S$ , for example the value of a partial derivative of a structural function at a given point or of a partial difference calculated at a given pair of points. Data are generated by some structure, we know not which, and we wish to discover the value of a characteristic of the data generating structure. Many structures with different values of a structural characteristic may generate identical conditional distribution functions,  $F_{Y|X}$ . Structures which generate the same conditional distribution function for  $Y$  given  $X$  are said to be *observationally equivalent*.

Data generated by a structure are informative about  $F_{Y|X}$ , but cannot alone distinguish one observationally equivalent structure from another. If the value of a structural characteristic varies within observationally equivalent structures then that value cannot be identified. So, in order to identify the value of a structural characteristic the class of admissible structures must be restricted so that there is no variation in the value of the characteristic within observationally equivalent structures.

The term “*model*” is used to describe a set of restrictions defining admissible structures. A model is a proper subset of the class of all structures, for example all structures in which the equations are restricted to be linear and  $F_{\varepsilon|X}$  is multivariate normal independent of  $X$ .

A model *identifies* a characteristic,  $\theta(S)$  in a structure  $S_0$  if that characteristic is the same in all structures which are admitted by the model and observationally equivalent to  $S_0$  (Koopmans and Reiersol (1950)). A characteristic  $\theta(S)$  is *uniformly identified* by a model if it is identifiable for every structure  $S$  admitted by the model.

It is helpful to have a simple means of determining whether a model uniformly identifies a structural characteristic. This is provided by the following Lemma.

**Lemma.** Consider a model, let  $S^a$  be the set of admissible structures such that  $\theta(S) = a$  and let  $A$  be the set of all values of  $\theta(S)$  generated by admissible structures. Let  $F_{Y|X}^S$  denote the conditional distribution function generated by a structure  $S$ . Suppose there exists a functional of the conditional distribution function of  $Y$  given  $X$ ,  $\mathcal{G}(F_{Y|X})$ , such that for each  $a \in A$ ,  $\mathcal{G}(F_{Y|X}^S) = a$  for all  $S \in S^a$ . Then  $\theta(S)$  is uniformly identified by the model.

<sup>15</sup>The term “structural characteristic” is due to Koopmans and Reiersol (1950). Hurwicz (1950) used the term “criterion”.

**Proof.** Consider any value of  $a_0 \in A$  and any structure  $S_0$  with  $\theta(S_0) = a_0$  and let  $S_0^*$  be the set of structures observationally equivalent to  $S_0$ . Consider any  $S' \in S_0^*$  and let  $\theta(S') = a'$ . If a functional  $\mathcal{G}$  with the stated property exists then  $\mathcal{G}(F_{Y|X}^{S'}) = a'$  and  $\mathcal{G}(F_{Y|X}^{S_0}) = a_0$ . Since  $S'$  and  $S_0$  are observationally equivalent  $F_{Y|X}^{S'} = F_{Y|X}^{S_0}$  and therefore  $a' = a_0$ . Therefore, if a functional  $\mathcal{G}$  with the stated property exists then, for any  $a_0 \in A$ , all structures observationally equivalent to any structure  $S_0$  with  $\theta(S_0) = a_0$  have the same value,  $a_0$ , of the structural characteristic, and so  $\theta(S)$  is uniformly identified by the model.

In practice it may not be possible to find a functional of  $F_{Y|X}$  with the required property even though the structural characteristic is uniformly identified. If, for some model, such a functional can be found then uniform identification of the structural feature by the model is assured and there is a clear route to estimation *via* the analog principle using  $\hat{\theta}(S) = \mathcal{G}(\hat{F}_{Y|X}^S)$ .

#### 4. A TWO EQUATION MODEL

This Section considers two equation structures and states and proves a Theorem which provides restrictions on structures, that is *defines a model*, under which certain partial differences of a structural function are uniformly identified. Issues arising from the result of the theorem and extension to structures with more than two equations are discussed in Section 5.

The conditions of the Theorem require structural equations to be triangular, complete, and to exhibit a degree of monotonicity with respect to variation in certain stochastic unobservables. From these conditions alone, two of the four results of the Theorem follow, namely that values delivered by the two structural functions at a point of interest are identifiable. From this we can immediately conclude that certain differences of structural functions are identifiable under these three conditions.

The remaining condition of the Theorem ensures that certain identifiable differences of structural functions are *partial* differences, a conclusion expressed in the final two results of the Theorem. This condition posits the existence of a set of instrumental values of the covariates such that variation in covariate values within this set:

1. results in no change in  $\tau_1^*$ - and  $\tau_2^*$ - conditional quantiles of  $\varepsilon_1$  and  $\varepsilon_2$ , and,
2. results in no variation in the values delivered by the structural function  $h_1$  through its  $X$  argument.

The Theorem is now stated and proved.

#### Theorem

Let  $Y_1$  and  $Y_2$  be scalar random variables, let  $X = \{X_k\}_{k=1}^K$  be a list of covariates and let  $\varepsilon_1$  and  $\varepsilon_2$  be unobservable scalar random variables.

Let  $Q_{\varepsilon_2|X}(\tau, x)$  denote the conditional  $\tau$ -quantile of  $\varepsilon_2$  given  $X = x$ , and let  $Q_{\varepsilon_1|\varepsilon_2 X}(\tau, e_2, x)$  denote the conditional  $\tau$ -quantile of  $\varepsilon_1$  given  $\varepsilon_2 = e_2$  and  $X = x$ .

Consider  $\{\tau_i^*\}_{i=1}^2 \in (0, 1) \times (0, 1)$ , and a set of *instrumental values*  $V^* \subseteq \mathfrak{R}^K$  of the conditioning variables whose membership may depend upon the value of  $\tau^*$ . Define

$$\begin{aligned} e_2^*(x) &\equiv Q_{\varepsilon_2|X}(\tau_2^*, x) \\ e_1^*(x) &\equiv Q_{\varepsilon_1|\varepsilon_2 X}(\tau_1^*, e_2^*(x), x). \end{aligned}$$

There are the following assumptions.

**A1 Triangularity.**  $Y_1$  and  $Y_2$  are determined by the following structural equations.

$$Y_1 = h_1(Y_2, X, \varepsilon_1, \varepsilon_2) \quad (3)$$

$$Y_2 = h_2(X, \varepsilon_2) \quad (4)$$

**A2 Completeness.** For each  $x \in V^*$ , the equations

$$Y_1 = h_1(Y_2, x, e_1^*(x), e_2^*(x))$$

$$Y_2 = h_2(x, e_2^*(x))$$

have a unique solution for  $Y_1$  and  $Y_2$ , denoted by  $y_1^*(x)$  and  $y_2^*(x)$ .

**A3 Monotonicity.**

- (a) For all  $x \in V^*$ , the function  $h_2(x, \varepsilon_2)$  is strictly monotonic (either decreasing for all  $x \in V^*$  or increasing for all  $x \in V^*$ ) with respect to variation in  $\varepsilon_2$ . Normalise  $h_2$  to be increasing with respect to variation in  $\varepsilon_2$ .
- (b) For all  $x \in V^*$  and, at  $Y_2 = y_2^*(x)$ ,  $\varepsilon_2 = e_2^*(x)$  the function  $h_1(y_2^*(x), x, \varepsilon_1, e_2^*(x))$  is weakly monotonic (either non-decreasing for all  $x \in V^*$  or non-increasing for all  $x \in V^*$ ) with respect to variation in  $\varepsilon_1$ . Normalise  $h_1$  to be non-decreasing with respect to variation in  $\varepsilon_1$ .

**A4 Quantile invariance.** For all  $\{x', x''\} \in V^*$

$$e_1^*(x') = e_1^*(x'')$$

$$e_2^*(x') = e_2^*(x'').$$

Denote the common values by  $e_1^*$  and  $e_2^*$ .

**A5 Order condition.** For all  $\{x', x''\} \in V^*$

$$h_1(y_2^*(x'), x', e_1^*, e_2^*) = h_1(y_2^*(x''), x'', e_1^*, e_2^*)$$

Consider  $\{x', x''\} \in V^*$  and define

$$\Delta_Q^*(x', x'') \equiv Q_{Y_1|Y_2X}(\tau_1^*, Q_{Y_2|X}(\tau_2^*, x'), x') - Q_{Y_1|Y_2X}(\tau_1^*, Q_{Y_2|X}(\tau_2^*, x''), x''). \quad (5)$$

Consider a third value of  $x$ ,  $x^*$ , possibly distinct from  $x$  and  $x'$  with  $\{x', x'', x^*\} \in V^*$  and define

$$\Delta_{h_1}^*(x', x'', x^*) \equiv h_1(y_2^*(x'), x^*, e_1^*, e_2^*) - h_1(y_2^*(x''), x^*, e_1^*, e_2^*).$$

Four results follow.

- (a). Under conditions (A1) - (A3), for any  $x \in V^*$  and any  $a$ :

$$y_2^*(x) = a \implies Q_{Y_2|X}(\tau_2^*, x) = a$$

and the model defined by conditions (A1) - (A3) uniformly identifies  $y_2^*(x)$  for  $x \in V^*$ .

- (b). Under conditions (A1) - (A3), for any  $x \in V^*$  and any  $a$ :

$$y_1^*(x) = a \implies Q_{Y_1|Y_2X}(\tau_1^*, Q_{Y_2|X}(\tau_2^*, x), x) = a$$

and the model defined by conditions (A1) - (A3) uniformly identifies  $y_1^*(x)$  for  $x \in V^*$ .

(c). Under conditions (A1) - (A5) for any  $\{x', x^*, x^+\} \in V^*$

$$h_1(y_2^*(x'), x^*, \varepsilon_1^*, \varepsilon_2^*) = h_1(y_2^*(x'), x^+, \varepsilon_1^*, \varepsilon_2^*),$$

for any  $\{x', x^*, x^+\} \in V^*$  and any  $a$ :

$$h_1(y_2^*(x'), x^*, \varepsilon_1^*, \varepsilon_2^*) = a \implies Q_{Y_1|Y_2X}(\tau_1^*, Q_{Y_2|X}(\tau_2^*, x'), x') = a$$

and the model defined by conditions (A1) - (A5) uniformly identifies  $h_1(y_2^*(x'), x^*, \varepsilon_1^*, \varepsilon_2^*)$  for  $\{x', x^*\} \in V^*$ .

(d). Under conditions (A1) - (A5) for any  $\{x', x'', x^*\} \in V^*$  and any  $a$

$$\Delta_{h_1}^*(x', x'', x^*) = a \implies \Delta_Q^*(x', x'') = a$$

and the model defined by conditions (A1) - (A5) uniformly identifies the partial difference  $\Delta_{h_1}^*(x', x'', x^*)$ , for any  $\{x', x'', x^*\} \in V^*$ .

### Proof

(a). First consider the identification of the value of  $y_2^*(x)$ , defined (see conditions (A1) and (A2)) as follows.

$$y_2^*(x) \equiv h_2(x, e_2^*(x)) \quad (6)$$

The monotonicity condition (A3) and the equivariance property of quantiles imply that, for any  $x \in V^*$ , since  $e_2^*(x)$  is the  $\tau_2^*$ -quantile of  $\varepsilon_2$  given  $X = x$ ,

$$h_2(x, e_2^*(x)) = Q_{Y_2|X}(\tau_2^*, x).$$

Therefore, for any  $a$ ,

$$y_2^*(x) = a \implies Q_{Y_2|X}(\tau_2^*, x) = a. \quad (7)$$

Applying the Lemma of Section 3 gives the result that the model defined by (A1) - (A3) uniformly identifies the value of  $y_2^*(x)$  for all  $x \in V^*$  since  $Q_{Y_2|X}(\tau_2^*, x)$  is a well defined functional of the conditional distribution of  $Y$  given  $X$  satisfying the condition of the Lemma. This completes the proof of part (a) of the Theorem<sup>16</sup>.

(b). Now consider identification of the value of  $y_1^*(x)$  defined (see conditions (A1) and (A2)) as follows.

$$y_1^*(x) \equiv h_1(y_2^*(x), x, e_1^*(x), e_2^*(x)) \quad (8)$$

Substitute for  $Y_2$  in equation (3) giving

$$Y_1 = h_1(h_2(x, \varepsilon_2), x, \varepsilon_1, \varepsilon_2)$$

and evaluate the right hand side at  $\varepsilon_2 = e_2^*(x)$  which gives the expression:

$$g(x, \varepsilon_1) = h_1(h_2(x, e_2^*(x)), x, \varepsilon_1, e_2^*(x)).$$

Considering variations in  $\varepsilon_1$ , the monotonicity condition (A3) and the equivariance property of quantiles imply that, for any  $x \in V^*$ , since  $e_1^*(x)$  is the  $\tau_1^*$ -quantile of  $\varepsilon_1$  given  $\varepsilon_2 = e_2^*(x)$  and  $X = x$ ,

$$h_1(h_2(x, e_2^*(x)), x, e_1^*(x), e_2^*(x)) = Q_{Y_1|\varepsilon_2X}(\tau_1^*, e_2^*(x), x) \quad (9)$$

where the left hand side here is  $g(x, e_1^*(x))$ .

<sup>16</sup>Note that this conclusion of the Theorem follows when  $h_2$  is *weakly* monotonic with respect to variation in  $\varepsilon_2$ .

Consider the right hand side of equation (9). The definition of  $y_2^*(x)$  given in equation (6) implies that the events  $(\varepsilon_2 = e_2^*(x) \cap X = x)$  and  $(Y_2 = y_2^*(x) \cap X = x)$  are identical, so conditioning on  $\varepsilon_2 = e_2^*(x)$  and  $X = x$  is the same as conditioning on  $Y_2 = y_2^*(x)$  and  $X = x$ . Therefore<sup>17</sup>

$$Q_{Y_1|\varepsilon_2 X}(\tau_1^*, e_2^*(x), x) = Q_{Y_1|Y_2 X}(\tau_1^*, y_2^*(x), x). \quad (10)$$

Consider the left hand side of equation (9). From the definition of  $y_2^*(x)$  given in equation (6)

$$h_1(h_2(x, e_2^*(x)), x, e_1^*(x), e_2^*(x)) = h_1(y_2^*(x), x, e_1^*(x), e_2^*(x)) \quad (11)$$

and using the definition of  $y_1^*(x)$  given in equation (8), on combining (9), (10) and (11), there is the following equation.

$$y_1^*(x) = Q_{Y_1|Y_2 X}(\tau_1^*, y_2^*(x), x) \quad (12)$$

Equation (7) implies that  $y_2^*(x)$  in (12) can be replaced by  $Q_{Y_2|X}(\tau_2^*, x)$  giving:

$$Q_{Y_1|Y_2 X}(\tau_1^*, y_2^*(x), x) = Q_{Y_1|Y_2 X}(\tau_1^*, Q_{Y_2|X}(\tau_2^*, x), x)$$

and so, for any  $x \in V^*$  and any  $a$ ,

$$y_1^*(x) = a \implies Q_{Y_1|Y_2 X}(\tau_1^*, Q_{Y_2|X}(\tau_2^*, x), x) = a. \quad (13)$$

Applying the Lemma of Section 3 gives the result that the model defined by (A1) - (A3) uniformly identifies the value of  $y_1^*(x)$  for all  $x \in V^*$  since  $Q_{Y_1|Y_2 X}(\tau_1^*, Q_{Y_2|X}(\tau_2^*, x), x)$  is a well defined functional of the conditional distribution of  $Y$  given  $X$  satisfying the condition of the Lemma. This completes the proof of part (b) of the Theorem.

(c). The quantile invariance condition (A4) implies that for all  $x \in V^*$  the terms  $e_1^*(x)$  and  $e_2^*(x)$  in equation (8) can be replaced by respectively  $e_1^*$  and  $e_2^*$  giving the following.

$$y_1^*(x) = h_1(y_2^*(x), x, e_1^*, e_2^*) \quad (14)$$

The order condition (A5) implies that, for any  $x \in V^*$  the second appearance of  $x$  in equation (14) can be replaced by  $x^*$  for any  $x^* \in V^*$  which gives the following.

$$y_1^*(x) = h_1(y_2^*(x), x^*, e_1^*, e_2^*) \quad (15)$$

Therefore, for all  $\{x', x^*, x^+\} \in V^*$ , setting  $x = x'$  in equation (15), and considering alternative values  $x^*$  and  $x^+$  for the second argument of  $h_1$  gives the following.

$$h_1(y_2^*(x'), x^*, e_1^*, e_2^*) = h_1(y_2^*(x'), x^+, e_1^*, e_2^*)$$

It follows from (13) and (15) that, for  $\{x', x^*\} \in V^*$  and any  $a$ ,

$$h_1(y_2^*(x'), x^*, e_1^*, e_2^*) = a \implies Q_{Y_1|Y_2 X}(\tau_1^*, Q_{Y_2|X}(\tau_2^*, x'), x') = a \quad (16)$$

Applying the Lemma of Section 3 gives the result that the model defined by (A1) - (A5) uniformly identifies the value of  $h_1(y_2^*(x'), x^*, e_1^*, e_2^*)$ , which is invariant with respect to  $x^* \in V^*$ , since  $Q_{Y_1|Y_2 X}(\tau_1^*, Q_{Y_2|X}(\tau_2^*, x'), x')$  is a well defined functional of the conditional distribution of  $Y$  given  $X$  satisfying the condition of the Lemma. This completes the proof of part (c) of the Theorem.

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<sup>17</sup>Note that if  $h_2$  were only *weakly* monotonic with respect to variation in  $\varepsilon_2$  this conclusion would *not* follow because there could be many values of  $e_2^*(x)$  implying the same value of  $y_2^*(x)$ .

(d). First recall that the partial difference  $\Delta_{h_1}^*(x', x'', x^*)$ , which is invariant to choice of  $x^* \in V^*$ , is defined as follows.

$$\Delta_{h_1}^*(x', x'', x^*) \equiv h_1(y_2^*(x'), x^*, e_1^*, e_2^*) - h_1(y_2^*(x''), x^*, e_1^*, e_2^*)$$

It follows directly from (16) that for any  $\{x', x'', x^*\} \in V^*$  and any  $a$ ,

$$\Delta_{h_1}^*(x', x'', x^*) = a \implies \Delta_Q^*(x', x'') = a.$$

Applying the Lemma of Section 3 gives the result that the model defined by (A1) - (A5) uniformly identifies the value of  $\Delta_{h_1}^*(x', x'', x^*)$ , since  $\Delta_Q^*(x', x'')$  is a well defined functional of the conditional distribution of  $Y$  given  $X$  satisfying the condition of the Lemma. This completes the proof of the final part of the Theorem.

## 5. REMARKS AND EXTENSIONS

**5.1. Rank condition, discreteness and parametric restrictions.** Part (d) of the Theorem is only of interest if the ‘‘rank condition’’,  $y_2^*(x') \neq y_2^*(x'')$  holds.

Even when this condition holds, the extent to which  $y_2^*(x)$  can be varied may be severely limited by the nature of the set of instrumental values. To take an extreme example, if there are just two admissible instrumental values (perhaps because  $X$  is a single binary instrument), then for any choice of  $\tau_2^*$ , and thus of  $e_2^*$ , only two values of  $Y_2$  can be generated and only one partial difference can be identified. Whether or not that is an interesting partial difference is a matter for case-by-case consideration.

If  $X$  does not show continuous variation but  $h_1$  is a smooth function of  $Y_2$  then the slope of a  $Y_2$ -chord of the structural function, that is:

$$\Delta_{h_1}^*(x', x'') / (y_2^*(x') - y_2^*(x'')),$$

can be identified as long as the rank condition is satisfied.

If  $h_1$  is restricted to be linear in  $Y_2$ , with a coefficient that may depend upon  $X$  and  $\varepsilon$ , then just two instrumental values are sufficient to globally identify the value of this coefficient at a value of  $X$  and  $\varepsilon$ . By extension, if  $h_1$  is restricted to be a degree  $M$  polynomial function of  $Y_2$ , with coefficients possibly depending on  $X$  and  $\varepsilon$ , then, as long as the conditions of the Theorem are satisfied,  $M + 1$  distinct instrumental values are sufficient to identify the  $M + 1$  coefficients of the polynomial.

**5.2. Weak instruments.** Even when the set of instrumental values has extensive coverage, variation across the set of instrumental values may still induce only limited variation in  $y_2^*(x)$ . This will be the case when  $h_2$  transmits the effect of variation in  $X$  only weakly. In this situation extensive understanding of the impact of  $Y_2$  on  $h_1$  cannot be obtained without further, for example, parametric, restrictions.

This ‘‘weak instrument’’ problem is additional to the weak instrument problem commonly discussed in the context of estimation which arises from the possibly poor quality of asymptotic approximations to the distributions of estimators based on estimation using numerous weak instruments.

**5.3. Discrete outcomes.** The results of the Theorem apply when the outcomes  $Y_1$  and  $Y_2$  have discrete, continuous or mixed distributions. However, results (b) - (d) of the Theorem are not likely to be useful when  $Y_2$  is not continuously distributed in a neighbourhood of the quantile  $e_2(x)$  of interest. Although the Theorem does apply when the outcome  $Y_2$  has a discrete distribution, the impact of the covariates,  $X$ , on the distribution of  $Y_2$  allowed by the Theorem is extremely limited when  $Y_2$  has a discrete distribution.

To see this, first note that since  $h_2$  is required (at the values of  $X$  of interest) to be strictly monotonic with respect to variation in  $\varepsilon_2$ ,  $Y_2$  can only have a discrete distribution if  $\varepsilon_2$  has a discrete distribution.

Suppose that  $\varepsilon_2$  is discrete. Since  $h_2$  is required to be strictly monotonic, there is a one-to-one correspondence between the points of support of the distribution of  $\varepsilon_2$  and the points of support of the distribution of  $Y_2$ . Consider a particular value which  $\varepsilon_2$  can take, say  $e_2^{(i)}(x)$ . The probability that  $Y_2$  take the value,  $y_2^{(i)}(x) = h_2(x, e_2^{(i)}(x))$  is equal to the probability that  $\varepsilon_2 = e_2^{(i)}(x)$  because  $h_2$  is required to be strictly monotonic. Variation in  $x$  via the first argument of  $h_2$  can change the *locations* of the points of support of  $Y_2$  but cannot alter the *probabilities* with which these points of support occur. Variation in these probabilities could arise because  $e_2^{(i)}(x)$  varies with  $x$ , but such variation is ruled out for values of  $x$  in a set of instrumental values.

This issue is now explored a little further. Any discrete distribution can be arbitrarily closely approximated by a continuous distribution. As an example, consider the case in which  $Y_2$  has *exactly* a Poisson distribution with mean  $\lambda(x)$ . This arises when  $h_2(x, \varepsilon_2)$  is defined as the non-decreasing function:

$$h_2(x, \varepsilon_2) = i, \quad \varepsilon_2 \in (F(i-1, \lambda(x)), F(i, \lambda(x))] \quad (17)$$

where  $\varepsilon_2$  is uniformly distributed on  $(0, 1)$  and

$$\begin{aligned} F(-1, \lambda(x)) &= 0 \\ F(i, \lambda(x)) &= e^{-\lambda(x)} \sum_{j=0}^i \frac{\lambda(x)^j}{j!}, \quad i \geq 0. \end{aligned}$$

Consider the function  $h_2^{(\beta)}(x, \varepsilon_2)$  defined for positive  $\beta$  as follows.

$$h_2^{(\beta)}(x, \varepsilon_2) = i + 1 - \left( \frac{F(i, \lambda(x)) - \varepsilon_2}{F(i, \lambda(x)) - F(i-1, \lambda(x))} \right)^\beta, \quad \varepsilon_2 \in (F(i-1, \lambda(x)), F(i, \lambda(x))]$$

With  $\varepsilon_2$  uniformly distributed on  $(0, 1)$  this generates a variate  $Y_2 = h_2^{(\beta)}(x, \varepsilon_2)$  which is the sum of a Poisson variate with mean  $\lambda(x)$  and an independently distributed variate,  $V$ , which has a Beta distribution on  $(0, 1)$  with distribution function  $F_V(v) = 1 - (1-v)^{1/\beta}$ .

As  $\beta$  approaches zero the probability mass of this Beta variate comes to be concentrated closer and closer to zero and  $h_2^{(\beta)}(x, \varepsilon_2)$  approaches  $h_2(x, \varepsilon_2)$  defined in equation (17). The Theorem of Section 4 applies when structures have  $Y_2$  generated in this fashion with any *positive* value of  $\beta$  but the Theorem does not apply when  $\beta = 0$  at which point there is a fundamental discontinuity.

For  $\beta > 0$  there is a one-to-one correspondence between a quantile<sup>18</sup>  $e_2(x)$  of the distribution of  $\varepsilon_2$  given  $X = x$  and  $y_2(x) = h_2^{(\beta)}(x, e_2(x))$  and so, in the proof of the Theorem we can use the identity

$$Q_{Y_1|\varepsilon_2 X}(\tau_1^*, e_2(x), x) = Q_{Y_1|Y_2 X}(\tau_1^*, y_2(x), x)$$

where  $y_2(x) = h_2^{(\beta)}(x, e_2(x))$ .

When  $\beta = 0$ ,  $Q_{Y_1|Y_2 X}(\tau_1^*, y_2(x), x)$  is a conditional quantile of the distribution of  $Y_1$  given  $Y_2$  and  $X$  which arises from the conditional distribution,  $F_{Y_1|\varepsilon_2 X}$ , as the ‘‘mixture’’:

$$F_{Y_1|Y_2 X}(y_1|y_2(x), x) = \int_{e_2 \in A(y_2(x), x)} F_{Y_1|\varepsilon_2 X}(y_1|e_2, x) dF_{\varepsilon_2|X}(e_2|x)$$

<sup>18</sup>Note that in this example  $\varepsilon_2$  is uniformly distributed on  $(0, 1)$ , independent of  $X$  and so  $e_2(x)$  does not in fact depend upon  $x$ .

where

$$A(y_2(x), x) = \{e_2 : h_2(x, e_2) = y_2(x)\}.$$

This observation suggests that the identification of characteristics of structures in which  $Y_2$  has non-trivial discrete variation is similar to the problem of identification of characteristics of structures with more sources of variation than outcomes and, as in those cases, requires restrictions of types different to, and in a sense stronger than, those considered in this paper.

**5.4. Estimation.** Quantile regression estimation methods (see Koenker and Bassett (1978)) can be employed to estimate the values of the structural characteristics identified by the Theorem.

Estimation could be parametric, semi- or non-parametric depending on the extent of additional structural restrictions one cares to impose. For parametric estimation, see Koenker and Bassett (1978), Koenker and d'Orey (1987); for semiparametric estimation see for example Chaudhuri, Doksum and Samarov (1997), Kahn (2001) and Lee (2002); for nonparametric estimation, see for example Chaudhuri (1991). The sampling properties of the chosen estimator will depend upon restrictions on structures additional to those considered in this paper.

Quantile regression estimation is well understood so estimation issues are not considered further in this paper, except in Section 5.6.

**5.5. Instrumental variables.** Regarding the order condition, (A5), the special case, familiar in the classical analysis of identification in parametric models with “exclusion” restrictions arises when  $X$  is partitioned into two subsets,  $X_{inc}$  and  $X_{exc}$  and  $X_{exc}$  does not feature in the  $h_1$  equation.

We then often talk of  $X_{exc}$  as *instrumental variables* and it will commonly be the case that within the set of instrumental values,  $x_{inc} = x_{inc}^*$ , some common value for all  $x \in V^*$ . Typical pairs of instrumental values in this case would have the form:

$$x' = \{x_{inc}^*, x'_{exc}\}, \quad x'' = \{x_{inc}^*, x''_{exc}\}.$$

In the absence of parametric restrictions we could allow  $X_{exc}$  to feature in the  $h_1$  equation but maintain the “order” restriction that  $h_1$  is insensitive to variations in  $X_{exc}$  at values of  $X$  in the set of instrumental values.

**5.6. Overidentification.** There is overidentification of the value of  $\Delta_{h_1}^*(x', x'', x^*)$  when there exists more than one pair  $\{x', x''\} \in V^*$  yielding a common value of  $\Delta_{h_1}^*(x', x'', x^*)$ . Then the efficiency of estimation will be enhanced if alternative estimates, based on different just identifying pairs,  $\{x', x''\}$ , are combined, for example using a minimum distance estimator. There is also scope for testing some of the overidentifying restrictions.

In the classical analysis of parametric identification with exclusion restrictions, overidentification arises in this two equation model when  $X_{exc}$  contains more than one covariate. This can be set in the context of the “instrumental values” of this paper by writing

$$X_{exc} = \{X_{exc,1}, X_{exc,2}\}$$

and noting that

$$\{x', x''\} = \{(x_{inc}^*, x'_{exc,1}, x_{exc,2}^+), (x_{inc}^*, x''_{exc,1}, x_{exc,2}^+)\}$$

and

$$\{x', x''\} = \{(x_{inc}^*, x_{exc,1}^+, x'_{exc,2}), (x_{inc}^*, x_{exc,1}^+, x''_{exc,2})\}$$

are then overidentifying pairs of instrumental values provided that both pairs produce *identical* values  $\{y_2(x'), y_2(x'')\}$  and that the two values of  $x'$  and  $x''$  both fall in  $V^*$ .



**5.7. Smooth structures.** If the  $Y_2$  derivative of the structural function exists, and  $X$  can vary continuously in the set of instrumental values inducing continuous variation in  $Y_2$  then, by considering<sup>19</sup> the limiting behaviour of  $\Delta_{h_1}^*(x', x'') / (y_2^*(x') - y_2^*(x''))$ , the identification of the  $Y_2$  derivative of  $h_1$  can be achieved, yielding the result given in Chesher (2001b).

To see this, consider the case in which all elements of  $x'$  and  $x''$  are identical except for one, denoted by  $x_\nabla$ . Consider the slope of a  $Y_2$ -chord of  $h_1$  obtained by moving from  $x'$  to  $x''$ , inducing a movement from  $y_2^*(x')$  to  $y_2^*(x'')$ , and suppose the rank condition,  $y_2^*(x') \neq y_2^*(x'')$  is satisfied. The slope of the chord is

$$A(x', x'') = \frac{\Delta_{h_1}^*(x', x'')}{y_2^*(x') - y_2^*(x'')}$$

and consider its limit (assumed to exist) as  $x' \rightarrow x''$ . Let the limiting value of  $x'$  and  $x''$  be denoted by  $x^*$ .

Let

$$A(x^*) = \lim_{x' \rightarrow x'' = x^*} A(x', x'').$$

If the limit exists then

$$A(x^*) = \nabla_{Y_2} h_1(y_2, x, \varepsilon_1, \varepsilon_2) \Big|_{y_2=y_2^*(x), x=x^*, \varepsilon_1=e_1^*(x), \varepsilon_2=e_2^*(x)} \quad (18)$$

which is the  $Y_2$ -partial derivative of the structural function  $h_1$  evaluated at the point indicated.

Write  $A(x^*)$  as:

$$A(x^*) = \lim_{x' \rightarrow x'' = x^*} \frac{\Delta_{h_1}^*(x', x'') / (x' - x'')}{(y_2^*(x') - y_2^*(x'')) / (x' - x'')}.$$

Then, if the required limits exist,

$$A(x^*) = \frac{\lim_{x' \rightarrow x'' = x^*} (\Delta_{h_1}^*(x', x'') / (x' - x''))}{\lim_{x' \rightarrow x'' = x^*} ((y_2^*(x') - y_2^*(x'')) / (x' - x''))}$$

and therefore:

$$A(x^*) = \frac{\nabla_{x_\nabla} h_1(y_2^*(x^*), x^*, e_1^*, e_2^*)}{\nabla_{x_\nabla} y_2^*(x^*)} \quad (19)$$

$$= \nabla_{Y_2} h_1(y_2^*(x^*), x^*, e_1^*, e_2^*) + \frac{\nabla_{X_\nabla} h_1(y_2^*(x^*), x^*, e_1^*, e_2^*)}{\nabla_{X_\nabla} y_2^*(x^*)}. \quad (20)$$

In (19)  $\nabla_{x_\nabla} h_1(y_2^*(x^*), x^*, e_1^*, e_2^*)$  is the partial derivative of  $h_1(y_2^*(x), x, e_1^*, e_2^*)$  with respect to  $x_\nabla$ , and  $\nabla_{x_\nabla} y_2^*(x^*)$  is the partial derivative of  $y_2^*(x) \equiv h_2(x, e_2^*)$  with respect to  $x_\nabla$ , both evaluated at  $x = x^*$ .

The second line, (20), follows on applying the chain rule, noting that  $x_\nabla$  affects  $h_1$  in (19) directly and *via*  $y_2^*(x)$ .

In (20)  $\nabla_{Y_2} h_1(y_2^*(x^*), x^*, e_1^*, e_2^*)$  is the partial derivative of  $h_1(Y_2, X, \varepsilon_1, \varepsilon_2)$  with respect to  $Y_2$ ,  $\nabla_{X_\nabla} h_1(y_2^*(x^*), x^*, e_1^*, e_2^*)$  is the partial derivative of  $h_1(Y_2, X, \varepsilon_1, \varepsilon_2)$  with respect to  $X_\nabla$ , both evaluated at  $y_2^*(x^*)$ ,  $x^*$ ,  $e_1^*$ ,  $e_2^*$ , and  $\nabla_{X_\nabla} y_2^*(x^*)$  is the partial derivative of<sup>20</sup>  $h_2(X, \varepsilon_2)$  with respect to  $X_\nabla$  evaluated at  $x^*$ ,  $e_2^*$ .

<sup>19</sup>Henceforth the argument  $x^*$  of  $\Delta_{h_1}^*$  is suppressed since in the model considered here (defined by conditions (A1) - (A5) of the Theorem)  $\Delta_{h_1}^*$  is invariant with respect to  $x^*$ .

<sup>20</sup>Recall  $y_2^*(x) \equiv h_2(x, e_2^*)$ .

Under certain conditions<sup>21</sup> the values of the derivatives in (20) and the value of the  $Y_2$ -partial derivative of the structural function evaluated at the point indicated in equation (18) are uniformly identified and for any  $a$ ,

$$A = a \implies \nabla_{Y_2} Q_{Y_1|Y_2X}(\tau_1^*, Q_{Y_2|X}(\tau_2^*, x^*), x^*) + \frac{\nabla_{X_\nabla} Q_{Y_1|Y_2X}(\tau_1^*, Q_{Y_2|X}(\tau_2^*, x^*), x^*)}{\nabla_{X_\nabla} Q_{Y_2|X}(\tau_2^*, x^*)} = a$$

where e.g.  $\nabla_{Y_2} Q_{Y_1|Y_2X}(\tau_1^*, Q_{Y_2|X}(\tau_2^*, x^*), x^*)$  is the  $y_2$ -derivative of  $Q_{Y_1|Y_2X}(\tau_1^*, y_2, x)$  evaluated at  $y_2 = Q_{Y_2|X}(\tau_2^*, x^*)$ ,  $x = x^*$ .

**5.8. Partial differences with respect to covariates.** Partial differences of  $h_1$  with respect to an element of  $X$  can be identified in a similar fashion. Consider an element  $X_\diamond$ , denote remaining elements of  $X$  by  $X_\blacklozenge$ , and suppose there exists a set of instrumental values  $V^*$  with elements  $x$  written as

$$x = (x_\diamond, x_\blacklozenge)$$

such that:

1. for all  $\{x', x''\} \in V^*$ ,

$$\begin{aligned} y_2^*(x') &= y_2^*(x'') \\ e_1^*(x') &= e_1^*(x'') \\ e_2^*(x') &= e_2^*(x'') \end{aligned}$$

with common values denoted by  $y_2^*$ ,  $e_1^*$  and  $e_2^*$ , and,

2. for all  $\{x', x''\} \in V^*$ ,

$$h_1(y_2^*, x'_\diamond, x'_\blacklozenge, e_1^*, e_2^*) = h_1(y_2^*, x''_\diamond, x''_\blacklozenge, e_1^*, e_2^*).$$

where the dependence of  $h_1$  on  $x_\diamond$  and  $x_\blacklozenge$  is made explicit in the notation.

For  $\{x', x'', x^*\} \in V^*$  define:

$$\Delta_{h_1, X_\diamond}^*(x'_\diamond, x''_\diamond, x^*_\blacklozenge) \equiv h_1(y_2^*, x'_\diamond, x^*_\blacklozenge, e_1^*, e_2^*) - h_1(y_2^*, x''_\diamond, x^*_\blacklozenge, e_1^*, e_2^*).$$

Then it can be shown that the model defined by (A1) - (A3) of the Theorem of Section 4 and conditions (1) and (2) above uniformly identifies the partial difference  $\Delta_{h_1, X_\diamond}^*(x'_\diamond, x''_\diamond, x^*_\blacklozenge)$ , which, note is invariant with respect to  $x^*_\blacklozenge$ , and that for any  $a$ ,

$$\Delta_{h_1, X_\diamond}^*(x'_\diamond, x''_\diamond, x^*_\blacklozenge) = a \implies \Delta_Q^*(x', x'') = a$$

where  $\Delta_Q^*(x', x'')$  is the difference of conditional quantile functions already defined in (5).

**5.9. Partial differences with respect to unobservables.** Now consider identification of partial differences of  $h_1$  with respect to variation in the stochastic unobservables. First consider differences with respect to variation in  $\varepsilon_1$ .

Choose a value of  $X$ ,  $x$ , and a probability  $\tau_2^*$ , define

$$\begin{aligned} e_2^*(x) &\equiv Q_{\varepsilon_2|X}(\tau_2^*, x) \\ y_2^*(x) &\equiv h_2(x, e_2^*(x)) \end{aligned}$$

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<sup>21</sup>See Chesher (2002).

choose two probability levels,  $\tau_{11}^*$  and  $\tau_{12}^*$ , define

$$\begin{aligned} e_{11}^*(x) &\equiv Q_{\varepsilon_1|\varepsilon_2 X}(\tau_{11}^*, e_2^*(x), x) \\ e_{12}^*(x) &\equiv Q_{\varepsilon_1|\varepsilon_2 X}(\tau_{12}^*, e_2^*(x), x) \end{aligned}$$

and consider

$$\Delta_{h_1, \varepsilon_1}^*(x) \equiv h_1(y_2^*(x), x, e_{11}^*(x), e_2^*(x)) - h_1(y_2^*(x), x, e_{12}^*(x), e_2^*(x))$$

which is clearly a partial difference with respect to variation in  $\varepsilon_1$ .

Results (a) and (b) of the Theorem imply that under conditions (A1) - (A3) (that is, triangularity, completeness and monotonicity)  $\Delta_{h_1, \varepsilon_1}^*(x)$  is uniformly identified and its value is delivered by the following difference of conditional quantile functions.

$$Q_{Y_1|Y_2 X}(\tau_{11}^*, Q_{Y_2|X}(\tau_2^*, x), x) - Q_{Y_1|Y_2 X}(\tau_{12}^*, Q_{Y_2|X}(\tau_2^*, x), x)$$

Now consider differences with respect to variation in  $\varepsilon_2$ .

Choose two values of  $X$ ,  $x'$  and  $x''$ , and two pairs of probabilities  $\{\tau_{11}^*, \tau_{12}^*\}$  and  $\{\tau_{21}^*, \tau_{22}^*\}$ . For any  $x$  and  $i \in \{1, 2\}$  define

$$\begin{aligned} e_{2i}^*(x) &\equiv Q_{\varepsilon_2|X}(\tau_{2i}^*, x) \\ y_{2i}^*(x) &\equiv h_2(x, e_{2i}^*(x)) \end{aligned}$$

and

$$e_{1i}^*(x) \equiv Q_{\varepsilon_1|\varepsilon_2 X}(\tau_{1i}^*, e_{2i}^*(x), x)$$

and consider

$$\Delta_{h_1, \varepsilon_2}^*(x', x'') \equiv h_1(y_{21}^*(x'), x', e_{11}^*(x'), e_{21}^*(x')) - h_1(y_{22}^*(x''), x'', e_{12}^*(x''), e_{22}^*(x''))$$

Assume that  $x'$  and  $x''$  are members of a set of instrumental values,  $V^*$ , which has the following properties.

1. For all  $\{x', x''\} \in V^*$

$$y_{21}^*(x') = y_{22}^*(x'') \quad (\text{a})$$

$$e_{11}^*(x') = e_{12}^*(x'') \quad (\text{b})$$

with common values denoted by  $y_2^*$  and  $e_1^*$ .

2. For all  $\{x', x''\} \in V^*$ , one or both of the following conditions hold

$$h_1(y_2^*, x', e_1^*, e_{21}^*(x')) = h_1(y_2^*, x'', e_1^*, e_{21}^*(x')) \quad (\text{a})$$

$$h_1(y_2^*, x', e_1^*, e_{22}^*(x')) = h_1(y_2^*, x'', e_1^*, e_{22}^*(x')) \quad (\text{b})$$

If conditions (1) and (2a) hold then  $\Delta_{h_1, \varepsilon_2}^*(x', x'')$  can be written as

$$\begin{aligned} \Delta_{h_1, \varepsilon_2}^*(x', x'') &= h_1(y_2^*, x', e_1^*, e_{21}^*(x')) - h_1(y_2^*, x'', e_1^*, e_{22}^*(x'')) \\ &= h_1(y_2^*, x'', e_1^*, e_{21}^*(x')) - h_1(y_2^*, x'', e_1^*, e_{22}^*(x'')), \end{aligned} \quad (21)$$

for any  $\{x', x''\} \in V^*$ . If conditions (1) and (2b) hold then  $\Delta_{h_1, \varepsilon_2}^*(x', x'')$  can be written as

$$\begin{aligned} \Delta_{h_1, \varepsilon_2}^*(x', x'') &= h_1(y_2^*, x', e_1^*, e_{21}^*(x')) - h_1(y_2^*, x'', e_1^*, e_{22}^*(x'')) \\ &= h_1(y_2^*, x', e_1^*, e_{21}^*(x')) - h_1(y_2^*, x', e_1^*, e_{22}^*(x'')), \end{aligned} \quad (22)$$

for any  $\{x', x''\} \in V^*$ . If condition (1) and *both* of (2a) and (2b) hold then  $\Delta_{h_1, \varepsilon_2}^*(x', x'')$  can be written as

$$\Delta_{h_1, \varepsilon_2}^*(x', x'') = h_1(y_2^*, x^*, e_1^*, e_{21}^*(x')) - h_1(y_2^*, x^*, e_1^*, e_{22}^*(x'')) \quad (23)$$

for any  $\{x', x'', x^*\} \in V^*$ .

Note that each of (21), (22) and (23) is a *partial* difference with respect to variation in  $\varepsilon_2$ . Arguing as in the proof of the Theorem of Section 4, each of these partial differences is uniformly identified with a value delivered by the following difference of conditional quantile functions

$$Q_{Y_1|Y_2X}(\tau_{11}^*, Q_{Y_2|X}(\tau_{21}^*, x'), x') - Q_{Y_1|Y_2X}(\tau_{12}^*, Q_{Y_2|X}(\tau_{22}^*, x''), x'')$$

where note that, by virtue of Condition (1a),

$$Q_{Y_2|X}(\tau_{21}^*, x') = Q_{Y_2|X}(\tau_{22}^*, x'').$$

At the point of estimation this latter condition may be easy to achieve in the sense that, with probability levels  $\tau_{21}^*$  and  $\tau_{22}^*$  chosen, and estimated conditional quantiles for  $Y_2$  given  $X$  to hand, one may be able to find  $x'$  and  $x''$  such that

$$\hat{Q}_{Y_2|X}(\tau_{21}^*, x') = \hat{Q}_{Y_2|X}(\tau_{22}^*, x'').$$

Achieving Condition (1b) is more problematic.

To satisfy Condition (1b) we must find probability levels,  $\{\tau_{11}^*, \tau_{12}^*\}$ , such that for the chosen probability levels  $\{\tau_{21}^*, \tau_{22}^*\}$  and instrumental values  $\{x', x''\}$  the following condition holds.

$$Q_{\varepsilon_1|\varepsilon_2X}(\tau_{11}^*, Q_{\varepsilon_2|X}(\tau_{21}^*, x'), x') = Q_{\varepsilon_1|\varepsilon_2X}(\tau_{12}^*, Q_{\varepsilon_2|X}(\tau_{22}^*, x''), x'')$$

It is not obvious how this could be done without additional structural restrictions. A restriction requiring  $\varepsilon_1$  and  $\varepsilon_2$  to be independently distributed given  $X$  with quantile invariance holding for variations of  $x$  in  $\{x', x''\}$  would suffice. Note that in that case we would require  $\tau_{11}^*$  to equal  $\tau_{12}^*$ . It is now demonstrated that if  $\tau_{11}^* = \tau_{12}^*$  then (21), (22) and (23) can be interpreted as a partial differences of a *normalised* version of the structural function  $h_1$ .

First note that a structure in which there is strongly monotonic variation of  $h_1$  with respect to  $\varepsilon_1$  and of  $h_2$  with respect to  $\varepsilon_2$  can always be written in terms of independently distributed stochastic unobservables which will be denoted by  $\eta_1$  and  $\eta_2$ . Let  $F_{\varepsilon_1|\varepsilon_2X}$  and  $F_{\varepsilon_2|X}$  denote the conditional distribution functions of respectively  $\varepsilon_1$  given  $\varepsilon_2$  and  $X$  and of  $\varepsilon_2$  given  $X$ , and define the random variables

$$\begin{aligned} \eta_2 &= F_{\varepsilon_2|X}(\varepsilon_2|x) \\ \eta_1 &= F_{\varepsilon_1|\varepsilon_2X}(\varepsilon_1|\varepsilon_2, x) \end{aligned}$$

so that

$$\varepsilon_2 = Q_{\varepsilon_2|X}(\eta_2|x) \quad (24)$$

$$\varepsilon_1 = Q_{\varepsilon_1|\varepsilon_2X}(\eta_1|Q_{\varepsilon_2|X}(\eta_2|x), x). \quad (25)$$

Then  $\{\eta_1, \eta_2\}$  are independently distributed random variables each uniformly distributed on  $(0, 1)$ , distributed independently of  $X$ .<sup>22</sup>

<sup>22</sup>This normalisation plays a central role in Imbens and Newey (2001). The transformations (24) and (25) on which it is based are familiar in the context of the generation of pseudo-random numbers,  $\varepsilon_1$  and  $\varepsilon_2$  with distributions  $F_{\varepsilon_1|\varepsilon_2X}$  and  $F_{\varepsilon_2|X}$  employing independently uniformly distributed pseudo-random numbers,  $\eta_1$  and  $\eta_2$ .

The structural equations  $h_1$  and  $h_2$  can be rewritten in terms of independently uniformly distributed  $\eta_1$  and  $\eta_2$  as

$$\begin{aligned} Y_1 &= h_1(Y_2, X, Q_{\varepsilon_1|\varepsilon_2 X}(\eta_1|Q_{\varepsilon_2|X}(\eta_2|X), X), Q_{\varepsilon_2|X}(\eta_2|X)) \\ Y_2 &= h_2(X, Q_{\varepsilon_2|X}(\eta_2|X)) \end{aligned}$$

alternatively as

$$\begin{aligned} Y_1 &= h_1^N(Y_2, X, \eta_1, \eta_2) \\ Y_2 &= h_2^N(X, \eta_2) \end{aligned}$$

where  $h_1^N$  and  $h_2^N$  are normalised structural functions. Note that if the quantiles of  $\varepsilon_1$  and  $\varepsilon_2$  vary with  $X$  then the dependence of  $h_1^N$  on  $X$  through its second argument will differ from the dependence of  $h_1$  on  $X$  through its second argument.

In terms of  $\eta_1$  and  $\eta_2$  we have, for  $i \in \{1, 2\}$ ,

$$\begin{aligned} \varepsilon_2 &= e_{2i}^*(x) \implies \eta_2 = \tau_{2i}^* \\ \varepsilon_1 &= e_{1i}^*(x) \implies \eta_1 = \tau_{1i}^* \end{aligned}$$

and so, if  $\tau_{11}^* = \tau_{12}^*$  with common value  $\tau_1^*$ , and Condition (1a) and, for example, Condition (2a) hold, then, for any  $\{x', x''\} \in V^*$ ,

$$\Delta_{h_1, \varepsilon_2}^*(x', x'') = h_1^N(y_2^*, x'', \tau_1^*, \tau_{21}^*) - h_1^N(y_2^*, x', \tau_1^*, \tau_{22}^*)$$

which is a partial difference of the *normalised* function  $h_1^N$  with respect to variation in  $\eta_2$ . Similarly if Condition (2b) holds then for any  $\{x', x''\} \in V^*$ ,

$$\Delta_{h_1, \varepsilon_2}^*(x', x'') = h_1^N(y_2^*, x', \tau_1^*, \tau_{21}^*) - h_1^N(y_2^*, x', \tau_1^*, \tau_{22}^*)$$

and if both Conditions (2a) and (2b) hold then

$$\Delta_{h_1, \varepsilon_2}^*(x', x'') = h_1^N(y_2^*, x^*, \tau_1^*, \tau_{21}^*) - h_1^N(y_2^*, x^*, \tau_1^*, \tau_{22}^*)$$

for any  $\{x', x'', x^*\} \in V^*$ .

It follows that under the triangularity, completeness and (strong) monotonicity conditions and if Condition (1a) and one or both of Conditions (2a) and (2b) hold then a partial difference of the normalised structural function  $h_1^N$  with respect to variation in  $\eta_2$  is uniformly identified and its value is delivered by the following difference in conditional quantile functions

$$Q_{Y_1|Y_2 X}(\tau_1^*, Q_{Y_2|X}(\tau_{21}^*, x'), x') - Q_{Y_1|Y_2 X}(\tau_1^*, Q_{Y_2|X}(\tau_{22}^*, x''), x'')$$

where, again note that  $Q_{Y_2|X}(\tau_{21}^*, x') = Q_{Y_2|X}(\tau_{22}^*, x'')$  by virtue of condition (1a). If the “rank condition”  $\tau_{12}^* \neq \tau_{22}^*$  is not satisfied then the partial difference is trivially zero.

**5.10. Larger structural systems.** The Theorem of Section 4 is easily extended to larger systems. The basic steps are outlined now.

Consider a single equation from an  $M$  equation structure

$$Y_1 = h_1(Y_2, \dots, Y_M, X, \varepsilon_1, \dots, \varepsilon_M)$$

and  $M - 1$  “reduced form” equations<sup>23</sup>

$$Y_i = h_i(X, \varepsilon_i, \dots, \varepsilon_M), \quad i = 2, \dots, M.$$

<sup>23</sup>These can be thought of as arising from a structural triangular system of equations in which each  $h_i$  involves  $Y_j$ ,  $j > i$ , and these  $Y_j$ 's have been recursively substituted out.

As before choose probability levels  $\tau^* = \{\tau_i^*\}_{i=1}^M$ , consider a set of instrumental values of covariates,  $V^* \subseteq \mathfrak{R}^K$ , for  $i = 1, \dots, M$ , recursively define  $e_i^*(x)$  as the conditional  $\tau_i^*$ -quantile of  $\varepsilon_i$  given  $X = x$  and  $\varepsilon_j = e_j^*(x)$ ,  $j > i$ , and define  $y_i^*(x)$ ,  $i > 1$ , and  $y_1^*(x)$  as follows.

$$\begin{aligned} y_i^*(x) &\equiv h_i(x, e_i^*(x), \dots, e_M^*(x)), \quad i = 2, \dots, M. \\ y_1^*(x) &\equiv h_1(y_2^*(x), \dots, y_M^*(x), x, e_1^*(x), \dots, e_M^*(x)) \end{aligned}$$

The triangularity condition (A1) of the Theorem is satisfied and assume that the completeness condition (A2) is satisfied.

Assume that an extended version of the monotonicity condition (A3) holds, namely that each function  $h_i$ ,  $i > 1$ , is strictly monotonic (normalised to be increasing) in  $\varepsilon_i$  when other arguments are evaluated at  $x$ ,  $e_j^*(x)$ ,  $j = i, \dots, M$ , with  $x \in V^*$ . The function  $h_1$  is required to be non-decreasing or non-increasing with respect to variation in  $\varepsilon_1$  and is normalised to be non-decreasing.

Assume that the **quantile invariance** condition holds for each  $e_i^*(x)$  which take values  $e_i^*$ ,  $i = 1, \dots, M$ , invariant with respect to  $x \in V^*$ .

Suppose the  $Y_j$ -partial difference of  $h_1$  is of interest, defined for some  $\{x', x'', x^*\}$  as follows.

$$\begin{aligned} \Delta_{h_1, Y_j}^*(x', x'') &\equiv h_1(y_2^*(x^*), \dots, y_{j-1}^*(x^*), y_j^*(x'), y_{j+1}^*(x^*), \dots, y_M^*(x^*), x^*, e_1^*, \dots, e_M^*) \\ &\quad - h_1(y_2^*(x^*), \dots, y_{j-1}^*(x^*), y_j^*(x''), y_{j+1}^*(x^*), \dots, y_M^*(x^*), x^*, e_1^*, \dots, e_M^*) \end{aligned}$$

Impose the **order condition**: for all  $(x', x'') \in V^*$

$$\begin{aligned} &h_1(y_2^*(x'), \dots, y_{j-1}^*(x'), y_j^*(x'), y_{j+1}^*(x'), \dots, y_M^*(x'), x', e_1^*, \dots, e_M^*) \\ &= h_1(y_2^*(x''), \dots, y_{j-1}^*(x''), y_j^*(x'), y_{j+1}^*(x''), \dots, y_M^*(x''), x'', e_1^*, \dots, e_M^*). \end{aligned}$$

Recursively define

$$\begin{aligned} Q_M^*(x) &\equiv Q_{Y_M|X}(\tau_M^*, x) \\ Q_{M-1}^*(x) &\equiv Q_{Y_{M-1}|Y_M X}(\tau_{M-1}^*, Q_M^*(x), x) \\ Q_{M-2}^*(x) &\equiv Q_{Y_{M-2}|Y_{M-1} Y_M X}(\tau_{M-2}^*, Q_{M-1}^*(x), Q_M^*(x), x) \\ &\vdots \\ &= \quad \quad \quad \vdots \end{aligned}$$

so that  $Q_1^*(x)$  is the iterated conditional  $\tau_1^*$ -quantile of  $Y_1$  given  $Y_2, \dots, Y_M$  in which each  $Y_i$ ,  $i > 1$ , is evaluated at its iterated conditional quantile given  $Y_{i+1}, \dots, Y_M$ .

Define the difference in the iterated conditional quantile function of  $Y_1$ :

$$\Delta_{Q_1}^*(x', x'') \equiv Q_1^*(x') - Q_1^*(x'')$$

Then an argument as in the proof of the Theorem of Section 4 lead to the result that the model uniformly identifies  $\Delta_{h_1, Y_j}^*(x', x'')$  for any  $\{x', x'', x^*\} \in V^*$ , and  $\Delta_{Q_1}^*(x', x'')$  delivers the value of this partial difference.

Chesher (2001b, 2002) shows how in smooth structures some or all first partial *derivatives* of structural functions in  $M$  equation systems can be identified as functionals of conditional quantile functions and how, by considering a local linearisation of the structural functions about a point at which identification of partial derivatives is required, the manipulations involved reduce to linear algebra similar to that introduced in Koopmans, Rubin and Leipnik (1950).

## 6. CONCLUSION

This paper has explored the limits to identification of characteristics, specifically partial differences of structural functions, in possibly nonseparable structures. This exploration has been limited to:

1. complete triangular structures,
2. structures exhibiting a degree of monotonicity in the effect of stochastic unobservables on the values produced by structural functions,
3. structures with at least as many observable outcomes as there are stochastic unobservables.

Under these conditions differences of structural functions are identifiable. If there exists a sufficiently rich set of instrumental values of covariates within which local quantile invariance and order conditions hold then the resulting model identifies *partial* differences of structural functions and the partial differences are non-trivial if a local rank condition holds.

If any of the three fundamental conditions enumerated above are weakened, it does not seem possible to achieve identification of partial differences without bringing additional restrictions to bear, even if the local quantile invariance and order conditions are maintained.

However there may be similarly weak sets of restrictions which can result in identification of partial differences of structural functions that do not involve all of (1) - (3) above. It seems unlikely that these sets of restrictions will be nested within those give here<sup>24</sup>.

This paper has studied a class of structural characteristics - partial differences of structural functions - that can be identified under weak conditions. Whether or not in any particular problem the members of this class are of interest is a matter for case by case consideration. In some cases it may be necessary to impose further restrictions if this class of identifiable structural characteristics is to contain members of interest.

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<sup>24</sup>In the sense that the class of admissible structures defined by the conditions of this paper will not be a proper subset of the class of admissible structures defined by alternative conditions that do not include all of (1)-(3).

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