



Comparing IV with structural models: What simple IV can and cannot identify

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ABSTRACT

This paper compares the economic questions addressed by instrumental variables estimators with those addressed by structural approaches. We discuss Marschak's Maxim: estimators should be selected on the basis of their ability to answer well-posed economic problems with minimal assumptions. A key identifying assumption that allows structural methods to be more informative than IV can be tested with data and does not have to be imposed.

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1. Introduction

The primary question regarding the choice of an empirical approach to analyzing economic data should be *What economic question does the analyst seek to answer?* Explicit economic models make it easier to formulate and answer economic questions. Advocates of atheoretical approaches to analyzing economic data appeal to randomization as an ideal and invoke IV (or matching or regression discontinuity designs) as a surrogate for randomization. However, even perfectly executed randomizations do not answer all questions of economic interest. There are important examples where structural models produce more information than experiments.¹

A valid instrument is not guaranteed to identify parameters of economic interest when responses to choices vary among individuals, and these variations influence choices taken.² Different valid

instruments answer different questions.³ The sign of the IV estimator can be different from that of the true causal effect.⁴

No one trained in economics can doubt the value of credible explicit economic models in interpreting economic data. They are designed to answer a variety of well-posed economic questions and to be invariant to classes of policy interventions.⁵ The problem with this approach is that after 60 years of experience with fitting structural models on a variety of data sources, empirical economists have come to appreciate the practical difficulty in identifying, and precisely estimating, the full array of structural parameters that answer the large variety of policy questions contemplated by the Cowles Commission economists – the fathers of structural estimation.⁶

Proponents of IV are less ambitious in the range of questions they seek to answer. The method often gains precision by asking

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¹ See Heckman (1992, 2008) and Heckman and Vytlacil (2007a,b).

² See Heckman and Vytlacil (2007b) for a comparison of what different approaches identify. Matching rules out selection on unobservables. Regression discontinuity estimators identify, at best, local effects.

³ Building on this point, Heckman et al. (forthcoming) develop and apply nonparametric tests for the presence of heterogeneous responses to treatment on which agents make choices.

⁴ Heckman et al. (2008b). This is true even under the “monotonicity” conditions of Imbens and Angrist (1994), as generalized to the vector case by Heckman and Vytlacil (2005) and Heckman et al. (2006c) unless one conditions on instruments correctly.

⁵ See the essays in Koopmans (1950). See also Heckman and Vytlacil (2007a).

⁶ Pencavel (1986) summarizes structural estimates of taxes on labor supply and reports absurd estimates, including one due to Jerry Hausman, which implied a negative marginal propensity to consume goods out of income. These and other estimates, reported in the literature some 20 years ago, fueled the flight of many empirical economists from structural models.

narrower questions. The problem that plagues the IV approach is that the questions it answers are usually *defined* as probability limits of estimators and not by well-formulated economic problems. Unspecified “effects” replace clearly defined economic parameters as the objects of empirical interest.

As noted by Marschak (1953), there is a middle ground. Marschak’s *Maxim* emphasizes that one should solve well-posed economic problems with minimal assumptions. Marschak noted that for many problems of policy analysis, it is not necessary to identify fully specified structural models with parameters that are invariant to classes of policy modifications — the goal of structural analysis as conceived by the Cowles pioneers and successor generations of structural economists.⁷ All that is required to conduct many policy analyses or to answer many well-posed economic questions are *combinations* of the structural parameters that are often much easier to identify than the individual parameters themselves.⁸

Heckman and Vytlačil (1999, 2005) bridge the structural and IV literatures. They develop an economically interpretable parameter — the marginal treatment effect (MTE) — which is a marginal willingness to pay for the benefit of treatment for persons at well-defined margins of choice. It is invariant to a class of policy modifications. The MTE can be identified by local variation in instruments. They show how different instrumental variables weight the MTE differently. These weights need not be positive for all values of the arguments of the MTE.⁹ For classes of well-posed economic questions, it is possible, under the conditions given in Heckman and Vytlačil (2005), to fashion functions of instruments that answer well-posed economic questions. Alternatively, it is possible to use an estimated MTE and construct weights to estimate economically interpretable parameters. This approach is unusual in the standard IV literature, which traditionally defines the parameter of interest to be an “effect” identified by an instrument.

Many economists follow Imbens and Angrist (1994) and interpret IV as identifying a weighted average of the gains to persons induced to change their choice (or state) by a change in the instrument. Imbens and Angrist work with a two choice model. Heckman et al. (2006c, 2008b) and Heckman and Vytlačil (2007b) extend this analysis to an ordered choice model and to general unordered choice models.¹⁰ This paper develops the unordered case further and gives a precise characterization of the generalization of the MTE that is appropriate for this case.

The original Imbens–Angrist intuition applies, but in general unordered choice models, agents attracted into a state by a change in an instrument come from many origin states, so there are many margins of choice. Structural models can identify the gains arising from these separate margins. This is a difficult task for IV without invoking structural assumptions. Structural models can

⁷ Heckman and Vytlačil (2007a) define structural models precisely following the seminal definition of Hurwicz (1962). These discussions formalize ideas in Marschak (1953).

⁸ See the discussion in Heckman (2008) and Heckman and Vytlačil (2007b).

⁹ MTE was introduced into the literature in the context of a selection model by Björklund and Moffitt (1987). The Local Average Treatment Effect (LATE) (Imbens and Angrist, 1994) is a discretized version of the MTE. The weights for special cases were derived by Yitzhaki (1989) and applied by Imbens and Angrist (1994). Those weights are always non-negative. Heckman and Vytlačil (1999, 2005, 2007b) and Heckman et al. (2006c) generalize the Imbens–Angrist–Yitzhaki analysis to the case of multiple instruments without restrictions and show how IV weights can be non-positive over certain intervals, but that they must integrate to one.

¹⁰ Angrist and Imbens (1995) propose an ordered choice version of their 1994 paper. As shown by Heckman et al. (2006c), their proposed extension has unsatisfactory features which can be removed by a careful reformulation of the IV method applied to the ordered choice model. See also Heckman and Vytlačil (2007b).

also identify the fraction of persons induced into a state coming from each origin state. IV alone cannot.

For some economic questions, these are unimportant distinctions. For others, they are crucial. For specificity, consider an analysis of the GED program. The GED is a test by which high school dropouts can exam certify to be the equivalents of ordinary high school graduates. Heckman et al. (2008a) show that the presence of a GED program induces some persons to drop out of high school. It also induces some persons who would remain dropouts to exam certify. Within this context we ask: *What are the wage benefits for those induced to take the GED from the dropout state? For those induced to drop out of high school? What proportion of persons induced to take a GED come from each of the other states?*

IV cannot answer these questions except under structural assumptions. It can identify the mean gross gain to the GED for those induced to take it, compared to the next best alternative. This is a weighted average of the effects from each possible origin state that the structural approach can separately identify. In the IV approach, when there are multiple origin states, the weights on the individual effects cannot be estimated without using structural methods. As shown in Heckman and Vytlačil (2007b), IV needs to be supplemented with explicit choice theory to answer many interesting questions, including questions of economic welfare regarding introduction of policies as well as distributional questions such as the percentage of persons harmed by a policy.

This paper demonstrates these points. We first establish a precise framework for discussing IV, and relate it to economic models.

2. The choice model and assumptions

Following Heckman et al. (2006c, 2008b) and Heckman and Vytlačil (2007b), consider the following model with multiple choices and associated multiple outcome states. Let \mathcal{J} denote the agent’s choice set, where \mathcal{J} contains a finite number of elements. For example, \mathcal{J} enumerates possible schooling states (e.g., GED, high school dropout, high school graduate). The value to the agent of choosing $j \in \mathcal{J}$ is

$$R_j(Z_j) = \vartheta_j(Z_j) - V_j, \quad (1)$$

where Z_j are the agent’s observed characteristics that affect the utility from choosing j , and V_j is the unobserved shock to the agent’s utility from choice j . We sometimes write R_j for $R_j(Z_j)$ to simplify notation. Let Z denote the random vector containing all unique elements of $\{Z_j\}_{j \in \mathcal{J}}$. We write $R_j(Z)$ for $R_j(Z_j)$, leaving implicit the condition that $R_j(\cdot)$ only depends on the elements of Z that are contained in Z_j . Let D_j be a variable indicating whether the agent would choose j if confronted with choice set \mathcal{J} ¹¹:

$$D_j = \begin{cases} 1 & \text{if } R_j \geq R_k \quad \forall k \in \mathcal{J} \\ 0 & \text{otherwise.} \end{cases}$$

Array the D_j into a vector D . Let Y be the outcome that would be observed if the agent faced choice set \mathcal{J} , defined as

$$Y = \sum_{j \in \mathcal{J}} D_j Y_j,$$

where Y_j is a potential outcome observed only if option j is chosen. Y_j is determined by

$$Y_j = \mu_j(X_j, U_j),$$

where X_j is a vector of the agent’s observed characteristics and U_j is an unobserved random vector. Let X denote the random vector

¹¹ Below, we invoke conditions so that ties, $R_j = R_k$ for $j \neq k$, occur with probability zero.

containing all unique elements of $\{X_j\}_{j \in \mathcal{J}}$. (Z, X, D, Y) is assumed to be observed by the analyst.¹²

Define $R_{\mathcal{J}}$ as the maximum obtainable value given the choice set \mathcal{J} :

$$R_{\mathcal{J}} = \max_{j \in \mathcal{J}} \{R_j\} = \sum_{j \in \mathcal{J}} D_j R_j. \tag{2}$$

This is the traditional representation of the decision process that if choice j is optimal, choice j is better than the “next best” option:

$$D_j = 1 \iff R_j \geq R_{\mathcal{J} \setminus j}.$$

Heckman et al. (2006c, 2008b) and Heckman and Vytlacil (2007b) show that this simple, well-known, representation is the key intuition for understanding how instrumental variables estimate the effect of a given choice versus the “next best” alternative. IV is a weighted average of the effects for people induced into a choice from different margins. Analogous to the definition of $R_{\mathcal{J}}$, we define $R_{\mathcal{J}}(z)$ to be the maximum obtainable value given choice set \mathcal{J} when instruments are fixed at $Z = z$,

$$R_{\mathcal{J}}(z) = \max_{j \in \mathcal{J}} \{R_j(z)\}.$$

Following the analysis in Heckman et al. (2006c, 2008b) and Heckman and Vytlacil (2007b), we assume:

- (A-1) The distribution of $(\{V_j\}_{j \in \mathcal{J}})$ is continuous.¹³
- (A-2) $\{(V_j, U_j)\}_{j \in \mathcal{J}}$ is independent of Z conditional on X .
- (A-3) $E|Y_j| < \infty$ for all $j \in \mathcal{J}$.
- (A-4) $\Pr(D_j = 1 | X) > 0$ for all $j \in \mathcal{J}$.

In addition, we assume an exclusion restriction that requires some additional notation.¹⁴ Let $Z^{[-l]}$ denote all elements of Z except for the l th component. We assume

- (A-5) For each $j \in \mathcal{J}$, there exists at least one element of Z , say $Z^{[l]}$, such that the distribution of $\vartheta_j(Z_j)$ conditional on $(X, Z^{[-l]})$ is continuous.

With these assumptions, one can generalize the analysis of Heckman and Vytlacil (1999, 2001, 2005) to the unordered case. Assumptions (A-1) and (A-2) imply that $R_j \neq R_k$ (with probability 1) for $j \neq k$, so that $\operatorname{argmax}_{j \in \mathcal{J}} \{R_j\}$ is unique (with probability 1). Assumption (A-2) assures the existence of an instrument. Assumption (A-3) is required for mean treatment parameters to be well defined. It also allows one to integrate to the limit and to produce well-defined means. Assumption (A-4) requires that at least some individuals participate in each choice for all X . Assumption (A-5) imposes the requirement that one be able to independently vary the index for the given value function. It imposes a type of exclusion restriction, that for any $j \in \mathcal{J}$, Z contains an element such that (i) it is contained in Z_j ; (ii) it is not contained in any Z_k for $k \neq j$, and (iii) $\vartheta_j(\cdot)$ is a nontrivial function of that element conditional on all other regressors.¹⁵

In a series of papers, Heckman and Vytlacil (1999, 2001, 2005, 2007b), develop the method of local instrumental variables (LIV) to estimate the marginal treatment effect (MTE) for the case of binary choices. We now define and interpret the MTE and LIV in the case of general unordered choices.

3. Interpreting local instrumental variables in the unordered case

We define local instrumental variables (LIV) using a variable that shifts people toward (or against) choice j by operating only on $R_j(Z_j)$. LIV identifies an average marginal return to j vs. the next best alternative across persons.¹⁶ However, without further assumptions, LIV will not decompose the average marginal return into its component parts corresponding to the effects for persons induced into j from each of the possible origin states.

To see this, consider a three outcome case, $\mathcal{J} = \{1, 2, 3\}$. For concreteness, we pursue the education example previously stated and let 1 be GED, 2 be high school dropout, and 3 be high school graduate. Our results are more general but the three outcome case is easy to exposit.

In this section, we assume that Z_1, Z_2, Z_3 are disjoint sets of regressors so $Z = (Z_1, Z_2, Z_3)$ but they are not necessarily statistically independent. We can easily relax this assumption but making it simplifies the notation. We condition on X and keep it implicit throughout the analysis of this paper.¹⁷ In this notation,

$$E(Y | Z) = E \left[\sum_{j=1}^3 Y_j D_j \mid Z \right] = E(Y_1 D_1 | Z) + E(Y_2 D_2 | Z) + E(Y_3 D_3 | Z). \tag{3}$$

$E(Y|Z)$ and its components can be estimated from data on (Y, Z, D) . IV is based on (3). From (2), choices are generated by the following inequalities:

- $D_1 = \mathbf{1}(R_1 \geq R_2, R_1 \geq R_3)$
- $D_2 = \mathbf{1}(R_2 \geq R_1, R_2 \geq R_3)$
- $D_3 = \mathbf{1}(R_3 \geq R_1, R_3 \geq R_2)$.

We define the marginal change in Y with respect to Z_1 . IV methods are based on such types of variation. The local instrumental variable estimator using Z_1 as an instrument is the sample analog of

$$\frac{\frac{\partial E(Y|Z)}{\partial Z_1}}{\frac{\partial \Pr(D_1=1|Z)}{\partial Z_1}} \Bigg|_{Z=z} = \text{LIV}(z),$$

where LIV is a function of z . In the case of three choices, there are two margins from which persons can be attracted into or out of choice 1 by Z_1 .¹⁸

From local variations in Z_1 , one can recover the following combinations of parameters from the data on $Y_1 D_1$:

$$\frac{\partial E(Y_1 D_1 | Z = z)}{\partial Z_1} = \frac{\partial}{\partial Z_1} \int_{-\infty}^{\vartheta_1(Z_1) - \vartheta_2(Z_2)} \int_{-\infty}^{\vartheta_1(Z_1) - \vartheta_3(Z_3)} y_1 f_{Y_1, V_1 - V_2, V_1 - V_3}(y_1, v_1 - v_2, v_1 - v_3) d(v_1 - v_3) d(v_1 - v_2) dy_1 \Bigg|_{Z=z}$$

¹² Depending on the choice model, Z may or may not include the X . For example, in a Roy model of schooling under perfect certainty (e.g. Willis and Rosen, 1979), X would be among the Z . In models of schooling under uncertainty (e.g. Cunha et al., 2005; Cunha and Heckman, 2007; Urzua, 2008) innovations in X unknown at the time schooling decisions are made would not be in Z . The key condition on Z is given in Assumption A-2.

¹³ Absolutely continuous with respect to the Lebesgue measure on $\prod_{j \in \mathcal{J}} \mathcal{R}$.

¹⁴ We work here with exclusion restrictions in part for ease of exposition. By adapting the analysis of Cameron and Heckman (1998) and Heckman and Navarro (2007), one can modify our analysis for the case of no exclusion restrictions if Z contains a sufficient number of continuous variables and there is sufficient variation in the ϑ_k function across k .

¹⁵ See Heckman and Vytlacil (2007b) for additional discussion.

¹⁶ See Heckman et al. (2006c) and Heckman and Vytlacil (2007b).

¹⁷ See Heckman and Vytlacil (2007b) for a more general analysis.

¹⁸ Recall that Z_1 only affects the utility associated with choice 1.

$$\left. \frac{\left(\frac{\partial E(Y|Z)}{\partial Z_1}\right)}{\left(\frac{\partial \vartheta_1}{\partial Z_1}\right)} \right|_{Z=z} = \left[\begin{array}{c} \text{Generalization of MTE for persons indifferent} \\ \text{between 1 and 2, where choice 3 is dominated} \\ [E(Y_1 - Y_2 | R_1(z_1) = R_2(z_2), R_1(z_1) \geq R_3(z_3))] \Pr(R_1(z_1) = R_2(z_2), R_1(z_1) \geq R_3(z_3)) \\ + [E(Y_1 - Y_3 | R_1(z_1) = R_3(z_3), R_1(z_1) \geq R_2(z_2))] \Pr(R_1(z_1) = R_3(z_3), R_1(z_1) \geq R_2(z_2)) \\ \text{Generalization of MTE for persons indifferent} \\ \text{between 1 and 3, where choice 2 is dominated} \end{array} \right].$$

Box I.

$$= \frac{\partial \vartheta_1(Z_1)}{\partial Z_1} \Big|_{Z_1=z_1} \left[\int y_1 \int_{-\infty}^{\vartheta_1(z_1) - \vartheta_3(z_3)} f_{Y_1, V_1 - V_2, V_1 - V_3}(y_1, \vartheta_1(z_1) - \vartheta_2(z_2), v_1 - v_3) d(v_1 - v_3) dy_1 + \int y_1 \int_{-\infty}^{\vartheta_1(z_1) - \vartheta_2(z_2)} f_{Y_1, V_1 - V_2, V_1 - V_3}(y_1, v_1 - v_2, \vartheta_1(z_1) - \vartheta_3(z_3)) d(v_1 - v_2) dy_1 \right]. \tag{4}$$

By similar reasoning, we can recover the following combination of parameters from the data on Y_2D_2 :

$$\frac{\partial E(Y_2D_2 | Z = z)}{\partial Z_1} = \frac{\partial}{\partial Z_1} \int y_2 \int_{-\infty}^{\vartheta_2(z_2) - \vartheta_1(z_1)} \int_{-\infty}^{\vartheta_2(z_2) - \vartheta_3(z_3)} f_{Y_2, V_2 - V_1, V_2 - V_3}(y_2, v_2 - v_1, v_2 - v_3) d(v_2 - v_3) d(v_2 - v_1) dy_2 \Big|_{Z=z} = \frac{-\partial \vartheta_1(Z_1)}{\partial Z_1} \Big|_{Z_1=z_1} \left[\int y_2 \int_{-\infty}^{\vartheta_2(z_2) - \vartheta_3(z_3)} f_{Y_2, V_2 - V_1, V_2 - V_3}(y_2, \vartheta_2(z_2) - \vartheta_3(z_1), v_2 - v_3) d(v_2 - v_3) dy_2 \right]. \tag{5}$$

From data on Y_3D_3 , we obtain the following combination of parameters:

$$\frac{\partial E(Y_3D_3 | Z_1 = z)}{\partial Z_1} = \frac{-\partial \vartheta_1(Z_1)}{\partial Z_1} \Big|_{Z_1=z_1} \int y_3 \int_{-\infty}^{\vartheta_3(z_3) - \vartheta_2(z_2)} f_{Y_3, V_3 - V_1, V_3 - V_2}(y_3, \vartheta_3(z_3) - \vartheta_1(z_1), v_3 - v_2) d(v_3 - v_2) dy_3. \tag{6}$$

Agents induced into 1 come from 2 and 3. There are two margins:

$$(R_1 = R_2) \quad \text{and} \quad (R_1 \geq R_3)$$

(margin of indifference between 1 and 2),

and

$$(R_1 = R_3) \quad \text{and} \quad (R_1 \geq R_2)$$

(margin of indifference between 1 and 3).

Unaided, IV does not enable analysts to identify the returns at each of the different margins. Instead, it identifies a weighted average of returns. It does not identify the density of persons at the various margins, i.e., the proportion of people induced into (or out of) 1 from each possible alternative state by a change in the instrument.

Collecting terms and rewriting in more easily interpretable components, the expression displayed in **Box I** generalizes the MTE

developed for a two choice unordered model.¹⁹ This is a weighted return to alternative 1 for persons coming from two separate margins: alternative 1 versus alternative 2, and alternative 1 versus alternative 3, i.e., the return to people induced into 1 from their next best choice. The weights are the proportion of people induced into 1 from each margin. This combination of parameters can be identified from IV. The components of the sum cannot be identified by IV without further assumptions. Note that it is possible that a group at one margin gains while a group at another margin loses. IV only estimates a net effect, which might be zero.

Notice that from representation (1) and the assumption that the Z_j ($j \in \mathcal{J}$) are distinct, pairwise monotonicity, an extension of the monotonicity assumption invoked by **Imbens and Angrist (1994)** for the binary choice case, is satisfied.²⁰ In the context of a model with multiple choices, pairwise monotonicity means the same pattern of flow between any two states is experienced by everyone. Thus, as Z_j increases, there is a flow from i to j but not from j to i (or vice versa). From (1), changing Z_1 induces all persons to move in the same direction (i.e. from 1 to 2 or 2 to 1 but not both, and from 1 to 3 or 3 to 1 but not both). Pairwise monotonicity does not rule out the possibility that a change in an instrument causes people to move in the direction from j to i but to move away from the direction from k to i for $j \neq k$, and $j, k \neq i$.

By the chain rule, the derivative of $\Pr(D_1 = 1 | Z)$ with respect to Z_1 is:

$$\frac{\partial \Pr(D_1 = 1 | Z = z)}{\partial Z_1} = \frac{\partial \vartheta_1}{\partial Z_1} \Big|_{Z_1=z_1} \left[\Pr(R_1(z_1) = R_2(z_2), R_1(z_1) \geq R_3(z_3)) + \Pr(R_1(z_1) = R_3(z_3), R_1(z_1) \geq R_2(z_2)) \right].$$

We can define LIV in terms of the preceding ingredients as

$$\text{LIV}(z) = \frac{\left(\frac{\partial E(Y|Z)}{\partial Z_1}\right)}{\left(\frac{\partial \Pr(D_1=1|Z)}{\partial Z_1}\right)} \Big|_{Z=z} = \left[\frac{E(Y_1 - Y_2 | R_1(z_1) = R_2(z_2), R_1(z_1) \geq R_3(z_3)) \omega_{12}}{+ E(Y_1 - Y_3 | R_1(z_1) = R_3(z_3), R_1(z_1) \geq R_2(z_2)) \omega_{13}} \right]. \tag{7}$$

The combination of terms can be identified by LIV from the data on (Y, D, Z) .

The IV weights are:

$$\omega_{12} = \frac{\Pr(R_1(z_1) = R_2(z_2), R_1(z_1) \geq R_3(z_3))}{\left[\Pr(R_1(z_1) = R_2(z_2), R_1(z_1) \geq R_3(z_3)) + \Pr(R_1(z_1) = R_3(z_3), R_1(z_1) \geq R_2(z_2)) \right]} \tag{8}$$

and

$$\omega_{13} = \frac{\Pr(R_1(z_1) = R_3(z_3), R_1(z_1) \geq R_2(z_2))}{\left[\Pr(R_1(z_1) = R_2(z_2), R_1(z_1) \geq R_3(z_3)) + \Pr(R_1(z_1) = R_3(z_3), R_1(z_1) \geq R_2(z_2)) \right]} \tag{9}$$

¹⁹ Heckman et al. (2006c) generalize the MTE to an ordered choice model. See also Heckman and Vytlacil (2007b).

²⁰ This is defined as “uniformity” in Heckman et al. (2006c).

The weights can be identified from a structural discrete choice analysis.²¹ They cannot be identified by an unaided instrumental variable analysis. Thus it is not possible to identify the component parts of (7) by LIV alone, i.e., one cannot separately identify the generalized MTEs:

$$E(Y_1 - Y_2 | R_1(z_1) = R_2(z_2), R_1(z_1) \geq R_3(z_3))$$

and

$$E(Y_1 - Y_3 | R_1(z_1) = R_3(z_3), R_1(z_1) \geq R_2(z_2)),$$

unless one invokes “identification at infinity” arguments or alternative arguments using local variation in regressors developed by Fox and Gandhi (unpublished).²² Carneiro et al. (forthcoming) and Heckman and Vytlačil (2007b) develop classes of economically interpretable parameters that do not require “identification at infinity” and that can be identified using estimated marginal treatment effects.

Using a structural model, one can estimate the components of (7) and determine the flow into (or out of) state 1 from all sources. We illustrate this point in Section 5. First we consider what standard IV estimates.

4. What does standard IV estimate?

To see what standard IV estimates, consider the following linear-in-schooling model of earnings that receives much attention in the literature in labor economics.²³ Let Y denote log earnings and write S as years of schooling. The model writes

$$Y = \alpha + \beta S + U \tag{10}$$

where

$$S = \sum_{j=1}^3 jD_j, \tag{11}$$

and D_j is defined as in Section 2. It is interpreted in this section as an approximation to the general model presented in Section 2. S is assumed to be correlated with U , and β is a random variable that may be statistically dependent on S . The model of Section 2 does not, in general, imply (10). Indeed, there is much empirical evidence against model (10).²⁴ An analysis of what IV estimates when linearity in S is imposed as an approximation, even though it may be inappropriate, is an interesting exercise because linearity is so often invoked.

²¹ Conditions for nonparametric identification of the multinomial discrete choice model are presented in Matzkin (1993, 1994). Conditions for nonparametric identification of the full choice model with outcomes are given in Heckman and Vytlačil (2007a, Appendix B). Conditions for identification of general dynamic discrete choice models are presented in Abbring and Heckman (2007). Conditions for identification in multinomial models that do not require “identification at infinity” are given in Fox and Gandhi (unpublished).

²² See Heckman and Vytlačil (2007b) who show how to vary Z_3 or Z_2 to effectively shut down one margin of choice. Specifically, for any fixed $Z_1 = z_1$, if $\lim_{Z_2 \rightarrow \bar{Z}_2} R_2(Z_2) \rightarrow -\infty$ and $\lim_{Z_3 \rightarrow \bar{Z}_3} R_3(Z_3) \rightarrow -\infty$ where \bar{Z}_2 and \bar{Z}_3 represent limit sets, then we can identify, respectively, the gains at the $3 \rightarrow 1$ margin in the limit set, and the gains in the $2 \rightarrow 1$ margin in the limit set. These assumptions require that one can vary Z_2 and Z_3 to shut down one or the other margin of choice. Under these assumptions and some additional mild regularity assumptions, the structural approach can identify distributions of $(Y_1 - Y_2)$ and $(Y_2 - Y_3)$ as we demonstrate in the example in Section 5 of this paper. “Identification at infinity” is a model-specific misnomer. It is an assumption that there are different sets each with non-negligible probability such that the probabilities of attaining various outcome states are arbitrarily close to one. “Identification at infinity” assumptions are justified naturally in truncated regression models. See Heckman (1987).

²³ We keep conditioning on X implicit.

²⁴ See Heckman et al. (2006a) for discussions of this model and various justifications for it. Heckman et al. (1996) present evidence against linearity of the earnings function in terms of years of schooling.

Suppose Z_1 is a valid instrument. We now interpret what

$$\Delta_{Z_1}^{IV} = \frac{\text{Cov}(Z_1, Y)}{\text{Cov}(Z_1, S)} \tag{12}$$

estimates. We do this by decomposing $\Delta_{Z_1}^{IV}$ into components analogous to the decomposition produced by Heckman et al. (2006c, 2008b) and Heckman and Vytlačil (2007b). The Appendix presents the derivation of the following decomposition of IV into our pairwise generalization of MTE for the unordered case (see Box II).

IV identifies a weighted average of gains to state 1 compared to the next best alternative which may be 2 or 3. The two terms of the decomposition are defined as generalized MTEs and are weighted averages of the gain of moving from state 2 to state 1 for persons on the margin of indifference between 1 and 2 and for whom 2 is a better choice than 3 (the first term) and the gain of moving from 3 to 1 for persons on the margin of indifference between 1 and 3 and for whom 3 is a better choice than 2 (the second term).²⁵

In the Appendix, we derive the weights on the generalized MTEs and show that they do not sum to 1 even when normalized by the denominator. The mathematical reason for this result is simple. The weights in the numerator do not sum to the weights in the denominator. The second term in the denominator receives twice as much weight as the corresponding term in the numerator. This is a consequence of the definition of S (11), which plays no role in the numerator term. Thus, IV applied to the general model produces an arbitrarily weighted sum of generalized MTEs with weights that do not sum to 1, and which, in general, places more weight on the first generalized MTE term than on the second term, compared to the weights placed on the corresponding terms in the denominator.²⁶ Using IV alone, we cannot decompose $\Delta_{Z_1}^{IV}$ into its component parts (see Box II), even though the weights can be identified from discrete choice analysis.^{27, 28}

4.1. The Mincer model

The Mincer (1974) model is a specialization of the general model discussed in Section 2 of this paper that justifies the precise functional form of Eq. (10).²⁹ This explains why the weights in

²⁵ Since Z_1 only affects $R(Z_1)$, it has no direct effect on the margin $2 \rightarrow 3$.

²⁶ Thus “2” appears only in the denominator and not in the numerator.

²⁷ The structural model is nonparametrically identified under the conditions in Appendix B of Heckman and Vytlačil (2007a).

²⁸ The decomposition shown in Box II is not unique. It arises from decomposing Y into

$$Y = D_1 Y_1 + D_2 Y_2 + D_3 Y_3$$

where we solve out $D_1 = 1 - D_2 - D_3$, to obtain

$$Y = Y_1 + D_2(Y_2 - Y_1) + D_3(Y_3 - Y_1).$$

We could also solve out $D_2 = 1 - D_1 - D_3$ to obtain

$$Y = Y_2 + D_1(Y_1 - Y_2) + D_3(Y_3 - Y_2)$$

or $D_3 = 1 - D_1 - D_2$ to obtain

$$Y = Y_3 + D_1(Y_1 - Y_3) + D_2(Y_2 - Y_3).$$

Each decomposition can be used to represent $\Delta_{Z_1}^{IV}$. For each decomposition, the leading terms on the right-hand side, (Y_1, Y_2, Y_3) , respectively, are uncorrelated with Z_1 by virtue of (A-2). Corresponding generalized MTEs can be defined for each decomposition. Z_1 affects the lower boundary of the opportunity set in

$$E(Y_2 - Y_3 | R(Z_2) \geq R(Z_1), R(Z_3) \geq R(Z_1)).$$

We choose the decomposition reported in the text for its greater interpretability.

²⁹ See Heckman et al. (2006a) for a discussion of the Mincer Model and the powerful body of evidence against it. Card (2001) provides one justification for functional form (10).

$$\Delta_{Z_1}^{IV} = \frac{\text{Cov}(Z_1, Y)}{\text{Cov}(Z_1, S)} = \frac{\left(\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \overbrace{E(Y_1 - Y_2 | V_2 - V_1 = v_2 - v_1, \vartheta_2(z_2) - \vartheta_3(z_3) \geq V_2 - V_3)}^{\text{Generalized MTE}(2 \rightarrow 1) \text{ not identified from LIV}} \times \underbrace{\eta_{\vartheta_2(z_2) - \vartheta_3(z_3), V_2 - V_1}(\vartheta_2(z_2) - \vartheta_3(z_3), v_2 - v_1)}_{\text{weight identified from discrete choice analysis}} d(v_2 - v_1) d(\vartheta_2(z_2) - \vartheta_3(z_3)) \right) + \left(\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \overbrace{E(Y_1 - Y_3 | V_3 - V_1 = v_3 - v_1, \vartheta_3(z_3) - \vartheta_2(z_2) \geq V_3 - V_2)}^{\text{Generalized MTE}(3 \rightarrow 1) \text{ not identified from LIV}} \times \underbrace{\eta_{\vartheta_3(z_3) - \vartheta_2(z_2), V_3 - V_1}(\vartheta_3(z_3) - \vartheta_2(z_2), v_3 - v_1)}_{\text{weight identified from discrete choice analysis}} d(v_3 - v_1) d(\vartheta_3(z_3) - \vartheta_2(z_2)) \right)}{\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \underbrace{[-\eta_{\vartheta_2(z_2) - \vartheta_3(z_3), V_2 - V_1}(\vartheta_2(z_2) - \vartheta_3(z_3), v_2 - v_1)]}_{\text{weight identified from discrete choice analysis}} d(v_2 - v_1) d(\vartheta_2(z_2) - \vartheta_3(z_3)) + 2 \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \underbrace{[-\eta_{\vartheta_3(z_3) - \vartheta_2(z_2), V_3 - V_1}(\vartheta_3(z_3) - \vartheta_2(z_2), v_3 - v_1)]}_{\text{weight identified from discrete choice analysis}} d(v_3 - v_1) d(\vartheta_3(z_3) - \vartheta_2(z_2))}.$$

Box II.

$$\Delta_{Z_1}^{IV} = \frac{\text{Cov}(Z_1, Y)}{\text{Cov}(Z_1, S)} = \left[\left(\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} E(\alpha | V_2 - V_1 = v_2 - v_1, \vartheta_2(z_2) - \vartheta_3(z_3) \geq V_2 - V_3) \times \eta_{\vartheta_2(z_2) - \vartheta_3(z_3), V_2 - V_1}(\vartheta_2(z_2) - \vartheta_3(z_3), v_2 - v_1) d(v_2 - v_1) d(\vartheta_2(z_2) - \vartheta_3(z_3)) \right) + \left(\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} E(\alpha | V_3 - V_1 = v_3 - v_1, \vartheta_3(z_3) - \vartheta_2(z_2) \geq V_3 - V_2) \times 2\eta_{\vartheta_3(z_3) - \vartheta_2(z_2), V_3 - V_1}(\vartheta_3(z_3) - \vartheta_2(z_2), v_3 - v_1) d(v_3 - v_1) d(\vartheta_3(z_3) - \vartheta_2(z_2)) \right) \right] \times \left[\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \eta_{\vartheta_2(z_2) - \vartheta_3(z_3), V_2 - V_1}(\vartheta_2(z_2) - \vartheta_3(z_3), v_2 - v_1) d(v_2 - v_1) d(\vartheta_2(z_2) - \vartheta_3(z_3)) + 2 \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \eta_{\vartheta_3(z_3) - \vartheta_2(z_2), V_3 - V_1}(\vartheta_3(z_3) - \vartheta_2(z_2), v_3 - v_1) d(v_3 - v_1) d(\vartheta_3(z_3) - \vartheta_2(z_2)) \right]^{-1}.$$

Box III.

the numerator and denominator (see Box II) are the same under the Mincer model. Specifically, the Mincer model is formulated in terms of log earnings for $Y_1, Y_2,$ and Y_3 :

$$Y_2 = \ln(1 + g) + Y_1, \\ Y_3 = \ln(1 + g) + Y_2 = 2 \ln(1 + g) + Y_1,$$

where g is a growth factor for income that varies in the population. Earnings at each schooling level depend on two parameters: (g, Y_1) . In this case, letting $\alpha = \ln(1 + g)$, gives the decomposition presented in Box III.

In this case, the weights now sum to 1. The weights for the numerator term now are the same as the weights for the denominator term. But again, unaided IV does not identify the component parts of the term bundled in IV – the mean gains at each margin.^{30, 31}

³⁰ An anonymous referee has correctly expressed the concern that in the case of an income-maximizing Mincer model under perfect certainty, the general unordered model would not apply. Indeed, the decision problem is not well defined. If $g > r$, the opportunity cost of funds, agents would choose the maximum amount of schooling. If $g < r$, the agent chooses no schooling. If $g = r$, the agent is indifferent between all levels of schooling. Thus, for our analysis to apply to the Mincer earnings equation, we have to assume that choices involve some combination of psychic costs, tuition, uncertainty or the like. The model of Keane and Wolpin (1997) is one of many frameworks that would justify an unordered choice model but could be consistent with a Mincer earnings equation. See Heckman et al. (2006a). We thank the referee for emphasizing this point to us.

³¹ The analogous decomposition (Box III), corresponding to an ordered choice model is presented in Heckman et al. (2006c) and Heckman and Vytlacil (2007b).

5. An example

It is instructive to summarize our analysis with an example. Consider a 3 choice model with associated outcomes. This corresponds to the GED, high school dropout and high school graduate example that we have used throughout the paper. Under conditions presented in Heckman and Vytlacil (2007a, Appendix B), the structural model is nonparametrically identified. A key assumption in their proof is the “identification at infinity” assumption previously discussed.³² This assumes the ability to vary (Z_1, Z_2, Z_3) freely and the existence of limit sets such that fixing any two of (Z_1, Z_2, Z_3) , one makes the R_j associated with Z_j arbitrarily small.³³

Heckman and Vytlacil (2007b) show that if one augments the IV assumptions with the same identification at infinity assumptions used in structural models, one can use IV in the limit to identify the limits of the components of (7). In the limit sets, one can identify

$$E(Y_1 - Y_2 | R_1(z_1) = R_2(z_2)) \tag{13}$$

and

$$E(Y_1 - Y_3 | R_1(z_1) = R_3(z_3)) \tag{14}$$

by setting Z_3 and Z_2 respectively to limit set values. Essentially one can use the limit sets to make a three choice model into a two choice model, and the standard results for the two choice

³² Alternatively, one can make functional form assumptions about the distribution of the error terms.

³³ See the conditions in footnote 23.

Table 1
Potential outcomes, choice model and parameterizations.

Outcomes	Choice model
$Y_j = \alpha_j + U_j$ with $j \in \mathcal{J} = \{1, 2, 3\}$ $Y = \sum_{j \in \mathcal{J}} Y_j D_j$	$D_j = \begin{cases} 1 & \text{if } R_j \geq R_k \forall k \in \mathcal{J} \\ 0 & \text{otherwise} \end{cases}$ $R_j = \gamma_j Z_j - V_j$ with $j \in \mathcal{J}$
Parameterization $(U_1, U_2, U_3, V_1, V_2, V_3) \sim N(\mathbf{0}, \Sigma_{UV}), (Z_1, Z_2, Z_3) \sim N(\mu_Z, \Sigma_Z)$	
$\Sigma_{UV} = \begin{bmatrix} 0.64 & 0.16 & 0.16 & 0.024 & -0.32 & 0.016 \\ 0.16 & 1 & 0.20 & 0.020 & -0.30 & 0.010 \\ 0.16 & 0.20 & 1 & 0.020 & -0.40 & 0.040 \\ 0.024 & 0.020 & 0.020 & 1 & 0.6 & 0.100 \\ -0.32 & -0.30 & -0.40 & 0.6 & 1 & 0.2 \\ 0.016 & 0.01 & 0.040 & 0.100 & 0.2 & 1 \end{bmatrix}$	$\mu_Z = (1.0, 0.5, 1.5)$ and $\Sigma_Z = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$
$[\alpha_1 \ \alpha_2 \ \alpha_3] = [0.3 \ 0.1 \ 0.7], [\gamma_1 \ \gamma_2 \ \gamma_3] = [0.2 \ 0.3 \ 0.1]$	

Table 2
Transition matrix obtained from the change in the instrument Z_1 . The instrument increases by 0.75 standard deviation.

		New Value of instrument ($\tilde{Z} = Z_1 + 0.75$)			Total
		$D_1 = 1$	$D_2 = 1$	$D_3 = 1$	
Original value of instrument (Z_1)	$D_1 = 1$	33.17%	0%	0%	33.17%
	$D_2 = 1$	3.20%	25.91%	0%	29.11%
	$D_3 = 1$	2.43%	0%	35.29%	37.72%
	Total	38.80%	25.91%	35.29%	100%

Table 3
Marginal gains identified from the change in the instrument Z_1 . The instrument increases by 0.75 standard deviation.

	Gains to switchers	Fraction of population switching
From 2 to 1	0.199	3.20%
From 3 to 1	-0.336	2.43%
Overall (IV estimate)	-0.032	5.63%

IV Estimate:
 $E[Y|\tilde{Z}_1] - E[Y|Z_1] = \frac{3.20}{3.20+2.43} \times 0.199 - \frac{2.43}{3.20+2.43} \times 0.336 = -0.032$

model apply.³⁴ Under these assumptions, and additional mild regularity assumptions, using structural methods, one can identify the distributions of (Y_1, Y_2) and (Y_1, Y_3) so that one can identify distributions of treatment effects, $Y_2 - Y_1$ and $Y_3 - Y_1$, in addition to the mean parameters identified by IV.³⁵ One can also identify the proportion of people induced into 1 from each alternative state using variation in the instrument.

Consider the model with the parameters presented in Table 1. This is a discrete choice model with associated outcome variables. The $Z_j, j = 1, \dots, 3$, are assumed to be scalar and mutually independent. They are normally distributed so they satisfy large support (“identification at infinity”) conditions. Table 2 shows how a change in Z_1 , which increases it by 0.75 standard deviations, shifts people across categories. This corresponds to making GED attainment easier.³⁶ The estimates reported in Table 2 can be obtained from a structural discrete choice model. The percentage initially in 1 (GED) increases from 33.17% to 38.8%. The percentage in 2 (dropout) decreases from 29.11% to 25.91%. The percentage in 3 (graduating high school) declines from 37.72% to 35.29%.

The IV estimate is -0.032. (See the last line of Table 3). This is the only number produced by an IV analysis using Z_1 as an instrument that changes within the specified range. The structural analysis in Table 3 shows that the net effect produced by the

change in Z_1 is composed of 2 terms. It arises from a gain of 0.199 for the switchers $2 \rightarrow 1$ (dropout to GED) and a loss of 0.336 ($3 \rightarrow 1$) (graduate to GED).

Fig. 1 shows what can be identified from the structural model. It plots the distributions of gross gains for persons going from 2 to 1 and from 3 to 1 as well as the overall distribution of gross gains to the switchers. Persons switching from 3 to 1 are harmed in gross terms by the policy that changes Z_1 , while those who switch from 2 to 1 gain in gross terms. In utility terms, (R_j), people are better off.³⁷ In terms of gross gains, about 56.8% of the people who switch from 2 to 1 are better off while 39.3% of the people who switch from 3 to 1 are better off. Overall, 49.2% are better off in gross terms even though the IV estimate is slightly negative. If one seeks to understand the distributional effects of the policy associated with a change Z_1 , the structural analysis is clearly much more revealing. The IV estimate, which is a mean gross gain aggregating over origin states, does not capture the rich information about choices afforded by a structural analysis. However, it does identify the average gain to program participants compared to the next-best alternatives. If that is the object of interest, linear IV is the right tool to use.

6. Summary and discussion

The choice between using IV or a more structural approach for a particular problem should be made on the basis of Marschak’s Maxim: use minimal assumptions to answer well-posed economic

³⁴ See Heckman and Vytlačil (2007b)

³⁵ The literature on “quantile treatment effects” uses IV to identify the quantiles of Y_1 and Y_2 separately but not the quantiles of $Y_1 - Y_2$. See Abbring and Heckman (2007).

³⁶ Heckman et al. (2008a) show that easing GED requirements promotes dropping out of school and causes some dropouts to become GEDs.

³⁷ This is imposed in a discrete choice model.

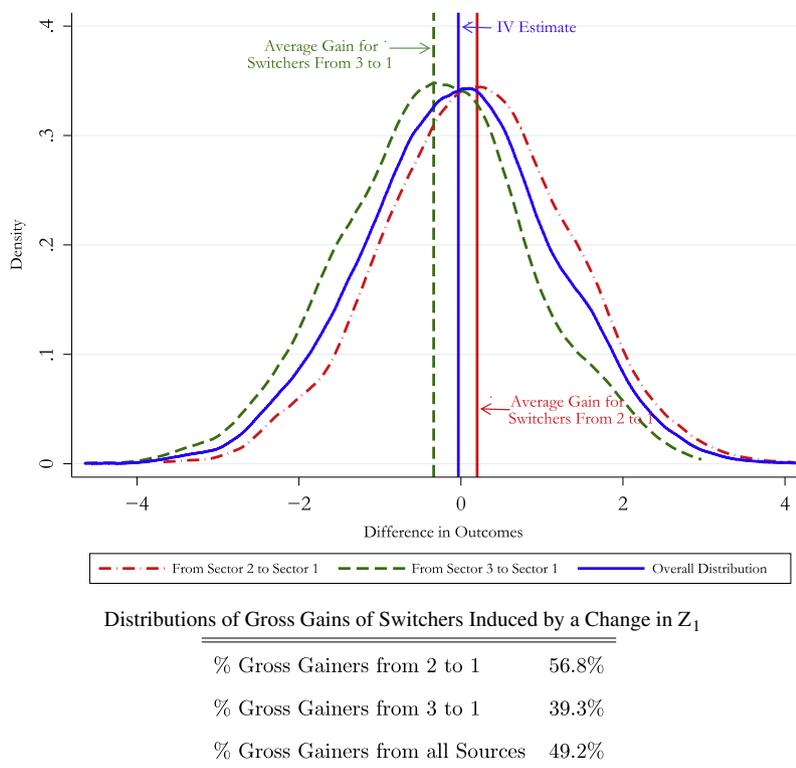


Fig. 1. Distribution of gains in outcomes induced by the change in the instrument Z_1 . The instrument increases by 0.75 standard deviation.

questions. Most IV studies do not clearly formulate the economic question being answered by the IV analysis. The probability limit of the IV estimator is defined to be the object of interest. In the binary outcome case, even if Z is a valid instrument, if Z is a vector, and analysts use only one component of the vector as an instrument, and do not condition on the other components of Z , the weights on the MTE can be negative over certain ranges. The practice of not conditioning on the other instruments is common in the literature.³⁸ In this case, IV can estimate the wrong sign for the true causal effect.³⁹ Recent analyses show how to improve on this practice and to design functions of standard instrumental variables that answer classes of well-posed economic questions.⁴⁰

We have discussed a model with three or more choices where there is no particular order among the choices. Such examples arise routinely in applied economics. In this case, under conditions specified in this paper, IV estimates a weighted average of the mean gross gain to persons induced into a choice state by a change in the instrument (policy) compared to their next best alternative.⁴¹ It averages the returns to a destination state over all origin states. It does not produce the distribution of gains overall or by each origin state. Again, as in the binary choice case, for vector Z , using one component of Z as an instrument, and not conditioning on the other components can produce negative weights so that the sign of an IV can be opposite to that of the true causal effect which can be identified by a structural analysis.

Structural methods provide a more complete description of the effect of the instrument or the policy associated with the instrument. They identify mean returns as well as distributions of returns for agents coming to a destination state from each margin.

They also identify the proportion of people induced into a state from each origin state.

Structural methods come at a cost. Unless distributional assumptions for unobservables are invoked, structural methods often require some form of an “identification at infinity” assumption.⁴² However, in the general case in which responses to treatment are heterogeneous, IV requires the same assumption if one seeks to identify average treatment effects.⁴³ An identification at infinity assumption can be checked in any sample so it does not require imposing *a priori* beliefs onto the data. Heckman et al. (2006b) present an example of how to test an identification at infinity assumption. See also the discussion in Abbring and Heckman (2007).⁴⁴ Recent advances by Fox and Gandhi (unpublished) show that in structural models generated by finite mixtures, identification at infinity is not required to establish model identification, although continuity properties on functions and some of the regressors that constitute their arguments are required.⁴⁵ Cunha et al. (forthcoming) present another approach for the nonparametric identification of structural models that does not rely on an identification at infinity assumption. Carneiro et al. (forthcoming) develop a rich class of economically interesting parameters that do not require identification at infinity and can be identified from local variation in instruments. An “identification at infinity” assumption is not intrinsic to the structural approach.

⁴² See Heckman and Vytlacil (2007a, Appendix B).

⁴³ See Heckman et al. (2006c, 2008b) and Heckman and Vytlacil (2007b).

⁴⁴ However, this assumption is not yet routinely checked in many structural analyses.

⁴⁵ The analysis of Fox and Gandhi (unpublished) shows that under their conditions it is possible to identify structural models with heterogeneity in choice equations that are ruled out by LATE-like monotonicity conditions. Thus models with two way flows between states that result from exogenous changes in instruments can be constructed, identified and estimated, and meaningful economic parameters can be identified without invoking “identification at infinity” or arbitrary conditions like “monotonicity” that are central to LATE.

³⁸ See e.g. Card (2001).

³⁹ See Heckman et al. (2006c).

⁴⁰ See Heckman and Vytlacil (2005, 2007b).

⁴¹ See Heckman et al. (2006c, 2008b) and Heckman and Vytlacil (2007b).

Many proponents of IV point to the strong distributional and functional form assumptions required to implement structural methods. They ignore recent progress in econometrics that identifies and empirically implements robust semiparametric and nonparametric approaches to structural analysis.⁴⁶ Recent developments respond to arguments against the use of explicit econometric models made by a generation of applied economists that emerged in the 1980s. Those arguments are more properly directed against 1980s versions of structural models that were based on linearity and normality. Structural econometricians in the 21st century have listened to the critics and have perfected their tools in response to the criticisms.

The appeal to standard IV as a preferred estimator is sometimes made on the basis of “simplicity and robustness”. Standard IV is certainly simple to compute although problems with weak instruments can make it empirically unstable.⁴⁷ Since, in the general case, different instruments identify different parameters, IV is not robust to the choice of instrument.⁴⁸ Since the sign of an IV can be different from the true causal effect, IV may even produce a misleading guide to policy or inference, so it is not robust.

The meaning of “simplicity” is highly subjective. How simple is the economic interpretation of IV? Certainly decomposing Δ^{IV} is not simple (see Box II). The fact that simple IV can estimate wrong signs for true causal effects should give pause to those who claim that it is “robust”. The weak instrument literature cautions us against uncritical claims about the sturdiness of IV estimators.

The ability of different statistical estimators to answer questions of economic interest, or to show why they cannot be answered, should drive the choice of empirical techniques for analyzing data. Consider a worst case for structural estimation. Suppose that application of recently developed procedures for testing for structural identification reveal that a structural model is not identified or is only partially identified. Does this conclusion suggest that IV is a better choice for an estimator? That disguising identification problems by a statistical procedure is preferable to an honest discussion of the limits of the data? For underidentified structural models, it is possible to conduct sensitivity analyses guided by economic theory to explore the consequences of ignorance about features of the model. With IV, unaided by structural analysis, this type of exercise is not possible. Problems of identification and interpretation are swept under the rug and replaced by “an effect” identified by IV that is often very difficult to interpret as an answer to an interesting economic question.

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We thank Donna Gilleskie, Daniel Schmierer, Greg Veramendi and an anonymous referee for helpful comments. This project was supported by NSF grant SES-0241858, NIH grant R01-HD043411, a grant from the Geary Institute, University College Dublin, and a grant from the American Bar Foundation.

Appendix. Derivation of the standard IV estimator

We first study the numerator of $\Delta^{IV}_{Z_1}$ in the text. Recall that we keep the conditioning on X implicit. Using $\tilde{Z}_1 = Z_1 - \bar{Z}_1$,

$$\text{Cov}(Y, Z_1) = E\left(\tilde{Z}_1(Y_1 D_1 + Y_2 D_2 + Y_3 D_3)\right).$$

Using $D_1 = 1 - D_2 - D_3$, we obtain

$$\begin{aligned} \text{Cov}(Y, Z_1) &= E\left(\tilde{Z}_1(Y_1 + (Y_2 - Y_1)D_2 + (Y_3 - Y_1)D_3)\right) \\ &= E\left(\tilde{Z}_1 Y_1\right) + E\left(\tilde{Z}_1(Y_2 - Y_1)D_2\right) \\ &\quad + E\left(\tilde{Z}_1(Y_3 - Y_1)D_3\right), \end{aligned}$$

where $E\left(\tilde{Z}_1 Y_1\right) = 0$. It is natural to decompose this expression using choice “1” as the base, because Z_1 only shifts $R_1(Z_1)$. The final two terms of the preceding expression can be written as

$$\begin{aligned} \text{Cov}(Y, Z_1) &= E\left(\tilde{Z}_1(Y_2 - Y_1)\mathbf{1}(R_2(Z_2) \geq R_1(Z_1), R_2(Z_2) \geq R_3(Z_3))\right) \\ &\quad + E\left(\tilde{Z}_1(Y_3 - Y_1)\mathbf{1}(R_3(Z_3) \geq R_1(Z_1), R_3(Z_3) \geq R_2(Z_2))\right) \\ &= E\left[\tilde{Z}_1(Y_2 - Y_1)\right. \\ &\quad \cdot \mathbf{1}((\vartheta_2(Z_2) - \vartheta_1(Z_1) \geq V_2 - V_1), (\vartheta_2(Z_2) - \vartheta_3(Z_3) \geq V_2 - V_3)) \\ &\quad \left.+ E\left[\tilde{Z}_1(Y_3 - Y_1)\right.\right. \\ &\quad \cdot \mathbf{1}((\vartheta_3(Z_3) - \vartheta_1(Z_1) \geq V_3 - V_1), (\vartheta_3(Z_3) - \vartheta_2(Z_2) \geq V_3 - V_2)) \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \tilde{z}_1(y_2 - y_1) \\ &\quad \cdot \left(\int_{-\infty}^{\vartheta_2(z_2) - \vartheta_1(z_1)} \int_{-\infty}^{\vartheta_2(z_2) - \vartheta_3(z_3)} \right. \\ &\quad \left. f_{Y_2 - Y_1, V_2 - V_1, V_2 - V_3}(y_2 - y_1, v_2 - v_1, v_2 - v_3) \right. \\ &\quad \left. d(v_2 - v_3) d(v_2 - v_1) d(y_2 - y_1)\right) \\ &\quad \cdot \tilde{f}_{\tilde{Z}_1, \vartheta_2(Z_2) - \vartheta_1(Z_1), \vartheta_2(Z_2) - \vartheta_3(Z_3)}(\tilde{z}_1, \vartheta_2(Z_2) - \vartheta_1(Z_1), \vartheta_2(Z_2) - \vartheta_3(Z_3)) \\ &\quad \cdot d(\vartheta_2(Z_2) - \vartheta_3(Z_3)) d(\vartheta_2(Z_2) - \vartheta_1(Z_1)) d\tilde{z}_1 \\ &+ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \tilde{z}_1(y_3 - y_1) \\ &\quad \cdot \left(\int_{-\infty}^{\vartheta_3(z_3) - \vartheta_1(z_1)} \int_{-\infty}^{\vartheta_3(z_3) - \vartheta_2(z_2)} \right. \\ &\quad \left. f_{Y_3 - Y_1, V_3 - V_1, V_3 - V_2}(y_3 - y_1, v_3 - v_1, v_3 - v_2) \right. \\ &\quad \left. d(v_3 - v_2) d(v_3 - v_1) d(y_3 - y_1)\right) \\ &\quad \cdot \tilde{f}_{\tilde{Z}_1, \vartheta_3(Z_3) - \vartheta_1(Z_1), \vartheta_3(Z_3) - \vartheta_2(Z_2)}(\tilde{z}_1, \vartheta_3(Z_3) - \vartheta_1(Z_1), \vartheta_3(Z_3) - \vartheta_2(Z_2)) \\ &\quad \cdot d(\vartheta_3(Z_3) - \vartheta_2(Z_2)) d(\vartheta_3(Z_3) - \vartheta_1(Z_1)) d\tilde{z}_1. \end{aligned}$$

By Fubini’s Theorem, we can simplify the expressions and obtain for the first term:

$$\begin{aligned} &\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} E(Y_2 - Y_1 | V_2 - V_1 = v_2 - v_1, \vartheta_2(Z_2) - \vartheta_3(Z_3) \geq V_2 - V_3) \\ &\quad \cdot \left\{ \int_{-\infty}^{\infty} \tilde{z}_1 \left[\left(\int_{-\infty}^{\vartheta_2(z_2) - \vartheta_3(z_3)} h_{V_2 - V_1, V_2 - V_3}(v_2 - v_1, v_2 - v_3) d(v_2 - v_3) \right) \right. \right. \\ &\quad \left. \left. \left(\int_{v_2 - v_1}^{\infty} \tilde{f}_{\tilde{Z}_1, \vartheta_2(Z_2) - \vartheta_1(Z_1), \vartheta_2(Z_2) - \vartheta_3(Z_3)}(\tilde{z}_1, \vartheta_2(Z_2) - \vartheta_1(Z_1), \vartheta_2(Z_2) - \vartheta_3(Z_3)) \right. \right. \right. \\ &\quad \left. \left. \left. d(\vartheta_2(Z_2) - \vartheta_1(Z_1)) \right) \right] d\tilde{z}_1 \right\} \\ &\quad d(\vartheta_2(Z_2) - \vartheta_3(Z_3)) d(v_2 - v_1). \end{aligned} \tag{15}$$

$h_{V_2 - V_1, V_2 - V_3}(\cdot)$ is the joint density of $V_2 - V_1, V_2 - V_3$. Define the weighting term in braces in (15) as $\eta_{\vartheta_2(Z_2) - \vartheta_3(Z_3), V_2 - V_1}(\vartheta_2(Z_2) - \vartheta_3(Z_3), v_2 - v_1)$. It is necessary to fix both $\vartheta_2(Z_2) - \vartheta_3(Z_3)$ and $v_2 - v_1$ in forming the weight. This weight can be estimated from a structural discrete choice analysis and the joint distribution of (Z, D_1, D_2, D_3) . The terms multiplying the weight are marginal treatment effects generalized to the unordered case. Eq. (15) cannot be decomposed using IV. An alternative representation of

⁴⁶ See e.g. Abbring and Heckman (2007), Carneiro et al. (2003), Cunha et al. (2007), Cunha et al. (forthcoming), Fox and Gandhi (unpublished) and Matzkin (1992, 1993, 2007). These recent developments in robust structural modeling have not yet made their way into widespread use in empirical structural analysis.

⁴⁷ See e.g. Stock and Staiger (1997) and the ensuing large literature on weak instruments.

⁴⁸ See Heckman et al. (2006c).

the term in braces, $\eta_{\vartheta_2(Z_2)-\vartheta_3(Z_3), V_2-V_1}(\vartheta_2(Z_2) - \vartheta_3(Z_3), v_2 - v_1)$ is

$$\begin{aligned} & \eta_{\vartheta_2(Z_2)-\vartheta_3(Z_3), V_2-V_1}(\vartheta_2(Z_2) - \vartheta_3(Z_3), v_2 - v_1) \\ &= E(Z_1 - E(Z_1) \mid \vartheta_2(Z_2) - \vartheta_3(Z_3) = \vartheta_2(Z_2) - \vartheta_3(Z_3), \\ & \quad \vartheta_2(Z_2) - \vartheta_1(Z_1) \geq v_2 - v_1) \\ & \cdot \Pr(\vartheta_2(Z_2) - \vartheta_3(Z_3) = \vartheta_2(Z_2) - \vartheta_3(Z_3), \\ & \quad \vartheta_2(Z_2) - \vartheta_1(Z_1) \geq v_2 - v_1). \end{aligned}$$

An analysis parallel with the preceding one shows that the second term can be written as

$$\begin{aligned} & \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} E(Y_3 - Y_1 \mid V_3 - V_1 = v_3 - v_1, \vartheta_3(Z_3) - \vartheta_2(Z_2) \geq V_3 - V_2) \\ & \cdot \left\{ \int_{-\infty}^{\infty} \tilde{z}_1 \left[\left(\int_{-\infty}^{\vartheta_3(Z_3) - \vartheta_2(Z_2)} h_{V_3-V_1, V_3-V_2}(v_3 - v_1, v_3 - v_2) \right. \right. \right. \\ & \quad \left. \left. \left. d(v_3 - v_2) \right) \cdot \left(\int_{v_3-v_1}^{\infty} f_{\tilde{z}_1, \vartheta_3(Z_3) - \vartheta_1(Z_1), \vartheta_3(Z_3) - \vartheta_2(Z_2)}(\tilde{z}_1, \vartheta_3(Z_3) - \vartheta_1(Z_1), \vartheta_3(Z_3) - \vartheta_2(Z_2)) \right. \right. \right. \\ & \quad \left. \left. \left. d(\vartheta_3(Z_3) - \vartheta_1(Z_1)) \right) \right] d\tilde{z}_1 \right\} \\ & d(\vartheta_3(Z_3) - \vartheta_2(Z_2)) d(v_3 - v_1). \end{aligned} \quad (16)$$

Define the term in braces in (16) as the weight $\eta_{\vartheta_3(Z_3) - \vartheta_2(Z_2), V_3 - V_1}(\vartheta_3(Z_3) - \vartheta_2(Z_2), v_3 - v_1)$.

To obtain the denominator for the IV, recall that $S = \sum_{j=1}^3 j D_j$. Substitute $D_1 = 1 - D_2 - D_3$,

$$\begin{aligned} \sum_{j=1}^3 j D_j &= (1 - D_2 - D_3) + 2D_2 + 3D_3 \\ &= 1 + D_2 + 2D_3. \end{aligned}$$

Then

$$\begin{aligned} \text{Cov}(S, \tilde{Z}_1) &= E(\tilde{Z}_1 D_2) + 2E(\tilde{Z}_1 D_3) \\ &= E(\tilde{Z}_1 (\mathbf{1}(R_2 \geq R_1, R_2 \geq R_3))) \\ & \quad + 2E(\tilde{Z}_1 (\mathbf{1}(R_3 \geq R_1, R_3 \geq R_2))). \end{aligned} \quad (17)$$

Using reasoning similar to that invoked for the analysis of the numerator terms, we obtain expressions for the terms corresponding to the two terms of (15) and (16). We obtain for the first term of (17)

$$\begin{aligned} & \int_{-\infty}^{\infty} \tilde{z}_1 \left[\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\vartheta_2(Z_2) - \vartheta_1(Z_1)} h_{V_2-V_1, V_2-V_3}(v_2 - v_1, v_2 - v_3) d(v_2 - v_3) \right. \\ & \left. \cdot \left(\int_{-\infty}^{\vartheta_2(Z_2) - \vartheta_3(Z_3)} h_{V_2-V_1, V_2-V_3}(v_2 - v_1, v_2 - v_3) d(v_2 - v_3) \right) \right. \\ & \quad \left. \times d(v_2 - v_1) d(\vartheta_2(Z_2) - \vartheta_3(Z_3)) d(\vartheta_2(Z_2) - \vartheta_1(Z_1)) \right] d\tilde{z}_1. \end{aligned} \quad (18)$$

By Fubini's Theorem, we obtain:

$$\begin{aligned} & \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \tilde{z}_1 \left[\int_{-\infty}^{\infty} \left(\int_{-\infty}^{\vartheta_2(Z_2) - \vartheta_3(Z_3)} h_{V_2-V_1, V_2-V_3}(v_2 - v_1, v_2 - v_3) d(v_2 - v_3) \right) \cdot \left(\int_{v_2-v_1}^{\infty} f_{\tilde{z}_1, \vartheta_2(Z_2) - \vartheta_1(Z_1), \vartheta_2(Z_2) - \vartheta_3(Z_3)}(\tilde{z}_1, \vartheta_2(Z_2) - \vartheta_1(Z_1), \vartheta_2(Z_2) - \vartheta_3(Z_3)) \right. \right. \\ & \quad \left. \left. d(\vartheta_2(Z_2) - \vartheta_1(Z_1)) \right) d(\vartheta_2(Z_2) - \vartheta_3(Z_3)) \right] d(v_2 - v_1) d\tilde{z}_1 \quad (19) \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \eta_{\vartheta_2(Z_2) - \vartheta_3(Z_3), V_2 - V_1}(\vartheta_2(Z_2) - \vartheta_3(Z_3), v_2 - v_1) d(v_2 - v_1) d(\vartheta_2(Z_2) - \vartheta_3(Z_3)). \end{aligned}$$

By parallel logic, we obtain for the second term in (17):

$$\begin{aligned} & 2 \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \tilde{z}_1 \left[\int_{-\infty}^{\infty} \left(\int_{-\infty}^{\vartheta_3(Z_3) - \vartheta_2(Z_2)} h_{V_3-V_1, V_3-V_2}(v_3 - v_1, v_3 - v_2) d(v_3 - v_2) \right) \right. \\ & \quad \left. \cdot \left(\int_{v_3-v_1}^{\infty} f_{\tilde{z}_1, \vartheta_3(Z_3) - \vartheta_1(Z_1), \vartheta_3(Z_3) - \vartheta_2(Z_2)}(\tilde{z}_1, \vartheta_3(Z_3) - \vartheta_1(Z_1), \vartheta_3(Z_3) - \vartheta_2(Z_2)) \right. \right. \\ & \quad \left. \left. d(\vartheta_3(Z_3) - \vartheta_1(Z_1)) \right) \right. \\ & \quad \left. d(\vartheta_3(Z_3) - \vartheta_2(Z_2)) \right] d(v_3 - v_1) d\tilde{z}_1 \\ &= 2 \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \eta_{\vartheta_3(Z_3) - \vartheta_2(Z_2), V_3 - V_1}(\vartheta_3(Z_3) - \vartheta_2(Z_2), v_3 - v_1) d(v_3 - v_1) d(\vartheta_3(Z_3) - \vartheta_2(Z_2)). \end{aligned}$$

These terms can be identified from a structural analysis using the joint distribution of (Z, D_1, D_2, D_3) . Collecting results, we obtain the decomposition presented in Box II in the text if we multiply both the numerator and denominator by -1 .

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