Causal analysis after Haavelmo

8th/last Lecture - Hedibert Lopes

Insper - Institute of Education and Research

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Causal analysis after Haavelmo[1]

From the abstract:

- Haavelmo distinguished causal parameters from their identification.
- Causal parameters are defined using hypothetical models that assign variation to some of the inputs determining outcomes while holding all other fixed.

- We embed Haavelmos framework into the recursive framework of DAGs...

- ... and compare with other DAG-based causality approaches.
- Discuss the limitations of methods that solely use DAGs.
- Extend our framework to consider models for simultaneous causality.

[1] Heckman and Pinto (2014) Causal analysis after Haavelmo *Econometric Theory*, 31(1), 115-151.

Haavelmo's (1943, 1944) fundamental contributions

- Formalized the distinction between **correlation** and **causation**[2].

  The causal effects of inputs on outputs are determined by the impacts of hypothetical manipulations of inputs on outputs which he distinguishes from correlations between inputs and outputs in observational data.

- Distinguished **fixing** from **conditioning** - central to structural econometrics.

- Haavelmo's notion of causality relies on a **thought experiment**

  Causal effects are not empirical statements or descriptions of actual worlds, but descriptions of hypothetical worlds obtained by varying – hypothetically – the inputs determining outcomes.

See also, Heckman (2005) The scientific model of causality. *Sociological Methodology*, 35,1-97. (with discussion by Sobel, pages 99-133), and Heckman (2008) Econometric causality. *International Statistical Review*, 76, 1-27.

[2] Fechner (1851), Yule (1895) and Galton (1896).

Haavelmo's notions of causality and DAGs

We start with a recursive framework less general than that of Haavelmo (1943). This allows us to represent causal models as DAGs which are intensively studied in the literature on Bayesian networks (Howard and Matheson, 1981; Pearl, 2000; Lauritzen, 1996)

We then consider the general nonrecursive framework of Haavelmo (1943, 1944) which cannot, in general, be framed as a DAG.

We do not create a new concept of causality, but rather propose a new framework within which to discuss it.

We show that Haavelmo's approach is a complete framework for the study of causality that accommodates the main tools of identification used in the current literature in econometrics, whereas an approach exclusively based on DAGs does not.

Causal operation of fixing

We show that the causal operation of fixing described in Haavelmo (1943) and Heckman (2005, 2008) is equivalent to statistical conditioning in a hypothetical model that assigns independent variation to inputs with regard to all variables not caused by those inputs.

We show the relationship between statistical conditioning in a hypothetical model and the do-operator.

Outline of the paper

- Section 2: Reviews Haavelmo's causal framework.
- Section 3: Assessing Haavelmo's contributions to the modern literature.
- Section 4: Fix vs do.
- Section 5: Limitations of DAGs in the IV case.
- Section 6: Extension to simultaneous equations.

Haavelmo's simple structural model

In order to examine his ideas, consider three variables Y, X, U associated with error terms $e = (\epsilon_U, \epsilon_X, \epsilon_Y)$ such that X, Y are observed by the analyst while variables U, e, are not.

He assumed that U is a confounding variable that causes Y and X.

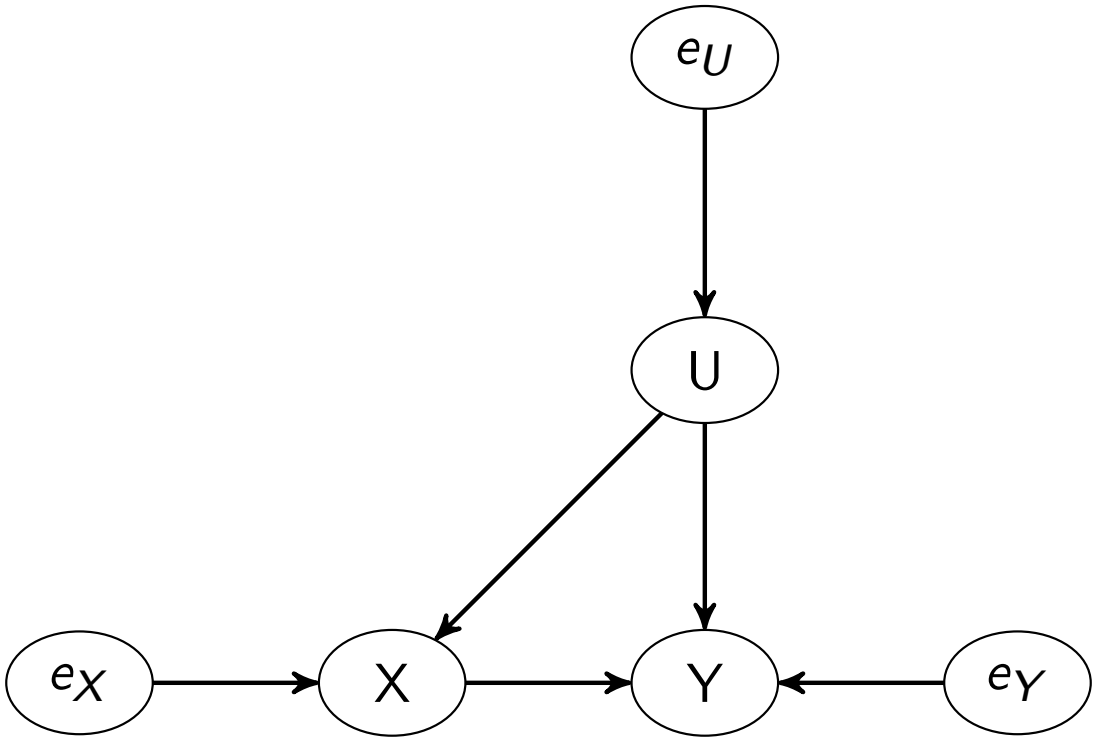
We represent this model through the following structural equations:

$$Y = f_Y(X, U, \epsilon_Y), \quad X = f_X(U, \epsilon_X), \quad \text{and} \quad U = f_U(\epsilon_U),$$

where e is a vector of mutually independent error terms with cumulative distribution function Q_e.

DAG

It is easy to see that $(X, U) \perp\!\!\!\perp \epsilon_Y$, $U \perp\!\!\!\perp \epsilon_X$ and X is not independent of ϵ_U.



Haavelmo defines the causal effect of X on Y as being generated by a *hypothetical manipulation* of variable X that does not affect the values that U or e take. This is called fixing X by a hypothetical manipulation.

Fixing

Outcome Y when X is fixed at x is denoted by

$$Y(x) = f_Y(x, U, \epsilon_Y)$$

and its expectation is given by

$$E_{(U,\epsilon_Y)}(Y(x)) = E(f_Y(x, U, \epsilon_Y)).$$

The average causal effect of X on Y when X takes values x and x' is given by

$$E(Y(x)) - E(Y(x'))$$

Conditioning is a statistical operation that accounts for the dependence structure in the data.

Fixing is an abstract operation that assigns independent variation to the variable being "fixed."

Standard linear regression

DGP for y: $Y = X\beta + U + \epsilon_Y$, with $E(\epsilon_Y) = 0$.

The expectation of outcome Y when X is fixed at x is given by

$$E(Y(x)) = x\beta + E(U).$$

The expectation of Y when X is conditioned on x is given by

$$E(Y|X = x) = x\beta + E(U|X = x).$$

If $E(U|X = x) = 0$, then

- OLS identifies β: $E(Y|X = x) = E(Y(x)) = x\beta$, and
- β generates a causal parameter: the ATE of a change in X on Y.

$E(U|X = x) \neq 0$

Potential confounding effects of unobserved variable U on X leads to difficulty in identifying the average causal effect of X on Y:

$$plim(\hat{\beta}) = \beta + \frac{cov(X, U)}{var(X)}.$$

While the concept of a causal effect does not rely on the properties of the data generating process, the identification of causal effects does.

Easy to show that fixing equals conditioning when $X \perp\!\!\!\perp U$, which is stronger than saying that $E(U|X = x) = 0$.

More on fixing vs conditioning

Haavelmo's key ideas are given by examples rather than by formal definitions.

His notation has led to some confusion in the statistical literature

We restate and clarify his framework in this paper.

In the discrete case,

$$\begin{aligned} \text{Conditioning} &: \quad Pr(Y, U|X = x) = Pr(Y|U, X = x)P(U|X = x) \\ \text{Fixing} &: \quad Pr(Y(x), U(x)) = Pr(Y|U, X = x)Pr(U), \end{aligned}$$

since the abstract operation of fixing X is assumed not to affect the marginal distribution of U, i.e. $U(x) = U$.

Fixing lies outside the scope of standard statistical theory and is often a source of confusion (Pearl, 2009, and Spirtes, Glymour and Scheines, 2000).

Hypothetical model vs SEM

The inconsistency between fixing and conditioning in the general case comes from the fact that fixing X is equivalent to setting the expression $f_X(f_U(\epsilon_U), X)$ to x without changing the probability distributions of ϵ_U, ϵ_X associated with the operation of conditioning on the event $X = x$.

To formalize Haavelmo's notions of causality, let a hypothetical model with error terms e and four variables including Y, X, U but also a new variable $\widetilde{X}$ with the property that $\widetilde{X} \perp\!\!\!\perp (X, U, e)$.

The hypothetical model shares the same structural equation as the empirical one but departs from it by replacing X with an $\widetilde{X}$-input, namely

$$Y = f_Y(\widetilde{X}, U, \epsilon_Y),$$

such that

$$Pr_E(Y(x)) = Pr_H(Y|\widetilde{X} = x).$$

Recasting Haavelmo's ideas

In this fundamentally recursive framework, a causal model consists of

- A set of variables $\mathcal{T} = \{T_1, \ldots, T_n\}$ associated with
- A set of mutually independent error terms $\epsilon = \{\epsilon_1, \ldots, \epsilon_n\}$ and
- A system of autonomous structural equations $\{f_1, \ldots, f_n\}$.

Causal relationships between a dependent variable T_i and its arguments are defined by

$$T_i = f_i(Pa(T_i), \epsilon_i),$$

where $Pa(T_i)$ and ϵ_i are called parents of T_i and are said to directly cause T_i.

If $Pa(T) = \emptyset$, then T (external variable) is not caused by any variable in $\mathcal{T}$.

Descendants and Children of T: $D(T)$ and $Ch(T)$

Observe DAGs rules out simultaneity – a central feature of Haavelmo's approach.

Local Markov Condition

Causal relationships are translated into statistical relationships in a DAG through a property termed the Local Markov Condition (LMC):

LMC: For all $T \in \mathcal{T}$, $T \perp\!\!\!\perp (\mathcal{T} \backslash \{D(T) \cup T\}) | Pa(T)$.

Under a recursive model, $(T_1, \ldots, T_n, \ldots, T_N)$ are ordered so that$(T_1, \ldots, T_{n-1})$ are non-descendants of T_n and thereby $Pa(T_n) \subset (T_1, \ldots, T_{n-1})$. Thus,

$$\begin{aligned} Pr(T_1, \ldots, T_n) &= \prod_{T_n \in \mathcal{T}} Pr(T_n | T_1, \ldots, T_{n-1}) \\ &= \prod_{T_n \in \mathcal{T}} Pr(T_n | Pa(T_n)). \end{aligned}$$

Table 1. Haavelmo empirical and hypothetical models

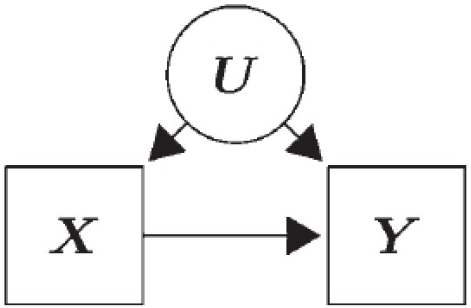
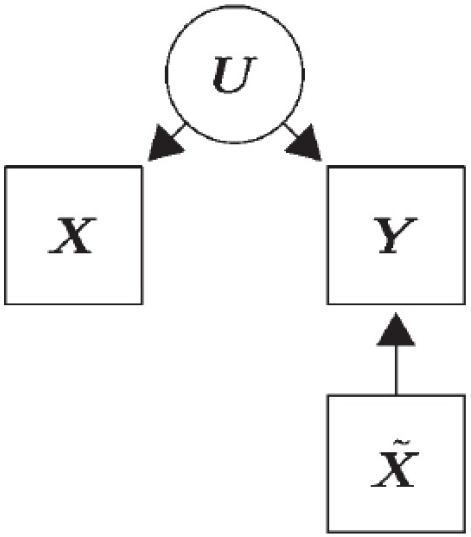
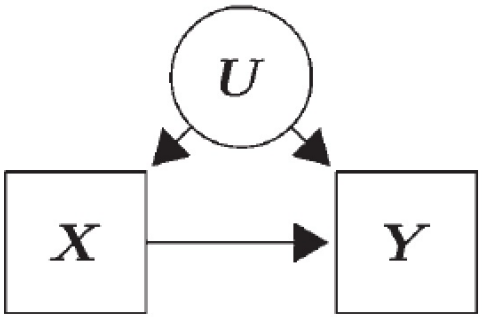
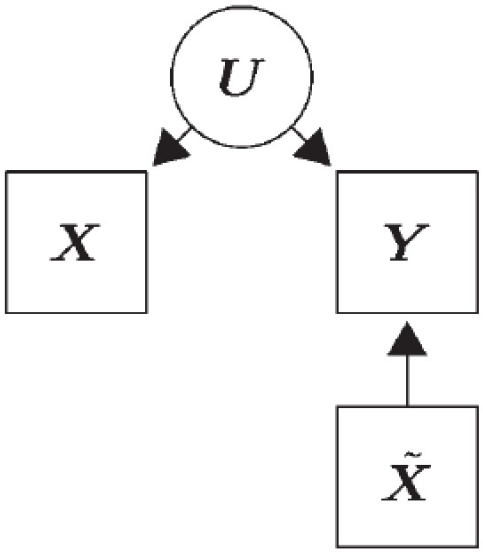
1. Haavelmo Empirical Model	2. Haavelmo Hypothetical Model
$\mathcal{T} = \{U, X, Y\}$ $\boldsymbol{\epsilon} = \{\epsilon_U, \epsilon_X, \epsilon_Y\}$ $Y = f_Y(X, U, \epsilon_Y)$ $X = f_X(U, \epsilon_X)$ $U = f_U(\epsilon_U)$	$\mathcal{T} = \{U, X, Y, \tilde{X}\}$ $\boldsymbol{\epsilon} = \{\epsilon_U, \epsilon_X, \epsilon_Y\}$ $Y = f_Y(\tilde{X}, U, \epsilon_Y)$ $X = f_X(U, \epsilon_X)$ $U = f_U(\epsilon_U)$
	

Table 1. Haavelmo empirical and hypothetical models

	
$Pa(U) = \varnothing,$ $Pa(X) = \{U\}$ $Pa(Y) = \{X, U\}$	$Pa(U) = Pa(\tilde{X}) = \varnothing,$ $Pa(X) = \{U\}$ $Pa(Y) = \{\tilde{X}, U\}$
	$Y \perp\!\!\!\perp X \mid (\tilde{X}, U)$ $X \perp\!\!\!\perp (\tilde{X}, Y) \mid U$ $\tilde{X} \perp\!\!\!\perp U$
$Pr_{\mathbf{E}}(Y, X, U) =$ $Pr_{\mathbf{E}}(Y \mid X, U) Pr_{\mathbf{E}}(X \mid U) Pr_{\mathbf{E}}(U)$	$Pr_{\mathbf{H}}(Y, X, U, \tilde{X}) =$ $Pr_{\mathbf{H}}(Y \mid \tilde{X}, U) Pr_{\mathbf{H}}(X \mid U) Pr_{\mathbf{H}}(U) Pr_{\mathbf{H}}(\tilde{X})$

We define the causal operation of fixing a variable in a model represented by a graph G by the intervention that sets a value to this variable in $\mathcal{T}$ in a fashion that does not affect the distribution of its nondescendants.

Fixing $X \in \mathcal{T}$ to x translates to setting $X = x$ for all X-inputs in the structural equations associated with variables in $Ch(X)$.

Pearl (2009) uses the term *doing* for what we call *fixing*.

The post-intervention distribution of variables in $\mathcal{T}$ when X is fixed at x is

$$\begin{aligned} Pr(\mathcal{T}\backslash\{X\}|\text{fix}(X) = x) &= \prod_{T \in \mathcal{T}\backslash\{\{X\}\cup Ch(X)\}} Pr(T|Pa(T)) \\ &\times \prod_{T \in Ch(X)} Pr(T|Pa(T)\backslash\{X\}, X = x). \end{aligned}$$

Versions of the above equation can be found in Pearl (2001), Spirtes et al. (2000), and Robins (1986).

The hypothetical model

Empirical model: data generating process.
Hypothetical model: model used to characterize causal effects.

The hypothetical model differs from the empirical model in two ways:

- First, it appends to the empirical model an external, hypothetical variable.
- Second, it replaces the action of existing inputs. If X is the target variable to be fixed in the empirical model, then the newly created hypothetical variable $\widetilde{X}$ replaces the X-input of one, some, or all variables in $Ch(X)$.

By sharing the same structural equations and distribution of error terms ϵ, the conditional probabilities of the hypothetical model can be written as

$$Pr_H(T|Pa_H(T)) = Pr_E(T|Pa_E(T)) \;\; \forall T \in \mathcal{T}_E \backslash Ch_H(\widetilde{X})$$

and

$$Pr_H(T|Pa_H(T)\backslash\{\widetilde{X}\}, \widetilde{X} = x) = Pr_E(T|Pa_E(T)\backslash\{X\}, X = x) \;\; \forall T \in Ch_H(\widetilde{X})$$

Theorem T-1

Let $\widetilde{X}$ be the hypothetical variable in the hypothetical model represented by G_H associated with variable X in empirical model G_E. Let W, Z be any disjoint set of variables in $T_E \backslash D_H(\widetilde{X})$. Then

$$Pr_H(W|Z) = Pr_H(W|Z, \widetilde{X}) = Pr_E(W|Z)$$

$\forall \{W, Z\} \subset \mathcal{T}_E \backslash D_H(\widetilde{X})$.

The distribution of non-descendants of $\widetilde{X}$ are the same in both hypothetical and empirical models.

Theorem T-2

Let $\widetilde{X}$ be the hypothetical variable in the hypothetical model represented by $G_H$associated with variable X in empirical model G_E and let W, Z be any disjoint set of variables in $\mathcal{T}_E$. Then

$$Pr_H(W|Z, X = x, \tilde{X} = x) = Pr_E(W|Z, X = x),$$

$\forall \{W, Z\} \subset \mathcal{T}_E$.

The distribution of variables conditional on X and $\widetilde{X}$ taking the same value x in the hypothetical model is equal to the distribution of the variables conditional on $X = x$ in the empirical model.

Corollary C-1. Matching

Let Z, W be any disjoint set of variables in$\mathcal{T}_E$ and let $\widetilde{X}$ be a hypothetical variable in model G_H associated with $X \in \mathcal{T}_E$ in model G_E such that, in the hypothetical model, $X \perp\!\!\!\perp W|(Z, \widetilde{X})$, then

$$Pr_H(W|Z, \widetilde{X} = x) = Pr_E(W|Z, X = x).$$

Variables Z are called matching variables.

In statistical jargon, it is said that matching variables solve the problem of confounding effects between a treatment indicator X and outcome W.

Pearl (1993) describes a graphical test called the "Back-Door" criterion that can be applied to a DAG in order to check if a set of variables satisfy the assumptions of Matching C-1.

Theorem T-3

The major benefit of the hypothetical model is that it allows us to perform causal operations using standard statistical tools.

The operation of fixing a variable in the empirical model is easily translated into statistical conditioning in the hypothetical model.

Theorem T-3. Let $\widetilde{X}$ be the hypothetical variable in G_H associated with variable X in the empirical model G_E, such that $Ch_H(\widetilde{X}) = Ch_E(X)$, then:

$$Pr_H(\mathcal{T}_E \backslash \{X\} | \widetilde{X} = x) = Pr_E(\mathcal{T}_E \backslash \{X\} | fix(X) = x).$$

Causal effects of a variable X on an outcome Y are characterized within the hypothetical model by the distribution of Y conditioned on hypothetical variable $\widetilde{X}$.

Identification of causal effects requires analysts to relate the hypothetical and empirical distributions in a fashion that allows the evaluation of causal effects examined in the hypothetical model using data generated by the empirical model.

Counterfactual outcomes involving fixing and conditioning. X denotes schooling choice: $X = 1$ for college education and $X = 0$ otherwise. The treatment-on-the-untreated parameter stands for the average causal effect of college education for the subsample of agents that choose not to go to college.This parameter is readily defined by

$$E_H(Y|\widetilde{X} = 1, X = 0) - E_H(Y|\widetilde{X} = 0, X = 0).$$

TABLE 3. Front-Door empirical and hypothetical models

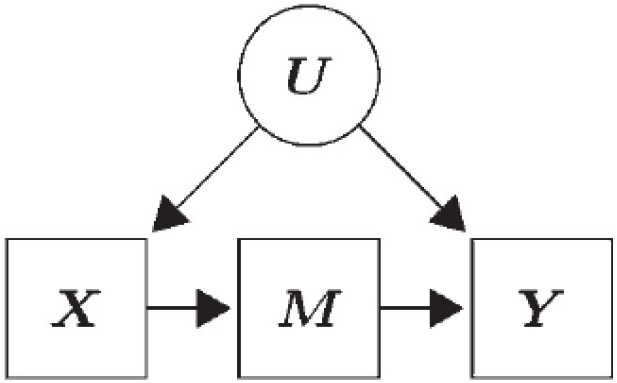
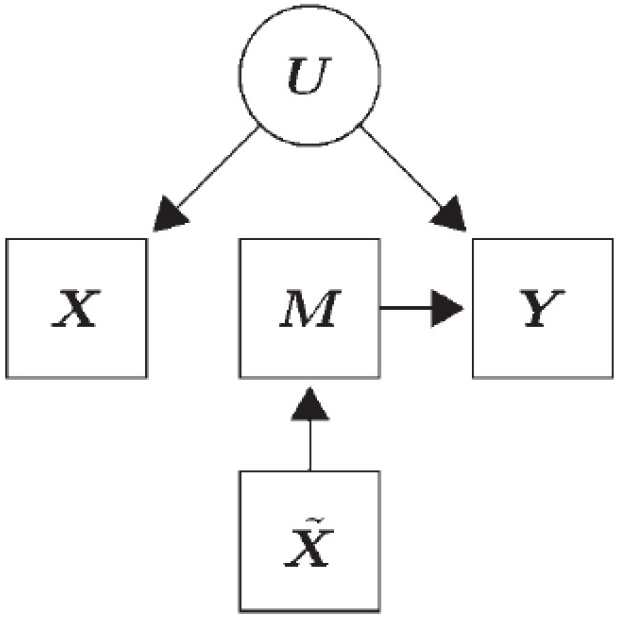
1. Pearl's "Front-Door" Empirical Model	2. Our Version of the "Front-Door" Hypothetical Model
$\mathcal{T} = \{U, X, M, Y\}$ $\epsilon = \{\epsilon_U, \epsilon_X, \epsilon_M, \epsilon_Y\}$ $Y = f_Y(M, U, \epsilon_Y)$ $X = f_X(U, \epsilon_X)$ $M = f_M(X, \epsilon_M)$ $U = f_U(\epsilon_U)$	$\mathcal{T} = \{U, X, M, Y, \tilde{X}\}$ $\epsilon = \{\epsilon_U, \epsilon_X, \epsilon_M, \epsilon_Y\}$ $Y = f_Y(M, U, \epsilon_Y)$ $X = f_X(U, \epsilon_X)$ $M = f_M(\tilde{X}, \epsilon_M)$ $U = f_U(\epsilon_U)$
	

TABLE 3. Front-Door empirical and hypothetical models

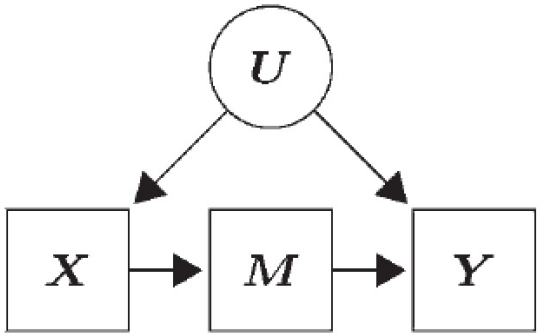
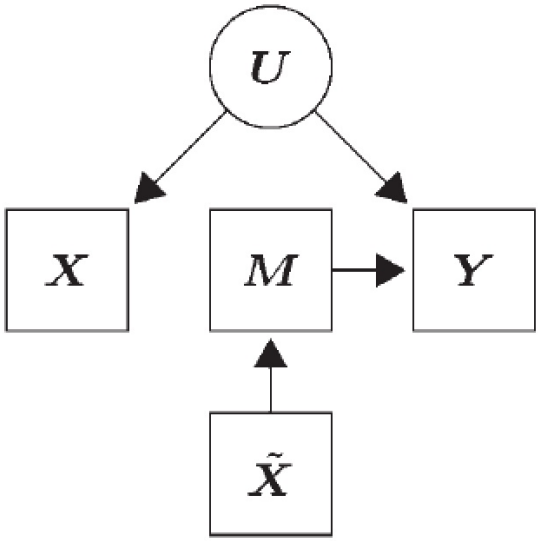
	
$Pa(U) = \varnothing$ $Pa(X) = \{U\}$ $Pa(M) = \{X\}$ $Pa(Y) = \{M, U\}$	$Pa(U) = Pa(\tilde{X}) = \varnothing$ $Pa(X) = \{U\}$ $Pa(M) = \{\tilde{X}\}$ $Pa(Y) = \{M, U\}$
$Y \perp\!\!\!\perp X \mid (M, U)$ $M \perp\!\!\!\perp U \mid X$	$Y \perp\!\!\!\perp (\tilde{X}, X) \mid (M, U)$ $M \perp\!\!\!\perp (U, X) \mid \tilde{X}$ $X \perp\!\!\!\perp (M, \tilde{X}, Y) \mid U$ $U \perp\!\!\!\perp (M, \tilde{X})$ $\tilde{X} \perp\!\!\!\perp (X, U)$
$Pr_{\mathrm{E}}(Y, M, X, U) =$ $Pr_{\mathrm{E}}(Y \mid M, U) Pr_{\mathrm{E}}(X \mid U) Pr_{\mathrm{E}}(M \mid X) Pr_{\mathrm{E}}(U)$	$Pr_{\mathrm{H}}(Y, M, X, U, \tilde{X}) =$ $Pr_{\mathrm{H}}(Y \mid M, U) Pr_{\mathrm{E}}(X \mid U) Pr_{\mathrm{H}}(M \mid \tilde{X}) Pr_{\mathrm{H}}(U) Pr_{\mathrm{H}}(\tilde{X})$
$Pr_{\mathrm{E}}(Y, M, U \mid do(X) = x) =$ $Pr_{\mathrm{E}}(Y \mid M, U) Pr_{\mathrm{E}}(M \mid X = x) Pr_{\mathrm{E}}(U)$	$Pr_{\mathrm{H}}(Y, M, U, X \mid \tilde{X} = x) =$ $Pr_{\mathrm{H}}(Y \mid M, U) Pr_{\mathrm{E}}(X \mid U) Pr_{\mathrm{H}}(M \mid \tilde{X} = x) Pr_{\mathrm{H}}(U)$

TABLE 5. Instrumental variable empirical and hypothetical models

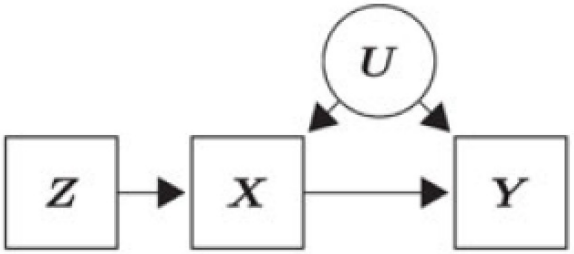
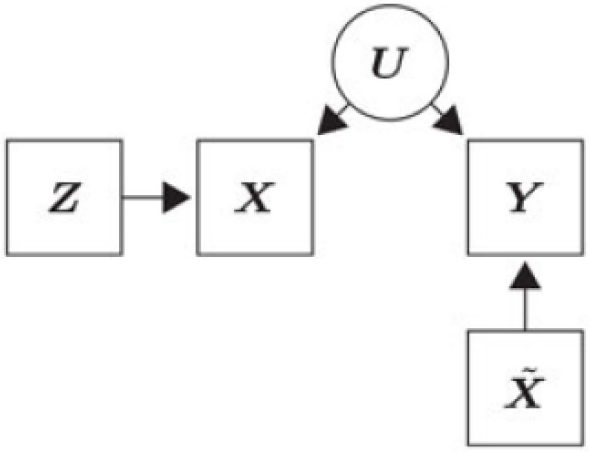
1. Instrumental Variable Empirical Model	2. Instrumental Variable Hypothetical Model
$\mathcal{T} = \{U, X, Z, Y\}$ $\boldsymbol{\epsilon} = \{\epsilon_U, \epsilon_X, \epsilon_Z, \epsilon_Y\}$ $Y = g_Y(X, U, \epsilon_Y)$ $X = g_X(U, Z, \epsilon_X)$ $Z = g_Z(\epsilon_Z)$ $U = g_U(\epsilon_U)$	$\mathcal{T} = \{U, X, Z, Y, \tilde{X}\}$ $\boldsymbol{\epsilon} = \{\epsilon_U, \epsilon_X, \epsilon_Z, \epsilon_Y\}$ $Y = g_Y(\tilde{X}, U, \epsilon_Y)$ $X = g_X(U, Z, \epsilon_X)$ $Z = g_Z(\epsilon_Z)$ $U = g_U(\epsilon_U)$
	

TABLE 5. Instrumental variable empirical and hypothetical models

$Pa(U) = Pa(Z) = \varnothing,$ $Pa(X) = \{U, Z\}$ $Pa(Y) = \{U, X\}$	$Pa(U) = Pa(U) = \varnothing,$ $Pa(X) = \{U, Z\}$ $Pa(Y) = \{U, \tilde{X}\}$
$Z \perp\!\!\!\perp U$ $Y \perp\!\!\!\perp Z \mid (X, U)$	$U \perp\!\!\!\perp (Z, \tilde{X})$ $Z \perp\!\!\!\perp (U, \tilde{X}, Y)$ $\tilde{X} \perp\!\!\!\perp (U, Z, X)$ $X \perp\!\!\!\perp (\tilde{X}, Y) \mid (U, Z)$ $Y \perp\!\!\!\perp (Z, X) \mid (U, \tilde{X})$
$Pr_{\mathrm{E}}(Y, Z, X, U) =$ $Pr_{\mathrm{E}}(Y \mid X, U) Pr_{\mathrm{E}}(X \mid U, Z) Pr_{\mathrm{E}}(Z) Pr_{\mathrm{E}}(U)$	$Pr_{\mathrm{H}}(Y, Z, X, U, \tilde{X}) =$ $Pr_{\mathrm{H}}(Y \mid \tilde{X}, U) Pr_{\mathrm{H}}(X \mid U, Z) Pr_{\mathrm{H}}(Z) Pr_{\mathrm{H}}(U) Pr_{\mathrm{H}}(\tilde{X})$
$Pr_{\mathrm{E}}(Y, Z, U \mid do(X) = x) =$ $Pr_{\mathrm{E}}(Y \mid X = x, U) Pr_{\mathrm{E}}(Z) Pr_{\mathrm{E}}(U)$	$Pr_{\mathrm{H}}(Y, Z, X, U \mid \tilde{X} = x) =$ $Pr_{\mathrm{H}}(Y \mid \tilde{X} = x, U) Pr_{\mathrm{H}}(X \mid U, Z) Pr_{\mathrm{H}}(Z) Pr_{\mathrm{H}}(U)$

The benefits and limitations of DAGs

Benefits

- Intuitively appealing description of models as causal chains.
- List the variables in a model and their causal relationships.
- No restrictions on functional forms of SEM.

Limitations

- DAGs lack the tools for invoking additional assumptions that could generate the identification of a model.
- There are many more tools in the econometric arsenal beyond conditional independence relationships.
- It is impossible to identify the causal effect of X on Y without using additional information.

TABLE 6. Summarizing the do-calculus of Pearl (2009) and the Haavelmo

Common Features of Haavelmo and Do-Calculus:		
Autonomy (Frisch, 1938) **Errors Terms:** ϵ mutually independent **Statistical Tools:** LMC and Graphoid Axioms apply **Counterfactuals:** Fixing or Do-operator is a causal, not statistical, operation		
Distinctive Features of Haavelmo and Do-Calculus:		
	Haavelmo	**Do-calculus**
Approach:	Thinks outside the box of the empirical model by constructing a new hypothetical model motivated by, but distinct from, the empirical model where fixing can be analyzed using standard tools of probability	Operates inside the box of the empirical model; Creates new graphical rules to introduce fixing into a probabilistic framework
Introduces:	Constructs a hypothetical model	Graphical rules
Identification:	Connects Pr_{H} and Pr_{E}	Iteration of do-calculus rules
Versatility:	Basic statistical principles apply	Creates new rules of statistics

Pearl's reflections

This paper reflects on a recent article by Heckman and Pinto (2013) in which they discuss a formal system, called *do*-calculus, that operationalizes Haavelmo's conception of policy intervention.

They replace the *do*-operator with an equivalent operator called "fix," highlight the capabilities of "fix," discover limitations in "do," and inform readers that those limitations disappear in "the Haavelmo approach."

I examine the logic of HP's paper, its factual basis, and its impact on econometric research and education.

HP in a nutshell

1. It replaces the do-operator with a a logically equivalent operator called "fix,"
2. It unveils the power of "fix" while exposing "limitations" of "do," and
3. It argues that it is "fix," not "do," which captures the original (yet implicit) intent of Haavelmo.

I am pleased of course that Heckman and Pinto took the time to learn the machinery of the *do*-calculus, be it in *do(x)*, *fix(x)*, *set(x)*, *exogenized(x)*, or *randomized(x)* dressing, and to lay it out before economists so that they too can benefit from its power.

Upgrading mainstream econometric literature

Though we differ on the significance of the difference between the "do" and the "fix" operators, the important thing is that HP call economists' attention to two facts that are practically unknown in the mainstream econometric literature:

1. Identification of causal parameters in the entire class of recursive nonparametric economic models is now a SOLVED PROBLEM, and this include counterfactual parameters related to "effect of treatment on the treated", mediation, attribution, external validity, heterogeneity, selection bias, missing data, and more.

2. The age-old confusion between regression and structural parameters (Pearl, 2009, pp. 368-374) can finally come to an end with the help of the notational distinction between "do/fix" vs. "see."

Students' homework

- Economics students should now be able to solve the eight toy problems I posed in Pearl (2013).
- Students can liberate themselves from the textbook confusion regarding the interpretation of structural parameters, as documented in Chen and Pearl (2013).

Heckman's doors' opening

HP's paper reflects Heckman's way of acknowledging the need to translate Haavelmo's ideas into tools of inference, and his determination to satisfy this need by rigorous mathematical means.

I am glad that he chose to do so in the style of *do*-calculus, namely, a calculus based on a hypothetical modification of the economic model, often called "surgery," in which variables are exogenized by local reconfiguring of selected equations.

Heckman's myopia

The fact that the do-calculus is merely one among several tools of inference that emerges in the framework of SCM has escaped HP's description, together with the fact that extensions to simultaneous causation, parametric restrictions, counterfactual reasoning, mediation, heterogeneity, and transportability follow naturally from the SCM framework, and have led to remarkable results.

More unfortunate perhaps is the fact that HP do not address the practical problems posed in Pearl (2013), which demonstrate tangible capabilities that economists could acquire from the SCM framework.

Consequently, the remedy proposed by HP does not equip economists with tools to solve these problems and, in this respect, it falls short of fully utilizing Haavelmo's ideas.

On the "limitations" of *do*-calculus

HP spend **inordinate amount of effort** seeking "limitations" in the *do*-operator, in the *do*-calculus, and presumably other methods of representing interventions that preceded HP's interpretation of Haavelmo's papers.

The semantical difference between "fix" and "do" is so infinitesimal that it does not warrant the use of two different labels.

HP argue that replacing $P(y|do(X = x))$ with $P_H(y|X = x)$ avoids the use of extra-statistical notation and gives one the comfort of staying within traditional statistics. The comfort however is illusionary and short-lived; it disappears upon realizing that the construction of P_H itself is an extra-statistical operation, for it requires extra-statistical information (e.g., the structure of the causal graph).

This craving for orthodox statistical notation is endemic of a long cultural habit to translate the phrase "holding X constant" into probabilistic conditionalization.

The habit stems from the absence of probabilistic notation for "holding X constant," which has forced generations of statisticians to use a surrogate in the form of "conditioning on X"; the only surrogate in their disposal.

This habit is responsible for a century of blunders and confusions:

- Probabilistic causality (Pearl, 2011; Suppes, 1970)
- Evidential decision theory (Jeffrey, 1965; Pearl, 2009)
- Simpson's paradox (Pearl, 2009)
- Fisher's error in handling mediation (Fisher, 1935; Rubin, 2005)
- Principal Stratification mishandling of mediation (Pearl, 2011a; Rubin, 2004)
- Misinterpretations of structural equations (Freedman, 1987; Hendry, 1995;
- Holland, 1995; Pearl, 2009; Sobel, 2008; Wermuth, 1992)
- Structural-regressional confusion in econometric textbooks today (Chen and Pearl, 2013).

Pearl's conclusion: HP's paper is a puzzle!

From the fact that HP went to a great length studying the do-calculus, replacing it with a clone called "fix", demonstrating the workings of "fix" on a number of laborious examples and presenting "fix" (not "do") as the legitimate heir of "the Haavelmo approach", one would assume that HP would invite economists to use the new tool of inference as long as they speak "fix" and not "do", and as long as they believe that "fix" is a homegrown product of "the Haavelmo approach."

But then the paper presents readers with a slew of "limitations" that apply equally to "fix" and "do" (recall, the two are logically equivalent) and promises readers that "Haavelmo's approach naturally generalizes to remove those limitations" (e.g., simultaneous causation, parametric restrictions, and more).

The main victim of HP's paper is the "fix-operator"; first anointed to demonstrate what "the Haavelmo approach" can do, then indicted with "major limitations" that only "the Haavelmo approach" can undo. What then is the role of the "fix-operator" in economics research? I hope the history of economic thought unravels this puzzle.