Regression and causation: a critical examination of six econometrics textbooks

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Abstract
This report surveys six influential econometric textbooks in terms of their mathematical treatment of causal concepts. It highlights conceptual and notational differences among the authors and points to areas where they deviate significantly from modern standards of causal analysis. We find that econonometric textbooks vary from complete denial to partial acceptance of the causal content of econometric equations and, uniformly, fail to provide coherent mathematical notation that distinguishes causal from statistical concepts. This survey also provides a panoramic view of the state of causal thinking in econometric education which, to the best of our knowledge, has not been surveyed before.

1. Introduction

The traditional and most popular formal language used in econometrics is the structural equation model (SEM). While SEMs are not the only type of econometric model, they are the primary subject of each introductory econometrics textbook that we have encountered. An example of an SEM taken from (Stock and Watson, 2011, p. 3) is modeling the effect of cigarette taxes on smoking. In this case, smoking, Y, is the dependent variable, and cigarette taxes, X, is the independent variable. Assuming that the relationship between the variables is linear, the structural equation is written $Y = \beta X + \varepsilon$. Additionally, if X is statistically independent of ε, often called exogeneity, linear regression can be used to estimate the value of β, the "effect coefficient".

More formally, an SEM consists of one or more structural equations, generally written as $Y = X^t\beta + \varepsilon$ in the linear case, in which Y is considered to be the dependent or effect variable, $X =< X_1, X_2, \ldots, X_n >$ a vector of independent variables that cause Y, and $\beta =< \beta_1, \beta_2, \ldots, \beta_n >$ a vector of slope parameters such that $x^t\beta$ is the expected value of Y given that we intervene and set the value of X to x. Lastly, ε is an error term that represents all other direct causes of Y, accounting for the difference between $x^t\beta$ and the actual values of Y[1]. If the assumptions underlying the model are correct, the model is capable of answering all causally related queries, including questions of prospective and introspective counterfactuals[2]. For purposes of discussion, we will use the simplest case in which there is only one structural equation and one independent variable and refer to the structural equation as $Y = \beta X + \varepsilon$.

The foundations for structural equation modeling in economics were laid by Haavelmo in his paper, "The statistical implications of a system of simultaneous equations" (Haavelmo, 1943). To Haavelmo, the econometric model represented a series of hypothetical experiments. In his 1944 paper, "The Probabilistic Approach in Econometrics", he writes:

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[1] A more precise definition of the SEM invokes counterfactuals and reads $\mathbf{X}^t \beta + \varepsilon = Y(u)$, where $Y_{\mathbf{X}}(u)$ is the counterfactual "the value that Y would take in unit u, had $\mathbf{X}$ been $\mathbf{x}$" (see Simon and Rescher 1966, Balke and Pearl 1995, Heckman 2000, Pearl 2012b, and Appendix A).

[2] Prospective counterfactual queries are queries of the form, "What value would Y take if X were set to x?" Introspective counterfactual queries are queries of the form, "What would have been the value of Y if X had been set to x?"

> "What makes a piece of mathematical economics not only mathematics but also economics is, I believe, this: When we have set up a system of theoretical relationships and use economic names for the otherwise purely theoretical variables involved, we have in mind some actual experiment, or some design of an experiment, which we could at least imagine arranging, in order to measure those quantities in real economic life that we think might obey the laws imposed on their theoretical namesakes" (Haavelmo, 1944, p. 5).

Using a pair of non-recursive equations with randomized ε's, Haavelmo shows that βx in the equation $y = \beta x + \varepsilon$ is not equal to the conditional expectation, $E[Y|x]$, but rather to the expected value of Y given that we intervene and set the value of X to x. This "intervention-based expectation" was later given the notation $E[Y|\mathbf{do}(x)]$ in (Pearl, 1995)[3].

In the years following Haavelmo's 1944 paper, this interpretation has been questioned and misunderstood by many statisticians. When Arthur Goldberger explained that βx may be interpreted as the expected value of Y "if x were fixed," Nanny Wermuth replied that since $\beta x \neq E[Y|x]$, "the parameters... cannot have the meaning Arthur Golberger claims" (Goldberger, 1992; Wermuth, 1992).

(Pearl, 2012b) summarizes the debate in the following way: For statisticians like Wermuth, structural coefficients have dubious meaning because they cannot be expressed in the language of statistics, while for economists like Goldberger, statistics has dubious substance if it excludes from its province all aspects of the data generating mechanism that do not show up in the joint probability distribution.

Econometric textbooks fall on all sides of this debate. Some explicitly ascribe causal meaning to the structural equation while others insist that it is nothing more than a compact representation of the joint probability distribution. Many fall somewhere in the middle – attempting to provide the econometric model with sufficient power to answer economic problems but hesitant to anger traditional statisticians with claims of causal meaning. The end result for many textbooks is that the meaning of the econometric model and its parameters are vague and at times contradictory.

We believe that the source of confusion surrounding econometric models stems from the lack of a precise mathematical language to express causal concepts. In the 1990s, progress in graphical models and the logic of counterfactuals led to the development of such a language (Pearl, 2000). Significant advances in causal analysis followed. For example, algorithms for the discovery of causal structure from purely observational data were developed (Verma and Pearl, 1990; Spirtes et al., 1993; Verma, 1993) and the problem of causal effect identifiability was effectively solved for non-parametric models (Pearl, 1995; Tian and Pearl, 2002; Huang and Valtorta, 2006; Shpitser and Pearl, 2006; Shpitser, 2008). These and other advances have had marked influence on several research communities (Glymour and Greenland, 2008; Morgan and Winship, 2007) including econometrics (Heckman, 2008; White and Chalak, 2009), but their benefits are still not fully utilized (Pearl, 2012b).The purpose of this report is to

[3] The expression $E[Y|\text{do}(x)]$ can also be interpreted as the expected value of Y in an ideal randomized experiment for a subject assigned treatment $X = x$. Clearly, $E[Y|\text{do}(x)]$ does not necessarily equal $E[Y|x]$. For example, the expected performance of an employee at an earning bracket of $X = x$ is different from the expected performance if management decides to set someone's earning to $X = x$. A simple recipe for computing $E[Y|\text{do}(x)]$ for a given model is provided in Appendix A, which provides formal definitions of counterfactuals and their relations to structural equations and the do(x) operator.

examine the extent to which these and other advances in causal modeling have benefited education in econometrics. Remarkably, we find that not only have they failed to penetrate the field, but even basic causal concepts lack precise definitions and, as a result, continue to be confused with their statistical counterparts.

In this paper, we survey six econometrics textbooks in order to analyze their interpretation and usage of the econometric model and compare them to modern standards of causal analysis.

2. Criteria for evaluation

In evaluating textbooks, we ask the following questions: What does the author believe is the purpose of an econometric model? To which problems can it be applied? How does the author interpret the model parameters and the structural equation? Does the author consider βx to be equal to the expected value of Y given x, $E[Y|x]$, or the expected value of Y given that we intervene and set X to x, $E[Y|\mathrm{do}(x)]$? Does the author make clear the assumptions necessary to answer the problems that econometrics is expected to solve?

To answer these questions, we formulated 11 evaluation criteria and grouped them under three categories. We also state the "ideal"[4] answers to these questions.

Applicability of econometric models

1. Does the author present example problems that require causal reasoning?
2. Does the author present example problems that require prediction alone?

A predictive problem is one of the form, "Given that we observe X to be x, what value can we expect Y to take?" Many econometrics textbooks begin with example problems that they expect econometric methods to solve. We use these examples to determine the author's view on the purpose and applicability of the econometric model. Since both predictive and causal problems are of interest to economists, both should be exemplified in econometrics textbooks.

Interpreting model parameters

3. Does the author state that each structural equation in the econometric model is meant to convey a causal relationship?
4. Does the author define β by the equality, $\beta X = E[Y|X]$?

Clearly, since the structural equation represents a causal relationship between *X* and *Y*, it is incorrect to *define* β by $\beta X = E[Y|X]$, though the equality may occasionally be satisfied.

5. Does the author define the error term as being the difference between $E[Y|X]$ and *Y* ?
6. Does the author interpret the error term as omitted variables that (together with *X*) determine *Y* ?
7. Does the author state that each structural equation in the econometric model is meant to capture a *ceteris paribus* or "everything else held fixed" relationship?

[4] By "ideal" we mean consistent with modern analysis, as expressed in articles dealing specifically with the causal interpretation of structural equation models (Heckman, 2008; Leamer, 2010; Nevo and Whinston, 2010; Keane, 2010; Pearl, 2012a).

The notion of *ceteris paribus* is sometimes used by economists and is closely tied to direct causation. If we hold all other variables fixed then any measured relationship between X and Y must be causal. When we write $\boldsymbol{Y = \beta X + \varepsilon}$, where ε represents all other direct causes of Y, then β must capture a *ceteris paribus* and, therefore, causal relationship between X and Y. It is for this reason that we examined whether the author explicitly states that the structural equation captures a *ceteris paribus* relationship.

8. Does the author assume that exogeneity of X is inherent to the model?

Economists consider X to be exogenous in the equation $\boldsymbol{Y = \beta X + \varepsilon}$ if X is independent of ε, where ε represents all factors that have influence on Y when X is fixed[5]. An example of exogeneity is an ideal randomized experiment. Subjects are randomly assigned to a treatment or control group, ensuring that X is distributed independently of all personal characteristics of the subject. As a result, X and ε are independent and X is exogenous. Clearly, if X is exogenous β can be estimated using linear regression.

However, if $\boldsymbol{\beta X}$ is incorrectly interpreted as $\boldsymbol{E\,[Y\,|\,X]}$ and ε incorrectly defined as $\boldsymbol{Y - E\,[Y|X]}$ (as is done in the text by Hill, Griffiths, and Lim) then ε will always be uncorrelated with X and the statement that X is uncorrelated with ε is vacuous.

Moreover, if all we care about is the conditional expectation then it does not matter whether confounders or other causal biases are present, as regression will allow proper estimation of the slope of the equation $\boldsymbol{E\,[Y|X] = \alpha X}$ so long as the relationship between X and $\boldsymbol{E\,[Y|X]}$ is linear. In contrast, forcing X to be exogenous (e.g. through a randomized experiment) will estimate the interventional expectation and not the conditional expectation, which are not necessarily equal.

While exogeneity allows for unbiased estimation of β, it should not be considered an implicit assumption of the model. β retains its causal interpretation as $\boldsymbol{\beta = \frac{\partial}{\partial X}\,E\,[Y|\mathrm{do}(X)]}$ regardless of whether X and ε are correlated or not.

Moreover, exogeneity is a sufficient but not a necessary condition for identification. By requiring that exogeneity be a default assumption of the model, we limit its application to trivial and uninteresting problems, providing no motivation to tackle more realistic problems (say, through the use of instrumental variables).

Distinguishing $E\,[Y|X]$ *and* $E\,[Y|\mathrm{do}(X)]$

9. Does the author make clear the difference in the assumptions needed for answering causal as opposed to predictive problems?
10. Does the author use separate notation for $\boldsymbol{E\,[Y|\mathrm{do}(X)]}$ and $\boldsymbol{E\,[Y|X]}$?
11. Does the author use separate notation for the slope of the line associated with $\boldsymbol{E\,[Y|X]}$ and that associated with $\boldsymbol{E[Y|\mathrm{do}(X)]}$?

[5] From a causal analytic perspective, X is exogeneous if $E\,[Y|X] = E\,[Y|\mathrm{do}(X)]$ (Pearl, 2000). However, for purposes of this paper, we will use the aforementioned definition in which X is exogenous if it is independent of ε. Note that if X is independent of ε then $E\,[Y|X] = E\,[Y|\mathrm{do}(X)]$. The converse may not hold. For example, when ε is a vector of factors with cancelling influences on Y

Many books present both predictive and interventional problems as applications for econometric analysis. Not all of them discuss the distinction between them despite the fact that they require fundamentally different assumptions and, at times, a different methodology. At the core of this distinction is whether the model is meant to estimate $E[Y|X]$ or $E[Y|\mathbf{do}(X)]$. Clearly, if $\beta X = E[Y|\mathbf{do}(X)]$ is estimated (as opposed to $E[Y|X]$) when attempting to make predictions, the answer may be drastically wrong. Utilizing explicit notation for the interventional distributions is essential for avoiding such errors.

Remarkably, all of the econometrics textbooks surveyed refer to the structural equation as the “regression” equation. This is another source of confusion because “regression” is used to refer to the best-fit line. Using the same term to refer to both the structural and best-fit lines further increases the confusion between interventions and predictions.

Results

We surveyed the following textbooks:

- Greene, W. *Econometric Analysis*. Pearson Education, New Jersey. 7th edition, 2012.
- Hill, R., Griffiths, W., and Lim, G. *Principles of Econometrics*. John Wiley & Sons Inc. New York. 4th edition, 2011.
- Kennedy, P. *A Guide to Econometrics*. Blackwell Publishers, Oxford. 6th edition, 2008.
- Ruud, P. *An Introduction to Classical Econometric Theory*. Oxford University Press, Oxford. 1st edition, 2000.
- Stock, J., Watson, M. *Introduction to Econometrics*. Pearson Education, Massachusetts. 3rd edition, 2011.
- Wooldridge. *Introductory Econometrics: A Modern Approach*. South-Western College Pub. 4th edition, 2009.

These are six highly popular and frequently cited introductory econometrics textbooks. Our results are summarized in Table 1.

Table 1: Summary of survey results

	Greene	Hill, Griffiths, Lim	Kennedy	Stock, Watson	Ruud	Wooldridge	Ideal
1.	Yes ✓	Yes ✓	No	Yes ✓	No[6]	Yes ✓	Yes
2.	No	Yes ✓	No	Yes ✓	Yes ✓	No	Yes
3.	No[7]	No	No	Yes ✓	No	Yes ✓	Yes
4.	No[8]	Yes ×	Yes ×	Yes[9] ×	No ✓	No ✓	No
5.	No ✓	Yes ×	No ✓	No ✓	No ✓	No ✓	No
6.	Yes ✓	Yes[10] ✓	Yes ✓	Yes ✓	No[11]	Yes ✓	Yes
7.	Yes ✓	No	No	No[12] ✓	No	Yes ✓	Yes
8.	Yes	Yes	Yes	No ✓	No[13] ✓	Yes	No
9.	No	No ×	No	Yes ✓	No	No	Yes
10.	No	No	No	No	No	No	Yes
11.	No	No	No	No	No	No	Yes

✓ denotes agreement with the ideal column,
× denotes a contradiction with another response in the same textbook

3.1 Greene (2012)

Greene writes, "The ultimate goal of the econometric model builder is often to uncover the deeper causal connections through elaborate structural, behavior models" (Greene, 2012, pp. 5-6). Consistent with this goal, Greene provides seven applications of econometric modeling as examples (*ibid.*, p. 3), each of which requires the estimation of causal effects. Among them are the effect of different policies on the economy, the effect of a voluntary training program in work environments, the effect of attending an elite college on future income, and the effect of smaller class sizes on student performance.

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[6] Mentions that latent variable models can be used for policy analysis but does not provide examples.
[7] Discusses the regression equation as capturing the deterministic relationship between the independent and dependent variables and writes that "the ultimate goal of the econometric model builder is often to uncover the deeper causal connections through elaborate structural, behavior models". (Greene, 2012, p. 2).
[8] States "The **regression** of **y** on **X** is the conditional mean, $E\,[\mathbf{y}|\mathbf{X}]$, so that without [exogeneity], $\mathbf{X}\beta$ is *not* the conditional mean function" (Greene, 2012, p. 21). Also, "The unknown parameters of the stochastic relationship $y_i = \mathbf{x}_i'\beta + \varepsilon_i$ are the objects of estimation... The **population regression** is $E\,[y_i|\mathbf{x}_i] = \mathbf{x}_i'\beta$ whereas our estimate of $E\,[y_i|\mathbf{x}_i]$ is denoted $\hat{y}_i = \mathbf{x}_i'\mathbf{b}$." (Greene, 2012, p.26).
[9] States "The first part of Equation (4.5), $\beta_0 + \beta_1 X_i$, is the **population regression line** or the **population regression function**. This is the relationship that holds between Y and X on average over the population. Thus, if you knew the value of X, according to this population regression line you would predict that the value of the dependent variable, Y, is $\beta_0 + \beta_1 X$" (Stock and Watson, 2011, p. 110).
[10] States that the error term is comprised of omitted factors that affect the independent variable, approximation errors that arise due to the functional specification being only an approximation, and any elements of "random behavior that may be present in each individual" (Hill et al., 2011).
[11] States that ε represents unobserved, explanatory random variables (Ruud, 2000, p. 493).
[12] While Stock and Watson do not discuss the relationship between β and *ceteris paribus* per se, they state that β represents a causal relationship and discuss its relationship to randomized experiments. As a result, they implicitly define βX as $E\,[Y\,|do(X)]$ and we denote agreement with the ideal response.
[13] Prior to introducing latent variable models, Ruud does not make any assumptions regarding exogeneity. He only writes, "if the mean of y conditional on X is $X\beta_0$, the OLS estimator is unbiased: $E[\hat{\beta}X] = \beta_0$" (Ruud, 2000, p. 173). After introducing the latent variable model as $y_n = \mathbf{x}_n'\beta_0 + \varepsilon_n$, he writes, "In each model that we describe, at least one of the explanatory variables in $\mathbf{x}_n$ is correlated with ε_n so that $E[\varepsilon_n|\mathbf{x}_n]$ is a function of $\mathbf{x}_n$ and, therefore, not zero. This in turn implies that $E[y_n|\mathbf{x}_n] \neq \mathbf{x}_n\beta_0$ and that the OLS fit of y_n to x_n will yield inconsistent estimates of β_0" (Ruud, 2000, p. 491).

Although Greene acknowledges the goal of economic modeling to be the establishment or estimation of "causal connections", he does not explicitly discuss the role of model parameters in pursuing this goal and refrains from attributing causal interpetation to β. Instead, he relates econometric models to the conditional expectation, writing, "The model builder, thinking in terms of features of the conditional distribution, often gravitates to the expected value, focusing attention on $\boldsymbol{E}[\boldsymbol{y}|\boldsymbol{x}]$..." (*ibid.*, p. 12). At the same time, Greene also suggests that β carries meaning beyond that of the conditional expectation, writing, "The regression of y on **X** is the conditional mean, $\boldsymbol{E}[\boldsymbol{y}|\boldsymbol{X}]$, so that without [exogeneity], $\boldsymbol{X\beta}$ is not the conditional mean function" (*ibid.*, p. 21). He does not, however, tell readers what β stands for, what it is used for, or why it justifies all the attention given to it in the book. Instead, he writes, "For modeling purposes, it will often prove useful to think in terms of 'autonomous variation.' One can conceive of movement of the independent variables outside the relationship defined by the model while movement of the dependent variable is considered in response to some independent or exogenous stimulus" (*ibid.*, p. 13). While this may be a legitimate way of thinking about causal effects, depriving "β" of its causal label creates the impression that economic models incorporate ill-defined parameters that require constant re-thinking to ascertain their interpretation[14].

Later, when discussing endogeneity and instrumental variables, Greene seems to suggest that a natural experiment and instrumental variable is needed to bestow causal meaning to β. He writes,

> "The technique of instrumental variables estimation has evolved as a mechanism for disentangling causal influences... when the instrument is an outcome of a 'natural experiment,' true exogeneity is claimed... On the basis of a natural experiment, the authors identify a cause-and-effect relationship that would have been viewed as beyond the reach of regression modeling under earlier paradigms" (*ibid.*, p. 252).

Here the reader wonders why the coefficient β, considered under endogeneity, would not deserve the title "cause and effect relationship" unless a good instrument is discovered by imaginative authors. Up to this point, Greene has made only passing references to the relationship between structural parameters (e.g., β), regression, and causality.

In section 19.6, "Evaluating Treatment Effects", however, Greene introduces potential outcomes and discusses causal effects explicitly (*ibid.*, p. 889); gone are the hesitation and ambiguities that marred the discussion of structural equations. Here, Rubin's notation for counterfactuals is introduced and Greene discusses the estimation of causal effects using regression, propensity score matching, and regression discontinuity (instrumental variables are mentioned in an earlier chapter). However, Greene provides no connections between treatment effects defined in this chapter and the structural equations that were the subject of discussion in the 18 earlier chapters. The impression is, in fact, created that the previous chapters were a waste of time for researchers aiming to estimate causal effects, which the book defines as, "The ultimate goal of the econometric model builder".

In section 19.6.1, "Regression Analysis of Treatment Effects", Greene presents the equation,

[14] In a personal correspondence (2012), Greene wrote, "The precise definition of effect of what on what is subject to interpretation and some ambiguity depending on the setting. I find that model coefficients are usually not the answer I seek, but instead are part of the correct answer. I'm not sure how to answer your query about exactly, precisely carved in stone, what β should be."

$earnings_i = x_i^t\beta + \delta C_i + \varepsilon_i$ and asks,

> "Does δ measure the value of a college education (assuming that the rest of the regression model is correctly specified)? The answer is no if the typical individual who chooses to go to college would have relatively high earnings whether or not he or she went to college..."

The answer is, in fact, YES[15]. The only way to interpret Greene's negative answer is to assume that the equation is regressional and that δ is simply the slope of the regression line. However, as mentioned above, Greene also suggests that "regression" parameters (*ibid.*, p. 21) are more than just slopes of regression lines. Indeed, this is the interpretation that is generally used throughout the textbook. This inconsistency is a major source of confusion to students attempting to understand the meaning of parameters like "β" or "δ". In summary, while Greene provides the most detailed account of potential outcomes and counterfactuals of all the authors surveyed, his failure to acknowledge the oneness of the potential outcomes and structural equation frameworks is likely to cause more confusion than clarity, especially in view of the current debate between two antagonistic and narrowly focused schools of econometric research (See Pearl 2009, p. 379-380).

3.2 Hill, Griffiths, and Lim (2011)

In the first chapter of the text by Hill, Griffiths, and Lim, the authors discuss the role of econometrics in aiding both prediction and policy making. On pp. 3-4, they present several problems as examples, some of which are causal and some of which are predictive:

- "A city council ponders the question of how much violent crime will be reduced if an additional million dollars is spent putting uniformed police on the street.
- "The owner of a local Pizza Hut must decide how much advertising space to purchase in the local newspaper, and thus must estimate the relationship between advertising and sales.
- "You must decide how much of your savings will go into a stock fund, and how much into a money market. This requires you to make predictions of the level of economic activity, the rate of inflation, and interest rates over your planning horizon (Hill et al., 2011)".

However, in explaining the meaning and usage of the econometric model, the text makes no mention of causal vocabulary and instead relies on statistical notions like conditional expectation. For example, on p. 43, they write, "the economic model summarizes what theory tells us about the relationship between [*x*] and the... $E(y|x)$" and the "simple regression function" of the model is defined as $E(y|x) = \beta_1 + \beta_2 x$ (*ibid.*, pp. 43) where β_1 is defined as $E(y|x = 0)$ and β_2 as $\frac{dE(y|x)}{dx}$. At no point is causality or *ceteris paribus* mentioned.

This interpretation leaves the econometric model unable to guide policy making and solve the aforementioned problems requiring causal inference. Indeed, these problems seem to be forgotten in chapter 2 when the econometric model is introduced and instead, we find only predictive examples: "An econometric analysis of the expenditure relationship can provide

[15] δ, in this structural equation, measures precisely the value of a college education, regardless of what sort of individuals choose to go to college. While the OLS estimation of δ will be biased, the meaning of δ remains none other but the "value of college education".

answers to some important questions, such as: If weekly income goes up by $20, how much will average weekly food expenditure rise? Or, could weekly food expenditures fall as income rises? How much would we predict the weekly expenditure on food to be for a household with an income of $800 per week?" (*ibid.*, p. 44).

At the same time, when discussing the assumptions inherent to the econometric model the text states that "the variable *x* is not random" (*ibid.*, p. 45) and explains this assumption using an example of a McDonald's owner "[setting] the price (*x*) and then [observing] the number of Big Macs sold (*y*) during the week. The following week the price could be changed, and again the data on sales collected." (*ibid.*, p. 46 - 47). Clearly, requiring that the data be generated by a process in which *X* is fixed by intervention suggests that $\beta_1 + \beta_2 x$ has meaning beyond that of the $E(y|x)$.

Later, the authors introduce the error term as $e = y - E(y|x)$ (*ibid.*, p. 46) and the regression equation is defined as $y = \beta_1 + \beta_2 x + e$. Using these definitions, they relax the assumption that *x* be "fixed" explaining that it is unnecessary so long as it is uncorrelated with the error term (*ibid.*, p. 402). Not only is the requirement that *e* be uncorrelated with *X* redundant when *e* is defined as the residual, $y - E(y|x)$, but relating it to the assumption that *x* is "not random" leaves readers in a state of total confusion regarding the meaning of *β*.

3.3 Kennedy (2008)

Kennedy introduces the structural model using an example where consumption, *C*, is the dependent variable, and income *Y* is the independent variable. He writes the structural equation as $C = f(Y) + \varepsilon$ or $C = \beta_1 + \beta_2 Y + \varepsilon_i$ in the linear case, where *ε* is a disturbance term, and adds, "Without the disturbance term the relationship is said to be *exact* or *deterministic*..." (Kennedy, 2008, p. 3). Kennedy then writes that "some econometricians prefer to define the relationship between *C* and *Y* discussed earlier as 'the mean of *C* conditional on *Y* is $f(Y)$,' written as $E(C|Y) = f(Y)$." This [says Kennedy] "spells out more explicitly what econometricians have in mind when using this specification" (*ibid.*, p. 9). This unfortunately is wrong; the conditional interpretation $E(C|Y) = f(Y)$ is precisely what econometricians *do not* have in mind in writing the structural equation $C = f(Y) + \varepsilon$.

Both Haavelmo (1943) and Goldberger (1992) have warned econometricians of the pitfalls lurking in this interpretation. Oddly, Kennedy is well aware of the difference between the two interpretations and writes: "The conditional expectation interpretation can cause some confusion" (*ibid.*), yet he fails to tell readers which of the two interpretations they should adopt and why the conditional interpretation does not capture "what econometricians have in mind when using this specification".

Kennedy later suggests that causality has no place in econometric modeling and all uses of the term "cause" should be replaced with "Granger-cause". He writes, "Granger developed a special definition of causality which econometricians use in place of the dictionary definition; strictly speaking, econometricians should say 'Granger-cause' in place of 'cause', but usually they do not" (*ibid.*, p. 63). As is well known, and as Granger repeatedly stated[16], "Granger causality" is a misnomer given to purely predictive notion that has nothing to do with causation. Thus, Kennedy views economic models to be used strictly in prediction tasks and not as guides to policy making. Unfortunately this contradicts a claim made later in

[16] Granger, in a personal communication with J. Pearl, Uppsala, 1991.

the book that econometric model *can* be used to simulate the effects of policy changes (*ibid.*, p. 343).

Like Hill, Griffiths, and Lim, on page 41, Kennedy writes that one of the assumptions of the "classical linear regression model" (CLR) is that "the observations on the independent variables... be fixed in repeated samples" (*ibid.*, p. 41). While it is not immediately clear whether "fixed in repeated samples" is meant to imply active intervention on the independent variable or merely "repeated at the same observed value of *x*", in a later chapter, Kennedy discusses when this assumption is violated and writes, "In many economic contexts the independent variables are themselves random (or stochastic) variables and thus could not have the same value in repeated samples" (*ibid.*, p. 137). He then writes that "the assumption of fixed regressors is made mainly for mathematical convenience... If the assumption is weakened to allow the explanatory variables to be stochastic but to be distributed independently of the error term, all the desirable properties of the OLS estimator are maintained..." (*ibid.*). From this the reader may conclude, albeit indirectly, that "fixing" is related to exogeneity, that *x* should be fixed by intervention, and that the structural equation does capture a causal relationship, contrary to Kennedy's earlier suggestion that causality has no place in econometrics.

3.4 Ruud (2000)

Rather than treating an econometric model as representing an economic theory and testing it against data, Ruud focuses almost entirely on regression techniques. To Ruud, the regression line, as well as the mean, median, mode, and standard deviation, is a worthy descriptor of the dataset. Much of the textbook is devoted to deriving statistical properties of OLS regression. The exogeneity assumption and the equation, $\boldsymbol{y} = \boldsymbol{\beta X} + \boldsymbol{\varepsilon}$, are introduced later in a chapter on instrumental variables as a latent variable model. Ruud mentions that latent variable models "play a key role in the economist's search for structure", "[assist] in the marriage of theoretical and empirical modeling", and can be used for policy analysis due to their "invariant features" (Ruud, 2000, p. 616) but does not discuss the way in which they can be used to accomplish the aforementioned goals and solve causal problems. Instead, he spends considerable effort explaining the statistics of latent variable models without discussing their relationship to structure and causality. In fact, causality is not discussed at all in the textbook beyond a passing mention that the causal effect and the conditional expectation are not the same. While this statistical approach is logically consistent, it leaves students unequipped to tackle causal problems.

3.5 Stock and Watson (2011)

The textbook by Stock and Watson explicitly discusses policy questions (hence cause-effect relations) in the econometric model. In the first chapter, they write that the "book examines several quantitative questions taken from current issues in economics. Four of these questions concern education policy, racial bias in mortgage lending, cigarette consumption, and macro-economic forecasting..." (Stock and Watson, 2011, p. 1). The authors acknowledge that three of these problems "concern causal effects" while "the fourth – forecasting inflation – does not" (*ibid.*, p. 9). Of the six textbooks surveyed, this text is the only one to address the difference in assumptions needed for causal versus predictive inference. They write, "when regression models are used for forecasting, concerns about external validity are very important, but concerns about unbiased estimation of causal effects are not" (*ibid.*, p. 327).

In addition to discussing the difference in predictive versus causal inference, the textbook also notes that coefficients of confounding variables added to regression equations for purposes of adjustment cannot be given a causal interpretation (*ibid.*, p. 232). At one point, the text even provides separate notation for such coefficients, labeling them δ as opposed to β (*ibid.*, p. 250). It would have been helpful to make this notational distinction consistent throughout the book, to clearly separate causal from regression coefficients, and to refrain from referring to structural equations as "regression".

The textbook also introduces the potential outcome framework to explain randomization and heterogeneous causal effects (*ibid.*, pp. 498-99). However, the relationship between potential outcomes and the structural equation is often obscured. For example, the authors write: "The potential outcomes framework, combined with a constant treatment effect, implies the regression model in [$Y_i = \beta_1 + \beta_2 X_i + u_i, i = 1, \dots, n$]" (*ibid.*, p. 514). The sentence is misleading on two counts. First, the equation is not regressional but structural. Second, the structural equation is not a consequence of the potential outcomes framework but the other way around; the equation provides the scientific basis from which the potential outcomes framework draws its legitimacy (Pearl, 2000; Heckman, 2005; Pearl, 2012b)[17]. Nevertheless, this and the textbook by Greene are the only two surveyed that introduce the potential outcomes notation, which is important for defining counterfactual questions such as the effect of treatment on the treated and indirect effects.

Additionally, in contrast to the previous textbooks, this text recognizes and discusses the causal nature of the exogeneity condition. They write, "The random assignment typically is done using a computer program that uses no information about the subject, ensuring that *X* is distributed independently of all personal characteristics of the subject. Random assignment makes *X* and *u* independent, which in turn implies that the conditional mean of *u* given *X* is zero. In observational data, *X* is not randomly assigned in an experiment. Instead, the best that can be hoped for is that *X* is *as if* randomly assigned, in the precise sense that $E(u_i|X_i) = 0$[18]" (Stock and Watson, 2011, p. 123).

While the textbook provides a clearer explanation of the difference between causal and statistical concepts than the other textbooks surveyed, it still falls victim to prevailing habits in the economics literature. For example, after presenting an example in which β measures a causal effect, the text turns around and suggests that $E[Y|x] = \beta x$ (*ibid.*, pp. 108-10)[19].

More seriously, the authors state that "the slope of the line relating *X* and *Y* is an unknown characteristic of the population joint distribution of *X* and *Y*" (*ibid.*, p. 107). While this is probably a semantic slip, it risks luring readers back into the dark era when economic models were thought to represent joint distributions (see "Econometric Models", Wikipedia, August 2012). The structural slope, β, is NOT a characteristic of the "joint distribution of *X* and *Y*"; it is a characteristic of the data generating process but has no counterpart in the joint distribution.

[17] Appendix 1 of (Pearl, 2012b) provides explicit discussion of this point and demonstrates how the experimental and quasi-experimental ramification of the potential outcome framework are derived from ordinary structural equations. See also Appendix A.
[18] This is not strictly true; one can do better than hope for an *as if* miracle. Identification techniques are available for models in which *X* is far from satisfying $E(u_i|x_i) = 0$ (Pearl, 2000).
[19] In a personal correspondence James Stock acknowledged this correctable oversight.

3.6 Wooldridge (2009)

The textbook by Wooldridge also explicitly ascribes causal meaning to the econometric model. He writes, "In most tests of econometric theory, and certainly for evaluating public policy, the economist's goal is to infer that one variable (such as education) has a causal effect on another variable (such as worker productivity)" (Wooldridge, 2009, p. 12). In contrast to Stock and Watson, who define causality in relation to a randomized experiment (Stock and Watson, 2011, p. 6), Wooldridge emphasizes the concept of *ceteris paribus*. He writes, "You probably remember from introductory economics that most economic questions are ceteris paribus by nature. For example, in analyzing consumer demand, we are interested in knowing the effect of changing the price of a good on its quantity demanded, while holding all other factors fixed. If other factors are not held fixed, then we cannot know the causal effect of a price change on quantity demanded[20]." (Wooldridge, 2009, p. 12).

Wooldridge is also more careful when interpreting the parameter, β. Rather than using the conditional expectation of Y given X, he writes that β is "the slope parameter in the relationship between y and x holding the other factors in u fixed" (*ibid.*, p. 23), where u represents the error term.

While Wooldridge provided a strong and generally consistent account of causality, he did not provide explicit notation for intervention thus letting the definitions of beta and epsilon rest entirely on verbal description. While this may be adequate for linear models, it prevents one from extending causal analysis to nonparametric models.

4. Discussion and recommendations

4.1 Potential points of improvement

Five of the six authors surveyed claim that exogeneity of X is necessary for unbiased estimation of β using linear regression, indirectly implying that β has meaning beyond that of a regression coefficient. Only two of them explicitly ascribe causal meaning to the model.

We believe that making clear the difference between the conditional expectation, $E[Y|X]$, and the interventional expectation, $E[Y|do(X)]$, will do much to clarify the meaning of the econometric model and help prevent both students and economists from confusing the two.

It is common for textbook authors to equate the conditional expectation with βX even when it is clear that the author considers βX to be $E[Y|do(X)]$ rather than $E[Y|X]$. Of the five authors that claim exogeneity is necessary for unbiased estimation of β using linear regression, three also claim that $E[Y|X] = \beta X$. Kennedy admitted (personal correspondence, 2001) that he was careless in the 1998 edition and had intended for the statement to be applicable only when X is exogenous. However, $E[Y|X]$ is precisely *not* what economists have in mind when authoring an econometric model. This fact becomes even more evident when adjusting for a confounder or using instrumental variables in cases where βX is not equal to $E[Y|X]$. Economists developed these techniques precisely because in their minds β represents the causal effect of X on Y, not some property of the joint distribution.

[20] Again, this is not strictly true. There are many techniques that allow unbiased estimation of causal effects even when other factors are not held fixed (Pearl, 2000).

We have limited our comparison criteria to features that hinder basic understanding of the meaning of structural economic models – the absence of distinct causal notation. Lines 10-11 of Table 1 represent this deficiency, which is common to all six textbooks. In addition to the confusion it causes, it also results in technical limitations including, for example, inability to extend causal analysis to nonparametric models and forgoing the benefits of Marschak's Maxim[21] (Heckman, 2010).

Another weakness that runs across all books surveyed is the absence of graphical models to assist in both understanding the causal content of the equations and performing necessary inferential functions that are not easily performed algebraically. Introducing simple graphical tools would enable econometric students to recognize the testable implications of a system of equations; locate instruments in such systems; decide if two systems are equivalent; if causal effects are identifiable; if two counterfactuals are independent given another; and whether a set of measurements will reduce bias; and, most importantly, read and scrutinize the causal and counterfactual assumptions that such systems convey. The power of these tools is demonstrated in (Pearl, 2012a) and we hope to see them introduced in next-generation econometric textbooks.

We fully recognize, though, that authors in economics are reluctant to adopt, or even examine the power of graphical techniques, which generations of economists have dismissed (under the rubric of "path analysis") as "informal", "heuristic", or "mnemonic" (Epstein, 1987; Pearl, 2009, p. 138-139). For example, only a handful of economists have come to realize that graphical models have laid to rest the problem of identification in the entire class of "nonadditive, nonseparable triangular models"[22], for both discrete and continuous variables. We therefore offer our recomendations (below) in terms of essential problem-solving skills without advocating a specific notation or technique.

4.2 What an ideal textbook should contain

First and foremost, an ideal textbook in econometrics should eradicate the century-old confusion between regression and structural equations. Structural and regression parameters should consistently be given distinct notation, for example, β_s vs. α_r . The term "regression" should not be used when referring to structural equations. The assumptions behind each structural equation should be made explicit and contrasted with those that underlie regression equations. Policy evaluation examples should demonstrate the proper use of structural versus regression parameters in achieving the target estimates.

Additionally, students should acquire the following tools and abilities:

1. Ability to correctly classify problems, assumptions and claims into two distinct categories: causal vs. associational.
2. Ability to take a given policy question, and articulate mathematically both the target quantity to be estimated, and the assumptions that one is prepared to make (and defend) to facilitate a solution.
3. Ability to determine, in simple models, whether control for covariates is needed for estimating the target quantities, what covariates need be controlled, what the resulting estimand is, and how it can be estimated using the observed data.

[21] Marschak Maxim refers to Jacob Marschak's (1953) observation that many policy questions do not require the estimation of each and every parameter in the system – a combination of parameters is all that is necessary – and that it is often possible to identify the desired combination without identifying the individual components.

[22] We are using the nomenclature of (Matzkin, 2007). By "handful" we include (White and Chalak, 2009) and (Hoover, 2009). The graphical solution can be found in (Shpitser and Pearl, 2006, 2008).

4. Ability to take a simple model, determine whether it has statistically testable implications, then apply data to test the model for misspecification.
5. Finally, students should be aware of nonparametric extensions to traditional linear structural equations. In particular, they should be able to solve problems of identification and misspecification in simple nonparametric models, where no commitment is made to the form of the equations or to the distribution of the disturbances.

Examples of specific problems requiring these abilities are illustrated in (Pearl, 2012b, Section 3.2).

5. Conclusion

The surveyed econometrics textbooks range from acknowledging the causal content of the SEM (e.g.Wooldridge, Stock and Watson) to insisting that it is nothing more than a compact representation of a joint distribution (e.g. Ruud). The rest fall somewhere in the middle, attempting to provide the model with power to answer economic questions but unwilling to accept its causal nature; the result is ambiguity and confusion. Nowhere is this more evident than in the text by Hill, Griffiths, and Lim in which definitions of the model parameters conflict with stated assumptions of the model. Other textbooks (e.g. Greene) are more careful about avoiding contradictions but their refusal to acknowledge the causal content of the model results in ambiguous descriptions like "autonomous variation". Finally, even textbooks that acknowledge the role of causality in econometrics fail to provide coherent mathematical notation for causal expressions, luring them into occasional pitfalls (e.g. equating β with a regression coefficient or some other property of the joint distribution of X and Y) and preventing them from presenting the full power of structural equation models.

The introduction of graphical models and distinct causal notation into elementary econometric textbooks has the potential of revitalizing economics education and bringing next generation economists to par with modern methodologies of modeling and inference.

Appendix A

This appendix provides formal definitions of interventions and counterfactuals as they have emerged from Haavelmo's interpretation of structural equations. For a more detailed account, including examples of policy-related tasks, see (Pearl, 2012b).

Key to this interpretation is a procedure for reading counterfactual information in a system of economic equations, formulated as follows:

Definition 1 (unit-level counterfactuals) (Pearl, 2000, p. 98)**.**
Let M be a fully specified structural model and X and Y two arbitrary sets of variables in M. Let M_X *be a modified version of M, with the equation(s) determining X replaced by the equation(s) X = x. Denote the solution for Y in the modified model by the symbol* $Y_{M_x}(u)$*, where u stands for the values that the exogenous variables take for a given individual (or unit) in the population. The counterfactual* $Y_X(u)$ *(Read: "The value of Y in unit u, had X been x") is defined by:*

$$Y_x(u) \equiv Y_{M_x}(u) \quad \text{(A.1)}$$

In words: The counterfactual $Y_x(u)$ in model M is defined by the solution for Y in the modified submodel M_X, with the exogenous variables held at U = u.

For example, consider the model depicted in Figure 1(a), which stands for the structural equations:

$$Y = f_Y(X, Z, U_Y)$$
$$X = f_X(Z, U_X)$$
$$Z = f_Z(U_Z)$$

Here, f_X, f_Y, f_Z are arbitrary functions and U_X, U_Y, U_Z are arbitrarily distributed omitted factors. The modified model M_X consists of the equations below and and is depicted in Figure 1b.

$$Y = f_Y(X, Z, U_Y)$$
$$X = x$$
$$Z = f_Z(U_Z)$$

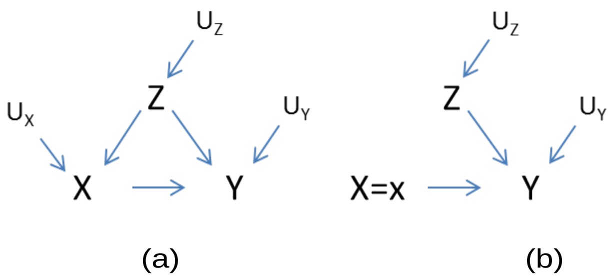

Figure 1

The counterfactual $Y_x(u)$ at unit $u = (u_X, u_Y, u_Z)$ would take the value $Y_x(u) = f_Y(x, f_Z(u_z), u_Y)$, which can be computed from the model. When *u* is unknown, the counterfactual becomes a random variable, written $Y_x(u) = f_Y(x, Z, U_Y)$ with *x* treated as constant, and *Z* and U_Y random variables governed by the original model.

Clearly, the distribution $P(Y_X = y)$ depends on both the distribution of the exogenous variables $P(Y_X, U_Y, Y_Z)$ and on the functions f_X, f_Y, f_Z. In the linear case, however, the expectation $E[Y_X]$ is rather simple.

Writing:

$$Y = aX + bZ + U_Y$$
$$X = cZ + U_X$$
$$Z = U_Z$$

gives

$$Y_x = ax + bZ + U_Y$$

and

$$E(Y_x) = ax + bE(Z)$$

Remarkably, the average effect of an intervention can be predicted without making any commitment to functional or distributional form. This can be seen by defining an intervention operator do(x) as follows:

$$P(Y = y|\text{do}(x)) \equiv P(Y_x = y) \equiv P_{M_x}(Y = y) \quad \text{(A.2)}$$

In words, the distribution of Y under the intervention do($X = x$) is equal to the distribution of Y in the modified model M_X, in which the dependence of Z on X is disabled (as shown in Figure 1b).

Accordingly, we can use M_X to define average causal effects:

Definition 2 (Average causal effect).

The average causal effect of X on Y, denoted by $E[Y|\text{do}(x)]$ *is defined by:*

$$E[Y|\text{do}(x)] \equiv E[Y_x] = E[Y_{M_x}] \quad \text{(A.3)}$$

Note that Definition 2 encodes the effect of interventions not in terms of the model's parameters but in the form of a procedure that modifies the structure of the model. It thus liberates economic analysis from its dependence on parameteric representations and permits a totally non-parametric calculus of causes and counterfactuals that makes the connection between assumptions and conclusions explicit and transparent.

If we further assume that the exogenous variables (U_X , U_Y , U_Z) are mutually independent (but arbitrarily distributed) we can write down the post-intervention distribution immediately, by comparing the graph of Figure 1b to that of Figure 1a. If the pre-intervention joint probability distribution is factored into (using the chain rule):

$$\boldsymbol{P(x, y, z) = P(z)P(x|z)P(y|x, z)}$$
(A.4)

the post-intervention distribution must have the factor $P(x|z)$ removed, to reflect the missing arrow in Figure 1b. This yields:

$$\boldsymbol{P(x, y, z|\text{do}(X = x_0)) = \begin{cases} P(z)P(y|x, z) & \text{if } x = x_0 \\ 0 & \text{if } x \neq x_0 \end{cases}}$$

In particular, for the outcome variable Y we have $\boldsymbol{P(y|do(x)) = \sum_z P(z)P(y|x, z)}$, which reflects the operation commonly known as "adjusting for Z" or "controlling for Z". Likewise, we have

$$\boldsymbol{E(Y|do(x)) = \sum_z P(z)E(Y|x, z)},$$

which can be estimated by regression using the pre-intervention data.

In the simple model of Figure 1a the selection of Z for adjustment was natural, since Z is a confounder that causes both X and Y. In general, the selection of appropriate sets for adjustment is not a trivial task; it can be accomplished nevertheless by a simple graphical procedure (called "backdoor") once we specify the graph structure (Pearl, 2009, p. 79).

Equation A.1 constitutes a bridge between structural equation models and the potential outcome framework advanced by (Neyman, 1923) and (Rubin, 1974), which takes the controlled randomized experiment as its guiding paradigm but encounters difficulties articulating modeling assumptions. Whereas structural models encode causal assumptions in the form of functional relationships among realizable economic variables, the potential outcome framework requires those same assumptions to be encoded as conditional independencies among counterfactual variables, an intractible cognitive task.

Appendix B

This appendix, which provides supporting quotes for Table 1, has been omitted from the journal version of this survey and can be found in the full version at <http://ftp.cs.ucla.edu/pub/stat_ser/r395.pdf>.

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References

Balke, A. and Pearl, J. (1995). Counterfactuals and policy analysis in structural mod- els. In *Uncertainty in Artificial Intelligence 11* (P. Besnard and S. Hanks, eds.). Morgan Kaufmann, San Francisco, 11–18.

Epstein, R. (1987). *A History of Econometrics*. Elsevier Science, New York.

Glymour, M. and Greenland, S. (2008). Causal diagrams. In *Modern Epidemiology* (K. Rothman, S. Greenland and T. Lash, eds.), 3rd ed. Lippincott Williams & Wilkins, Philadelphia, PA, 183–209.

Goldberger, A. (1992). Models of substance; comment on N. Wermuth, 'On block- recursive linear regression equations'. *Brazilian Journal of Probability and Statistics* **6** 1–56.

Greene, W. (2012). *Econometric Analysis*. 7th ed. Pearson Education, New Jersey.

Haavelmo, T. (1943). The statistical implications of a system of simultaneous equations. *Econometrica* **11** 1–12. Reprinted in D.F. Hendry and M.S. Morgan (Eds.), *The Founda- tions of Econometric Analysis*, Cambridge University Press, 477–490, 1995.

Haavelmo, T. (1944). The probability approach in econometrics (1944)*. Supplement to *Econometrica* 12 12–17, 26–31, 33–39. Reprinted in D.F. Hendry and M.S. Morgan (Eds.), *The Foundations of Econometric Analysis*, Cambridge University Press, New York, 440–453, 1995.

Heckman, J. (2000). Causal parameters and policy analysis in economics: A twentieth century retrospective. *The Quarterly Journal of Economics* **115** 45–97.

Heckman, J. (2005). The scientific model of causality. *Sociological Methodology* **35** 1–97.

Heckman, J. (2008). Econometric causality. *International Statistical Review* **76** 1–27.

Heckman, J. (2010). Building bridges between structural and program evaluation ap- proaches to evaluating policy. *Journal of Economic Literature* **48** 356–398.

Hill, R., Griffiths, W. and Lim, G. (2011). *Principles of Econometrics*. 4th ed. John Wiley & Sons Inc., New York.

Hoover, K. (2009). Counterfactuals and causal structure. *Available at SSRN 1477531* .

Huang, Y. and Valtorta, M. (2006). Pearl's calculus of intervention is complete. In *Proceedings of the Twenty-Second Conference on Uncertainty in Artificial Intelligence* (R. Dechter and T. Richardson, eds.). AUAI Press, Corvallis, OR, 217–224.

Keane, M. P. (2010). A structural perspective on the experimentalist school. *Journal of Economic Perspectives* **24** 47–58.

Kennedy, P. (2008). *A Guide to Econometrics*. Sixth ed. MIT Press, Cambridge, MA.

Leamer, E. E. (2010). Tantalus on the road to asymptopia. *Journal of Economic Perspec- tives* **24** 31–46.

Matzkin, R. (2007). Handbook of econometrics. Elsevier, Amsterdam.

Morgan, S. and Winship, C. (2007). *Counterfactuals and Causal Inference: Methods and Principles for Social Research (Analytical Methods for Social Research)*. Cambridge University Press, New York, NY.

Nevo, A. and Whinston, M. D. (2010). Taking the dogma out of econometrics: Structural modeling and credible inference. *Journal of Economic Perspectives* **24** 69–82.

Neyman, J. (1923). On the application of probability theory to agricultural experiments. Essay on principles. Section 9. *Statistical Science* 5 465–480.

Pearl, J. (1995). Causal diagrams for empirical research. *Biometrika* 82 669–710.

Pearl, J. (2000). *Causality: Models, Reasoning, and Inference*. Cambridge University Press, New York. 2nd edition, 2009.

Pearl, J. (2009). *Causality: Models, Reasoning, and Inference*. 2nd ed. Cambridge University Press, New York.

Pearl, J. (2012a). The causal foundations of structural equation modeling. In *Handbook of Structural Equation Modeling* (R. H. Hoyle, ed.). Guilford Press, New York. In press.

Pearl, J. (2012b). Trygve Haavelmo and the emergence of causal calculus. Tech. Rep. R- 391, Department of Computer Science, University of California, Los Angeles, CA. Written for *Econometric Theory*, special issue on Haavelmo Centennial.

Rubin, D. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology* **66** 688–701.

Ruud, P. (2000). *An Introduction to Classical Econometric Theory*. Oxford University Press, Oxford.

Shpitser, I. (2008). *Complete Identification Methods for Causal Inference*. Ph.D. thesis, Computer Science Department, University of California, Los Angeles, CA.

Shpitser, I. and Pearl, J. (2006). Identification of conditional interventional distributions. In *Proceedings of the Twenty-Second Conference on Uncertainty in Artificial Intelligence* (R. Dechter and T. Richardson, eds.). AUAI Press, Corvallis, OR, 437–444.

Shpitser, I. and Pearl, J. (2008). Complete identification methods for the causal hierarchy. *Journal of Machine Learning Research* **9** 1941–1979.

Simon, H. and Rescher, N. (1966). Cause and counterfactual. *Philosophy and Science* **33** 323–340.
Spirtes, P., Glymour, C. and Scheines, R. (1993). *Causation, Prediction, and Search*. Springer-Verlag, New York.

Stock, J. and Watson, M. (2011). *Introduction to Econometrics*. 3rd ed. Addison-Wesley, New York.

Tian, J. and Pearl, J. (2002). A general identification condition for causal effects. In *Pro- ceedings of the Eighteenth National Conference on Artificial Intelligence*. AAAI Press/The MIT Press, Menlo Park, CA, 567–573.

Verma, T. (1993). Graphical aspects of causal models. Tech. Rep. R-191, UCLA, Computer Science Department.

Verma, T. and Pearl, J. (1990). Equivalence and synthesis of causal models. In *Pro- ceedings of the Sixth Conference on Uncertainty in Artificial Intelligence*. Cambridge, MA. Also in P. Bonissone, M. Henrion, L.N. Kanal and J.F. Lemmer (Eds.), *Uncertainty in Artificial Intelligence 6*, Elsevier Science Publishers, B.V., 255–268, 1991.

Wermuth, N. (1992). On block-recursive regression equations. *Brazilian Journal of Probability and Statistics* (with discussion) **6** 1–56.

White, H. and Chalak, K. (2009). Settable systems: An extension of pearl's causal model with optimization, equilibrium and learning. *Journal of Machine Learning Research* **10** 1759–1799.

Wooldridge, J. (2009) Should instrumental variables be used as matching variables? Tech. Rep.<https://www.msu.edu/~ec/faculty/wooldridge/current%20research/treat1r6.pdf> Michigan State University, MI

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