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Working Paper

Proxy variables and nonparametric identification of causal effects

Working Paper, No. 2016:12

Provided in Cooperation with:

IFAU - Institute for Evaluation of Labour Market and Education Policy, Uppsala

Suggested Citation: DeLuna, Xavier; Fowler, Philip; Johansson, Per-Olov (2016) : Proxy variables and nonparametric identification of causal effects, Working Paper, No. 2016:12, Institute for Evaluation of Labour Market and Education Policy (IFAU), Uppsala

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ISSN 1651-1166

Proxy variables and nonparametric identification of causal effects^a

by

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June 30, 2016

Abstract

Proxy variables are often used in linear regression models with the aim of removing potential confounding bias. In this paper we formalise proxy variables within the potential outcome framework, giving conditions under which it can be shown that causal effects are nonparametrically identified. We characterise two types of proxy variables and give concrete examples where the proxy conditions introduced may hold by design.

Keywords: average treatment effect, observational studies, potential outcomes, unobserved confounders

JEL-codes: C14

^aWe are grateful to Ingeborg Waernbaum and Inga Laukaityte for helpful comments that have improved the paper. Financial support from the Swedish Council for Working Life and Social Research (DNR 2009-0826) is gratefully acknowledged.

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1 Introduction

Proxy variables are often used in empirical economics and other empirical sciences as substitutes for unobserved confounders when conducting observational studies. However, using substitute variables does not necessarily reduce bias due to confounding to zero and may even increase bias (Frost 1979). Thus, we call herein proxy variables only such substitute variables which yield identification of a causal effect of interest. Proxy variables have previously been defined in the literature in the context of linear models, using for instance linear projection orthogonality conditions; see Wooldridge (2010, pp. 67–72).

In this note we formalise proxy variables within the potential outcome framework (Imbens and Wooldridge 2009), giving conditions for which it can be shown that causal effects are nonparametrically identified. This allows us to clarify the use of proxy variables in a general context. Moreover, our approach also allows us to characterise two types of proxy variables, one directly related to the earlier definition mentioned above, and a new type of proxy variable not previously considered in the literature. We also give examples where the proxy conditions introduced may hold by design.

2 Theory on proxy variables

We consider a study with the aim to evaluate the effect of a binary treatment T on an outcome Y . Let Y_1 and Y_0 be potential outcomes if treated ($T = 1$) and not treated ($T = 0$), respectively, \mathbf{X} a set of observed pre-treatment covariates related to T and Y (observed confounders), and \mathbf{U} a set of unobserved pre-treatment covariates also related to T and Y (unobserved confounders). We assume that the observed outcome for any given unit is $Y = TY_1 + (1 - T)Y_0$, i.e. that the consistency and the stable unit treatment value assumption hold (see Rubin 1980). Letting $A \perp\!\!\!\perp B \mid C$ denote that A is conditionally independent of B given C (Dawid 1979), the following assumptions are used in the sequel.

Assumption 1 (Unconfoundedness).

$$i) \quad T \perp\!\!\!\perp Y_0 \mid (\mathbf{X}, \mathbf{U}),$$

$$ii) \quad T \perp\!\!\!\perp Y_1 \mid (\mathbf{X}, \mathbf{U}).$$

Assumption 2 (Common support).

- i) $\Pr(T = 0 \mid \mathbf{X}, \mathbf{U}) > 0$,
- ii) $\Pr(T = 1 \mid \mathbf{X}, \mathbf{U}) > 0$.

If in Assumptions 1 and 2 the set of unobserved covariates \mathbf{U} is empty, then the average causal effect $\tau = E(Y_1 - Y_0)$ and the average causal effect on the treated $\tau^t = E(Y_1 - Y_0 \mid T = 1)$ are identified. While if \mathbf{U} is empty only for Assumptions 1*i* and 2*i* then only τ^t is identified (Imbens and Wooldridge 2009).

In observational studies, it may be the case that, although \mathbf{U} is not observed, we have observed variables which may act as proxies for \mathbf{U} . We now give conditions characterising proxy variables useful for identification of average causal effects. Let \mathbf{P} denote a non-empty set of pre-treatment variables not included in the covariate sets defined so far, $\mathbf{P} \not\subseteq \{\mathbf{X}, \mathbf{U}\}$, and let \mathbf{U} be non-empty such that $Y_0 \not\perp T \mid \mathbf{X}$ and/or $Y_1 \not\perp T \mid \mathbf{X}$. A proxy variable will then need to satisfy $Y_0 \perp T \mid (\mathbf{X}, \mathbf{P})$ (and $Y_1 \perp T \mid (\mathbf{X}, \mathbf{P})$) in order for τ^t (τ) to be identified. A set of conditions describing useful proxy properties for \mathbf{P} are as follows.

Assumption 3 (Proxy Type I).

$$\begin{array}{l} \text{[irrelevance for outcome]} \quad \text{[proxy property]} \\ \hline \text{i) } Y_0 \perp (T, \mathbf{P}) \mid (\mathbf{X}, \mathbf{U}) \quad \text{iii) } T \perp \mathbf{U} \mid (\mathbf{X}, \mathbf{P}) \\ \text{ii) } Y_1 \perp (T, \mathbf{P}) \mid (\mathbf{X}, \mathbf{U}) \end{array}$$

This first type of proxy is similar in spirit to Wooldridge's (2010) definition of proxy variables. A proxy variable of Type I is an irrelevant variable for explaining the potential outcomes given the confounders \mathbf{X}, \mathbf{U} (Assumptions 3*i–ii*). A variable irrelevant for the outcome is useful for identification (see Proposition 1 below) when it makes \mathbf{U} irrelevant for the treatment (Assumption 3*iii*).

We consider further another type of useful proxy variable, which to our knowledge has not been formalised in the literature.

Assumption 4 (Proxy Type II).

$$\begin{array}{cc} \text{[irrelevance for treatment]} & \text{[proxy property]} \\ \hline i) \quad T \perp\!\!\!\perp (Y_0, \mathbf{P}) \mid (\mathbf{X}, \mathbf{U}) & iii) \quad Y_0 \perp\!\!\!\perp \mathbf{U} \mid (\mathbf{X}, \mathbf{P}) \\ ii) \quad T \perp\!\!\!\perp (Y_1, \mathbf{P}) \mid (\mathbf{X}, \mathbf{U}) & iv) \quad Y_1 \perp\!\!\!\perp \mathbf{U} \mid (\mathbf{X}, \mathbf{P}) \end{array}$$

Thus, a proxy variable of Type II is such that it is irrelevant for explaining the treatment assignment given the confounders (\mathbf{X}, \mathbf{U}) (Assumptions 4*i–ii*). A variable irrelevant for the treatment is useful for identification (see Proposition 2 below) when it makes \mathbf{U} irrelevant for the outcome (Assumptions 4*iii–iv*).

We will also need an extension of the common support assumption for identification purposes.

Assumption 5 (support on proxy).

$$\begin{array}{l} i) \quad \Pr(T = 0 \mid \mathbf{X}, \mathbf{P}) > 0, \\ ii) \quad \Pr(T = 1 \mid \mathbf{X}, \mathbf{P}) > 0. \end{array}$$

Lemma 1 (Dawid (1979)). *For any variables A, B, C and D , it follows that:*

$$A \perp\!\!\!\perp B \mid C \text{ and } A \perp\!\!\!\perp D \mid (B, C) \iff A \perp\!\!\!\perp (D, B) \mid C.$$

Proposition 1. *If Assumptions 3*i*, 3*iii*, and 5*i* hold, then τ^t is identified. Moreover, if also Assumptions 3*ii* and 5*ii* hold, then both τ and τ^t are identified.*

Proof. By Lemma 1 we have that

$$T \perp\!\!\!\perp \mathbf{U} \mid (\mathbf{X}, \mathbf{P}) \text{ and } T \perp\!\!\!\perp Y_0 \mid (\mathbf{U}, \mathbf{X}, \mathbf{P}) \iff T \perp\!\!\!\perp (Y_0, \mathbf{U}) \mid (\mathbf{X}, \mathbf{P}). \quad (1)$$

The first part of the left-hand side of (1) holds by Assumption 3*iii*. The second part of the left-hand side of (1) holds by Assumption 3*i*, using Lemma 1 to note that $Y_0 \perp\!\!\!\perp (T, \mathbf{P}) \mid (\mathbf{X}, \mathbf{U}) \Rightarrow Y_0 \perp\!\!\!\perp T \mid (\mathbf{U}, \mathbf{X}, \mathbf{P})$. Since the left-hand side of (1) holds, it follows that $T \perp\!\!\!\perp (Y_0, \mathbf{U}) \mid (\mathbf{X}, \mathbf{P})$, which by Lemma 1 implies that $T \perp\!\!\!\perp Y_0 \mid (\mathbf{X}, \mathbf{P})$. Thus, that Assumption 5*i* holds yields identification of τ^t . Similarly, if Assumption 3*ii* holds, then $T \perp\!\!\!\perp Y_1 \mid (\mathbf{X}, \mathbf{P})$. Finally, if Assumptions 3 and 5 hold, then τ is identified. ■

Proposition 2. *If Assumptions 4i, 4iii, and 5i hold, then τ^t is identified. Moreover, if also Assumptions 4ii, 4iv, and 5ii hold, then both τ and τ^t are identified.*

Proof. The proof is similar to the proof of Proposition 1 and thus omitted. ■

3 Proxy variables by design

Proxy variables may be obtained by design and here we give some examples. For the sake of simplicity, we focus on univariate proxy variables P in the sequel.

3.1 Proxy Type I: outcome prediction

We characterise here a natural situation where a proxy of Type I arises. Let

$$Y_0 = h(\mathbf{X}, \mathbf{U}) + \varepsilon_Y, \quad (2)$$

where ε_Y is exogenous and $h(\mathbf{X}, \mathbf{U}) = E(Y_0 | \mathbf{X}, \mathbf{U})$. Assume that a prediction P of Y_0 , made before the treatment assignment, is available such that

$$P = h(\mathbf{X}, \mathbf{U}) + \varepsilon_P, \quad (3)$$

where $\varepsilon_P \perp (\mathbf{X}, \mathbf{U}, Y_0)$ and $E(\varepsilon_P) = 0$, i.e. the prediction is unbiased. Consider further a study design where the treatment assignment is a function of P and \mathbf{X} as follows:

$$T^* = k(P, \mathbf{X}) + \varepsilon_T, \quad (4)$$

for some function $k(\cdot)$, with ε_T exogenous and where $Var(\varepsilon_T) > 0$. Let the treatment assignment be such that $T = 1$ if $T^* > 0$ and $T = 0$ otherwise. By exogeneity of ε_Y , we have that $Y_0 \perp (T, P) | (\mathbf{X}, \mathbf{U})$, i.e. Assumption 3i holds. Also, $T \perp \mathbf{U} | (\mathbf{X}, P)$ by design, i.e., Assumption 3iii is fulfilled. Suppose further that $k(\cdot)$ and ε_T are chosen in such a way that Assumption 5i is fulfilled. Note that the design error ε_T is necessary in order for $Pr(T = 0 | \mathbf{X}, P) > 0$. Then τ^t is identified by Proposition 1.

Example 1 (Outcome prediction proxy by design). Consider the situation where a treatment T is a social program for the unemployed, whose effect on duration to employ-

ment, Y , we want to evaluate. Suppose treatment is assigned by case workers after interviews with eligible individuals. A set of individual and labor market characteristics \mathbf{X} are recorded at the time of the interview. At that time, the case worker also makes a prediction P of the unemployment duration, would the individual not be assigned to treatment (i.e., a prediction of Y_0). Then, arguably the case workers will provide an unbiased prediction of Y_0 , based on \mathbf{X} and other unobserved information \mathbf{U} obtained at interview, i.e. such that (2–3) hold. Furthermore, if we believe that P summarises all information in \mathbf{U} necessary to make the treatment assignment decision, such that (4) holds, then P is a proxy of Type I. In practice, the latter statement may be difficult to ensure by design and an analysis of the sensitivity to Assumption 3iii may be useful.

3.2 Proxy Type II: lagged outcome

A Type II proxy variable may be available in a follow up setting with three time periods, $t = 0, 1, 2$. Assume that the outcome Y is observed at time $t = 2$. Further, let \mathbf{X} and \mathbf{U} be defined at baseline ($t = 0$), with \mathbf{X} potentially including the outcome measured at $t = 0$. We also observe the outcome at $t = 1$, denoted Y^l , simultaneously as treatment T is assigned. Then, with such a design it may be realistic to assume that

$$\begin{aligned} Y^l &= l(\mathbf{X}, \mathbf{U}) + \varepsilon_L, & T^* &= m(\mathbf{X}, \mathbf{U}) + \varepsilon_T, \\ T &= 1 \text{ if } T^* > 0 \text{ and } T = 0 \text{ otherwise,} \end{aligned}$$

for some functions $l(\cdot)$ and $m(\cdot)$ and where ε_L and ε_T are exogenous error terms. Furthermore, if we have

$$Y_0 = q(\mathbf{X}, Y^l) + \varepsilon_Y, \tag{5}$$

for some function $q(\cdot)$ and where the error term ε_Y is exogenous, then $T \perp (Y^l, Y_0) \mid (\mathbf{X}, \mathbf{U})$. Thus, by design $P = Y^l$ fulfills Assumption 4i, i.e. Y_l is irrelevant for the treatment assignment T . Moreover, $Y_0 \perp \mathbf{U} \mid (\mathbf{X}, Y^l)$, i.e. Assumption 4iii also holds. The validity of (5) should be investigated through a sensitivity analysis. Finally, to guarantee that 5i holds here, a sufficient condition is that Assumption 2 holds together with $Pr(\mathbf{U} \mid \mathbf{X}, Y^l) > 0$.

Example 2 (Lagged outcome proxy design). An example of a lagged outcome proxy design is given in Wooldridge (2010, Ex. 4.4), where data on Michigan manufacturing firms are discussed with the purpose to estimate the effect of job training grants (T) on firms' productivity. A factor giving a measure of the latter is log scrap rate (number of items out of 100 that must be scrapped), here denoted by Y . Wooldridge used years 1988 and 1987 for the purpose of illustration, that is where T and outcome Y are measured in 1988, and argued that Y_{87} (log scrap rate in 1987) is a proxy of Type I, i.e. in our framework such that $T \perp\!\!\!\perp U \mid Y_{87}$, where U represents unobserved productivity factors. However, one may arguably think that it is more realistic to view Y_{87} as a proxy of Type II, i.e. such that $Y \perp\!\!\!\perp U \mid Y_{87}$.

4 Parametric modelling

We now turn our attention to a linear model where a variable P is a proxy variable of Type I. Suppose that we have potential outcomes such that:

$$Y_0 = \alpha_0 + \boldsymbol{\beta}'_0 \mathbf{X} + \gamma U + \varepsilon_0, \quad (6)$$

$$Y_1 = \alpha_1 + \boldsymbol{\beta}'_1 \mathbf{X} + \gamma U + \varepsilon_1, \quad (7)$$

where ε_j , $j = 0, 1$, are exogenous variables with mean zero and independent of each other. Let P be such that (3) holds. Then $Y_j \perp\!\!\!\perp (P, T) \mid (\mathbf{X}, U)$, $j = 0, 1$, and Assumptions 3i–ii are fulfilled.

By Lemma 1 it follows from Assumption 3 that $Y_j \perp\!\!\!\perp P \mid (\mathbf{X}, U, T)$, $j = 0, 1$. By consistency it follows that $Y \perp\!\!\!\perp P \mid (\mathbf{X}, U, T)$. This implies that $E(Y \mid T, \mathbf{X}, U, P) = E(Y \mid T, \mathbf{X}, U)$, which is in analogy with the redundancy condition in Wooldridge (2010, p. 68). Furthermore, let

$$U = E(U \mid \mathbf{X}, P) + r, \quad (8)$$

where $E(U \mid \mathbf{X}, P) = \boldsymbol{\theta}_0 + \boldsymbol{\theta}' \mathbf{X} + \phi P$ and assume that $r \perp\!\!\!\perp T \mid (\mathbf{X}, P)$. Then, $U \perp\!\!\!\perp T \mid (\mathbf{X}, P)$, i.e. P fulfills Assumption 3iii. Given (8) it also follows that $L(U \mid 1, \mathbf{X}, P, T) = L(U \mid 1, \mathbf{X}, P)$, where $L(A \mid B)$ is the linear projection of A on B . This corresponds to condition

(4.26) in Wooldridge (2010, p. 68). In summary, in this situation P is a proxy of Type I and a proxy as defined by Wooldridge (2010). If Assumption 5 holds, then, by Proposition 1, τ is identified. Note however that if γ in (6) and (7) instead is γ_0 and γ_1 respectively, then identification is not achieved through a linear model.

5 Discussion

Proxies are often used in empirical economics in order to block unobserved confounding in observational studies. In this paper we have given formal conditions under which proxies yield nonparametric identification of average causal effects.

In many applications, an unobserved characteristic is replaced by an observed variable believed to be a function of the former, in the spirit of (3). For example, in Wooldridge (2010, Ex. 4.3), ability is replaced by IQ. The key issue is whether such a variable is a proxy as defined in this article, and in particular whether Assumption 3iii holds or not. In the ability-IQ situation, it seems reasonable to believe that $IQ = fct(\text{Ability}) + \varepsilon_{IQ}$. However, assuming that $T^* = fct(IQ) + \varepsilon_T$ (in the sense of (4)) is not realistic since one would instead expect $T^* = fct(\text{Ability}) + \varepsilon_T$ to hold. Thus, IQ is not a proxy as defined herein, but rather a measure of ability with error. Conditioning on the latter may yield bias; see Pearl (2010).

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