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Dynamic treatment effects[☆]

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ABSTRACT

This paper develops robust models for estimating and interpreting treatment effects arising from both ordered and unordered multi-stage decision problems. Identification is secured through instrumental variables and/or conditional independence (matching) assumptions. We decompose treatment effects into direct effects and continuation values associated with moving to the next stage of a decision problem. Using our framework, we decompose the IV estimator, showing that IV generally does not estimate economically interpretable or policy-relevant parameters in prototypical dynamic discrete choice models, unless policy variables are instruments. Continuation values are an empirically important component of estimated total treatment effects of education. We use our analysis to estimate the components of what LATE estimates in a dynamic discrete choice model.

1. Introduction

This paper develops a robust empirical framework for estimating treatment effects arising from multi-stage decision models and interpreting them using economic theory. The bulk of the empirical treatment effect literature estimates models for binary choices. Although there is research on treatment effects for multiple choices,[3] little analysis has been done for models of dynamic treatment effects.[4] Yet, much of economics is about dynamic choices and their consequences.

Fig. 1 presents a schematic for one simple multi-stage choice model we analyze. It is in the form of the ordered choice model that is implicit in the multi-stage analysis of Angrist and Imbens (1995).[5] The stages could correspond to a sequence of educational choices. All agents start at stage "0". Some transit to "1", while others stay at "0" forever, and some of those who go to "1"

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3 See Heckman and Vytlacil (2007b) and Heckman and Pinto (2015a).

4 See, however, Murphy (2003) and Heckman and Navarro (2007). This paper builds on the analysis reported in the latter reference. Angrist and Imbens (1995) develop a statistical model for multiple treatment effects that can be applied to a dynamic choice setting. Their paper identifies a LATE for an ordered choice model. (See Vytlacil, 2006a,b.) We identify a more general range of parameters for both ordered and unordered models.

5 See Vytlacil (2006a,b) who establishes the equivalence between the two representations.

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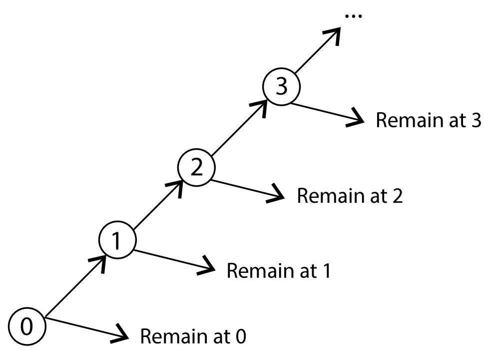

Fig. 1. An ordered multi-stage dynamic decision model.

stop there while others go on, etc. At each stage, agents update their information sets and decide whether or not to transit to the next stage. Associated with each final stage is a set of potential outcomes. After we analyze this simple ordered model, we analyze a more general unordered model.

A large econometric literature analyzes dynamic discrete choice.[6] These models tightly parameterize agent decision rules using the Bellman equation and generally rely on strong functional form assumptions and computationally intensive methods to secure their estimates.[7] The complexity of the computational methods employed often makes replication and sensitivity analyses with these models difficult. In many applications, the sources of identification are not clear.[8] Rust (1994) shows that an important class of these models is nonparametrically non-identified.[9] Blevins (2014) shows how adding continuous state variables aids in securing nonparametric identification.

This paper steps back from the structural literature and presents a computationally tractable yet economically interpretable framework that enables analysts to identify their models, conduct sensitivity analyses, and test some of the key assumptions maintained in the dynamic discrete choice literature. At the same time, it extends the treatment effect literature by considering dynamic treatment regimes, and by introducing choice-theoretic underpinnings.

This paper builds on and extends the literature on the Marginal Treatment Effect (MTE) that unifies the treatment effect literature with economics without imposing strong functional form assumptions or assumptions about specific decision rules adopted by agents.[10] Empirical applications of the MTE focus on binary choices. Extensions of IV to ordered choice models and more general unordered multi-state choice models demonstrate the need to incorporate explicit choice theory into analyses in order to identify a range of economically interpretable treatment effects beyond LATE parameters.[11] Previous analyses based on MTE and LATE rely exclusively on instrumental variables to identify parameters.

This paper extends the literature by using conditional independence assumptions as well as instrumental variable assumptions as possible sources of identification. Conditional independence assumptions are used extensively in the dynamic discrete choice literature (see, e.g., Rust, 1994 and Blevins, 2014) and the matching literature (see, e.g., Rosenbaum and Rubin, 1983). They are especially well motivated if analysts have rich data on the determinants of choices. We extend the matching literature by considering models with mismeasured match variables on which analysts have multiple measurements.

This paper also builds on previous analyses of dynamic treatment effects presented in Cunha et al. (2007) and Heckman and Navarro (2007). We implement and extend the ordered choice model of Cunha et al. (2007) to allow for general stage-specific cost and preference shocks associated with learning as well as dynamically inconsistent preferences (see, e.g., Laibson, 2003) and for an unordered choice model. Using our model we can test for the empirical relevance of *ex-post* regret. We extend the work of Heckman and Navarro (2007) by building a more explicit economic framework of dynamic treatment effects which decomposes them into direct effects and continuation values for both ordered and unordered models. Additionally, we link their work to the matching literature, and draw on recent advances in identifying factor models.

Our analysis links treatment effect models to state space models where analysts can proxy unobservables. The proxies can be the true values of variables measured with error as in factor models (see Schennach, 2013).

This paper proceeds in the following way. Section 2 presents models for ordered and unordered choice, and distinguishes the approach pursued in this paper from that pursued in the previous literature. Section 3 defines dynamic treatment effects and their decomposition into direct effects and continuation values as well as a variety of other economically interpretable treatment parameters. Section 4 discusses some identification criteria for these models. Section 5 uses these models to interpret what instrumental variables estimate. Section 6 presents empirical estimates of the causal effects of schooling on earnings, decomposing them into direct and continuation value components. It tests and rejects some key maintained assumptions in dynamic discrete choice theory, and compares estimates of economically interpretable parameters with LATE. We use our analysis to estimate what LATE can and cannot estimate in dynamic discrete choice models. When possible, we resolve LATE into economically interpretable components. Section 7 concludes.

2. Models for ordered and unordered dynamic discrete choice and associated outcomes

This paper develops a multi-stage ordered sequential choice model with transitions at the nodes shown in Fig. 1. For specificity, it is useful to think of the nodes as corresponding to specific schooling levels through which individuals can transit or at which they can stop. An unordered model is analyzed after we analyze the ordered model depicted in Fig. 1. Let $\mathcal{J}$ denote an *ordered* set of possible terminal states. At each node there are only two possible choices: remain at j or transit to $j+1$. $D_j = 0$ if a person at j does not stop there and goes on to $j+1$. $D_j = 1$ if the person stops at j. $D_j \in \mathcal{D}$, the set of possible transition decisions that can be taken by the individual over the decision horizon. Let $\mathcal{S} = \{0, \ldots, \bar{s}\}$ denote the finite and bounded set of stopping states with $S = s$ if the agent stops at $s \in \mathcal{S}$, so $D_s = 1$. Define $\bar{s}$ as the highest attainable element in $\mathcal{S}$. We assume that the environment is time-stationary and decisions are irreversible.[12]

$Q_j = 1$ indicates that an agent *gets to* decision node j. $Q_j = 0$ if the person never gets there. The history of nodes visited by an agent can be described by the collection of the Q_j such that $Q_j = 1$.

6 See e.g. Rust (1994), Keane and Wolpin (1997), Cameron and Heckman (1998), Heckman and Navarro (2007), Cunha et al. (2007), Aguirregabiria (2010), and Blevins (2014).

7 See Adda and Cooper (2003) and Keane et al. (2011).

8 However, Taber (2000) and Blevins (2014) present nonparametric identification analyses under separability and conditional independence assumptions.

9 Magnac and Thesmar (2002) clarify and extend his analysis.

10 See Heckman and Vytlacil (1999, 2005, 2007a,b), Carneiro et al. (2010), and Eisenhauer et al. (2015b).

11 Heckman et al. (2006, 2008) and Heckman and Pinto (2015a).

12 This model is also analyzed in Cunha et al. (2007) and in Heckman and Navarro (2007).