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Fixed effects instrumental variables estimation in correlated random coefficient panel data models

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Abstract

We provide a set of conditions sufficient for consistency of a general class of fixed effects instrumental variables (FE-IV) estimators in the context of a correlated random coefficient panel data model, where one ignores the presence of individual-specific slopes. We discuss cases where the assumptions are met and violated. Monte Carlo simulations verify that the FE-IV estimator of the population averaged effect performs notably better than other standard estimators, provided a full set of period dummies is included. We also propose a simple test of selection bias in unbalanced panels when we suspect the slopes may vary by individual.

JEL classification: C23; C33

Keywords: Correlated random coefficient model; Population averaged effect; Average treatment effect; Fixed effects; Instrumental variables

1. Introduction

In both cross-section and panel data settings, there is substantial interest in estimating population averaged effects (PAEs), including average treatment effects (ATEs), in the correlated random coefficient (CRC) model. Models with both exogenous explanatory variables and endogenous regressors have been investigated in recent years. Angrist (1991) discusses the conditions for consistency of ATE estimates in models with binary endogenous variables and no exogenous covariates. A set of sufficient assumptions required for consistent ATE estimates with continuous endogenous regressors in a CRC model can be found in Wooldridge (2003). Both papers study estimation with random sampling from a cross-section.

The possibility that treatment effects might depend on individual-specific heterogeneity motivated Imbens and Angrist (1994). to introduce the "local ATE" (LATE) as an evaluation parameter, which provides a useful interpretation of the instrumental variables estimator when the effect of a binary treatment varies across units. That emphasis on LATE led to a reinterpretation of IV estimates in many empirical applications, and spurred

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a great deal of research on interpreting IV estimators in a variety of contexts. Heckman and Vytlacil (2005) provide a recent unification, including a discussion of whether we should be interested in parameters such as LATE.

The understanding that IV generally consistently estimates LATE in simple settings is useful, but often we are interested in estimating the expected effect for a randomly drawn unit from the underlying population. Plus, strict interpretation of LATE as the ATE among units induced into treatment by the switching of an instrumental variable—such as program eligibility—is limited to special cases. Here we study estimation of population average effects, or ATEs, in a general panel data model with heterogeneous slopes. By estimating population average effects we can easily estimate the aggregate effects of various policies, such as increasing the amount of job training among the population of manufacturing workers.

Wooldridge (2005a) studied general fixed effects estimators with strictly exogenous regressors in the CRC model with panel data, and derived conditions under which generalized fixed effects estimators—generalized in the sense that they sweep away unit-specific trends—are consistent for the PAE. In this paper, we study the model in Wooldridge (2005a) but, in addition to allowing correlation between the instruments and the unobserved heterogeneity, we allow some explanatory variables to be correlated with the idiosyncratic error. The main result is a set of sufficient conditions under which fixed effects instrumental variables (FE-IV) estimators consistently estimate the PAE, even when the individual-specific slopes are ignored. The results include the commonly used FE two stage least squares estimator (FE-2SLS) as a special case, but also more general FE-IV estimators that sweep away individual-specific time trends. The conditions are most likely to apply when the endogenous explanatory variables are continuous, as in Wooldridge (2003) for the cross-sectional case.

The remainder of the paper is organized as follows. In Section 2 we introduce the model and briefly review existing results. Section 3 contains the main consistency result, and Section 4 covers examples where the conditions will—and will not—hold. Section 5 contains a Monte Carlo study that shows how the FE-IV estimator, with a full set of time period dummies, outperforms its obvious competitors. The simulation results support the results in Sections 3 and 4.

In Section 6, we expand on earlier work by allowing the random trend part of the structural equation to be misspecified. Interestingly, it is still possible to estimate the averaged slopes under reasonable assumptions. Section 7 considers unbalanced panels, characterizes the nature of any sample selection problem, and proposes simple variable addition tests that can be used when the slopes are thought to be individual-specific. Section 8 contains a brief conclusion.

2. Model specification and previous results

The model of interest is a CRC model studied in Wooldridge (2005a). For a random draw i from the population, the model is

$$y_{it} = \mathbf{w}_t\mathbf{a}_i + \mathbf{x}_{it}\mathbf{b}_i + u_{it}, \quad t = 1, \ldots, T, \tag{2.1}$$

where y_{it} is a dependent variable, $\mathbf{w}_t$ is a $1 \times J$ vector of aggregate time variables, which we treat as nonrandom, $\mathbf{a}_i$ is a $J \times 1$ vector of individual-specific slopes on the aggregate variables, $\mathbf{x}_{it}$ is a $1 \times K$ vector of endogenous covariates that change across time, $\mathbf{b}_i$ is a $K \times 1$ vector of individual-specific slopes, and u_{it} is an idiosyncratic error. As discussed in Wooldridge (2005a), we require $J < T$. So, if we have two time periods, we can only allow a scalar individual-specific intercept, a_i. If $T = 3$, we can allow individual-specific linear trends, too. Higher order trend terms are allowed as T increases.

Eq. (2.1) is a CRC model when the individual specific slopes, $\mathbf{b}_i$ (as well as the elements in $\mathbf{a}_i$), are allowed to be correlated with $\mathbf{x}_{it}$. For example, a simple CRC wage equation might look like

$$\log(wage_{it}) = a_{i1} + a_{i2}t + b_{i1}training_{it} + b_{i2}union_{it} + b_{i3}married_{it} + u_{it}, \tag{2.2}$$

where, in addition to the standard level effect a_{i1}, each individual is allowed to have his or her own unobserved growth in wages, a_{i2}. In addition, the time-varying explanatory variables have individual-specific returns. The variable *training* might be hours spent in job training, and the CRC model allows the return to training to be individual-specific and correlated with the amount of training—as a standard model of human capital accumulation would suggest.