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Modelling optimal instrumental variables for dynamic panel data models ☆

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ABSTRACT

This paper considers a new two-stage instrumental variable estimator of panel data models with predetermined or endogenous explanatory variables. The instruments are fitted values from period-specific first-stage equations based on all available lags, which are similar to those in standard GMM estimation. The difference is that first-stage fitted values are not unrestricted but are chosen to satisfy the constraints implied by a VAR process with random effects. As a result the number of free first-stage parameters is dramatically reduced, while retaining predictive power from all lags. The estimators are asymptotically efficient when the VAR restrictions hold, but remain consistent if they do not. Since the instruments are parameterized using a fixed number of coefficients for any value of T, the properties of the resulting estimators are not fundamentally affected by the relative dimensions of T and N, contrary to standard panel GMM. Empirical illustrations are reported using firm- and country-level panel data.

1. Introduction

This paper considers a new instrumental variable method for estimating panel data models with general predetermined or endogenous explanatory variables. The instruments are fitted values from period-specific first-stage equations based on all available lags. First-stage coefficients are chosen to satisfy the constraints implied by a stable multivariate process. This is proposed as a framework for modelling optimal instruments in panel data analysis.

A popular method in dynamic panel data estimation is GMM, which is consistent in short panels, robust, has general applicability, and provides a well-defined notion of optimality (Holtz-Eakin et al., 1988; Arellano and Bond, 1991). However, in practice the application of GMM often entails too many moment conditions for acceptable sampling properties in either finite or large samples when the time series dimension is not fixed (Alvarez and Arellano, 2003).

For autoregressive models there are also available likelihood-based methods which exhibit better finite sample properties than GMM but can be seriously biased if certain auxiliary assumptions are violated. Moreover, these methods cannot be readily extended to cover models with endogenous or general predetermined variables.[1] There is therefore an acute robustness-efficiency trade-off in the choice among existing techniques. In addition, some methods are designed for short panels of large cross-sections, while others target long panels of small cross-sections, but there is a vacuum in between. The

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[1] Alvarez and Arellano (2004) and Moral-Benito (2013) developed likelihood-based estimators of autoregressive models and models with general predetermined variables, respectively, that are robust in the sense that remain fixed-T large-N consistent under the same assumptions as standard panel GMM techniques.

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literature does not seem to have much to offer to researchers interested in "small N, small T" panels or other panels that are not easily classifiable.

GMM estimators can be regarded as providing implicit models for the optimal instruments. The problem is that in the panel context these models are often overparameterized, leading to poor properties in finite samples and double asymptotics. This paper provides a framework for parsimonious modelling of optimal instruments in panel data, which is, first, coherent with the fixed T, large N perspective; second, has good theoretical properties in a double asymptotic setup, and thirdly provides estimators with the same robustness features as popular GMM methods. More research is needed on panel data methodology from a time series perspective, and this paper is intended as a contribution towards a marriage of the cross-sectional (fixed T) and time-series (long T) perspectives.

Recent results by Newey and Smith (2004) on the higher order properties of empirical likelihood (EL) and GMM indicate that panel EL estimators may exhibit better finite sample properties than their GMM counterparts. However, while the double asymptotic properties of panel EL estimation remain to be explored, the fact that a panel EL estimator will be inconsistent for fixed N, large T (as long as it is based on an increasing number of moment conditions) suggests that EL estimation will be less robust to double asymptotic plans than the instrumental variable methods considered in this paper.

The paper is organized as follows. Section 2 presents the model, links GMM with the parametric optimal-instrument perspective, and introduces projection-restricted simple IV estimation (SIV). Section 3 discusses the asymptotic biases of one-step GMM when both T and N tend to infinity. It is shown that the order of magnitude of the bias depends on whether the explanatory variables are predetermined or endogenous, and that in the latter situation GMM is inconsistent. In Section 4 we present an auxiliary random effects VAR model for the vector of instruments, and obtain sequential linear projections of the effects. Section 5 describes the form of optimal instruments and provides several examples. Section 6 considers pseudo maximum likelihood estimation (PML) of the auxiliary VAR model. Section 7 discusses the properties of feasible projection-restricted IV estimators with and without strictly endogenous variables, and the calculation of asymptotic standard errors. Section 8 contains empirical illustrations and Monte Carlo simulations. Section 8.1 reports estimates of autoregressive employment and wage equations from firm panel data; Section 8.2 presents the results of a simulation exercise calibrated to the previous firm panel, and Section 8.3 reports estimates of country growth convergence rates using a panel of 92 countries observed at five-year intervals. Finally, Section 9 ends with some concluding remarks and plans for future work. All proofs and technical details are contained in Appendices.

2. Model and optimal instruments: overview

2.1. A sequential conditional mean model

Let us consider a fixed effects panel data model of the form

$$y_{it} = x_{it}'\beta + \eta_i + \varepsilon_{it} \quad (t=1,\dots,T;\ \ i=1,\dots,N), \tag{1}$$

together with the conditional mean assumption

$$E(\varepsilon_{it}|z_i^t) \equiv E_t(\varepsilon_{it}) = 0 \tag{2}$$

where $z_i^t = (z_{i1}', \dots, z_{it}')'$ and $(y_i^T, x_i^T, z_i^T, \eta_i)$ are *iid* random variables; η_i represents an unobservable individual effect and z_{it} is a vector of instrumental variables.

The following remarks about the nature of the explanatory variables and the instruments are relevant. First, if an explanatory variable x_{kit} is predetermined for $\varepsilon_{i(t+j)}$, then $x_{ki(t-j)}$ is a component of z_{it}. Second, an x_{kit} may also be strictly endogenous in the sense of not being predetermined for any lead of ε. Finally, z_{it} may contain external instruments that are not part of x_{it} or its lags.

An example of this type of model is an equation from a VAR with individual effects. Other examples are partial adjustment equations with predetermined regressors, or a structural relationship between endogenous variables. As illustrations of the latter we consider below cross-country growth and household consumption Euler equations.

2.2. Information bound and optimal instruments

Since the distribution of $\eta_i|z_i^T$ is unrestricted, all information about β is in the conditional moments for the errors in differences or forward orthogonal deviations

$$E_t(y_{it}^* - x_{it}^{*\prime}\beta) = E_t(\varepsilon_{it}^*) = 0 \quad (t=1,\dots,T-1) \tag{3}$$

where starred variables denote orthogonal deviations:

$$\varepsilon_{it}^* = \left(\frac{T-t}{T-t+1}\right)^{1/2}\left[\varepsilon_{it} - \frac{1}{(T-t)}(\varepsilon_{i(t+1)} + \cdots + \varepsilon_{iT})\right]. \tag{4}$$

The advantage of orthogonal deviations is that if ε_{it} is homoskedastic and serially uncorrelated so is ε_{it}^* (Arellano and Bover, 1995).

Two-wave panel: If $T=2$ there is just one equation in deviations (which coincides with first-differences):

$$E(y_{i1}^* - x_{i1}^{*\prime}\beta|z_i^1) = E_1(\varepsilon_{i1}^*) = 0 \tag{5}$$