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Tue Gørgens and Allan H. Würtz

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Department of Economics and Business Economics
Aarhus University
Fuglesangs Allé 4
DK-8210 Aarhus V
Denmark

Email: oekonomi@au.dk
Tel: +45 8716 5515

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Tue Gørgens[*] Allan H. Würtz[†]

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Abstract: This note considers the estimation of dynamic threshold regression models with fixed effects using short panel data. We examine a two-step method, where the threshold parameter is estimated nonparametrically at the N-rate and the remaining parameters are estimated by GMM at the $\sqrt{N}$-rate. We provide simulation results that illustrate the potential advantages of the new method in comparison with pure GMM estimation. The simulations also highlight the importance the choice of instruments in GMM estimation.

Highlights:

- Estimation of nonlinear dynamic panel data models with fixed effects.
- N-consistent nonparametric estimator of threshold parameters.
- Nonlinear transformations of lagged outcomes are useful instruments.

Keywords: Threshold regression; dynamic models; endogeneity; panel data; GMM estimation; integrated difference kernel IDK estimator; superconsistency.

JEL classification: C23, C24, C26.

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[*]Research School of Economics, The Australian National University, Acton ACT 2601, Australia. Email: tue.gorgens@anu.edu.au.

[†]CREATES and Department of Economics and Business Economics, Aarhus University, Fuglesangs Allé 4, DK-8210 Aarhus V, Denmark. Email: awurtz@econ.au.dk.

1 Introduction

Threshold regression models allow for shifts in economic relationships when the threshold variable crosses the threshold parameter. This note combines two recent econometric advances in estimating threshold regression models with endogeneity using short panel data sets.

Seo and Shin (2016) extended GMM estimation techniques for linear dynamic panel data models to threshold panel data models where both the regressors and the threshold variable may be endogenous. Their setup includes certain nonlinear dynamic panel data models such as the self-exciting threshold autoregressive (SETAR) model. We refer to this estimator as the pure GMM estimator. It has the usual properties, including $\sqrt{N}$-consistency and asymptotic normality, where N denotes the sample size.

Yu and Phillips (2018) considered the estimation of threshold regression models with endogenous regressors and threshold variable using i.i.d. data. They developed a (nonparametric) integrated difference kernel (IDK) estimator of the threshold parameter. They showed that the IDK estimator is N-consistent. Other parameters in the model can be estimated at the usual $\sqrt{N}$-rate by GMM, taking the estimated threshold parameter as given. The distribution of the IDK estimator is nonstandard.

We explain how the ideas of Yu and Phillips (2018) can be adapted to the panel data context to obtain an N-consistent estimator of the threshold parameter. The improvement in asymptotic efficiency of the threshold estimator spills over to the GMM estimators of the remaining parameters, since there is effectively one less parameter to estimate. Yu and Phillips (2018) considered a single structural equation with a single threshold variable. After eliminating the fixed effects by first-differencing, we have $T-2$ first-differenced structural equations, and each equation involves two threshold variables, where T denotes the number of time periods. We construct two estimators for each equation, and compute their overall average.

We conduct a small simulation study to illustrate the potential advantage of the IDK+GMM combination over pure GMM estimation and to investigate the importance of the choice of instruments. Even for estimating linear dynamic panel data models, the question of which moments to match remains largely unresolved (e.g. Ahn and Schmidt, 1995; Arellano, 2016). Seo and Shin (2016) and Yu and Phillips (2018) offered different ad hoc suggestions for threshold models. The simulations confirm that the IDK+GMM estimator tend to have much smaller root mean square errors (RMSE) than the pure GMM estimator. The simulations also show that large reductions in RMSE are available by adding nonlinear transformations of lagged outcomes to the standard set of instruments.

2 The SETAR panel data model

For conciseness, we focus on the SETAR model which is widely used in the time series literature (e.g. Tong and Lim, 1980). We comment on some extensions in the concluding remarks. For $i = 1, \ldots, N$ individuals and $t = 1, \ldots, T$ times, let y_{it} be a scalar observed random variable. The observations are assumed to be independent across individuals, but not across time. The basic SETAR panel data model is

$$\begin{aligned} y_{it} &= y_{it-1}\alpha_1^* + 1(y_{it-1} > \gamma^*)y_{it-1}\alpha_2^* + 1(y_{it-1} > \gamma^*)\alpha_3^* + u_{it}, \\ u_{it} &= c_i + v_{it}, \end{aligned} \qquad t = 2, \ldots, T, \tag{1}$$

where c_i is a time-invariant individual-specific unobserved random variable, and v_{it} is a time- and individual-specific unobserved random variable. The overall constant term is subsumed into c_i as usual. The lowercase Greek letters denote unknown parameters, and superscripts $*$ indicate "true" values. The threshold parameter is γ^*. For simplicity, define $\xi = (\gamma, \alpha_1, \alpha_2, \alpha_3)$. The parameter space consists of all $\xi \in \mathbb{R}^4$. Assume that all random variables have finite means and variances and that

$$\mathsf{E}(v_{it}|c_i, y_{i1}, \ldots, y_{it-1}) = 0, \quad t = 2, \ldots, T. \tag{2}$$

An additional smoothness assumption will be introduced in section 4.

3 GMM estimator

We begin with the pure GMM estimator. Assumption (2) implies that for any function $f : \mathbb{R} \times \mathbb{R}^4 \to \mathbb{R}$ we have

$$\mathsf{E}(f(y_{is}, \xi) v_{it}) = 0, \quad \forall \xi \in \mathbb{R}^4, \quad s = 1, \ldots, t-1, \quad t = 2, \ldots, T. \tag{3}$$

Assumption (2) therefore implies an abundance of moment restrictions that can be used to estimate the unknown parameters.

Suppose a finite set has been selected and stacked in a M-vector, say $p_{it}(\xi)$. Holtz-Eakin et al. (1988) and Arellano and Bond (1991) proposed a set of linear moment restrictions on the second moments of the data for the linear dynamic panel data model ($\alpha_2^* = 0$, $\alpha_3^* = 0$, and $p_{it}(\xi) = y_{it-2}$). Generalising their set to the present context gives

$$\mathsf{E}(p_{is}(\xi) \Delta u_{it}) = 0, \quad \forall \xi \in \mathbb{R}^4, \quad s = 1, \ldots, t-1, \quad t = 3, \ldots, T. \tag{4}$$

Han and Kim (2014) and Gørgens et al. (2016) pointed out that there are also useful restrictions on the first moments of the data; namely

$$\mathsf{E}(\Delta u_{it}) = 0, \quad t = 3, \ldots, T. \tag{5}$$

Note Δu_{it} and u_{iT} are defined using the true parameter values and expectations are taken using the true parameter values.

Define $y_i = (y_{i1}, \ldots, y_{iT})'$ and let $g(y_i, \xi)$ be a vector of random variables such that the stacked moment restrictions can be written as $\mathsf{E}[g(y_i, \xi^*)] = 0$. A GMM estimator of ξ^* is defined as the global minimiser, $\hat{\xi}$, of the GMM objective function,

$$\hat{Q}(\xi) = \left[N^{-1} \sum_{i=1}^{N} g(x_i, \xi) \right]' \hat{W} \left[N^{-1} \sum_{i=1}^{N} g(x_i, \xi) \right], \tag{6}$$

where $\hat{W}$ is a given weight matrix. The objective function attains its minimum on an interval of γ values. The ambiguity can be resolved by defining $\hat{\gamma}$ as the midpoint.

Despite nondifferentiability of the objective function with respect to γ, the asymptotic distribution of the GMM estimator is typically normal. Define the matrices $G = \mathsf{D}_\xi \mathsf{E}[g(x_i, \xi^*)]$ and $\Omega = \mathsf{E}(g(y_i, \xi^*)g(y_i, \xi^*)')$, where D_ξ denotes the partial derivative. Seo and Shin (2016) proved that if $\hat{W} \to^p \Omega^{-1}$, $G'\Omega^{-1}G$ is nonsingular, and other regularity conditions are satisfied, then

$$\sqrt{N}(\hat{\xi} - \xi^*) \to^d \mathrm{N}(0, (G'\Omega^{-1}G)^{-1}). \tag{7}$$

In particular, the GMM estimator is $\sqrt{N}$-consistent.

4 IDK estimator

After first-differencing the structural equation (1) and taking the conditional expectation, we get

$$\begin{aligned} \mathsf{E}(\Delta y_{it}|y_{it-2}, y_{it-1}) = \Delta y_{it-1}\alpha_1^* + 1(y_{it-1} > \gamma^*)(y_{it-1}\alpha_2^* + \alpha_3^*) \\ - 1(y_{it-2} > \gamma^*)(y_{it-2}\alpha_2^* + \alpha_3^*) + \mathsf{E}(\Delta v_{it}|y_{it-2}, y_{it-1}), \quad t = 3, \ldots, T. \end{aligned} \tag{8}$$

The idea of the IDK estimator is to exploit the discontinuities that occur when y_{it-1} or y_{it-2} are near γ^*. To rule out discontinuities occurring elsewhere, in addition to (2) assume that

$$\mathsf{E}(\Delta v_{it}|y_{it-2} = a, y_{it-1} = b) \text{ is continuous in } (a, b), \quad t = 3, \ldots, T. \tag{9}$$

Let γ^- and γ^+ indicate limits from below and above, and define the functions A_t and B_t by

$$A_t(y, \gamma) = \mathsf{E}(\Delta y_{it}|y_{it-2} = y, y_{it-1} = \gamma^+) - \mathsf{E}(\Delta y_{it}|y_{it-2} = y, y_{it-1} = \gamma^-), \quad t = 3, \ldots, T, \tag{10}$$

and

$$B_t(\gamma, y) = \mathsf{E}(\Delta y_{it} | y_{it-2} = \gamma^-, y_{it-1} = y) - \mathsf{E}(\Delta y_{it} | y_{it-2} = \gamma^+, y_{it-1} = y),$$
$$t = 3, \ldots, T. \quad (11)$$

By (9) we have

$$A_t(y, \gamma) = B_t(\gamma, y) = \{1(\gamma^+ > \gamma^*) - 1(\gamma^- > \gamma^*)\}(\gamma^* \alpha_2^* + \alpha_3^*)$$
$$= \begin{cases} 0 & \text{if } \gamma \neq \gamma^*, \\ \gamma^* \alpha_2^* + \alpha_3^* & \text{if } \gamma = \gamma^*, \end{cases} \quad t = 3, \ldots, T. \quad (12)$$

Note that $\gamma^* = \arg\max_\gamma A_t(y, \gamma)^2$ and $\gamma^* = \arg\max_\gamma B_t(y, \gamma)^2$ for all $y \in \mathbb{R}$. Furthermore, $\gamma^* \alpha_2^* + \alpha_3^* \neq 0$ is a necessary condition for (12) to uniquely identify γ^*.

To achieve N-consistency, our estimators of γ^* are based on taking a density-weighted average of A_t and B_t. Let r_t denote the joint density of (y_{it-2}, y_{it-1}) and let p_t denote the marginal density of y_{it}. Define R_t^A by

$$R_t^A(\gamma) = \mathsf{E}\big[A_t(y_{it-2}, \gamma)^2 r_t(y_{it-2}, \gamma)^2\big] = \int_{-\infty}^{\infty} A_t(y, \gamma)^2 r_t(y, \gamma)^2 p_{t-2}(y)\, dy,$$
$$t = 3, \ldots, T, \quad (13)$$

and R_t^B by

$$R_t^B(\gamma) = \mathsf{E}\big[B_t(\gamma, y_{it-1})^2 r_t(\gamma, y_{it-1})^2\big] = \int_{-\infty}^{\infty} B_t(\gamma, y)^2 r_t(\gamma, y)^2 p_{t-1}(y)\, dy,$$
$$t = 3, \ldots, T. \quad (14)$$

Then $\gamma^* = \arg\max_\gamma R_t^A(\gamma)$ and $\gamma^* = \arg\max_\gamma R_t^B(\gamma)$, provided certain regularity conditions hold, including that r_t is bounded away from 0 in an open neighbourhood where $y_{it-2} = \gamma^*$ or $y_{it-1} = \gamma^*$.

The estimators of R_t^A and R_t^B are implemented using generalised kernels. Let k be a univariate kernel function with support $[-1,1]$, and let h denote the bandwidth. To keep the notation simple, we use the same bandwidth everywhere. The empirical objective functions for estimating γ^* are

$$R_t^A(\gamma) = \frac{1}{N}\sum_{i=1}^{N}\Bigg(\frac{1}{N-1}\sum_{\substack{j=1\\ j\neq i}}^{N}\Delta y_{jt}K_h(y_{jt-2}-y_{it-2})k_h^+(y_{jt-1}-\gamma) - \frac{1}{N-1}\sum_{\substack{j=1\\ j\neq i}}^{N}\Delta y_{jt}K_h(y_{jt-2}-y_{it-2})k_h^-(y_{jt-1}-\gamma)\Bigg)^2, \quad t=3,\dots,T, \tag{15}$$

and

$$R_t^B(\gamma) = \frac{1}{N}\sum_{i=1}^{N}\Bigg(\frac{1}{N-1}\sum_{\substack{j=1\\ j\neq i}}^{N}\Delta y_{jt}K_h(y_{jt-1}-y_{it-1})k_h^-(y_{jt-2}-\gamma) - \frac{1}{N-1}\sum_{\substack{j=1\\ j\neq i}}^{N}\Delta y_{jt}K_h(y_{jt-1}-y_{it-1})k_h^+(y_{jt-2}-\gamma)\Bigg)^2, \quad t=3,\dots,T, \tag{16}$$

where

$$K_h(q) = \frac{1}{h}k\left(\frac{q}{h}\right), \tag{17}$$

$$k_h^-(q) = \frac{1(-1<\frac{q}{h}<0)\frac{1}{h}k(\frac{q}{h})}{\int_{-1}^{0}k(v)\,dv}, \tag{18}$$

$$k_h^+(q) = \frac{1(0<\frac{q}{h}<1)\frac{1}{h}k(\frac{q}{h})}{\int_{0}^{1}k(v)\,dv}. \tag{19}$$

Define the estimators $\hat{\gamma}_t^A = \arg\max_\gamma R_t^A(\gamma)$ and $\hat{\gamma}_t^B = \arg\max_\gamma R_t^B(\gamma)$ for $t = 3,\dots,T$. To improve efficiency, we construct an overall estimator $\hat{\gamma}$ by taking the average of all $\hat{\gamma}_t^A$ and $\hat{\gamma}_t^B$.

The setup here differs somewhat from that of Yu and Phillips (2018), who considered a single structural equation with a single threshold variable. Here we have $T-2$ first-differenced structural equations, and each equation involves two threshold variables. The latter means that it is necessary to condition on both y_{it-2} and y_{it-1} in (8), and gives rise to the two distinct estimators based on A_t and B_t, respectively. Whether there is a better way of combining the estimators than simply averaging is a topic for future research.

Yu and Phillips (2018) proved that the IDK estimator is N-consistent under certain regularity conditions. The asymptotic distribution is nonstandard. Their results apply directly to each of our estimators, $\hat{\gamma}_t^A$ and $\hat{\gamma}_t^B$ for $t = 3, \ldots, T$. Taking the overall average does not affect the N-consistency and reduces the variance.

Having estimated γ^*, the α^*s can be estimated in a second step at the $\sqrt{N}$-rate by GMM as described in section 3 after redefining $\xi = (\alpha_1, \alpha_2, \alpha_3)$. Since $\hat{\gamma}$ converges at the N-rate, the asymptotic distribution is the same as if γ^* is known.

5 Simulation results

To illustrate the potential advantage of the IDK+GMM estimator over pure GMM and to investigate the importance of the choice of instruments, we conducted a small simulation study for one of the designs used by Seo and Shin (2016). The DGP is defined in the table note. For simplicity, all results for the GMM estimators presented here are one-step estimators using the optimal weight matrix.

The top panel of table 1 shows our baseline results which use only the untransformed lagged outcome variables as instruments, as suggested by Seo and Shin (2016). The RMSE for the pure GMM estimator are monotonically decreasing at rates suggesting $\sqrt{N}$-consistency, as expected. The RMSE for the IDK+GMM estimator are much lower, especially for γ, and the convergence rates are compatible with N-consistency for γ and $\sqrt{N}$-consistency for the αs.

Given the disparate convergence rates we expect the RMSE ratio for γ to diverge, while the RMSE ratios for the αs should converge to finite limit values corresponding to the ratio of the asymptotic variances of the respective GMM estimators. The numbers shown in the right-most four columns in table 1 are compatible with these expectations. When $N = 800$, the efficiency gain for γ is huge, nearly a factor of 20. The gains for the αs are also large, with RMSE for pure GMM more than twice the RMSE for the IDK+GMM estimator.

In the remainder of table 1 we consider different sets of instruments. The second panel shows big reductions in RMSE for the pure GMM estimator when a constant term is also used as an instrument. Han and Kim (2014) and Gørgens et al. (2016) found similar improvements for the linear model. The improvements are relatively less for the IDK+GMM estimator.

Since the structural equation is nonlinear, one might expect that nonlinear transformations of lagged outcomes could be useful instruments. Based on the suggestion by Yu and Phillips (2018), we added $y_{it-1}1(y_{it-1}{>}\hat{\gamma})$ to the set of instruments. The third panel in table 1 shows that this does not improve the RMSE for the pure GMM estimator. On the contrary, the estimation noise in the instruments adds significantly to the RMSE. The results are more promising for the IDK+GMM estimator, where substantial reductions in RMSE are observed.

In the fourth panel, we have added quadratic and cubic transformations of the lagged dependent variable, and in the fifth panel we have added threshold functions where the threshold depends on percentiles of the data rather than the structural parameter. Compared to the baseline results in the first panel, when $N = 800$ the RMSE drop to less than a quarter for the pure GMM and to less than two fifths for the IDK+GMM estimator.

To conclude, it is clear that the IDK+GMM combination potentially offers a huge advantage over pure GMM estimation. Also, the last two panels in table 1 show that adding fixed nonlinear transformations of the lagged dependent variable can be highly effective when estimating nonlinear equations.

6 Concluding remarks

We have focused on the SETAR model in this note. A more general threshold regression panel data model is

$$\begin{aligned} y_{it} &= x_{it}'\alpha_1^* + 1(q_{it} > \gamma^*)x_{it}'\alpha_2^* + 1(q_{it} > \gamma^*)\alpha_3^* + u_{it}, \\ u_{it} &= c_i + v_{it}, \end{aligned} \qquad t = 1, \ldots, T, \tag{20}$$

where x_{it} is a vector of possibly endogenous variables, q_{it} is a possibly endogenous scalar variable, and α_1^*, α_2^* and α_3^* are conformable parameter vectors. It is straightforward to construct an IDK+GMM estimator analog to the SETAR case, and similar efficiency gains are available.

The IDK estimator we have described utilises discontinuities in the conditional expectation function given in (8). It will fail if $\gamma^*\alpha_2^* + \alpha_3^* = 0$, because then (8) is continuous. However, in this case the partial derivatives of (8) may be discontinuous at $y_{it-2} = \gamma^*$ or $y_{it-1} = \gamma^*$, so IDK estimation is still possible (e.g. Yu and Phillips, 2018; Porter and Yu, 2015).

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Table 1: Simulation results

N	RMSE pure GMM				RMSE IDK+GMM				Pure / IDK			
	γ	α_1	α_2	α_3	γ	α_1	α_2	α_3	γ	α_1	α_2	α_3
Instruments: y_{it-1}												
50	0.47	0.30	0.57	1.45	0.07	0.24	0.33	0.58	6.6	1.3	1.8	2.5
100	0.39	0.26	0.48	1.10	0.04	0.19	0.27	0.47	9.0	1.3	1.8	2.3
200	0.36	0.23	0.44	1.09	0.03	0.15	0.21	0.38	14.1	1.6	2.1	2.8
400	0.31	0.20	0.38	0.85	0.01	0.11	0.16	0.30	21.1	1.8	2.4	2.9
800	0.22	0.17	0.30	0.47	0.01	0.08	0.12	0.23	27.6	2.1	2.6	2.1
Instruments: constant, y_{it-1}												
50	0.37	0.25	0.45	1.11	0.07	0.21	0.28	0.54	5.3	1.2	1.6	2.0
100	0.31	0.21	0.36	0.77	0.04	0.17	0.23	0.45	7.2	1.2	1.6	1.7
200	0.28	0.19	0.35	0.81	0.03	0.13	0.17	0.37	10.9	1.4	2.0	2.2
400	0.24	0.16	0.30	0.55	0.01	0.10	0.13	0.29	16.4	1.6	2.4	1.9
800	0.18	0.13	0.25	0.47	0.01	0.07	0.09	0.22	22.4	1.9	2.7	2.1
Instruments: constant, y_{it-1}, $y_{it-1}1(y_{it-1}>\hat{\gamma})$												
50	0.56	0.37	0.70	1.95	0.07	0.15	0.17	0.46	7.9	2.5	4.2	4.2
100	0.52	0.34	0.61	1.72	0.04	0.12	0.12	0.38	12.3	2.8	5.2	4.6
200	0.50	0.29	0.56	1.63	0.03	0.10	0.08	0.31	19.2	3.0	7.1	5.2
400	0.42	0.26	0.47	1.24	0.01	0.08	0.05	0.25	28.8	3.3	9.0	4.9
800	0.38	0.23	0.44	1.10	0.01	0.06	0.03	0.20	47.3	4.0	12.5	5.6
Instruments: constant, y_{it-1}, y_{it-1}^2, y_{it-1}^3												
50	0.15	0.14	0.21	0.40	0.07	0.13	0.17	0.33	2.2	1.1	1.2	1.2
100	0.09	0.10	0.14	0.24	0.04	0.09	0.12	0.23	2.2	1.1	1.2	1.0
200	0.06	0.07	0.10	0.16	0.03	0.06	0.08	0.16	2.4	1.1	1.3	1.0
400	0.05	0.05	0.07	0.12	0.01	0.04	0.05	0.11	3.1	1.2	1.4	1.0
800	0.04	0.04	0.06	0.08	0.01	0.03	0.04	0.08	4.6	1.3	1.6	1.0
Instruments: constant, y_{it-1}, $y_{it-1}1(y_{it-1}>y_{0.33})$, $y_{it-1}1(y_{it-1}>y_{0.67})$												
50	0.06	0.13	0.16	0.26	0.07	0.12	0.16	0.28	0.9	1.0	1.0	0.9
100	0.05	0.09	0.12	0.19	0.04	0.08	0.11	0.19	1.1	1.1	1.1	1.0
200	0.04	0.07	0.10	0.14	0.03	0.06	0.07	0.14	1.7	1.2	1.3	1.0
400	0.04	0.06	0.07	0.11	0.01	0.04	0.05	0.10	2.5	1.3	1.5	1.0
800	0.03	0.05	0.06	0.08	0.01	0.03	0.03	0.07	4.2	1.5	1.9	1.1

RMSE: root mean square error; y_q: percentile q of y_{it}. The DGP is $\gamma^* = 0$, $\alpha_1^* = -0.5$, $\alpha_2^* = 1.2$, $\alpha_3^* = -2.5$, $c_i = 0.7$, $v_{it} \sim \text{Normal}(0,1)$, and $y_{i,-30} \sim \text{Normal}(0,1)$. The estimations use data for $1 \leq t \leq 10$. All experiments have 5000 simulated samples. The bandwidths are 6.5 times the standard deviation of regressors.

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