# Moment Conditions for Dynamic Panel Logit Models with 

 Fixed Effectswith Martin Weidner (Oxford)

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## Econometric Motivation: Nonlinear Panel Data Models

A dependent variable in time period $t, Y_{i t}$, is modelled as

$$
Y_{i t} \sim f\left(\cdot \mid X_{i}^{T}, Y_{i}^{t-1}, A_{i} ; \theta\right) \quad \text { or } \quad Y_{i t} \sim f\left(\cdot \mid X_{i}^{t}, Y_{i}^{t-1}, A_{i} ; \theta\right)
$$

- Interested in learning about $\theta$ from data for a small (finite) number of time periods, $T$.
- Nonparametric in the relationship between the heterogeneity term, $A_{i}$, and $X_{i}^{\top}$.
- This is sometimes referred to as a "fixed effects" approach.

The problem: You cannot simply difference $A_{i}$ away.
So what can we do?

## The Focus of This Research (all with Martin Weidner)

Various Logit Models

- Simple logit with lagged dependent variables and strictly exogenous $X$.
- Ordered logit version (also with Chris Muris).
- Multinomial logit version.
- Simultaneous logit version (also with Hu and Kyriazidou)


## Approaches

$$
Y_{i t} \sim f\left(\cdot \mid X_{i}^{T}, Y_{i}^{t-1}, A_{i} ; \theta\right)
$$

- Conditional Likelihood
- Find (if you can) a sufficient statistic, $S_{i}$, for $A_{i}$.
- Maximize likelihood conditional on $A_{i}$.
- Rasch (1960), Andersen (1970),Hausman, Hall, and Griliches (1984), Chamberlain (1985), Magnac (2000), Aguirregabiria, Gu, and Luo (2020), and others.
- Conditional Maximum Score Version of Same Idea
- Manski (1987), Abrevaya (1999) (kind of), and others.


## Approaches (continued)

- Moment conditions
- Case by case: Honoré (1992), Wooldridge (1997)*, Honoré and Hu (2004)*, Kitazawa (2013), and others
- More systematic: Bonhomme (2012), Bonhomme and Graham (in progress)*,
- Moment Inequalities
- Pakes and Porter (2016), Aristodemou (2018), Pakes, Porter, Shepard, and Calder-Wang (in progress) and others
- Conditional Maximum Score can also be thought of in this way
- Other "Tricks"
- Chen, Khan and Tang (2019) and others
- Sometimes Apply to "Textbook" Models. Sometime Reverse Engineer Models
- Al-Sadoon, Li, and Pesaran (2017), Bartolucci and Nigro (2010)


## Moment Conditions Bonhomme (2012)

If we can find a function $m$ such that

$$
E\left[m\left(Y_{i}^{T}, Y_{i 0}, X_{i}^{T}, \theta\right) \mid Y_{i 0}, X_{i}^{T}, A_{i}\right]=0
$$

then we would have the conditional moment conditions

$$
E\left[m\left(Y_{i}^{T}, Y_{i 0}, X_{i}^{T}, \theta\right) \mid Y_{i 0}, X_{i}^{T}\right]=0
$$

and the unconditional moments

$$
E\left[m\left(Y_{i}^{T}, Y_{i 0}, X_{i}^{T}, \theta\right) g\left(Y_{i 0}, X_{i}^{T}\right)\right]=0
$$

got any function $g$ such that the moments exist.

But how do we find the moment function, $m$ ?

Go back to the model,

$$
P\left(Y_{i t}=1 \mid Y_{i}^{t-1}, X_{i}^{T}, A_{i}\right)=\frac{\exp \left(Y_{i t-1} \gamma+X_{i t}^{\prime} \beta+A_{i}\right)}{1+\exp \left(Y_{i t-1} \gamma+X_{i t}^{\prime} \beta+A_{i}\right)}
$$

with $T=3$ (total number of time-periods is 4 )
We are looking for (a vector of) function(s), $m$, such that

$$
E\left[m\left(Y_{0}, Y_{1}, Y_{2}, Y_{3}, X, \gamma_{0}, \beta_{0}\right) \mid X, Y_{0}, A\right]=0
$$

and hence

$$
E\left[m\left(Y_{0}, Y_{1}, Y_{2}, Y_{3}, X, \gamma_{0}, \beta_{0}\right) \mid X, Y_{0}\right]=0
$$

for all values, $\left(\gamma_{0}, \beta_{0}\right)$, of the true parameters.
If we knew $m$, then we could do GMM without worrying about the distribution of $A$.

## This Is Actually Trivial

Since $\left(Y_{1}, Y_{2}, Y_{3}\right)$ can take 8 values, we write this explicitly as

$$
\begin{aligned}
\sum_{\left(y_{1}, y_{2}, y_{3}\right) \in\{0,1\}^{3}} \operatorname{Pr}\left(Y_{1}=y_{1}, Y_{2}=y_{2}, Y_{3}=y_{3} \mid Y_{0}\right. & \left.=y_{0}, X=x, A=\alpha\right) \\
& \times m\left(y_{0}, y_{1}, y_{2}, y_{3}, x, \gamma_{0}, \beta_{0}\right)=0 .
\end{aligned}
$$

The model gives the vector of probabilities (conditional on $\left(Y_{0}, X, A\right)$ ) as a function of the parameters.

We are looking for the $m$ 's (there are 8 , and they cannot all be 0 ).

## Proceed Numerically

For concrete values of $y_{0}, x, \beta, \gamma$ and one value of $\alpha$,

$$
\begin{aligned}
\sum_{y_{1}, y_{2}, y_{3}} \operatorname{Pr}\left(Y_{1}=y_{1}, Y_{2}=y_{2}, Y_{3}=y_{3} \mid Y_{0}=y_{0},\right. & X=x, A=\alpha) \\
& \times m\left(y_{0}, y_{1}, y_{2}, y_{3}, x, \gamma_{0}, \beta_{0}\right)=0
\end{aligned}
$$

gives one equation.
With $Q$ values of $\alpha$, there will be $Q$ equations.

- Pick $\left(\alpha_{1}, \alpha_{2}, \cdots, \alpha_{Q}\right)$. with $Q>8$. Try to solve for the m's.
- If we can find a non-zero solution (numerically) and it does not depend on the $\alpha$ 's then there is hope. This is important. We will quickly know whether something is likely to be possible or not.
- In our case, it did look like it was possible.


## But Then What?

Solving

$$
\sum_{y_{1}, y_{2}, y_{3}} \operatorname{Pr}\left(\left(Y_{1}, Y_{2}, Y_{3}\right)=\left(y_{1}, y_{2}, y_{3}\right) \mid Y_{0}=y_{0}, X=x, A=\alpha_{1}\right) m\left(y_{0}, y_{1}, y_{2}, y_{3}, x, \gamma_{0}, \beta_{0}\right)=0 .
$$

$$
\sum_{y_{1}, y_{2}, y_{3}} \operatorname{Pr}\left(\left(Y_{1}, Y_{2}, Y_{3}\right)=\left(y_{1}, y_{2}, y_{3}\right) \mid Y_{0}=y_{0}, X=x, A=\alpha_{2}\right) m\left(y_{0}, y_{1}, y_{2}, y_{3}, x, \gamma_{0}, \beta_{0}\right)=0 .
$$

$$
\sum_{y_{1}, y_{2}, y_{3}} \operatorname{Pr}\left(\left(Y_{1}, Y_{2}, Y_{3}\right)=\left(y_{1}, y_{2}, y_{3}\right) \mid Y_{0}=y_{0}, X=x, A=\alpha_{Q}\right) m\left(y_{0}, y_{1}, y_{2}, y_{3}, x, \gamma_{0}, \beta_{0}\right)=0
$$

can be a mess, although there are tricks to make it easier.

For example, ...

We are looking for $m\left(y_{0}, y_{1}, y_{2}, y_{3}, x, \gamma_{0}, \beta_{0}\right)$ such that

$$
\sum_{y_{1}, y_{2}, y_{3}} \operatorname{Pr}\left(\left(Y_{1}, Y_{2}, Y_{3}\right)=\left(y_{1}, y_{2}, y_{3}\right) \mid Y_{0}=y_{0}, X=x, A=\alpha\right) m\left(y_{0}, y_{1}, y_{2}, y_{3}, x, \gamma_{0}, \beta_{0}\right)=0
$$

for all $\alpha$.
Of course

$$
\begin{aligned}
& \lim _{\alpha \rightarrow \infty} \operatorname{Pr}\left(\left(Y_{1}, Y_{2}, Y_{3}\right)=(1,1,1) \mid Y_{0}=y_{0}, X=x, A=\alpha\right)=1 \\
& \lim _{\alpha \rightarrow-\infty} \operatorname{Pr}\left(\left(Y_{1}, Y_{2}, Y_{3}\right)=(0,0,0) \mid Y_{0}=y_{0}, X=x, A=\alpha\right)=1
\end{aligned}
$$

So it is reasonable to guess that the solution will have

$$
\begin{aligned}
& m\left(y_{0}, 1,1,1, x, \gamma_{0}, \beta_{0}\right)=0 \\
& m\left(y_{0}, 0,0,0, x, \gamma_{0}, \beta_{0}\right)=0
\end{aligned}
$$

These kind of "tricks" become more relevant for more complicated models.

Moment functions for $T=3$, where $y=\left(y_{1}, y_{2}, y_{3}\right)$
Let $x_{t s}=x_{t}-x_{s}$. Define

$$
\begin{aligned}
& m_{y_{0}}^{(a)}(y, x, \beta, \gamma)= \begin{cases}\exp \left(x_{12}^{\prime} \beta+y_{0} \gamma\right) & \text { if } y=(0,1,0), \\
\exp \left(x_{13}^{\prime} \beta-\left(1-y_{0}\right) \gamma\right) & \text { if } y=(0,1,1), \\
-1 & \text { if }\left(y_{1}, y_{2}\right)=(1,0), \\
\exp \left(x_{32}^{\prime} \beta\right)-1 & \text { if } y=(1,1,0), \\
0 & \text { otherwise, }\end{cases} \\
& m_{y_{0}}^{(b)}(y, x, \beta, \gamma)= \begin{cases}\exp \left(x_{23}^{\prime} \beta\right)-1 & \text { if } y=(0,0,1), \\
-1 & \text { if }\left(y_{1}, y_{2}\right)=(0,1), \\
\exp \left(x_{31}^{\prime} \beta-y_{0} \gamma\right) & \text { if } y=(1,0,0), \\
\exp \left(\left(1-y_{0}\right) \gamma+x_{21}^{\prime} \beta\right) & \text { if } y=(1,0,1), \\
0 & \text { otherwise. }\end{cases}
\end{aligned}
$$

## Key Result: These Moment Conditions Work For All $\alpha$

Theorem: If the outcomes $Y=\left(Y_{1}, Y_{2}, Y_{3}\right)$ are generated from the above panel logit $\operatorname{AR}(1)$ with $T=3$, then for all $y_{0} \in\{0,1\}, x \in R^{K \times 3}, \alpha \in R$,

$$
\begin{aligned}
& E\left[m_{y_{0}}^{(a)}\left(Y, X, \beta_{0}, \gamma_{0}\right) \mid Y_{0}=y_{0}, X=x, A=\alpha\right]=0, \\
& E\left[m_{y_{0}}^{(b)}\left(Y, X, \beta_{0}, \gamma_{0}\right) \mid Y_{0}=y_{0}, X=x, A=\alpha\right]=0 .
\end{aligned}
$$

## Are There More? Does This Generalize?

What about $T>3$ ? Yes. The expressions are in the paper with Weidner.
What About More Lags? Yes. We also have results about that.

Expressions are in the paper.

## Relation to Existing Results

- Kitazawa (2013) also derives valid moment conditions for this model that eliminate $A_{i}$. For the $\operatorname{AR}(1)$ model with $T=3$, they coincide with ours.
- For $x_{2}=x_{3}$ the moment conditions are transformations of the first order conditions for maximizing the conditional log-likelihood in Honoré and Kyriazidou (2000) (and Cox (1958) and Chamberlain (1985)).
- Kruiniger (2020) and Dobronyi, Gu, and Kim (2021) proves that for the model with one lag, we have derived all the available moment equality conditions.
- A recent related paper by Dobronyi, Gu, and Kim (2021) also consider moment inequalities to characterize the sharp identified set when the model is not point-identified.


## If I Had More Time, I Would Talk About

Natural things to talk about:

- Identification
- Turn the conditional moments into a GMM estimation strategy
- Monte Carlo (It works OK, but there is stuff to be done computationally)
- Empirical Illustration (Employment Status; the results make sense)

Potential weakness:

- This is awfully specific to the logit case.
- So perhaps you should not care after all?


## Is It Worth It? (Preliminary)

$$
P\left(Y_{i t}=1 \mid Y_{i}^{t-1}, X_{i}^{T}, A_{i}\right)=F\left(Y_{i t-1} \gamma+X_{i t}^{\prime} \beta+A_{i}\right)
$$

$F$ perhaps not logistic.
Very simple (preliminary) design

- $T=4 ; k=3 ; 100$ draws of $X$ 's, then probability limit.
- $\gamma=1, \beta=(\pi / \sqrt{3}, 0,0)^{\prime}$.
- $A_{i} \sim N(0,2)$ (Essentially)
- $X_{i t}$ 's i.i.d. over time conditional on $A_{i}$ :
- $X_{1}=(N(0,1)+A) / \sqrt{2}-1 / 4$;
- $X_{2}=(N(0,1)+1\{A>0\}-1\{A<0\}) / \sqrt{2}$;
- $X_{3}=2 \cdot\left(N(0,1)+1\left\{X_{1}>0\right\}\right)-1$.
$\gamma$ and $\beta$ are the probability limits of our estimator (one of them)
Bounds calculated using Pakel and Weidner (2022).

Choices of $F$ (Mixtures of Normals: Mean 0, Variance $\pi^{2} / 3$ )

Corresponding densities


Marginal Effects $(T=4)$

$$
E\left[P\left(Y_{4}=1 \mid Y_{3}^{*}=1\right)-P\left(Y_{4}=1 \mid Y_{3}^{*}=0\right)\right]
$$

|  | Logistic | Flat | Bimodal | Asymmetric |
| :---: | :---: | :---: | :---: | :---: |
| True | 0.145 | 0.150 | 0.132 | 0.085 |
| Assume Logit | $(0.142,0.149)$ | $(0.147,0.155)$ | $(0.131,0.134)$ | $(0.087,0.087)$ |
| LPM + IV | 0.091 | 0.092 | 0.089 | 0.068 |

$$
E\left[\frac{\partial P\left(Y_{4}=1\right)}{\partial x_{41}}\right]
$$

|  | Logistic | Flat | Bimodal | Asymmetric |
| :---: | :---: | :---: | :---: | :---: |
| True | 0.257 | 0.276 | 0.153 | 0.152 |
| Assume Logit | $(0.247,0.269)$ | $(0.255,0.296)$ | $(0.159,0.160)$ | $(0.154,0.155)$ |
| LPM + IV | 0.299 | 0.319 | 0.158 | 0.171 |

## Extensions: Ordered Logit Model

## Honoré, Muris and Weidner (under revision) :

$$
Y_{i t}=\left\{\begin{array}{lll}
1 & \text { if } & Y_{i t}^{*} \in\left(-\infty, \lambda_{1}\right] \\
2 & \text { if } & Y_{i t}^{*} \in\left(\lambda_{1}, \lambda_{2}\right] \\
\vdots & & \\
Q & \text { if } & Y_{i t}^{*} \in\left(\lambda_{Q-1}, \infty\right)
\end{array}\right.
$$

where

$$
Y_{i t}^{*}=X_{i t}^{\prime} \beta+\sum_{q=1}^{Q} \gamma_{q} 1\left\{Y_{i, t-1}=q\right\}+A_{i}+\varepsilon_{i t}
$$

and $\varepsilon_{i t}$ is i.i.d. logistically distributed.
Theory and empirical illustration.

## Extensions: Multinomial Logit Model

## Honoré and Weidner (in progress)

There are $Q \in\{2,3,4, \ldots\}$ possible for a variable $Y_{i t} \in\{1,2, \ldots, Q\}$ and that $Y_{i t}$ is generated by the model

$$
Y_{i t}=\underset{q \in\{1,2, \ldots, Q\}}{\operatorname{argmax}} U_{q i t},
$$

for $t \in\{1,2, \ldots, T\}$, with latent variable given by

$$
U_{q t}=\sum_{r=1}^{Q} \gamma_{q r} 1\left\{Y_{t-1}=r\right\}+X_{t}^{\prime} \beta_{q}+A_{q}+\varepsilon_{q t} .
$$

So far only theory.

## Extensions: Bivariate Model of Schmidt and Strauss (1975)

Honoré, Hu, Kyriazidou and Weidner (2022) consider the econometric model

$$
\begin{aligned}
& P\left(Y_{1, i t}=c_{1}, Y_{2, i t}=c_{2} \mid\left\{Y_{1, i s}, Y_{2, i s}\right\}_{s<t},\left\{Y_{1, i s}\right\}_{s=1}^{T},\left\{X_{2, i s}\right\}_{s=1}^{T}, A_{1, i}, A_{2, i}\right) \\
= & \frac{\exp \left(c_{1}\left(Z_{1, i t}+A_{1, i}\right)+c_{2}\left(Z_{2, i t}+A_{2, i}\right)+c_{1} c_{2} \rho\right)}{1+\exp \left(Z_{1, i t}+A_{1, i}\right)+\exp \left(Z_{2, i t}+A_{2, i}\right)+\exp \left(Z_{1, i t}+A_{1, i}+Z_{2, i t}+A_{2, i}+\rho\right)}
\end{aligned}
$$

for $t=1,2,3$ and $c_{1}, c_{2} \in\{0,1\}$ where

$$
\begin{aligned}
& Z_{1, i t}=X_{1, i t}^{\prime} \beta_{1}+Y_{1, i t-1} \gamma_{11}+Y_{2, i t-1} \gamma_{12} \\
& Z_{2, i t}=Y_{2, i t}^{\prime} \beta_{2}+Y_{1, i t-1} \gamma_{21}+Y_{2, i t-1} \gamma_{22}
\end{aligned}
$$

(Not as obscure as it looks)

## Extensions: Moment Conditions for Other Models?

- Probit? No!
- Mixture of Logits? Yes! For larger $T$. For example, a static mixture of 56 logits will generate 7 moment conditions when $T=9$. Compare to Chamberlain (2010), Johnson (2004) and Davezies, D'Haultfoeuille, and Mugnier (2020)
- $Y_{i t} \sim \operatorname{binomial}\left(M, \frac{\exp \left(Y_{i t-1} \gamma+X_{i t}^{\prime} \beta+A_{i}\right)}{1+\exp \left(Y_{i t-1} \gamma+X_{i t}^{\prime} \beta+A_{i}\right)}\right)$ ? Yes, looks like it.
- Multinomial model of Pakes, Porter, Shepard, and Calder-Wang (in progress)?

$$
\begin{gathered}
\mathrm{Y}_{i t}=\underset{q \in\{1,2, \ldots, Q\}}{\operatorname{argmax}} \mathrm{U}_{q i t}, \\
U_{q i t}=\left(-P_{q, i, t}-1\left\{Y_{i, t-1} \neq d\right\} \kappa\right) B_{i}+A_{q, i}+\varepsilon_{q i t}
\end{gathered}
$$

Does not look like it.

## Extensions: Moment Conditions for Entry Games?

- Static entry games? Bresnahan and Reiss (1991), Tamer (2003).

$$
\begin{aligned}
& Y_{1 t}=1\left\{X_{1 t}^{\prime} \beta-\gamma Y_{2 t}+A_{1}+\varepsilon_{1 t}>0\right\} \\
& Y_{2 t}=1\left\{X_{2 t}^{\prime} \beta-\gamma Y_{1 t}+A_{2}+\varepsilon_{2 t}>0\right\}
\end{aligned}
$$

Yes, looks like it.

- Dynamic entry games (put in lags above)?

$$
\begin{aligned}
& Y_{1 t}=1\left\{X_{1 t}^{\prime} \beta-\gamma Y_{2 t}+\delta_{\text {self }} Y_{1, t-1}-\delta_{\text {other }} Y_{2, t-1}+A_{1}+\varepsilon_{1 t}>0\right\}, \\
& Y_{2 t}=1\left\{X_{2 t}^{\prime} \beta-\gamma Y_{1 t}+\delta_{\text {self }} Y_{2, t-1}-\delta_{\text {other }} Y_{1, t-1}+A_{2}+\varepsilon_{2 t}>0\right\}
\end{aligned}
$$

Not sure.

