xtfeis.ado: Linear Fixed Effects Models with Individual Slopes

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Outline

The Problem. Consider growth curves

- Fixed Effect framework: the ultimate method for causal analysis with non-experimental data

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- Problem recognized (Allison 1990, Heckman & Hotz 1989, Polachek & Kim 1994, Winship & Morgan 1999, Morgan & Winship 2007)

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  - major example: unobserved effect changes over time
- Problem recognized (Allison 1990, Heckman & Hotz 1989, Polachek & Kim 1994, Winship & Morgan 1999, Morgan & Winship 2007)
- but seldomly solved in practice

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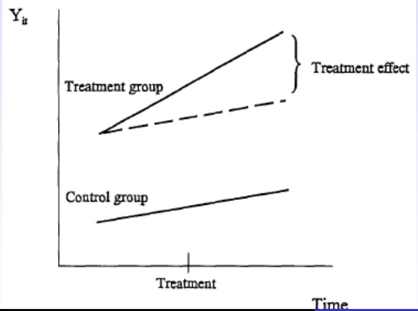

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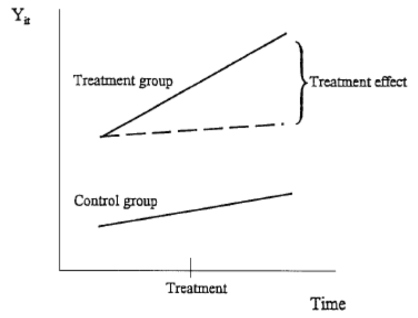

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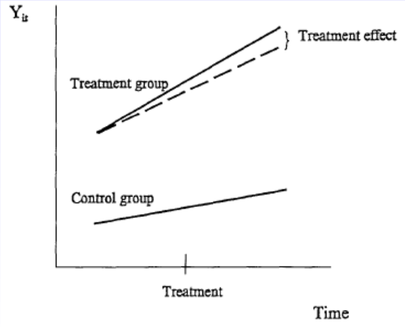

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- 1., 2., 3.? Theories seldomly strong enough to decide

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- ϵ_{it} : idiosyncratic time-varying disturbance term

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    and analog for indep. variables
  - transform "'by hand"' possible, but very very slow

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  - Since $\Omega_i Z_i = 0$, α_{1i} and α_{2i} are eliminated
- Conventional FE is a special case where $Z_i = (1)$ is $(N \times 1)$ vector of constants
- Random growth model is another special case where $Z_i = (1, t)$ is $(N \times 2)$ matrix of constants and time variable

Stata ado `xtfeis.ado`

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- Syntax: `xtfeis` *`varlist`*`, [slope(`*`varlist`*`)] [noconstant] [cluster(`*`clustvar`*`)]`

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Simulation setup

- set up panel data set with 3000 cases ($N = 1000,\ T = 3$)

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- Estimate treatment effect $\hat{\beta}$ using 5 different models
- repeat 1000 times
- get mean of $\hat{\beta}$, s.e., % coefs. diff. from true β

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Pooled OLS	.214	.010	100

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Fixed Effects IS	<.001	.011	5.1

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Change score	-.050	.008	100

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ANCOVA	-.005	.009	10.8
Change score	-.050	.008	100
Fixed Effects	-.060	.010	100
Fixed Effects IS	$<$.001	.011	4.6

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- controls: divorce, remarriage, number of children, yrs. education, tenure, year dummies

Results: Effect of marriage on male wages

GSOEP			**NLSY**		
Model	$\hat{\beta}$	robust s.e.	Model	$\hat{\beta}$	robust s.e.
POLS	.078**	(.014)	POLS	.146**	(.010)
FE	.036**	(.013)	FE	.082**	(.008)
FE-IS	.015	(.010)	FE-IS	.021*	(.008)

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