Special Topics in Applied Econometrics
2) Non-Linear Models

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Antwerp University, 13 - 17 February 2012

2) NON-LINEAR MODELS:
$\rightarrow$ Agenda

- $\Rightarrow$ Introduction to Non-Linear Models
- The Probit Model
- The Tobit Model
- Panel Sample Selection
- Issues With Cross-Country Regressions

2.1) Introduction to Non-Linear Models

- In the previous chapter we learned that least squares yields consistent and asymptotically normal estimators when the model $E(y|\mathbf{x})$ is linear in its parameters
- In this chapter we depart from models in which y is a linear function of the explanatory variables
- In non-linear models non-linear estimators will be used for statistical inference
- A useful estimation procedure to estimate parameters in a non-linear context is the maximum likelihood (ML) method

2.1) Introduction to Non-Linear Models (ctd.) $\Rightarrow$ Maximum Likelihood Estimation

- General idea: we have a sample of data and, assuming an underlying probability density function (pdf) with parameter θ, want to know which value of θ makes the sample of data most likely
- For example, drawing three numbers, y_1, y_2, y_3 from a given distribution with *known* parameter vector θ, $f(y_1, y_2, y_3)$ gives us the probability that these three realisations are drawn if they are independent:

$$f(y_1, y_2, y_3|\theta) = f(y_1|\theta)f(y_2|\theta)f(y_3|\theta)$$

- The pdf of $f(y|\theta)$ of the random variable Y assigns each concrete value of $Y = y_i$ a probability:

$$f(y|\theta) = P(Y = y_i|\theta)$$

2.1) Introduction to Non-Linear Models (ctd.) ⇒Maximum Likelihood Estimation

- If we have a random data sample $y_1, ..., y_N$ of independent observations we obtain the joint pdf via multiplying the independent pdfs:

$$f(y_1, ..., y_N|\theta) = f(Y = y_1|\theta) \cdot f(Y = y_2|\theta) \cdot ... \cdot f(Y = y_N|\theta)$$
$$= \prod_{i=1}^{N} f(Y = y = i|\theta) \quad (1)$$

- Equation (1) shows the probability that the data sample realizes for a given parameter θ
- The likelihood function L interprets this joint pdf as a function with unknown parameter θ for a given data sample $y_1, ..., y_N$:

$$L(\theta|Y) = l(\theta|Y = y_1) \cdot l(\theta|Y = y_2) \cdot ... \cdot l(\theta|Y = y_N)$$
$$= \prod^{N} l(\theta|y_i) \quad (2)$$

2.1) Introduction to Non-Linear Models (ctd.) $\Rightarrow$Maximum Likelihood Estimation

- Maximum likelihood method consists of choosing θ such that the probability of observing the data sample is highest:

$$max_{\theta} L(\theta|Y)$$

- Since taking the log of a function is a monotonous transformation, it is straightforward (and easier) to maximize the Log-likelihood:

$$ln\ L(\theta|Y) = \sum_{i=1}^{N} l(\theta|y_i)$$

- First and second order conditions for a maximum are $\frac{\partial ln\ L}{\partial \theta} = 0$ and $\frac{\partial^2 ln\ L}{\partial^2 \theta} < 0$
- Matlab's function 'fminuncon' can be used to minimize $-ln\ L(\theta|Y)$

2) NON-LINEAR MODELS: $\rightarrow$ Agenda

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- $\Rightarrow$ The Probit Model
- The Tobit Model
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2.2) The Probit Model
⇒ The Pooled Probit Model

- Suppose that the latent variable y_{it}^* follows

$$y_{it}^* = \mathbf{x}_{it}'\theta + e_{it} \tag{3}$$

  where
  - e_{it} is independent of $\mathbf{x}_{it}$ and standard normally distributed
  - θ is a parameter vector of interest
- instead of observing y_{it}^* we observe only a binary variable indicating the sign of y_{it}^*:

$$y_{it} = 1 \text{ if } y_{it}^* > 0$$
$$y_{it} = 0 \text{ if } y_{it}^* \leq 0$$

2.2) The Probit Model
⇒ The Pooled Probit Model

- The distribution of y_{it} given $\mathbf{x}_{it}$ is obtained by

$$\begin{aligned} P(y_{it} = 0|\mathbf{x}_{it}, \theta) &= P(y^*_{it} \leq 0|\mathbf{x}_{it}, \theta) \\ &= P(\mathbf{x}_{it}\theta + e_{it} \leq 0|\mathbf{x}_{it}, \theta) \\ &= P(e_{it} \leq -\mathbf{x}_{it}\theta|\mathbf{x}_{it}, \theta) \\ &= \mathbf{\Phi}(-\mathbf{x}_{it}\theta) \text{ using property CD.4 in Wooldridge (2004)} \\ &= 1 - \mathbf{\Phi}(\mathbf{x}_{it}\theta) \qquad (4) \end{aligned}$$

  where $\mathbf{\Phi}$ is the standard normal cumulative density function (cdf)

- Using symmetry of the normal distribution we find

$$P(y_{it} = 1|\mathbf{x}_{it}, \theta) = \mathbf{\Phi}(\mathbf{x}_{it}\theta) \qquad (5)$$

2.2) The Probit Model
$\Rightarrow$ The Pooled Probit Model

- Combining Equations (4) and (5), the density of y_{it} given $\mathbf{x}_{it}$ and θ is

$$f(y|\mathbf{x}_{it};\theta) = [\mathbf{\Phi}(\mathbf{x}_{it}\theta)]^{y}\,[1-\mathbf{\Phi}(\mathbf{x}_{it}\theta)]^{(1-y)} \tag{6}$$

- Taking log of Equation (6), the log likelihood for a sample of observations $i = 1, ..., N$ and $t = 1, ..., T$ is given by

$$L(\theta|y_{it},\mathbf{x}_{it}) = \sum_{i=1}^{N}\sum_{t=1}^{T}\{y_{it}\,log\,[\mathbf{\Phi}(\mathbf{x}_{it}\theta)] + (1-y_{it})log\,[1-\mathbf{\Phi}(\mathbf{x}_{it}\theta)]\}$$

- The maximum likelihood estimator solves

$$max_{\theta}\; L(\theta|y_{it},\mathbf{x}_{it}) \tag{7}$$

2.2) The Probit Model
⇒ The Pooled Probit Model

- A robust estimator for the asymptotic variance of $\hat{\theta}$ is given by

$$Avar(\hat{\theta}) = \left[\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{A}_{it}\hat{\theta}\right]^{-1}\left[\sum_{i=1}^{N}\mathbf{s}_i(\hat{\theta}\mathbf{s}_i(\hat{\theta})'\right]\left[\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{A}_{it}\hat{\theta}\right]^{-1} \qquad (8)$$

  where

$$\mathbf{A}_{it}(\hat{\theta}) = \frac{\left\{\phi(\mathbf{x}_{it}\hat{\theta})\right\}^2 \mathbf{x}_{it}'\mathbf{x}_{it}}{\mathbf{\Phi}(\mathbf{x}_{it}\hat{\theta})\left[1 - \mathbf{\Phi}(\mathbf{x}_{it}\hat{\theta})\right]}$$

  and

$$\mathbf{s}_i(\theta) = \sum_{t=1}^{T}\mathbf{s}_{it}(\theta) = \sum_{t=1}^{T}\frac{\phi(\mathbf{x}_{it}\theta)\mathbf{x}_{it}'[y_{it} - \mathbf{\Phi}(\mathbf{x_{it}}\theta)]}{\mathbf{\Phi}(\mathbf{x}_{it}\hat{\theta})\left[1 - \mathbf{\Phi}(\mathbf{x}_{it}\theta)\right]}$$

  with ϕ the standard normal pdf

2.2) The Probit Model
⇒ The Pooled Probit Model

- The asymptotic variance of the estimated parameter vector can also be obtained via using the hessian matrix, $\hat{\mathbf{H}}$ obtained from the maximization:

$$Avar(\hat{\beta})' = \mathbf{H}^{-1} \tag{9}$$

2.2) The Probit Model
⇒ Hands-On

Hands-On 1.5

2.2) The Probit Model
$\Rightarrow$ Unobserved Effects Probit Model

- Unobserved effects probit models take the following two assumptions:
  - $$\begin{aligned} (y_{it} = 1|\mathbf{x}_{it}, c_i) = & \quad \mathbf{\Phi}(\mathbf{x}_{it}\beta + c_i) \quad t = 1, ..., T \text{ for } \mathbf{x}_i t \\ (y_{it} = 0|\mathbf{x}_{it}, c_i) = & \quad 1 - \mathbf{\Phi}(\mathbf{x}_{it}\beta + c_i) \quad t = 1, ..., T \text{ for } \mathbf{x}_i t \end{aligned} \qquad (10)$$

    where $\mathbf{\Phi}$ is the standard normal cdf
    '$\mathbf{x}_{it}$ is strictly exogenous conditional on c_i'
  - $\mathbf{y}_i = (y_{i1}, y_{i2}, ..., y_{iT})'$ are independent conditional on $(\mathbf{x}_{it}, c_i)$, $t = 1, ..., T$ for $\mathbf{x}_{it}$

2.2) The Probit Model
⇒ Unobserved Effects Probit Model (ctd.)

- In a non-linear context the unobserved effects cannot be easily eliminated as in the linear context and thus need to be estimated
- Neyman and Scott (1948) considered inference when some parameters are common (the β) but there are additionally an infinity of parameters (the c_i), each of which depends only on a finite number of observations
- The common parameters are of interest, whereas the latter are called incidental parameters
- With T fixed and $N \to \infty$ (common assumption in panel data context), each c_i depends on fixed T observations and there are infinitely many c_i since $N \to \infty$
- The incidental parameters are inconsistently estimated
- Inconsistent estimation of incidental parameters 'contaminates' estimation of the common parameters

2.2) The Probit Model
$\Rightarrow$ Unobserved Effects Probit Model: Random Effects

- The RE maximum likelihood estimator assumes that the individual effects are normally distributed with $c_i \sim N(0, \sigma_c^2)$
- The RE MLE of β and σ_c^2 maximizes the log-likelihood

$$L(\beta, \sigma_c^2) = \sum_{i=1}^{N} ln\, f(\mathbf{y}_i | \mathbf{X}_i, \beta, \sigma_c^2) \tag{11}$$

where

$$f(\mathbf{y}_i | \mathbf{X}_i, \beta, \sigma_c^2) = \int_{-\infty}^{\infty} f(\mathbf{y}_i | \mathbf{X}_i, \beta) \frac{1}{\sqrt{2\pi\sigma_c^2}} exp(\frac{-c_i}{2\sigma_c^2})^2 dc_i \tag{12}$$

with

$$f(\mathbf{y}_i | \mathbf{X}_i, \beta) = \prod_{t=1}^{T} \mathbf{\Phi}(\mathbf{x}_{it}\beta + c_i)^{y_{it}} (\mathbf{\Phi}(\mathbf{x}_{it}\beta + c_i)^{(1-y_{it})}) \tag{13}$$

2.2) The Probit Model
⇒ Unobserved Effects Probit Model: Random Effects (ctd.)

- Note that Φ denotes the standard normal cdf
- Since there is no closed-form solution for the integral in Equation (11) it is standard to integrate the unobserved effects, c_i, out
- This can be done numerically using Gaussian quadrature methods

- The assumption in the RE model that $c_i \sim N(0, \sigma_c^2)$ is very restrictive
- Ideally we could estimate the quantities of interest without restricting the relationship between the c_i and the $\mathbf{x}_{it}$
- This would however require estimating the c_i along with the $\mathbf{x}_{it}$ which gives rise to the incidental parameters problem

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- $\Rightarrow$ The Tobit Model
- Panel Sample Selection
- Issues With Cross-Country Regressions

2.3) The Tobit Model
$\Rightarrow$ Pooled Tobit Model

- The pooled Tobit model is given by

$$y_{it} = max(0, \mathbf{x}_{it}'\beta + u_{it}); \;\; t = 1, 2, ..., T \tag{14}$$

  with

  - $u_{it}|\mathbf{x}_{it} \sim N(0, \sigma^2)$
  - u_{it} is independent of $\mathbf{x}_{it}$ but this does not imply strict exogeneity of $\mathbf{x}_{it}$, that is, $\mathbf{x}_{it}$ can contain lagged dependent variables
  - u_{it} is allowed to be serially dependent

2.3) The Tobit Model
⇒ Pooled Tobit Model (ctd.)

- The pooled estimator maximizes the log-likelihood function

$$L(\beta, \sigma^2) = \sum_{i=1}^{N} \sum_{t=1}^{T} \{ \mathbf{1}[y_{it} = 0] log[1 - \mathbf{\Phi}(\frac{\mathbf{x}'_{it}\beta}{\sigma})] + \mathbf{1}[y_{it} > 0] log[\phi(\frac{y_{it} - \mathbf{x}'_{it}\beta}{\sigma})] - \frac{log(\sigma^2)}{2} \} \quad (15)$$

where

- $\mathbf{\Phi}$ is the normal cdf with mean 0 and variance σ^2
- ϕ is the normal pdf with mean 0 and variance σ^2

2.3) The Tobit Model
$\Rightarrow$ Pooled Tobit Model (ctd.)

- Omitting a constant that does not affect maximization, Equation (15) can be written as

$$1[y_{it} = 0] log[1 - \mathbf{\Phi}(\frac{\mathbf{x}'_{it}\beta}{\sigma})] - [y_{it} > 0] \left\{ \frac{(y_{it} - \mathbf{x}'_{it}\beta)^2}{2\sigma^2} \right\} \qquad (16)$$

2.3) The Tobit Model
$\Rightarrow$ Pooled Tobit Model (ctd.)

- The asymptotic variance of the estimated parameter vector can be obtained via using the hessian matrix, $\hat{\mathbf{H}}$ obtained from maximization:

$$Avar(\hat{\beta}, \sigma_u^2)' = \hat{\mathbf{H}}^{-1} \tag{17}$$

2.4) Panel Sample Selection
$\Rightarrow$ Hands-On

Hands-On 1.6

2.3) The Tobit Model
⇒ Unobserved Effects Tobit Model

- The unobserved effects Tobit Model can be stated as follows:

$$y_{it} = max(0, \mathbf{x}'_{it}\beta + c_i + u_{it}); \;\; t = 1, 2, ..., T \tag{18}$$

- Assumptions:
  - $u_{it}|\mathbf{x}_{it}, c_i \sim N(0, \sigma_u^2); \;\; t = 1, 2, ..., T)$ for $\mathbf{x}_{it}$
  - $\mathbf{x}_{it}$ are strictly exogenous
- Due to non-linearity, the unobserved heterogeneity cannot be easily eliminated. Hence, unless one makes strong assumptions on c_i (RE), the parameters need to be estimated unrestricted (FE) which results in the incidental parameters problem

2.3) The Tobit Model
⇒ Random Effects Tobit Model

- Under the assumption that $c_i \sim N(0, \sigma_c^2)$, the likelihood to maximize is given by

$$L(\beta, \sigma_u^2, \sigma_c^2) = ln\ f(\mathbf{y}_i | \mathbf{X}_i, \beta, \sigma_u^2, \sigma_c^2) \tag{19}$$

where

$$f(\mathbf{y}_i | \mathbf{X}_i, \beta, \sigma_u^2, \sigma_c^2) = \int_{-\infty}^{\infty} f(\mathbf{y}_i | \mathbf{X}_i, \beta, \sigma_u^2) \frac{1}{\sqrt{2\pi\sigma_c^2}} exp(\frac{c_i}{2\sigma_c^2}) d\ c_i$$

with

$$f(\mathbf{y}_i | \mathbf{X}_i, \beta, \sigma_u^2) = \prod_{t=1}^{T} [\frac{1}{\sigma_u} \phi_{it}]^{d_{it}} [1 - \Phi_{it}]^{1-d_{it}}$$

where

$$\phi_{it} = \phi(\frac{y_{it} - c_i - \mathbf{x}_{it}'\beta}{\sigma_u}),\ \ \Phi_{it} = \Phi(\frac{c_i + \mathbf{x}_{it}'\beta}{\sigma_u})$$

2.3) The Tobit Model
$\Rightarrow$ Random Effects Tobit Model (ctd.)

- $d_{it} = 1$ if $y_{it} > 0$ and $d_{it} = 0$ if $y_{it} = 0$
- ϕ and Φ denote the standard normal pdf and cdf, respectively
- Since Equation (19) involves a one-dimensional integral, numerical integration using Gaussian quadrature is needed to compute the estimator

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2.4) Panel Sample Selection

- Pioneered by Heckman (1979)
- If the data sample used for investigation is non-random, inference may be plagued by sample selection bias
- systematic exclusion of subsets of data can impact statistical significance of estimated parameters or result in biased parameter estimates

2.4) Panel Sample Selection
⇒ Pooled Panel

Consider the following panel data model with sample selection

$$y_{it}^{*} = \boldsymbol{x}_{it}'\beta + e_{it} \tag{20}$$

('participation effects equation'),

$$d_{it}^{*} = \boldsymbol{z}_{it}'\gamma + v_{it} \tag{21}$$

('participation selection equation'), with

$$d_{it} = \begin{cases} d_{it}^{*} \text{ if } d_{it}^{*} > 0, \\ 0 \text{ otherwise,} \end{cases} \tag{22}$$

$$y_{it} = \begin{cases} y_{it}^{*} \text{ if } d_{it} = 1, \\ \text{`unspecified' otherwise,} \end{cases} \tag{23}$$

2.4) Panel Sample Selection $\Rightarrow$ Pooled Panel (ctd.)

- Sample selection can result if the error terms in Equations (20) and (21) are correlated
- Example:
  - Participation effects equation: y_{it} =real GDP per capita growth of countries participating in IMF loan programs
  - Participation selection equation: $d_{it} = 1$ if country participates in IMF loan program and 0 otherwise
  - The independent variable 'willingness of Government to implement reforms' will have explanatory power in both equations, (20) and (21), however is not observed
  - hence, 'Government willingness...' is contained in e_{it} and v_{it}
  - if $\mathbf{x}_{it}$is uncorrelated with 'Government willingness...', there is no sample selection bias
  - if $\mathbf{x}_{it}$ is correlated with 'Government willingness...', for example, if it contains the variable 'Investment', then all estimated coefficients in Equation (20) may be biased

2.4) Panel Sample Selection $\Rightarrow$ Pooled Panel (ctd.)

- Under the assumption that e_{it} and v_{it} are jointly normally distributed, the 'Heckit' procedure can be used to correct for sample selection bias. It consist of the following steps:
  - Estimate Equation (21) using all observations
  - Calculate the inverse Mills ratio, $\hat{\lambda}_{it}$ which serves to take account of the correlation between e_{it} and v_{it}:

$$\hat{\lambda}_{it} = \frac{\phi(\mathbf{z}'_{it}\hat{\gamma})}{\Phi(\mathbf{z}'_{it}\hat{\gamma})}$$

  - Using the selected sample, that is, all observations for which y_{it} is observed, estimate Equation (20), augmented by $\hat{\lambda}_{it}$ as additional explanatory variable

DISCUSSION

2.4) Panel Sample Selection
$\Rightarrow$ Hands-On

Hands-On 1.7

2.4) Panel Sample Selection
⇒ Unobserved Effects Panel Models

- Participation effects and participation selection equations should have the same underlying model structure, that is, pooled, FE, or RE
- Clearly, the assumptions underlying the pooled structure are very restrictive
- More sophisticated models exist, but they are computationally rather involved

2.4) Panel Sample Selection
⇒ Unobserved Effects Panel Models: Random Effects

Drawing upon Vella (1998) and Vella and Verbeek (1999) Binder and Bluhm (2011) consider the following random effects panel data model with sample selection and endogeneity:

$$y_{it}^* = \mu_i + d_{it}\theta + \boldsymbol{x}_{it}'\boldsymbol{\beta} + e_{it} \tag{24}$$

('participation effects equation'),

$$d_{it}^* = \alpha_i + \boldsymbol{z}_{it}'\boldsymbol{\gamma} + v_{it} \tag{25}$$

('participation selection equation'), with

$$d_{it} = \begin{cases} d_{it}^* \text{ if } d_{it}^* > 0, \\ 0 \text{ otherwise,} \end{cases} \tag{26}$$

$$y_{it} = \begin{cases} y_{it}^* \text{ if } d_{it} > 0, \\ \text{`unspecified' otherwise} \end{cases} \tag{27}$$

2.4) Panel Sample Selection $\Rightarrow$ Unobserved Effects Panel Models: Random Effects (ctd.)

Following Vella and Verbeek (1999), one may obtain endogeneity/sample selection bias-corrected estimates as follows:

- Assume $E(\epsilon_{it}|\boldsymbol{Z}_i, \boldsymbol{u}_i) = \tau_1 u_{it} + \tau_2 \bar{u}_i$, where $\epsilon_{it} = \mu_i + e_{it}$ and $u_{it} = \alpha_i + v_{it}$.
- Observe that $E(y^*_{it}|\boldsymbol{Z}_i, d_i) = d_{it}\theta + \boldsymbol{x}'_{it}\boldsymbol{\beta} + E(\epsilon_{it}|\boldsymbol{Z}_i, d_i)$.
- Compute estimate of $E(\epsilon_{it}|\boldsymbol{Z}_i, d_i)$ using the generalized residuals of the participation selection equation and numerical integration to filter out country-specific effects in u_{it}.

- Following Mundlak (1978) and Semykina and Wooldridge (2010), they invoke a decomposition of the country-specific effects into a systematic component due to observables and a remainder random unobserved component:

Augmented Participation Selection Equation

$$\begin{aligned} \alpha_i &= \zeta + \boldsymbol{g}'_i\boldsymbol{\kappa} + r_i \\ \Rightarrow d^*_{it} &= \zeta + \boldsymbol{g}'_i\boldsymbol{\kappa} + \boldsymbol{z}'_{it}\gamma + \tilde{u}_{it}, \\ \text{where } \tilde{u}_{it} &= r_i + v_{it} \end{aligned} \tag{28}$$

Augmented Participation Effects Equation

$$\begin{aligned} \mu_i &= \psi + \boldsymbol{q}'_i\boldsymbol{\phi} + \chi_i \\ \Rightarrow y^*_{it} &= \psi + \boldsymbol{q}'_i\boldsymbol{\phi} + d_{it}\theta + \boldsymbol{x}'_{it}\boldsymbol{\beta} + \tilde{\epsilon}_{it}, \\ \text{where } \tilde{\epsilon}_{it} &= \chi_i + e_{it} \end{aligned} \tag{29}$$

2.4) Panel Sample Selection
$\Rightarrow$ Unobserved Effects Panel Models: Fixed Effects (ctd.)

- Under Equations (28) and (29), they therefore allow for a less restrictive specification than Vella and Verbeek (1999), and capture a fixed effects specification in the spirit of Mundlak (1978) and Semykina and Wooldridge (2010)
- The null of the RE specification can be tested against the FE specification by investigating whether κ and ϕ

2.4) Panel Sample Selection ⇒ Digression: The Conditional Effects of IMF Loan Programs[I]

During recent financial crisis calls were voiced to give IMF expanded role in ensuring **macroeconomic stability and growth**. Main contribution:

- use a **novel econometric framework** which takes account of endogeneity, sample selection, and **state dependence**;
- develop an **index of institutional development**.

Question analyzed

What are the effects of conditional IMF loan programs on output growth?

[I] Binder and Bluhm (2011)

2.4) Panel Sample Selection $\Rightarrow$ On the Conditional Effects of IMF Program Participation on Output Growth (ctd.)

When investigating effects of IMF program participation on output growth endogeneity bias arising through **sample selection** needs to be corrected.

To capture conditionality of IMF loans, model effects of program participation as a **flexible function** of countries' institutional development.

Participation effects equation with state dependence:

$$y_{it}^* = \psi + \boldsymbol{q}_i'\boldsymbol{\xi} + d_{it}\theta(w_{it}) + \boldsymbol{x}_{it}'\boldsymbol{\beta} + \tau_1 \hat{u}_{it} + \tau_2 \bar{\hat{u}}_i + \epsilon_{it} \tag{30}$$

where

y_{it}^* = Growth of real GDP per capita

ψ = Constant

$\boldsymbol{q}_i$ = Variables capturing country-specific fixed effect

d_{it} = Loan-quota ratio

w_{it} = Institutional development

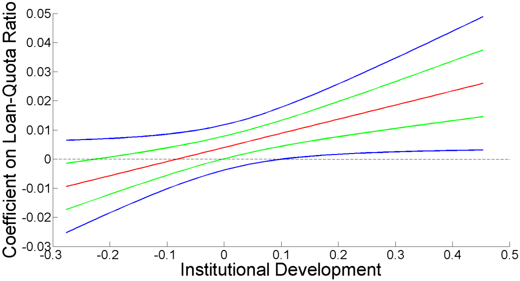
$\boldsymbol{x}_{it}$ = Control variables

u_{it} = Correction term from first step estimation

ϵ_{it} = random error term

2.4) Panel Sample Selection
⇒ Estimates of Participation Effects Equation[I]

Independent Variables	Coefficients
Loan-Quota Ratio	0.004 [1.024]
Loan-Quota Ratio × *Institutional Development*	0.049** [2.002]



[I] $y_{it}^{*} = \psi + \boldsymbol{q}_i'\boldsymbol{\xi} + d_{it}\theta(w_{it}) + \boldsymbol{x}_{it}'\boldsymbol{\beta} + \tau_1 \hat{u}_{it} + \tau_2 \bar{\hat{u}}_i + \epsilon_{it}$, where the dependent variable is the growth rate of real GDP per capita. Further right hand side variables (not displayed) are investment share, inflation, democracy, mean fertility rate, institutional development, and a constant. The number of observations is 773 and the adjusted R^2 is 0.053. The F-test for joint significance of all explanatory variables is significant ($p \prec 0.000$).

2.4) Panel Sample Selection
⇒ Conclusion

We adduce evidence that effects of conditional IMF loan programs on output growth

- **vary systematically** with our index of institutional development;
- are **positive only** if program participation is coupled with **sufficient** institutional development.

Countries which decide to turn to IMF for funding appear well advised to comply with conditionality and improve their institutional environment.

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- $\Rightarrow$ Issues With Cross-Country Regressions

2.5) Issues With Cross-Country Regressions

"In the past decade there have been several large cross-country panel data sets that have been assembled. These data sets cover many areas: foreign exchange rates, economic growth, agricultural productivity and so on. These data sets have been considered a 'gold mine' by those working in the respective areas, as well as those interested in panel data techniques. The recent work on cross-country regressions is also like looking at a black cat in a dark room."
Maddala (1999)

2.5) Issues With Cross-Country Regressions $\Rightarrow$ Data Problems

- Cross-country datasets generally very unreliable
- For studies on economic development data need to be closely investigated and corrected (human capital)
- Growth results based on PWT 'fragile'.
  But
  - anyway difficult to draw specific policy conclusions from heterogenous datasets
  - help to identify which variables matter for development

2.5) Issues With Cross-Country Regressions
⇒ Example 1 for Misleading Conclusions in Cross-Country Studies

- Sala-i-Martin (1997) studies the determinants of growth
- He finds that, inter alia' the variables 'open economy' and 'rule of law' to have significantly positive coefficients.
- However, among the religious variables, Confucian, Buddist and Moslem have significant and positive coefficients and Protestant and Catholic have significant negative coefficients.
- Policy conclusion: To promote U.S. economic growth, efforts should be made to convert all Christians in the U.S. into Confucians, Buddists or Moslems.

2.5) Issues With Cross-Country Regressions
⇒ Example 2 for Misleading Conclusions in Cross-Country Studies

- Wall (1995) uses the data from 95 non-communist non-OPEC countries from the Penn-World Tables and estimated the following regression:

$$g = \alpha + b_c D_c + b_b D_b + \epsilon$$

  where

  - g = growth rate of real per-capita income between 1960 and 1990,
  - D_c and D_b are dummies to indicate cricket and baseball playing countries.

- His results are

$$g = 103.9 - 43.0 D_c + 80.3 * D_b$$

with all coefficients being highly significant

2.5) Issues With Cross-Country Regressions ⇒ Example 2 for Misleading Conclusions in Cross-Country Studies (ctd.)

From the results he concludes that:

- For emerging countries without a history of cricket or baseball, baseball instruction and subsidies should be an immediate priority. US and Japan can provide these subsidies.
- For countries playing cricket, cricket should be abolished but this is a for- midable task similar to economic reform of the formerly communist countries.

SUMMARY

- The incidental parameters problem
- The panel probit model
    - pooled
    - RE
    - FE
- The panel tobit model
    - pooled
    - RE
    - FE
- Panel sample selection

SUMMARY (ctd.)

- Further issues with cross-country regressions in addition to the points raised before:
  - data unreliability (human capital)
  - growth regressions not suitable to draw firm policy conclusions but can identify variables 'that matter'
  - growth regressions should feature economic intuition, they require careful interpretation

Digression: A Game of Catch-Up

DISCUSSION