Estimating the Growth Effect of FDI Using A Quantile Panel Data Model with Partially Varying Coefficients

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Motivation

Motivations: Can host countries benefit from FDI?

- The common econometric (panel) model used to describe how FDI effects on economic growth is given below

$$\begin{aligned} EconomicGrowth &= c_0 + c_1 FDI + c_2 HumanCapital \\ &\quad + c_3 FDI \times HumanCapital + c_4 X, \quad (1) \end{aligned}$$

  where X is a vector of some control variables, say, geography, demography and policy variables, and FDI is the foreign direct investment.
- Two issues related to model (1) to be addressed: First, X should be allowed to include the lagged variables so that the model becomes a dynamic panel model. Second, the endogeneity issue is very challenging; Li and Liu (2004) and Henderson, Papageorgiou and Parmeter (2012).

Motivations: Can host countries benefit from FDI?

- Contradictory empirical results in the literature
  - Positive effects: Blomstrom, Lipsey and Zejan (1992), Borensztein, De Gregorio and Lee (1998), De Mello (1999), Ghosh and Wang (2009), Kottaridi and Stengos (2010)
  - Failed to find beneficial effects: Haddad and Harrison (1992), Aitken and Harrison (1999), Lipsey (2003), and Carkovic and Levine (2005)
  - Grog and Strobl (2001): a meta analysis of 21 studies from 1974 to 2001, of which 13 studies reported positive results, 4 studies reported negative effects and the remaining 4 studies reported inconclusive evidence.
- Mixed empirical evidences: Nonlinearity and Heterogeneity

Motivations: Can host countries benefit from FDI?

Some papers point out these issues in the literature

- Nonlinearity:
  Lipsey and Zejan (1992), Durlauf and Johnson (1995), Borensztein, De Gregorio and Lee (1998), Nunnemkamp (2004), Henderson, Papageorgiou and Parmeter (2012) and Kottaridi and Stengos (2010)
- Heterogeneity:
  Luiz and De Mello (1999), Xu (2000), Grog and Strobl (2001), Kottaridi and Stengos (2010)

Motivations: Nonlinearity

The nonlinearity in FDI effects is mainly due to the so called **absorptive capacity** in host countries, the fact that host countries need some minimum (initial) conditions to absorb the spillovers from FDI.

- Borensztein, De Gregorio and Lee (1998) found that a threshold stock of human capital in host countries is necessary for them to absorb beneficial effects of advanced technologies brought from FDI.
- Hermes and Lensink (2003), Alfaroa, Chandab, Kalemli-Ozcan and Sayek (2004) and Durham (2004) focused on the local financial market conditions of a country's absorptive capacity.

Motivations: Nonlinearity

Most existing methods in the literature to deal with the nonlinear issue are mainly as follows:

- A: By simply using some parametric nonlinear models: including an interacted term in the regression or running a threshold regression. But the problem is that a parametric nonlinear model has the risk of model misspecification.
- B: By nonparametric models: Henderson, Papageorgiou and Parmeter (2012) and Kottaridi and Stengos (2010) adopted nonparametric regressions into a growth model. But the problem is that there exists the curse of dimensionality in nonparametric estimation.

Motivations: Nonlinearity

To overcome the aforementioned difficulties and problems, a functional coefficient model may be the right technique in this empirical study to characterize the correlation between the economic growth and FDI under different initial conditions and to describe the nonlinearity; see Cai (2010) for details. Also, Cai (2010) argued that a functional coefficient model has some ability to characterize the heterogeneity.

Motivations: Heterogeneity

- Heterogeneity among countries is another concern in cross-country studies. Different results can be obtained by using different types of data.
- **Cross sectional or time series data**: Grog and Strobl (2001) found that whether a cross sectional or time series data had been used matters for estimating the effect of FDI on economic growth, because both the cross sectional and time series models cannot control the country-specific heterogeneity.

Motivations: Heterogeneity

Recent literature focused on panel data:

- Including individual effects: only allows a location shift for each individual country and it is often inadequate to deal with the heterogeneity effects of FDI on economic growth across countries;
  Blomstrom, Lipsey, and Zejan (1996), Ghosh and Wang (2009), Haddad and Harrison (1993)
- Splitting sample: loses some sample information and degrees of freedom; the applied researchers often split sample without following the theoretical guideline of the selection of thresholds;
  Luiz and De Mello (1999), Kottaridi and Stengos (2010)

Motivations: Heterogeneity

To accommodate the heterogeneity, we will employ quantile method to analyze the effect of FDI on economic growth.

- Under the quantile framework, the estimation can be done on different quantile levels to characterize the various shapes of distribution.
- This technique is especially useful when the conditional distribution is heterogenous, asymmetric, fat-tailed, censored, or truncated.
- It can characterize how FDI makes different effects on economic growth for different countries; say, for high-incoming and middle-incoming countries or for OECD and non-OECD countries.

The Empirical Model

To deal with the above two issues, the following semiparametric conditional quantile panel data model is proposed

$$\mathbf{Q}_\tau(y_{it} \mid U_i, \mathbf{X}_{it}, \alpha_i) = \alpha_i + \beta_{1,\tau}(U_i)(\mathrm{FDI}/Y)_{it} + \beta_{2,\tau}\log(\mathrm{DI}/Y)_{it} + \beta_{3,\tau}n_{it} + \beta_{4,\tau}h_{it} + \beta_{5,\tau}((\mathrm{FDI}/Y)_{it} \times h_{it}),$$

- y_{it}: the growth rate of GDP per capita; n_{it}: the logarithm of population growth rate; h_{it}: the human capital; U_i is the initial condition (the logarithm of GDP per capita) in each country i
- *FDI* and *DI* refer to foreign direct investment and domestic investment respectively and Y represents the total output;
- α_i is the individual effect used to control the unobserved country-specific heterogeneity.

Literature Review

Linear Quantile Model

- Linear Quantile Panel Data Model, for $0 < \tau < 1$,

$$Q_\tau(\boldsymbol{X}_{it}) = \alpha_i + \boldsymbol{X}_{it}'\beta_\tau, \quad 1 \le i \le N, \quad 1 \le t \le T,$$

  where α_i is fixed effect or random effect and $Q_\tau(\boldsymbol{X}_{it})$ is the conditional quantile satisfying $P(y_{it} \le Q_\tau(\boldsymbol{X}_{it})|\boldsymbol{X}_{it}) = \tau$.
- Koenker (2004) proposed two methods to estimate β_τ with fixed effects by assuming $T \to \infty$.
  - The first method is to solve a piecewise linear quantile loss function by using interior point methods.
  - The second is the so called penalized quantile regression method, in which the quantile loss function is minimized by adding L_1 penalty on fixed effects.

Linear Quantile Panel Data Model

- For fixed T, **Abrevaya and Dahl (2008)** followed the idea from Chamberlian (1984) (correlated random effects + linear projection) to consider

$$Q_\tau(\boldsymbol{X}_{it}) = \alpha_i + \boldsymbol{X}_{it}'\beta_\tau, \quad \alpha_i = \Sigma_{t=1}^{T}\boldsymbol{X}_{it}'\boldsymbol{\delta}_t + v_i.$$

- For fixed T, **Gamper-Rabindram, Khan and Timmins (2008)** allowed the random effects to be correlated with $\boldsymbol{X}_i$ nonparametrically

$$Q_\tau(\boldsymbol{X}_{it}) = \alpha_i + \boldsymbol{X}_{it}'\beta_\tau, \quad \alpha_i = \phi(\boldsymbol{X}_{i1}, \cdots, \boldsymbol{X}_{iT}) + v_i.$$

Remark: A fully nonparametric setting of $\phi(\cdot)$ may lead to a problem of curse of dimensionality and becomes infeasible in practice.

Our Model

Our Model

- Partially varying-coefficient panel data model with correlated random effects

$$Q_\tau(Y_{it} \mid U_{it}, \mathbf{X}_{it}, \alpha_i) = \mathbf{X}'_{it,1}\gamma_\tau + \mathbf{X}'_{it,2}\beta_\tau(U_{it}) + \alpha_i \quad (2)$$

  - α_i is correlated random effect
  - γ_τ is the constant coefficient, $\beta_\tau(U_{it})$ is the functional coefficient
  - U_{it} is the smoothing variable
- When $U_{it} = U_i$ for any t, the functional coefficients are only variant for different individuals, and this setting is commonly applied in the empirical studies. In the empirical part of our paper, we analyze the effect of FDI on economic growth by assuming that it is variant across different countries, because of the different absorptive capacity of different countries.

Our Model

In this paper, we focus on the case: $U_{it} = U_i$ for any t

$$Q_\tau(Y_{it} \mid U_i, \mathbf{X}_{it}, \alpha_i) = \mathbf{X}'_{it,1}\gamma_\tau + \mathbf{X}'_{it,2}\beta_\tau(U_i) + \alpha_i \quad (3)$$

where

- $\alpha_i = \phi(\mathbf{X}_{i1}, \cdots, \mathbf{X}_{iT}) + v_i = \Sigma_{t=1}^{T}\mathbf{X}'_{it}\delta_t(U_i) + v_i$
- U_i is the smoothing variable and in our empirical example, U_i is the initial condition in each country i
- Note that model (3) can be generalized to a more general setting for the smoothing variable $U_{it} = \eta'\mathbf{W}_{it}$, single index method; see Fan, Yao and Cai (2003).

Our Model

To identify the heteroscedasticity, by following **Abrevaya and Dahl (2008)**, we assume that

- I1. v_i is independent of $(U_i, \mathbf{X}_i)$ with $\mathbf{X}_i = (\mathbf{X}_{i1}, \cdots, \mathbf{X}_{iT})$;
- I2. $Q_\tau(Y_{it}|U_i, \mathbf{X}_i, v_i) = Q_\tau(Y_{it}|U_i, \mathbf{X}_{it}, v_i)$.

Assumption I1 is a common assumption used in the literature of correlated random effects; see Abrevaya and Dahl (2008). It restricts the quantiles of v_i do not depend upon $\mathbf{X}_i$. Assumption I2 allows for arbitrary forms of heteroscedasticity only through $\mathbf{X}_{it}$. Note that the I2 might rule out the case of dynamic panel data models.

Our Model

Under the above assumptions, model (3) can be re-expressed (use the same notation) as

$$Q_\tau(y_{it} \mid U_i, X_i, v_i) = X'_{it,1}\gamma_\tau + X'_{it,2}\beta_\tau(U_i) + \Sigma_{s=1}^{T} X'_{is}\delta_s(U_i) + v_i$$

which is a semiparametric quantile panel model.

- The estimates of γ_τ and $\beta_\tau(U_i)$ can be obtained by estimating two different periods through taking subtraction, for $t \neq s$,
  - $\gamma_\tau = \partial Q_\tau(y_{it} \mid U_i, X_i, v_i)/\partial X_{it,1} - \partial Q_\tau(y_{is} \mid U_i, X_i, v_i)/\partial X_{it,1}$
  - $\beta_\tau(U_i) = \partial Q_\tau(y_{it} \mid U_i, X_i, v_i)/\partial X_{it,2} - \partial Q_\tau(y_{is} \mid U_i, X_i, v_i)/\partial X_{it,2}$
- Therefore, we need one more important assumption that I3. $T \geq 2$.

This assumption is to ensure that γ_τ and $\beta_\tau(\cdot)$ are identified.

Our Model

- However, in order to avoid running two separating conditional quantile models, we adopt Abrevaya and Dahl (2008)'s pooling regression strategy by stacking covariates. We now consider the following transformed model from (3),

$$Q_\tau(y_{it} | U_i, \mathbf{Z}_{it}, v_i) = \mathbf{Z}'_{it,1}\gamma_\tau + \mathbf{Z}'_{it,2}\boldsymbol{\theta}_\tau(U_i) + v_i, \qquad (4)$$

  where $\boldsymbol{\theta}_\tau(U_i) = (\beta'_\tau(U_i), \delta'_1(U_i), \cdots, \delta'_T(U_i))'$.
- To estimate the above semiparametric model with random effect, we propose a three-stage estimation procedures as follows.

Estimation Procedures

The first stage

- To estimate the functionals and parameters in (4), the main idea is to use the integrated quasi-likelihood method and an approximation approach.
- First, we estimate γ_τ. To do so, we treat all coefficients as functional coefficients depending on U_i; that is $\gamma_\tau = \gamma_\tau(U_i)$. Then, for a given u_0, a grid point which can be taken to be any value within the domain of U_i, when U_i is close to u_0, $\gamma_\tau(U_i)$ and $\boldsymbol{\theta}_\tau(U_i)$ are approximated by $\gamma_\tau(U_i) \approx \gamma_0 = \gamma_\tau(u_0)$ and $\boldsymbol{\theta}_\tau(U_i) \approx \boldsymbol{\theta}_0 = \boldsymbol{\theta}_\tau(u_0)$.

The first stage

- The model is estimated as a fully functional-coefficient model and the locally penalized objective function is given by

$$\min_{\gamma_0,\theta_0,\theta_1} \sum_{i=1}^{N}\sum_{t=1}^{T} \rho_\tau(Y_{it} - \mathbf{Z}'_{it,1}\gamma_0 - \mathbf{Z}'_{it,2}\theta_0 - \mathbf{Z}'_{it,2}\theta_1(U_i - u_0) - \tilde{v}_i$$
$$K_h(U_i - u_0) + \sum_{i=1}^{N}\psi(\tilde{v}_i), \quad (5)$$

where $\boldsymbol{\theta}_1 = \partial\boldsymbol{\theta}_\tau(u_0)/\partial u_0$, $\rho_\tau(y) = y[\tau - I_{y<0}]$ is the so-called check function, $K_h(u) = K(u/h)/h$, $K(\cdot)$ is a kernel function, $\psi(\cdot)$ is a penalty function and $\tilde{v}_i$ satisfies some equations.

The second stage

- Second, we employ the average method to achieve the root-N consistent estimator of γ_τ

$$\hat{\gamma}_\tau = \frac{1}{N}\sum_{i=1}^{N}\hat{\gamma}_\tau(U_i). \quad (6)$$

- We will show that $\hat{\gamma}_\tau$ is $\sqrt{N}$-consistent.
- Note that the estimate in (6) might not be efficient. To obtain the efficient estimate of γ_τ, we can use a weighted average with the optimal weight.

The third stage

- Finally, to estimate functionals, plug $\hat{\gamma}_\tau$ into model (4) and denote the partial residual by $Y^*_{it} = Y_{it} - Z_{it,1}{}'\hat{\gamma}_\tau$. Then, the functional coefficients can be estimated by using the local linear quantile estimation as

$$\min_{\theta_0,\theta_1} \sum_{i=1}^{N}\sum_{t=1}^{T} \rho_\tau(Y^*_{it} - Z_{it,2}{}'\boldsymbol{\theta}_0 - Z_{it,2}{}'\boldsymbol{\theta}_1(U_i - u_0) - \tilde{v}_i)$$
$$K_h(U_i - u_0) + \sum_{i=1}^{N}\psi(\tilde{v}_i). \quad (7)$$

Estimation

- In the above estimation procedure, indeed, regard $\boldsymbol{\delta}_s(U_i)$ as $\boldsymbol{\delta}_{s,\tau}(U_i)$. Therefore, it would be interesting to test if all $\{\boldsymbol{\delta}_{s,\tau}(U_i)\}$ do not depend on τ if they are independent of τ.
- We leave this issue as future work.

Asymptotic Results

THEOREM 1

Theorem 1: Suppose that Assumptions A and I hold, we have

$$\sqrt{N}(\hat{\gamma}_\tau - \gamma_\tau - \boldsymbol{B}_\gamma) \xrightarrow{D} N(0, \Sigma_\gamma), \quad (8)$$

where
$\Sigma_\gamma = \frac{\tau(1-\tau)}{T} E\{e_1'(\Omega^*(U_i))^{-1}[\Omega(U_i) + \sum_{t=2}^{T} \frac{2(T-t+1)}{T}\Omega_{1t}(U_i)](\Omega^*(U_i))^{-1}e_1\}$
and $\boldsymbol{B}_\gamma = \mu_2 h_1^2(2\boldsymbol{B}_1^* - \boldsymbol{B}_2^*)$ in which
$\boldsymbol{B}_1^* = e_1' E[(\Omega^*(U_i))^{-1}\dot{\Omega}^*(U_i)\begin{pmatrix} 0 \\ \dot{\theta}_\tau(U_i) \end{pmatrix}]$,
$\boldsymbol{B}_2^* = e_1' E[(\Omega^*(U_i))^{-1}\Theta(U_i)]$,
$\Theta(U_i) = E\{\dot{f}_{Y|U,Z}(Q_\tau(U_i, Z_{it}))Z_{it}[Z_{it,2}'\dot{\theta}_\tau(U_i)]^2|U_i\}$ and
$e_1' = (\boldsymbol{I}_{K_1^*}, \boldsymbol{0}_{K_1^* \times K_2^*})$.

THEOREM 2

Theorem 2: Suppose that Assumptions A and I hold, we have

$$\sqrt{Nh_2}(\hat{\beta}_\tau(u_0) - \beta_\tau(u_0) - \frac{h_2^2}{2}\mu_2\ddot{\beta}_\tau(u_0)) \to N(0, \Sigma_\beta(u_0)),$$

where $\Sigma_\beta(u_0) = \frac{\tau(1-\tau)\nu_0}{Tf_U(u_0)} e_2'\Sigma(u_0)e_2$ with
$\Sigma(u_0) = (\Omega_2^*(u_0))^{-1}[\Omega_2(u_0) + \sum_{t=2}^{T} \frac{2(T-t+1)}{T}\Omega_{1t,2}(u_0)](\Omega_2^*(u_0))^{-1}$.

Constructing Confidence Interval

- From Theorem 2, to construct the confidence interval with bias ignored, we need to obtain consistent estimate for Σ_γ, where $\Sigma_\gamma = \frac{\tau(1-\tau)}{T} E\{e_1'(\Omega^*(u_0))^{-1}[\Omega(u_0) + \sum_{t=2}^{T} \frac{2(T-t+1)}{T}\Omega_{1t}(u_0)](\Omega^*(u_0))^{-1}e_1\}$.
- Important components need to be estimated: $\Omega^*(u_0)$, $\Omega(u_0)$, and $\Omega_{1t}(u_0)$.
  - $\Omega^*(u_0) = E(Z_{it}Z_{it}'f_{Y|U,Z}(Q_\tau(u_0, Z_{it}))|u_0)$
  - $\Omega(u_0) = E(Z_{it}Z_{it}'|u_0)$
  - $\Omega_{1t}(u_0) = E(Z_{i1}Z_{it}'|u_0)$
- By Cai and Xu (2008), consistent estimates of $\Omega(u_0)$, $\Omega_{1t}(u_0)$, and $\Omega^*(u_0)$ can be constructed as follows.

Constructing Confidence Interval

- $\hat{\Omega}_{NT}(u_0) = (NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} Z_{it} Z_{it}' K_h(U_i - u_0)$,

  $\hat{\Omega}_{NT,1t}(u_0) = (N(T-t))^{-1} \sum_{i=1}^{N} \sum_{s=1}^{T-t} Z_{is} Z_{i(s+t)}' K_h(U_i - u_0)$.
  - Indeed, $\hat{\Omega}_{NT}(u_0) = f_U(u_0)\Omega(u_0) + o_p(1)$, and $\hat{\Omega}_{NT,1t}(u_0) = f_U(u_0)\Omega_{1t}(u_0) + o_p(1)$.
- To estimate $\Omega^*(u_0) = E(Z_{it} Z_{it}' f_{Y|U,Z}(Q_\tau(u_0, Z_{it}))|u_0)$, we need to estimate $\hat{f}_{Y|U,Z}(Q_\tau(u_0, z))$.
  - One method is to apply the Nadaraya-Watson type (or local linear) double-kernel method of Fan, Yao and Tong (1996):

$$\hat{f}_{Y|U,Z}(Q_\tau(u_0, Z_{it})) = \frac{\sum_{i=1}^{N} \sum_{t=1}^{T} K_h(U_i - u_0, Z_{it} - z) L_h(Y_{it} - Q_\tau(u_0, z))}{\sum_{i=1}^{N} \sum_{t=1}^{T} K_h(U_i - u_0, Z_{it} - z)}.$$

Testing Constancy of Varying Coefficients

Testing Constancy

- We apply the similar idea from Cai and Xiao (2012). However, we construct the test statistics, which is different from Cai and Xiao (2012)'s, to check the constancy of the functional coefficients $\beta_\tau(u)$; that is to test

  $H_0 : \beta_\tau(u) = \beta_\tau$, versus H_1: coefficients $\beta_\tau(u)$ are varying.
- Under the null hypothesis,

$$T_N = \sum_{j=1}^{q} ||\sqrt{Nh_2}\hat{\Sigma}_\beta(u_j)^{-1/2}(\hat{\beta}_\tau(u_j) - \hat{\beta}_\tau)||^2$$

  where $\{u_j\}_{j=1}^q$ are any distinct points within the domain of U_i, and $T_N \to \chi^2(qK_2)$.

Testing Constancy

- Thus, one can reject the null if T_N is too large.
- The above testing procedure has the advantage that its limiting distribution is free of nuisance parameter and quantiles. As an alternative, we may consider a bootstrap based test, which may give some finite sample improvement. Another issue related to the proposed test is the choice of finite distinct points $\{u_j\}_{j=1}^q$.

Testing Constancy

- In practice, we may consider, say choosing lower quartile, median, and upper quartiles, or we may construct the test based on all deciles. In some applications, different choices of q and the points $\{u_j\}_{j=1}^q$ may potentially lead to different conclusions in finite sample, thus it would be desirable to consider all points u on the domain U_i, and treat $\widetilde{\beta}(u)$ as a process in u, and Kolmogorov-Smirnov or Cramer-von-Mises type tests may be constructed. Of course, it would be warranted as a future research topic to investigate the properties of those test statistics.

Monte Carlo Simulation

Monte Carlo Simulation

We consider the following data generating process

$$Q_\tau(Y_{it}|U_i, \mathbf{X}_i, v_i) = \gamma_{0,\tau} + X_{it,1}\gamma_{1,\tau} + X_{it,2}\beta_\tau(U_i) + \sum_{t=1}^{T} X_{it,2}\delta_t(U_i) + v_i,$$

where the smoothing variable U_i is generated from *iid* $\mathrm{U}(-2.5, 2.5)$, $X_{it,1}$ and $X_{it,2}$ are respectively generated from the *iid* $\mathrm{U}(0,3)$ and $\mathrm{U}(0,2)$, v_i is generated from the *iid* $\mathrm{N}(0,1)$, and Y_{it} is generated base on Skorohod representation. The constant coefficients are set by $\gamma_{0,\tau} = 2 + \tau$ and $\gamma_{1,\tau} = -1.5 + \tau$. The functional coefficients are defined as $\beta_\tau(u) = 0.5\cos(2u) + u/3 + \tau$, $\delta_1(u) = \sin(1.5u)$, and $\delta_2(u) = 1.5e^{-u^2} - 0.75$.

Monte Carlo Simulation

- We take $T = 2$ and $N = 200$, 400 and 800. For a given sample size, we repeat 500 times to calculate the MADE.
- We compare the estimation results using different bandwidths, such as $h_1 = 5\,N^{-2/5}$ and $h_2 = c\,N^{-1/5}$, where c is chosen from 1.5, 1.7, 2, 2.2, 2.5, 2.7, 3.0, $\cdots$.
- From the simulation results we can conclude that the estimation of constant coefficients is not sensitive to the choice of the bandwidth when the first step is under-smoothed, and the estimation of $\beta_\tau(\cdot)$ is quite stable when the bandwidth selection is chosen within a reasonable range. The optional bandwidth of functional coefficients is around $h_2 = 2.7\,N^{-1/5}$.

Simulation Results

Table 1: The Median and SD of the MADE for $\hat{\gamma}_{0,\tau}$, $\hat{\gamma}_{1,\tau}$ and $\hat{\beta}_\tau(\cdot)$

	$\tau = 0.15$			$\tau = 0.5$			$\tau = 0.75$		
	$\gamma_{0,\tau}$	$\gamma_{1,\tau}$	$\beta_\tau(\cdot)$	$\gamma_{0,\tau}$	$\gamma_{1,\tau}$	$\beta_\tau(\cdot)$	$\gamma_{0,\tau}$	$\gamma_{1,\tau}$	$\beta_\tau(\cdot)$
200	0.2786	0.1569	0.2548	0.2244	0.1163	0.2089	0.2462	0.1362	0.2111
	(0.2356)	(0.1474)	(0.0838)	(0.1960)	(0.1003)	(0.0605)	(0.2324)	(0.1207)	(0.0620)
400	0.2001	0.1410	0.1993	0.1543	0.0839	0.1585	0.1817	0.1115	0.1635
	(0.1660)	(0.1039)	(0.0650)	(0.1259)	(0.0684)	(0.0470)	(0.1478)	(0.0893)	(0.0518)
800	0.1659	0.1243	0.1678	0.1041	0.0574	0.1210	0.1499	0.0896	0.1342
	(0.1347)	(0.0835)	(0.0495)	(0.0961)	(0.0514)	(0.0342)	(0.1223)	(0.0728)	(0.0405)

Empirical Example

Data

- Our data set includes 95 countries or regions from 1970 to 1999.
- All the data are available to be downloaded from World Development Indicators (WDI) and United Nations Conference on Trade and Development (UNCTAD).

The Empirical Model

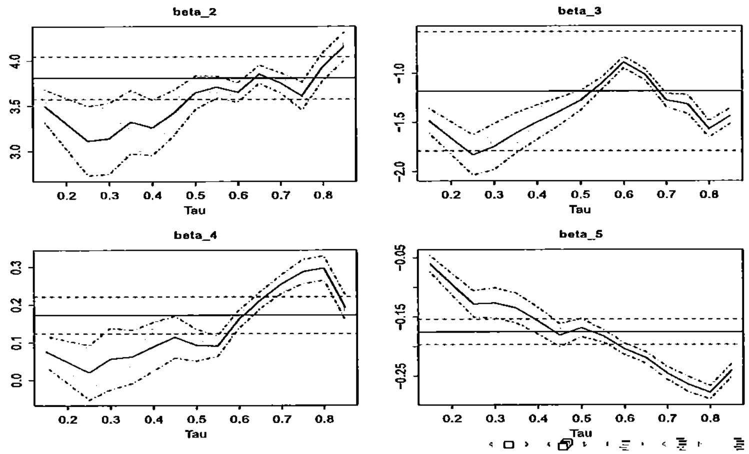
- The following semiparametric conditional quantile panel data model given in (??) is used to model this data

$$\mathbf{Q}_\tau(y_{it} \mid U_i, \mathbf{X}_{it}, \alpha_i) = \alpha_i + \beta_{1,\tau}(U_i)(\mathrm{FDI}/Y)_{it} + \beta_{2,\tau}\log(\mathrm{DI}/Y)_{it} + \beta_{3,\tau} n_{it} + \beta_{4,\tau} h_{it} + \beta_{5,\tau}((\mathrm{FDI}/Y)_{it} \times h_{it}),$$

  - y_{it}: the growth rate of GDP per capita; n_{it}: the logarithm of population growth rate; h_{it}: the human capital;
  - *FDI* and *DI* refer to foreign direct investment and domestic investment respectively and Y represents the total output;
  - α_i is the individual effect;
  - U_i is the initial condition (the logarithm of GDP per capita) in each country i.

Empirical Results: Parametric part

- The parametric coefficients $\hat{\beta}_{j,\tau}$ for $2 \leq j \leq 5$.



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Empirical Results: Parametric part

- Previous figures present estimates of 4 constant coefficients $\beta_{j,\tau}$ under different quantiles.
  - Horizontal axis: different quantiles.
    Vertical axis: the values of estimators.
  - The curves in solid line denote the estimates under different quantiles and the dashed lines are the corresponding 90% confidence intervals.
  - For all coefficients, we can observe that most quantile estimates are outside the 90% confidence intervals of the conditional mean estimates, which implies that the conditional mean model is not sufficient to summarize the empirical economic growth relation.

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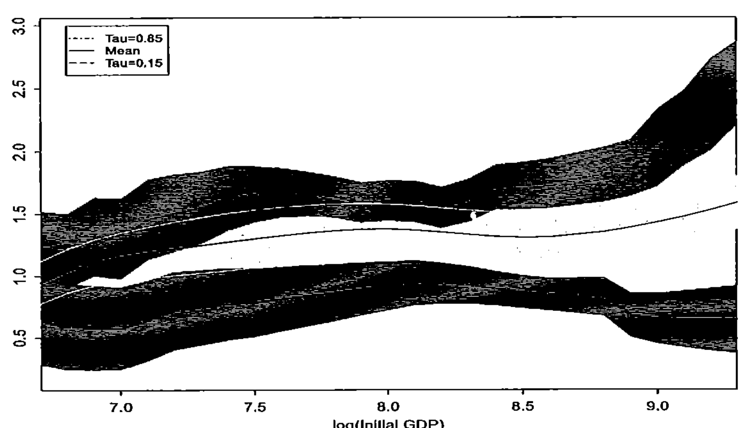
Empirical Results: Nonparametric part

- The functional coefficient $\hat{\beta}_{1,\tau}(\cdot)$ for $(FDI/Y)_{it}$.



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Empirical Results: Nonparametric part

- This figure displays the estimates of varying coefficients when $\tau = 0.15$ and 0.85 together with the conditional mean.
  - Horizontal axis: different U_i. Vertical axis: the values of estimates.
  - The dark shaded areas represent the 90% confidence intervals.
  - It shows that higher-quantile countries or regions can benefit more from FDI than lower-quantile ones.
  - It also presents empirical evidence that countries or regions with better initial conditions can absorb relatively large beneficial effects from FDI inflows.

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The Empirical Model

- We tested if the coefficient functions $\beta_{j,\tau}(\cdot)$ for $1 \leq j \leq 5$ are constant or not.

Table 2: *p*-values of Constancy Test

τ	$\beta_{1,\tau}$	$\beta_{2,\tau}$	$\beta_{3,\tau}$	$\beta_{4,\tau}$	$\beta_{5,\tau}$
0.15	0.42951	0.99999	0.99999	0.99999	0.99999
0.5	0.17098	0.99999	0.99999	0.99999	0.99999
0.65	0.00000	0.99999	0.99999	0.99999	0.99999
0.85	0.00000	0.99999	0.99999	0.99999	0.99999

Testing Results of Constancy of the Coefficients in Quantile Model

- For the constancy of $\beta_{1,\tau}(U_i)$: The p-values are 0.42951, 0.17098, 0.00000 and 0.00000 for $\tau = 0.15$, 0.5, 0.65 and 0.85 quantiles, respectively. The tests of $\tau = 0.65$, and 0.85 strongly reject the null of constancy, which implies that the impact of FDI on growth depends on the initial conditions.
- For the constancy of $\beta_{j,\tau}(U_i)$, $j \neq 1$, all p-values are larger than 5%, which implies that they are indeed constant. That is why we only consider the semiparametric model given in (9).

Conclusion

Summary

- In this paper, motivated by the empirical work, we propose a partially varying-coefficient quantile panel data model with correlated random effects to estimate the nonlinear effect of FDI on economic growth and also to account for the heterogeneity.
- Our paper makes both methodological and theoretical contributions to the econometrics literature. In particular, we propose a three-stage approach to estimate the parameters and functional coefficients and show that the estimation of parameters is $\sqrt{N}$-consistent and derive the asymptotic normality. Further, we propose a consistent estimation of the covariance matrix so that one can construct a confidence interval. Finally, a simple test is adopted for testing the constancy of functional coefficients.

Future Research

Future Research Related to This Talk

- Our model with fixed effect would be also interesting and challenging in econometrics and it would be warranted as a future research topic. Indeed, we are working on this problem.
- As pointed out in the recent literature such as Henderson, Papageorgiou and Parmeter (2012), the endogeneity of FDI in growth estimation is a challenging problem and we will explore this issue.
- If model (1) contains the lagged variables, then it becomes a dynamic quantile panel model. How to handle this case?
- Other econometric issues such as the aforementioned testing problems and bandwidth selection are needed to be addressed.

Thank you