Inequality and development: Evidence from semiparametric estimation with panel data

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Highlights

► Nonparametric and semiparametric models on Kuznet’s equality-development relationship. ► Sample of 75 countries for the period 1962–2003. ► Kuznet’s inverted-U relationship confirmed when development has reached a threshold. ► The result is robust whether or not the control variables are included in the model. ► The findings throw new lights on the inequality-development relationship.
Inequality and development: Evidence from semiparametric estimation with panel data

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\textbf{A B S T R A C T}

Evidences from nonparametric and semiparametric unbalanced panel data models with fixed effects show that Kuznet’s inverted-U relationship is confirmed when economic development reaches a threshold. The model tests justify semiparametric specification. The integrated net contribution of control variables to inequality reduction is significant.

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1. Introduction

The mixed empirical results on Kuznet’s inverted-U relationship between inequality and economic development using parametric quadratic models have been improved by nonparametric studies using cross-section data with nonparametric functional forms or higher-than-second-order nonlinearity (Li et al., 1998; Barro, 2000; Bulir, 2001; Iradian, 2005; Mushinski, 2001; Huang, 2004; Lin et al., 2006). This paper conducts a nonparametric and semiparametric investigation on the inverted-U relationship with unbalanced panel data. The analysis incorporates heterogeneity across economies. The following sections discuss the data and model specification, present the methodology with unbalanced panel data, conduct estimations and tests and conclude the paper.

2. Data and model specification

The Gini coefficient data and the inequality proxy are obtained from the World Bank “Project on Inequality”.\footnote{\textsuperscript{1}} The unbalanced panel Gini coefficient data contains 75 countries (with at least two years’ data) with 704 observations for the period 1962–2003. Real GDP per capita (in 2005 constant price) is the proxy for development. Such economic and policy variables obtained from the Penn World Table and WDI as openness (openk, percentage share of trade in GDP in 2005 constant price), urbanization (urbanize, urban population as percentage of total population), investment (ki, share of investment in real GDP per capita), growth, and inflation (annual percentage of GDP deflator), are taken as control variables. Table 1 shows the basic statistics.

The nonparametric panel data model with fixed effects is

\[
g_{\text{it}} = g(\text{lgdp}_{\text{it}}) + u_i + v_{\text{it}},
\]

where the functional form of \( g(\cdot) \) is unspecified, \( \text{lgdp}_{\text{it}} \) is the logarithm of real GDP per capita. Each country \( i \) has \( m_i \) observations. Individual effects \( u_i \) are fixed effects which are correlated with \( \text{lgdp}_{\text{it}} \) with an unknown correlation structure. The error term \( v_{\text{it}} \) is assumed to be i.i.d. with finite variance and mean-independent of \( \text{lgdp}_{\text{it}} \), namely, \( E(v_{\text{it}}|\text{lgdp}_{\text{it}}) = 0 \).

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\footnote{The “Inequality around the World” and “All the Ginis” dataset are compiled from Deininger–Squire (1960–1996), WIDER (1950–1998) and World Income Distribution (1985–2000) datasets. “Giniall” gives the Gini coefficients from household survey for 1067 country/years. The coefficients with “Di = 1” are chosen. The December 2006 version and recent years’ data are used. See Milanovic (2005).}
The semiparametric counterpart of Model (1) with control variables is:
\[
\begin{align*}
gen_{it} = g(lgdp_{it}) + \gamma_i + \delta_{it}, \\
t = 1, 2, \ldots, m_i; \quad i = 1, 2, \ldots, n,
\end{align*}
\]
where \(v_{it}\) is also assumed to be mean-independent of \(x_{it}\). Since the regressor “growth” may be endogenous (Huang et al., 2009), its lagged form is used in the model.

When \(g(\cdot)\) is parametric quadratic, cubic or fourth-degree polynomial functions of \(lgdp_{it}\), (1) and (2) become parametric unbalanced panel data models with fixed effects. Columns 1–3 of Table 2 report the parametric estimation results. Note that a fourth-degree polynomial function is still significant although the coefficient estimates in quadratic and cubic forms are also significant. This casts doubts on the conventional quadratic specification for the relationship.

### 3. Nonparametric estimation and testing method

Let \( y = \text{gini} \) and \( z = \text{lgdp}_{it} \). Models (1) and (2) are estimated by the iterative procedure modified from Henderson et al. (2008) for unbalanced panel data. Model (1) is used to illustrate the specific modification. To remove the fixed effects, we write

\[
\tilde{y}_{it} = y_{it} - \gamma_i = g(z_{it}) - g(z_i) + \nu_{it} - v_{it} = g(z_{it}) - g(z_i) + v_{it}.
\]

Denote \( \tilde{y}_i = (\tilde{y}_{i2}, \ldots, \tilde{y}_{im}) \), \( \hat{v}_i = (\hat{v}_{i2}, \ldots, \hat{v}_{im}) \), \( \hat{g}_i = (\hat{g}_{i2}, \ldots, \hat{g}_{im}) \). The variance–covariance matrix of \( \hat{v}_i \) and its inverse are calculated as \( \Sigma_i = \sigma_i^2 (m_i - 1) e_i \) and \( \Sigma_i^{-1} = \sigma_i^2 (m_i - 1) e_i' e_i \), where \( e_i = (1, \ldots, 1)' \) is a \((m_i - 1) \times 1\) vector of ones. The criterion function is given by

\[
\tilde{S}(g_i) = \frac{1}{2} \left( \tilde{y}_i - g_i \hat{v}_i e_i \right)' \Sigma_i^{-1} \left( \tilde{y}_i - g_i \hat{v}_i e_i \right),
\]

\( i = 1, 2, \ldots, n \).

Denote the first derivatives of \( \tilde{S}(g_i) \) with respect to \( g_{it} \) as \( \tilde{S}_{it}(g_i, g_{it}), t = 1, 2, \ldots, m_i \). Then

\[
\begin{align*}
\tilde{S}_{it}(g_i, g_{it}) &= -e_{m-i-1} \Sigma_i^{-1} (\tilde{y}_i - g_i + g_{it} \hat{v}_i e_i), \\
\tilde{S}_{it}(g_i, g_{it}) &= c_{i-t-1} \Sigma_i^{-1} (\tilde{y}_i - g_i + g_{it} \hat{v}_i e_i), \quad t \geq 2,
\end{align*}
\]

where \( c_{i-t} = (m_i - 1) \times 1 \) matrix with \((t - 1)\)th element/other elements being 1/0. Denote \((\alpha_0, \alpha_1)' \equiv (g(z), dg(z)/dz)' \). It can be estimated by solving the first order conditions of the above criterion function iteratively:

\[
\frac{n}{1} \frac{1}{m} \sum_{i=1}^{m} K_{g_{it}} (z_{it} - \hat{g}_{it}) \tilde{S}_{it}(g_i, g_{it}) \times \left( \hat{g}_{i(1)}, \ldots, \hat{g}_{i(1)}(z_{im}) \right) = 0,
\]

where the argument \( \tilde{S}_{it}(g_i, g_{it}) \) for \( s \neq t \) and \( G_t(\alpha_0, \alpha_1)' \) when \( s = t \) and \( \hat{g}_{i(1)}(z_{im}) \) is the \((1 - 1)\)th iterative estimates of \((\alpha_0, \alpha_1)' \). Here \( G_{it} (\equiv (1, z_{it} - \hat{z}_{it})/h) \) and \( k(h) = h^{-1} k(v/h), k(\cdot) \) is the kernel function. The next iterative estimator of \((\alpha_0, \alpha_1)' \) is equal to \((\hat{g}_{it}(z), \hat{g}_{it}(z))' \).

The null hypothesis \( H_0 \) is parametric model with \( g(z) = 0 \). For example, \( \theta_0 (z, \gamma) = \gamma_0 + \gamma_1 z + \gamma_2 z^2 \). The alternative \( H_1 \) is that \( g(z) \) is nonparametric. The statistic for testing this null is

\[
\hat{p}_n = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{m} \sum_{t=1}^{m} \left( \theta_0 (z_{it}, \gamma) - \hat{g}_{i(1)}(z_{it}) \right)^2,
\]

\( \hat{p}_n \) is a consistent estimator of the parametric model with fixed effects; \( \hat{p}(-) \) is the iterative consistent estimator of Model (1).

Second, test parametric against semiparametric model with control variables in Model (2). The null \( H_0 \) is parametric model with \( g(z) = 0 \). The alternative is that \( g(z) \) is nonparametric. The statistic for testing this null is

\[
\hat{p}_n^{(2)} = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{m} \sum_{t=1}^{m} \left( \theta_0 (z_{it}, \gamma) + x_{it}' \hat{\beta} - \hat{g}_{i(1)}(z_{it}) - x_{it}' \hat{\beta} \right)^2,
\]

where \( \hat{\beta} \) and \( \hat{\beta} \) are consistent estimators in the parametric panel data model with fixed effects; \( \hat{p}(-) \) and \( \hat{p}(-) \) are the iterative consistent estimator of Model (2).
Table 2

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Parametric model</th>
<th>Semiparametric model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>lgdpcc</td>
<td>37.6012</td>
<td>128.5883</td>
</tr>
<tr>
<td></td>
<td>(2.7174)</td>
<td>(26.8926)</td>
</tr>
<tr>
<td>lgdpcc^2</td>
<td>-2.0888</td>
<td>-12.7812</td>
</tr>
<tr>
<td></td>
<td>(0.1491)</td>
<td>(3.1476)</td>
</tr>
<tr>
<td>lgdpcc^3</td>
<td>-0.4110</td>
<td>0.1209</td>
</tr>
<tr>
<td></td>
<td>(0.0047)</td>
<td>(0.0129)</td>
</tr>
<tr>
<td>lgdpcc^4</td>
<td>-0.4796</td>
<td>-0.3543</td>
</tr>
<tr>
<td></td>
<td>(0.0841)</td>
<td>(0.0841)</td>
</tr>
<tr>
<td>Growth(−1)</td>
<td>0.1056</td>
<td>0.1065</td>
</tr>
<tr>
<td></td>
<td>(0.0196)</td>
<td>(0.0196)</td>
</tr>
<tr>
<td>Openk</td>
<td>0.0420</td>
<td>0.0408</td>
</tr>
<tr>
<td></td>
<td>(0.0047)</td>
<td>(0.0047)</td>
</tr>
<tr>
<td>Urbanize</td>
<td>0.0866</td>
<td>0.0565</td>
</tr>
<tr>
<td></td>
<td>(0.0216)</td>
<td>(0.0234)</td>
</tr>
<tr>
<td>Ki</td>
<td>-0.1036</td>
<td>-0.0906</td>
</tr>
<tr>
<td></td>
<td>(0.0166)</td>
<td>(0.0171)</td>
</tr>
<tr>
<td>Inflation</td>
<td>0.0013</td>
<td>0.0013</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.0003)</td>
</tr>
</tbody>
</table>

The dependent variable is Gini. The numbers in the parentheses are standard errors of the coefficient estimates. Intercept estimates in parametric models are not reported.

Table 3

<table>
<thead>
<tr>
<th>Quantile of ln(gdpcc)</th>
<th>Nonparametric model (1)</th>
<th>Semiparametric model (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>z</td>
<td>g(z)</td>
<td>Std. err.</td>
</tr>
<tr>
<td>2.5</td>
<td>7.2014</td>
<td>34.1085</td>
</tr>
<tr>
<td>25.0</td>
<td>8.7307</td>
<td>43.3724</td>
</tr>
<tr>
<td>50.0</td>
<td>9.4323</td>
<td>43.3724</td>
</tr>
<tr>
<td>75.0</td>
<td>10.2808</td>
<td>36.1586</td>
</tr>
<tr>
<td>95.0</td>
<td>10.4110</td>
<td>36.1586</td>
</tr>
</tbody>
</table>

Third, test the null nonparametric model (1) against the semiparametric model (2). The statistic for testing this null is $L_0^3 = \frac{1}{m} \sum_{i=1}^{m} \sum_{s=1}^{n} (\hat{g}(z_i) - \tilde{g}(z_i) - \tilde{\beta})^2$, where $\hat{g}(\cdot)$ is the iterative consistent estimator in Model (1) while $\tilde{g}(\cdot)$ and $\tilde{\beta}$ are the iterative consistent estimator of Model (2).

We apply bootstrap procedures to approximate the finite sample null distributions of test statistics and obtain the bootstrap probability values for the three tests.

4. Results

In the estimation, the kernel is the Gaussian function and the bandwidth is chosen according to rule of thumb. All bootstrap replications are set to be 400. The last column in Table 2 reports the coefficient estimation for the control variables in the parametric part of Model (2). Except “urbanize”, the coefficient estimates of all other control variables are close to those in parametric models, showing that growth, openness and inflation (investment) significantly increase (reduce) inequality.

In Table 3, the nonparametric function $g(\cdot)$ is estimated at some quantile points of ln(gdpcc) by using nonparametric Model (1) and semiparametric Model (2). In all these cases, the nonparametric estimates are slightly larger than their semiparametric counterparts, implying that the overall effect of control variables on inequality is negative. These policy and economic characteristics variables indeed can affect inequality.

Figs. 1 and 2 illustrate the nonparametric estimation of $g(\cdot)$ in Models (1) and (2), respectively, where lower and upper bounds of 95% confidence intervals are also drafted. The estimates are acceptable though the estimation has boundary effects. The two curves of $g(\cdot)$ in Figs. 1 and 2 look similar, implying that the control variables, though having an overall impact, play little role in the estimation of nonlinear shape of $g(\cdot)$. Huang (2004) also reported such findings. The estimation is robust to the control variables. However, the inverted-U hypothesis is confirmed only when ln(gdpcc) arrives at 7.2, about $1340 of GDP per capita (about 2.5% quantile, see Table 3). For the case less than this level, inequality decreases with development, though insignificantly, with a very wide confidence interval. This implies that the inverted-U hypothesis does not significantly hold at low stage of development.

Fig. 3 compares the two curves of $g(\cdot)$ estimated by nonparametric and semiparametric models. The vertical difference between the two curves shows the contribution of control variables to reduction in inequality. The net integrated effect of the control
variables is positive in reducing inequality. When the development level is below $\exp(9) \approx 8100$, the net integrated effect has no significant difference across different development levels. However, when the development level is above $\exp(10) \approx 22000$, the control variables have a larger integrated effect on inequality, implying that policy instruments and economic performance play a larger role in reducing inequality in the more developed than in less developed economies. For an economy with development between $8100$ and $22000$, the integrated effect of control variables on inequality is economically insignificant.

Table 4 presents three kinds of tests in Models (1) and (2). All the nulls are rejected at 1% significant level, showing that parametric form in (1) is inappropriate, but semiparametric specification in (2) is more appropriate for our sample. This justifies our analysis on the estimation of semiparametric model (1).

5. Conclusion

This paper uses nonparametric and semiparametric unbalanced panel data models with fixed effects to study the validity of the inequality and development relationship. Specification tests justify the flexible semiparametric model. The results show that Kuznet's inverted-U relationship is confirmed only when the development level arrives at a threshold. The inverted-U does not significantly hold when development is less than the threshold. This result is robust whether or not the control variables are included in the model. The integrated contribution of control variables to reduction of inequality is positive. Policy instruments and economic performance play a larger role in reducing inequality in more developed than in less developed economies.

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Appendix. The sample in the study 75 countries and years:

References


