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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.

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Inequality and development: Evidence from semiparametric estimation with panel data

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ABSTRACT

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; Bulíř, 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".[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

$$gini_{it} = g(lgdppc_{it}) + u_i + v_{it}, \quad t = 1, 2, \ldots, m_i; \quad i = 1, 2, \ldots, n, \tag{1}$$

where the functional form of $g(\cdot)$ is unspecified, $lgdppc_{it}$ 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 $lgdppc_{it}$ with an unknown correlation structure. The error term v_{it} is assumed to be i.i.d. with finite variance and mean-independent of $lgdppc_{it}$, namely, $E(v_{it}|lgdppc_{it}) = 0$.

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[1] 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).

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Table 1
The basic statistics.

	Gini	*gdppc*	Openk	Urbanize	Ki	Growth	Deflator
Minimum	17.800	561.519	5.293	0.000	2.110	−21.603	−8.000
Maximum	63.660	63419.400	399.217	94.940	56.141	16.469	4107.000
Mean	38.689	13712.587	57.848	36.457	25.099	2.187	41.129
Std-deviation	10.285	9109.813	49.738	19.816	8.032	4.651	249.507

The semiparametric counterpart of Model (1) with control variables is:

$$gini_{it} = g(lgdppc_{it}) + x_{it}'\beta + u_i + v_{it}, \quad t = 1, 2, \cdots, m_i; \quad i = 1, 2, \ldots, n, \tag{2}$$

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 $lgdppc_{it}$, (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 $y = gini$ and $z = lgdppc$. 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

$$\tilde{y}_{it} \equiv y_{it} - y_{1t} = g(z_{it}) - g(z_{i1}) + v_{it} - v_{i1} \equiv g(z_{it}) - g(z_{i1}) + \tilde{v}_{it}.$$

Denote $\tilde{y}_i = (\tilde{y}_{i2}, \ldots, \tilde{y}_{im_i})'$, $\tilde{v}_i = (\tilde{v}_{i2}, \ldots, \tilde{v}_{im_i})'$, $g_i = (g_{i2}, \ldots, g_{im_i})'$. The variance–covariance matrix of $\tilde{v}_i$ and its inverse are calculated as $\Sigma_i = \sigma_v^2(I_{m_i-1} + e_{m_i-1}e_{m_i-1})$ and $\Sigma_i^{-1} = \sigma_v^{-2}(I_{m_i-1} - e_{m_i-1}e_{m_i-1}/m_i)$, where I_{m_i-1} is an identity matrix of dimension $m_i - 1$ and e_{m_i-1} is a $(m_i - 1) \times 1$ vector of ones. The criterion function is given by

$$\Xi_i(g_i, g_{i1}) = -\frac{1}{2}(\tilde{y}_i - g_i + g_{i1}e_{m_i-1})'\Sigma_i^{-1}(\tilde{y}_i - g_i + g_{i1}e_{m_i-1}), \quad i = 1, 2, \ldots, n.$$

Denote the first derivatives of $\Xi_i(g_i, g_{i1})$ with respect to g_{it} as $\Xi_{i,tg}(g_i, g_{i1})$, $t = 1, 2, \ldots, m_i$. Then

$$\Xi_{i,1g}(g_i, g_{i1}) = -e_{m_i-1}'\Sigma_i^{-1}(\tilde{y}_i - g_i + g_{i1}e_{m_i-1}),$$
$$\Xi_{i,tg}(g_i, g_{i1}) = c_{i,t-1}'\Sigma_i^{-1}(\tilde{y}_i - g_i + g_{i1}e_{m_i-1}), \quad t \geq 2,$$

where $c_{i,t-1}$ is a $(m_i - 1) \times 1$ 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:

$$\sum_{i=1}^{n} \frac{1}{m_i} \sum_{t=1}^{m_i} K_h(z_{it} - z) G_{it} \Xi_{i,tg} \times \left(\hat{g}_{[l-1]}(z_{i1}), \ldots, G_{it}(\alpha_0, \alpha_1)', \ldots, \hat{g}_{[l-1]}(z_{im_i})\right) = 0,$$

where the argument $\Xi_{i,tg}$ is $\hat{g}_{[l-1]}(z_{is})$ for $s \neq t$ and $G_{it}(\alpha_0, \alpha_1)'$ when $s = t$, and $\hat{g}_{[l-1]}(z_{is})$ is the $(l-1)$th iterative estimates of $(\alpha_0, \alpha_1)'$. Here $G_{it} \equiv (1, (z_{it} - z)/h)'$ and $k_h(v) = h^{-1}k(v/h)$, $k(\cdot)$ is the kernel function. The next iterative estimator of $(\alpha_0, \alpha_1)'$ is equal to $\left(\hat{g}_{[l]}(z), \hat{g}_{[l]}(z)\right)' = D_1^{-1}(D_2 + D_3)$, where

$$D_1 = \sum_{i=1}^{n} \frac{1}{m_i} \left(e_{m_i-1}'\Sigma_i^{-1}e_{m_i-1}K_h(z_{i1} - z)G_{i1}G_{i1}' + \sum_{t=2}^{m_i} c_{i,t-1}'\Sigma_i^{-1}c_{i,t-1}K_h(z_{it} - z)G_{it}G_{it}' \right),$$

$$D_2 = \sum_{i=1}^{n} \frac{1}{m_i} \left(e_{m_i-1}'\Sigma_i^{-1}e_{m_i-1}K_h(z_{i1} - z)G_{i1}\hat{g}_{[l-1]}(z_{i1}) + \sum_{t=2}^{m_i} c_{i,t-1}'\Sigma_i^{-1}c_{i,t-1}K_h(z_{it} - z)G_{it}\hat{g}_{[l-1]}(z_{it}) \right),$$

$$D_3 = \sum_{i=1}^{n} \frac{1}{m_i} \left(-K_h(z_{i1} - z)G_{i1}e_{m_i-1}'\Sigma_i^{-1}H_{i,[l-1]} + \sum_{t=2}^{m_i} K_h(z_{it} - z)G_{it}c_{i,t-1}'\Sigma_i^{-1}H_{i,[l-1]} \right),$$

and $H_{i,[l-1]}$ is an $(m_i - 1) \times 1$ vector with elements

$$\left(\tilde{y}_{it} - (\hat{g}_{[l-1]}(z_{it}) - \hat{g}_{[l-1]}(z_{i1}))\right), \quad t = 2, \ldots, m_i.$$

The series method is used to obtain an initial estimator for $g(\cdot)$. The convergence criterion for the iteration is set to be

$$\sum_{i=1}^{n} \frac{1}{m_i} \sum_{t=2}^{m_i} \left(\hat{g}_{[l]}(z_{it}) - \hat{g}_{[l-1]}(z_{it})\right)^2 \Big/ \sum_{i=1}^{n} \frac{1}{m_i} \sum_{t=2}^{m_i} \hat{g}_{[l-1]}^2(z_{it}) < 0.01.$$

Further, the variance σ_v^2 is estimated by

$$\hat{\sigma}_v^2 = \frac{1}{2n} \sum_{i=1}^{n} \frac{1}{m_i - 1} \sum_{t=2}^{m_i} (y_{it} - y_{i1} - (\hat{g}(z_{it}) - \hat{g}(z_{i1})))^2.$$

The variance of the iterative estimator $\hat{g}(z)$ is calculated as $\kappa(nh\hat{\Omega}(z))^{-1}$, where $\kappa = \int k^2(v)\mathrm{d}v$, and $\hat{\Omega}(z) = \frac{1}{n}\sum_{i=1}^{n}\frac{m_i-1}{m_i}\sum_{t=2}^{m_i} K_h(z_{it} - z)/\hat{\sigma}_v^2$.

For the model selection to be data-driven, we modify the specification tests to suit for unbalanced panel data models. We have three specification tests:

First, test parametric against nonparametric model in Model (1). The null hypothesis H_0 is parametric model with $g(z) = \theta_0(z, \gamma)$. 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 $I_n^{(1)} = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{m_i}\sum_{t=1}^{m_i}(\theta_0(z_{it}, \hat{\gamma}) - \hat{g}(z_{it}))^2$, where $\hat{\gamma}$ is a consistent estimator of the parametric model with fixed effects; $\hat{g}(\cdot)$ 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 $g(z) = \theta_0(z, \gamma)$. The alternative is that $g(z)$ is nonparametric. The statistic for testing this null is $I_n^{(2)} = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{m_i}\sum_{t=1}^{m_i}(\theta_0(z_{it}, \tilde{\gamma}) + x_{it}'\tilde{\beta} - \hat{g}(z_{it}) - x_{it}'\hat{\beta})^2$, where $\tilde{\gamma}$ and $\tilde{\beta}$ are consistent estimators in the parametric panel data model with fixed effects; $\hat{g}(\cdot)$ and $\hat{\beta}$ are the iterative consistent estimator of Model (2).

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Table 2
Parametric estimation results.

	Parametric model			Semiparametric model
	1	2	3	
lgdppc	37.6012	128.5883	−1084.22	
	(2.7174)	(26.8926)	(214.77)	–
lgdppc^2	−2.0888	−12.7812	201.146	
	(0.1491)	(3.1476)	(37.717)	–
lgdppc^3	–	0.4110	−16.2023	
		(0.1209)	(2.9214)	–
lgdppc^4	–	–	0.4796	
			(0.0843)	–
Growth(−1)	0.1056	0.1065	0.1063	0.1077
	(0.0196)	(0.0196)	(0.0196)	(0.0477)
Openk	0.0420	0.0408	0.0410	0.0409
	(0.0047)	(0.0047)	(0.0047)	(0.0108)
Urbanize	0.0866	0.0565	0.0654	0.0216
	(0.0216)	(0.0234)	(0.0234)	(0.0558)
Ki	−0.1036	−0.0906	−0.0933	−0.1084
	(0.0166)	(0.0171)	(0.0171)	(0.0417)
Inflation	0.0013	0.0013	0.0013	0.0013
	(0.0003)	(0.0003)	(0.0003)	(0.0008)

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
Nonparametric estimation of $g(\cdot)$ at different points of $\ln(gdppc)$.

Quantile of $z = \ln(gdppc)$		Nonparametric model (1)		Semiparametric model (2)	
%	z	$g(z)$	Std. err.	$g(z)$	Std. err.
2.5	7.2014	34.1085	2.9719	32.7535	2.8225
25.0	8.7307	43.3724	1.4581	42.4299	1.3848
50.0	9.4323	38.9278	1.2869	38.7704	1.2222
75.0	9.9073	36.0767	1.0948	35.5236	1.0398
95.0	10.2808	36.1586	1.4052	34.3298	1.3346
97.5	10.3490	36.1649	1.5553	34.0305	1.4771

Third, test the null nonparametric model (1) against the semiparametric model (2). The statistic for testing this null is $I_n^{(3)} = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{m_i}\sum_{t=1}^{m_i}(\tilde{g}(z_{it}) - \hat{g}(z_{it}) - x_{it}'\hat{\beta})^2$, where $\tilde{g}(\cdot)$ is the iterative consistent estimator in Model (1) while $\hat{g}(\cdot)$ and $\hat{\beta}$ 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 (reduces) inequality.

In Table 3, the nonparametric function $g(\cdot)$ is estimated at some quantile points of $\ln(gdppc)$ 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 $\ln(gdppc)$ 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.

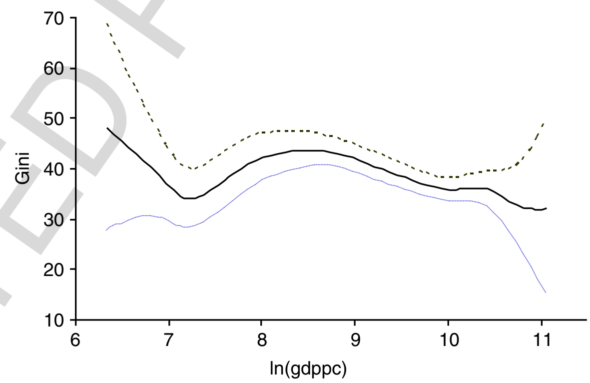

Fig. 1. $g(\cdot)$ from nonparametric model (1).

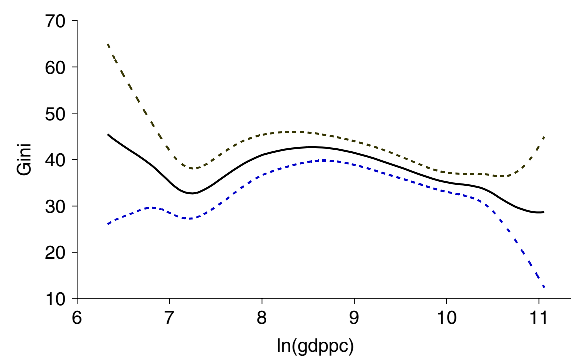

Fig. 2. $g(\cdot)$ from semiparametric model (2).

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

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Table 4
Model specification tests.

Model	Hypotheses	I_n statistic (p-value)	Model selected
Model (1)	H_0: Quadratic H_1: Nonparametric	9.256 (0.000)	Nonparametric
	H_0: Cubic H_1: Nonparametric	7.375 (0.003)	Nonparametric
Model (2)	H_0: Quadratic H_1: Semiparametric	11.467 (0.003)	Semiparametric
	H_0: Cubic H_1: Semiparametric	11.401 (0.003)	Semiparametric
(1) and (2)	H_0: Nonparametric (1) H_1: Semiparametric (2)	5.211 (0.000)	Semiparametric

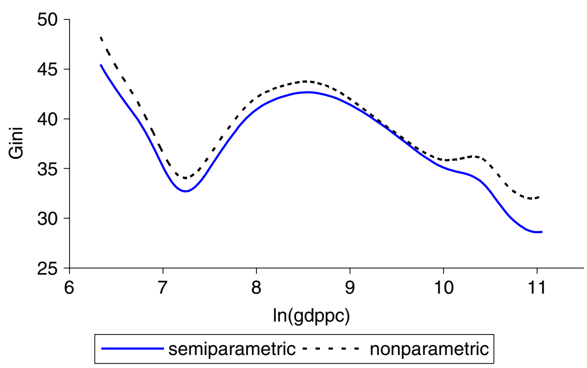

Fig. 3. Comparing $g(\cdot)$ from estimating (1) and (2).

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 $\exp(10) \approx \$22,000$, 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 \$22,000, 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.

Uncited references

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Chen, 2003.

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

Argentina, 1989, 92, 98, 2001. Armenia, 1994–97. Australia, 1967–69, 76, 78–79, 81–82, 85–86, 89–90, 94–96, 2002. Austria, 1987, 91, 95, 2000. Bahamas, 1970, 73, 75, 77, 79, 86, 88, 91–93. Bangladesh, 1963, 66, 67, 69, 73, 77, 78, 81, 83, 86. Barbados, 1979, 96. Belarus, 1995–97, 2002. Belgium, 1979, 85, 88, 92, 96, 2000. Brazil, 1970, 72, 76, 78–91, 93, 96, 98, 2002. Bulgaria, 1981–97, 2003. Canada, 1965, 67, 69, 71, 73–75, 77, 79, 81–88, 91, 94, 97, 2000. Chile, 1968, 71, 80–94, 98, 2000. China, 1970, 75, 78, 80, 82–99, 2001. Colombia 1964, 70, 71, 74, 78, 88, 91, 94, 98, 2003. Costa Rica, 1961, 69, 71, 77, 79, 81, 83, 86, 89, 93, 98, 2001. Cyprus, 1990, 96. Czech Republic, 1991–97, 2002. Denmark, 1963, 76, 78–95, 97, 2000. Dominican Republic, 1976, 84, 89, 92, 96, 97, 2003. Ecuador, 1968, 88, 93, 94, 95, 98, 2003. El Salvador, 1965, 77, 89, 94, 95, 97, 2002. Estonia, 1990–94. Finland, 1962, 77–84, 87, 91, 95, 2000. France, 1962, 65, 70, 75, 79, 81, 84, 89, 95. Gabon, 1975, 77. Germany, 1973, 75, 78, 80, 81, 83–85, 89, 94, 97, 98, 2000. Guatemala, 1986, 87, 89, 98, 2002. Honduras, 1968, 89–94, 98, 2003. Hong Kong, 1971, 73, 76, 80, 81, 86, 91, 96, 98. Hungary, 1972, 77, 82, 87, 89, 91, 93–97, 99. Ireland, 1973, 80, 87, 94, 99, 2000. Israel, 1986, 92, 97. Italy, 1967–69, 71–84, 86, 87, 89, 91, 93, 95, 98, 2000. Jamaica, 1958, 2003. Japan, 1962–65, 67–82, 85, 88–90, 93, 98, 2002. Kazakhstan, 1993, 96, 2002. South Korea, 1965, 66, 70, 71, 76, 80, 82, 85, 88, 93, 98, 2003. Latvia, 1995, 96, 98, 2002. Luxembourg, 1985, 91, 94, 98, 2000. Malaysia, 1967, 70, 73, 76, 79, 84, 89, 95, 97. Mexico, 1963, 68, 69, 75, 77, 84, 89, 92, 94, 98, 2002. Nepal, 1976, 77, 84. Netherlands, 1962, 75, 77, 79, 81–83, 1985–99. New Zealand, 1973, 75, 77, 78, 80, 82, 83, 85–87, 89–91. Nicaragua, 1998, 2001. Nigeria, 1959, 81, 82. Norway, 1962, 63, 67, 73, 76, 79, 82, 84–91, 95, 96, 2000. Pakistan, 1963, 64, 66, 67, 69, 70. Panama, 1969, 70, 79, 80, 89, 95, 97, 2002. Paraguay, 1990, 95, 98, 2001. Peru, 1961, 71, 81, 96, 2002. Philippines, 1961, 65, 71, 75, 85, 88, 91, 94, 97. Poland, 1991–97. Portugal, 1973, 80, 89–91, 94, 97. Puerto Rico, 1963, 69, 79, 89. Romania, 1989–92, 94, 98. Russian Federation, 1990, 93–96, 98. Senegal, 1960, 95. Singapore, 1973, 78, 80, 89, 92, 97, 2003. Slovak Republic, 1988–97, 2005. Slovenia, 1991–93, 97, 2002. South Africa, 1990, 93, 95. Spain, 1965, 73, 75, 94, 2000. Sri Lanka, 1963, 69, 73, 79, 80, 81, 86, 87. Sweden, 1963, 67, 75, 76, 80–96, 2000. Switzerland, 1982, 92, 2002. Thailand, 1962, 68, 69, 71, 75, 81, 86, 88, 90, 92. Trinidad & Tobago, 1971, 76, 81, 88, 94. Turkey, 1968, 73, 87, 94, 2003. United Kingdom, 1964–76, 79, 85, 86, 91, 95, 2002. United States, 1960–91, 94, 97, 2000. Uruguay, 1989, 92, 98. Uzbekistan, 1990, 2002. Venezuela, Rep, 1962, 71, 76–79, 81, 87, 89, 90, 93, 99, 2000.

References

Barro, R.J., 2000. Inequality and growth in a panel of countries. Journal of Economic Growth 5, 5–32.

Bulíř, A., 2001. Income inequality: does inflation matter? IMF Staff Papers 48, 139–159.

Chen, B.-L., 2003. An inverted-*U* relationship between inequality and long-run growth. Economics Letters 78, 205–212.

Henderson, D.J., Carroll, R.J., Li, Q., 2008. Nonparametric estimation and testing of fixed effects panel data models. Journal of Econometrics 144, 257–275.

Huang, H.-C.R., 2004. A flexible nonlinear inference to the Kuznets hypothesis. Economics Letters 84, 289–296.

Huang, H.-C.R., Lin, Y.-C., Yeh, C.-C., 2009. Joint determinations of inequality and growth. Economics Letters 103, 163–166.

Iradian, G., 2005 Inequality, poverty, and growth: cross-country evidence. IMF Working Paper No. 05/28.

Li, H., Squire, L., Zou, H.-F., 1998. Explaining international and intertemporal variations in income inequality. Economic Journal 108, 26–43.

Lin, S.-C., Huang, H.-C., Weng, H.-W., 2006. A semiparametric partially linear investigation of the Kuznets' hypothesis. Journal of Comparative Economics 34, 634–647.

Milanovic, B., 2005. Worlds Apart: Measuring International and Global Inequality. Princeton University Press.

Mushinski, D.W, 2001. Using non-parametric to inform parametric tests of Kuznets' Hypothesis. Applied Economics Letters 8, 77–79.

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