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Abstract: In this paper Kuznets' U–curve hypothesis is tested on two unbalanced panel data sets of 47 and 62 countries, for the period 1970–93, using two-way fixed and random effects models. Several competing model specifications are estimated and the one best fitting the data is selected by appropriate model selection procedures. It is shown that there is no hard empirical evidence to support the usual econometric model formulations and the U–curve hypothesis.

Key words: Kuznets' hypothesis, U–curve hypothesis, income inequality, panel data, fixed effects model.

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1. Introduction

Myths and mythology are part of our culture. Economics has long been a breeding ground for "scientific myths". The British–Austrian philosopher Karl Popper once said that "Science must begin with myths and the criticism of myths". In this short paper we do our best to act along these lines.

Simon Kuznets, in his famous 1955 paper, laid down the foundations of one of the most widely belived myths in economics when he proposed that "as economic development occurs, income inequality first increases and after some 'turning point' starts declining". This has since been known as the U–curve hypothesis. The myth of the U–curve hypothesis persisted for more than forty years, mainly because it seems to be rational and, at the same time, satisfies our natural desire for social justice. We can be relieved as, at least in the long run, increasing wealth decreases inequality. The invisible hand(s) of Justicia is working again. But is there any hard evidence to support the theory?

The literature dealing with this hypothesis is extremely large (see *Lecaillon et al.* [1984] for a survey and *Fields and Rogerson* [1993] and *Milanovic* [1994] for some recent results). In principle, as it is about a dynamic process, it should empirically be tested using long time series of a given country as it goes across the many phases of its progress. Unfortunately, data sets enabling researchers to carry out this type of analysis are not available and extremely difficult to construct. Therefore, the econometric practice to carry out such testing has been, so far, to use cross sectional data of countries at different levels of development (see, for example, *Ram* [1988, 1989, 1991]).

The problems related to the use of such data sets to test this hypothesis are well known (*Saith* [1983]) and numerically reflected in the extreme sensitivity of most estimation results. The cross sectional approach, moreover, relies on two very strong assumptions. First, a complete homogeneity across countries is implicit *i.e.,* all countries in the sample behave in the same way, at least as far as income inequality is concerned in its relation to GDP per capita. Second, this approach neglects dynamics, *i.e.,* the above relationship was assumed to be unaffected by business (economic) cycles, or any other time dependent factors. As these assumptions are unrealistically restrictive it is important to test the U–curve hypothesis within a modelling framework that allows for country wise and time heterogeneity as well. Such a framework is provided by the use of panel data and the related fixed and/or random effects models.

Most empirical studies performed the testing of this hypothesis by estimating a simple linear regression model of the form

$$INQ_i = \alpha + \beta_1 Y_i + \beta_2 Y_i^2 + u_i \quad i = 1, \ldots, N \tag{1}$$

where INQ_i is a measure of income inequality for a given country i in the sample, Y_i is the log of the per capita GDP (as a proxy of the level of development) and u_i is the usual disturbance term. If the β parameters turned out to be significant and of the right (opposite) sign, the U–curve hypothesis was assumed to be confirmed by the data. No competing model specifications were tried and no real model selection was performed, even though it was clear from all empirical studies that the explanatory variables in model (1) do not explain satisfactorily the behaviour of the dependent variable. This type of causal empiricism supported in most previous studies the myth.

In this paper we test thoroughly the U–curve hypothesis using two–way fixed, random and mixed effects models on two unbalanced panel data sets of forty–seven and sixty–two countries for the period 1970–1992. We estimate several alternative model formulations and select the one which best fits the data by appropriate model selection procedures.

2. The model and the data

The competing model specifications considered are made up of two parts. One which reflects the functional form relating INQ to Y and another which takes care of the countrywise and time heterogeneity of the data. The following models were estimated:

1. $INQ_{it} = \beta_0 + \beta_1 Y_{it} + \beta_2 Y_{it}^2 + \alpha_i + \lambda_t + u_{it}$
2. $INQ_{it} = \beta_0 + \beta_1 Y_{it} + \beta_2 Y_{it}^2 + \beta_3 Y_{it}^3 + \alpha_i + \lambda_t + u_{it}$
3. $INQ_{it} = \beta_0 + \beta_1 Y_{it}^4 + \alpha_i + \lambda_t + u_{it}$
4. $INQ_{it} = \beta_0 + \beta_1 \ln Y_{it} + \beta_2 Y_{it}^3 + \alpha_i + \lambda_t + u_{it}$
5. $INQ_{it} = \beta_0 + \beta_1 \exp Y_{it} + \alpha_i + \lambda_t + u_{it}$
6. $INQ_{it} = \beta_0 + \beta_1 \exp Y_{it} + \beta_2 Y_{it}^2 + \alpha_i + \lambda_t + u_{it}$
7. $INQ_{it} = \beta_0 + \beta_1 \exp Y_{it} + \beta_2 \exp Y_{it}^2 + \beta_3 \exp Y_{it}^3 + \alpha_i + \lambda_t + u$

$$i = 1, \ldots, N \quad t = 1, \ldots, T$$

where α_i and λ_t are the country and time specific effects. We considered these specific effects as fixed parameters (fixed effects model), as random variables (random effects model) and also α_i as random (given the large number of countries in the sample) and λ_t as fixed (mixed effects model). All this produced 21 competing formulations. The Bayesian information criterion (BIC) was used to select the model best fitting the data.

In order to have a relatively consistent data base, data were collected from only two sources. The real GDP per capita measures are from the Penn World Tables 5.6,[1] while the Gini coefficients are from the *Deininger and Squire* [1996] (DS) data set.[2]

The DS data base was published in 1996 and is undoubtedly the most comprehensive and most reliable of its kind. It actually consists of two sets: a low quality full set and a smaller high quality subset. In order to achieve an acceptable level of consistency and quality, the high quality Gini data points must satisfy three conditions: 1) data must be based on household surveys rather than aggregate, national accounts; 2) the coverage of the population must be fairly comprehensive, *i.e.,* the survey cannot cover just some segment of the population like tax–payers or urban dwellers; 3) all sources of income, wage and non–wage earnings alike, must be taken into account. Also, we only considered those countries which had at least four (years of) high quality observations.

At the end of the day, our small high quality data set comprised of 423 observations, while the large, more heterogenous data set of 627 observations.

3. Estimation results

The usual procedures to test the U–curve hypothesis produced results similar to those reported in Table 1. As the parameters are jointly and individually significant with the expected signs and magnitude, the hypothesis was thought to be verfied. It can be seen from Table 2 however, that even within this framework, the results can be changed by augmenting the model to a third degree polynomial. This model is chosen against the previous one by the BIC and also the likelihood ratio (LR) test. We have just thrown the U–curve out the window, as this polynomial has an S shape. Country and time specific heterogeneity, however, has still to be taken into account.

The specific effects were then incorporated into the model and the model selection procedure carried out. The results indicated that models 3–7 and the random and mixed effects specifications should be discarded, as they have much less explanatory power than models 1 and 2 with fixed effects. Although models 1 and 2 produced

[1] This data set is available on the Internet, *e.g.,* from the NBER webserver (http://www.-nber.org/pwt56.html).

[2] Available from the World Bank's webserver (http://www.worldbank.org/html/prdmg-/grwthweb/datasets.htm).

similar BIC values, the criterion (as well as the likelihood ratio test) favoured model 2 for both data sets. So the accepted wisdom that model 1 is the right model for this problem had to be revised again, even for the formulations including specific heterogeneity.

It can be seen from Tables 3 and 4 that most of the country specific and many of the time specific parameters are highly significant implying that the data sets and the models cannot be considered homogenous across countries. This also means that any purely cross sectional studies in this area should be regarded as invalid, as they miss, by construction, this country wise heterogeneity. Similarly, any model that neglects the dynamic nature of the problem (time heterogeneity) is inadequate.

So is this the end of the story and should an S–curve hypothesis replace the U–curve? Certainly not! Let us test now two different restricted versions of model 2 against the unrestricted model, where the restrictions imposed are:

$$R_1: \quad \beta_1 = \beta_2 = \beta_3 = 0 \qquad \textit{i.e.}, \text{ specific effects only, and}$$
$$R_2: \quad \alpha_i = 0, \ \ \lambda_t = 0 \ \forall i, t \qquad \textit{i.e.}, \text{ no specific effects.}$$

It can be seen from the results in Table 5, that both the BIC and the formal tests pick up the unrestricted specification as the correct model. However, it is also clear that the margin of this selection is very narrow, and most of the behaviour of the dependent variable is actually explained by the specific effects. This is also evident from the BIC values of the R_1 and R_2 models, which make it obvious that the specific effects must be included, but also, that R_1 gives a sensible model while R_2 does not. This means that it is not the GDP per capita which explains income inequalities but rather the individual characteristics of a country and time factors. This should not be a real surprise. There are more and more countries where the average lack of wealth is such that it does not stop the development of inequalities (*e.g.,* the Philippines, Thailand, as a matter of fact most countries with large positive country specific effect). On the other hand, in several rich countries the Gini coefficient is growing parallel to the GDP per capita, reflecting that the welfare state is in crisis (*e.g.,* Denmark, Japan, Sweden, etc.) or that growth is actually based on this inequality (*e.g.,* Singapore). It is worth mentioning here that for some developed countries (where long enough series are available, like the UK, USA) time series of both the Gini coefficient and the GDP per capita have a unit root and seem to be cointegrated (using the Dickey–Fuller test). This shows nicely that the accepted wisdom about these variables does not apply here, and also, that dynamics must be taken into account. The behaviour of the ex-socialist countries is also peculiar as medium levels of GDP per capita are related to low (but increasing) wealth inequalities (reflected by large negative country specific effects).

Given the importance of the relationship between economic growth and inequality in economics, perhaps more attention should be paid to country specific factors like social structure, political system, natural resourses, etc. It is quite safe to say that this relationship is much more complex than the simplistic mechanisms assumed by many models, especially those related to exogenous growth.

4. Conclusion

In this paper we tested Kuznets' U–curve hypothesis on two unbalanced panel data set of 47 and 62 countries, for the period 1970–93, using two-way fixed and random effects models. Based on a careful and thorough econometric analysis we can conclude that there is no hard empirical evidence to support this hypothesis. Income inequalities are more likely to be explained by complex country specific factors, and they essentially do not depend on the level of development.

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Table 1:
Estimation Results Without Specific Effects, Model 1

Variable	Param. Estimate	std. Error
	Small Data Set	
const.	-82.435	42.203
(Y_{it})	31.009	10.200
$(Y_{it})^2$	-82.435	32.203
	Large Data Set	
const.	-99.659	36.164
(Y_{it})	37.657	8.7796
$(Y_{it})^2$	-2.5159	0.5286

Table 2:
Estimation Results Without Specific Effects, Model 2

Variable	Param. Estimate	std. Error
	Small Data Set	
const.	-2628.7	431.09
(Y_{it})	967.47	158.14
$(Y_{it})^2$	-115.96	19.217
$(Y_{it})^3$	4.5904	0.7737
	Large Data Set	
const.	-1991.1	386.31
(Y_{it})	737.81	142.66
$(Y_{it})^2$	-88.260	17.446
$(Y_{it})^3$	3.4749	0.7067

Table 3:
Estimation Results for the Large Data Set
Model 2, Fixed Individual and Time Effects
Large Data Set

Variable	Param. Estimate	std. Error
const.	-343.76	294.26
(Y_{it})	137.42	89.37
$(Y_{it})^2$	-16.372	7.3475
$(Y_{it})^3$	0.6443	0.3502
Argentina	1.99737	1.72544
Australia	1.96816	2.21508
Austria	-5.73345	2.40206
Banglades	-2.69031	2.59334
Barbados	-1.48697	1.52894
Belgium	-2.10407	1.96411
Brazil	18.70171	1.20001
Bulgaria	-13.15603	1.28818
Canada	-5.67949	2.12292
Chile	14.14252	1.08889
China	-6.58101	2.34100
Colombia	12.91344	1.45570
Costa Rica	7.62145	1.39721
Czechoslovakia	-16.69189	1.53036
Denmark	-7.59566	1.84561
Dominica	9.06457	2.48003
Finland	-10.08598	1.67685
France	0.34984	2.30351
Germany	-3.62149	1.90415
Ghana	-1.02492	3.30379
Greece	1.63509	1.99309
Honduras	15.57974	2.63924
Hong Kong	4.77120	1.81843
Hungary	-13.00537	1.82974
India	-4.38324	2.52085
Indonesia	0.51308	2.33539
Iran	7.56034	1.99397
Israel	-1.84572	2.30408
Italy	-1.65117	1.58600

Table 3 (cont.):
Estimation Results for the Large Data Set

Variable	Param. Estimate	std. Error
Jamaica	10.42299	1.83876
Japan	-2.14780	1.49556
Jordan	-2.24996	2.03276
Kenya	24.31895	3.13204
Korea	-1.32517	1.65660
Malaysia	11.85182	1.53789
Mexico	14.42312	1.83111
Morocco	7.45626	2.17086
Netherlands	-7.89103	1.78288
New Zealand	-1.92568	1.68011
Nigeria	-1.08063	2.55319
Norway	-4.62967	2.00972
Pakistan	-4.57516	2.43710
Panama	12.71451	2.12093
Peru	10.41435	2.03116
Philippines	8.59912	2.52552
Poland	-12.21775	1.17099
Singapore	4.96532	1.34680
South Africa	12.58416	2.05993
Soviet Union	-10.73434	2.27580
Spain	-8.47627	1.72975
Sri Lanka	2.42888	2.28655
Sweden	-5.04627	1.96326
Taiwan	-8.07849	1.04924
Thailand	7.49664	1.72595
Tunisia	7.81365	2.15409
Turkey	6.88577	2.11641
UK	-10.18415	1.50166
Uruguay	3.84939	1.45496
USA	-0.91660	2.22337
Venezuela	7.65169	1.60930
Yugoslavia	-10.02152	1.09668
Zambia	20.02606	2.77348

Table 3 (cont.):
Estimation Results for the Large Data Set

Variable	Param. Estimate	std. Error
1970	3.73872	0.93928
1971	3.99216	0.96433
1972	1.27957	1.12859
1973	-0.19688	0.85888
1974	1.62724	1.05547
1975	3.10821	0.80474
1976	1.04631	0.77091
1977	-0.85440	0.93486
1978	-0.63872	0.89679
1979	1.06329	0.85321
1980	0.44367	0.71723
1981	-1.41289	0.70394
1982	-3.46002	0.83524
1983	-2.11240	0.88643
1984	-0.29540	0.82100
1985	-2.65929	0.80394
1986	-1.57432	0.78684
1987	-1.99856	0.81738
1988	-2.97335	0.82679
1989	1.10318	0.75622
1990	-0.50544	0.89852
1991	-0.39786	0.95444
1992	2.88510	1.14384
R^2	0.8425	
$\overline{R}^2$	0.8171	
F	33.16	

Table 4:
Estimation Results for the Small Data Set
Model 2, Fixed Individual and Time Effects

Variable	Param. Estimate	std. Error
const.	-193.00	125.33
(Y_{it})	87.279	42.707
$(Y_{it})^2$	-10.851	5.094
$(Y_{it})^3$	0.43995	0.30935
Australia	4.54807	1.38351
Banglades	-2.89285	2.00890
Belgium	-7.06498	1.55427
Brazil	22.05117	0.85696
Bulgaria	-11.03294	0.79039
Canada	-3.03604	1.38449
China	-4.44012	1.80766
Colombia	15.25012	1.26984
Costa Rica	9.67422	1.09299
Czechoslovakia	-14.75211	1.07783
Denmark	-1.98965	1.58687
Dominica	10.39523	1.61005
Finland	-4.34664	1.08421
France	5.08587	1.48109
Germany	-2.70127	1.42125
Ghana	-1.92753	2.53382
Honduras	16.02362	1.86895
Hong Kong	7.12704	1.06706
Hungary	-10.90901	1.10238
India	-5.85101	2.03227
Indonesia	-3.14552	1.81547
Iran	8.40048	1.32875
Italy	0.79559	0.96011

Table 4 (cont.):
Estimation Results for the Small Data Set

Variable	Param. Estimate	std. Error
Jamaica	6.27209	1.33976
Japan	0.27432	0.89880
Korea	-0.15875	1.18381
Malaysia	14.49114	1.21249
Mexico	17.84085	1.19168
Netherlands	-5.47688	1.12624
New Zealand	0.27794	1.07873
Norway	-0.63045	1.37038
Pakistan	-5.50662	1.89735
Panama	16.37232	1.46201
Philippines	9.57213	1.84128
Poland	-10.13872	0.78086
Singapore	5.65544	1.12058
Soviet Union	-8.44779	1.33700
Spain	-7.02809	1.07817
Sri Lanka	3.15821	1.63081
Sweden	-2.56382	1.26926
Taiwan	-6.09792	0.68182
Thailand	10.48351	1.30239
Tunisia	6.24866	1.53257
UK	-7.71823	0.92124
USA	1.76843	1.47630
Venezuela	9.94531	0.94979
Yugoslavia	-2.29150	0.92807

Table 4 (cont.):
Estimation Results for the Small Data Set

Variable	Param. Estimate	std. Error
1970	2.42489	0.98682
1971	3.39715	0.72087
1972	1.67413	0.89923
1973	-1.17409	0.63993
1974	1.80908	0.91608
1975	1.64802	0.70020
1976	1.32549	0.59340
1977	-1.90401	0.63281
1978	0.91787	0.61699
1979	1.46491	0.59731
1980	-1.02891	0.53834
1981	0.02275	0.53203
1982	-3.23387	0.63834
1983	-1.69551	0.57514
1984	-1.08849	0.60050
1985	-2.14646	0.54244
1986	0.25284	0.52189
1987	-1.86974	0.54262
1988	-1.99596	0.51950
1989	2.29179	0.45729
1990	0.99032	0.56944
1991	-0.31620	0.61347
1992	1.77142	0.83482
R^2	0.932	
$\overline{R}^2$	0.991	
F	66.6	

Table 5:
Testing Restrictions in Model 2

Models		
	Small Data Set	
	LR test	F test
Unrestricted vs. R_1	6.062	8.769
Unrestricted vs. R_2	1043.1	87.754
	BIC	
Unrestricted	-1043.6	
R_1	-1055.7	
R_2	-1486.4	
	Large Data Set	
	LR test	F test
Unrestricted vs. R_1	3.077	6.500
Unrestricted vs. R_2	1018.5	37.407
	BIC	
Unrestricted	-1886.2	
R_1	-1893.8	
R_2	-2277.8	