Population Aging and its Effect on the Inequality: An Extended Empirical Study of the Kuznets' Inverted U-hypothesis

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ABSTRACT

To investigate the relationship between population aging and inequality, we used three test methodologies such as panel data analysis, inverse logistic function estimation, and nonparametric kernel estimation. We compute the Gini index using the Luxembourg Income Study (LIS). Old age dependency ratio and other variables came from the World Development Indicator 2003 (WDI2003).

The estimation result by using the panel data analysis, inverse logistic function estimation, and nonparametric kernel estimation shows that Kuznets' hypothesis does not hold in our sample and degree of inequality increase at increasing rate as old age dependency ratio goes up. And we also find the policy implication that tax policy may weaken the effect of the population aging on inequality.

I. Introduction

According to the Kuznets(1955, 1963), there exists an inverted U-shaped relationship between income inequality and economic development: The income inequality gets worsened in the earlier stage of economic development, and then it reaches its peak in the mid-stage, and finally it is getting improved after the peak. The inverted U-shaped curve has been tested numerously in many works to prove empirically since Kuznets(1955).

Recently, however, reliability of the Kuznets' hypothesis was refuted. Degrees of the inequality turned to get worsened in the developed countries, implying that Kuznets' inverted-U hypothesis does not hold. Why does this happen? Some studies such as World Bank (2002), Fraser Institute (2002), and Lee and Park (2002) considered the effect of the economic freedom from globalization on inequality to prove the inconsistency.

However, we shed light to the effect of the population aging, which can play role as a factor negating the Kuznets' hypothesis. It is because OECD countries have experienced dramatic changes in the demographic characteristics in the past few decades. Fertility rates in almost all OECD countries have declined to the rate below 2.1, which is a critical level for maintaining a stable population. Life expectancy has dramatically extended from 66 in 1960s to 77 in the present. The recent survey undertaken by the United Nations expects the share of the old-aged population to be doubled, on average, over the next 50 years in the major industrialized countries. As a result, many countries suffered from both the sharp decreases in the working population and the increase in the social welfare expenditure for larger population of the elderly and the poor. This gives rise to a presumption that population aging affects the income inequality. The increase in the share of the old aged 65 and above can make the overall inequality worse, since poverty ratio of the elderly is almost twice as that of the people aged 15-64.

Some researches such as An and Lee(1991), Deinginger and Squire(1998), and An(2003) refuted the reliability of the researches that confirm the Kuznets' hypothesis. They point out the problems of the test methodologies used so far confirming Kuznets' hypothesis.

In this paper, thus, we attempt to investigate the relationship between population aging and inequality using three test methodologies such as panel data analysis, inverse logistic function estimation, and nonparametric kernel estimation to solve the problems of the test methodologies.

This paper is organized as follows: The first section of this paper briefly introduces the importance of population aging, and explains the motivation of analyzing the relationship between population aging and growth. The second section of the paper introduces the related papers. In the third section, we present the econometric method used to test the relationship between population aging and inequality, data, and variables. Estimating result is introduced in the fourth section. Finally, in the fifth section, we conclude.

II. Previous researches

Kuznets (1955, 1963) performed the first systematic work on changes in income equality at different stages of economic development. The well-known Kuznets hypothesis postulated an 'inverted-U' relationship between the income and the inequality, according to which the degree of inequality would first increase and then decrease with economic growth. Kuznets' original hypothesis relied on historical experience of several developed economies. He employed a two-sector hypothetical economy to show the possibility of the inverted-Y pattern. He also compared developed and underdeveloped countries by measuring the income shares of various groups and observed that income inequality is more severe in underdeveloped countries.

The work of Kuznets was followed by numerous empirical studies. Kravis(1960) used eleven countries' data on income share, the Gini coefficient, a coefficient of variation, and the standard deviation of the logarithm of income to draw a conclusion supporting UH. Adelman and Morris (1973) compiled data for 43 developing countries and presented evidence supporting UH. Paukert(1973) expanded Adelman and Morris' data up to 56 countries and confirmed UH.

The most frequently cited studies in the UH literatures are those of Ahluwalia(1976a,1976b). Ahluwalia used data sets compiled by Jain (1975) with more countries added. He took income share of the top 20%, the middle 40%, the bottom 40% and the bottom 60% of the population in 62 countries as dependent variables and regressed them on log (GNP) and (log (GNP))^2 to infer the inverted-U hypothesis from the signs of the estimated coefficients of log(GNP) and (log(GNP))^2. He claimed that the inverted-U pattern is a "stylized fact."

Recently, however, there have been studies that refute reliability of the Kuznets' hypothesis. Saith(1985) pointed out several problems with Ahluwalia's results including their sensitivity to the dropping or adding of a few observations. An and Lee (1991) questioned the test methodologies used so far confirming Kuznets' hypothesis. Using the time-series data in Korea, An (2003) found that the Korea economy seldom supports the Kuznets' Hypothesis. According to Deinginger and Squire (1996, 1998), recently, degrees of the inequality in developed countries increased. Although Kuznets' hypothesis has been confirmed in many empirical studies, we have to be more careful when we discuss Kuznets' hypothesis.

Comparing with the researches related on the relationship between inequality and development, it is difficult to find the papers analyze directly how demographic changes affected the inequality. However we could found some implications from the Deaton and Paxson(1994, 1997). Using the micro data from the United States, Great Britain, Taiwan, and Thailand, Deaton and Paxson (1994, 1997) showed that inequality in consumption, income, and earnings increased with age within cohorts of individuals. These results implied that increasing the share of the old people in the total population might aggravate inequality.

III. Methodologies, data, and variables

1. Test Methodologies

This paper uncovers three major problems commonly observed in the previous empirical studies confirming the Kuznets' hypothesis and proposes new methodologies resolving those problems. These methods contain panel data approach, inverse-logistic approach, and non-parametric kernel fit

The first problem is that those studies of Kuznets' hypothesis used cross-country data rather than an analysis of historical trends over time because of the insufficiency of time-series data for each country that was observed. Learned from one country's time-series data cannot be applied to the other countries unless they share something in common. On the other hand, every country is unique in a certain sense. Hence, a better way to test Kuznets' hypothesis is to employ panel data, taking into account time-invariant country-specific effects.

There are some attempts to test the Kuznets' hypothesis using the panel data set. Tsakloglou (1988) compiled a panel data set. But, instead of invoking estimation methods useful for panel data, he grouped countries by the geographic location and used dummy variables for locations. So the time-invariant country-specific effect has not been properly accounted for in the literature. In this paper, however, we will use a panel data analysis that can properly explain the time-invariant country-specific.

The second problem is that the previous test results relied on specific functional forms generating inverted-U shaped curve. Tsakloglou(1988) observed that Kuznets' hypothesis is a vague statement, for there exist many different functional forms which can generate the inverted-U shape. For instance, Y=ax + b(1/x) as well as Y=ax+bx^2 can yield the inverted-U shape, depending on (a, b). Hence specifying the regression function as a quadratic form and drawing conclusions from it may be misleading. The best way to resolve this problem is the Non-parametric Kernel Regression, which does not depend on any functional form but estimates the functional form itself

The third problem comes from the boundedness of the dependent variable to [0, 1] in its range. The range of income inequality measures is limited, so that any well-fit regression function can have ups and downs in which may pass as an inverted-U shape. In this case, Kuznets' hypothesis becomes vague. And such bounds cause estimations of the regression function with the bounded dependent variable to yield the inverted-U shape, although the true function is not nonlinear. To resolve this problem we employed inverse logistic function estimation.

To explain the nonparametric kernel regression and inverse logistic function estimation more detail, we employed a general model enough to accommodate all our estimation method.

$$y_{it} = H(r(x_{it}, \beta, z_i, \gamma) + \mu_{it}), \quad t = 1, 2, \cdots T_i, \quad i = 1, 2, \cdots, N \qquad (1)$$

where x_{it} is the dependent variables, z_i is the time-invariant variables including the intercept and country-specific effect, H is a nonlinear function mapping $(-\infty,\infty)$ to [0, 1], $r(\cdot)$ is the regression function of our interest and T_i is the number of observation for the i th country.

Equation (1) is general in that it takes into account the fact that the range of y_{it} is [0,1] by employing H, which may unknown. Equation (1) also considers the possibility of an unknown form of the regression function and time-invariant variables that differ by country. Depending on how much we are willing to assume in (1), we have a variety of models with different interpretations of

The first model, perhaps the easiest one to implement, is

$$y_{it} = H(x_{it}'\beta + z_i'\gamma + \mu_{it}) \quad (2)$$

With H known where x_{it} is k×1 vector of variables, and z_i is a column vector of time-invariant variables. Then, inverting H, we get

$$y_{it}^* \equiv H^{-1}(y_{it}) = x_{it}'\beta + z_i'\gamma + \mu_{it} \quad (3)$$

One choice for H is the logit function $H(z) = 1/(1+e^{-z})$ and fit the model

$$\log(y/(1-y)) = x_{it}'\beta + z_i'\gamma + \mu_{it}. \qquad (4)$$

We call this model 'inverse logistic model' and use a panel data analysis that can properly explain the time-invariant country-specific.

For nonparametric kernel regression, we ignore the bound on y but allow an unspecified regression function:

$$y_{it} = r(x_{it}, \beta, z_i, \gamma) + \mu_{it}. \qquad (5)$$

where r is unknown.

To control the country specific effect, we must take the first difference.

$$y_{it} - y_{i,t-1} = r(x_{it}) - r(x_{i,t-1}) + u_{it} - u_{i,t-1} \qquad (6)$$

We cannot, however, separate $r(x_{it})$ from $r(x_{i,t-1})$, and thus we cannot directly apply a nonparametric regression technique to (5), too.

If $r(x_{it}) - r(x_{i,t-1}) \cong r(x_{it} - x_{i,t-1})$ holds, then equation (6) becomes

$$y_{it} - y_{i,t-1} = r(x_{it} - x_{i,t-1}) + u_{it} - u_{i,t-1} \qquad (7)$$

And we can apply a nonparametric regression technique to equation (7). But it means that r is approximately linear. Hence when we allow r to be unknown, it seems better to interpret UH as a relationship between changes in GNP and inequality rather than as a relationship between the levels of GNP and inequality.

With an iid sample with N observations, a kernel estimator for f(x) is given by

$$f(x) = \frac{1}{Nh^k} \sum_i K \frac{x_i - x}{h} \qquad (8)$$

Where K is a kernel that is weighting function such as a normal density, $h \Rightarrow 0$ as $N \Rightarrow \infty$, and k is the dimension of x_i. The smaller $|x_i - x|$ is, the larger the weight that is given to the ith observation. So equation (8) is a weighted number of observations falling in a neighborhood of x. The presence of smoothing parameter h makes the neighborhood shrink to 0 as $N \Rightarrow \infty$. Equation (8) is a generalization of estimating f(x) by a histogram where the group interval length plays the same role as h.

It is known that the choice of K is not crucial for the estimate but the choice of h is critical. Although there are many theoretical suggestions of how to choose h, in practice h is usually chosen by a trial and error until local variation of the estimated curve disappear and a certain trend is detected.

In our analysis, we use the product standard normal kernel.

2. Data and variables

The number of countries used in our analysis is 19. The countries were chosen from the Luxembourg Income Study and total observations in this paper are 87. The data used in this paper are from the following sources: Data on inequality are from Luxembourg Income Study(LIS). Data on the other variables are from the world development indicator 2003 published by World Bank.

Details on the variables used in the regression are in <table1> and basic statistics are in <table 2> Means of the important variables are reported in <table 3>.

IV. Empirical Results

1. Panel Regression Results

In <table 4>, we attempt to estimate four specifications of the regression equations concerning the shapes of the relationship between before-tax Gini and LGDP or between before-tax Gini and OAGDEP. In our formulation, we tested a linear relationship in Spec.1 and Spec.3 and tested a quadratic form relationship in Spec.2 and Spec. 4. We, initially, tested the cubic relationship but it was not statistically significant. Thus we did not report it.

We did the two tests so as to find the best fitted model for our analysis. First, in the null hypothesis, which means that there does not exist the country specific effect, it is rejected in all cases at the 1-percentage significance level for Lagrange Multiplier test. It says that the panel data analysis such as fixed effect model estimation or random effect model estimation is better than the simple pooled regression. Second, in the Hausman test for the null hypothesis that there exists the random effect, we found that the four cases were rejected at the 5-percentage significance level. These tests show us that the analysis had better be interpreted using the fixed effect model estimation result.

In our analysis the linear specification between before-tax Gini and LPGDP in spec.1 appears a significantly positive relationship. But the quadratic specification in spec.2 is not statistically significant, i.e. inverted-U shaped relationship does not appear. It implies that Kuznets' hypothesis does not hold in our sample.

The relationship between before-tax Gini and OAGDEP in spec.3 appears a significant positive relationship and the quadratic specification in Spec.4 is also significant and positive. It means that degree of inequality increase at an increasing rate as the old age dependency ratio goes up.

Table 5 shows the estimation results of before-tax Gini as the dependent variables and LPGDP, OAGDEP, and the other variables as the independent ones. According to the result of the LM-test and Hausman test, in all cases, we found that the fixed effect model is more useful than the random effect model. The empirical results are almost the same as those in Table 4 in all specifications. The relationship between before-tax Gini coefficient and LPGDP is significant and positive. And the relationship between before-tax Gini coefficient and OAGDEP in spec.7 appears a significant positive relationship and the quadratic specification in Spec.8 is also significant and positive.

Table 6 and Table 7 represent the panel regression results using after-tax Gini coefficient as the dependent variables. The empirical analysis shows little difference from before-tax Gini coefficient results. An interesting finding emerges from the empirical comparison of before-tax Gini coefficient with after-tax Gini coefficient. In other word, the coefficient values of both LPGDP and OAGDEP with respect to the case of after-tax Gini index are lower than in before-tax case. This implies that the impact of the development or the demographic changes on the inequality can be decreased due to the tax policy. Also it offers a policy implication that the tax policy can improve the unequal distribution resulted from the aging phenomenon.

2. Inverse Logistic function

Table 8-9 says the estimation results of the inverse logistic function whose dependent variable is before-tax Gini index. It is almost the same as the results from the panel data estimates. Table 10-11 is the results of the inverse logistic function using after-tax Gini as a dependent variable. But Spec. 32 in the Table 11 tells us that the random effect model is a better tool for our analysis, for the null hypothesis is not rejected for the Hausman test. Nevertheless, the signs and significance level conform to the other specification results. Except for this, the other results are the same as the panel data results.

The coefficient values of LPGDP and OAGDEP with after-tax Gini index as dependent variables is lower than that with before-tax Gini, which is the same as the inverse logistic function estimation. In this result, it is found that the tax policy can improve an unequal income distribution resulted from the aging.

3. Nonparametric Kernel Fit

Figure1 and Figure 2 show the relationship between LPGDP and before-tax or after-tax Gini coefficients in the kernel method. As we already mentioned above, the kernel fit is useful if it is interpreted as the relationship between changes of log (per capita GDP) and Gini coefficients rather than the relationship between level of log (per capita GDP) and the Gini coefficients. In this context, the horizontal axis in Figure 1 and 2 represents the change of the LPGDP, i.e., the growth rate of GDP in a country. From this perspective, we can find in Figure 1 and 2 that before- and after-tax Gini indexes changes infinitesimally as the growth rate of per capita GDP changes.

Now let's explain Figure 3 and 4. These are the results of the relationship between OAGDEP and before- or after-tax Gini indexes. Interestingly, Gini coefficient decreases at the incipient stage and then increases, but at the end point of the stages it decreases again as is shown in Figure 3. The problem is that two stages, as it were, the first and last stage, cannot be looked on as the reliable trends, because the number of the observations is very small. Considering this, we can conclude that before-tax Gini index increases as OAGDEP grows up. It conforms to the above-mentioned result, which implies that Gini coefficient increases as

OAGDEP gets larger. It makes senses in that OAGDEP grows at an increasing rate as the aging keeps going on.

On the other hand, after-tax Gini index was not influenced by OAGDEP, as can be seen in Figure 4.

We summarize the following findings from the kernel analyses. First, the growth rate of the per capita GDP does not have an effect on the before- and after- tax income distribution. Second, before-tax Gini coefficient increases in accordance with the size of OAGDEP, while after-tax Gini coefficients have no relation to that. Third, a tax policy can improve an unequal income distribution resulted from the aging. In sum, it can be said that these conclusions are the same as results from both the panel data analysis and inverse logistic function estimation.

V. Conclusion

To investigate the relationship between population aging and inequality, we used three test methodologies such as panel data analysis, inverse logistic function estimation, and nonparametric kernel estimation.

Estimation results using panel data analysis show that the linear specification between inequality and LPGDP appears a significantly positive relationship, but the quadratic specification is not statistically significant. It implies that Kuznets' inverted-U hypothesis does not hold in our sample. And they also show that the relationship between inequality and OAGDEP appears a significant positive relationship and the quadratic specification is also significant and positive. It means that degree of inequality increase at an increasing rate as the old age dependency ratio goes up. These results are the same as results from both the inverse logistic function estimation and nonparametric kernel estimation.

Our study needs to be extended to the researches related on the policy that weaken the effect of the population aging. Our result that the coefficient values of both LPGDP and OAGDEP with respect to the case of after-tax Gini index are lower than that in before-tax case can offer some implication. This result implies that the impact of the development or the demographic changes on the inequality can be decreased due to the tax policy, i.e. the tax policy may improve the unequal distribution resulted from the aging phenomenon.

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<Table 1> Description of the variables used in the empirical analysis

The variables used in this paper include the following variables:

- Dependent variable
  - PREGINI : before-tax Gini coefficient
  - POSTGINI : after-tax Gini coefficient
- Independent variables
  - LGDP: log GDP per capita expressed in 1995 Purchasing Power Parities(PPP).
  - OAGDEP: Old age dependency ratio is used for the indicators of the aging.
  - PGR : Population growth rate
  - URBANR : Ratio of the population lived in the urban area
  - TRADEGDP: import and export per GDP.

<Table 2> Basic Statistics

variable	Means	Standard Deviation	# of observation
PREGINI	0.3952	0.0555	87
POSTGINI	0.2942	0.0647	87
LPGDP	9.8602	0.5668	87
OAGDEP	19.4275	4.7211	87
PGR	0.7425	0.6398	87
URBANR	78.6702	10.0550	87
TRADEGDP	67.7936	42.4375	87

<Table 3> Means of the important variables in each countries

COUNTRY	PREGINI	POSTGINI	LPGDP	OAGDEP
Australia	0.3927	0.2970	9.8030	16.0317
Belgium	0.3266	0.2333	10.1354	22.3633
Canada	0.3782	0.2916	9.7790	15.7000
Denmark	0.4431	0.2520	10.4394	22.6992
Finland	0.3957	0.2208	10.1874	20.6430
France	0.3886	0.2896	10.0580	21.3989
Germany	0.3671	0.2623	10.1002	22.3951
Ireland	0.4140	0.3305	9.7183	17.8250
Israel	0.4065	0.3130	9.5082	15.2780
Italy	0.3958	0.3113	9.7917	22.1368
Luxembourg	0.3045	0.2373	10.4825	19.6692
Mexico	0.4916	0.4778	8.1022	7.1571
Netherlands	0.3482	0.2588	10.0714	18.3881
Norway	0.3637	0.2313	10.2456	24.3673
Spain	0.3469	0.3105	9.4183	18.8516
Sweden	0.4182	0.2160	10.1102	26.4035
Switzerland	0.3863	0.3080	10.6423	21.0494
UK	0.4173	0.3090	9.7010	23.2254
USA	0.4255	0.3407	10.1290	18.1665

<Table 4>　Panel Data Analysis: PREGINI 1

	Spec. 1		Spec. 2		Spec. 3		Spec. 4	
	FEM	REM	FEM	REM	FEM	REM	FEM	REM
LPGDP	0.1808 ***	0.1431 ***	-0.3769	-1.3299 ***				
	(0.0259)	(0.0230)	(0.7858)	(0.5201)				
LPGDP2			0.0282	0.0746 ***				
			(0.0397)	(0.0266)				
OAGDEP					0.0208 ***	0.0172 ***	-0.0142	-0.0288 **
					(0.0028)	(0.0025)	(0.0150)	(0.0124)
OAGDEP2							0.0009 **	0.00116 ***
							(0.0004)	(0.0003)
R-square	0.7418	0.3129	0.7437	0.3357	0.7562	0.3567	0.7754	0.4149
LM-test	8.83 ***		7.60***		10.93***		8.02***	
Hausman test	10.11***		7.99**		8.70***		8.48**	

Note: standard errors in ( ).　*: 10%, **: 5%, ***: 1% significance level

<Table 5>　Panel Data Analysis: PREGINI 2

	Spec. 5		Spec. 6		Spec. 7		Spec. 8	
	FEM	REM	FEM	REM	FEM	REM	FEM	REM
LPGDP	0.0956***	0.0709**	0.1039***	0.0845***	0.0924**	0.0547	0.1008**	0.0835**
	(0.0342)	(0.0311)	(0.0326)	(0.0291)	(0.0457)	(0.0360)	(0.0434)	(0.0342)
PGR					0.0026	0.0129	-0.0103	-0.0036
					(0.0146)	(0.0137)	(0.0146)	(0.0139)
URBANR					0.0004	0.0007	0.0026	0.0011
					(0.0035)	(0.0021)	(0.0034)	(0.0018)
TRADEGDP					-0.0003	-0.0003	-0.0002	-0.0002
					(0.0004)	(0.0003)	(0.0004)	(0.0003)
OAGDEP	0.0133***	0.0124***	-0.0264*	-0.0396***	0.0142***	0.0142***	-0.0322*	-0.0416***
	(0.0038)	(0.0035)	(0.0146)	(0.0130)	(0.0043)	(0.0039)	(0.0169)	(0.0150)
OAGDEP2			0.0010***	0.0013***			0.0011***	0.0013***
			(0.0004)	(0.0003)			(0.0004)	(0.0003)
R-square	0.7821	0.4170	0.8057	0.4851	0.7849	0.4189	0.8095	0.4826
LM-test	10.74***		9.67***		7.79***		7.17***	
Hausman test	9.45***		9.16**		10.60*		11.68*	

Note: standard errors in ( ).　*: 10%, **: 5%, ***: 1% significance level

<Table 6> Panel Data Analysis: POSTGINI 1

	Spec. 9		Spec. 10		Spec. 11		Spec. 12	
	FEM	REM	FEM	REM	FEM	REM	FEM	REM
LPGDP	0.0657 *** (0.0122)	0.0538 *** (0.0115)	0.4075 (0.3688)	-0.0698 (0.3168)				
LPGDP2			-0.0173 (0.0186)	0.0064 (0.0161)				
OAGDEP					0.0056 *** (0.0015)	0.0042 *** (0.0014)	-0.0087 (0.0080)	-0.0157 ** (0.0072)
OAGDEP2							0.0004 * (0.0002)	0.0005 *** (0.0002)
R-square	0.9579	0.2056	0.9584	0.2231	0.9504	0.0986	0.9528	0.1608
LM-test	31.87***		27.35***		31.28***		25.44***	
Hausman test	8.48***		8.18***		7.72***		8.07**	

Note: standard errors in ( ). *: 10%, **: 5%, ***: 1% significance level

<Table 7> Panel Data Analysis: POSTGINI 2

	Spec. 13		Spec. 14		Spec. 15		Spec. 16	
	FEM	REM	FEM	REM	FEM	REM	FEM	REM
LPGDP	0.0602 *** (0.0175)	0.0496 *** (0.0165)	0.0638 *** (0.0170)	0.0545 *** (0.0160)	0.0744 *** (0.0233)	0.0534 *** (0.0202)	0.0781 *** (0.0225)	0.0622 *** (0.0195)
PGR					-0.0028 (0.0075)	0.0011 (0.0072)	-0.0086 (0.0076)	-0.0062 (0.0074)
URBANR					-0.0017 (0.0018)	-0.0008 (0.0013)	-0.0007 (0.0018)	-0.0002 (0.0012)
TRADEGDP					0.0000 (0.0002)	0.0000 (0.0002)	0.0001 (0.0002)	0.0000 (0.0002)
OAGDEP	0.0009 (0.0019)	0.0006 (0.0019)	-0.0162 ** (0.0076)	-0.0213 *** (0.0071)	0.0003 (0.0022)	0.0007 (0.0021)	-0.0203 ** (0.0088)	-0.0246 *** (0.0082)
OAGDEP2			0.0004 ** (0.0002)	0.0005 *** (0.0002)			0.0005 ** (0.0002)	0.0006 *** (0.0002)
R-square	0.9580	0.2061	0.9612	0.2758	0.9586	0.2108	0.9622	0.2826
LM-test	27.63***		28.79***		23.79***		25.20***	
Hausman test	8.66**		8.86**		9.42*		10.33	

Note: standard errors in ( ). *: 10%, **: 5%, ***: 1% significance level

<Table 8> Inverse Logistic: PREGINI 1

	Spec. 17		Spec. 18		Spec. 19		Spec. 20	
	FEM	REM	FEM	REM	FEM	REM	FEM	REM
LPGDP	0.7686 *** (0.1107)	0.6063 *** (0.0983)	-2.0000 (3.3583)	-5.8810 *** (2.1878)				
LPGDP2			0.1400 (0.1697)	0.3284 *** (0.1118)				
OAGDEP					0.0883 *** (0.0120)	0.0726 *** (0.0107)	-0.0598 (0.0643)	-0.1223 ** (0.0529)
OAGDEP2							0.0038 ** (0.0016)	0.00493 *** (0.0014)
R-square	0.7392	0.3093	0.7418	0.3321	0.7523	0.3497	0.7713	0.4071
LM-test	8.80***		7.70***		10.73***		8.04***	
Hausman test	10.13***		8.21***		8.71***		8.45**	

Note: standard errors in ( ). *: 10%, **: 5%, ***: 1% significance level

<Table 9> Inverse Logistic: PREGINI 2

	Spec. 21		Spec. 22		Spec. 23		Spec. 24	
	FEM	REM	FEM	REM	FEM	REM	FEM	REM
LPGDP	0.4102 *** (0.1467)	0.3028 ** (0.1332)	0.4454 *** (0.1403)	0.3610 *** (0.1251)	0.3874 * (0.1957)	0.2279 (0.1536)	0.4224 ** (0.1867)	0.3500 ** (0.1467)
PGR					0.0173 (0.0627)	0.0618 (0.0586)	-0.0367 (0.0628)	-0.0075 (0.0596)
URBANR					0.0019 (0.0151)	0.0029 (0.0088)	0.0113 (0.0148)	0.0046 (0.0076)
TRADEGDP					-0.0015 (0.0016)	-0.0013 (0.0014)	-0.0008 (0.0016)	-0.0009 (0.0013)
OAGDEP	0.0558 *** (0.0163)	0.0520 *** (0.0151)	-0.1122 * (0.0626)	-0.1691 *** (0.0556)	0.0608 *** (0.0184)	0.0606 *** (0.0168)	-0.1325 * (0.0727)	-0.1729 *** (0.0642)
OAGDEP2			0.0042 *** (0.0015)	0.0055 *** (0.0013)			0.0047 *** (0.0017)	0.0056 *** (0.0015)
R-square	0.7785	0.4105	0.8020	0.4777	0.7820	0.4142	0.8056	0.4751
LM-test	10.63 ***		9.68***		7.54***		6.97***	
Hausman test	9.49***		9.14**		10.68*		11.68*	

Note: standard errors in ( ). *: 10%, **: 5%, ***: 1% significance level

<Table 10> Inverse Logistic: POSTGINI 1

	Spec. 25		Spec. 26		Spec. 27		Spec. 28	
	FEM	REM	FEM	REM	FEM	REM	FEM	REM
LPGDP	0.3143 *** (0.0579)	0.2569 *** (0.0545)	1.4718 (1.7584)	-0.7928 (1.4932)				
LPGDP2			-0.0585 (0.0888)	0.0536 (0.0757)				
OAGDEP					0.0273 *** (0.0070)	0.0203 *** (0.0065)	-0.0487 (0.0377)	-0.0793 ** (0.0340)
OAGDEP2							0.0019 ** (0.0009)	0.0025 *** (0.0009)
R-square	0.9556	0.2073	0.9559	0.2227	0.9480	0.1028	0.9511	0.173
LM-test	33.10***		29.94***		30.65***		27.55***	
Hausman test	8.68***		8.02**		7.96***		8.06**	

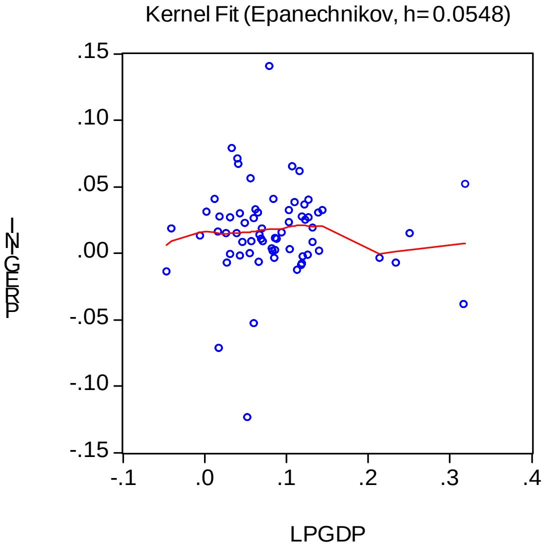
Note: standard errors in ( ). *: 10%, **: 5%, ***: 1% significance level

<Table 11> Inverse Logistic: POSTGINI 2

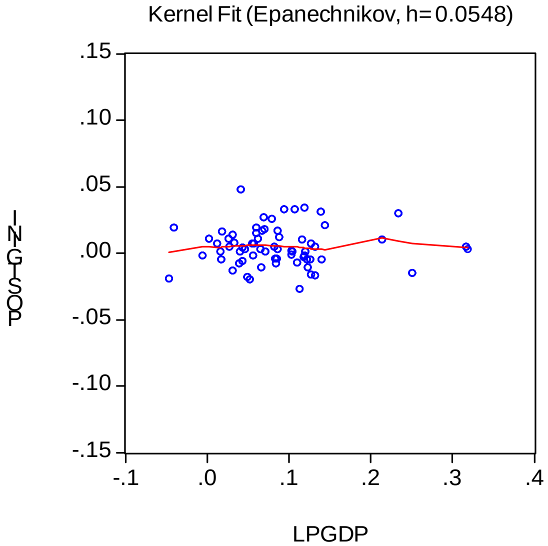
	Spec. 29		Spec. 30		Spec. 31		Spec. 32	
	FEM	REM	FEM	REM	FEM	REM	FEM	REM
LPGDP	0.2836 *** (0.0830)	0.2335 *** (0.0784)	0.3022 *** (0.0800)	0.2593 *** (0.0755)	0.3660 *** (0.1102)	0.2596 *** (0.0954)	0.3846 *** (0.1058)	0.3029 *** (0.0918)
PGR					-0.0104 (0.0353)	0.0087 (0.0338)	-0.0391 (0.0356)	-0.0275 (0.0346)
URBANR					-0.0108 (0.0085)	-0.0054 (0.0063)	-0.0058 (0.0084)	-0.0022 (0.0058)
TRADEGDP					-0.0001 (0.0009)	-0.0001 (0.0008)	0.0003 (0.0009)	0.0002 (0.0008)
OAGDEP	0.0048 (0.0092)	0.0036 (0.0088)	-0.0843 ** (0.0357)	-0.1070 *** (0.0336)	0.0023 (0.0104)	0.0044 (0.0098)	-0.1008 ** (0.0412)	-0.1204 *** (0.0386)
OAGDEP2			0.0022 ** (0.0009)	0.0028 *** (0.0008)			0.0025 ** (0.0010)	0.0030 *** (0.0009)
R-square	0.9558	0.2086	0.9599	0.2890	0.9569	0.2209	0.9611	0.2986
LM-test	28.59***		31.10***		24.80***		27.21***	
Hausman test	8.88**		8.91**		9.48*		10.30	

Note: standard errors in ( ). *: 10%, **: 5%, ***: 1% significance level

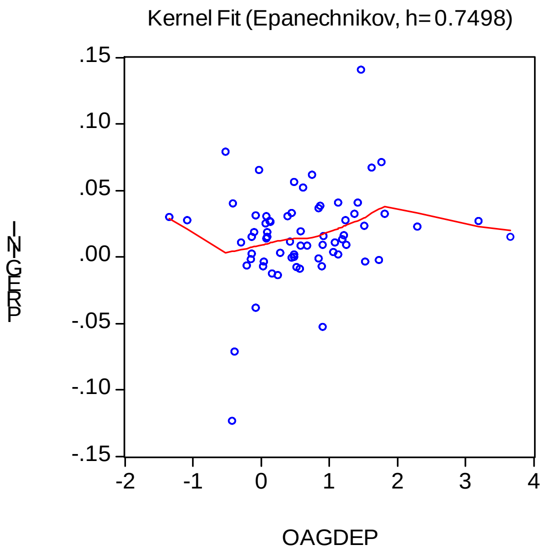
<Figure 1> PREGINI and LPGDP



<FIGURE 2> POSTGINI and LPGDP



<Figure 3> PREGINI and OAGDEP



<Figure 4> POSTGINI and OAGDEP