Nexus of Demographic Change, Structural Transformation and Economic Growth in South Asia

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The economic growth depends on changes in the demographic profile of a country. However, the demographic change over economic growth has positive and negative relationships in the literature. Further, testing a Kuznets model of economic growth is not adequately estimated in the field of demographic and structural transformation in South Asia. The study uses panel data model for understanding the structural change over the demographic changes of the South Asian economies. A panel unit root test and GMM dynamic panel data model will be evaluated with the use of Kuznets curve approach. The results of GMM dynamic panel data estimation show a strong relationship among CO2 emission, demographic profile and economic growth. It revealed that 1% increase in GDP increases 3.033% of the CO2 emission. However, increase of 1% demographic profile of the South Asia decreases CO2 emission by 0.058%. Thereby, the changes of demographic profile with respect to the changes of economic growth can reduce the environmental degradation and promote sustainability in development policies.

Key words: Panel Data, GMM, Kuznets Curve, Demographic Profile, Economic Growth

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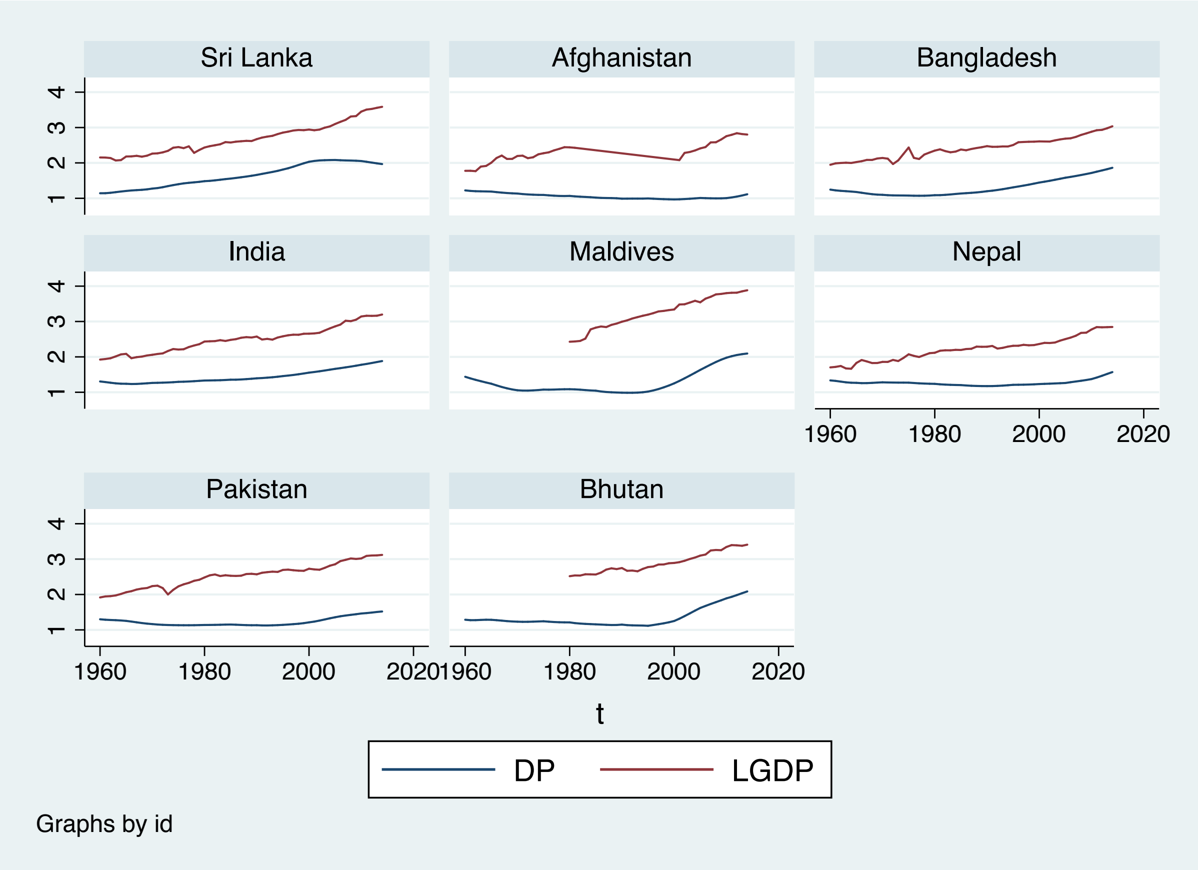
1. Introduction

The economic growth under the sustainability is critical arguments in today's economic forums. How influential is the structural change of demographic profile in economic growth of South Asia is one of the key questions in the development economics. The research is developed to address the interaction between demographic change, structural transformation and economic growth with respect to the demographic profile defined: the ratio of working age to non-working age population. The economic growth relationships under the Kuznets Hypothesis are not tested for the context of South Asia. This study was carried out to understand the nexus of economic growth and environmental degradation under the changes of demographic profile of South Asia.

Two key variables in the paper are demographic profile and economic growth that are plotted in the following graph for South Asian countries.



Graph 1: Demographic profile (DP): Ratio of working age to non-working age population and GDP growth

Demographic change has often been absent from consideration. But new thinking and evidence have highlighted the powerful contribution that demographic change can make to economic growth, and this line of inquiry has some salient implications for understanding growth in South Asia and assessing and shaping its future prospects. The change in the age structure of the population create potential for faster economic growth, demographic dividend. The working age share of the population – which is reflected in the ratio of working age to non-working age population- is a crucial indicator of country's potential for reaping a demographic dividend.

In this paper, how demographic profile of a country can influence the economic growth and environmental degradation in South Asia has examined. The empirical model like GMM panel data estimation has been paid less attention in evaluating the Kuznets Curve for South Asia. The structural changes of the economic growth in line with the changes of demographic change have not been tested for the sustainability.

The paper is organized in six sections including this introduction. The second section presents a brief review of the literature on economic growth, CO2 emission in evidence the role of demographic factors. The third section explores the data over last 54 years. The methodological procedures adopted for estimating the GMM dynamic panel data model are presented in the fourth section and the results are discussed in the fifth section. Finally, the conclusion was included in the sixth section.

2. Literature review

Following Grossman and Krueger (1991, 1993) and Douglas and Selden (1995), the growth-environmental performance nexus has been tested by various researchers. Their work offers empirical evidence that environmental degradation increases at initial level of economic growth and then starts to decline at a higher level of economic growth (Suri and Chapman, 1998; Friedl and Getzner, 2003; Stern, 2004; Dinda and Coondoo, 2006; and Coondoo and Dinda, 2008). Generally, it is difficult to find an inverted-U form relation for the CO2 emission. A number of studies working on CO2 emissions find an ever-increasing positive correlation between CO2 and economic growth for example Chang (2010) for China, Ozturk and Acaravci (2010) for Turkey and Pao and Tsai (2010) for Russia. However, Martínez-Zarzoso and Morancho (2004), Cole (2003), Vollebergh et al. (2005), Galeotti et al. (2006) and Apergis and Payne (2010), who employ panel data methods, report an inverted U-shaped function for CO2 emissions.

Furthermore, the role of energy consumption in CO2 emissions should not be neglected while discussing the environmental performance and economic growth nexus. A substantial number of researches have been devoted towards analyzing the energy consumption and economic growth nexus (Ozturk, 2010). Therefore, researchers think that it will be more fitting if economic growth and energy consumption is analyzed simultaneously in a single multivariate model. This approach is used by Ang (2007), Soytas et al. (2007), Halicioglu (2009), and Jalil and Mahmud (2009), Narayan and Narayan (2010), Apergis and Payne (2010) and Shahbaz et al. (2010) to test the both nexus in a single framework.

The next strand in investigating the emission dynamics is to test the relationship between the dynamics of demographic factors and environmental performance, and economic growth. Shi (2003) and Cole and Neumayer (2004) found a positive link between CO2 emissions and a set of other explanatory variables including population, urbanization and energy intensity. In addition, few studies have discussed population density as an additional explanatory variable in the EKC framework (Cole et al. 1997; Panayotou 1993, 1995). More recently, Dhakal (2009) examines the relationship between urbanization and CO2 emissions in China. Dhakal (2009) indicates that around 40% contribution in CO2 emissions is due to an 18% increase in population. Shahbaz et al. (2010) investigate the relationship between CO2 emissions, energy consumption, economic growth and trade openness for Pakistan. Their results support the EKC hypothesis when energy consumption and trade openness variables are added to the standard GDP variable. Leitao (2015) examined the relationship between energy consumption and foreign direct investment (FDI) in Portugal for the period 1990- 2011. The empirical results illustrate that the income per capita and political globalization present a positive impact on energy consumption. The selected components of globalization show that these variables promote Portuguese FDI. The variables of income per capita and the squared income per capita validate the EKC assumptions.

Grossman and Krueger (1991) investigated the environmental impacts of the North American Free Trade Agreement on sulphur dioxide emissions and smoke emissions and found that a cubic polynomial of per capita GDP was the preferred functional form. In a later paper, Grossman and Krueger (1995) used panel data available from Summers and Heston (1991) and GEMS for the years 1979 to 1990 to investigate the presence of an EKC relationship for four environmental indicators: urban air pollution, oxygen quality in river basins, contamination of river basins by faecal matter, and heavy metal contamination of river basins. The sample size varies depending on the particular emission under investigation. In this analysis, the reduced form empirical specification included a cubic for real GDP per capita.

Additional location specific characteristics were included to improve the precision of the estimation by reducing the variance of the residuals in the relationship between pollution emissions and GDP per capita. Using GMM estimation of dynamic panel data model, this analysis provided evidence of an EKC relationship for demographic and other indicators.

There exists empirical support for the emergence of an EKC for atmospheric pollutants. For instance, Stern and Common (2001) investigate the presence of an EKC for emissions of sulphur using a panel of 73 countries between the years 1960 and 1990. Their results provide evidence of a global inverted-U shaped EKC. For the OECD subsample, random effects estimation produces consistent results and again reveals an inverted-U shaped EKC. The EKC for the non-OECD sub-sample is monotonic. Interestingly, when estimating the fixed time effects for the World sample, Stern and Common find a decline in emissions, ceteris paribus. The average rate of this decline is 1.5 percent per year. Selden and Song (1994) use cross-national panel data to investigate the EKC for four air pollutants. Using the same data used by Grossman and Krueger (1991 and 1995), Selden and Song find evidence of the emergence of an EKC for suspended particulate matter, sulphur dioxide, nitrous oxide and carbon monoxide using pooled cross section, fixed effects and random effects estimation. A limited number of empirical studies provide support for the emergence of the EKC relationship with respect to land degradation. For example, Cropper and Griffiths (1994) find evidence of an inverted-U shaped relationship for the rate of deforestation in Latin America and Africa, while Antle and Heidebrink (1995) found that an EKC emerged for park and forest amenities. Interestingly, Kaufmann, Davidsdottir, Garnham and Pauly (1998) found a U-shaped relationship between per capita income and atmospheric concentration of sulphur dioxide.

3. Data

Macroeconomic data was gathered from WDI of the World Bank and UN data for demographic profile. Panel data from 1960 to 2014 has been collected from the above sources, and the demographic profile: ratio of working age to non-working age population was standardized and converted into logarithm. The following table 1 depicted the summary statistics of the variables used for the empirical analysis.

Table 1: Summary statistics of the variables

Variable	Mean	Standard Deviation	Min	Max	Observations
LGDP	2.5605	0.4534	1.6653	3.8831	381
LTO	8.6978	0.9492	5.7409	11.0886	365
LCO_2	-0.6127	0.5458	-2.1025	0.5221	407
$LGDP^2$	6.7614	2.4554	2.7734	15.0787	381
$LGDP^3$	18.4166	10.3552	4.6188	58.5525	381
LEC	2.4746	0.2102	1.9325	2.9369	225
LPD	2.1350	0.6347	0.6908	3.1260	432
LDP	1.3176	0.2738	0.9684	2.0951	440

The variables are: LGDP is the logarithm of per capita gross domestic products; LTO is the logarithm of trade openness; LCO_2 is the logarithm of CO_2 emission; $LGDP^2$ is the logarithm of square of gross domestic products; $LGDP^3$ is the logarithm of cube of gross domestic products; LEC is the logarithm of energy consumption; LPD is the logarithm of population density; and LDP is the logarithm of demographic profile.

Panel Unit root tests

The panel data was tested against the stationary nature of the series using different panel unit root tests and the results are included in the annex.

4. Empirical Model

The empirical model consists of three stages for understanding the nexus of the variables because of endogeneity issue. The first stage is composed of panel data model with random effect GLS and fixed effect models. Second, the panel data model was developed with Arellano-Bond dynamic panel-data estimation and system dynamic panel-data estimation models. Third, GMM estimation of dynamic panel data was analyzed.

Panel data are well suited for examining dynamic effects, as in the first-order model,

$$\begin{aligned} y_{it} &= x_{it}'\beta + \gamma y_{i,t-1} + \alpha_i + \varepsilon_{it} \\ &= w_{it}'\delta + \alpha_i + \varepsilon_{it} \end{aligned}$$

where the set of right hand side variables, w_{it} now includes the lagged dependent variable, $y_{i,t-1}$. Adding dynamics to a model in this fashion is a major change in the interpretation of the equation. Without the lagged variable, the independent variables represent the full set of information that produce observed outcome y_{it}. With the lagged variable, now in the equation, the entire history of the right hand side variables, so that any measured influence is conditioned on this history; in this case, any impact of x_{it} represents the effect of new information. Substantial complications arise in estimation of such a model. In both the fixed and random effects settings, the difficulty is that the lagged dependent variable is correlated with the disturbance, even if it is assumed that ε_{it} is not itself autocorrelated. For the moment, consider the fixed effects model as an ordinary regression with a lagged dependent variable.

A regression is included a stochastic regressor that is dependent across observations. In that dynamic regression model, the estimator based on T observations is biased in finite samples, but it is consistent in T. The finite sample bias is of order 1/T. The same result applies here, but the difference is that whereas before obtaining our large sample results by allowing T to grow large, in this setting, T is assumed to be small and fixed, and large-sample results are obtained with respect to n growing large, not T. The fixed effects estimator of $\delta = [\beta, \gamma]$ can be viewed as an average of n such estimators. Assume for now that $T \geq K + 1$ where K is the number of variables in x_{it}. Then, from,

$$\hat{\delta} = \left[\sum_{i=1}^{n} W_i' M^0 W_i\right]^{-1} \left[\sum_{i=1}^{n} W_i' M^0 y_i\right]$$

$$= \left[\sum_{i=1}^{n} W_i' M^0 W_i\right]^{-1} \left[\sum_{i=1}^{n} W_i' M^0 d_i\right]$$

$$= \sum_{i=1}^{n} F_i d_i$$

where the rows of the T x (K+ 1) matrix W_i are w_{it} and M^0 is the TxT matrix that creates deviations from group means. Each group specific estimator, d_i is inconsistent, as it is biased in finite samples and its variance does not go to zero as n increases. This matrix-weighted average of n inconsistent estimators will also be inconsistent.

The problem is more transparent in the random effects model. In the model

$$y_{it} = \gamma y_{i,t-1} + x_{it}'\beta + u_i + \varepsilon_{it}$$

The lagged dependent variable is correlated with the compound disturbance in the model, since the same u_i enters the equation for every observation in group i. Neither of these results renders the model inestimable, but they do make necessary some technique other than our familiar LSDV or FGLS estimators. The general approach, which has been developed in several stages in the literature, relies on instrumental variables estimators and, most recently [Arellano and Bond (1991) and Arellano and Bover (1995)] on a GMM estimator. For example, in either the fixed or random effects cases, the heterogeneity can be swept from the model by taking first differences, which produces;

$$y_{it} - y_{i,t-1} = \delta(y_{i,t-1} - y_{i,t-2}) + (x_{it} - x_{i,t-1})'\beta + (\varepsilon_{it} - \varepsilon_{i,t-1})$$

This model is still complicated by correlation between the lagged dependent variable and the disturbance (and by its first-order moving average disturbance). But without the group effects, there is a simple instrumental variables estimator available. Assuming that the time series is long enough, one could use the lagged differences, $(y_{i,t-2} - y_{i,t-3})$, or the lagged levels, $y_{i,t-2}$ and $y_{i,t-3}$, as one or two instrumental variables for $(y_{i,t-1} - y_{i,t-2})$. By this construction, then, the treatment of this model is a standard application of the instrumental variables technique that was developed. This illustrates the flavor of an instrumental variable approach to estimation. But, as Arellano et al. and Ahn and Schmidt (1995) have shown, there is still more information in the sample that can be brought to bear on estimation, in the context of a GMM estimator, which we now consider.
Extending the Hausman and Taylor (HT) formulation of the random effects model to include the lagged dependent variable;

$$
\begin{aligned}
y_{it} &= \gamma y_{i,t-1} + x'_{1it}\beta_1 + x'_{2it}\beta_2 + z'_{1i}\alpha_1 + z'_{2i}\alpha_2 + \varepsilon_{it} + u_i \\
&= \delta' w_{it} + \varepsilon_{it} + u_i \\
&= \delta' w_{it} + \eta_{it}
\end{aligned}
$$

where

$$w_{it} = [y_{i,t-1} + x'_{1it} + x'_{2it} + z'_{1i} + z'_{2i}]'$$

is now a (1 + K1 + K2 + L1 + L2) x 1 vector. The terms in the equation are the same as in the Hausman and Taylor model. Instrumental variables estimation of the model without the lagged dependent variable is discussed in the previous section on the HT estimator. Moreover, by just including $y_{i,t-1}$ in x_{2it} ,we see that the HT approach extends to this setting as well, essentially without modification. Arellano et al. suggest a GMM estimator, and show that efficiency gains are available by using a larger set of moment conditions. In the previous treatment, used a GMM estimator constructed as follows:

The set of moment conditions used to formulate the instrumental variables were;

$$E\left[\begin{pmatrix} \underline{x_{1it}} \\ \underline{x_{2it}} \\ \underline{z_{1i}} \\ \overline{x}_{1i} \end{pmatrix}(\eta_{it} - \overline{\eta}_i)\right] = E\left[\begin{pmatrix} \underline{x_{1it}} \\ \underline{x_{2it}} \\ \underline{z_{1i}} \\ \overline{x}_{1i} \end{pmatrix}(\varepsilon_{it} - \overline{\varepsilon}_i)\right] = 0$$

This moment condition is used to produce the instrumental variable estimator. We could ignore the non-scalar variance of η_{it} and use simple instrumental variables at this point. However, by accounting for the random effects formulation and using the counterpart to feasible GLS, we obtain the more efficient estimator. As usual, this can be done in two steps. The inefficient estimator is computed in order to obtain the residuals needed to estimate the variance components. Hausman and Taylor's steps 1 and 2, Steps 3 and 4 are used in the GMM estimator based on these estimated variance components.

The basic panel data models is defined as:

$$
\begin{aligned}
ln(CO_{2it}) = \alpha + \beta_1 ln(GDP_{it}) + \beta_2 ln(GDP_{it}^2) + \beta_3 ln(GDP_{it}^3) + \beta_4\ ln\ (DP_{it}) + \beta_5\ ln\ (TO_{it}) \\
+ \beta_6\ ln\ (PD_{it}) + \beta_7\ ln\ (EC_{it}) + e_{it}
\end{aligned}
$$

In GMM Panel data approach with the use of three instrumental variables such as Population density (PD), Energy Consumption (EC) and Trade Openness (TO) will be used for the analysis, in addition to the endogenous variables (X) such as GDP per capita, and Demographic Profile (DP). It is obvious that the dependent variable as CO2 emission per GDP per capita is endogenous, and bi-directional relationship with the GDP. Hence, GMM Panel data model was applied.

5. Results

Three stage of analysis will be performed in order to develop a robust estimation of the relationships between economic growth and demographic profile under the Kuznets hypothesis.

Stage I:
The panel data model was developed in terms of random effect GLS and fixed effect models. The results of two models were presented in Table 3.

Table 3: Result of random effect and fixed effect models

D.Var: LCO2	Random Effect GLS Regression	P>|z|	Fixed Effect	P>|z|
LGDP	10.6503 (6.19)*	0.085	1.2154 (1.59)**	0.044
LGDP2	-3.1226 (2.29)	0.174	-0.4269 (0.59)	0.472
LGDP3	0.1200 (0.28)	0.251	0.0517 (0.07)	0.475
LDP	-0.2278 (0.136)*	0.095	-0.4770 (0.067)***	0.007
LTO	0.0925 (0.034)***	0.007	-0.0092 (0.010)	0.383
LEC	0.4017 (0.14)***	0.005	0.7542 (0.13)***	0.000
LPD	-0.0156 (0.085)	0.856	1.2982 (0.13)***	0.000
Constant	-14.137 (5.44)***	0.009	-6.6062 (1.35)***	0.000

Standard errors are in parenthesis. Significance level; *** represent 1%, while * is 10%; Robust estimation of the results.

According to the above Table 3 in the random effect model, GDP, Demographic Profile (DP) were significant at the 10% while Trade openness, and Energy consumption were significant at 1% significant level. In fixed effect model, GDP is significant at 5% level, and DP, EC and PD are significant at 1% level. However as literature suggested, the first stage do not support the contribution to the environmental degradation to the demographic profile with endogeneity issue.

Stage II
The panel data model was developed in terms of Arellano-Bond dynamic panel-data estimation and system dynamic panel-data estimation models. The results of two models were presented in Table 4.

The Arellano-Bond GMM estimator is used to cope up with several econometric issues;
1. The CO2 emission variables in $CO2_{it}$ are assumed to be endogenous. Because causality may run in both directions – from economic growth to Co2 emission and vice versa – these regressors may be correlated with the error term.
2. Time-invariant country characteristics (fixed effects), such as demographics, may be correlated with the explanatory variables. The fixed effects are contained in the error term in equation (1), which consists of the unobserved country-specific effects, v_i, and the observation-specific errors, e_{it}: $u_{it} = u_i + e_{it}$
3. The presence of the lagged dependent variable $CO2_{it-1}$ gives rise to autocorrelation.

To solve problem 1 (and problem 2) it is usually used fixed-effects instrumental variables estimation (two-stage least squares or 2SLS). The exogenous instruments that used were the following: the aggregate long-term CO2 emission to the countries in our sample as a group as a percentage of the sum of their cumulative GDP, an index of trade openness and energy consumption. However, the first-stage statistics of the 2SLS regressions showed that the instruments were weak. With weak instruments the fixed-effects IV estimators are likely to be biased in the way of the OLS estimators. Therefore, the Arellano – Bond (1991) difference GMM estimator first proposed by Holtz-Eakin, Newey and Rosen (1988) is used. Instead of using only the exogenous instruments listed above lagged levels of the endogenous regressors in $CO2_{it}$ (GDP, EC, TO and PD) are also added. This makes the endogenous variables pre-determined and, therefore, not correlated with the error term in equation. To cope with problem 2 (fixed effects) the difference GMM uses first-differences to transform equation into;

$$\Delta CO_{2it} = \beta_1 \Delta CO_{2it-1} + \beta_2 \Delta GDP_{it} + \beta_3 \Delta X_{it} + \Delta u_{it}$$

By transforming the regressors by first differencing the fixed country-specific effect is removed, because it does not vary with time. From error equation;

$\Delta u_{it} = \Delta v_i + \Delta e_{it}$ or $\Delta u_{it} - \Delta u_{i,t-1} = e_i - e_{i,t-1}$

The first-differenced lagged dependent variable is also instrumented with its past levels.

Finally the Arellano-Bond estimator was designed for small T large N panels. In large T panels a shock to the countries fixed effect, which shows in the error term, will decline with time. Similarly, the correlation of the lagged dependent variable with the error term will be insignificant (Roodman, 2006). In these cases, it does not necessarily have to use the Arellano-Bond estimator.

Table 4: Result of Arellano-Bond dynamic panel-data estimation and System dynamic panel-data estimation models

D. Var: LCO2	**Arellano-Bond dynamic panel-data estimation**	**P>|z|**	**System dynamic panel-data estimation**	**P>|z|**
LCO2. L1	0.6364 (0.004)***	0.000	0.9262 (0.02)***	0.000
LGDP	-0.2501 (1.19)***	0.004	1.0621 (1.09)***	0.003
LGDP2	0.0620 (0.49)	0.890	-0.3312 (0.405)	0.414
LGDP3	-0.2640 (0.006)***	0.024	0.0354 (0.49)	0.472
LDP	-0.0149 (0.004)***	0.009	0.1270 (0.037)**	0.046
LTO	-0.0829 (0.011)***	0.000	-0.0010 (0.07)	0.909
LEC	0.4034 (0.11)***	0.000	0.0189 (0.004)	0.640
LPD	0.4804 (0.01)	0.685	-0.0167 (0.02)	0.413
Constant	-1.9899 (1.09)**	0.070	-1.0932 (0.979)	0.264

Standard errors are in parenthesis. Significance level; *** represent 1%, while * is 10%; Robust estimation of the results.

Accordingly, the results of the Arellano-Bond dynamic panel-data estimation shows that CO2 emission, GDP, DP, TO, and EC are significant predictors of the CO2 emission or environmental degradation at 1% significant level. However, the System dynamic panel-data estimation is not a satisfactory predictor of the demographic profile and environmental degradation or economic growth.

Stage III

Occasionally the lagged levels of the regressors are poor instruments for the first-differenced regressors. In this case, it is necessary to use the augmented version –System GMM, which uses the level equation. To obtain a system of two equations: one differenced and one level. By adding the second equation additional instruments can be obtained. Thus the variables in levels in the second equation are instrumented with their own first differences. This usually increases the efficiency.

Table 3: Result of GMM Dynamic Panel-data Estimation Model

D. Var: LCO2	Dynamic panel-data estimation (GMM)
LGDP	3.0331 (0.42)***
LGDP2	-0.8005 (0.15)***
LGDP3	0.0907 (0.02)***
LDP	-0.0579 (0.02)***
Constant	-4.5107 (0.38)***
Instrumental variables: LEC, LPD, and LTO Standard errors are in parenthesis. Significance level; *** represent 1%, ** represent 5% while * is 10%; Robust estimation of the results.	

As the output table above shows, using system GMM increased efficiency. There are, however, two important points to be made about using system GMM. First, because system GMM uses more instruments than the difference GMM it may not be appropriate to use system GMM with a dataset with a small number of countries.

Second, in a panel with fixed effects including the equation in levels requires a new assumption – the first-differenced instruments used for the variables in levels should not be correlated with the unobserved country effects. Roodman (2006) discusses how this assumption depends on assumptions about the initial conditions. Some authors prefer to include in the level's equation only those variables, which are uncorrelated with the fixed effects. The results of the GMM dynamic panel data estimation provide a strong correlation of the CO2 emission and Demographic profile and economic growth. It revealed that 1% increase in GDP increases 3.033% of the CO2 emission. Moreover, increase of 1% demographic profile of the South Asia decreases CO2 emission by 0.058%.

6. Conclusion

As economic behavior of the agents changes over the cycle of life, economic growth can be influenced by demographic change. In this paper, the importance of demographic change to the economic growth in South Asia was developed using Kuznets Curve hypothesis. Most of the empirical literature in the region investigates on economic diversions, but less on the empirical analysis like GMM estimation of the panel data. Following the recent developments in the theoretical and empirical literature on economic growth, where demographic change is explicitly modeled, the Kuznets equations were estimated for evaluating how demographic change would be related to the economic growth and environmental degradation in countries.

The paper emphasis a recently developed econometric application with careful evaluation of the panel data models to fit the best solution for the endogeneity issues. Also, as suggested by Arrellano and Bond (1991), it seems relevant to work with estimation techniques robust to endogeneity problems using GMM methods. Therefore, the advance of this research comprehends dealing with these issues in the context of the estimation of GMM panel data models. A panel with fixed effects including the equation in levels requires a new assumption – the first-differenced instruments used for the variables in levels should not be correlated with the unobserved country effects. Some authors prefer to include in the levels equation only those variables, which are uncorrelated with the fixed effects. The results of the GMM dynamic panel data estimation provide a strong association with the CO2 emission and Demographic profile and economic growth. It revealed that 1% increase in GDP increases 3.033% of the CO2 emission. Moreover, increase of 1% demographic profile of the South Asia decreases CO2 emission by 0.058%.

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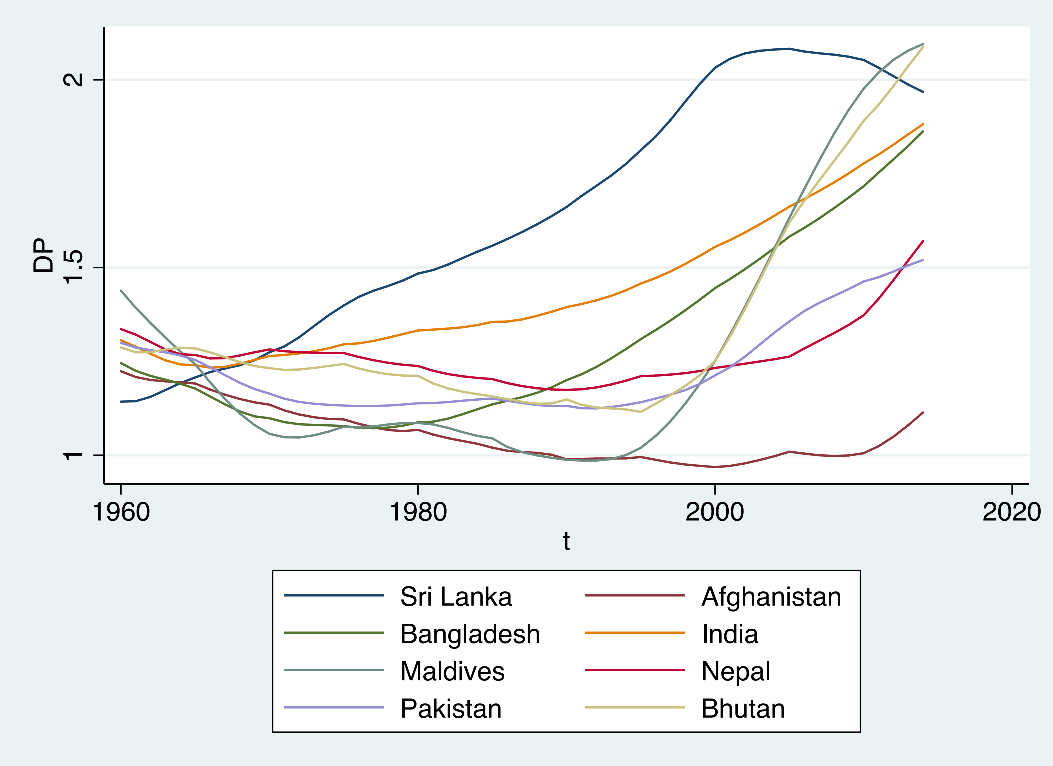
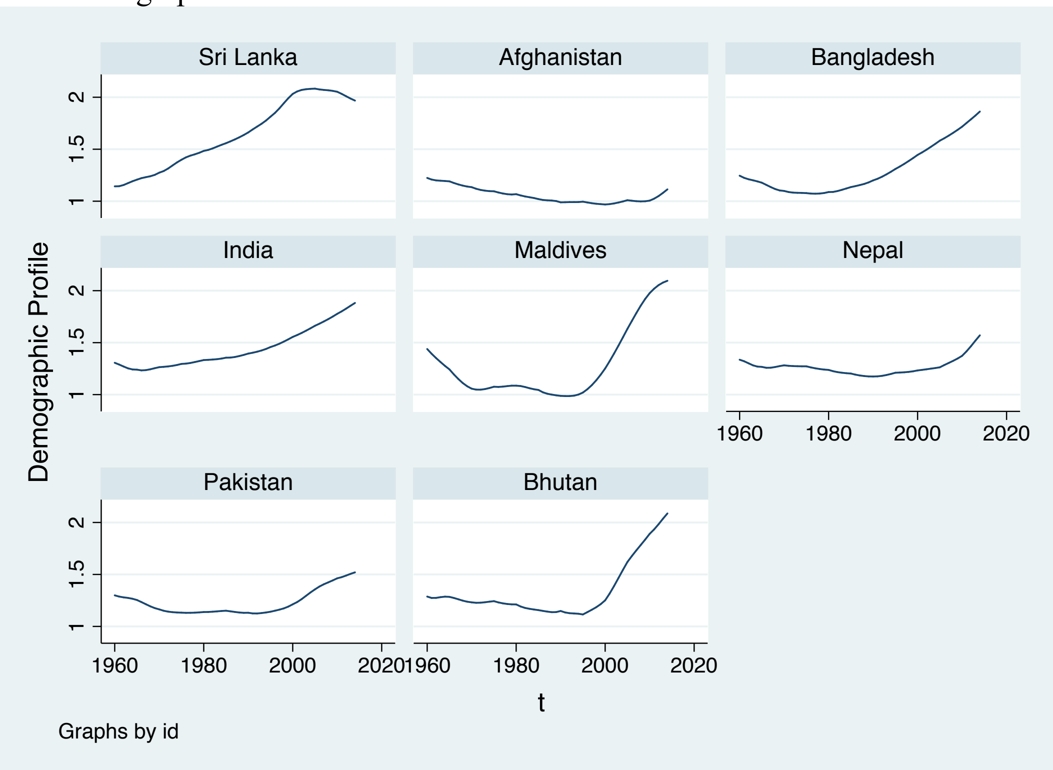
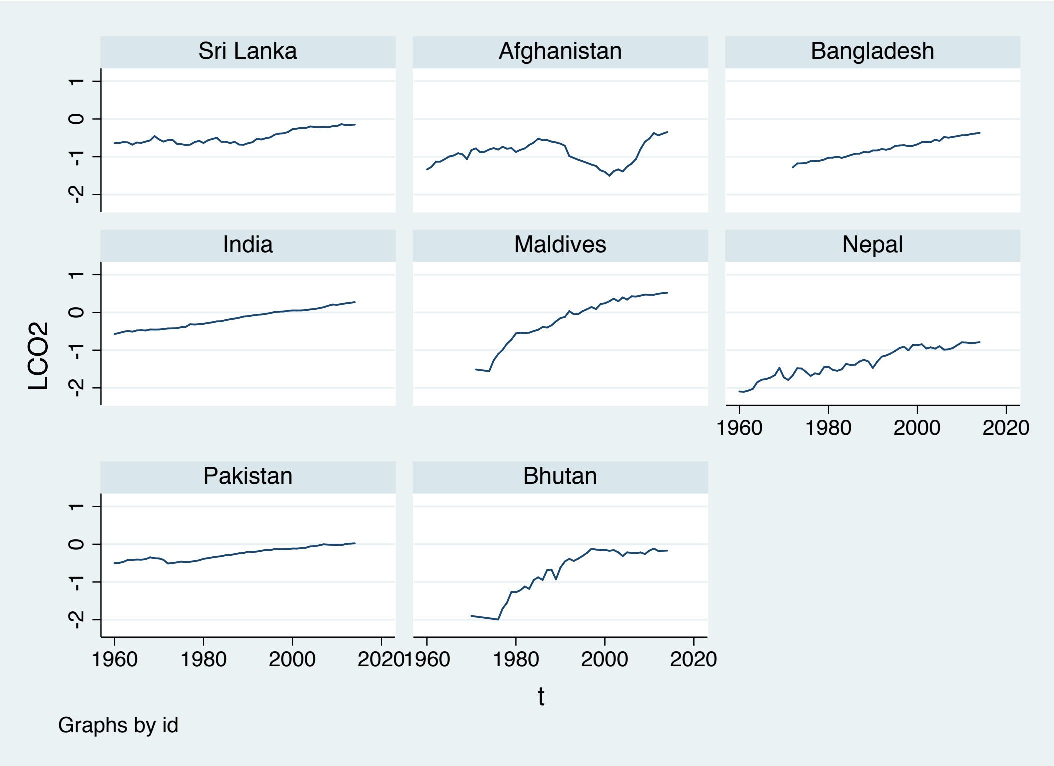
The following Annex provides the different relationships of the estimation.

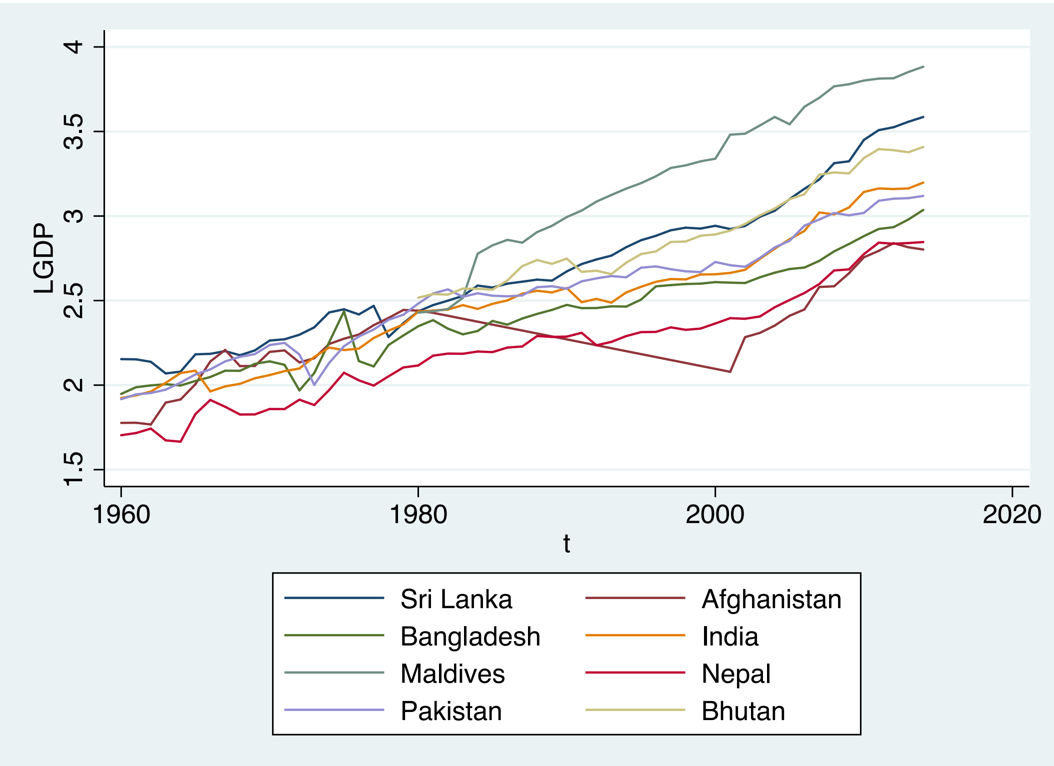


DP: Demographic Profile





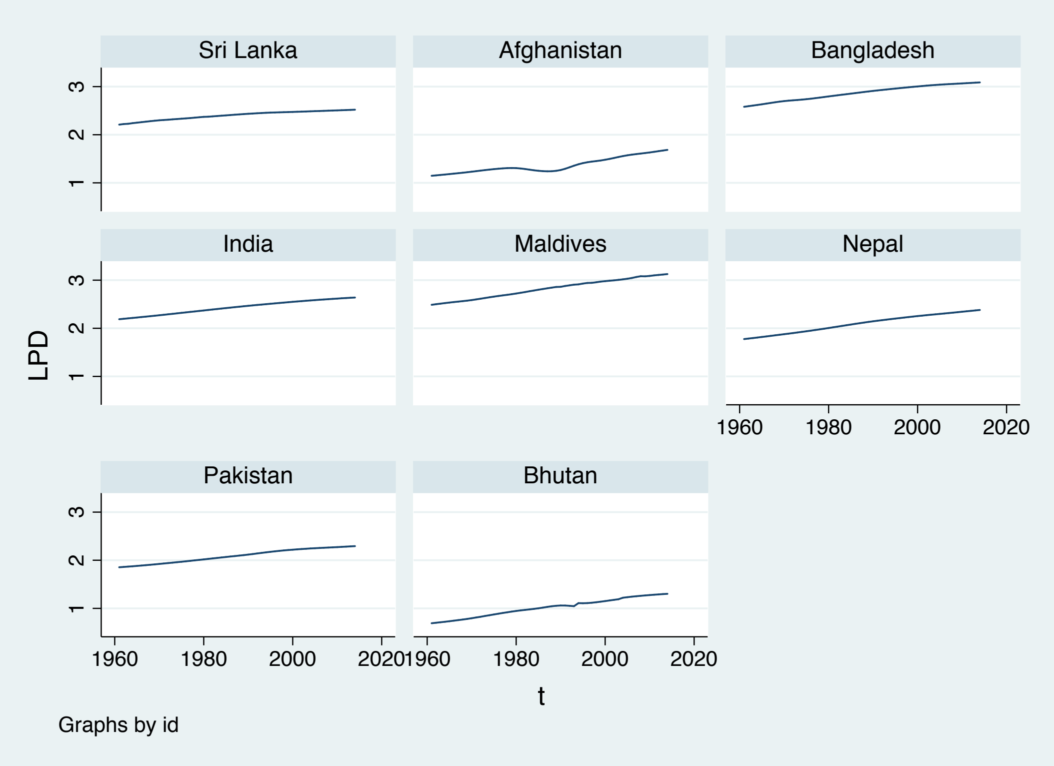
CO2 emission



GDP growth rates of South Asian Countries

Variable	Type	Level	Levin-Lin-Chu test	Im-Pesaran-Shin	ADF Fisher-type	PP-Fisher type
lnCO2	Intercept	Level	10.8061	11.8010	0.2448	0.1610
		D.lnCO2	-4.5889***	-5.9574***	68.4591***	137.5050***
	Intercept +	Level	5.2467	7.8123	1.4972	2.6271
	Trend	D.lnCO2	-6.0404***	-7.3473***	84.0004***	153.3990***
lnGDP	Intercept	Level	0.5388	0.4428	13.5771	20.8658
		D.lnGDP	-6.6252***	-8.2076***	123.0890***	240.5320***
	Intercept +	Level	0.8235	-0.6367	20.2145	26.0367
	Trend	D.lnGDP	-4.6299***	-4.4802***	-4.9458***	213.1790***
$lnGDP^2$	Intercept	Level	8.7481	6.6455	3.5434	4.7856
		D.lnGDP2	-9.2080***	-11.5091***	150.4810***	196.4630***
	Intercept +	Level	4.6491	4.5988	6.7498	8.0509
	Trend	D.lnGDP2	-10.3447***	-12.5836***	151.7190***	207.5420***
$lnGDP^3$	Intercept	Level	0.6338	0.4028	11.5361	10.8568
		D.lnGDP3	-7. 5262***	-9.2736***	125.0090***	244.3202***
	Intercept +	Level	0.8235	-0.6367	20.2145	26.0367
	Trend	D.lnGDP3	-4.6942***	-4.4280***	-5.9558***	313.7490***
lnPD	Intercept	Level	2.1478	1.8085	10.6101	19.3994
		D.lnPD	-5.4300***	-13.7764***	189.8120***	318.0250***
	Intercept +	Level	0.3524	-1.0343	23.6536	51.0574
	Trend	D.lnPD	-3.1064***	-12.7138***	162.3130***	306.4000***
lnTO	Intercept	Level	-2.3939***	-1.6357	39.9463**	16.4165
		D.lnTO	-7.0964***	-9.8762***	124.4240***	220.5950***
	Intercept +	Level	-2.3672	-1.3443	27.1111	19.1449
	Trend	D.lnTO	-6.4409***	-9.2145***	105.6290***	514.7700***
lnEC	Intercept	Level	3.1728	1.5765	10.6134	17.3684
		D.lnEC	-7.4390***	-14.8464***	198.8920***	378.3255***
	Intercept +	Level	0.2434	-3.5237	24.6365	53.3692
	Trend	D.lnEC	-4.1364***	-14.3713***	158.3235***	296.4025***
lnDP	Intercept	Level	-2.2932***	-1.6375	38.4463**	15.4135
		D.lnDP	-7.1966***	-9.3762***	132.4404***	222.5795***
	Intercept +	Level	-2.6722	-1.3337	26.1261	13.1493
	Trend	D.lnDP	-7.4140***	-8.1435***	106.6249***	522.7724***

*** indicates the rejection of the null hypothesis of non-stationary (Levin, Lin and Chu(2002), Im, Pesaran and Shin(2003), Fisher-Type test using ADF and PP-test (Maddala and Wu(1999) and Choi(2001)) or stationary (Hadri(1999)) at least at the 1 percent level of significance.



PD: Population Density