The Dynamics of Growth, Poverty, and Inequality: A Panel Analysis of Regional Data from Thailand and the Philippines*

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Abstract

This paper empirically investigates the relationship among growth, poverty, and inequality in Thailand and the Philippines, using panel data of provinces compiled from household expenditure microdata. The empirical model attempts to avoid the potential bias due to the fact that the entire distribution of individual-level consumption changes over time and empirical variables for growth, poverty, and inequality are often compiled from the consumption distribution. The system GMM estimation results robustly suggest that inequality reduced the subsequent growth rate of per-capita consumption and differences in inequality explain a substantial portion of the Philippine-Thai difference in growth and poverty reduction since the late 1980s.

Keywords: poverty, inequality, pro-poor growth, convergence, Thailand, the Philippines.

JEL classification codes: I32, O15.

1 Introduction

This paper compares the economic performance of Thailand and the Philippines, two Southeast Asian economies that were very similar in population size, type of economy (the market economy), and income per capita in the late 1970s and the early 1980s. This similarity, together with the fact that Thailand is regarded as one of the high performing Asian economies in the context of the "Asian miracle," while the Philippines is not (World Bank, 1993), makes the comparison interesting from development perspective. According to the World Bank's *World Development Indicators*, by 2000, Thailand's per-capita GDP was between two and three times as high as the Philippines'; and whereas the poverty headcount index in 2000 using one US$ (PPP) per day as the poverty line was below 2% in Thailand, it was 14.6% in the Philippines. What are the structural differences between them that are responsible for the disparity in economic performance? This paper empirically investigates this question focusing on the dynamic relationship among growth, poverty, and inequality. Unique panel data on province-level per-capita consumption, poverty, and inequality are compiled from microdatasets of household expenditure surveys, covering similar periods: 1988-2004 for Thailand and 1985-2003 for the Philippines.

The relationship among growth, inequality, and poverty has been one of the central issues in development economics (Galor and Zeira, 1993; Alesina and Rodrik, 1994; Bourguignon, 2004; Shorrocks and van der Hoeven, 2004). At one point, a central issue of the debate was the purported trade-off between growth and inequality, as exemplified by Kuznets' inverted U-hypothesis that suggested that inequality rises during the initial stages of development and then declines. More recent studies, however, have shown that in a number of countries, such a pattern cannot be observed over time (Deininger and Squire, 1998). Thus, the emphasis of the debate has shifted to explaining the diversity of countries' experiences, focusing on the effect of initial inequality on subsequent growth. Whereas the conventional view, referring to the role of incentives or saving-rate-differentials, holds that inequality is necessary for growth, development economists found that initial inequality harms subsequent growth (Galor and Zeira, 1993; Alesina and Rodrik, 1994). Although there are several studies that have come to the opposite conclusion (e.g., Li and Zou, 1998; Forbes, 2000), the existing evidence using cross-country growth regressions, on balance, seems to lend more support to the view that inequality is harmful to growth.[1] To summarize the current status of research, it could be said that the consensus is that “initial conditions matter, specific country structures matter, and time horizons matter” (Shorrocks and van der Hoeven, 2004, p.11), and that “there are a number of concerns about the data and methods” (Ravallion, 2004, p.71). A comparative study of two economies attempting this line of research and using semi-macro panel data is rare in the literature, and the authors are not aware of such a study for the case of Thailand and the Philippines.

Against this background, this paper attempts to shed new light on the discussion from the viewpoint of the utilization of information contained in a typical dataset used for such analyses. When a household expenditure survey dataset is available, we can aggregate the data to compile empirical variables for mean consumption, poverty, and inequality. Since the three variables in any given period are dependent by construction, regressing one on the others brings in a potential bias. We thus regress one on the lagged variables to avoid the bias. This specification reflects the fact that the entire distribution of real per-capita consumption changes over time. In addition, since we use regional panel datasets, it is less likely that we will encounter serious comparability problems due to heterogeneity in survey designs and processing (Ravallion, 2004).

Our investigation is motivated by the debate on how to define pro-poor growth or inclusive growth. One possible indicator of pro-poor growth is the growth elasticity of poverty, i.e., the percentage decline in the poverty headcount index when the economy grows by one percent. As shown by Kakwani (1993), the elasticity to a counterfactual growth pattern that holds the entire Lorenz curve unchanged depends on the shape of the Lorenz curve and the location where the poverty line falls on the curve. Kakwani et al. (2004) and Heltberg (2004) examine these elasticities empirically using recent microdatasets. Another methodology is the use of Lorenze-curve-preserving growth as a benchmark to evaluate the impact of growth on poverty, such as the decomposition by Datt and Ravallion (1992) or the simulation by Kakwani and Son (2006). These exercises are valid ways to describe dynamic changes that occurred to the entire distribution of individual-level consumption. However, it is difficult to infer the structural relationship between growth/inequality and poverty reduction from these exercises since the changes in poverty, average income, and inequality in the same period are linked by construction. This paper attempts to de-link them for the case of Thailand and the Philippines.

The paper is organized as follows. Section 2 describes the datasets, showing the growth, poverty, and inequality dynamics observed in the two countries. Section 3 presents the empirical model, which is estimated by a system GMM method to control for potential biases due to the dynamic structure. Section 4 presents our empirical results. It first provides the system GMM estimation results and compares them with results obtained using other estimation methods commonly found in the literature. The section then presents simulation results to quantify the determinants of consumption growth and poverty reduction in the two countries. Section 5 concludes the paper.

2 Data

2.1 Data Sources and Definitions of Empirical Variables

We compile panel data of provinces in Thailand (1988-2004) and the Philippines (1985-2003) from microdatasets of household expenditure surveys, choosing province as the unit of analysis. The data source for Thailand is the *Household Socio-Economic Survey* (HSES). The HSES is conducted by the National Statistical Office of the Government of Thailand. Since 1998, the HSES has been conducted every year. A nationally representative sample is drawn each time and surveyed using a detailed questionnaire on household demographics, income, and consumption, covering approximately 11,000 to 35,000 households. In this paper, nine rounds of the HSES spanning a period of 17 years (1988, 1990, 1992, 1994, 1996, 1998, 2000, 2002, 2004) were employed. Since the number of provinces increased after the 1992 survey from 73 to 76, the panel dataset is unbalanced.

The data source for the Philippines is the *Family Income and Expenditure Survey* (FIES). The FIES is conducted by the National Statistics Office, Republic of the Philippines. Every three years, a nationally representative sample is drawn and surveyed using a detailed questionnaire on items similar to those in Thailand. The sample size is approximately 17,000 to 38,000 households. In this paper, seven rounds of the FIES spanning 19 years (1985, 1988, 1991, 1994, 1997, 2000, 2003) were employed. Since the number of provinces increased after the 1994 survey from 77 to 82, the panel dataset is unbalanced.

From these datasets for the two countries, the three groups of empirical variables of concern were estimated for province j in year t, that is, $\ln y_{jt}$ (the log of mean consumption per capita, denoted *Consumption* in the following figures/tables), $Ineq_{jt}$ (inequality measures), and Pov_{jt} (poverty measures).[2] Real per-capita consumption was calculated by dividing total household consumption expenditure by the number of household members and the government price index. To calculate poverty measures, we employed the official poverty lines. In both countries, the government designates the official poverty line based on the cost of basic needs including food and non-food expenditures. In the empirical analyses, we examine the sensitivity of our results with respect to the poverty line. Sample observations with logical inconsistencies and sample observations with per-capita consumption in the top 1% or the bottom 1% were deleted in calculating these province-level variables. Following the literature, four variables were calculated as potential shifters of consumption distribution, which will be used as additional explanatory variables for the growth-inequality-poverty dynamics: *Education*, *Urban*, *Agriculture*, and *Aged*. The definitions and summary statistics of these and other empirical variables are reported in Table 1.

2.2 Trends in Mean Consumption, Poverty, and Inequality

Figure 1(a) plots the time series of $\ln y_{jt}$ (denoted *Consumption*) for Thailand. Since there are 73 or 76 provinces in each year, the unweighted mean of $\ln y_{jt}$ across j in year t and the national mean are plotted, together with dots showing the maximum and the minimum of $\ln y_{jt}$ across j in year t. The slope of the time series plot of *Consumption* in the figure shows that Thailand's economy registered steady growth except between 1996 and 1998 in the wake of the Asian financial crisis. Throughout the period, the growth rate of mean consumption across provinces was higher than that of national mean consumption, suggesting that less populous provinces experienced higher growth than more populous ones. The range between the maximum and the minimum remained more or less the same during the seventeen years.

Figure 1(b) plots similar information for $Ineq_{1jt}$ (denoted *Gini*). Between 1988 and 2002, inequality in Thailand declined slightly both at the national level and at the province level. However, not all provinces experienced a reduction in inequality during this period. The mean across provinces remained at a similar level and the minimum of $Ineq_{1jt}$ across j in period t increased rather than decreased. Because the maximum of $Ineq_{1jt}$ across j decreased, the figure seems to suggest an, albeit weak, inequality convergence. The trend changed in 2004, when the inequality measure increased in many provinces in Thailand.

Finally, the time series of Pov_{1jt} (denoted *Poverty*) is plotted in Figure 1(c). The figure shows a substantial fall in poverty headcount ratios both at the national and the provincial level. It seems that the rapid growth of *Consumption* was a major contributor to the rapid poverty reduction in Thailand, enhanced by a slight decline in inequality at the national level until 2002. The rate of poverty decline at the national level was similar to that of the mean across provinces, suggesting that poverty reduction was experienced throughout the country.

Figures 2(a) to 2(c) plot similar time series of *Consumption*, *Gini*, and *Poverty* for the Philippines. Figure 2(a) shows that the economy of the Philippines enjoyed steady growth until 1997. As in Thailand, the economy contracted during the Asian financial crisis, but the negative impact on *Consumption* was smaller than in Thailand. In addition, judging from the slope of *Consumption*, the growth rate of mean consumption at the national level was similar to that of the province-level means, suggesting that growth occurred in both rich and poor provinces. The range between the maximum and the minimum remained similar during the nineteen years.

The inequality level remained flat or increased slightly in the Philippines both at the national and provincial levels (Figure 2(b)). This could be one of the reasons why the rate of poverty reduction in the Philippines was not as impressive as in Thailand. The rate of poverty decline at the national level was similar to that at the provincial level (Figure 2(c)).

The shapes of Figures 1(b), 1(c), 2(b), and 2(c) did not change much when we chose different measures of inequality and poverty or when we use different poverty lines in calculating poverty measures, including 2 US$ (PPP) a day instead of the national poverty lines. The insensitivity to the exact choice of inequality (poverty) measure is as expected since the inequality measures included in $Ineq_{jt}$ are highly correlated with each other and the poverty measures included in Pov_{jt} are highly correlated with each other (Table 2). In Thailand, the five inequality measures have correlation coefficients ranging from 0.801 to 0.984 and the five poverty measures have correlation coefficients ranging from 0.924 to 0.999. Similarly, in the Philippines, the correlation coefficients of the five inequality measures range from 0.712 to 0.991 and the correlation coefficients of the five poverty measures range from 0.876 to 0.994. For this reason, we employ the empirical specification in the next section using one each from inequality and poverty measures.

In contrast, the correlation coefficients between $\ln y_{jt}$ and poverty measures are highly negative, while those between poverty measures and inequality measures are moderately positive. This confirms that, in these two countries, higher average consumption and lower inequality are associated with lower poverty. This is as expected since they are calculated from the same microdata of household expenditures. The positive correlation between the inequality and the poverty measures is not very high, however, especially in the Philippines. The correlation coefficients are in the range from 0.147 to 0.243 in Thailand and in the range from -0.012 to 0.274 in the Philippines.

2.3 Potential Concerns in Using Provincial Aggregate Data

The choice of province makes us worry about the potential impact of between-province migration on within-province inequality since a province in a country is not an independent economy. Fortunately, our preliminary analyses based on labor force surveys (available on request) reveal that most migration in these two countries occurs within provinces and the income changes experienced by between-province migrants were small. Therefore, the potential bias due to between-province migration is likely to be small. Combining the analysis in this paper with migration dynamics is left for further study.

Another concern in using provincial aggregates could be measurement error due to the fact that both HSES and FIES are designed to generate reliable estimates at the regional, and not at the provincial levels. This implies that the exact values of average per-capita consumption, poverty measures, or inequality measures at the provincial level should be taken with caution. To deal with this problem, we adopt three strategies. First, we use the sample for all econometric exercises excluding provincial observations associated with fewer than or equal to 50 sample households in the original microdata. When we marginally changed the threshold value from 50, all estimation results remained robust. Second, as described in the next section, in all estimation models, province fixed effects and year fixed effects are included. These fixed effects control for measurement error due to the non-representativeness of the original micro data at the provincial level. Nevertheless, if the remaining components of the measurement error (i.e., its time-varying province-level components) are highly correlated with time-varying province-level explanatory variables, our empirical results will be biased due to the endogeneity problem. To assess whether this is the case, our third strategy is to run a series of robustness checks using empirical models based on different spatial configurations, including the one based on the initial province boundaries with a coarser spatial configuration.

A related concern is that some of the geographic units are not strictly comparable between the earlier years and the later years due to changes in district boundaries. The last two strategies in the previous paragraph, i.e., the use of fixed effects in regression and the robustness check with respect to spatial configurations, are meant to control for the potential measurement error due to border changes as well. In examining the robustness, we also attempt regressions using the subsample corresponding to districts that did not experience border changes during the study period.

3 Empirical Model

3.1 The Dynamics of the Distribution of Consumption

Our aim is to investigate the structural relationship among growth, inequality, and poverty, whose trends were described in the previous section. We begin with a theoretical discussion, assuming an economy consisting of individuals whose welfare level is represented by y_{it} (real consumption expenditure per capita for individual i in year t). The cumulative distribution of y_{it} across individuals is expressed by the function $F_t(y_{it})$. From this distribution, we can compile aggregate variables that are of interest, such as mean consumption, inequality measures, and poverty measures. In other words, all are partial parameters that characterize and aggregate the shape of the entire distribution. Thus, picking out one of them and then regressing it on the others, such as regressing the poverty headcount index on the average consumption and the Gini index, does not contribute much to the understanding of the dynamic mechanisms underlying growth, poverty, and inequality. Rather, such an approach simply is a description of $F_t(y_{it})$.

$F_t(y_{it})$ is assumed to evolve through the following dynamics. In period t, we observe $F_t(y_{it})$. Due to policy interventions or unexpected shocks, denoted by vector X_t, the distribution in the next period will be different from the current one. Thus, what we observe in the next period, $F_{t+1}(y_{i,t+1})$, is determined by $F_t(y_{it})$ and X_t. The mapping of $F_{t+1}(y_{i,t+1})$ into the space of $F_t(y_{it})$ and X_t is what we are interested in. However, characterizing this mapping is not possible since it is a mapping of one entire distribution into another, conditional on vector X_t. Instead, we attempt to estimate *functions* that associate *parameters* characterizing the current distribution with *parameters* characterizing the next period distribution, conditional on vector X_t. As parameters characterizing the distribution of y_{it}, we focus on $\ln y_t$ (log of the average consumption), $Ineq_t$ (vector of inequality measures), and Pov_t (vector of poverty measures).

We use $\ln y_t$ instead of y_t because the logarithmic form allows us to directly compare our empirical results with those of existing studies and also because the error terms become less heteroskedastic after the logarithmic transformation. By estimating these functions, we can infer the structural relationships between poverty, growth, and inequality. For instance, when we find a negative effect of $Ineq_{1,t-1}$ (Gini coefficient) and a positive but less-than-unity effect of $Pov_{1,t-1}$ (poverty headcount index) on Pov_{1t} from such a specification, we can interpret this as showing that an increase in inequality from period $t-2$ to $t-1$ increases the speed of poverty reduction from period $t-1$ to t and that a lower initial Gini coefficient increases the speed of reduction of the poverty headcount index in subsequent periods.[3] By taking one period lag, the correlation between the poverty headcount index and the average consumption (inequality) becomes much smaller.[4] This is the advantage of using such specification in avoiding the spurious correlation, such as shown in Table 2.

3.2 Specification of the Empirical Model

The model discussed above was for a representative economy, corresponding to a province in this paper. Denoting each province by subscript j, we estimate the following system of three equations:

$$\ln y_{jt} = \beta_{11} \ln y_{j,t-1} + \beta_{12} Ineq_{1,j,t-1} + \beta_{13} Pov_{1,j,t-1} + X_{j,t-1}\theta_1 + \alpha_{1j} + \eta_{1t} + \epsilon_{1jt}, \quad (1)$$

$$Ineq_{1jt} = \beta_{21} \ln y_{j,t-1} + \beta_{22} Ineq_{1,j,t-1} + \beta_{23} Pov_{1,j,t-1} + X_{j,t-1}\theta_2 + \alpha_{2j} + \eta_{2t} + \epsilon_{2jt}, \quad (2)$$

$$Pov_{1jt} = \beta_{31} \ln y_{j,t-1} + \beta_{32} Ineq_{1,j,t-1} + \beta_{33} Pov_{1,j,t-1} + X_{j,t-1}\theta_3 + \alpha_{3j} + \eta_{3t} + \epsilon_{3jt}, \quad (3)$$

where α stands for the unobservable and time-invarying characteristics of economy j, η represents unobservable macro shocks that affect all economies in period t, and ϵ is an idiosyncratic error term. The inclusion of α and η is also meant to minimize the bias due to measurement error associated with the non-representativeness of the original micro data at the provincial level or with border changes. In the theoretical discussion, X_t was defined as a vector of variables that affect the distribution of $F(.)$. In the empirical specification, the vector is decomposed into X_{jt} (observable factors), η_t (factors that are unobservable but that can be controlled for by utilizing the panel structure of the dataset), and ϵ_{jt} (factors that are unobservable and that cannot be controlled for).

As shown in the previous section, individual measures included in $Ineq_{jt}$ are highly collinear with each other and that individual measures included in Pov_{jt} are also highly collinear with each other. Therefore, we pick up one each in the model above. Our choice of particular measures of $Ineq_{1jt}$ and Pov_{1jt} is simply determined by convenience and we could choose other measures as well. We run a series of robustness checks, changing particular choices of inequality and poverty measures.

To facilitate the comparison of our results with those in the literature, we also estimate a restricted version of the above system, where $\beta_{13} = \beta_{23} = \beta_{33} = 0$. This results in the following restricted system:

$$\begin{aligned} \ln y_{jt} &= \beta_{11} \ln y_{j,t-1} + \beta_{12} Ineq_{1,j,t-1} + X_{j,t-1}\theta_1 + \alpha_{1j} + \eta_{1t} + \epsilon_{1jt}, \quad (4) \\ Ineq_{1jt} &= \beta_{21} \ln y_{j,t-1} + \beta_{22} Ineq_{1,j,t-1} + X_{j,t-1}\theta_2 + \alpha_{2j} + \eta_{2t} + \epsilon_{2jt}, \quad (5) \\ Pov_{1jt} &= \beta_{31} \ln y_{j,t-1} + \beta_{32} Ineq_{1,j,t-1} + X_{j,t-1}\theta_3 + \alpha_{3j} + \eta_{3t} + \epsilon_{3jt}, \quad (6) \end{aligned}$$

In both specifications (1)-(3) and (4)-(6), we can investigate whether the growth rate is higher for provinces with lower initial consumption by investigating whether parameter β_{11} is between zero and one. In this sense, this parameter is analogous to the income convergence parameter discussed in the literature.[5] The difference in steady states of $\ln y_{jt}$ is partially controlled for by fixed effects, α_{1j}. $X_{j,t-1}$ not only controls for the difference in exogenous shocks that affect the entire distribution of per-capita consumption, but also controls for any potential difference in the convergence speed attributable to observables. Similarly, if parameter β_{22} is between zero and one, this implies that inequality tends to decline in regions/countries with higher initial inequality, analogous to the inequality convergence found by Bénabou (1996) and Ravallion (2003). Since our system includes three endogenous variables, β_{11} is not exactly the same as the income convergence parameter and β_{22} is not exactly the same as the inequality convergence parameter. In the system of equations (1)-(3), there is a convergence if all of the three characteristic roots for the 3-by-3 matrix comprising β have absolute values less than one. Similarly, in the system of equations (4)-(6), there is a convergence if both of the two characteristic roots for the matrix $(\beta_{11}, \beta_{12}; \beta_{21}, \beta_{22})$ have absolute values less than one.

In our specification, parameter β_{12} captures the effect of lagged inequality on growth. If it is negative, this indicates that economies or regions with higher initial inequality grow more slowly. However, our specification does not nest the one used by Banerjee and Duflo (2003), who showed that the growth rate is a non-linear (inverse U-shaped) function of a lagged change in inequality. To expand the specification to nest their specification is left for future research. On the other hand, it may be of interest to compare the determinants of poverty à la equation (6) with those derived under the specifications adopted by Besley and Burgess (2002), who regress Pov_{1jt} on $\ln y_{jt}$ and $Ineq_{1jt}$ without lags. We thus estimate the following model as well:

$$Pov_{1jt} = \gamma_1 \ln y_{jt} + \gamma_2 Ineq_{1jt} + \alpha_{3j} + \eta_{3t} + \epsilon_{3jt}. \quad (7)$$

A final note should be added on the estimation method. The system to be estimated has a lagged dependent variable on the right-hand side. Therefore, we need to control for any possible bias arising from the structure of our model, known as the dynamic panel data (DPD) structure. In estimating a model with a DPD structure, most studies employ pooled OLS, fixed-effects estimation, or first-difference GMM methods. However, as demonstrated by Bond et al. (2001), the first-difference GMM estimators may not be appropriate for small sample estimations. To overcome this problem, Blundell and Bond (1998) propose an alternative method of system GMM estimation. In this paper, we thus employ the system GMM estimation method as our main approach and compare the results with those obtained using pooled OLS or fixed-effects methods.

4 Empirical Results

4.1 Estimation Results of the Regression Model

4.1.1 Thailand

The estimation results of equations (1)-(3) for Thailand are shown in Table 3. Each equation was estimated using the system GMM method proposed by Blundell and Bond (1998) and applied to growth regressions by Bond et al. (2001).[6] In all specifications, the Hansen J test, which is reported at the bottom of the column, indicates that the overidentifying restrictions implied by this GMM procedure are not rejected. The AR(2) test for autocorrelation of order 2 indicates that the null hypothesis of no autocorrelation is not rejected.

The table shows the estimation results of two versions, both with province-specific effects α_j but different in the list of additional variables: one with year effects (η_t) only, and the other with η_t and $X_{j,t-1}$ (*Education*, *Urban*, *Agriculture*, and *Aged*). The signs and statistical significance of the β parameters in the two versions are qualitatively the same. Using the model with more control variables, β_{11} is estimated to be 0.75, which is significantly different from zero at the 1% level and from one at the 5% level. The regression results thus indicate that the growth rate is slightly higher for provinces with lower initial consumption.

The parameter corresponding to inequality convergence, β_{22}, is estimated to be 0.30 (in the model with fewer control variables) or 0.29 (in the model with more control variables). Both are significantly smaller than one at the 1% level, indicating inequality convergence, consistent with findings based on cross-country data (Bénabou, 1996; Ravallion, 2003) and casual observation of Figure 1(b).

The effect of inequality on subsequent growth is one of the most debated issues in development economics. In our model, this effect is captured by parameter β_{12}. For Thailand, the parameter estimate is -1.62 (in the model with more control variables), which is significantly different from zero at the 1% level. When the lagged value of *Gini* increases by its standard deviation (0.0489), growth decreases by 0.079, which is about 1.1% of the mean of *Consumption*. This is an economically significant number since the growth rates of *Consumption* between each survey period are in the range of 3.4 to 18.4% except between the 1996 and 1998 surveys. The estimated coefficient on the lagged consumption variable, β_{21}, is -0.06 or -0.07 (significant at 1%). Thus, provinces in which the initial consumption level was high tended to become more equal in the subsequent period than provinces with a low initial consumption level.

The initial levels of *Consumption*, *Gini*, and *Poverty* all affect the subsequent level of *Poverty* with the expected signs and with statistical significance. As expected, the effect of lagged consumption (β_{31}) is negative and the effect of lagged inequality (β_{32}) is positive. Judging from the absolute values of these coefficients in Table 3 and the standard deviations of *Consumption* and *Gini* in Table 1, a change of one standard deviation has a slightly stronger effect on poverty reduction in the case of *Consumption* than in the case of *Gini*. One coefficient which has not been analyzed in the previous literature is β_{33}. The coefficient estimate for this is 0.193 when all control variables are included and 0.197 when only year effects are included (Table 3). Both are significantly different from one. Therefore, provinces with a higher level of poverty in the preceding period ($Poverty_{t-1}$) tended to experience faster poverty reduction.[7]

For comparison, Table 4 reports the results obtained from pooled OLS or fixed-effect methods. Since the coefficients on $X_{j,t-1}$ are similar, the table reports only those coefficients on lagged values of *Consumption*, *Gini*, and *Poverty*. We find that, first, the sign and the significance test results for the pooled OLS are similar to the system GMM results. Second, the results based on the fixed effect specifications differ considerably from the system GMM results. Most of the coefficient estimates based on the fixed effect approach are statistically insignificant. The difference is mainly due to the difference in the size of the coefficients. In general, the system GMM results show larger coefficients (in absolute values) than the fixed effect results. The difference is particularly significant for coefficients β_{11} and β_{22}. The fixed effect estimates for these parameters are positive but statistically less significant, making β_{22} statistically insignificant. Since the pooled OLS and the fixed effects estimates may be biased due to the DPD structure, we adopt the system GMM estimates for the simulation exercises in the next subsection.

The system GMM estimation results were found robust, as shown in Table 5.[8] First, the results were insensitive to the definition of poverty lines[9] (check 1, Table 5) or to the spatial configurations (check 2, Table 5). When we further merged provinces so that the borders were closer to the regional level for which the surveys were meant to be representative, the qualitative results remained the same. From these observations, we conclude that the measurement error due to the non-representativeness of micro data at the province level has been sufficiently controlled by our regression specifications. Since our choice of particular measures of $Ineq_{1jt}$ (the Gini coefficient) and Pov_{1jt} (the headcount poverty measure) was arbitrary, we also tried other measures of inequality and poverty (see Table 2 for the list) as a robustness check. Out of twenty-five possible combinations, we tried eight in addition to the basic specification: we first replaced *Gini* in the basic specification by one of the other four measures of inequality, and then replaced *Poverty* by one of the other four measures of poverty. The results are very similar to those reported in Table 3. Among the parameters of concern, we found that β_{13} (the effect of poverty on subsequent growth) becomes larger and statistically significant when *Gini* is replaced by general entropy (GE) measures and *Poverty* is replaced by the squared poverty gap index (FGT(2)); β_{21} (the effect of average consumption on subsequent change in inequality) and β_{23} (the effect of poverty on subsequent change in inequality) become statistically less significant when *Poverty* is replaced by other poverty measures; and β_{33} becomes less significant when GE or FGT(2) measures are used.

To facilitate comparison with existing studies, estimation results based on a restricted model consisting of equations (4)-(6) are reported in Table 6, together with the results for equation (7). The system (4)-(6) may be preferable when Pov_{1jt} is highly collinear with the linear combination of $\ln y_{jt}$ (or $\ln y_{j,t-1}$) and $Ineq_{1jt}$ (or $Ineq_{1j,t-1}$). A comparison of Tables 3 and 6 shows that β_{11} is underestimated in the constrained model.

The effect on *Poverty* of *Consumption* is negative and that of *Gini* is positive, as expected, both in specifications (6) and (7). The coefficient on *Consumption* is significant at the 1% level in three cases out of four. The coefficient on *Gini* is significant under specification (7) only. The coefficients in equation (7) are more susceptible to spurious correlation than those in equation (6) because consumption, inequality, and poverty are all calculated from microdata for the same year. Therefore, as far as the dynamic effects of growth and inequality on poverty are concerned, the coefficients in equation (3) (Table 3) or those in equation (6) (Table 6) are better indicators than those in equation (7) (Table 6).

4.1.2 The Philippines

The estimation results of equations (1)-(3) for the Philippines are reported in Table 7. In all specifications, the Hansen J test and the AR(2) test indicate that the null hypotheses are not rejected. The signs of the β parameters are exactly the same in the two versions and the lists of statistically significant coefficients are similar. The estimate for β_{11} is 1.13 when more control variables are included. The coefficient is significantly different from zero but not significantly different from one. It becomes 1.06 when only year effects are included, which is not significantly different from unity, either. Therefore, the GMM estimation results do not indicate that there is a tendency for the growth rate to be higher for provinces with lower initial consumption. The estimate for β_{22}, the parameter corresponding to inequality convergence, is around 0.4 and significantly smaller than one. Thus, the results in Table 7 suggest that there is a strong tendency for inequality to decline in provinces with higher initial inequality. Since Figures 2(a) and 2(b) show neither converging nor diverging tendencies, the system GMM results in favor of income divergence and inequality convergence can be explained by the additional explanatory variables.[10]

The effect of inequality on subsequent growth, β_{12}, is negative and large in both specifications. The parameter estimate is -1.43 (in the model with more control variables), which is significantly different from zero at the 1% level. When the lagged value of *Gini* increases by its standard deviation (0.0488), growth decreases by 0.069, which is about 0.81% of the mean of *Consumption*. Thus, the adverse effect of inequality on subsequent growth is slightly smaller in the Philippines than in Thailand, mainly because of the difference in the size of β_{12}. However, since the Philippines have experienced slower economic growth, an adverse effect of the same magnitude is likely to have been more painful in the Philippines. To examine the net impact of these elements, the adverse effect of initial inequality on growth and poverty reduction will be investigated further in simulation analyses below.

The estimate for parameter β_{33}, which captures the effect of lagged poverty on current poverty, is 0.332 when the additional control variables are included and 0.346 when only year effects are included (Table 7). Since both are significantly smaller than one, this indicates that poorer provinces experienced faster poverty reduction. In terms of the annual effect, the estimate corresponding to parameter β_{33} for the Philippines is 0.777, while that for Thailand is 0.596, based on the specification with more control variables.[11] Therefore, poverty is more persistent in the Philippines than in Thailand (poorer regions experience faster poverty reduction and this tendency is stronger in Thailand than in the Philippines).

The robustness check of our results for the Philippines to the estimation method shows patterns similar to those for Thailand. Table 8 shows that, first, the sign and the significance of test results are similar in the pooled OLS and in the system GMM approach, and second, results based on the fixed effect specifications are associated with smaller coefficients than those based on the system GMM approach. However, the contrast between the system GMM and the fixed effect results is less pronounced for the Philippines than for Thailand. As far as the statistically significant coefficients are concerned, the three estimation methods in general yield qualitatively similar results. One qualitative difference is the size of parameter β_{11}. In the system GMM estimation, the estimates for β_{11} are larger than unity, while in the alternative estimations shown in Table 8, they are smaller than unity, with a statistically significant difference from unity in the case of the fixed effect results.

When other measures of inequality/poverty, different poverty lines, or different spatial configurations were tried, qualitatively the same results were obtained for the Philippines.[12] For example, when *Gini* was replaced by GE measures, or when *Poverty* was replaced by FGT(1) poverty measures, estimates for parameter β_{12} were smaller and had a higher statistical significance. As shown in Table 9 (check 2 and 3), the results were insensitive to the spatial configurations, which confirms that the measurement error due to the non-representativeness of micro data at the province level has been sufficiently controlled by our regression specifications.

To facilitate comparison with existing studies regarding the size of β_{11} and β_{22}, a restricted model consisting of equations (4) and (5) is estimated and the results are reported in Table 10 for the Philippines. They show that β_{11} is now smaller than unity even when using GMM estimation, although its difference from unity is not statistically significant. Therefore, the possibility of income divergence in the Philippines is not ruled out. On the other hand, the results regarding the size of β_{22} remain unchanged — the parameter is always positive with statistical significance and its magnitude is much smaller than unity, which is consistent with inequality convergence, in line with Bénabou's (1996) and Ravallion's (2003) findings.

As in Thailand, the magnitudes of the positive effect of *Consumption* and the negative effect of *Gini* on *Poverty* are sensitive to the specification in the the Philippines (compare last two columns of Table 10): the coefficients in equation (7) are about three times as large as those in equation (6). This again warns against the use of specification (7) when the dynamic effects of growth and inequality on poverty are of concern. However, the difference in the magnitudes is smaller in the Philippines than in Thailand. This is consistent with the contrast in the magnitudes of parameter β_{33} in Tables 3 and 7. It is larger for the Philippines than for Thailand, indicating that poverty is more persistent in the Philippines than in Thailand. Because of this persistence, the bias due to the use of specification (6) in place of specification (7) is smaller in the Philippines.

4.2 Simulating the Sources of Growth and Poverty Reduction

4.2.1 Simulation methods

Given the estimation results in the previous subsection, how much of the consumption growth shown in Figures 1(a) and 2(a) and the poverty reduction shown in Figures 1(c) and 2(c) can be attributed to (i) initial differences in mean consumption, poverty, and inequality; and (ii) differences in the marginal impact of the lagged values of mean consumption, poverty, and inequality (differences in β)?

We simulate these sources of growth and poverty reduction by calculating counterfactual dynamic paths of the two economies under several scenarios. Since our original micro data cover different periods, we choose 1988 and 2000 as the comparison years (i.e., the two years when we have microdata for both countries; see Figures 1 and 2). First, based on the parameter estimates in Tables 3 and 7, we calculate the fitted values of residuals as follows:

$$\ln y_{jt} = \hat{\beta}_{11} \ln y_{j,t-1} + \hat{\beta}_{12} Ineq_{1,j,t-1} + \hat{\beta}_{13} Pov_{1,j,t-1} + X_{j,t-1}\hat{\theta}_1 + \hat{\alpha}_{1j} + \hat{\eta}_{1t} + \hat{\epsilon}_{1jt}, \quad (8)$$

$$Ineq_{1jt} = \hat{\beta}_{21} \ln y_{j,t-1} + \hat{\beta}_{22} Ineq_{1,j,t-1} + \hat{\beta}_{23} Pov_{1,j,t-1} + X_{j,t-1}\hat{\theta}_2 + \hat{\alpha}_{2j} + \hat{\eta}_{2t} + \hat{\epsilon}_{2jt}, \quad (9)$$

$$Pov_{1jt} = \hat{\beta}_{31} \ln y_{j,t-1} + \hat{\beta}_{32} Ineq_{1,j,t-1} + \hat{\beta}_{33} Pov_{1,j,t-1} + X_{j,t-1}\hat{\theta}_3 + \hat{\alpha}_{3j} + \hat{\eta}_{3t} + \hat{\epsilon}_{3jt} \quad (10)$$

For the first type of simulations (the impact of the initial differences), we introduce an additional shock to one of the left-hand-side variables, say, inequality, in 1988. Then we sequentially solve the dynamic system until the year 2000, keeping the values of X, $\hat{\beta}$, $\hat{\theta}$, $\hat{\alpha}$, $\hat{\eta}$, and $\hat{\epsilon}$ constant. For the second type of simulations (the impact of the differences in β), we assign a counterfactual value to one of the parameters in β (say, replacing $\hat{\beta}_{12}$ for the Philippines with $\hat{\beta}_{12}$ for Thailand) in 1988 and onwards.[13] Then we sequentially solve the dynamic system until the year 2000, keeping the values of X, $\hat{\theta}$, $\hat{\alpha}$, $\hat{\eta}$, $\hat{\epsilon}$, and the other parameters of $\hat{\beta}$ constant.

4.2.2 The dynamic impact of inequality

Simulation results focusing on the impact of inequality on subsequent growth and poverty reduction are reported in Table 11. In the first row, the baseline values that replicate the observed dynamic paths are reported. In the Philippines, the annual growth rate of consumption was 1.14% during the 1988-2000 period, which was associated with a poverty reduction (in terms of the headcount index) at an annual rate of 0.72%. Both of these numbers are smaller than those for Thailand: consumption grew at a rate of 3.72% and the headcount poverty index declined at a rate of 2.06% per annum during the 1988-2000 period. The baseline numbers clearly show the contrast between the Philippines and Thailand.

In Simulation 1, we add a shock to equation (2) in 1988 so that the inequality level in that year is halved from the actual value both in the Philippines and Thailand. The reduction in $Ineq_{1j,t-1}$ in the right-hand side of equations (1)-(3) increases growth rates and decreases inequality and poverty in the next period. By the year 2000, the cumulative effect on the growth of consumption and on poverty reduction is substantial. In the Philippines, the annual growth rate of consumption would have been much higher at 2.45% during the 1988-2000 period, which would have been associated with a higher rate of poverty reduction of 1.00%. Qualitatively the same change would have occurred in Thailand: consumption would have grown at a rate of 5.57% and the headcount poverty index would have declined at a rate of 2.43% per annum during the 1988-2000 period.

The counterfactual growth rate in Thailand is higher than that in the Philippines, but the magnitude of the change from the baseline is higher in the case of the Philippines (where the counterfactual growth rate is more than twice as high as the actual growth rate) than in the case of Thailand (where it is 1.5 times as high). Halving initial inequality raises the rate of consumption growth and the size of the additional growth rate depends on the value of β_{11}. As mentioned in the previous subsection, the value of β_{11} was larger in the Philippines than in Thailand. Our interpretation is that the simulation results mainly reflect the difference of this coefficient. In addition, the value of β_{12} for Thailand is larger that for the Philippines. Therefore, the cumulative adverse effect of inequality on growth is larger in Thailand than in the Philippines because the initial inequality levels are almost the same in both countries (0.36 and 0.35 in Thailand and the Philippines in 1988, respectively). The same is true of the poverty reduction rate. The counterfactual poverty reduction rate in Thailand is higher than that in the Philippines, but the magnitude of the change from the baseline in the Philippines (1.38 times) is higher than that in Thailand (1.18 times). The value of β_{32} for Thailand is larger than that for the Philippines. This indicates that the cumulative adverse effect of inequality on poverty reduction in Thailand is larger than in the Philippines. The results of

Simulation 1 thus demonstrate that the high level of initial inequality was one of the main contributors to the slow growth and poverty reduction in both countries.

In Simulation 2(a), we replace the value of β_{12} for the Philippines with that for Thailand and the value of β_{12} for Thailand with that for the Philippines. As shown in Tables 3 and 7, the estimate for β_{12} for Thailand is larger than for the Philippines, implying that the marginal adverse effect of inequality on subsequent growth is larger in Thailand. The simulation results in Table 11 thus show the total, cumulative adverse effect of inequality on subsequent growth due to the difference in the marginal impact of the lagged values of inequality in the two countries. The cumulative effect is substantial by the year 2000. In the Philippines, the annual growth rate of consumption would have been negative (-9.73%) during the 1988-2000 period, which would have been associated with an *increase* of poverty at an annual rate of 0.10%. Thus, the Philippines were very fortunate that the actual value of β_{12} was lower than the value used in the counterfactual scenario corresponding to that for Thailand. In sharp contrast, growth and poverty reduction in Thailand would have been faster if the economy had had a lower value of β_{12}, as in the Philippines: consumption would have grown at 10.96% and the headcount poverty index would have declined by 3.16% per annum during the 1988-2000 period. With this rate of poverty reduction, the headcount poverty index would have been zero in 2000 for the majority of provinces in Thailand.

As a variant of Simulation 2(a), we replace the values of β_{12}, β_{22}, and β_{32} in Simulation 2(b). This simulation captures the whole impact of the difference in the marginal effects of the lagged inequality variable through the structure shown in equations (1)-(3). The simulation results for Thailand are qualitatively similar to those of Simulation 2(a). The adverse effect of inequality on subsequent growth or poverty reduction is smaller if we use the estimates for the Philippines instead of those for Thailand in simulating the Thai economy.

The results of Simulation 2 thus show that the negative impact of inequality on subsequent economic growth was one of the main factors contributing to the slow poverty reduction in Thailand ("slow" relative to its phenomenal growth rate). Thailand's experience is often regarded as a case of a low growth elasticity of poverty combined with substantial economic growth, resulting in a reasonably high pace of poverty reduction (Kakwani et al., 2004; Booth, 1997). Our analysis sheds new light on this phenomenon from the viewpoint of the dynamic relationships among growth, inequality, and poverty. On the other hand, the results of Simulation 2(b) for the Philippines are somewhat different from those of Simulation 2(a). With parameter β_{12} replaced by the parameter corresponding to Thailand, the adverse effect of inequality on subsequent growth or poverty reduction should be larger in the simulated Philippine economy. This is indeed the case for poverty reduction as shown in the negative rate of simulated paths of poverty reduction. However, because of indirect effects through β_{22} and β_{32}, the growth rates would have been higher under Simulation 2(b) than the baseline. The simulated Philippine economy is thus characterized by higher inequality than actually observed. The incorporation of the indirect impacts is one of the advantages of our approach of investigating the whole dynamics of growth, inequality, and poverty.

To have an idea on the impact of the structural difference between Thailand and the Philippines on more recent situations, we projected how things are expected to go by 2015 (the target year for the Millennium Development Goals) given the simulation scenarios.[14] It was found that the ill-effects of inequality is likely to constrain poverty reduction in the Philippines, while the ill-effects of inequality on poverty will likely disappear in Thailand regardless of the scenarios due to the growth effect on poverty reduction.

5 Conclusion

This paper empirically analyzed the dynamics of, and relationships among, growth, poverty, and inequality, using unique province-level panel data for the Philippines (1985-2003) and Thailand (1988-2004) compiled from microdatasets of household expenditure surveys. The system GMM estimation results showed that in Thailand, inequality reduced the speed of subsequent growth and poverty reduction directly, while in the Philippines it did so indirectly. The magnitudes of the marginal effects of inequality were found to be larger in Thailand than in the Philippines. We also suggested that the fixed effect estimation might underestimate the marginal effect of inequality on subsequent changes in inequality and the marginal effect of the initial consumption level on subsequent consumption growth. Our results show that in Thailand there is a strong tendency for growth to be higher for provinces with lower initial consumption whereas such a tendency is weak in the Philippines. On the other hand, our results show a clear tendency in both countries for inequality to decline in provinces with higher initial inequality, which is consistent with the inequality convergence discussed in the literature. Regarding the specification of the poverty determinants, our analysis suggested that the regression of current poverty on current inequality and average consumption may overestimate the true dynamic effects of growth and inequality on poverty reduction.

Simulation results based on the parameter estimates showed that the difference between the two countries in the initial inequality level and the difference in its marginal impact explained a substantial portion of the Philippine-Thai difference in economic growth and poverty reduction during the late 1980s and the 1990s. The comparison of the two economies sheds new light on the structural difference among Asian countries. Mechanisms underlying the differences in initial inequality levels and in their marginal impact, however, still remain in a blackbox. Investigating these mechanisms utilizing microdata for the two countries is an issue left for future research.

Notes

1 See Perotti (1996), Aghion et al. (1999), and Jones (2002) for a more comprehensive review of the relationship between inequality and growth.

2 The dataset is available on request from the authors.

3 In this specification, the effects of the lagged variables of higher orders are assumed away. This implies a Markov assumption that, regardless of where the economy was located in $t-2$, the distribution $F_t(y_{it})$ is completely determined by X_{t-1} and the lagged distribution $F_{t-1}(y_{i,t-1})$. It would be desirable to test this assumption by investigating the significance of higher order lags empirically. This is not attempted in this paper, since our datasets are not sufficiently long.

4 The correlation coefficients for the subsample used in regression (excluding those observations associated with fewer than or equal to 50 sample households) are as follows:

Thailand	$\ln y_{t-1}$	$Pov_{1,t-1}$	$Ineq_{1,t-1}$
$\ln y$	0.805	-0.645	-0.390
Pov_{1t}	-0.680	0.664	0.349
$Ineq_{1t}$	-0.323	0.304	0.485
The Philippines	$\ln y_{t-1}$	$Pov_{1,t-1}$	$Ineq_{1,t-1}$
$\ln y_t$	0.878	-0.802	0.002
Pov_{1t}	-0.802	0.841	0.020
$Ineq_{1t}$	-0.062	0.108	0.589

5 Since terms other than lagged consumption are included, such as $X_{j,t-1}$, this parameter is analogous to the one characterizing conditional convergence (Jones, 2002).

6 The results presented here are based on equation-by-equation system GMM estimation. Estimating equations (1), (2), and (3) simultaneously provides a gain in efficiency. However, because the number of periods in our panel datasets is small, a panel VAR approach is not feasible in our case. Therefore, for the pooled OLS and fixed effect specifications only, we also estimated the system of equations (1)-(3), and the results were qualitatively the same as those reported in this paper.

7 To examine whether the system of equations (1)-(3) is characterized by a convergence as a whole, we calculated the three characteristic roots for the 3-by-3 matrix comprising β. For the model with more control variables reported in Table 3, they were 0.849, 0.257, and 0.132. All have absolute values less than one and the null hypothesis of overall convergence was not rejected at the 10% level, based on a bootstrapped empirical distribution of the standard errors of these coefficients.

8 Full and more detailed results of the robustness checks are available on request.

9 The robustness with respect to the use of 2 US$ (PPP) poverty lines shows that the effects of different operationalization of the cost-of-basic needs approach in the two countries on the econometric results are negligible.

10 The three characteristic roots for β in the model with more control variables reported in Table 7 were 1.234, 0.418, and 0.210. Because the first root is larger than one, the null hypothesis of overall convergence was rejected at the 5% level based on a bootstrapped empirical distribution of the standard errors of these coefficients.

11 To obtain annual rates, we linearly interpolated during the two year interval (Thailand) or the three year interval (the Philippines). The annual poverty persistent parameter for Thailand is then $\frac{1}{2}\beta_{33} + \frac{1}{2}$, while that for the Philippines is $\frac{1}{3}\beta_{33} + \frac{2}{3}$.

12 Full and more detailed results of the robustness checks are available on request.

13 Since the estimated parameters for Thailand correspond to the two year interval and those for the Philippines correspond to the three year interval, we adjusted these parameters by linear interpolation. See also endnote 11.

14 The simulation results are available on request. However, we have to be careful in its interpretation, since this extrapolation exercise does not incorporate information available after 2004.

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Table 1. Summary statistics of regression variables

A. Thailand

Variable	Definition	Obs.	Mean	Std. Dev.	Min.	Max.
Consumption	Log of mean consumption per capita in each province in real Baht.	675	7.324	0.302	6.374	8.204
Gini	Gini coefficient of per-capita consumption in each province.	675	0.358	0.049	0.213	0.494
Poverty	Headcount poverty index in each province based on per-capita consumption.	675	0.184	0.150	0.000	0.773
Education	Ratio of households whose head has tertiary education (more than 12 years of schooling).	675	0.152	0.070	0.021	0.475
Urban	Ratio of households who live in urban areas.	675	0.339	0.205	0.000	1.000
Agriculture	Ratio of households whose head is engaged in agriculture.	675	0.529	0.197	0.007	0.961
Aged	Population share of individuals aged more than or equal to 65.	675	0.160	0.052	0.000	0.336

B. The Philippines

Variable	Definition	Obs.	Mean	Std. Dev.	Min.	Max.
Consumption	Log of mean consumption per capita in each province in real Pesos.	556	8.564	0.336	7.765	9.686
Gini	Gini coefficient of per-capita consumption in each province.	556	0.356	0.049	0.200	0.515
Poverty	Headcount poverty index in each province based on per-capita consumption.	556	0.498	0.181	0.047	0.907
Education	Ratio of households whose head has tertiary education (more than 10 years of schooling).	556	0.157	0.071	0.014	0.439
Urban	Ratio of households who live in urban areas.	556	0.349	0.224	0.039	1.000
Agriculture	Ratio of households whose head is engaged in agriculture.	556	0.510	0.196	0.002	0.853
Aged	Population share of individuals aged more than or equal to 65.	556	0.130	0.054	0.000	0.354

Table 2. Bivariate correlation coefficients of mean per-capita consumption expenditure, inequality measures, and poverty measures

	Consump -tion	FGT(0)	FGT(1)	FGT(2)	Watt's Index	Clark-Watt's Index (-1)	GE(-1)	GE(0)	GE(1)	GE(2)	Gini
Consumption		-0.788	-0.751	-0.707	-0.736	-0.713	-0.023	-0.088	-0.120	-0.079	-0.115
FGT(0)	-0.899		0.969	0.924	0.955	0.930	0.193	0.232	0.237	0.175	0.243
FGT(1)	-0.840	0.953		0.988	0.998	0.989	0.185	0.218	0.219	0.160	0.223
FGT(2)	-0.778	0.892	0.986		0.996	0.999	0.179	0.206	0.204	0.147	0.207
Watt's Index	-0.811	0.921	0.992	0.992		0.996	0.183	0.214	0.214	0.155	0.217
Clark-Watt's Index (-1)	-0.770	0.876	0.975	0.994	0.993		0.179	0.207	0.205	0.148	0.209
GE(-1)	0.127	-0.012	0.086	0.133	0.124	0.152		0.984	0.928	0.801	0.964
GE(0)	0.054	0.076	0.159	0.193	0.191	0.210	0.981		0.975	0.866	0.991
GE(1)	-0.029	0.171	0.232	0.253	0.256	0.266	0.907	0.968		0.948	0.967
GE(2)	-0.082	0.219	0.258	0.266	0.271	0.274	0.712	0.805	0.919		0.845
Gini	0.073	0.055	0.138	0.173	0.171	0.190	0.968	0.991	0.951	0.771	

Note: Figures reported above the diagonal are correlation coefficients for Thailand (the number of observations is 675) while figures reported below the diagonal are for the Philippines (the number of observations is 556).

Table 3. System-GMM estimation results, Thailand

L.H.S. variable=	*Consumption* (*t*)		*Gini* (*t*)		*Poverty* (*t*)	
Specification A: With year effect only						
Consumption (*t*-1)	0.6704	***	-0.0665	***	-0.0975	***
	(0.080)		(0.009)		(0.032)	
Gini (*t*-1)	-1.6969	***	0.3013	***	0.4738	***
	(0.180)		(0.060)		(0.095)	
Poverty (*t*-1)	0.2789	***	0.0059		0.1972	**
	(0.092)		(0.021)		(0.083)	
Intercept	3.1780	***	0.7906	***	0.6244	**
	(0.596)		(0.069)		(0.247)	
Wald chi-square test (Chi2(10))	687.82	***	414.93	***	497.14	***
Hansen J test (Chi2 (34))	38.78		32.51		28.60	
AR(1) in first difference, z statistic	-6.03	***	-5.99	***	-5.51	***
AR(2) in first difference, z statistic	0.15		1.00		-0.84	
Specification B: With year effect and controls						
Consumption (*t*-1)	0.7511	***	-0.0552	***	-0.1128	***
	(0.102)		(0.013)		(0.039)	
Gini (*t*-1)	-1.6184	***	0.2932	***	0.3664	***
	(0.216)		(0.069)		(0.112)	
Poverty (*t*-1)	0.2844	***	0.0021		0.1929	**
	(0.079)		(0.020)		(0.083)	
Education (*t*-1)	-0.4143	*	-0.0449		0.2071	*
	(0.219)		(0.046)		(0.111)	
Urban (*t*-1)	-0.0871		0.0343	**	0.0108	
	(0.081)		(0.013)		(0.035)	
Agriculture (*t*-1)	-0.0181		0.0378	**	0.0454	
	(0.084)		(0.016)		(0.033)	
Aged (*t*-1)	-0.0932		-0.0418		-0.0326	
	(0.165)		(0.040)		(0.093)	
Intercept	2.7077	***	0.6877	***	0.7124	**
	(0.735)		(0.100)		(0.288)	
Wald chi-square test (Chi2(14))	771.35	***	616.38	***	534.92	***
Hansen J test (Chi2 (34))	37.96		31.17		29.77	
AR(1) in first difference, z statistic	-6.16	***	-5.85	***	-5.22	***
AR(2) in first difference, z statistic	0.13		1.16		-0.70	

Notes: The number of observations is 577 and the number of groups in the panel is 76 (those provinces with fewer than or equal to 50 observations were dropped). Robust standard errors are shown in parenthesis. The level of statistical siginificance is shown as *** prob<0.01, * prob<0.05, * prob<0.1.

Table 4. Results based on different estimation methods, Thailand

L.H.S. variable=	*Consumption* (*t*)		*Gini* (*t*)		*Poverty* (*t*)	
Specification 1: Pooled OLS estimation, A: With year effect only						
Consumption (*t* -1)	0.7036	***	-0.0463	***	-0.1572	***
	(0.035)		(0.008)		(0.021)	
Gini (*t* -1)	-1.1218	***	0.4625	***	0.4588	***
	(0.146)		(0.035)		(0.088)	
Poverty (*t* -1)	0.0970		0.0202		0.1862	***
	(0.071)		(0.017)		(0.043)	
Specification 1: Pooled OLS estimation, B: With year effect and controls						
Consumption (*t* -1)	0.5869	***	-0.0267	**	-0.1583	***
	(0.047)		(0.011)		(0.029)	
Gini (*t* -1)	-0.9038	***	0.3918	***	0.3449	***
	(0.164)		(0.039)		(0.099)	
Poverty (*t* -1)	0.0945		0.0181		0.1704	***
	(0.071)		(0.017)		(0.043)	
Specification 2: Fixed effect estimation, A: With year effect only						
Consumption (*t* -1)	0.2632	***	0.0066		-0.1254	***
	(0.049)		(0.011)		(0.031)	
Gini (*t* -1)	-0.4792	**	0.0188		0.1650	
	(0.191)		(0.045)		(0.119)	
Poverty (*t* -1)	-0.0275		0.0127		-0.0029	
	(0.073)		(0.017)		(0.045)	
Specification 2: Fixed effect estimation, B: With year effect and controls						
Consumption (*t* -1)	0.2516	***	0.0106		-0.1496	***
	(0.057)		(0.013)		(0.035)	
Gini (*t* -1)	-0.4385	**	0.0189		0.0578	
	(0.200)		(0.047)		(0.122)	
Poverty (*t* -1)	-0.0061		0.0149		-0.0304	
	(0.074)		(0.017)		(0.045)	

Notes: See Table 3 for the notation and the sample size. Parameter estimates for other right-hand-side variables and test results are omitted for brevity. Full results analogous to those in Table 3 are available on request.

Table 5. Robustness of the System-GMM estimation results, Thailand

L.H.S. variable=	*Consumption* (*t*)		*Gini* (*t*)		*Poverty* (*t*)	
Robustness check 1: Poverty measures redefined on the 2 PPP dollars a day poverty line						
Consumption (*t*-1)	0.7293	***	-0.0549	***	-0.0385	
	(0.098)		(0.013)		(0.031)	
Gini (*t*-1)	-1.5858	***	0.2970	***	0.2083	**
	(0.211)		(0.068)		(0.084)	
Poverty (*t*-1)	0.3088	***	0.0030		0.3542	***
	(0.102)		(0.025)		(0.089)	
Robustness check 2: The provincial data were adjusted to the initial provincial borders						
Consumption (*t*-1)	0.7561	***	-0.0597	***	-0.1160	***
	(0.108)		(0.014)		(0.041)	
Gini (*t*-1)	-1.5718	***	0.3079	***	0.3880	***
	(0.211)		(0.071)		(0.116)	
Poverty (*t*-1)	0.2696	***	-0.0049		0.1703	*
	(0.081)		(0.019)		(0.088)	
Robustness check 3: Combining the above two alterations						
Consumption (*t*-1)	0.7435	***	-0.0587	***	-0.0411	
	(0.106)		(0.014)		(0.032)	
Gini (*t*-1)	-1.5482	***	0.3061	***	0.2311	**
	(0.206)		(0.070)		(0.090)	
Poverty (*t*-1)	0.2831	***	-0.0017		0.3447	***
	(0.103)		(0.024)		(0.089)	

Notes: All three specifications were estimated with year effects and controls so that they are comparable to Specification B of Table 3. The number of observations is 562 and the number of groups in the panel is 73 (those provinces with fewer than or equal to 50 observations were dropped) for robustness check 2 & 3. Parameter estimates for other right-hand-side variables and test results are omitted for brevity. Full results analogous to those in Table 3 are available on request.

Table 6. Estimation results for the constrained model, Thailand

	System of equation comprising (4), (5), and (6)						Fixed effect estimation of single equation (7)		
	System GMM estimation				Fixed effect est.				
L.H.S. variable=	*Consumption* (*t*)		*Gini* (*t*)		*Poverty* (*t*)			*Poverty* (*t*)	
Specification A: With year effect only									
Consumption (*t*-1)	0.5824	***	-0.0683	***	-0.0135		*Consumption* (*t*)	-0.3014	***
	(0.067)		(0.008)		(0.019)			(0.016)	
Gini (*t*-1)	-1.5628	***	0.3083	***	0.1325	*	*Gini* (*t*)	0.7571	***
	(0.175)		(0.055)		(0.078)			(0.067)	
Specification B: With year effect and controls									
Consumption (*t*-1)	0.6754	***	-0.0561	***	-0.1389	***	*Consumption* (*t*)	-0.3277	***
	(0.093)		(0.011)		(0.031)			(0.030)	
Gini (*t*-1)	-1.5221	***	0.2976	***	0.0439		*Gini* (*t*)	0.4757	***
	(0.219)		(0.066)		(0.121)			(0.111)	

Notes: See Table 4.

Table 7. System-GMM estimation results, the Philippines

L.H.S. variable=	*Consumption* (*t*)		*Gini* (*t*)		*Poverty* (*t*)	
Specification A: With year effect only						
Consumption (*t* -1)	1.0562	***	-0.0791	***	-0.2347	**
	(0.246)		(0.026)		(0.097)	
Gini (*t* -1)	-1.2602	***	0.3705	***	0.1690	
	(0.394)		(0.122)		(0.160)	
Poverty (*t* -1)	0.4261		-0.0988	**	0.3460	*
	(0.376)		(0.044)		(0.194)	
Intercept	-0.2077		0.9591	***	2.2222	**
	(2.222)		(0.223)		(0.904)	
Wald chi-square test (Chi2(8))	903.61	***	48.38	***	770.43	***
Hansen J test (Chi2 (19))	21.67		27.12		25.44	
AR(1) in first difference, z statistic	-5.60	***	-4.81		-6.09	***
AR(2) in first difference, z statistic	1.54		-0.02		1.65	*
Specification B: With year effect and controls						
Consumption (*t* -1)	1.1323	***	-0.1278	***	-0.0965	
	(0.211)		(0.030)		(0.087)	
Gini (*t* -1)	-1.4304	***	0.3974	***	0.0551	
	(0.341)		(0.122)		(0.124)	
Poverty (*t* -1)	0.8535	***	-0.0953	**	0.3316	*
	(0.233)		(0.046)		(0.190)	
Education (*t* -1)	-0.1492		0.1012		0.1530	
	(0.311)		(0.079)		(0.144)	
Urban (*t* -1)	0.2678	***	-0.0212		-0.2107	***
	(0.076)		(0.024)		(0.052)	
Agriculture (*t* -1)	-0.1820		-0.0925	***	0.1441	**
	(0.120)		(0.029)		(0.069)	
Aged (*t* -1)	0.4215	**	0.0896		-0.2737	**
	(0.191)		(0.062)		(0.115)	
Intercept	-1.0535		1.3891	***	1.0991	
	(1.840)		(0.255)		(0.811)	
Wald chi-square test (Chi2(12))	1916.36	***	106.32	***	1582.88	***
Hansen J test (Chi2 (19))	16.32		23.67		22.60	
AR(1) in first difference, z statistic	-4.78	***	-4.86	***	-5.38	***
AR(2) in first difference, z statistic	1.29		-0.34		0.67	

Notes: The number of observations is 449 and the number of groups in the panel is 82 (those provinces with fewer than or equal to 50 observations were dropped). Robust standard errors are shown in parenthesis. The level of statistical siginificance is shown as *** prob<0.01, * prob<0.05, * prob<0.1.

Table 8. Results based on different estimation methods, the Philippines

L.H.S. variable=	*Consumption* (*t*)		*Gini* (*t*)		*Poverty* (*t*)	
Specification 1: Pooled OLS estimation, A: With year effect only						
Consumption (*t*-1)	0.9907	***	-0.0573	***	-0.1504	***
	(0.050)		(0.013)		(0.031)	
Gini (*t*-1)	-0.5299	***	0.6289	***	0.0319	
	(0.147)		(0.039)		(0.091)	
Poverty (*t*-1)	0.1019		-0.0723	***	0.6256	***
	(0.092)		(0.024)		(0.056)	
Specification 1: Pooled OLS estimation, B: With year effect and controls						
Consumption (*t*-1)	0.8121	***	-0.0788	***	-0.0762	**
	(0.055)		(0.015)		(0.035)	
Gini (*t*-1)	-0.6170	***	0.5934	***	0.0715	
	(0.143)		(0.040)		(0.090)	
Poverty (*t*-1)	0.2282	**	-0.0525	**	0.5518	***
	(0.088)		(0.025)		(0.056)	
Specification 2: Fixed effect estimation, A: With year effect only						
Consumption (*t*-1)	0.2826	***	-0.0119		-0.1501	**
	(0.104)		(0.028)		(0.066)	
Gini (*t*-1)	-0.4393	*	0.0183		0.1941	
	(0.242)		(0.065)		(0.154)	
Poverty (*t*-1)	0.0358		0.0046		0.1236	
	(0.135)		(0.036)		(0.086)	
Specification 2: Fixed effect estimation, B: With year effect and controls						
Consumption (*t*-1)	0.2526	**	-0.0270		-0.1359	**
	(0.106)		(0.029)		(0.068)	
Gini (*t*-1)	-0.5006	**	0.0085		0.2267	
	(0.242)		(0.065)		(0.155)	
Poverty (*t*-1)	0.0519		0.0106		0.1014	
	(0.136)		(0.037)		(0.087)	

Notes: See Table 7 for the notation and the sample size. Parameter estimates for other right-hand-side variables and test results are omitted for brevity. Full results analogous to those in Table 7 are available on request.

Table 9. Robustness of the System-GMM estimation results, the Philippines

L.H.S. variable=	*Consumption* (*t*)		*Gini* (*t*)		*Poverty* (*t*)	
Robustness check 1: Poverty measures redefined on the 2 PPP dollars a day poverty line						
Consumption (*t* -1)	1.0155	***	-0.0897	***	-0.0755	
	(0.188)		(0.028)		(0.062)	
Gini (*t* -1)	-1.5150	***	0.3334	**	0.1495	
	(0.416)		(0.133)		(0.147)	
Poverty (*t* -1)	0.7130	***	-0.0203		0.4496	***
	(0.263)		(0.051)		(0.115)	
Robustness check 2: The provincial data were adjusted to the initial provincial borders						
Consumption (*t* -1)	0.9412	***	-0.0826	***	-0.0655	
	(0.176)		(0.023)		(0.060)	
Gini (*t* -1)	-1.2886	***	0.3155	***	0.1391	
	(0.317)		(0.106)		(0.141)	
Poverty (*t* -1)	0.5671	***	-0.0237		0.3277	**
	(0.196)		(0.035)		(0.144)	
Robustness check 3: Combining the above two alterations						
Consumption (*t* -1)	1.0066	***	-0.0724	**	-0.0668	
	(0.191)		(0.030)		(0.060)	
Gini (*t* -1)	-1.5185	***	0.3023	**	0.1390	
	(0.385)		(0.118)		(0.141)	
Poverty (*t* -1)	0.6962	***	0.0008		0.4579	***
	(0.266)		(0.051)		(0.107)	

Notes: All three specifications were estimated with year effects and controls so that they are comparable to Specification B of Table 7. The number of observations is 440 and the number of groups in the panel is 77 (those provinces with fewer than or equal to 50 observations were dropped) for robustness check 2 & 3. Parameter estimates for other right-hand-side variables and test results are omitted for brevity. Full results analogous to those in Table 7 are available on request.

Table 10. Estimation results for the constrained model, the Philippines

	System of equation comprising (4), (5), and (6)						Fixed effect estimation of single equation (7)		
	System GMM estimation				Fixed effect est.				
L.H.S. variable=	*Consumption* (*t*)		*Gini* (*t*)		*Poverty* (*t*)			*Poverty* (*t*)	
Specification A: With year effect only									
Consumption (*t* -1)	0.8498	***	-0.0286	***	-0.2361	***	*Consumption* (*t*)	-0.6588	***
	(0.076)		(0.009)		(0.034)			(0.018)	
Gini (*t* -1)	-0.9913	***	0.2788	***	0.4085	***	*Gini* (*t*)	1.0519	***
	(0.284)		(0.106)		(0.123)			(0.067)	
Specification B: With year effect and controls									
Consumption (*t* -1)	0.7583	***	-0.0802	***	-0.2004	***	*Consumption* (*t*)	-0.6601	***
	(0.124)		(0.016)		(0.039)			(0.023)	
Gini (*t* -1)	-0.8880	***	0.3145	***	0.3302	**	*Gini* (*t*)	1.0390	***
	(0.255)		(0.110)		(0.127)			(0.078)	

Notes: See Table 8.

Table 11. Simulation results for the dynamic impact of inequality, 1988-2000

	The Philippines		Thailand	
	Annual growth rate of per-capita consumption expenditure (%)	Annual rate of poverty reduction (%)	Annual growth rate of per-capita consumption expenditure (%)	Annual rate of poverty reduction (%)
Baseline	1.14	0.72	3.72	2.06
Counterfactual simulations				
Simulation 1: Adding a shock to equation (2) in 1988 so that the inequality level in that year is halved from the actual value	2.45	1.00	5.57	2.43
Simulation 2(a): Replacing the value of β_{12} (the marginal effect of lagged inequality on growth) with the value of the other country)	-9.73	-0.10	10.96	3.16
Simulation 2(b): Replacing the values of β_{12}, β_{22}, and β_{32} (the marginal effects of lagged inequality on growth, inequality and poverty, respectively) with the values of the other country)	1.83	-0.35	4.86	3.39

Figure 1(a): Time Series of *Consumption* , Thailand

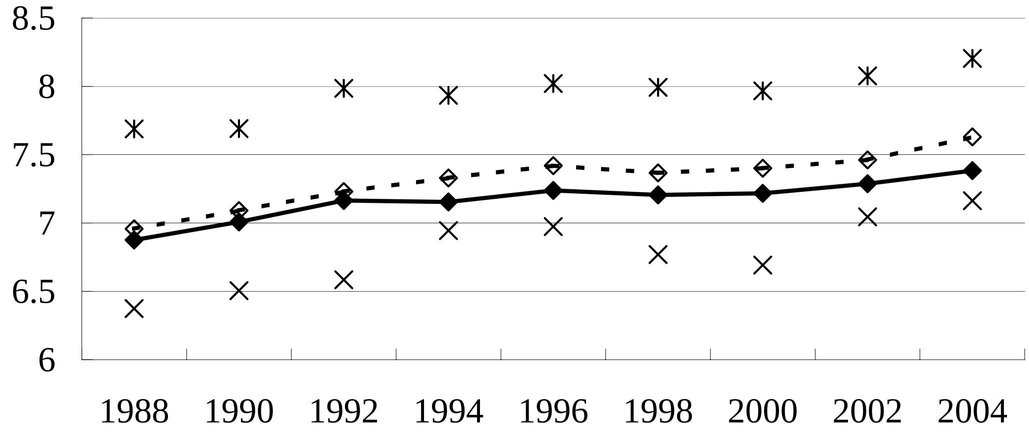

Figure 1(b): Time Series of *Gini* , Thailand

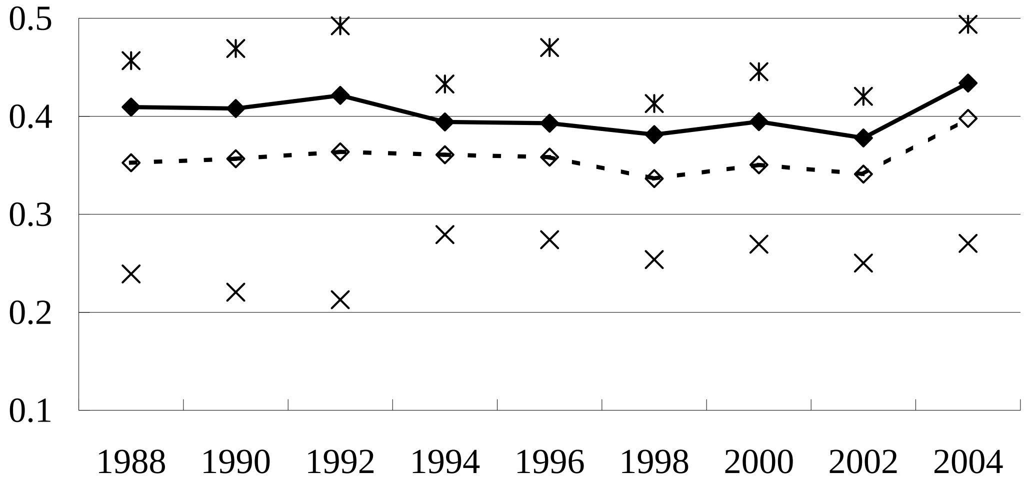

Figure 1(c): Time Series of *Poverty* , Thailand

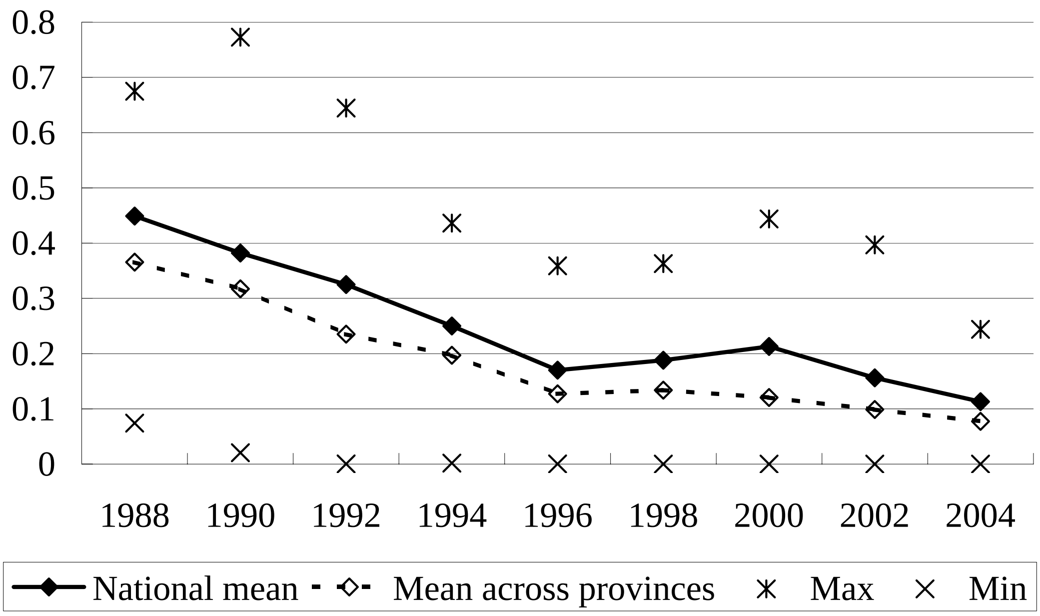

Figure 2(a): Time Series of *Consumption* , the Philippines

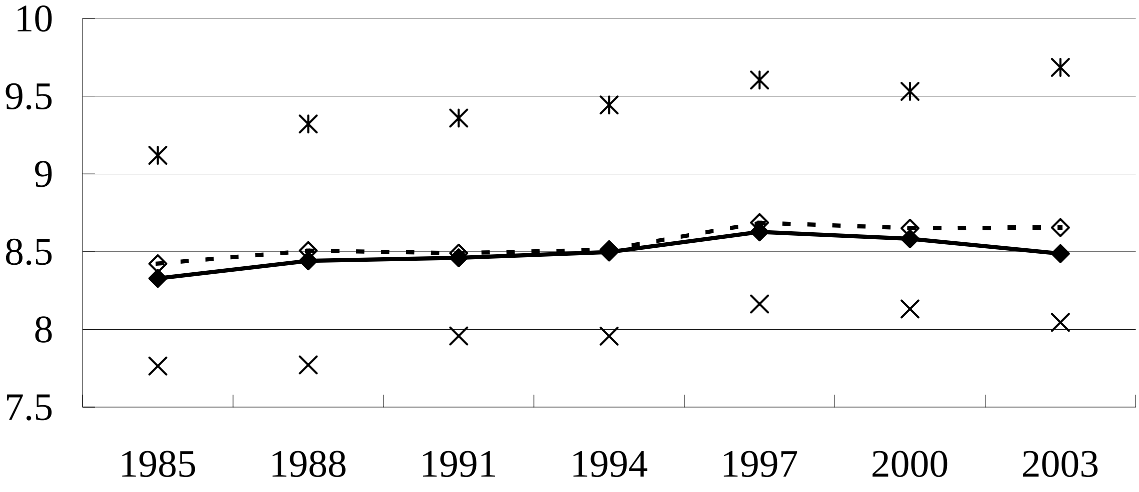

Figure 2(b): Time Series of *Gini* , the Philippines

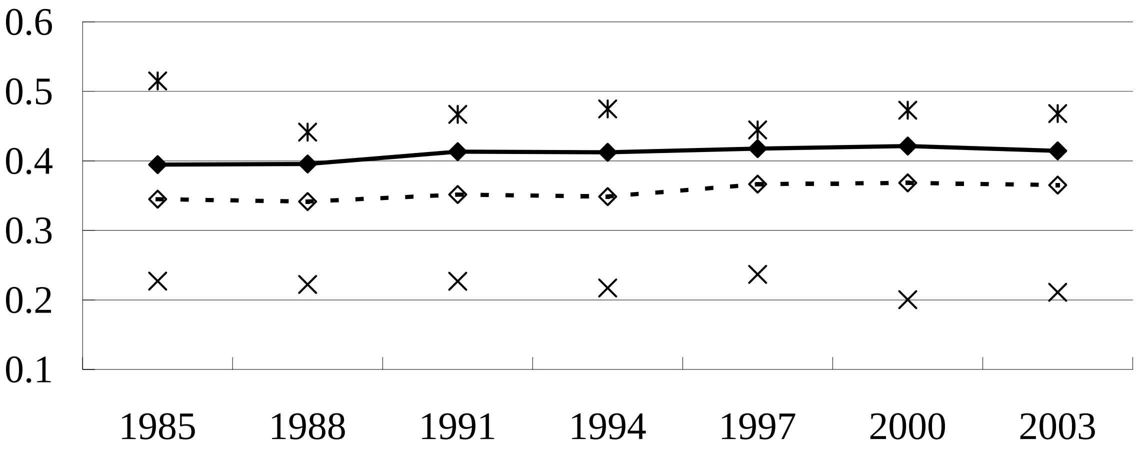

Figure 2(c): Time Series of *Poverty* , the Philippines