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

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Abstract

We propose a new methodological framework to empirically analyze the dynamics of growth, poverty, and inequality that incorporates the fact that the entire distribution of a welfare indicator, say, real per-capita consumption, changes over time, and that empirical variables for growth, poverty, and inequality are often compiled from the distribution of the welfare indicator. Empirical models derived from this framework are applied to a unique panel dataset of provinces in the Philippines (1985-2003) and Thailand (1988-2004), compiled from microdata on household expenditures. The system GMM estimation results suggest that inequality reduced the subsequent growth rate of per-capita consumption in both countries and differences in inequality explain a substantial portion of the Philippine-Thai difference in growth and poverty reduction during the late 1980s and the 1990s.

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

JEL classification codes: I32, O15.

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1 Introduction

The relationship between 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).

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 with an indicator representing individual welfare, say, real per-capita consumption, the usual procedure is to aggregate the data and to compile empirical variables for mean consumption, poverty, and inequality. This process seems odd, however, since, in any given period, the three variables are dependent by construction. We thus propose a new methodological framework in which we pay due attention to the fact that the entire distribution of real per-capita consumption changes over time and to the problem of compiling the empirical variables for mean consumption, poverty, and inequality from the same microdata of individual consumption in a given year.[2]

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

[2] Also see Quah (2007) for ongoing research, based on a motivation similar to ours, on characterizing the

To understand why this is a problem, we can refer to the debate on how to define pro-poor growth.[3] 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. These exercises are valid ways to describe dynamic changes that occurred to the entire distribution. However, it is difficult to infer the structural relationship between growth and poverty reduction from these exercises since the changes in the poverty headcount index and those in average incomes in the same period are linked by construction. The purpose of this paper is to attempt to de-link them.

We apply the methodology developed here to datasets from the Philippines and Thailand. Unique panel data on provincial-level per-capita consumption, poverty, and inequality are compiled from microdatasets of household expenditure surveys, covering similar periods: 1985-2003 for the Philippines and 1988-2004 for Thailand. The exercise using these panel data is presented as an illustration to show how our methodology works. But the exercise is also of great empirical interest, since Thailand is one of the high performing Asian economies in the context of the "Asian miracle," while the Philippines is not (World Bank (1993)). A comparative study of two economies using semi-macro panel datasets is rare in the literature. By investigating the cases of the Philippines and Thailand, therefore, we can deepen our understanding of the structural differences between them that are responsible for the disparity in economic performance. Note that in the early 1980s, per-capita GDP levels in the two countries were very similar, while 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 (World Bank (2004)). 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)).

The paper is organized as follows. Section 2 provides the analytical framework for the

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entire distribution of the welfare indicator.

[3] See, for example, the dialogue published in the International Poverty Centre's *One Pager* (UNDP, online: http://www.undp.org/povertycentre/ipcpublications.htm).

examination of growth, poverty, and inequality dynamics. It also derives the specifications for the empirical analysis, which are estimated by a system GMM method to control for biases due to the dynamic structure of the empirical model. Section 3 describes the datasets, showing the growth, poverty, and inequality dynamics observed in the two countries. 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 these two countries. Section 5 concludes the paper.

2 Analytical Framework

2.1 The Dynamics of the Entire Distribution of Per-Capita Consumption

2.1.1 Setting

We assume an economy consisting of individuals whose welfare level is represented by y_{it}, such as real consumption per capita. Subscript i stands for individual i and subscript t for 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 growth, inequality measures, and poverty measures.

Since y_{it} is in currency units, small fractions may not have much economic meaning. We therefore assume that the function $F_t(y_{it})$ can be approximated by a step function with cells with the same width on the y_{it} axis. In other words, we assume that the density function associated with $F_t(y_{it})$ can be expressed as a discrete probability distribution function with a fixed and finite number of cells with the same width. We denote this probability function by $\pi_{nt} \equiv \pi_t(y_{nt})$ where $n = 1, 2, ..., N$ is the subscript for each cell. Then,

Mean consumption: $y_t = \sum_{n=1}^{N} \pi_{nt} y_{nt}$,

Consumption growth: $\Delta y_t = y_t - y_{t-1}$.

In this paper, we investigate relative inequality measures that satisfy axioms of symmetry, replication invariance, scale invariance, and the Pigou-Dayton principle of transfers

(Foster and Sen (1997)), such as

Gini index: $Ineq_{1t} = \frac{1}{2y_t}\sum_{n=1}^{N}\sum_{n'=1}^{N}\pi_{nt}\pi_{n't} \mid y_{nt} - y_{n't} \mid,$

Class of general entropy measures: $I_t(\alpha) = \frac{1}{\alpha(1-\alpha)}\sum_{n=1}^{N}\pi_{nt}\left[1 - \left(\frac{y_{nt}}{y_t}\right)^{\alpha}\right].$

The class of general entropy measures includes (in order of lower inequality aversion):

Half the square of the coefficient of variation: $Ineq_{2t} = I_t(2)$,

Theil index: $Ineq_{3t} = I_t(1) = \sum_{n=1}^{N}\pi_{nt}\frac{y_{nt}}{y_t}\ln\left(\frac{y_{nt}}{y_t}\right),$

Mean logarithmic deviation: $Ineq_{4t} = I_t(0) = \sum_{n=1}^{N}\pi_{nt}\ln\left(\frac{y_t}{y_{nt}}\right),$

General entropy measure with parameter -1: $Ineq_{5t} = I_t(-1)$.

Similarly, we investigate poverty measures that are frequently employed in empirical studies and satisfy the focus axiom and decomposability (Foster and Sen (1997)). Letting P denote a set defined on n for $y_{nt} < z$ with z defined as the absolute poverty line:

Poverty headcount index: $Pov_{1t} = \sum_{n\in P}\pi_{nt},$

Poverty gap index: $Pov_{2t} = \sum_{n\in P}\pi_{nt}\left(1 - \frac{y_{nt}}{z}\right),$

Squared poverty gap index: $Pov_{3t} = \sum_{n\in P}\pi_{nt}\left(1 - \frac{y_{nt}}{z}\right)^2,$

Watt's poverty measure: $Pov_{4t} = \sum_{n\in P}\pi_{nt}\ln\left(\frac{z}{y_{nt}}\right)$, and

Clark-Watt's measure with parameter -1: $Pov_{5t} = \sum_{n\in P}\pi_{nt}\left(\frac{z}{y_{nt}} - 1\right).$

We are interested in the relationships between growth, inequality, and poverty. However, as shown clearly in the above definitions, all empirical variables of mean consumption, inequality, and poverty are compiled from the same distribution of $F_t(y_{it})$ or π_{nt}. 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 (Pov_{1t}) on the average welfare level (y_t) and inequality such as the Gini index ($Ineq_{1t}$) 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 the entire distribution of $F_t(y_{it})$ or π_{nt}. Finding a negative effect of y_t and a positive effect of $Ineq_{1t}$ on Pov_{1t} from such specifications cannot be interpreted as showing the structural relationships between poverty, growth, and inequality. Instead, it should be interpreted as showing the shape of $F_t(y_{it})$ or π_{nt}. Similarly, taking differences and finding a negative effect of Δy_t and a positive effect of $\Delta Ineq_{1t}$ on ΔPov_{1t} cannot be interpreted as showing the structural relationships between poverty, growth, and inequality, either. Instead, it should be interpreted as showing the shapes of $F_t(y_{it})$ and $F_{t-1}(y_{i,t-1})$. Thus, the finding of a positive effect of consumption growth and a negative effect of inequality change on poverty reduction from such specifications is misleading and spurious in the sense that it does not imply any dynamic relationship between inequality (growth) and poverty. Existing studies such as Besley and Burgess (2002), Sawada (2004) do not pay sufficient attention to this fact.

2.1.2 Dynamics

We now describe the dynamics of the model. In period t, we observe $F_t(y_{it})$ or π_{nt}. 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. In other words, the basic idea for the empirical exercise is:

Left-hand side variables = vector of $\ln y_t$, $Ineq_t$ (vector of $Ineq_{kt}$, k=1,2,...), and Pov_t (vector of Pov_{kt}, k=1,2,...).

Right-hand side variables = vector of X_{t-1}, $\ln y_{t-1}$, $Ineq_{t-1}$, and Pov_{t-1}.

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 heteroscedastic after the logarithmic transformation. By estimating this system of equations, we can infer the structural relationships between poverty, growth, and inequality. For instance, when we find a negative effect of $Ineq_{1,t-1}$ and a positive but less-than-unity effect of $Pov_{1,t-1}$ on Pov_{1t} from such a specification, we can interpret this as showing that a lower initial Gini coefficient increases the speed of reduction of the poverty headcount index.

In the specification above, 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 $F_{t-1}(y_{i,t-1})$.[4]

2.1.3 The poverty-growth-inequality triangle

In the theoretical literature on the relationships between poverty, mean consumption, and inequality, two benchmark cases have been examined in detail.

(i) **A mean-preserving spread**: This increases any measure included in $Ineq_t$, while leaving y_t unaffected by definition. The effect of a mean-preserving spread on Pov_t depends on the exact choice of the poverty measure and the position of the poverty line relative to the mean consumption level and the location where the mean-preserving spread occurs. Thus, in general, the sign of the effect is indeterminate. When the mean-preserving spread occurs for some individuals whose y_{it} is less than z and the poverty measure adopted is based on an individual poverty score function that is decreasing and convex in y_{it}/z for $y_{it} < z$, it is known that the poverty measure increases (or more precisely, does not decrease).

(ii) **Lorenz-curve-preserving growth**: This case is useful in decomposing the change in poverty measures into growth and redistribution components (Datt and Ravallion (1992)). When an economy grows by shifting the entire distribution by a certain percentage without changing the shape of the distribution at all, y_t increases while any measure included in $Ineq_t$ remains unaffected. Since any poverty measure included in Pov_t decreases in such

[4]It would be desirable to test this assumption by investigating the significance of higher order lags empirically. This is not attempted in the empirical part of this paper, since our datasets are not sufficiently long.

a case, simulating Lorenz-curve-preserving growth can quantify the pure effects of growth on poverty *à la* Datt and Ravallion (1992). Although this is a powerful empirical tool to decompose the observed changes in poverty, it is not very useful for analyzing the impact of policies on future poverty since we know very little about the conditions under which Lorenz-curve-preserving growth can be a good proxy for actual circumstances or about policy tools to achieve Lorenz-curve-preserving growth.[5]

Although the motivation of studies examining these two benchmarks is similar to that of this paper, we have to be careful about the restrictive assumptions underlying the examination of changes in the distribution $F_t(y_{it})$ — the real world rarely presents cases that are reasonably close to a mean-preserving spread or to Lorenz-curve-preserving growth. Nevertheless, because of the intuition these two cases provide, we tend to think that growth usually decreases poverty and an increase in inequality usually increases poverty. But this is not always true once we move beyond the two restrictive cases of the mean-preserving spread and Lorenz-curve-preserving growth.

As a simple example of moving beyond the two restrictive cases, consider the relationships between mean consumption y_t, the Gini index $Ineq_{1t}$, and the poverty headcount index Pov_{1t}. The entire distribution of y_{it} is given by π_{nt} ($\pi_{nt} > 0 \quad \forall n$). Initially, $0 < Pov_{1t} < 1$; moreover, those below the poverty line are distributed in at least two cells. In other words, we have a set of initial values of π_{nt} whose sum is equal to unity, from which we calculate the set of initial values of $(y_t, Ineq_{1t}, Pov_{1t})$. Can we find a slightly different set of π_{nt} that preserves the first two elements of the initial values of $(y_t, Ineq_{1t}, Pov_{1t})$ but increases/decreases the third one? When $N > 3$, the answer is yes, since there are only four restrictions on π_{nt} (the sum should be unity, and the values of y_t, $Ineq_{1t}$, and Pov_{1t} are given). In other words, we can find a case with no growth and no change in the Gini index but an increase (decrease) in the poverty headcount index. Similarly, for cases where the number of poverty measures is more than one and that of inequality measures is more than one, we can generally find a combination of π_{nt} with no growth and no change in all of the inequality and poverty measures except one (either an increase or decrease), as long as N is sufficiently large.[6]

[5]A recent study by Kakwani and Son (2006) estimated how much it would cost to achieve the Millennium Development Goal of halving poverty, assuming either Lorenz-curve-preserving growth, Lorenz-curve-spreading growth, or Lorenz-curve-shrinking growth, keeping the curvature of the Lorenz curve constant.

[6]If the restrictions imposed on π_{nt} by the value of each inequality/poverty measure are all linear, this argument is trivially true. However, most of these restrictions are non-linear. Therefore, mathematically, it is possible that there are multiple solutions, all of which are outside the economically reasonable range. However, this never occurs in our numerical examples as long as we use the inequality/poverty measures

Therefore, by treating y_t, inequality measures $Ineq_t$, and poverty measures Pov_t as different measures to describe the entire distribution of y_{it}, we can deepen our understanding of the poverty-growth-inequality triangle. Our approach attempts to characterize the poverty-growth-inequality triangle by taking into account the dynamic structure that generates the entire distribution of y_{it} over time.

2.2 Empirical Specification and Estimation Methodology

The model discussed above was for a representative economy. We assume that data for a collection of such economies are available for the empirical analysis. Each individual economy is denoted by subscript j and could be a country or a region within a country. Thus, the model is revised to look as follows:

Left-hand side variables = vector of $\ln y_{jt}, Ineq_{jt}$ (vector of $Ineq_{kjt}$, k=1,2,...), and Pov_{jt} (vector of Pov_{kjt}, k=1,2,...).

Right-hand side variables = vector of $X_{j,t-1}, \ln y_{j,t-1}, Ineq_{j,t-1}$, and $Pov_{j,t-1}$.

In the empirical application, it is likely that 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. If the multicollinearity problem is severe, as turns out to be the case for the Philippines and Thailand, the following system of three equations is estimated:

$$\begin{aligned}
\ln y_{jt} &= \beta_{11} \ln y_{j,t-1} + \beta_{12} Ineq_{1,j,t-1} + \beta_{13} Pov_{1,j,t-1} + X_{j,t-1}\theta_1 + \alpha_{1j} + \eta_{1t} + \epsilon_{1jt}, && (1)\\
Ineq_{1jt} &= \beta_{21} \ln y_{j,t-1} + \beta_{22} Ineq_{1,j,t-1} + \beta_{23} Pov_{1,j,t-1} + X_{j,t-1}\theta_2 + \alpha_{2j} + \eta_{2t} + \epsilon_{2jt}, && (2)\\
Pov_{1jt} &= \beta_{31} \ln y_{j,t-1} + \beta_{32} Ineq_{1,j,t-1} + \beta_{33} Pov_{1,j,t-1} + X_{j,t-1}\theta_3 + \alpha_{3j} + \eta_{3t} + \epsilon_{3jt}, && (3)
\end{aligned}$$

where α stands for the unobservable and time-invaryıng characteristics of economy j, η represents unobservable macro shocks that affect all economies in period t, and ϵ is an idiosyncratic error term. In the theoretical model, X_t was defined as a vector of variables that affect the distribution of $F(.)$. In the empirical specification, the vector is decomposed

listed above and set their initial levels at those found in empirical studies. Numerical results are available on request.

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).

Our choice of particular measures of $Ineq_{1jt}$ and Pov_{1jt} is simply determined by convenience and we could choose other measures as well. Even if multicollinearity among individual measures of inequality is present, each measure may nevertheless contain information not contained in the other. For instance, Datt and Ravallion (1992) have shown that redistribution did occur and affected changes in poverty in India even though the Gini coefficient did not change much. To examine this possibility, 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:

$$\ln y_{jt} = \beta_{11} \ln y_{j,t-1} + \beta_{12} Ineq_{1,j,t-1} + X_{j,t-1}\theta_1 + \alpha_{1j} + \eta_{1t} + \epsilon_{1jt}, \quad (4)$$

$$Ineq_{1jt} = \beta_{21} \ln y_{j,t-1} + \beta_{22} Ineq_{1,j,t-1} + X_{j,t-1}\theta_2 + \alpha_{2j} + \eta_{2t} + \epsilon_{2jt}, \quad (5)$$

$$Pov_{1jt} = \beta_{31} \ln y_{j,t-1} + \beta_{32} Ineq_{1,j,t-1} + X_{j,t-1}\theta_3 + \alpha_{3j} + \eta_{3t} + \epsilon_{3jt}, \quad (6)$$

In both specifications (1)-(3) and (4)-(6), we can investigate whether the growth rate is higher for regions/countries 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.[7] 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 equa-

[7] 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)).

tions (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 of 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) and Sawada (2004), who do not pay sufficient attention to the fact that Pov_{1jt}, $\ln y_{jt}$, and $Ineq_{1jt}$ are all compiled from the same distribution. We thus estimate the following model as well:

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

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.

3 Data

3.1 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. We choose provinces as the unit of analysis. Currently, there are 76 provinces in Thailand and 82 provinces in the Philippines. Because we use regional panel datasets calculated from microdata, it is less likely that we will encounter serious comparability problems in our datasets.[8]

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.[9]

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.[10]

From these datasets for the two countries, the three groups of left-hand-side variables 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). 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. 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 provincial-level variables. Following the literature, four

[8]On the other hand, a province in a country is not an independent economy so that we have to worry about the potential impact of between-province migration on within-province inequality. Fortunately, our preliminary analyses based on labor force surveys 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.

[9]This implies that some of the geographic units are not strictly comparable between the first three and the last six surveys. Adjusting for changes in provincial boundaries is left for future research. However, the bias as a consequence of not adjusting for these changes is likely to be small since the regression results reported in the next section are qualitatively the same as those based on a balanced-panel subset covering only provinces that did not experience boundary changes.

[10]See previous footnote for a discussion of the implications.

variables were calculated for X_{jt}: *Education*, *Urban*, *Agriculture*, and *Aged*. The definitions and summary statistics of these and other empirical variables are reported in Table 1 for Thailand and Table 2 for the Philippines.

3.2 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 provincial-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. This is because 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. To confirm this, Tables 3 and 4 show the correlation coefficients among $\ln y_{jt}$, five measures included in $Ineq_{jt}$, and five measures included in Pov_{jt}. 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 (Table 3). 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 0.993 (Table 4). Because of the high correlation, we estimate a model of equations (1)-(7) in the next section, in which only one each from $Ineq_{jt}$ and Pov_{jt} is included.

Regarding the correlation among $\ln y_{jt}$, poverty measures, and inequality measures, 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. 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 (Table 3) and in the range from -0.016 to 0.274 in the Philippines (Table 4).

4 The Dynamic Relationships between Growth, Poverty, and Inequality in the Philippines and Thailand

4.1 Estimation Results

4.1.1 Thailand

The estimation results of equations (1)-(3) for Thailand are shown in Table 5. 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).[11] 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. Note that casual observation of Figure 1(a) also suggests income divergence.

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 issue 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 *Con-*

[11]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.

sumption 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 5 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 5). 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.[12]

For comparison, Table 6 reports the results obtained when using 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.

[12]To examine whether the system of equations (1)-(3) is associated with 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 5, they were 0.8486, 0.2571, and 0.1316. 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.

Since our choice of particular measures of $Ineq_{1jt}$ (the Gini coefficient) and Pov_{1jt} (the headcount poverty measure) was arbitrary, we tried other measures of inequality and poverty 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 Tables 5 and 6. 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.[13]

To facilitate comparison with existing studies, estimation results based on a restricted model consisting of equations (4)-(5) are reported in Table 7, together with the results for equations (6) and (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 5 and 7 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 5) or those in equation (6) (Table 7) are better indicators than those in equation (7) (Table 7).

4.1.2 The Philippines

The estimation results of equations (1)-(3) for the Philippines are reported in Table 8. 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

[13]These estimation results are available on request.

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 8 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.[14]

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. For this reason, 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 8). Since both are significantly different from one, this indicates that provinces which were poorer 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.[15] Therefore, poverty is more persistent in the Philippines than in Thailand (poorer regions

[14] The three characteristic roots for β in the model with more control variables reported in Table 8 were 1.2335, 0.4182, and 0.2096. 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.

[15] 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 $\frac{1}{3}\beta_{33} + \frac{2}{3}$.

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 similar patterns to those for Thailand. Table 9 shows that, first, the sign and the significance 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 9, they are smaller than unity, with a statistically significant difference from unity in the case of the fixed effect results.

To examine the robustness of 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. 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.

In the case of the Philippines (Table 10), as in that of Thailand, the magnitudes of the positive effect of *Consumption* and the negative effect of *Gini* on *Poverty* are sensitive to the specification: 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 5 and 8. 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.

When other measures of inequality and poverty were tried, qualitatively the same results were obtained for the Philippines. 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.

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 5 and 8, we calculate the fitted values of residuals as follows:

$$\begin{aligned}
\ln y_{jt} &= \hat{\beta}_{11} \ln y_{j,t-1} + \hat{\beta}_{12} Ineq_{1,j,t-1} + \hat{\beta}_{13} Pov_{1,j,t-1} + X_{j,t-1}\hat{\theta}_1 + \hat{\alpha}_{1j} + \hat{\eta}_{1t} + \hat{\epsilon}_{1jt}, \quad (8)\\
Ineq_{1jt} &= \hat{\beta}_{21} \ln y_{j,t-1} + \hat{\beta}_{22} Ineq_{1,j,t-1} + \hat{\beta}_{23} Pov_{1,j,t-1} + X_{j,t-1}\hat{\theta}_2 + \hat{\alpha}_{2j} + \hat{\eta}_{2t} + \hat{\epsilon}_{2jt}, \quad (9)\\
Pov_{1jt} &= \hat{\beta}_{31} \ln y_{j,t-1} + \hat{\beta}_{32} Ineq_{1,j,t-1} + \hat{\beta}_{33} Pov_{1,j,t-1} + X_{j,t-1}\hat{\theta}_3 + \hat{\alpha}_{3j} + \hat{\eta}_{3t} + \hat{\epsilon}_{3jt} \quad (10)
\end{aligned}$$

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.[16] 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.

[16] 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 footnote 15.

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 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 5 and 8, 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 triangle 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 the triangle structure.

5 Conclusion

This paper proposed a framework to empirically analyze the dynamics of, and relationships among, growth, poverty, and inequality, in which due attention is paid to the fact that the entire distribution of real per-capita consumption changes over time and that the three empirical variables of growth, poverty, and inequality are often compiled from the same microdataset. Implications were derived from this framework regarding the dynamic relationships among growth, inequality, and poverty. As an illustration, the dynamic relationship thus derived was investigated using unique provincial-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. The mechanisms underlying differences in initial inequality levels and in their marginal impact, however, still remain a blackbox. Investigating these mechanism utilizing microdata for these two countries is an issue left for future research.

References

[1] Aghion, P., E. Caroli, and C. Garcia-Penalosa. 1999. "Inequality and Economic Growth: The Perspective of the New Growth Theories." *Journal of Economic Literature*, vol.37, no.4, pp.1615-1660.

[2] Alesina, A. and D. Rodrik. 1994. "Distributive Politics and Economic Growth." *The Quarterly Journal of Economics*, vol.109, no.2, pp.465-490.

[3] Banerjee, A.V. and E. Duflo. 2003. "Inequality and Growth: What Can the Data Say?" *Journal of Economic Growth*, vol.8, no.3, pp.267-299.

[4] Bénabou, R. 1996. "Inequality and Growth." In B. Bernanke and J. Rotemberg (eds.) *National Bureau of Economic Research Macroeconomics Annual.* MIT Press, Cambridge, pp.11-74.

[5] Besley, T. and R. Burgess. 2003. "Halving Global Poverty." *Journal of Economic Perspective*, vol.17, no.3, pp.3-22.

[6] Blundell, R. and S. Bond. 1998. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics*, vol.87, no.1, pp.115-143.

[7] Bond, S., A. Hoeffler, and J. Temple. 2001. "GMM Estimation of Empirical Growth Models." *C.E.P.R. Discussion Papers*, No.3048, Centre for Economic Policy Research, London.

[8] Booth, A. 1997. "Rapid Economic Growth and Poverty Decline: A Comparison of Indonesia and Thailand 1981-1990," *Journal of International Development*, vol.9, no.2, pp.169-187.

[9] Bourguignon, F. 2004. "The Poverty-Growth-Inequality Triangle." *Indian Council for Research on International Economic Relations*, New Delhi.

[10] Datt, G. and M. Ravallion. 1992. "Growth and Redistribution Components of Changes in Poverty Measures: A Decomposition with Applications to Brazil and India in the 1980s." *Journal of Development Economics*, vol.38, no.2, pp.275-295.

[11] Deininger, K. and L. Squire. 1998. "New Ways of Looking at Old Issues : Inequality and Growth." *The Journal of Development Economics*, vol.57, no.2, pp.259-287.

[12] Fields, G.S. 2001. *Distribution and Development: A New Look at the Developing World.* New York : Russell Sage Foundation.

[13] Forbes, K. 2000. "A Reassessment of Relationship between Inequality and Growth." *American Economic Review*, vol.90, no.4, pp.869-887.

[14] Foster, J.E. and A.K. Sen. 1997. "On Economic Inequality After a Quarter Century," Annexe to A.K. Sen, *On Economic Inequality, Enlarged Edition*, Oxford: Clarendon Press, pp.107-219.

[15] Galor, O. and J. Zeira. 1993. "Income Distribution and Macroeconomics." *Review of Economic Studies*, vol.60, no.1, pp.35-52.

[16] Heltberg, R. 2004. "The Growth Elasticity of Poverty." In A.F. Shorrocks, A.F. and R. van der Hoeven (eds.), *Growth, Inequality, and Poverty: Prospects for Pro-Poor Economic Development*, Oxford: Oxford University Press, pp.81-91.

[17] Jones, C.I. 2002. *Introduction to Economic Growth. Second Edition*, New York: W.W. Norton and Company Inc.

[18] Kakwani, N. 1993. "Poverty and Economic Growth with Application to Côte D'Ivoire." *Review of Income and Wealth.* vol.39, no.2, pp.121-139.

[19] Kakwani, N., S. Khandker, and H.H. Son. 2004. "Pro-Poor Growth: Concepts and Measurement with Country Case Studies," *Working Papers*, no.1, UNDP International Poverty Centre.

[20] Kakwani, N. and H.H. Son. 2006. "How Costly is it to Achieve the Millennium Development Goal of Halving Poverty between 1990 and 2015?" *Working Papers*, no.19, UNDP International Poverty Centre.

[21] Li, H. and H. Zou. 1998. "Income Inequality is not Harmful for Growth : Theory and Evidence."*Review of Development Economics*, vol.2, no.3, pp.318-334.

[22] Perotti, R. 1996. "Growth, Income Distribution, and Democracy: What the Data Say."*Journal of Economic Growth*,vol.1, no.2, pp.149-187.

[23] Quah, D. 2007. "Growth and Distribution," mimeo. LSE. April 2007.

[24] Ravallion, M. 1998. "Does Aggregation Hide the Harmful Effects of Inequality on Growth?" *Economics Letters*, vol.61, no.1, pp.73-77.

[25] ——. 2003. "Inequality Convergence." *Economics Letters*, vol.80, no.3, pp.351-356.

[26] ——. 2004. "Looking Beyond Averages." In A.F. Shorrocks, A.F. and R. van der Hoeven (eds.), *Growth, Inequality, and Poverty: Prospects for Pro-Poor Economic Development*, Oxford: Oxford University Press, pp.62-80.

[27] Sawada, Y. 2004. "An Assessment of Philippine Performance in Reducing Poverty by Using the Millennium Development Goals as the Benchmark." A background paper for the Philippines Poverty Assessment, World Bank.

[28] Shorrocks, A.F. and R. van der Hoeven (eds.). 2004. *Growth, Inequality, and Poverty: Prospects for Pro-Poor Economic Development*. Oxford: Oxford University Press.

[29] World Bank. 1993. *The East Asian Miracle: Economic Growth and Public Policy*. Oxford: Oxford University Press.

[30] ——. 2004. *World Development Indicators*, World Bank.

Table 1: Summary statistics of regression variables, Thailand

Variable	Definition	Obs.	Mean	Std. Dev.	Min.	Max.
Consumption	Log of mean consumption per capita in each province in real Baht.	675	7.3239	0.3022	6.3739	8.2043
Gini	Gini coefficient of per-capita consumption in each province.	675	0.3575	0.0489	0.2129	0.4938
Poverty	Headcount poverty index in each province based on per-capita consumption.	675	0.1843	0.1500	0.0000	0.7727
Education	Ratio of households whose head has tertiary education (more than 12 years of schooling).	675	0.1525	0.0703	0.0208	0.4751
Urban	Ratio of households who live in urban areas.	675	0.3395	0.2049	0.0000	1.0000
Agriculture	Ratio of households whose head is engaged in agriculture.	675	0.5287	0.1972	0.0074	0.9608
Aged	Population share of individuals aged more than or equal to 65.	675	0.1595	0.0516	0.0000	0.3357

Table 2: Summary statistics of regression variables, the Philippines

Variable	Definition	Obs.	Mean	Std. Dev.	Min.	Max.
Consumption	Log of mean consumption per capita in each province in real Pesos.	556	8.5641	0.3363	7.7646	9.6856
Gini	Gini coefficient of per-capita consumption in each province.	556	0.3557	0.0488	0.2005	0.5150
Poverty	Headcount poverty index in each province based on per-capita consumption.	556	0.4984	0.1815	0.0469	0.9071
Education	Ratio of households whose head has tertiary education (more than 10 years of schooling).	556	0.1574	0.0708	0.0138	0.4385
Urban	Ratio of households who live in urban areas.	556	0.3493	0.2242	0.0387	1.0000
Agriculture	Ratio of households whose head is engaged in agriculture.	556	0.5098	0.1965	0.0021	0.8529
Aged	Population share of individuals aged more than or equal to 65.	556	0.1302	0.0539	0.0000	0.3538

Table 3: Bi-variate correlation coefficients of mean per-capita consumption expenditure, inequality measures, and poverty measures in Thailand

	Consumptio n	FGT(0)	FGT(1)	FGT(2)	Watt's Index	Clark-Watt's Index (-1)	GE(-1)	GE(0)	GE(1)	GE(2)	Gini
Consumption	1.0000										
FGT(0)	-0.7879	1.0000									
FGT(1)	-0.7513	0.9691	1.0000								
FGT(2)	-0.7074	0.9243	0.9877	1.0000							
Watt's Index	-0.7364	0.9545	0.9980	0.9956	1.0000						
Clark-Watt's Index (-1)	-0.7133	0.9302	0.9889	0.9993	0.9964	1.0000					
GE(-1)	-0.0234	0.1929	0.1848	0.1789	0.1829	0.1791	1.0000				
GE(0)	-0.0884	0.2323	0.2179	0.2060	0.2137	0.2067	0.9837	1.0000			
GE(1)	-0.1195	0.2368	0.2194	0.2042	0.2139	0.2054	0.9275	0.9753	1.0000		
GE(2)	-0.0791	0.1745	0.1595	0.1469	0.1550	0.1482	0.8006	0.8660	0.9478	1.0000	
Gini	-0.1151	0.2427	0.2226	0.2070	0.2171	0.2085	0.9639	0.9912	0.9671	0.8449	1.0000

Table 4: Bi-variate correlation coefficients of mean per-capita consumption expenditure, inequality measures, and poverty measures in the Philippines

	Consumptio n	FGT(0)	FGT(1)	FGT(2)	Watt's Index	Clark-Watt's Index (-1)	GE(-1)	GE(0)	GE(1)	GE(2)	Gini
Consumption	1.0000										
FGT(0)	-0.8993	1.0000									
FGT(1)	-0.8395	0.9529	1.0000								
FGT(2)	-0.7782	0.8915	0.9855	1.0000							
Watt's Index	-0.8109	0.9205	0.9918	0.9924	1.0000						
Clark-Watt's Index (-1)	-0.7704	0.8760	0.9745	0.9937	0.9932	1.0000					
GE(-1)	0.1265	-0.0116	0.0863	0.1329	0.1240	0.1520	1.0000				
GE(0)	0.0542	0.0761	0.1586	0.1929	0.1908	0.2103	0.9807	1.0000			
GE(1)	-0.0288	0.1705	0.2324	0.2526	0.2559	0.2663	0.9068	0.9677	1.0000		
GE(2)	-0.0821	0.2189	0.2582	0.2661	0.2707	0.2735	0.7119	0.8046	0.9190	1.0000	
Gini	0.0728	0.0552	0.1381	0.1727	0.1711	0.1898	0.9683	0.9911	0.9510	0.7713	1.0000

Table 5: System-GMM estimation results, Thailand

	L.H.S. variable = *Consumption* (*t*)				L.H.S. variable = *Gini* (*t*)				L.H.S. variable = *Poverty* (*t*)			
(With year effect only)	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	0.67039	0.08014	8.37	0.000	-0.06647	0.00904	-7.36	0.000	-0.09754	0.03204	-3.04	0.002
Gini (*t* -1)	-1.69689	0.17992	-9.43	0.000	0.30126	0.05954	5.06	0.000	0.47377	0.09456	5.01	0.000
Poverty (*t* -1)	0.27886	0.09177	3.04	0.002	0.00594	0.02052	0.29	0.772	0.19720	0.08283	2.38	0.017
Intercept	3.17803	0.59649	5.33	0.000	0.79058	0.06899	11.46	0.000	0.62437	0.24724	2.53	0.012
Wald chi-square test	Chi2 (10) = 687.82		Prov > chi2 = 0.000		Chi2 (10) = 414.93		Prov > chi2 = 0.000		Chi2 (10) = 497.14		Prov > chi2 = 0.000	
Hansen J test	Chi2 (34) = 38.78		Prov > chi2 = 0.263		Chi2 (34) = 32.51		Prov > chi2 = 0.541		Chi2 (34) = 28.60		Prov > chi2 = 0.729	
AR(1)	z= -6.03		Prov > z = 0.000		z= -5.99		Prov > z = 0.000		z= -5.51		Prov > z = 0.000	
AR(2)	z= 0.15		Prov > z = 0.885		z= 1.00		Prov > z = 0.318		z= -0.84		Prov > z = 0.399	
(With year effect and controls)	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	0.75115	0.10175	7.38	0.000	-0.05522	0.01323	-4.17	0.000	-0.11283	0.03854	-2.93	0.003
Gini (*t* -1)	-1.61844	0.21614	-7.49	0.000	0.29317	0.06877	4.26	0.000	0.36639	0.11186	3.28	0.001
Poverty (*t* -1)	0.28438	0.07930	3.59	0.000	0.00210	0.02026	0.10	0.917	0.19295	0.08251	2.34	0.019
Education (*t* -1)	-0.41435	0.21917	-1.89	0.059	-0.04492	0.04636	-0.97	0.333	0.20707	0.11063	1.87	0.061
Urban (*t* -1)	-0.08710	0.08100	-1.08	0.282	0.03427	0.01326	2.58	0.010	0.01079	0.03487	0.31	0.757
Agriculture (*t* -1)	-0.01811	0.08403	-0.22	0.829	0.03785	0.01582	2.39	0.017	0.04536	0.03268	1.39	0.165
Aged (*t* -1)	-0.09324	0.16517	-0.56	0.572	-0.04181	0.03980	-1.05	0.293	-0.03258	0.09297	-0.35	0.726
Intercept	2.70775	0.73539	3.68	0.000	0.68770	0.10035	6.85	0.000	0.71238	0.28806	2.47	0.013
Wald chi-square test	Chi2 (14) = 771.35		Prov > chi2 = 0.000		Chi2 (14) = 616.38		Prov > chi2 = 0.000		Chi2 (14) = 534.92		Prov > chi2 = 0.000	
Hansen J test	Chi2 (34) = 37.96		Prov > chi2 = 0.294		Chi2 (34) = 31.17		Prov > chi2 = 0.607		Chi2 (34) = 29.77		Prov > chi2 = 0.675	
AR(1)	z= -6.16		Prov > z = 0.000		z= -5.85		Prov > z = 0.000		z= -5.22		Prov > z = 0.000	
AR(2)	z= 0.13		Prov > z = 0.894		z= 1.16		Prov > z = 0.248		z= -0.70		Prov > z = 0.481	

Note: The number of observations is 577 and the number of groups in the panel is 76.

Table 6: Results based on different estimation methods, Thailand

L.H.S. variable = *Consumption* (*t*)

1. Pooled OLS				
(With year effect only)	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	0.70365	0.03467	20.29	0.000
Gini (*t* -1)	-1.12180	0.14618	-7.67	0.000
Poverty (*t* -1)	0.09705	0.07092	1.37	0.172
(With year effect and controls)	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	0.58694	0.04733	12.40	0.000
Gini (*t* -1)	-0.90382	0.16366	-5.52	0.000
Poverty (*t* -1)	0.09450	0.07089	1.33	0.183
2. Fixed effects				
(With year effect only)	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	0.26325	0.04918	5.35	0.000
Gini (*t* -1)	-0.47916	0.19149	-2.50	0.013
Poverty (*t* -1)	-0.02751	0.07299	-0.38	0.706
(With year effect and controls)	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	0.25162	0.05661	4.44	0.000
Gini (*t* -1)	-0.43850	0.19986	-2.19	0.029
Poverty (*t* -1)	-0.00614	0.07404	-0.08	0.934

L.H.S. variable = *Gini* (*t*)

1. Pooled OLS				
(With year effect only)	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	-0.04629	0.00832	-5.57	0.000
Gini (*t* -1)	0.46255	0.03506	13.19	0.000
Poverty (*t* -1)	0.02017	0.01701	1.19	0.236
(With year effect and controls)	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	-0.02674	0.01128	-2.37	0.018
Gini (*t* -1)	0.39180	0.03900	10.05	0.000
Poverty (*t* -1)	0.01809	0.01689	1.07	0.285
2. Fixed effects				
(With year effect only)	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	0.00659	0.01145	0.58	0.565
Gini (*t* -1)	0.01875	0.04457	0.42	0.674
Poverty (*t* -1)	0.01269	0.01699	0.75	0.456
(With year effect and controls)	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	0.01064	0.01318	0.81	0.420
Gini (*t* -1)	0.01885	0.04652	0.41	0.685
Poverty (*t* -1)	0.01487	0.01724	0.86	0.389

L.H.S. variable = *Poverty* (*t*)

1. Pooled OLS				
(With year effect only)	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	-0.15717	0.02085	-7.54	0.000
Gini (*t* -1)	0.45878	0.08793	5.22	0.000
Poverty (*t* -1)	0.18621	0.04266	4.37	0.000
(With year effect and controls)	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	-0.15825	0.02864	-5.53	0.000
Gini (*t* -1)	0.34490	0.09904	3.48	0.001
Poverty (*t* -1)	0.17036	0.04290	3.97	0.000
2. Fixed effects				
(With year effect only)	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	-0.12538	0.03053	-4.11	0.000
Gini (*t* -1)	0.16503	0.11888	1.39	0.166
Poverty (*t* -1)	-0.00285	0.04531	-0.06	0.950
(With year effect and controls)	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	-0.14957	0.03468	-4.31	0.000
Gini (*t* -1)	0.05778	0.12242	0.47	0.637
Poverty (*t* -1)	-0.03039	0.04535	-0.67	0.503

Note: Parameter estimates for other right-hand-side variables and test results are omitted for brevity. Full results analogous to those in Table 5 are available on request.

Table 7: Estimation results for the constrained model, Thailand

System GMM estimation results

(With year effect only)	L.H.S. variable = *Consumption* (*t*)				L.H.S. variable = *Gini* (*t*)			
	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	0.58244	0.06681	8.72	0.000	-0.06834	0.00772	-8.85	0.000
Gini (*t* -1)	-1.56277	0.17467	-8.95	0.000	0.30831	0.05521	5.58	0.000
Intercept	3.81615	0.50083	7.62	0.000	0.80270	0.06669	12.04	0.000
Wald chi-square test	Chi2 (9) = 667.57		Prov > chi2 = 0.000		Chi2 (9) = 410.11		Prov > chi2 = 0.000	
Hansen J test	Chi2 (34) = 37.21		Prov > chi2 = 0.324		Chi2 (34) = 33.94		Prov > chi2 = 0.471	
AR(1)	z= -6.33		Prov > z = 0.000		z= -5.99		Prov > z = 0.000	
AR(2)	z= -0.22		Prov > z = 0.830		z= 1.03		Prov > z = 0.302	

Fixed effect estimation results, L.H.S. variable = *Poverty* (*t*)

(With year effect only)	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	-0.01350	0.01888	-0.72	0.475
Gini (*t* -1)	0.13247	0.07838	1.69	0.092
Intercept	0.13107	0.12603	1.04	0.299
F test for 0 slope	F (8, 439) = 24.03		Prov > F = 0.000	
F test that all u_i=(	F (75, 439) = 3.67		Prov > F = 0.000	

Fixed effect estimation results, L.H.S. variable = *Poverty* (*t*)

(With year effect only)	Coef.	Std. Err.	t-stat	P>t
Consumption (*t*)	-0.30138	0.01627	-18.52	0.000
Gini (*t*)	0.75709	0.06681	11.33	0.000
Intercept	1.97931	0.10721	18.46	0.000
F test for 0 slope	F (9, 514) = 124.75		Prov > F = 0.000	
F test that all u_i=0	F (75, 514) = 3.85		Prov > F = 0.000	

System GMM estimation results

(With all controls)	L.H.S. variable = *Consumption* (*t*)				L.H.S. variable = *Gini* (*t*)			
	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	0.67536	0.09292	7.27	0.000	-0.05610	0.01125	-4.99	0.000
Gini (*t* -1)	-1.52205	0.21850	-6.97	0.000	0.29760	0.06598	4.51	0.000
Education (*t* -1)	-0.40296	0.22206	-1.81	0.070	-0.04542	0.04618	-0.98	0.325
Urban (*t* -1)	-0.10405	0.08579	-1.21	0.225	0.03435	0.01314	2.61	0.009
Agriculture (*t* -1)	0.00437	0.08685	0.05	0.960	0.03723	0.01616	2.30	0.021
Aged (*t* -1)	-0.13554	0.16474	-0.82	0.411	-0.04255	0.03986	-1.07	0.286
Intercept	3.27333	0.67149	4.87	0.000	0.69345	0.08967	7.73	0.000
Wald chi-square test	Chi2 (13) = 749.98		Prov > chi2 = 0.000		Chi2 (13) = 607.70		Prov > chi2 = 0.000	
Hansen J test	Chi2 (34) = 36.8		Prov > chi2 = 0.341		Chi2 (34) = 31.78		Prov > chi2 = 0.577	
AR(1)	z= -6.38		Prov > z = 0.000		z= -5.85		Prov > z = 0.000	
AR(2)	z= 0.26		Prov > z = 0.792		z= 1.17		Prov > z = 0.240	

Fixed effect estimation results, L.H.S. variable = *Poverty* (*t*)

(With all controls)	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	-0.13888	0.03077	-4.51	0.000
Gini (*t* -1)	0.04395	0.12060	0.36	0.716
Education (*t* -1)	0.39129	0.11795	3.32	0.001
Urban (*t* -1)	-0.11651	0.04048	-2.88	0.004
Agriculture (*t* -1)	0.01937	0.04534	0.43	0.669
Aged (*t* -1)	-0.04989	0.11024	-0.45	0.651
Intercept	1.19590	0.21897	5.46	0.000
F test for 0 slope	F (13, 500) = 42.21		Prov > F = 0.000	
F test that all u_i=(	F (75, 500) = 2.50		Prov > F = 0.000	

Fixed effect estimation results, L.H.S. variable = *Poverty* (*t*)

(With all controls)	Coef.	Std. Err.	t-stat	P>t
Consumption (*t*)	-0.32774	0.02952	-11.10	0.000
Gini (*t*)	0.47573	0.11109	4.28	0.000
Education (*t*)	0.21466	0.10372	2.07	0.039
Urban (*t*)	-0.10597	0.03556	-2.98	0.003
Agriculture (*t*)	0.09468	0.04254	2.23	0.026
Aged (*t*)	-0.06808	0.09940	-0.68	0.494
Intercept	2.42355	0.20184	12.01	0.000
F test for 0 slope	F (14, 567) = 88.40		Prov > F = 0.000	
F test that all u_i=0	F (75, 567) = 2.46		Prov > F = 0.000	

Note: The number of observations is 577 and the number of groups in the panel is 76.

Table 8: System-GMM estimation results, the Philippines

	L.H.S. variable = *Consumption* (*t*)				L.H.S. variable = *Gini* (*t*)				L.H.S. variable = *Poverty* (*t*)			
(With year effect only)	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	1.05618	0.24625	4.29	0.000	-0.07910	0.02589	-3.06	0.002	-0.23471	0.09749	-2.41	0.016
Gini (*t* -1)	-1.26020	0.39378	-3.20	0.001	0.37046	0.12203	3.04	0.002	0.16899	0.15989	1.06	0.291
Poverty (*t* -1)	0.42608	0.37560	1.13	0.257	-0.09875	0.04423	-2.23	0.026	0.34604	0.19374	1.79	0.074
Intercept	-0.20768	2.22235	-0.09	0.926	0.95911	0.22305	4.30	0.000	2.22216	0.90389	2.46	0.014
Wald chi-square test	Chi2 (8) = 903.61		Prov > chi2 = 0.000		Chi2 (8) = 48.38		Prov > chi2 = 0.000		Chi2 (8) = 770.43		Prov > chi2 = 0.000	
Hansen J test	Chi2 (19) = 21.67		Prov > chi2 = 0.301		Chi2 (19) = 27.12		Prov > chi2 = 0.102		Chi2 (19) = 25.44		Prov > chi2 = 0.147	
AR(1)	z= -5.60		Prov > z = 0.000		z= -4.81		Prov > z = 0.000		z= -6.09		Prov > z = 0.000	
AR(2)	z= 1.54		Prov > z = 0.123		z= -0.02		Prov > z = 0.982		z= 1.65		Prov > z = 0.098	

(With year effect and controls)	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	1.13230	0.21070	5.37	0.000	-0.12780	0.02970	-4.30	0.000	-0.09647	0.08693	-1.11	0.267
Gini (*t* -1)	-1.43039	0.34073	-4.20	0.000	0.39743	0.12219	3.25	0.001	0.05513	0.12379	0.45	0.656
Poverty (*t* -1)	0.85348	0.23336	3.66	0.000	-0.09527	0.04597	-2.07	0.038	0.33156	0.18976	1.75	0.081
Education (*t* -1)	-0.14917	0.31131	-0.48	0.632	0.10116	0.07856	1.29	0.198	0.15301	0.14375	1.06	0.287
Urban (*t* -1)	0.26780	0.07573	3.54	0.000	-0.02125	0.02444	-0.87	0.385	-0.21072	0.05224	-4.03	0.000
Agriculture (*t* -1)	-0.18204	0.12041	-1.51	0.131	-0.09248	0.02949	-3.14	0.002	0.14409	0.06910	2.09	0.037
Aged (*t* -1)	0.42152	0.19064	2.21	0.027	0.08959	0.06156	1.46	0.146	-0.27370	0.11515	-2.38	0.017
Intercept	-1.05348	1.83983	-0.57	0.567	1.38907	0.25497	5.45	0.000	1.09906	0.81066	1.36	0.175
Wald chi-square test	Chi2 (12) = 1916.36		Prov > chi2 = 0.000		Chi2 (12) = 106.32		Prov > chi2 = 0.000		Chi2 (12) = 1582.88		Prov > chi2 = 0.000	
Hansen J test	Chi2 (19) = 16.32		Prov > chi2 = 0.636		Chi2 (19) = 23.67		Prov > chi2 = 0.209		Chi2 (19) = 22.60		Prov > chi2 = 0.255	
AR(1)	z= -4.78		Prov > z = 0.000		z= -4.86		Prov > z = 0.000		z= -5.38		Prov > z = 0.000	
AR(2)	z= 1.29		Prov > z = 0.196		z= -0.34		Prov > z = 0.731		z= 0.67		Prov > z = 0.504	

Note: The number of observations is 449 and the number of groups in the panel is 82.

Table 9: Results based on different estimation methods, the Philippines

1. Pooled OLS	L.H.S. variable = *Consumption* (*t*)				L.H.S. variable = *Gini* (*t*)				L.H.S. variable = *Poverty* (*t*)			
(With year effect only)	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	0.99071	0.05018	19.74	0.000	-0.05733	0.01323	-4.33	0.000	-0.15042	0.03086	-4.87	0.000
Gini (*t* -1)	-0.52989	0.14743	-3.59	0.000	0.62889	0.03888	16.17	0.000	0.03187	0.09068	0.35	0.725
Poverty (*t* -1)	0.10195	0.09179	1.11	0.267	-0.07230	0.02421	-2.99	0.003	0.62559	0.05646	11.08	0.000
(With year effect and controls)	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	0.81214	0.05487	14.80	0.000	-0.07876	0.01528	-5.15	0.000	-0.07621	0.03460	-2.20	0.028
Gini (*t* -1)	-0.61699	0.14321	-4.31	0.000	0.59336	0.03989	14.88	0.000	0.07153	0.09031	0.79	0.429
Poverty (*t* -1)	0.22824	0.08838	2.58	0.010	-0.05247	0.02461	-2.13	0.034	0.55176	0.05573	9.90	0.000
2. Fixed effects												
(With year effect only)	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	0.28259	0.10389	2.72	0.007	-0.01190	0.02799	-0.43	0.671	-0.15013	0.06637	-2.26	0.024
Gini (*t* -1)	-0.43925	0.24183	-1.82	0.070	0.01830	0.06515	0.28	0.779	0.19414	0.15449	1.26	0.210
Poverty (*t* -1)	0.03578	0.13501	0.26	0.791	0.00459	0.03637	0.13	0.900	0.12360	0.08625	1.43	0.153
(With year effect and controls)	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t
Consumption (*t* -1)	0.25263	0.10598	2.38	0.018	-0.02700	0.02856	-0.95	0.345	-0.13586	0.06778	-2.00	0.046
Gini (*t* -1)	-0.50063	0.24211	-2.07	0.039	0.00855	0.06525	0.13	0.896	0.22667	0.15485	1.46	0.144
Poverty (*t* -1)	0.05194	0.13572	0.38	0.702	0.01064	0.03658	0.29	0.771	0.10136	0.08680	1.17	0.244

Note: Parameter estimates for other right-hand-side variables and test results are omitted for brevity. Full results analogous to those in Table 8 are available on request.

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

	System GMM estimation results									Fixed effect estimation results					Fixed effect estimation results			
	L.H.S. variable = *Consumption* (*t*)				L.H.S. variable = *Gini* (*t*)					L.H.S. variable = *Poverty* (*t*)					L.H.S.variable = *Poverty* (*t*)			
(With year effect only)	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t		Coef.	Std. Err.	t-stat	P>t		Coef.	Std. Err.	t-stat	P>t
Consumption (*t*-1)	0.84976	0.07634	11.13	0.000	-0.02862	0.00863	-3.32	0.001	*Consumption* (*t*-1)	-0.23611	0.03371	-7.01	0.000	*Consumption* (*t*)	-0.65882	0.01778	-37.06	0.000
Gini (*t*-1)	-0.99125	0.28399	-3.49	0.000	0.27881	0.10634	2.62	0.009	*Gini* (*t*-1)	0.40847	0.12344	3.31	0.001	*Gini* (*t*)	1.05189	0.06723	15.65	0.000
Intercept	1.67888	0.68209	2.46	0.014	0.50981	0.08474	6.02	0.000	*Intercept*	2.42889	0.27335	8.89	0.000	*Intercept*	5.80165	0.14425	40.22	0.000
Wald chi-square test	Chi2 (7) =395.70		Prov > chi2 = 0.000		Chi2 (7) = 42.86		Prov > chi2 = 0.000		F test for 0 slope	F (7, 382) = 41.18		Prov > F = 0.000		F test for 0 slope	F (8, 463) = 268.44		Prov > F = 0.000	
Hansen J test	Chi2 (19) = 21.40		Prov > chi2 = 0.315		Chi2 (19) = 29.66		Prov > chi2 = 0.056											
AR(1)	z= -5.94		Prov > z = 0.000		z= -4.71		Prov > z = 0.000		F test that all u_i=(	F (81, 382) = 5.01		Prov > F = 0.000		F test that all u_i=(	F (84, 463) = 10.83		Prov > F = 0.000	
AR(2)	z= 1.33		Prov > z = 0.185		z= 0.08		Prov > z = 0.939											
(With all controls)	Coef.	Std. Err.	t-stat	P>t	Coef.	Std. Err.	t-stat	P>t		Coef.	Std. Err.	t-stat	P>t		Coef.	Std. Err.	t-stat	P>t
Consumption (*t*-1)	0.75834	0.12428	6.10	0.000	-0.08018	0.01610	-4.98	0.000	*Consumption* (*t*-1)	-0.20039	0.03926	-5.10	0.000	*Consumption* (*t*)	-0.66009	0.02350	-28.09	0.000
Gini (*t*-1)	-0.88795	0.25514	-3.48	0.001	0.31450	0.10978	2.86	0.004	*Gini* (*t*-1)	0.33017	0.12704	2.60	0.010	*Gini* (*t*)	1.03900	0.07768	13.38	0.000
Education (*t*-1)	-0.11497	0.29895	-0.38	0.701	0.08916	0.07783	1.15	0.252	*Education* (*t*-1)	-0.00878	0.14623	-0.06	0.952	*Education* (*t*)	0.12208	0.08961	1.36	0.174
Urban (*t*-1)	0.26631	0.08110	3.28	0.001	-0.02481	0.02415	-1.03	0.304	*Urban* (*t*-1)	0.08951	0.09134	0.98	0.328	*Urban* (*t*)	0.04170	0.05547	0.75	0.453
Agriculture (*t*-1)	-0.08466	0.12878	-0.66	0.511	-0.10176	0.02823	-3.60	0.000	*Agriculture* (*t*-1)	0.17355	0.08567	2.03	0.044	*Agriculture* (*t*)	0.11463	0.05292	2.17	0.031
Aged (*t*-1)	0.27221	0.18182	1.50	0.134	0.10626	0.05837	1.82	0.069	*Aged* (*t*-1)	0.23838	0.14919	1.60	0.111	*Aged* (*t*)	0.07972	0.09276	0.86	0.391
Intercept	2.35321	1.07243	2.19	0.028	0.96824	0.14791	6.55	0.000	*Intercept*	1.97644	0.33758	5.85	0.000	*Intercept*	5.71813	0.20433	27.98	0.000
Wald chi-square test	Chi2 (11) = 2318.32		Prov > chi2 = 0.000		Chi2 (11) = 90.45		Prov > chi2 = 0.000		F test for 0 slope	F (11, 365) = 27.32		Prov > F = 0.000		F test for 0 slope	F (11, 361) = 133.02		Prov > F = 0.000	
Hansen J test	Chi2 (19) = 18.37		Prov > chi2 = 0.498		Chi2 (19) = 25.11		Prov > chi2 = 0.157											
AR(1)	z= -5.53		Prov > z = 0.000		z= -4.84		Prov > z = 0.000		F test that all u_i=(	F (81, 365) = 3.80		Prov > F = 0.000		F test that all u_i=(	F (81, 361) = 9.02		Prov > F = 0.000	
AR(2)	z= 1.03		Prov > z = 0.302		z= -0.26		Prov > z = 0.793											

Note: The number of observations is 449 and the number of groups in the panel is 82.

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
Simulation 1: Adding a shock to equation (2) in 1988 so that the inequality level in that year is halved from the actual value				
Counterfactual	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)				
Counterfactual	-9.73	-0.10	10.96	3.16
Simulation 2(b): Replacing the values of $\beta_{12,}$ β_{22}, and β_{32} (the marginal effects of lagged inequality on growth, inequality and poverty, respectively) with the values of the other country)				
Counterfactual	1.83	-0.35	4.86	3.39

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

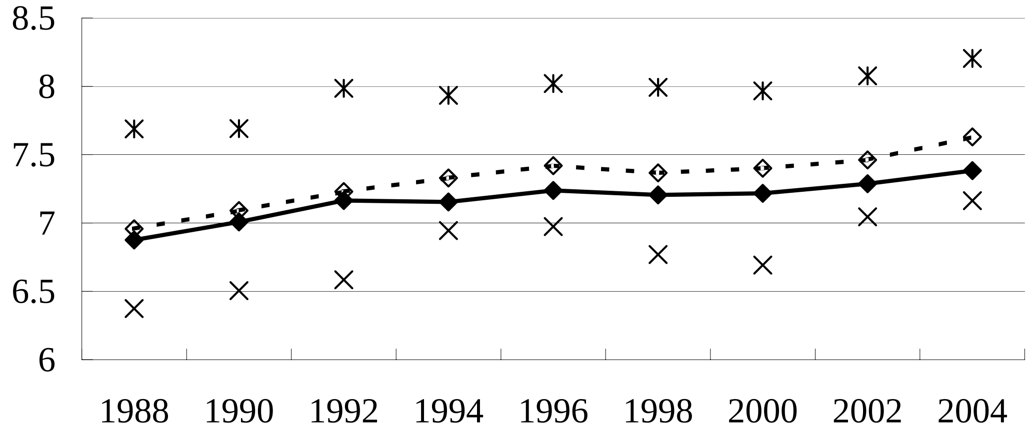

Figure 1(b): Time Series of *Gini* , Thailand

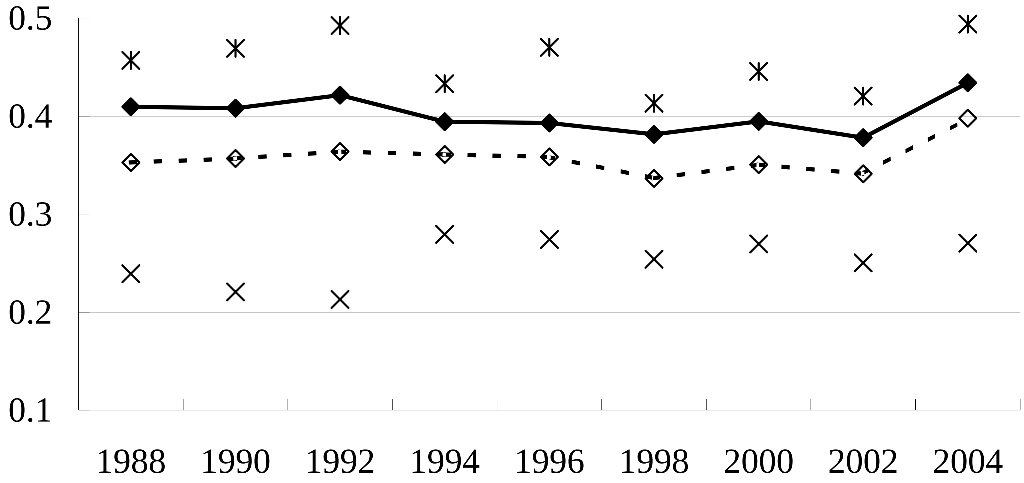

Figure 1(c): Time Series of *Poverty* , Thailand

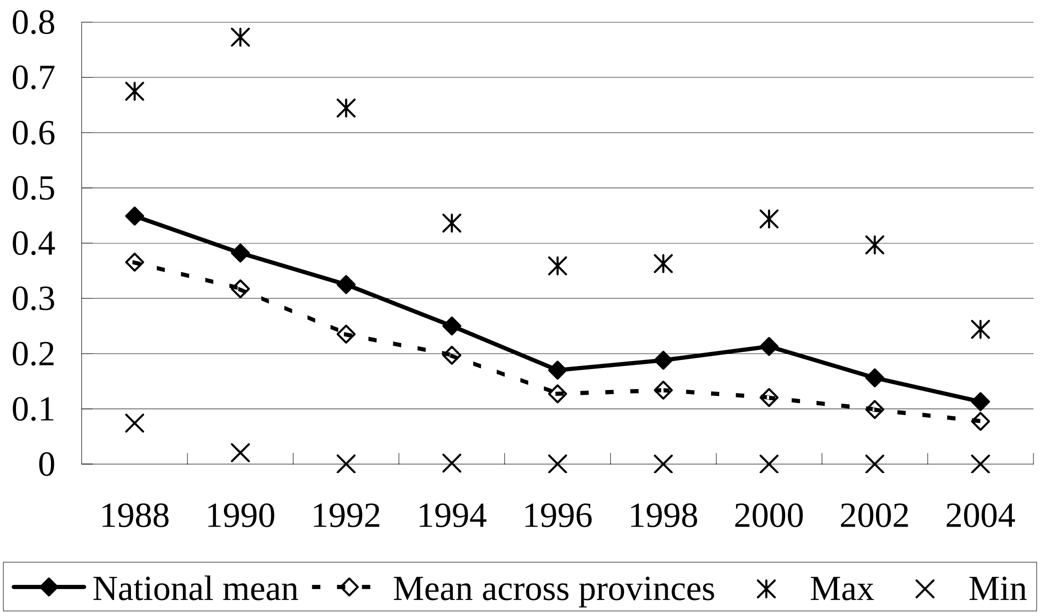

Figure 2(a): Time Series of *Consumption* , the Philippines

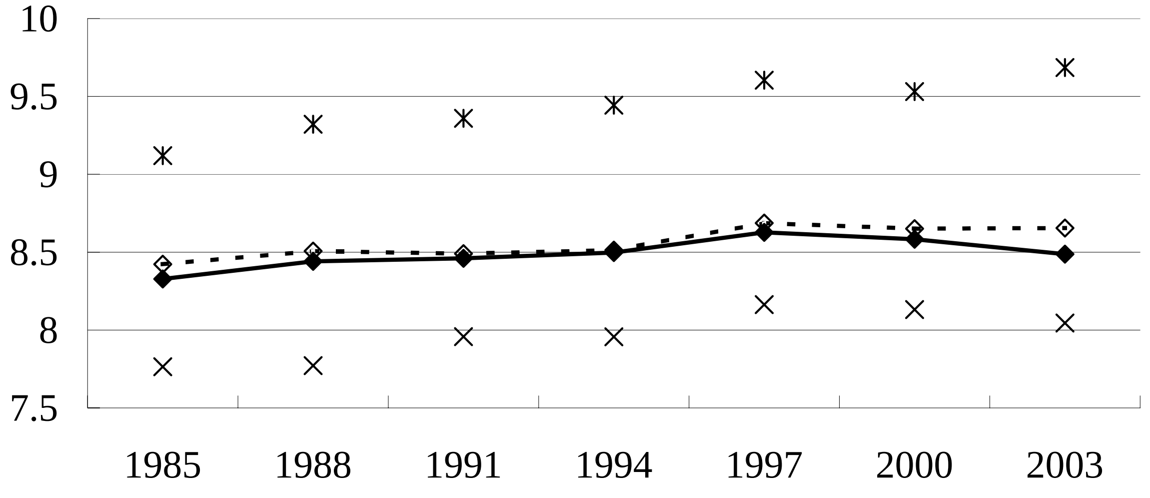

Figure 2(b): Time Series of *Gini* , the Philippines

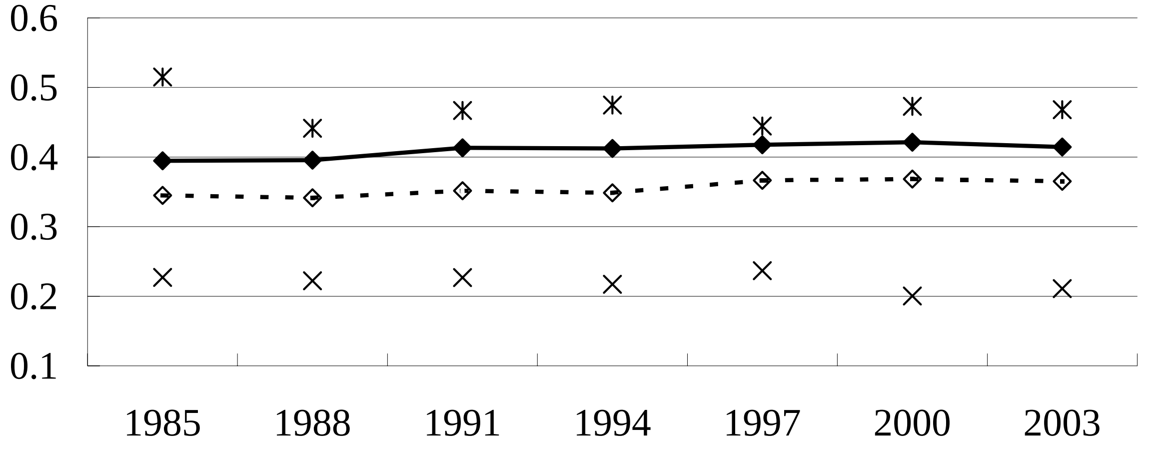

Figure 2(c): Time Series of *Poverty* , the Philippines